Assessing Financial Distress: "A Comparative Analysis of Altman Z-Score and Machine Learning Models Within a Technology Adoption Framework"

***Dr.T.Hymavathi Kumari**
****Ms.Akankhya Panda**
*Associate Professor, IIAM B-School, Vizag,Email ID: hymavathi@tenneti@gmail.com
**Assistant Professor, IIAM B-School, Vizag, Email ID: akankhya08panda@gmail.com

ABSTRACT

Financial distress is an unfavourable situation that a company may experience at any point in its lifetime. All the company stakeholders are interested in its financial stability since they have different kinds of interests. Consequently, it is management's responsibility to take all the necessary measures to prevent financial distress in any company.

This study assesses the financial distress of the top five companies by market capitalisation in the automobile industry listed in the NSE and operating in India for a period of seven years from 2019 to 2025 using the Altman Z-score model. The same data set was calculated using the Altman Z, Score test with ML, based on tools such as Python, using Artificial Intelligence, by applying the same variables to compare the result accuracy.

The present analysis technology aims to illuminate how technological tools supplement traditional methods. By integrating traditional and technological models, this research demonstrates the relevance of both models, and these findings assist managers in selecting tools that are appropriate for their strategic goals and implementation. The study found that comparing the trends in the data and the AI-generated computations for financial decisions revealed consistent trends, but the results calculated by Python were generally more accurate, easier to predict, and more useful for financial decision-making. AI-generated results, unlike static ones, are mathematically superior and linked with the technological implementation.

Keywords:

Financial Distress, bankruptcy, Altman Z-Score,

Introduction:

Financial distress is a direct consequence of a company's inability to generate the required revenues to meet its financial obligations. It is usually triggered by the presence of high fixed costs in the company's cost structure and a large volume of illiquid assets. In the long run, financial distress can evolve into bankruptcy and credit rating deterioration. Financial distress is a situation in which the company's revenues are not enough to meet its financial obligations. Mismanagement, in general, could be the underlying cause of the problem. This includes investing too much in unprofitable projects or financing poorly, dividend policies, as well as inefficient working capital management. If the firm experiences financial distress, this will result in its stock rating being downgraded. Consequently, investors will require higher interest rates on the loans they grant to the business. Financial distress must be dealt with urgently as it will inevitably lead to the company's bankruptcy. Financial distress is a condition that signals managers to be cautious in their financial dealings and even take more decisive steps to address the problem. Eventually, financial distress could lead to bankruptcy.

Bankruptcy is a legal procedure that essentially wipes the slate clean for individuals or businesses that are unable to meet their debt obligations. The survival and expansion of companies depend on how well they manage to check their financial status within a fixed period of time. Knowing a company's future position is very helpful, even if it is large or performs other types of business (Svabova et al. , 2020). Financial distress refers to the condition of a company that experiences financial problems, such as the inability to pay dividends, meet obligations, or carry out operations (Beaver, 1966). In the past, companies in distress had more viable alternatives to turn around their situations. This, in effect, led to the development of various methods for evaluating companies' financial health depending on their sizes and effects on lenders and other stakeholders (Svabova et al. , 2020). Although numerous studies have recently proposed the use of machine learning techniques to predict financial distress, scant research has been conducted to compare the new methods with the traditional ones, such as the Altman Z-score, especially when the same datasets are used. Asghar (2023, pp. 80, 91) points out this research gap by stating that only a handful of studies have employed machine learning techniques on original data. This paper is committed to bridging this gap by performing a systematic assessment and comparison of both methods using the same data sources.

The Altman Z-Score Test:

The Altman Z-Score measures the financial strength of the company and shows the chances of becoming bankrupt. It is based on the five ratios namely,

X1= “Working Capital/Total Asset ratio” (WC/TA*100)

X2= “Retained Earnings to Total Asset ratio” (RE/TA*100)

X3= “EBIT to Total asset ratio” (EBIT/TA*100)

X4= “Market value of Equity to book value of Liabilities” (MVE/L*100)

X5= “Sales to Total Asset ratio” (S/TA)

$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5$

$Z > 2.99$ is safe; 1.81–2.99 is grey; < 1.81 is distress

Limitations of Z, Score:

However, the model is not without limitations. Z, Score is merely a suggestive score, and numerous factors can be considered to assess financial distress. Moreover, it is not a model suitable for companies in their growing stage, as typically they are characterised by heavy capital expenditure during the first stages of their establishment.

Review of Literature:

Various studies have been conducted worldwide to grasp the phenomenon of “Financial Distress” of companies.

The investigations contend with the deployment of different ratios to assess the situation, including liquidity ratios, leverage ratios, solvency ratios, and turnover ratios. In fact, all of these ratios are incorporated in the Altman Z, Score. Here, findings from the studies are presented:

The onset of predicting the financial doom of businesses through the employment of ratio analysis was attributed to Beaver (1966). Beaver resorted to univariate analysis, which is a traditional method of financial ratio interpretation (Beaver, 1966).

A year later, in 1968, Altman came up with a groundbreaking model that implemented multivariate discriminant analysis (MDA) with five financial ratios. Finch et al. (2008) investigated the impact of well-functioning governance practices on the avoidance of financial distress. Their discoveries suggest that governance characterised by, for example, a higher ratio of independent directors to insiders on the board as well as a larger ownership stake by insiders, can be very instrumental in the prevention of financial distress.

Elijelly (2004) executed an investigation entitled Liquidity Profitability Trade-Off: An empirical investigation in an emerging market, which was focused on joint stock companies in Saudi Arabia. The study unveiled the existence of a reverse connection between liquidity levels and a firm's profitability. Celli, M. (2015):

Bhunia A and Sarkar R conducted a study on 46 private sector pharmaceutical companies that were listed on a recognised Indian stock exchange. They applied multiple discriminant analyses using sixteen financial ratios, which included liquidity, solvency, and profitability ratios, to evaluate the financial distress of the firms. Seven of the sixteen ratios analysed were found to be the most significant in their ability to predict financial distress.

The MDA model was more than 85 per cent accurate in predicting financial failure that actually happened five years later. The set of financial ratios chosen has a very high correlation with the overall health of a company, which makes it possible to predict not only its success but also its failure in advance. The pioneering model was called the Altman Z, and it has become a popular tool in the areas of accounting and finance research ever since. (Georgiev & Petrova, 2015).

Additionally, this model was constructed only by using a sample of publicly traded companies in the United States. Studies have shown that the same model loses its predictive power in different countries due to changes in the economic environment across nations (Karas & Srbov, 2019).

The z-score is a model that can generate warnings for both the manufacturing and non-manufacturing sectors. (Aayushi Pandya, 2021). The study illustrated that the company experienced a financial crisis and moved into the grey area in 2005, after which the company's name was delisted from the NSE. This model obviously unveiled the situation of financial distress, and, therefore, it is crucial to study the model for financial distress. (Adam Shisia, 2014) The research was aimed at investigating Bankruptcy of private hotels in Greece, and the outcome was that this industry went into liquidation.

One year before bankruptcy, the company calculated the Altman Z-score, and it was in the red zone. (Diakomihalis, 2012) In light of this, the objective of this paper is to comprehend, review, and modify the Altman Z-score model concerning the Turkish context and to determine its feasibility for both publicly traded and non-traded companies in Turkey. Moreover, the coefficients will be re-evaluated, and the most accurate parameters will be estimated by the MDA model, quadratic discriminant analysis, and one of the most commonly used machine learning models, Random Forest, using the variables proposed by Altman.

Objectives of the study:

The objectives of the study are as follows:

- ➢ To predict the financial status of the top five selected Automobile companies listed in NSE, ranked by Market Capitalization in India, by applying the Altman Z, Score model for a period of seven years, i. e. , from 2019, 2025
- ➢ To assess the Z, Score results of the same companies by the use of Machine Learning tools
- ➢ To compare the traditional Altman Z, Score results with the Machine Learning tool-generated results. To analyse the accuracy of the result by using AI tools.
- ➢ To analyse the accuracy of the result by using AI tools

Research Methodology:

The study examines the financial distress of the top five market capitalisation automobile companies listed in the National Stock Exchange of India over the period of seven years, i. e. , from 2019 to 2025. These are Maruti Suzuki India Limited, Mahindra & Mahindra Limited, Bajaj Auto Limited, Eicher Motors Limited, and Hyundai Motor India Limited. Hence, the condition of these firms may reflect the general condition of the Automobile Industry in India. This research is based on secondary data sourced from Screener. in, Yahoo Finance, and the published annual reports of these companies. The following is the brief profile of the selected companies.

Maruthi Suzuki Limited:

Maruti Suzuki India Limited, founded in 1981, is the largest passenger vehicle manufacturer in India and a leading force in the auto sector. The company holds a market share of around 40- 45% of the total passenger vehicle market in India, which makes it the undisputed leader of the market.

Maruti Suzuki offers its customers the choice of hatchbacks, sedans, compact SUVs, and utility vehicles. The company has well-known models such as Swift, Baleno, Dzire, and Brezza. Maruti Suzuki's triumph is mainly attributed to the combination of low prices, fuel efficiency, efficient engines, a wide service network, and brand loyalty. It operates a sales and service network covering the entire country with more than 3, 000 outlets. The company is continuing to invest in electric and hybrid mobility solutions in line with future market trends. Maruti Suzuki is an important player in the Indian manufacturing ecosystem as it contributes to local sourcing and employment.

Mahindra & Mahindra:

Mahindra & Mahindra Limited, established in 1945 in India, is a prominent multinational company spanning the sectors of automobiles, farm equipment, and financial services. The company commands a market share of about 1517% in the SUV and utility vehicle segment in India. Its automotive portfolio features Scorpio, XUV700, Thar, and Bolero, which are widely acclaimed for their robustness and performance. Besides, Mahindra is the largest tractor manufacturer in the world by volume, thus significantly contributing to its diversified revenue stream. Mahindra is actively investing in electric mobility and connected vehicle technology, indicating its commitment to future growth. Additionally, the company is dedicated to eco-friendly practices and expanding in the rural market to consolidate its presence.

Bajaj Auto Limited:

Bajaj Auto Limited, established in 1945, is Pune-based and one of India's top two and three-wheeler manufacturers. The company holds a 44-46% market share in the domestic motorcycle segment, making it one of the most dominant two-wheeler brands in India. Besides that, Bajaj Auto is the world's largest exporter of three-wheeler vehicles and has a substantial presence in the markets of Asia, Africa, and Latin America. The company's motorcycles, widely known for their performance and fuel efficiency, include the Pulsar, Platina, and Domainer. Bajaj is still active in the electric mobility sector through collaborations and R&D. The company is committed to innovation, quality, and export to remain relevant and grow in competitive markets.

Eicher Motors Limited:

Eicher Motors Limited, launched in 1948 in India, is a leading manufacturer of motorcycles and commercial vehicles. Eicher is most known for its brand Royal Enfield motorcycles that have a commanding share of around 8788% in India in the mid-size (250750cc) motorcycle segment. The company, through a joint venture with Volvo (VECV), also operates in the truck and light commercial vehicle segment. Brand loyalty, innovative designs, and manufacturing quality are the main factors of its success. The company is expanding globally through exports to over 50 countries. Eicher has a large dealer and service network that ensures high customer reach. Eicher, with its strategic growth, strong product portfolio, and high segment leadership, is a major player in India's mobility industry.

Hyundai Motor Company:

Hyundai Motor Company, established in 1967 in South Korea, ranks among the largest automobile manufacturers in the world. In 1996, the company ventured into the Indian market, and within a short span of time, it became one of the top-selling brands. Hyundai manufactures hatchbacks, sedans, SUVs, and electric vehicles. i20, Creta, and Venue are some of the popular models of the company. The company, which holds around 1517% of the Indian passenger vehicle market, is ranked among the top three automakers. Worldwide, Hyundai has a yearly vehicle sales volume of more than 4 million in diverse markets. Its success is mainly fuelled by its affordable pricing, fuel, efficient vehicles, and a strong dealer network. The company remains competitive by focusing on innovation, digital connectivity, and quality standards. Hyundai is also spending money on electric and green mobility solutions to be compatible with sustainability goals.

Limitations Of The Study:

The study has been confined to analysing the financial distress situation of the top five Indian automobile companies over the last seven years only, i. e. , from 2019 to 2025. The Z-Score outcomes are compared by employing machine learning tools to find the accuracy.

One of the technological drawbacks may be the limitation of the study. The results of this research may not apply to small and medium, cap companies in India. The time period could have been extended for better inferences. The research is limited to companies operating in India.

Though the ML-calculated Z-score is mathematically better, no Z-score can give absolute assurance of future performance. It is a forecasting model with approximately 80- 90% accuracy in predicting bankruptcy within two years.

Data Analysis and Results:

Table 1: Maruthi Suzuki Limited:

year	X1 (WC/TA	X2 (RE/TA)	X3 (EBIT/TA	X4 (Mcap/LT lib)	X5 (Sales/TA)	Final Score	Financial Stability
2019	50%	21%	17%	1%	135%	2.81	Grey zone
2020	53%	16%	12%	1%	119%	2.45	Grey Zone
2021	53%	11%	8%	0%	99%	2.03	Grey Zone
2022	56%	8%	8%	1%	118%	2.23	Grey Zone
2023	53%	5%	13%	0%	139%	2.53	Grey Zone
2024	50%	10%	16%	3%	123%	2.52	Grey Zone
2025	48%	15%	15%	6%	116%	2.48	Grey Zone

Table 2: Mahindra & Mahindra Ltd:

year	X1 (WC/TA	X2 (RE/TA)	X3 (EBIT/TA	X4 (Mcap/LT lib)	X5 (Sales/TA)	Final Score	Financial Stability
2019	51%	7%	9%	1%	65%	**1.67**	**DistressZone**
2020	56%	7%	6%	1%	45%	**1.43**	**DistressZone**
2021	61%	7%	7%	1%	45%	**1.52**	**DistressZone**
2022	57%	10%	9%	2%	52%	**1.65**	**DistressZone**
2023	59%	13%	10%	2%	59%	**1.83**	**DistressZone**
2024	63%	16%	11%	3%	59%	**1.93**	**DistressZone**
2025	62%	17%	11%	3%	58%	**1.95**	**DistressZone**

Table 3: BAJAJ AUTO:

Year	X1 (WC/TA	X2 (RE/TA)	X3 (EBIT/TA	X4 (Mcap/LT lib)	X5 (Sales/TA)	Final Score	Financial Stability
2019	75%	42%	17%	737%	87%	7.35	Safe
2020	76%	53%	20%	792%	115%	8.19	Safe
2021	77%	44%	15%	777%	89%	7.59	Safe
2022	80%	48%	14%	832%	79%	7.88	Safe
2023	76%	54%	15%	1553%	94%	12.42	Safe
2024	70%	62%	16%	131%	93%	3.97	Safe
2025	76%	48%	16%	27%	83%	3.10	Safe

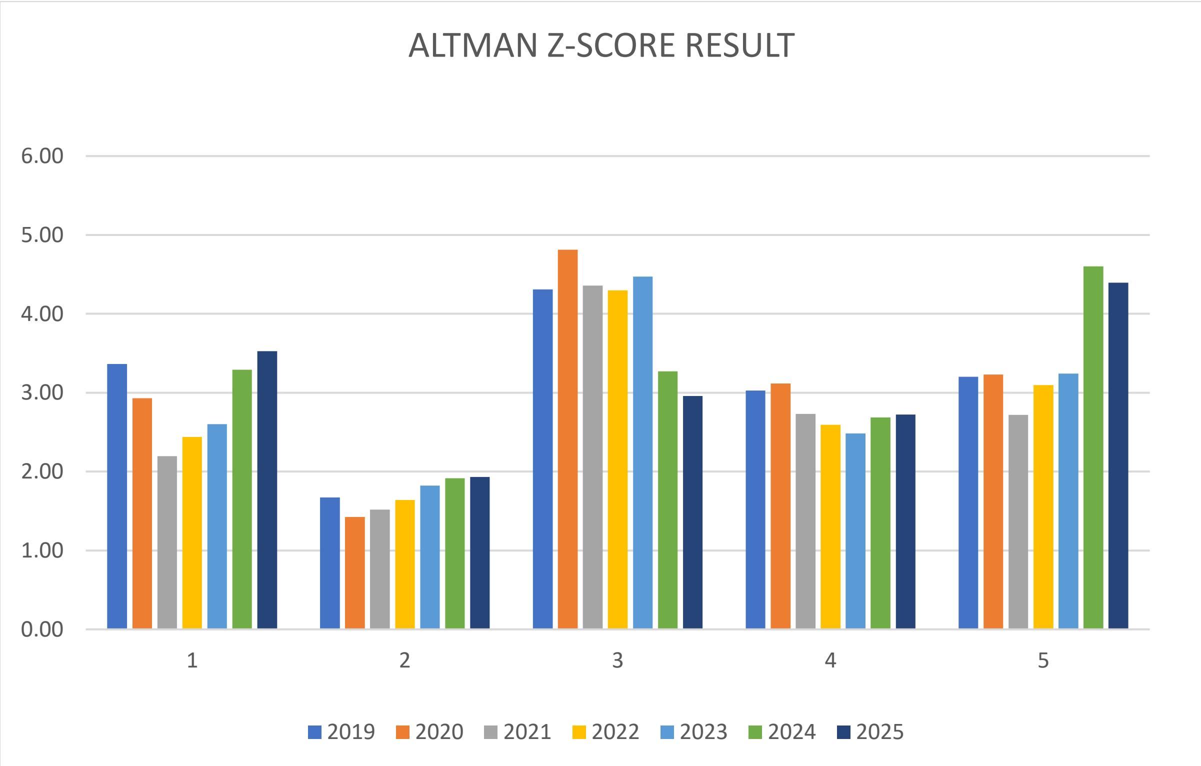
Table 4: EICHER MOTORS LIMITED:

year	X1 (WC/TA	X2 (RE/TA)	X3 (EBIT/TA	X4 (Mcap/LT lib)	X5 (Sales/TA)	Final Score	Financial Stability
2019	64%	41%	25%	329%	79%	4.91	Strong
2020	63%	53%	23%	278%	79%	4.72	Strong
2021	63%	55%	15%	324%	63%	4.60	Strong
2022	64%	55%	11%	817%	54%	7.35	Strong
2023	66%	52%	11%	394%	54%	4.79	Strong
2024	67%	52%	15%	321%	62%	4.57	Strong
2025	67%	53%	16%	439%	61%	5.32	Strong

Table 5: HYUNDAI:

Year	X1 (WC/TA	X2 (RE/TA)	X3 (EBIT/TA	X4 (Mcap/LT lib)	X5 (Sales/TA)	Final Score	Financial Stability
2019	38%	11%	21%	8%	187%	3.23	Strong
2020	28%	22%	19%	13%	192%	3.29	Strong
2021	30%	20%	16%	11%	153%	2.77	Strong
2022	36%	24%	19%	8%	168%	3.13	Strong
2023	40%	20%	22%	9%	175%	3.28	Strong
2024	11%	46%	35%	12%	267%	4.66	Strong
2025	30%	53%	30%	16%	230%	4.47	Strong

Chart-1

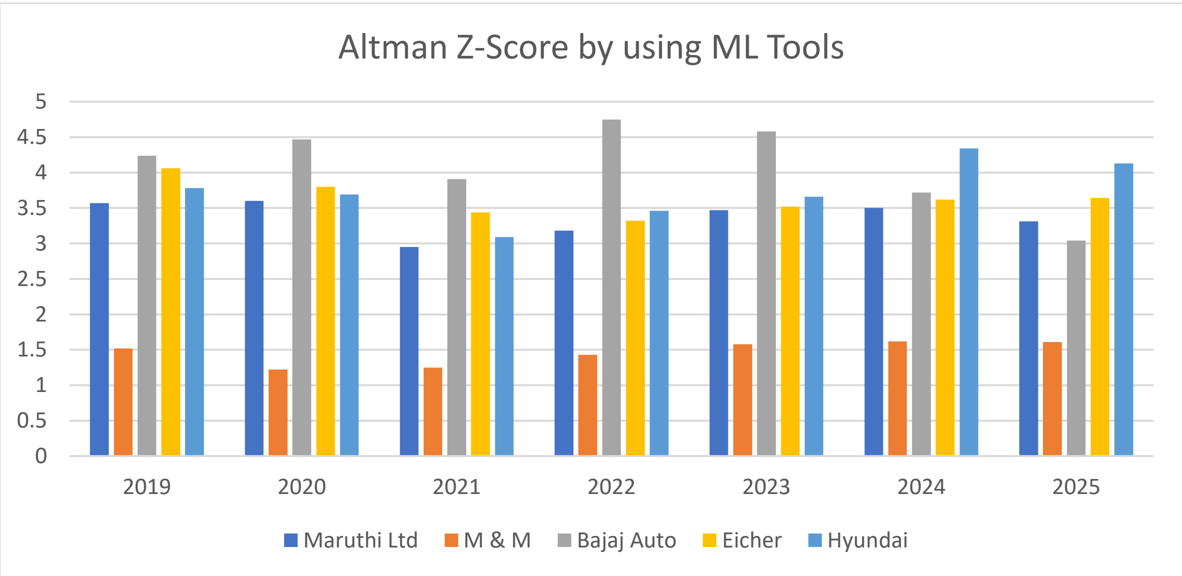


Altman Z-Score Analysis by using Machine Learning Tools:

Table 6:

Year	Maruthi Ltd	M & M	Bajaj Auto	Eicher	Hyundai
2019	3.57	1.52	4.24	4.06	3.78
2020	3.6	1.22	4.47	3.8	3.69
2021	2.95	1.25	3.91	3.44	3.09
2022	3.18	1.43	4.75	3.32	3.46
2023	3.47	1.58	4.58	3.52	3.66
2024	3.5	1.62	3.72	3.62	4.34
2025	3.31	1.61	3.04	3.64	4.13

Chart-2:



Comparative Analysis of Altman Z-Score by using Traditional Method and by using Machine Learning Tools:

Table 7: Maruthi Suzuki Limited:

	Traditional		ML Tools	
	Maruthi Suzuki Ltd			
Year	**Result**	**Zone**	**Result**	**Zone**
2019	3.57	Safe	3.37	Safe
2020	3.6	Safe	2.93	Grey
2021	2.95	Grey	2.19	Grey
2022	3.18	Safe	2.44	Grey
2023	3.47	Safe	2.60	Grey
2024	3.5	Safe	3.29	Safe
2025	3.31	Safe	3.53	Safe

Table 8: Mahindra & Mahindra

	Traditional		ML Tools	
	Mahindra & Mahindra			
Year	Result	Zone	Result	Zone
2019	1.52	Distress	1.67	Distress
2020	1.22	Distress	1.42	Distress
2021	1.25	Distress	1.52	Distress
2022	1.43	Distress	1.64	Distress
2023	1.58	Distress	1.82	Grey
2024	1.62	Distress	1.91	Grey
2025	1.61	Distress	1.93	Grey

Table 9: Bajaj Auto Limited

	Traditional		ML Tools	
	Bajaj Auto			
Year	Result	Zone	Result	Zone
2019	4.24	Safe	4.31	Safe
2020	4.47	Safe	4.81	Safe
2021	3.91	Safe	4.36	Safe
2022	4.75	Safe	4.30	Safe
2023	4.58	Safe	4.47	Safe
2024	3.72	Safe	3.27	Safe
2025	3.04	Safe	2.96	Safe

Table 10: Eicher Motors Limited

	Traditional		ML Tools	
	Eicher			
Year	Result	Zone	Result	Zone
2019	4.06	Safe	3.03	Safe
2020	3.8	Safe	3.12	Safe
2021	3.44	Safe	2.73	Grey
2022	3.32	Safe	2.59	Grey
2023	3.52	Safe	2.49	Grey
2024	3.62	Safe	2.69	Grey
2025	3.64	Safe	2.73	Grey

Table 11: Hyundai:

	Traditional		ML Tools	
Hyundai				
Year	Result	Zone	Result	Zone
2019	3.78	Safe	3.20	Safe
2020	3.69	Safe	3.23	Safe
2021	3.09	Safe	2.72	Grey
2022	3.46	Safe	3.10	Safe
2023	3.66	Safe	3.24	Safe
2024	4.34	Safe	4.60	Safe
2025	4.13	Safe	4.39	Safe

From the above Table Nos. 7,8,9,10, and 11, it can be concluded that the following:

- For Maruthi Suzuki Company, in the year 2021, showing a grey zone according to the traditional method and under technical analysis, 2020,2021,2022 and 2023 showing grey zone.
- For Mahindra & Mahindra Company, under the traditional method, showing all the years are in the distress zone and according to technical analysis, 2023,2024,2025 showing Grey Zone.
- For Bajaj Auto Limited, both methods show Safe Zone.
- For Eicher Motors Limited, under the traditional method, showing all years' results are Safe Zone and under technical analysis, 2021 to 2025 years show Grey Zone.
- For Hyundai, under the traditional method, showing all years' results are Safe Zone, and under technical analysis, 2021 shows Grey Zone.

From the above Analysis, the following Empirical Findings and Conclusions can be drawn:

EMPIRICAL FINDINGS AND RESULTS:,

- Comparing the results provided by Python, the calculated Machine Learning results are generally more accurate for financial decision-making. ,
- Both sets of results correctly identify the company's movement between zones over the seven years. However, there are slight variations in the exact Z-score values due to how the underlying financial ratios were extracted and weighted. ,
- The (Machine Learning/Python) generated results by using AI are considered more accurate for several technical reasons:, Manual calculations of Altman Z, scores are highly susceptible to rounding errors or "cascading" mistakes where one wrong ratio value affects the final score.
- By using Python to extract and process the data, the model ensures that the arithmetic is performed with absolute precision. ,
- The Altman Z-score formula uses very specific weights. Small differences in how many decimal places are kept during calculation can shift a company from the "Safe Zone" to the "Grey Zone".
- There are several versions of the Z-score (original public, private manufacturing, and non-manufacturing). By using a programmatic script, AI can make sure that the Original Z-Score Model for Public Manufacturing Firms is the one that is consistently applied to all years, thus, there is no accidental mixing of weights from other models.
- ML-generated figures are not just static numbers. They also offer a "contribution analysis, for instance. The AI model might be showing that the fall in 2021 was a result of the Sales/Total Assets ratio (X_5) change; thus, it is X_5 that caused the dip, not just giving a final number.
- The ML result maintains high precision throughout the calculation steps. There are multiple variants of the Z-score (original public, private manufacturing, and non-manufacturing). AI use of a programmatic script ensures the Original Z-Score Model for Public Manufacturing Firms is applied consistently across all years.

Conclusion:

Financial distress is a situation where a firm fails to generate enough cash flows from operations to meet its obligations, which in turn causes the firm to experience a decline in profitability, pressure on its liquidity, and an increased risk of default. Research indicates that if these symptoms are disregarded, financial distress may turn into insolvency that can have serious repercussions for shareholders, creditors, employees, and other stakeholders.

REFERENCES:

Aayushi, P., & D. B. (2021). Application of Altman Z-score model on selected Indian companies and public and private sector banks to predict bankruptcy. *International Journal of Creative Research Thoughts*, 9(7), 2511–2518.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589–609.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71–111.

Bhunia, A., & Sarkar, R. (2011). A study of financial distress based on MDA. *Journal of Management Research*, 2, 1–11.

Celli, M. (2015). Can Z-score model predict listed companies' failures in Italy? An empirical test. *International Journal of Business and Management*, 10(3), 57–69.

Chellasamy, P., & Kunnamudaiyar, S. (2021). Prediction of financial distress using Altman's Z-score: A study of selected footwear companies in India. *International Journal of Creative Research Thoughts*, 9(7), 72–78.

Diakomihalis, M. N. (2012). The accuracy of Altman's models in predicting hotel bankruptcy. *International Journal of Accounting and Financial Reporting*, 2(2), 1–18.

Eljelly, A. M. A. (2004). Liquidity–profitability trade-off: An empirical investigation in an emerging market. *International Journal of Commerce and Management*, 14(2), 48–61.

Fich, E. M., & Slezak, S. L. (2008). Can corporate governance save distressed firms from bankruptcy? An empirical analysis. *Review of Quantitative Finance and Accounting*, 30(2), 225–251.

International Journal of Innovative Science and Research Technology. (2023). *[Article on financial distress / Altman Z-score]* (IJISRT23OCT1585) [PDF]. https://www.ijisrt.com/assets/upload/files/IJISRT23OCT1585.pdf

Screener. (n.d.). *Screener – Stock analysis and screening tool for investors in India*. https://www.screener.in

Shisia, A., Wanjare, S., & others. (2014). An in-depth analysis of the Altman's failure prediction model on corporate financial distress in Uchumi Supermarket in Kenya. *European Journal of Business and Management*, 6(19), 27–41.

Svabova, L., Michalkova, L., Durica, M., & others. (2020). Business failure prediction for Slovak small and medium-sized companies. *Sustainability*, 12(4572), 1–14. https://doi.org/10.3390/su12114572

Yahoo Finance. (n.d.). *Yahoo Finance – Stock market live, quotes, business & finance news*. https://finance.yahoo.com