International Journal of Commerce and Economics
www.commercejournal.in
E-ISSN: 2664-7540
Received: 12-10-2026, Accepted: 11-11-2026, Published: 26-11-2026
Volume 8, Issue 4, 2026, Page No. 27-31

Predicting corporate financial distress in India: A comparative analysis of traditional statistical models and machine learning approaches

Dr. Rajidi Rammohan Reddy
Associate Professor, Department of Management Studies, Trinity College of Engineering and Technology Peddapalli, Telangana, India
DOI: https://doi.org/10.66856/ijce.2026.8.4.8070

Abstract
Corporate financial distress rarely emerges without warning. Deteriorating profitability, weakening liquidity, rising leverage and changes in the wider economic environment may signal that a firm is moving towards serious financial difficulty. This study examines the prediction of business failure among Indian listed companies by comparing established accounting-based prediction models with selected machine-learning techniques. The study draws on a balanced sample of 140 companies—70 classified as failed and 70 as non-failed—with financial and related information covering 2007–2023. The synopsis reports the use of 52 candidate variables, followed by principal component analysis (PCA), which reduced the set to 28 selected variables spanning profitability, liquidity, leverage, operating efficiency, ownership structure, firm age and macroeconomic conditions. Traditional approaches considered include the modified Altman Z-score, Ohlson O-score, Springate, Taffler and Zmijewski models. Machine-learning approaches include Random Forest, Support Vector Machine (SVM), Logistic Regression, Neural Network, Decision Tree and ensemble learning. The reported results identify Random Forest as the strongest overall classifier, with an accuracy of 99.52% and an AUC–ROC of 1.000 in the reported model comparison. In the time-horizon analysis, Random Forest recorded accuracies of 91.07%, 91.43% and 88.21% for three-, two- and one-year prediction windows, respectively. The results also indicate that failed firms exhibit weaker profitability and liquidity and greater financial instability. The study contributes an India-focused comparison of accounting-based and computational prediction approaches. However, unusually high classification results and inconsistencies across some reported statistical tables require further validation using firm-level data, leakage-safe temporal testing and clearly documented model specifications before the findings are treated as externally generalisable.

Keywords: Business failure, financial distress, corporate bankruptcy, Indian companies, machine learning, Random Forest, financial ratios, early-warning systems

Introduction

Business failure is consequential not only for the company concerned but also for its lenders, investors, employees, suppliers and the wider economy. A distressed firm may experience an erosion of liquidity, persistent operating losses, mounting debt-service obligations and declining market confidence before formal insolvency or liquidation occurs. Identifying these warning signals early can create an opportunity for management to restructure operations, renegotiate liabilities or revise investment and financing decisions.

The prediction of corporate failure has developed from the examination of individual accounting ratios to multivariate statistical models and, more recently, machine-learning systems. Beaver (1966) [6] demonstrated the usefulness of financial ratios as indicators of failure, while Altman (1968) [2] introduced a multivariate discriminant approach that combined several dimensions of financial performance. Ohlson (1980) [9] subsequently used a probabilistic framework. These contributions established an enduring foundation for financial distress research.

The relevance of these models to India deserves careful empirical examination. Indian firms operate within a distinctive institutional, regulatory and financing environment. Differences in ownership structures, access to capital, sectoral conditions and macroeconomic exposure may affect the relationship between accounting indicators and corporate failure. A model developed in another economy may therefore require recalibration before it is applied to Indian companies.

This study compares traditional failure-prediction models with machine-learning methods using a sample of Indian listed companies. Its central premise is that a useful early-warning system should not depend on a single ratio or model family. Rather, it should consider multiple dimensions of corporate condition and be assessed at more than one forecast horizon.

Literature Review and Conceptual Background

1. Financial ratios and accounting-based prediction

Financial ratios remain central to failure prediction because they translate accounting statements into interpretable indicators of a firm's condition. Liquidity ratios reflect the capacity to meet short-term obligations; profitability ratios capture the ability to generate returns from assets and capital; leverage ratios indicate the extent to which operations are financed through debt; and efficiency ratios provide evidence about the use of assets and working capital. Beaver (1966) and Altman (1968) [2, 6] established the predictive relevance of such measures. Ohlson (1980) [9] expanded the approach through a probabilistic model, while later work has continued to examine the value and limitations of accounting-based indicators.

2. Beyond accounting information

Financial statements do not capture every source of vulnerability. Ownership patterns, institutional

shareholding, board oversight, leadership quality, company age and the capacity to respond to market change may also shape resilience. Balasubramanian *et al*. (2019) [5], in an Indian context, examined financial and non-financial variables together and highlighted the relevance of institutional shareholding. Macroeconomic conditions—including economic growth, inflation and interest rates—may affect firms through demand, input costs and the cost of borrowing. Acosta-González *et al*. (2017) provide an example of research integrating macroeconomic and accounting information.

3. Machine learning and model comparison

Machine-learning techniques offer a flexible way to identify nonlinear relationships and interactions among predictors. Random Forest and ensemble methods combine multiple decision structures; support vector machines seek separating boundaries; neural networks learn complex functional relationships; and decision trees offer comparatively transparent rules. Their flexibility is not a guarantee of superior out-of-sample performance. Small samples, class imbalance, data leakage, overfitting and changing economic conditions can produce apparently impressive results that do not persist in future periods. Pereira *et al*. (2014) [10] compare statistical and artificial-intelligence approaches, while Appiah *et al*. (2015) [4] review methodological issues in corporate failure prediction.

4. Indian evidence and research gap

Indian studies have evaluated established models and developed sector-specific or locally re-estimated approaches. Singh and Mishra (2016) [12] compared accounting-based bankruptcy models for Indian companies. Balasubramanian *et al*. (2019) [5] considered both financial and non-financial indicators. The synopsis also refers to evidence that Altman's model may not classify all Indian sectors consistently. Despite this work, a need remains for transparent comparisons across traditional and machine-learning methods, especially where financial, ownership-related and macroeconomic variables are considered together and prediction is assessed at different lead times.

The present study addresses this gap by bringing together five traditional models, six machine-learning approaches and a set of 28 selected predictors. Its contribution is primarily comparative and context-specific; the evidence should not be interpreted as proof that one algorithm will perform equally well across all Indian industries or future market conditions.

Research Objectives and Questions

The study has five objectives: (i) identify financial, non-financial and macroeconomic factors associated with business failure among Indian companies; (ii) evaluate traditional prediction models; (iii) compare traditional models with machine-learning approaches; (iv) develop an integrated prediction framework relevant to the Indian corporate environment; and (v) examine predictive performance across one-, two- and three-year horizons.

The corresponding research questions concern the determinants of failure, the performance of established models, the relative performance of machine-learning methods, the value of combining different predictor groups and the stability of model performance across forecast horizons.

Research Methodology

1. Research design and sample

The synopsis describes a quantitative, comparative and longitudinal research design using publicly listed Indian companies. The initial pool comprised 177 companies. Following data-availability screening, the final sample comprised 140 firms: 70 classified as failed and 70 as non-failed. The stated observation period is 2007–2023. Failed firms were identified by reference to financial-distress-related delisting, liquidation proceedings or bankruptcy filing. Non-failed firms were described as continuously listed and not experiencing the specified failure events.

The synopsis identifies Prowess CIME, Moneycontrol, Trendlyne, BSE and NSE as sources for company-level information, and RBI, World Bank and IMF databases as sources for macroeconomic indicators. The final paper should report the exact extraction dates, company identifiers, accounting-year alignment and event dates. These details are necessary for replication and for confirming that predictor information was available before each prediction date.

2. Variables

The study began with 52 financial, non-financial and macroeconomic candidate variables. PCA was used to reduce dimensionality, and 28 variables were retained for the prediction framework. The selected variables reported in the synopsis are presented in Table 1.

Dimension	Selected variables
Profitability	NI/TA (net income to total assets); ROA; ROE; ROCE; EBIT/TA
Liquidity and working capital	Current ratio (CR); quick ratio (QR); CA/TA; WC/TA
Leverage and debt service	Debt-to-equity (D/E); interest coverage ratio (ICR); total debt/total assets (TD/TA); cash flow/debt (CF/D)
Operating efficiency	Inventory turnover (ITR); asset turnover (ATO); fixed-asset turnover (FAT); sales/total assets (SL/TA)
Retained resources	Retained earnings/total assets (RE/TA)
Ownership and firm characteristics	Promoter holdings (PH); public holdings (PUBH); institutional investors' holdings (IIH); company age (AGE)
Macroeconomic conditions	Inflation (INFL); real interest rate (RIR); consumer confidence index (CCI); business confidence index (BCI); GDP; purchasing managers' index (PMI)

3. Analytical procedures

The reported analytical sequence comprised data preparation, treatment of missing observations and outliers, feature selection through PCA, model estimation and comparative evaluation. Descriptive statistics and independent-samples t-tests were used to examine differences between failed and non-failed firms. Logistic regression was used to examine predictor groups through three specifications: financial variables alone; non-financial and macroeconomic variables; and a combined

specification. The synopsis also reports likelihood-ratio comparisons.

Traditional models examined were the modified Altman Z-score, Ohlson O-score, Springate, Taffler and Zmijewski models. Machine-learning models included Random Forest, SVM, Logistic Regression, Neural Network, Decision Tree and ensemble methods. The reported evaluation measures include accuracy, precision, recall, F1-score and AUC–ROC. The synopsis describes a 70:30 training/testing division for the machine-learning workflow and reports separate evaluation for three-, two- and one-year horizons.

For a journal-ready replication, the train/test division should be specified at company level and, preferably, by time. All preprocessing, feature selection and tuning must be fitted within training folds only. Where the same firm contributes multiple years, firm-level separation is required to prevent observations from one company appearing in both training and test sets. For forward-looking prediction, a chronological split is preferable to a random split.

Results

1. Descriptive patterns and differences between firm groups

The synopsis reports a clear contrast in profitability between the two groups. Non-failed firms had a mean net income-to-total-assets ratio of 0.09 and mean ROA of 0.10, while failed firms recorded corresponding means of −0.08 and −0.09. The reported pattern is consistent with the expectation that sustained losses and weak asset returns accompany financial distress.

The synopsis also reports greater dispersion in the return measures of failed firms. ROE among failed firms had a standard deviation of 38.13, and ROCE had a standard deviation of 22.89. This volatility suggests that averages alone may not adequately describe the financial condition of distressed firms. The independent-samples tests identified significant group differences for the current ratio (p = 0.00098) and quick ratio (p = 0.00117), indicating differences in short-term liquidity.

Indicator	Non-failed firms (mean)	Failed firms (mean)	Interpretation reported
Net income / total assets	0.09	−0.08	Profitability contrast
Return on assets	0.10	−0.09	Asset returns are negative in failed group
ROE	0.19	1.13; SD = 38.13	High dispersion among failed firms
ROCE	0.21	0.93 (as printed in synopsis)	Value requires verification against source data
Current ratio	—	—	Group difference reported; p = 0.00098
Quick ratio	—	—	Group difference reported; p = 0.00117

Note: The synopsis prints a failed-firm mean ROCE of 0.93, which appears inconsistent with the accompanying interpretation that failed firms have weaker capital utilisation. This value has deliberately not been silently corrected and must be checked against the underlying output.

2. PCA and variable reduction

PCA was applied to the 52 candidate variables, and the synopsis reports 28 retained variables. The reported chi-square statistic is 5858.527 with 52 degrees of freedom and $p < 0.001$. The selected variables cover profitability, liquidity, leverage, efficiency, ownership, firm age and macroeconomic conditions. For publication, the PCA reporting should be supplemented with the correlation matrix, KMO statistic, Bartlett's test, component-retention rule, eigenvalues, explained variance and loading thresholds. A chi-square statistic alone is not sufficient to establish that PCA has selected the most predictive variables.

3. Logistic regression specifications

Three logistic-regression specifications were considered: a financial-only model, a model containing non-financial and macroeconomic indicators, and a combined model. The synopsis reports likelihood-ratio statistics for pairwise comparisons. However, one comparison is reported with a negative chi-square value (−147.93) and p = 1.000, which is not a valid conventional likelihood-ratio statistic for nested models. The model nesting, log-likelihood values, degrees of freedom and test calculations therefore require rechecking. No firm conclusion about the relative fit of these specifications is drawn here.

4. Traditional prediction models

Traditional model	Non-failed accuracy	Failed accuracy
Modified Altman	1.0000	0.9886
Ohlson	1.0000	0.9742
Springate	1.0000	1.0000
Taffler	1.0000	1.0000
Zmijewski	0.9615	1.0000

The synopsis reports a repeated-measures ANOVA result of $F = 0.00079$ and p = 0.97822, interpreted as no statistically significant difference in accuracy among the five traditional models. The very high class-specific accuracy figures should be checked against the underlying confusion matrices and the precise definition of accuracy. In particular, it is important to confirm that the original model cut-offs were applied consistently and that the reported values were calculated on an independent test set.

5. Machine-learning model performance

The reported overall comparison identifies Random Forest as the strongest classifier, with accuracy of 99.52% and AUC–ROC of 1.000. The ensemble model recorded 98.10% accuracy and AUC–ROC of 0.9994. Neural Networks achieved 96.19% accuracy and AUC–ROC of 0.9863. Logistic Regression recorded 85.71% accuracy and AUC–ROC of 0.9210, while SVM recorded 76.67% accuracy and AUC–ROC of 0.8808. The synopsis also describes Decision

Tree performance as strong, although the precise overall test metrics are not separately stated in the extracted narrative.

Machine-learning model	Reported accuracy	Reported AUC–ROC
Random Forest	99.52%	1.0000
SVM	76.67%	0.8808
Logistic Regression	85.71%	0.9210
Neural Network	96.19%	0.9863
Ensemble / Boosting	98.10%	0.9994
Decision Tree	Not clearly stated in narrative	Not clearly stated in narrative

These figures suggest that tree-based and ensemble approaches may capture patterns that are not represented adequately by a single linear decision boundary. Nevertheless, an AUC of 1.000 and accuracy approaching 100% in a sample of 140 firms are unusually strong results in a complex prediction problem. They should be treated as preliminary until independently reproduced with a leakage-safe validation design, class-wise confusion matrices, confidence intervals and an external or temporal holdout sample.

6. Performance across prediction horizons

Model	Three-year accuracy	Two-year accuracy	One-year accuracy
Random Forest	91.07%	91.43%	88.21%
Ensemble (Boosting)	88.93%	89.64%	87.14%
Logistic Regression	85.00%	86.79%	85.71%
SVM	86.43%	87.50%	85.36%
Decision Tree	87.50%	88.93%	84.64%
Neural Network	84.64%	83.57%	83.93%

Random Forest had the highest reported accuracy at each horizon in this table, although its three-year and two-year results were close. The synopsis reports a Kruskal–Wallis statistic of 2.44 with $p = 0.296$, indicating no statistically significant difference in accuracy across the three horizons. The reported median accuracies were 86.97 for three years, 88.22 for two years and 85.54 for one year. The result should be interpreted cautiously: the table does not show the number of independent test observations at each horizon or uncertainty around each estimate.

7. Comparative tests

The synopsis reports a Wilcoxon test comparing the testing accuracy for failed and non-failed firms ($W = 3$, $p = 0.465$), with medians of 0.99 and 0.97, respectively. It also reports a Mann–Whitney U statistic of 20 ($n_1 = 10$, $n_2 = 10$; $p = 0.023$) for a comparison between traditional and machine-learning accuracy values. The latter result suggests a difference in the reported samples, but the synopsis contains a separate table of paired accuracy values that is not reconciled with the near-perfect class-specific results in the traditional-model table. The unit of analysis and construction of these test samples must be documented before inferential claims are retained.

Discussion

Three broad observations emerge from the reported analysis. First, profitability and liquidity appear to distinguish failed firms from non-failed firms. Negative mean ROA and net income-to-assets values in the failed group are consistent with the view that persistent losses weaken a firm's ability to finance operations and meet obligations. The significant differences reported for current and quick ratios further underline the importance of short-term liquidity monitoring.

Second, the inclusion of ownership and macroeconomic variables recognises that corporate distress is not solely an accounting phenomenon. Promoter and institutional ownership may influence monitoring, access to capital and governance, while inflation, real interest rates, GDP and confidence indicators may shape the operating environment. Their incremental predictive contribution, however, must be established through correctly specified nested models and out-of-sample comparisons.

Third, the synopsis reports stronger classification performance for Random Forest and ensemble methods than for SVM and Logistic Regression. This is a useful direction for further investigation, but it does not justify treating the highest reported score as definitive. Model performance depends on the definition of failure, sample construction, forecast date, class balance, preprocessing, feature selection, hyperparameter tuning and the separation of training and testing observations. An apparent perfect score can arise when information from after the failure event enters the predictors or when closely related observations from the same firm occur in both data partitions.

The horizon analysis adds a further practical dimension. A prediction made three years before a failure is more valuable for strategic intervention than a warning issued shortly before the event, but it is also inherently more difficult. The reported results show modest differences across horizons and no statistically significant variation in the Kruskal–Wallis test. A stronger future design would estimate horizon-specific models using information available strictly before each forecast date.

Implications

1. Implications for corporate management

Managers can use a structured early-warning dashboard to monitor profitability, liquidity, debt-service capacity and operating efficiency. Particular attention should be given to persistent deterioration rather than a single adverse year. Working-capital discipline, timely receivables collection, realistic debt commitments and regular stress testing can help identify emerging vulnerabilities.

2. Implications for lenders and investors

Lenders and investors may use accounting-based scores as an initial screening device and machine-learning outputs as

supplementary risk signals. Model outputs should not replace credit analysis, sector knowledge or qualitative due diligence. Probability calibration and transparent explanations are important when a prediction may influence lending, investment or restructuring decisions.

3. Implications for regulators and policymakers

Aggregated early-warning indicators may help identify concentrations of distress across sectors and firm-size groups. Any regulatory use should be supported by representative data, transparent validation, explainability and safeguards against model bias. A prediction system should support—not substitute for—professional assessment and statutory insolvency procedures.

Limitations and Future Research

The study is constrained by the limited sample of 140 firms and incomplete financial information for some failed companies. The sample is restricted to Indian listed companies and may not represent unlisted firms, micro and small enterprises or all industry segments. External shocks are not fully captured. The synopsis itself recognises the risk of overfitting in neural networks and decision trees.

Several reporting issues also need resolution before publication: (i) the failed-firm ROCE figure conflicts with the accompanying interpretation; (ii) a negative likelihood-ratio chi-square statistic is reported; (iii) the traditional-model accuracy table and the separate comparative-accuracy table are not reconciled; (iv) the overall Random Forest result is substantially higher than its horizon-specific results; and (v) the exact event dates, observation unit, split procedure, feature-selection timing and model settings are not fully specified in the synopsis. These are not editorial details; they affect the validity of the empirical conclusions.

Future research should use a larger and more diverse firm-year dataset, distinguish distress from formal legal insolvency, define failure events consistently and employ temporal validation. Researchers should report sensitivity, specificity, precision, recall, F1-score, ROC-AUC, PR-AUC, calibration and confidence intervals. Class imbalance should be addressed transparently, and feature selection and tuning should occur inside training folds. SHAP values or other interpretable methods may help explain the contribution of predictors. External validation across sectors and later economic periods would provide stronger evidence of generalisability.

Conclusion

This study examines business failure prediction among Indian listed companies through a comparison of traditional accounting-based models and machine-learning approaches. The synopsis reports that failed firms have weaker profitability and liquidity profiles and that Random Forest and ensemble techniques achieve strong classification performance. It also identifies a broad set of financial, ownership-related and macroeconomic indicators that may contribute to an integrated early-warning framework.

The central practical message is that corporate failure prediction should combine financial diagnosis with careful attention to the firm's wider operating environment. The central methodological message is equally important: high accuracy is meaningful only when the evaluation design rules out information leakage and provides a realistic test of future performance. Subject to verification of the underlying data and statistical outputs, the study offers a useful foundation for further India-focused research on data-driven corporate distress monitoring.

References

1. Acosta-González E, Fernández-Rodríguez F, Ganga H. Predicting corporate financial failure using macroeconomic variables and accounting data. Computational Economics,2019:53(1):227–257. https://doi.org/10.1007/s10614-017-9737-x
2. Altman EI. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance,1968:23(4):589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x
3. Altman EI. The success of business failure prediction models. Journal of Banking & Finance,1984:8(2):171–198. https://doi.org/10.1016/0378-4266(84)90003-7
4. Appiah KO, Chizema A, Arthur J. Predicting corporate failure: A systematic literature review of methodological issues. International Journal of Law and Management,2015:57(5):461–485. https://doi.org/10.1108/IJLMA-04-2014-0032
5. Balasubramanian SA, G.S. R, P. S, Natarajan T. Modeling corporate financial distress using financial and non-financial variables. International Journal of Law and Management,2019:61(3/4):457–484. https://doi.org/10.1108/IJLMA-04-2018-0078
6. Beaver WH. Financial ratios as predictors of failure. Journal of Accounting Research,1966:4:71–111. https://doi.org/10.2307/2490171
7. Blum M. Failing company discriminant analysis. Journal of Accounting Research,1974:12(1):1–25. https://doi.org/10.2307/2490525
8. Dimitras A, Zanakis S, Zopounidis C. A survey of business failures with an emphasis on prediction methods and industrial applications. European Journal of Operational Research,1996:90(3):487–513. https://doi.org/10.1016/0377-2217(95)00070-4
9. Ohlson JA. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research,1980:18(1):109–131. https://doi.org/10.2307/2490395
10. Pereira J, Basto M, Ferreira-Da-Silva A. Comparative analysis between statistical and artificial intelligence models in business failure prediction. Journal of Management and Sustainability,2014:4(1). https://doi.org/10.5539/jms.v4n1p114
11. Shumway T. Forecasting bankruptcy more accurately: A simple hazard model. The Journal of Business,2001:74(1):101–124. https://doi.org/10.1086/209665
12. Singh BP, Mishra AK. Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies. Financial Innovation,2016:2(1). https://doi.org/10.1186/s40854-016-0026-9
13. Wilcox JW. A simple theory of financial ratios as predictors of failure. Journal of Accounting Research,1971:9(2):389–395. https://doi.org/10.2307/2489944