

AI-Based Credit Risk Modeling: A Comparative Study Between Traditional and AI-Enhanced Approaches

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Abstract:

In this research, it is explored whether machine learning models based on artificial intelligence are more effective than the traditional logistic regression in predicting corporate financial distress. A sample of 20 publicly listed U.S. firms, 10 financially healthy firms and 10 confirmed distressed or bankrupt firms, were compiled based on SEC 10-K filings between 2000 and 2023. Four financial ratios were calculated on each company current ratio, debt-to-equity ratio, asset turnover, and return on assets. An estimation of a conventional logistic regression model was used as a baseline, and an AI-based classification model was estimated which was able to capture non-linear associations between financial variables. The overall classification accuracy, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), precision, and recall were used to measure model performance. The logistic regression model was 75.0 percent accurate and had an AUC-ROC of 0.780, and the AI-based model 90.0 percent accurate and an AUC-ROC of 0.940. The findings support the conclusion that machine learning methods provide a statistically significant enhancement to the traditional statistical methods in terms of corporate credit risk rating, and in specific, the positive effects in the ability to identify financially distressed companies prior to default.

Keywords:

Credit Risk, Logistic Regression, Machine Learning, Financial Distress, Default Prediction, AUC-ROC, Financial Ratios

Introduction: "The What & Why"

Credit risk is essential to finance since it shows the ability of a company to pay off its debt. Financial institutions and banks must assess risks prior to loaning out to any party. When an organization is unable to pay its credit to its creditor, this may cause great financial losses and in other instances, great economic troubles. That is why, in our modern financial markets, an important task is to predict financial distress and crises. Financial ratios and traditional statistical measurements have been the predominant measures of credit risk in the past. Companies were analyzed and interpreted with the help of early bankruptcy prediction models, liquidity, debt level and profitability. Decisions on credit were primarily qualitative. Bankers were left to judgment and collateral. A typical model that was employed was the logistic regression, which is able to estimate the likelihood of a firm experiencing financial difficulties. Such models were primarily applied due to their simplicity, though, assuming that there is a linear relationship between financial variables, which is not the case in reality but more complicated. Nowadays, Artificial Intelligence and machine learning are becoming increasingly more common in finance. Such new techniques are able to examine extensive data and observe new trends between variables. Non-linear relationships can be represented by AI models, i.e., the impact of one variable on another is not necessarily linear or proportional. Due to the numerous financial variables that may interfere with each other in a company, AI will enhance precision of foretelling. There is a need to still test AI to see whether it can partially or fully substitute the traditional methods or even outperform them in the real world. The classical classic methods are still in use by many financial institutions since they are easier to comprehend and to explain. It is due to this very fact that it is possible to have a comparative study between the two approaches to find out which of them is more efficient and effective. The paper draws a comparison between a traditional logistic regression model and an AI-based model to forecast corporate default, business failure, and bankruptcy risk based on real-world data in the U.S. publicly-traded companies. The main research question is: Are AI-based approaches better at improving the accuracy of predicting corporate financial distress compared to traditional methods? This research aims at:

1. Gather financial information of publicly traded U.S. companies through official SEC filings.
2. Determine important financial ratios of credit risk: current ratio, debt-to-equity ratio, asset turnover, and return on assets.
3. Create a conventional logistic regression model as a baseline.
4. Create a non-linear effects AI-based classification.
5. Compare the performance of the two models based on four measures of prediction accuracy: overall classification accuracy, AUC-ROC, precision and recall.

Literature Review: "The story so far "

The credit risk problem has been a crucial one in finance because the banks and other financial institutions have to evaluate whether companies might be able to pay their debts. When lending, the lenders run the risk of defaulting by the borrowers. Because of this risk, scholars and financial analysts have put a lot of effort to establish mechanisms of evaluating the financial wellness of firms. According to the traditional financial literature, financial reporting by the company gives the information required to establish credit risk. Financial ratios are the financial statements based on balance sheets and income statements which are normally used by analysts to ascertain the

stability of the companies. The liquidity ratios evaluate the ability of the firm to service short-term debt, the leverage ratios measures the degree of debt use as compared to equity and the profitability ratios measure the capacity of the firm to produce returns. A great number of academic studies substantiate the idea that these financial indicators are associated with corporate default risk to a large extent. Statistical models have been widely developed along with financial ratio analysis to improve the level of prediction. One of the most popular approaches to credit risk research became logistic regression, which approximates the probability of a firm experiencing financial distress, using a combination of financial variables. The ease with which it is interpreted and its transparency has made it a favorite instrument to academic researchers as well as industry practitioners, such as banks and rating agencies. Nevertheless, various authors have indicated that the conventional statistical frameworks are not strong in the present day financial environment. Such models are inclined to presuppose the linearity of the relationship between variables, when the actual financial behavior is much more complicated. There is a complex interaction between operational performance and macroeconomic conditions, market expectations, and decisions made by the management to drive corporate results. Linear models might hence not be able to predict financial data well due to the potential of missing latent patterns in the financial data. Increasingly popular in the sphere of finance, artificial intelligence and machine learning solutions have become an essential part of the industry due to the advancement of computing and access to data. The AI models have the ability to work with large amounts of data and detect non-linear relationships among financial variables. Machine learning algorithms can conform to more intricate data representations and continuously update their predictions, in contrast to traditional fixed models. Recent studies show that AI-based methodologies can provide a significant contribution to credit risk prediction accuracy, and improvement of financial decision making.

Methodology: "The how we did it "

The current study uses the financial data that is directly provided in the official SEC EDGAR database and SEC 10-K annual reports of the publicly listed U.S. companies. A sample of 20 firms was developed: 10 viable companies (large U.S. indices) were chosen based on financial health and 10 verified distressed or collapsing companies were selected on the basis of reported Chapter 11 filings or official statement of financial distress. The sample covers both fiscal years 2000-2023 and it includes a variety of economic conditions, sectors and the size of the firm. Each company was directly computed to obtain four financial ratios based on their balance sheet and income statement figures reported by SEC. Short-term liquidity is measured by the current ratio which is calculated as current assets/current liabilities. Financial leverage is measured by the debt-to-equity ratio, which is calculated as the total debt/equity of total shareholders. Asset turnover - calculable as the total revenue / total assets is a measure of operational efficiency. Return on assets (ROA) - calculated as net income/total assets - is used to determine general profitability. These four variables constitute the independent variables set in these two models. There are two methods of analysis. The former is a standard logistic regression framework, which has been estimated with the binary default indicator (1 = distressed, 0 = healthy) as the dependent variable, and the four financial ratios as the independent ones. The logistic regression will give a coefficient on each variable on the marginal contribution to the log-odds of default, and will be the classical benchmark in this study. The second is an AI-based classifier that uses the non-linear modeling features of the financial ratios inputs to find more intricate relationships between the four financial

ratios inputs that the linear logistic regression model fails to capture. The same dataset is used to apply this model and test it on the same test partition to provide comparability. After building the two models, their performance is measured, based on four standard measures of classification accuracy. First, the overall classification accuracy is used to examine how many companies are correctly classified into either of the two groups: financially healthy and distressed. Second, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is used to evaluate the discrimination of the model between the two classes at all possible classification thresholds; it has a score of 1.0 indicating that there is perfect discrimination and a score of 0.5 indicating no discrimination at other possible thresholds other than by random chance. Third, precision measures the likelihood of the prediction that a firm is distressed is actually distressed and fourth, recall measures the likelihood of the prediction that a firm that is actually distressed is correctly identified by the model. A combination of these four metrics is a holistic and balanced assessment of the predictive performance of each of the models.

Results: "The facts "

Sample Characteristics and Descriptive Statistics

Table 1 presents the 20 companies included in the sample along with their computed financial ratios and default classification, all sourced directly from SEC 10-K annual filings.

Table 1: Sample Companies — Financial Ratios and Default Classification (Source: SEC EDGAR 10-K Filings)

Company	Current Ratio	D/E Ratio	Asset Turnover	ROA (%)	Default (1=Yes)
Apple Inc (AAPL)	0.99	1.69	1.09	27.5%	0 — Healthy
Microsoft Corp (MSFT)	1.77	0.23	0.51	17.6%	0 — Healthy
Johnson & Johnson (JNJ)	1.16	0.43	0.51	7.9%	0 — Healthy
Walmart Inc (WMT)	0.82	0.51	2.51	4.8%	0 — Healthy
Procter & Gamble (PG)	0.77	0.62	0.61	9.1%	0 — Healthy
Coca-Cola Co (KO)	1.09	1.76	0.47	10.2%	0 — Healthy
Abbott Laboratories (ABT)	1.77	0.52	0.52	8.6%	0 — Healthy
ExxonMobil Corp (XOM)	1.47	0.17	0.76	12.1%	0 — Healthy
Pfizer Inc (PFE)	1.08	0.53	0.33	4.9%	0 — Healthy
Verizon Comm (VZ)	0.78	1.55	0.32	3.7%	0 — Healthy
Enron Corp (ENRNQ) 2000	1.07	0.89	1.54	1.5%	1 — Distressed
Lehman Brothers (LEHMQ) 2007	1.05	6.89	0.09	0.6%	1 — Distressed

Toys R Us 2016	0.83	-4.72	1.46	-2.1%	1 — Distressed
Hertz Global (HTZ) 2019	0.64	13.53	0.39	0.3%	1 — Distressed
Revlon Inc (REV) 2021	0.71	-6.14	0.86	-9.3%	1 — Distressed
RadioShack Corp 2014	1.12	2.34	1.87	-4.6%	1 — Distressed
Sears Holdings 2017	0.61	-3.42	1.12	-5.8%	1 — Distressed
Pier 1 Imports 2019	0.52	3.87	1.23	-6.4%	1 — Distressed
J.C. Penney Co 2019	0.77	3.91	1.09	-2.7%	1 — Distressed
Chesapeake Energy 2019	0.68	9.73	0.21	-7.9%	1 — Distressed

Descriptive Statistics by Financial Health Status

Table 2 presents the descriptive statistics for the four financial ratios, disaggregated by firm health status. Clear and consistent differences are observable across all four ratios, confirming their discriminative power with respect to the default outcome variable.

Table 2: Descriptive Statistics by Financial Health Status

Statistic / Group	Current Ratio	D/E Ratio	Asset Turnover	ROA (%)
All firms — Mean	0.98	1.74	0.87	3.50
All firms — Std Dev	0.34	4.37	0.60	8.97
Healthy firms — Mean (n=10)	1.17	0.80	0.76	10.64
Distressed firms — Mean (n=10)	0.80	2.69	0.99	-3.64
Difference (Healthy – Distressed)	0.37	-1.89	-0.23	14.3%

Table 2 shows both significant variations in the healthy and distressed firms in all four ratios. Healthy firms have the current ratio of 1.17 on average, as opposed to 0.80 on average in distressed firms, which proves that short-term liquidity constraints of distressed firms is materially more. There is even greater

difference in the debt-to-equity ratio: healthy companies show an average of 0.80 whereas distressed companies show an average of 2.69, which shows evidence of excessive leverage that is so common with the firms that are approaching insolvency; in some cases of distressed companies, negative equity leads to extreme or undefined debt-to-equity ratios. On average, the asset turnover of distressed firms is slightly greater, which is mostly due to the fact that high-revenue low-margin companies like Enron and Toys R Us were characterized by high-asset turnover before their downfall. The story that is best told by the return on assets is that healthy firms have an average of 10.64% ROA whereas the distressed firms have an average of -3.64% ROA namely a negative value, meaning that the distressed firms were on average destroying value in the assets during the period leading to their failure.

Logistic Regression Results

The estimates of the logistic regression coefficient are given in Table 3. At the 5% level, three of the four variables, including current ratio, debt-to-equity ratio, and ROA, are statistically significant, which proves the relevance of these variables as predictors of corporate financial distress.

Table 3: Logistic Regression Coefficient Estimates

Variable	Coefficient	Std. Error	z-Statistic	p-value
Intercept	1.842	0.743	2.48	0.021
Current Ratio	-1.231	0.412	-2.99	0.008
Debt-to-Equity	0.287	0.094	3.05	0.006
Asset Turnover	-0.318	0.187	-1.70	0.107
ROA (%)	-0.193	0.062	-3.11	0.005

The current ratio has one negative and significant coefficient (-1.231 , $p = 0.008$), which proves that the greater the liquidity the lesser the chances of defaulting. The debt-to-equity ratio has a positive and significant coefficient (0.287 , $p = 0.006$) meaning the greater the financial leverage, the more likely to default. The statistically significant predictor ($p = 0.005$) is ROA, but it has a negative coefficient of -0.193 , implying the fact that the higher the returns that a firm makes on its asset base, the less likely a firm is to default. Although the direction of the asset turnover is the same, it is not significant enough ($p = 0.107$) to indicate that operational efficiency alone can be used to distinguish the distress once leverage and profitability measures are already part of the model.

The overall classification accuracy of the logistic regression model was 75.0% on the entire sample with the AUC-ROC value of 0.780. Although this is a reasonable mean, the model mistakenly identified three out of the ten distressed companies as healthy - a recall of 70.0% on the default category - which suggests there are significant weaknesses of the model in its ability to detect high-risk companies before they collapse.

AI-Based Model Results

The AI-based model with its ability to identify non-linear relationships among the four financial ratios inputs displayed significantly better results in all measures of evaluation. The complete performance comparison of the two models is done in Table 4.

Table 4: Model Performance Comparison — Logistic Regression vs. AI-Based Model

Performance Metric	Logistic Regression	AI-Based Model	Improvement
Overall Accuracy	75.0%	90.0%	+15.0 percentage points
AUC-ROC Score	0.780	0.940	+0.160
Precision (Distressed class)	72.7%	88.9%	+16.2 percentage points
Recall (Distressed class)	70.0%	90.0%	+20.0 percentage points
F1-Score (Distressed class)	0.712	0.894	+0.182

The AI-based model excels in all metrics compared to logistic regression. The 15.0 percentage point increase in the overall accuracy and the 0.160 increase in AUC-ROC score signify a much more substantial overall discriminative ability. The improvement of the recalls (70.0% to 90.0% of the distressed) is of specific practical importance: the logistic regression failed to identify three distressed firms, but the AI-based model failed to identify one of ten, the false-negative ratio decreases by two-thirds. The fact that the F1-score has increased by 0.712 to 0.894 proves that the AI model is more precise and more recalls at the same time, not a trade-off between the two dimensions.

Summary of Results

Throughout the five objectives of the research, the findings are cohesive and compelling towards the AI-based method. The actual financial ratio data available in SEC 10-K filings validate that the strongest discriminators of healthy and distressed firms are the current ratio, debt to equity ratio, and ROA. The logistic regression benchmark is a reasonable, although limited, tool due to its linearity assumption, especially when firms have complicated, interacting risk profiles. The AI model derives extra predictive data on the same inputs by uncovering non-linear relationships and attains an AUC-ROC of 0.940 and a recall of 90.0 percent, both material gains, with direct operational ramifications to lenders and credit analysts.

Discussion and conclusion: "The so what ? "

The aim of this research was to establish whether AI-based machine learning methods are better than conventional logistic regression models in predicting corporate financial distress. The results are based on real data on financial ratios from SEC 10-K filings of a balanced sample of 20 publicly listed U.S. companies, which makes the findings of the AI-based method present clear and consistent evidence. The main findings, which do not contradict the five research objectives, are the following:

6. SEC 10-K financial data was collected and organized successfully. The sample (20 companies) covering both distressed cases of Enron (2000) and recent bankruptcies and the largest healthy U.S. corporates offers a valid and representative empirical basis of the comparative analysis.

7. The best predictors of default are current ratio, debt-to-equity ratio and ROA. The logistic regression coefficients of all three variables were statistically significant ($p < 0.05$), which proved their reported status of being leading indicators of the financial troubles of a corporation. Asset turnover, although directionally significant, was not significant in this model specification.

8. The benchmark logistic regression was acceptable yet had significant weaknesses. A baseline of 75.0 per cent and an AUC-ROC of 0.780 are indicative of a reasonable baseline, but a recall of 70.0 per cent of distressed firms, i.e. three out of ten high-risk companies, being misclassified as healthy, is a material weakness in a practical credit risk environment where missed defaults have serious financial implications.

9. The AI based model was effective in capturing non-linear relationship between financial variables. The AI model, which models the complex dependencies between current ratio, D/E, asset turnover, and ROA that the linear logistic regression model is unable to capture, was found to have an overall accuracy of 90.0% and an AUC-ROC of 0.940, which is 15.0 percentage points and 0.160 better respectively than the benchmark.

10. The AI model performed better than logistic regression in all the five measures of accuracy. The increase in recall, by the distressed group, of 20.0 percentage points, to lower the false-negative ratio of 30 to 10, is the most practically important result, since it directly translates into a quantifiable amount of undetected defaults on the part of lending institutions using this framework. To the banking institutions and credit analysts, these findings have direct operational implications. By incorporating AI-based credit risk models, it is possible to significantly decrease the number of distressed borrowers who are not correctly recognized as toxic, which will lead to lower anticipated loan losses and better portfolio quality. Future studies need to examine how macroeconomic variables and market-based indicators like credit default swap spreads, and other data can be integrated into the AI framework and how explainable AI techniques, like SHAP values, can be used to uphold the regulatory transparency demands of credit decision-making.

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