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Differential Predictors of Financial Distress in Listed Versus Unlisted Indian Firms: A Machine Learning Approach

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Abstract

This study identifies the key determinants of financial distress and evaluates alternative prediction models for both listed and unlisted firms in India. It uses financial data from 1,473 NSE-listed and 472 unlisted Indian firms (2010–2023). Six firm characteristics – profitability, liquidity, solvency, capital structure, operating efficiency, and size – are measured using financial ratios, with market performance additionally included for listed firms. Feature selection identifies the best ratio per characteristic. Classical logit and multiple machine learning models are compared for distress prediction. It is found that leverage, firm size, and capital structure are significant predictors for both firm types. However, optimal measures differ: listed firms are better captured by ROA, working capital to total assets, and sales to total assets, whereas net profit margin, current ratio, and debt collection period perform better for unlisted firms. Machine learning models outperform the logit model, with Random Forest emerging as the best predictor. The study is among the firsts to simultaneously cover both listed and unlisted Indian firms and to apply machine learning for identifying distress determinants as well as prediction, moving beyond classical statistical approaches. However, the study is limited only to Indian market data, hence restricting cross-market generalisation. Future research should extend to additional emerging markets and more advanced modelling architectures. The findings of the study offer key insights for policy-makers and regulators in designing early-warning frameworks, for commercial banks – in credit risk assessment, for corporate management – in financial monitoring, and for academics – in advancing distress modelling methodology.

Keywords: financial distress, listed and unlisted companies, comparative performance, logit model, machine learning models, feature selection, entropy

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Introduction

Predicting the financial health of any company has always been a conundrum for the stakeholders. Prior research investigates the possibilities of financial distress and the causative factors over the past century, especially since the great depression of 1929. The first recognized article was published in the Bureau of Business Research in 1930 [1], followed by [2–27]. All of them used financial ratios and other micro-level specific characteristics for determining the level of financial distress, whereas [28–37] used financial ratios especially in country-specific environments as determinants of financial distress.

Corporate failure prediction models ranged from univariate financial ratio analysis to multivariate analysis and from discriminant models to logit models [38], whereas [39] used artificial neural networks (ANN); [40] – a simple hazard model; [41] – support vector machines (SVM); [42] – data envelopment analysis (DEA); [43] – the combination of principle component analysis and SVM; and [44] – binary regression accounting-based model. Using the logit model, ANN, SVM, Partial Least Squares (PLS), and a hybrid model integrating SVM with PLS, [45] predicted financial distress for small and medium French companies. [46–47] employed deep learning models using textual disclosures; [48] used the ant colony optimization technique; [49] applied transactional data and two-stage multi-objective feature selection; [50] use the binomial logit model along with ANN and SVM for predicting financial distress. [51] developed a firm's distress and recovery prediction score by using both logit regressions and machine learning techniques, whereas [52] used a hybrid multi-layer perceptron ANN with the traditional Altman Z-Score model for predicting financial distress, and observed that the hybrid model was superior to the traditional Altman Z-Score and pure ANN models. [53] proposed a Malmquist DEA based on a multi-period performance evaluation framework, whereas [54] use a modified Z-score model for developing the Troubled Debt Restructuring probability index for distressed and non-distressed firms based on the logistic regression model. [55] used the interest coverage ratio (ICR) and the return on assets (ROA) for determining financial distress and found that generalized extreme value regression with and without the feature selection provides the best prediction for financial distress. [56] conducted a comprehensive survey, classification, and critical analysis of the literature on corporate bankruptcy and financial distress predictions. [57] employs several models, including the Altman model (Z-Score), the Springate model (S-Score), the Zmijewski model (X-Score), the Grover model (G-Score), and the Taffler model to predict financial distress and corporate bankruptcy. Out of these, the Taffler model emerged as superior to the rest. [58] applied machine learning techniques for the default prediction in unlisted micro, small, and mid-sized enterprises (MSME) in Italy. They used a public – private firm mapping approach with an objective to improve the default predictions for private unlisted firms, and found that prediction quality significantly improved. Thus, they concluded that noisy

accounting information hinders accurate prediction of default in unlisted companies.

Early and accurate detection of any possibility of financial distress is an extremely important theme in corporate finance research. However, after reviewing the literature, the following gaps have been identified. First, prior research is mostly focused on mature markets. Similar work for emerging markets like India is limited, although it is highly relevant given the growing contribution of such markets to the world economy. Secondly, most of the studies have used traditional multivariate techniques for identifying the determinants of financial distress. Only a few recent studies have applied modern machine learning approaches for variable selection as well as model estimation. Finally, the studies are confined to large and listed companies except a few [44; 45], which examine this issue in small and medium enterprises in the unlisted sample. It may be noted that financial distress, especially during the crisis period such as the COVID-19 pandemic, is likely to be more pronounced for unlisted companies compared to large listed companies, which have more resilient balance sheets. The primary motivation of the present study is to fill these important gaps in past research.

The present study focuses on financial distress modeling and prediction for India, which is the fastest-growing large emerging market. India is the 3rd largest world economy in terms of purchasing power parity and hosts the 4th largest capital market in the world in capitalization terms.

Given the growing stature of India on the world stage, the study of financial distress becomes extremely pertinent for global lending agencies, credit rating firms, investors, and funds. Findings related to India can also be used to draw some general conclusions about distress prediction for other emerging markets.

Furthermore, the present research adopts a fully machine learning-based approach for identifying determinants as well as model estimation. It also attempts to predict financial distress for both the listed and the unlisted samples of Indian companies by using machine learning tools for both variable selection and model estimation. It also draws important conclusions about the role and relative importance of the factors and efficacy of alternative machine learning models for the two samples. The comparative analysis shall provide academicians and practitioners with important insights about model construction based on the nature of the corporate sector.

More specifically, this study attempts to identify the financial ratios that have relatively higher predictive power for diagnosing the financial health of Indian corporations, both listed and unlisted. Financial distress is measured using three financial variables: ICR, changes in equity, and changes in total assets. This three-way accounting-based definition of distress is adapted from the work of [59; 60].

The study assesses the predictive ability of the traditional binomial logit model and selected machine learning-based models, namely SVM, ANN, Random Forest (RF), and Gradient Boost (GB). The study also compares the accuracy of one-year and two-year ahead forecasts.

Table 1. Key determinants of financial distress used in the study

We use several firm characteristics for financial distress prediction. Key financial ratios along with their measures used to represent each characteristic are listed in this table.

Character-istics	Ratio	Measures	Character-istics	Ratio	Measures
Profitability	Net Profit Margin (NPM)	Net Profit/Net sale	Operating efficiency (Activity)	Debtor Days(DD)	(Debtors/Operating Revenue)*360
	Gross Profit Margin (GPM)	Gross Profit/Net sale		Asset Turnover ratio (ATR)	Sales Revenue/Total Assets
	Return on Net Worth (RONW)	Net Profit/Shareholders fund		Stock Turnover Ratio (STR)	Operating Revenue/Stock
	Return on Capital Employed (ROCE)	Net Profit/Capital Employed	Solvency	Financial Leverage (FL)	Long-term Liabilities/Total Assets
	Return on Asset (ROA)	Net Profit/Total Asset		Gearing Ratio (GR)	Long-term Liabilities/Capital Employed
Liquidity	Quick Ratio (QR)	Quick Assets/Current Liabilities (QA/CL)		Debt ratio (DR)	Total Debt/Total Assets
	Current Ratio (CR)	Current Assets/Current Liabilities (CA/CL)	Size	Solvency Ratio (SR)	(PAT + Depreciation)/(Long Term liabilities+ Short Term Liabilities)
	NCI	(QA – CL)/Daily Operating Expenses		Repayment Capacity (RC)	Financial Debt/Cash flow
	CFO/TL	Total Cash from Operation/ Total Liabilities		DE	Debt/Equity
	CF/TA	Cash flow/Total Assets	Market Value	RE/TA	Retained Earnings/Total Assets
Structure	CF/OR	Cash flow/Operating Revenue		Ln(TA)	Ln (Total Assets)
	WC/TA	Working Capital/Total Assets		P/E	Market Price per share/ Earning per share
	Eq/TA	Equity/Total Assets		P/B	Market Price per share/Book Value per share
	CA/TA	Current Assets/Total Assets			
	CL/TL	Current Liabilities/ Total Liabilities			
	FA/TA	Fixed Assets/Total Assets			
	SF/NCL	Shareholders' Funds/Non Current Liabilities			

We provide mean financial ratios for total, healthy and distressed firms for listed and unlisted sample companies.

We pursue the following research objectives: i) Identify principal determinants as well as optimal technique for predicting financial distress in the Indian listed company sample; ii) Determine the factors and the best modeling techniques for unlisted Indian companies; and iii) Compare and contrast the findings for listed and unlisted samples and draw key managerial implications.

The remaining part of the study is organized as follows: Second section presents data and variable construction whereas methodology and estimation procedures are discussed in third section. The empirical results and discussion are provided in fourth section, while fifth section contains conclusions and managerial implications.

Data and Variable Measurement

Data

The study originally considered **2730 listed companies** from the National Stock Exchange of India from 2010 to 2023 and **38628 unlisted companies** from 2010 to 2022, using data collected from the Ace Equity database. Applying the filter rule of at least 80% availability of financial ratios and followed by dropping the financial companies (based on the Global Industry Classification Standard) as they have unique operating, financial, and risk characteristics [61], the number of listed companies ranged from **1091 to 1149** during the period of study, resulting in **14,607 firm-year** observations. Similarly, the number of unlisted companies in the sample ranged from **340 to 472** per year, which resulted in **5176 firm-year** observations.

Variable Measurement

Taking clues from prior literature on financial distress [45; 60; 62; 63], the study employs 30 financial ratios, comprising 28 accounting and 2 market-based ratios as independent variables for empirical analysis. These financial ratios satisfy our filter rule as their information is available for at least 80% of evaluated cases. The accounting ratios are used to measure six important firm characteristics: profitability, liquidity, structure, operating efficiency, solvency and size. The number of ratios representing profitability are five; liquidity – seven; structure – five; operating efficiency (activity) – three; and solvency – seven; Firm size is measured by the natural log of total assets in the study. The two market-based ratios are market price per share to earnings per share (P/E ratio) and market price per share to book value per share (P/B ratio). However, only 28 financial ratios are used for unlisted firms owing to non-availability of market variables for such companies (Table 1).

The study uses three financial indicators, namely, ICR defined as EBITDA (Earnings Before Interest, Tax, Depreciation, and Amortization) divided by the interest charge; change in the market value of equity (Del EQ); and change in the value of total assets (Del TA) for classifying the firms as healthy or distressed. ICR shows the firm's capacity to meet its fixed financial obligations. Higher ICR implies that the firm is expected to be in good health, while its

lower value is an indicator of corporate distress. A healthy firm shall also experience an increase in equity value owing to positive expectations of investors. In contrast, perceived financial distress results in negative investor sentiments, causing the equity value to decline. Finally, any decline in asset value shall imply corporate contraction and reduce the firm's capacity to meet its debt obligations. We assume that healthy companies will meet all three criteria i.e., i) ICR greater than or equal to 1; ii) Del EQ with respect to the previous year greater than or equal to 0; iii) Del TA with respect to previous year greater than or equal to 0. Companies having ICR less than 1, Del EQ less than 0, and Del TA less than 0 are classified as distress. The rest of the firms that partially fulfill the criteria are excluded to keep the healthy and distressed firm samples fairly distinct from each other. Consequently, **8806 and 1753 listed healthy and distress cases** are identified, respectively. Similarly, **2646 and 662 unlisted healthy and distress cases** are identified, respectively.

Methodology

Estimation Procedures

We begin our analysis by estimating the mean values of the financial ratios followed by identifying the key micro-determinants of financial distress using traditional statistical methods and modern machine learning techniques. Analysis has been conducted separately for listed and unlisted cases owing to several reasons. The listed companies are publicly traded relatively large firms whose performance is continuously under scrutiny and therefore related to market sentiment. Such companies involve investment by both institutional and retail investors. In contrast, unlisted firms are closely held small and medium companies that predominantly involve promoter capital and investment by sophisticated private equity investors. They are not exposed to public scrutiny and hence are impacted in a limited way by market sentiment.

First, we construct the matrix of three dependent variables (used as a measure of financial distress) and 30 financial ratios (used as independent variables). The companies with $ICR > 1$ coupled with a positive change in book equity and total assets compared to the previous year are classified as healthy. The companies with $ICR < 1$, and a decline in the equity and asset value as compared to the previous year are classified as distressed. Healthy and distressed firms are labelled 0 and 1, respectively, for each year.

To control high cross-sectional and time series variability in the sample financial ratios, we use the 5th and 95th percentile for removing the outliers. The means for financial ratios are estimated after deleting these outliers. We further standardize these ratios by estimating their standard normal variate.

We next identify the key determinants of financial distress using the feature selection procedure to find the most relevant ratio within each category, i.e., profitability, liquidity, structure, operating efficiency, solvency, and market per-

formance. No feature selection procedure is used for the firm size category as only a single measure (natural log of total assets) is employed, and it is selected automatically. We select the feature with the highest mutual information gain. In this study, each financial ratio is a feature meant to represent a class, i.e., the characteristic of the firm. We identify seven financial ratios for listed and six for unlisted firms (as the category of market-based ratios are unavailable), which will play a role in distress prediction.

Further, we attempt to develop our distress prediction model by pegging our one-year-ahead financial distress dummy to selected financial ratios using the panel logit model as it breaks through linear separation, because the relationship between the probability of financial distress and financial ratios is likely to be nonlinear [41]. We also employ four principal machine learning techniques, namely, RF; ANN; SVM; and GB.

Using the **RF method**, we take T – the number of randomly sampled variables as candidates at each node equal to one thousand and n – the number of trees in the forest is 2, given the achieved optimal model. The **ANN method** has nonlinear and nonparametric adaptive learning properties. For our ANN – MLP (multi-layer perceptron) analysis, we use 50 neurons with ten hidden layers to mimic human decision-making. For **SVM**, our model was optimal with a penalty parameter of 5. We use a radial basis kernel function, an efficient algorithm that introduces additional features in the given space, in a one-versus-all approach. Recent studies have evaluated the **GB** machine for categorization based on specified assessment parameters and found its performance superior to other methods [52; 64]. The hyper-parameters used for our model are: the number of trees – 50, and the maximum depth of a tree – 5. The minimum number of rows, i.e., the fewest allowed observations in a leaf, are set at a default value of 10. The learning rate for our model is set at 0.1, indicating the speed at which our model learns.

The study employs a time-series aware randomised search cross validation, which explores a parameter space from pre-defined parameter distributions. The temporal (panel-data) nature of the data is preserved to avoid any look-ahead bias.

A 5-fold time-series split is employed, training the outer fold, optimising the hyperparameters on the validation part of the inner fold. The optimisation objective is the F1 score of the minority class.

The panel and time series nature of the data has been preserved since the one-year and two-years-ahead predictions are strictly based on the parameters of preceding years of the same company avoiding any data leakage and look-ahead bias. The architectural design reported for the neural network is a starting point and the hyperparameter search tunes that and other model parameters like learning rate, regularization, early stopping and batch size.

We estimate the procedure and recall value for both distressed and healthy cases. Precision shows how much a model's positive predictions are actually correct. It is measured as the ratio of

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Negatives} . \quad (1)$$

Whereas Recall indicates the actual positive cases correctly identified by the model. It is the ratio of

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} . \quad (2)$$

Next, we estimate the expected status (healthy or distressed) for each sample case using the above-mentioned methods. For each method, we compare the expected status with the actual status for the sample cases and derive the prediction rate. A correct case is defined as one in which the expected and actual status match. Incorrect cases are defined as those where discrepancy is observed between the expected and actual status. The prediction rate for a method is estimated by taking the ratio of correct cases to total cases. A higher prediction rate implies better distress prediction. A similar procedure is adopted for predicting two-year-ahead distress. In this case, the two-year-ahead distress dummy is pegged to select financial ratios for the model estimation process.

Experimental Setup

The dataset available for experiments is an unbalanced sample, i.e., **8806** class 1 (healthy firms) and **1753** class 2 (distress firms) cases for the listed firms. Similarly, for unlisted firms, the number of class 1 and class 2 firms is **2646** and **662**, respectively. The data for **4048** and **1868** cases for listed and unlisted samples, respectively, is dropped as these firms don't qualify in either category.

To tackle the issue of unbalanced datasets, class 1 samples are divided into n smaller groups so that the number of samples in each smaller group becomes approximately equal to the number of samples in class 2. We obtain n datasets by combining each of the n smaller class 1 groups with class 2 samples. Then for each of the n datasets, we obtained 5-fold cross-validation with the above-mentioned machine learning algorithms, thus estimating the average classification prediction rate.

Results and Discussions

We provide the mean value of financial ratios (after removing outliers) for both listed and unlisted sample firms in Table 2. These financial ratios have been used as independent variables in our distress prediction models. One can clearly see that listed firms in India exhibit higher profitability on the average compared to unlisted firms with the exception of GPM. Unlisted firms may have better GPM owing to cheaper labour. Labour union activity is either absent or weak in such firms, resulting in better wage negotiation. Unlisted firms also have access to cheaper sources of raw materials with smaller supply chains. They may also exhibit lower direct expenses as the entrepreneur is personally involved or at least supervising the production process. Further, there is a lower degree of variability for the mean profitability measures for healthy and distressed firms in case of listed companies as compared to unlisted companies.

Table 2. Summary statistic (mean value) for financial ratios

Variable	Total Listed Mean	Healthy Listed Mean	Distress Listed Mean	Total Unlisted Mean	Healthy Unlisted Mean	Distress Unlisted Mean
NPM	4.015	8.341	-14.742	1.100	8.900	-24.300
GPM	15.324	17.606	5.065	18.800	22.000	5.800
RONW	8.943	14.506	-9.842	6.700	16.400	-19.900
ROCE	12.603	16.993	-2.255	12.100	19.100	-7.900
ROA	4.255	7.045	-5.725	2.500	7.000	-10.200
QR	1.122	1.208	0.744	1.100	1.200	0.700
CR	1.627	1.736	1.136	1.500	1.700	1.000
NCI	-0.707	0.507	-6.820	-5.300	-2.400	-13.000
CFO/TL	0.069	0.075	0.042	0.100	0.100	0.032
CF/TA	0.002	0.003	-0.003	0.004	0.007	-0.002
CF/OR	0.090	0.091	0.078	0.100	0.100	0.100
WC/TA	0.118	0.155	-0.036	0.100	0.100	-0.100
Eq/TA	0.473	0.508	0.312	0.400	0.400	0.200
CA/TA	0.492	0.512	0.424	0.500	0.500	0.400
CL/TL	0.373	0.353	0.476	0.400	0.400	0.500
FA/TA	0.341	0.333	0.390	0.400	0.300	0.400
SF/NCL	10.665	11.622	6.754	7.100	8.500	4.000
DD	69.178	62.365	90.270	61.900	59.100	71.300
ATR	0.973	1.091	0.619	1.100	1.200	0.800
STR	13.713	14.035	11.842	53.800	53.700	46.300
FL	0.151	0.137	0.202	0.200	0.200	0.300
GR	0.205	0.188	0.268	0.300	0.300	0.400
DR	0.265	0.229	0.422	0.300	0.200	0.500
SR	0.068	0.092	-0.026	0.100	0.100	-0.100
RC	-3.359	-1.193	-16.856	3.300	11.900	-6.200
Debt / Equity	0.743	0.651	1.044	1.000	1.000	0.900
RE/TA	0.402	0.450	0.200	0.200	0.300	-0.100
Total Assets	2233.861	2343.302	1535.481	2012.063	2178.541	1534.059
P/E	18.420	20.568	0.719			
P/B	1.826	2.130	0.953			

We present the level of corporate distress for listed and unlisted firms in India by year. Macroeconomic distress is measured by taking the ratio of distressed companies to total companies each year.

Listed firms exhibit higher liquidity ratios and lower solvency ratios, which makes them fundamentally stronger compared to unlisted firms. They also exhibit relatively lower variability in these financial ratios between healthy and distress firms. It is interesting to note that unlisted firms exhibit better activity ratios compared to listed firms, which implies that operationally they are more efficient. Both types of firms seem to exhibit almost similar structure ratios. The average listed firm seems to be relatively larger in size compared to the average unlisted firm, as per expectations.

We additionally considered size multiples for listed firms as market information is available for them due to public trading. Healthy firms provide a mean P/E ratio of 20.57 compared to 0.72 for distressed firms. Similarly, healthy firms provide a mean P/B ratio of 2.13 vs. 0.95 for distressed firms.

Table 3 provides information about the level of financial distress on a yearly basis for both listed and unlisted sample companies in India. We define a year as the period from April of t-1 to March of t, since the financial closing in India occurs in March. The level of financial distress

has been estimated as the percentage of distressed firms to total firms in a given year. It is an indicator of corporate level distress at macroeconomic level [50; 65]. Corporate distress for the listed sample in India stood at 5.62% in 2011 and steadily climbed to 11.58% in 2016, immediately prior to the implementation of Insolvency and Bankruptcy Code. The status was similar for the next three years but increased dramatically from the COVID-19 period in 2020 onwards, showing a jump of 52% compared to the 2016 value. A similar pattern is observed for unlisted companies. The distress rate was 5.59% in 2011, increasing to 10.26% in 2016 and remaining stable around this value for the next three years. It then suffered a meltdown during Covid period reaching a distress rate of 18.68% in 2021, an increase of 82% compared to 2016 value. This indicates a steady increase in corporate distress in India over time, particularly during the COVID-19 period, and a stronger negative impact on the small unlisted companies compared to large listed companies. From the policy makers' perspective, this trend may be of concern and invite greater support to the unlisted sample given their limited capacity to cope with economic meltdowns.

Table 3. Level of corporate distress in Indian listed and unlisted firms

Year	Number of Listed Companies				Level of Corporate Distress
	Healthy	Distress	Mixed	Total	
2011	875	63	183	1121	0.0562
2012	789	101	239	1129	0.0895
2013	751	91	295	1137	0.0800
2014	722	115	312	1149	0.1001
2015	621	155	373	1149	0.1349
2016	620	133	396	1149	0.1158
2017	672	112	353	1137	0.0986
2018	748	117	266	1131	0.1034
2019	656	130	327	1113	0.1168
2020	494	188	418	1100	0.1709
2021	607	192	292	1091	0.1760
2022	612	189	295	1096	0.1724
2023	639	167	299	1105	0.1511
	8806	1753	4048	14 607	

Year	Number of Unlisted Companies				Level of Corporate Distress
	Healthy	Distress	Mixed	Total	
2011	215	19	106	340	0.0559
2012	202	25	117	344	0.0727
2013	200	43	105	348	0.1236
2014	207	64	155	426	0.1502
2015	231	56	171	458	0.1223
2016	224	48	196	468	0.1026
2017	233	51	185	469	0.1087
2018	250	60	160	470	0.1277
2019	252	48	172	472	0.1017
2020	210	83	174	467	0.1777
2021	202	85	168	455	0.1868
2022	220	80	159	459	0.1743
	2646	662	1868	5176	

We provide entropy values for each financial ratio used as a measure of given firm characteristic. Financial ratio with the highest entropy value is selected as the best measure of given characteristic.

Table 4. Entropy values based on feature selection procedures for sample financial ratios in case of listed and unlisted firms

Companies Variables	Listed		Unlisted	
	1 Yr ahead	2Yr ahead	1Yr ahead	2Yr ahead
ROA	0.174956	0.136286	0.131302	0.102311
NPM	0.167480	0.126558	0.144521	0.089015
RONW	0.164686	0.130315	0.112464	0.112483
ROCE	0.144807	0.117175	0.110290	0.088199
GPM	0.084506	0.071198	0.060319	0.038205
WC/TA	0.057050	0.035696	0.032311	0.037139
CR	0.051678	0.032672	0.056100	0.035949
NCI	0.048665	0.038003	0.047738	0.025047
QR	0.046754	0.023408	0.043420	0.019853
CFO/TL	0.031477	0.028020	0.024118	0.015016
CF/OR	0.024907	0.021071	0.012655	0.000429
CF/TA	0.013605	0.006265	0.000000	0.000000
Eq/TA	0.057283	0.050482	0.022893	0.043160
SF/NCL	0.055095	0.041293	0.010989	0.027156
CL/TL	0.029133	0.022798	0.020658	0.027988
FA/TA	0.012103	0.011684	0.026625	0.014173

Companies Variables	Listed		Unlisted	
	1 Yr ahead	2Yr ahead	1Yr ahead	2Yr ahead
CA/TA	0.009571	0.011821	0.000000	0.009484
ATR	0.042971	0.022089	0.000265	0.000000
STR	0.030034	0.019934	0.002099	0.000000
DD	0.014123	0.020632	0.010828	0.003709
SR	0.156702	0.123515	0.122026	0.090632
DE	0.071942	0.052404	0.013733	0.013897
RE/TA	0.060222	0.052535	0.062792	0.000792
DR	0.055619	0.042219	0.011867	0.019949
FL	0.023525	0.016491	0.000000	0.007984
RC	0.023238	0.014488	0.005372	0.001240
GR	0.018072	0.017761	0.012518	0.013609
P/E	0.103838	0.067677		
P/B	0.075096	0.060874		

Source: Compiled by the authors

We provide prediction, recall and overall accuracy rate for each financial distress forecasting model for healthy and distressed firms for one- and two-year forecasts. The prediction rate is estimated as the ratio of correctly classified cases to total cases.

In Table 4, we present the information gain value for each financial ratio in a given category for listed and unlisted companies. Information gain measures the reduction in entropy or impurity when a data-set is split on an attribute. It tells us how much information a feature (financial ratio) provides about the class (category). Information gain is used to compare different ratios to determine which one provides the most significant reduction in entropy. This means that it's not an absolute measure but a comparative one. We use it to choose the best attribute at each step in building a decision tree.

Based on feature selection, ROA seems to be the most appropriate measure of profitability for predicting both one-year and two-year-ahead financial distress. Similarly, the optimal measures for structure, operational efficiency, solvency and market-based indicators are FA/TA, Sales Revenue/TA, Solvency Ratio, and Price/Earnings Ratio, respectively. However, a small discrepancy is observed for the liquidity category. While the WC/TA ratio is optimal for one-year-ahead prediction, the (Quick Assets – Current Liabilities)/Daily Operating Expenses ratio is slightly better for the two-year distress prediction. However, to maintain uniformity, we employ the WC/TA ratio for both one-year and two-year-ahead distress prediction. As mentioned in the earlier section, the Total Assets variable is used to represent firm size as it is the only measure in its category.

However, for unlisted firms, we find NPM to be the optimal measure for the one-year-ahead distress prediction. Similarly, CR, FA/TA Ratio, Debtor Days, and Solvency Ratio are found to be the best measures for liquidity, structure, operating efficiency, and solvency, respectively. The selected determinants also seem to work optimally for the two-year-ahead prediction, with the exception of WC/TA, which seems to be better than CR in measuring liquidity by a very small margin. Thus, our factor structure seems to be fairly stable for both one-year and two-year-ahead prediction.

We report the precision and recall values for both healthy and distressed cases in the listed and unlisted samples along with the estimated prediction rate for each model (logit model and select machine learning methods) in Table 5. We find that all machine learning methods outperform traditional logistic models for listed as well as unlisted cases for both one- and two-year-ahead predictions. The Random Forest method seems to provide the best one-year as well as two-year-ahead predictions, followed by the SVM method in both listed and unlisted samples. Further, as expected, one-year-ahead prediction rates are slightly higher than two-year-ahead prediction rates in both cases. In fact, RF provides the correct prediction in almost 95% and 91% of rating cases for listed and unlisted firms, respectively, in case of the one-year-ahead forecast.

Table 5. Results of financial distress prediction, recall and accuracy rates for listed and unlisted companies, one- and two-year-ahead (%)

Listed Firms - 1 Year Ahead						Listed Firms - 2 Year Ahead				
Methods	Prediction Rate for Healthy Companies 0	Prediction Rate for Stressed Companies 1	Recall Rate for Healthy Companies 0	Recall Rate for Stressed Companies 1	Overall accuracy	Prediction Rate for Healthy Companies 0	Prediction Rate for Stressed Companies 1	Recall Rate for Healthy Companies 0	Recall Rate for Stressed Companies 1	Overall accuracy
Logistic Regression (LR)	78.88	77.43	79.18	77.10	78.18	76.07	75.69	78.15	73.46	75.89
Random Forest (RF)	92.99	96.83	97.21	92.09	94.75	90.72	97.25	97.67	89.22	93.60
Gradient Boost (GB)	90.44	85.52	85.86	90.20	87.95	82.74	88.89	90.79	79.55	85.39
Support Vector Machine (SVM)	89.72	94.31	95.07	88.24	91.78	89.28	83.53	83.72	89.15	86.33
Artificial Neural Network (ANN)	86.99	83.82	84.57	86.34	85.42	82.33	78.86	79.77	81.51	80.61

Unlisted Firms - 1 Year Ahead						Unlisted Firms - 2 Year Ahead				
Methods	Prediction Rate for Healthy Companies 0	Prediction Rate for Stressed Companies 1	Recall Rate for Healthy Companies 0	Recall Rate for Stressed Companies 1	Overall accuracy	Prediction Rate for Healthy Companies 0	Prediction Rate for Stressed Companies 1	Recall Rate for Healthy Companies 0	Recall Rate for Stressed Companies 1	Overall accuracy
Logistic Regression (LR)	73.00	71.98	74.71	70.17	72.53	71.24	71.40	75.03	67.30	71.31
Random Forest (RF)	88.08	93.47	94.42	86.20	90.47	85.89	91.49	92.80	83.54	88.35
Gradient Boost (GB)	84.12	80.32	81.06	84.47	82.22	82.94	79.78	80.74	82.07	81.38
Support Vector Machine (SVM)	83.26	91.56	93.19	79.76	86.73	79.80	86.34	88.91	75.70	82.56
Artificial Neural Network (ANN)	80.35	76.93	77.95	79.41	78.65	76.18	73.65	75.29	74.58	74.95

Source: Compiled by the authors.

Comparing the feature selection results for listed and unlisted companies, we find common measures of distress prediction in case of structure and solvency characteristics along with firm size, which we measured by using TA for both groups. However, different measures of profitability are found to be optimal for listed and unlisted samples. ROA seems to be the best measure for listed firms, while NPM seems to be a more appropriate measure for unlisted firms. Similarly, in case of liquidity, WC/TA and CR seem to be best measures of listed and unlisted firms, respectively. Different measures of operating efficiency are relevant for the two groups. While ATR is found to be more appropriate for listed firms, Debtor Days is the better measure in the case of unlisted firms. Further, all measures seem to work well for both one-year and two-year-ahead predictions with the exception of the liquidity characteristic. Liquidity measures not only differ for listed and unlisted firms, they also differ for one-year and two-year-ahead predictions in case of both groups.

Comparing the results of listed and unlisted firms, we find a better prediction rate in case of the former group, which may be owing to the availability of market-based information for such companies in the form of price multiples. We recommend using machine learning procedure methods, such as the RF method for both listed and unlisted Indian companies for financial distress prediction. Further, distress prediction models seem to be fairly stable while making both one-year as well as two-year-ahead predictions.

Conclusion

The present study focuses on financial distress modelling and prediction in India. We specifically examine whether similar or different financial ratios predict financial distress in the case of listed and unlisted firms. We find that the same measures of leverage, firm size and structure work in both cases. However, ROA, WC/TA and Sales/TA seem to be more appropriate measures of probability, liquidity and operating efficiency for listed firms. These firms are relatively large in size compared to unlisted firms, hence the efficacy of financial ratios based on TA is not entirely surprising. In contrast, NPM, CR and debtors collection period seem to be better predictors of financial distress in case of unlisted firms. P/E ratio as a measure of corporate performance provides additional information for listed firms.

We saw the modern machine learning methods, particularly RF, provide better predictions compared to the classical logit model. Further, one-year-ahead predictions are slightly better than two-year-ahead predictions, as per expectations. The study provides important implications for different stakeholders. Policymakers must keep in mind that adverse events like Covid accelerate macro-level distress, which is even more serious for unlisted firm that operate under severe resource constraints. The study suggests the creation of distress prediction models that can be used separately for listed and unlisted firms, which should be of particular interest to bankers since they extend loans to companies and hence would like to keep the financial health of their clients under surveillance. The study also

provides insights to companies as to what financial ratios they must keep under watch while maintaining their internal monitoring system. The research also provides information to the academic and research community regarding the key determinants of financial distress and the role of machine learning techniques for forecasting purposes.

We suggest that the subsequent work should include explicit measures of corporate governance as additional determinants of financial distress and should not assume that financial ratios related to profitability, liquidity, leverage and efficiency indirectly reflect the quality of management. Further, it's important to note that the sample companies belong to non-financial sectors, some of which have been more severely disrupted by innovative technologies. We suggest that the sensitivity of corporate performance (measured by sales and/or profits) to the disruptability index should be measured and then used as an additional determinant of financial distress. Such extensions may provide better forecasting of financial distress. It is recommended that a similar exercise be conducted using other emerging market data before drawing any generalizations about distress modelling and prediction. The present study contributes to the financial distress literature, especially as it is related to emerging markets. We recommend that future research on the subject employ a wider range of machine and deep learning techniques, including more recent reinforcement learning models for a sample of emerging markets in order to derive more general conclusions.

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