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Financial Distress Prediction of BSE-SME firms using Support Vector Machine

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Abstract: **The aptitude to predict financial distress has become an important research topic of today because it could provide an early warning to the company. The current research mainly focused on the accuracy of the model of Support Vector Machine and Logistic Regression. Also this study identified the variables, which could contribute more to the accuracy of the model. The study used financial ratios on the BSE- listed Small Medium Enterprises, during the period of 2015 to 2019. The study found that the logit model yielded an accuracy rate of 85.55% but the SVM- Polynomial model yielded 97.3% accuracy. The sample financial variables such as IBT on Sales, EBIT/ Total Assets, Operating Cash Flow/ Current Liability Ratio, Growth on Interest Before Tax, Working Capital / Sales Ratio and, Return on Capital Employed have significantly contributed to the prediction of the financial distress of sample Small and Medium Enterprises. The study concluded that the SVM Polynomial model was a more balanced and efficient one.**

Keywords: **Financial distress prediction, BSE-SMEs, Support Vector Machine, Financial Ratios, Logit Analysis.**

1. INTRODUCTION

The ability to predict the financial distress of firms has become an important research topic of today because it could provide an early warning for the company. According to **Investopedia (2019**), the financial distress is a condition in which a company cannot generate revenue or income because it is unable to meet its financial obligations. This is usually due to high fixed costs and high illiquid assets or revenues sensitive to economic downturns. SMEs are important for the sound economic system of countries, including India. But lending to SMEs is riskier than lending to large corporations (**Altman & Sabato, 2006**). Hence Indian commercial banks need to develop appropriate credit risk model, specific to SMEs. Credit risk model is considered to be an important area, which generated a lot of interest among the research community and triggered research to find solutions for many problems (Altman & Sabato, 2006; Berger & Udell, 2002; Ciampi & Gordini, 2008; Fantazzini & Figini, 2009; Lin et al., 2012; Saurina & Trucharte, 2004). MSMEs have rightly been identified as the engine of growth for the Indian economy. They not only contribute over 37 percent to the GDP of Indian's economy but also employ more than 80 million people. Hence the growth of MSMEs is essential and inevitable for the sustainable and equitable growth of the economy. Bankruptcy is a legal proceeding by which a company declares its inability to pay its bills, gives a chance to catch up on missed payments, gets a fresh financial start by temporarily or permanently preventing creditors from collecting debts and sustain current operations **(Nidhi Arora et al., 2014).** Bankruptcy does not only affect the organization itself but it also affects the overall economy of the country. The commercial banks are still one of the largest sources of financing for MSMEs in India but they have been traditionally reluctant to address the financial needs of this segment on account of low ticket size, higher risks and higher costs involved. Hence more accurate predictions, close to reality, would help the firms to have more precise decision basis and bankruptcy prediction pattern is one of the tools, which could estimate the future financial condition of companies.

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2. REVIEW OF LITERATURE

Agostino Di Ciaccio and Giovanni Cialone (2019) used insolvency prediction analysis, for Italian small firms and their results found that all the models revealed good performances (including logistic regression) better than those obtained in previous works. **Senthil Arasu B., et al.(2019)** confirmed that accuracy rate was between 84% and 86% for the MLP technique and accuracy rate was between 92% and 93% for the QUEST technique. Sensitivity analysis showed that the returns on long-term fund, net profit margin, and operating margin were three critical variables, which affected the business health. **Senthil Arasu B., et al. (2019)** found that the prediction models (ANN-MLP and QUEST) with financial variables had a prediction accuracy of 85.19% and 86.11% respectively, whereas these models with combinations of financial and non-financial variables, predicted with comparatively better accuracy of 89.81% and 91.67% respectively. **Obradovi C, et al. (2018)** developed an insolvency prediction model, for the companies in the Republic of Serbia. The overall prediction level of the test was found to be 82.5%. **Muhammad M. Ma'aji, et al. (2018)** analyzed the financial distress prediction of Malaysian SMEs. The study developed a financial distress prediction model combining financial, non-financial and governance variables and analysed the level of influence of major corporate governance characteristics. The accuracy rate in the holdout sample was at 91.2%. **Hamid Wagas, RohaniMd-Rus(2018)** predicted the financial distress, using of O-score and logit model for Pakistani firms. It was found that the estimated prediction models provided more precise results, with overall accuracy of 91.7% and 93.3% respectively. **Behr and Weinblat (2017)** found that the insolvent companies were younger than their solvent counterparts. **Ozdagoglu G et al.,(2017)** confirmed that all the three methods (decision tree, logistic regression, and artificial neural network) had performed well and the ANN had the best performance and it outperformed the other two classical methods. **Flavio Barboza et al., (2017)** analysed bankruptcy prediction, using Machine Learning Models. **Bagher Asgarnezhad Nouri, etal.,(2016)** found that the accuracy of bankruptcy models, based on accounting and market variables, was at 91.2% and 82.1% respectively. **Cultrera and Bredart (2016)** analyzed bankruptcy prediction of Belgian SMEs. It was found that the logit model was able to predict the bankrupt and healthy firms, with an accuracy rate of 82.97% and 75.22% respectively. The study found that smaller and younger Belgian SMEs were more likely to go bankrupt. **Mihalovic,M. (2016)** suggested that the model, based on a logit function, outperformed the classification accuracy of the discriminant model. The most significant predictor of impending firms´ failure, appeared to be Net Income to Total Assets, Current Ratio and Current Liabilities to Total Assets.

The previous studies predicted the financial distress of listed companies in different countries of the world. Very few studies examined the financial distress prediction in Micro Small Medium Enterprises MSMEs in India, by using data mining techniques. To fill the research gap, this present study focused on financial distress prediction of MSMEs by using data mining techniques of Support Vector Machine.

3. SCOPE OF THE STUDY

The financial distress prediction has become a significant research area because it could provide early warnings to the company. But the accuracy of the prediction is still questionable. More prediction ability ensures more precise decisions. Hence this present study focused on the financial distress prediction, with the help of financial indicators, using data mining tool namely, Support Vector Machine.

4. OBJECTIVES OF THE STUDY

The present study was carried out, with the following objectives.

- To determine how accurately Support Vector Machine classified the sample companies, as unsuccessful or successful.
- To assess the accuracy level of the classification models, namely Logistic Regression and Support Vector Machine, using various performance measures.
- To identify the variables, which could contribute more to the accuracy of the model

5. METHODOLOGY

5.1 Data and Research Method

This study considered all the BSE –SME listed companies. There were 230 companies, listed in BSE-SME, as on December 2019. But the study considered only 125 companies as the sample while 105 companies were not considered due to non availability of required data, during the study period of 2015 to 2019. These 125 sample companies were classified into Manufacturing, Services, Import & Export, Commodity & Equity, Banking & Finance, Investment, Logistic, Entertainment, Architecture, Infrastructure, Construction, and Food process. The sample had observed 625 cases.. Each case record was proposed to measure using 24 financial ratios, based on previous studies. But of these 24 ratios, the study used only 18 variables for the analysis and 6 remaining ratios were not used due to multi-collinearity problem. It is to be noted that 15 financial ratios (such as CR, QR, ATR, ROCE, ITR, NPM, EBIT/TA, RETA, CFO/CL, IBT/Sales, GROIBT, CA/TA, W.C/Sales, W.C/TA, TL/TA) were used as independent variables while only one ratio, namely, Return on Assets (ROA) was used as the dependent variable. The sample variables (ratios) were selected as they were capable of gauging the liquidity, profitability, financial solidity, and operating performances of sample firms.

5.2 Measurement of Model Performance

The performance of confusion matrix model is provided in **Table -1,** which presents the valuable information about the performance classifier of firms, by comparing actual and predicted classes **(Kohavi and Provost, 1998)**. The study also used performance measures (**Table-2**) such as overall accuracy, error rate, sensitivity, specificity, precision, F-measure, and the Area Under the Curve (AUC), to validate the model performance.

Table 1: Confusion Matrix for the Financial Performance of Firms

Actual	Predicted	
	Unsuccessful	Successful
Unsuccessful	True Negative(TN)	False Positive(FP)
Successful	False Negative(FN)	True Positive(TP)

Source: Senthil Arasu et al.,(2019)

Table 2: List of Performance Measures

Performance measures	***Formula***
Overall accuracy	(TP + TN) / (TP + TN + FP + FN)
Error rate	(1 – overall accuracy)
Sensitivity	(TP) / (TP + FN)
Specificity	(TN) / (TN + FP)
Precision	(TP) / (TP + FP)
F-measure	2 × [(Precision × Sensitivity) / (Precision + Sensitivity)]
Type 1 error	(Number of unsuccessful cases classified as successful) / (Number of cases classified as successful) × 100
Type 2 error	(Number of successful cases classified as unsuccessful) / (Number of cases classified as unsuccessful) × 100

Source: Senthil Arasu et al.,(2019)

5.3 Tools used for the Analysis

5.3.1 Logit Analysis(LA)

The equation of LA (**Ohlson, 1980)** is as follows:

$P(x) = 1 / [\, 1 + e^{-(bo + b1 \cdot X1 + b2 \cdot X2 + + bn \cdot Xn)}] \ldots$

where:

- P(x) - the probability of failure for a firm
- bi - the coefficient for each independent variable, and
- Xj - the actual value for each independent variable

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The application of LA requires four steps as follow:

a. Calculation of a series of financial ratios,

b. Multiplication each ratio with its corresponding coefficient,

c. Summing up the result of each coefficient to form a new variable *y*, and

d. Calculation of the probability of financial distress for a company as 1/ (1+ e−y) .

The independent variables, with a negative coefficient, increased the probability of financial distress due to the fact that they reduced e-y towards zero, with the result that the financial distress (probability function) approached 1/1, or 100 percent. Likewise, the independent variables, with a po-sitive coefficient, reduced the probability of financial distress **(Ohlson, 1980)**

5.3.2 Support Vector Machine (SVM)

SVM is a relatively new machine learning technique, based on statistical learning theory **(Kim et al., 2002)**. It is based on the principle of structural risk minimization, but not zxon the principle of empirical risk minimization.

SVM is one of the most popular Supervised Learning algorithms popularly used for Classification as well as Regression problems. The goal of the SVM algorithm is to create the best line or decision boundary. Comparatively this model gives highest accuracy than the other classification models. The accuracy and generalization performance of SVM is better than that of BPN as the training set size (**Kyung shik shin et.all -2005)**

SVM is also suitable for relatively small number of samples. This present study used only 125 SME's. So this study applied SVM model. For the proof of comparison of traditional with Machine learning techniques, it also applied traditional classification model of Logistic regression. The training algorithm only depends on the data through dot products in H, i.e. on functions of the form $\Phi(x_i)\cdot\Phi(x_j)$. Now if there were a "kernel function" K such that

$K(x_i,x_j) = \Phi(x_i)\cdot\Phi(x_j)$,

The study used K in the training algorithm. One example is radial basis functions (RBF) or gaussian kernels where, H is infinite dimensional and hence it would not be easy to work with Φ explicitly. Training model requires the choice of:

- The kernel function, which determines the shape of the decision surface.
- parameters in the kernel function (eg: for the gaussian kernel: variance of the Gaussian, for the polynomial kernel: degree of the polynomial)
- The regularization parameter λ.

6. RESULTS AND DISCUSSIONS OF THE STUDY

6.1. Analysis of Descriptive Statistics

The results of descriptive statistics used for both unsuccessful and successful companies stated that the average receivables ratio recorded the highest mean value (17.65), followed by the current ratio of unsuccessful companies but in the case of successful companies, the lowest mean value was recorded as compared to the unsuccessful firms. The values for growth of income before tax, cash from operation ratio, IBT/ Sales ratio, Inventory Turnover ratio, return on capital employed, Net profit margin, and Return on Asset ratio of successful firms, were higher than that of unsuccessful companies. The value of standard deviation (risk) for unsuccessful companies was high in the case of all ratios, except for growth on income before tax during the study period.

6.2. Analysis of Cross-Correlation and Multicollinearity Test of Sample Variables in the case of Sample Firms

The results of correlation and multicollinearity statistics of sample variables, in the case of sample firms, are given in **Table - 3**. It is understood that the asset turnover ratio was significantly correlated with the receivables turnover ratio, at the value of 1% level. The current ratio was negatively correlated with EBIT to total asset ratio and total liabilities to total asset ratio and positively correlated with working capital to total asset ratio, at the significant of one percent level. Similarly, the retained earnings to total asset ratio was negatively correlated with current ratio, at 1% significant level. It

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is clear that the net income to sales ratio was positively correlated with EBIT to TA, working capital to sales and NPM at 1% significant level. The growth on net income was negatively correlated with ITR at 1% significant level. Similarly, the receivable turnover ratio was negatively correlated with CA to TA ratio. The coefficient values, for sample variables, were low and less than 0.5 during the study period.

To ensure that the correlations, among sample ratios, did not suffer from multicollinearity that could affect logit model results, the variance inflation factor and a tolerance value of each independent variable were checked. The suggested cut-off for the VIF was 1-5 (**Senthil Arasu et.al 2019**), but the calculated tolerance value was 0-1. The analysis of this study showed that all variables had VIF of more than one and a tolerance value of less than one. Hence the above variables did not face the problem of multicollinearity.

Table 3: Results of Pearson Cross Correlation and Multicollinearity Diagnostic Test

Financial Ratios	ATR	CR	RETA	IBTSales	CFOCL	GrowIBT	DebtEqity	AVR	CATA	EBITTA	LogEBITInt	WCapSales	WCapTA	TLTA	ITR	ROCE	NPM
ATR	1	-0.068	-0.024	-0.041	0.034	-0.05	-0.029	.122**	.087*	0.076	0.047	-0.047	-0.041	0.055	0.029	-0.003	0
		0.088	0.557	0.305	0.393	0.221	0.471	0.002	0.029	0.059	0.244	0.241	0.306	0.172	0.468	0.944	0.992
CR	-0.068	1	-0.021	0.005	-.096*	-0.02	-0.02	0.02	0.026	-.105**	-.091*	0.063	.119**	-.258**	-0.039	-0.02	0.021
	0.088		0.604	0.898	0.016	0.594	0.625	0.624	0.517	0.008	0.023	0.119	0.003	0	0.332	0.61	0.604
RETA	-0.024	-0.021	1	-.101*	0.006	-.087*	-0.008	-0.006	-.115**	-.094*	-0.043	-0.01	-0.06	0.072	-0.02	-0.021	-.085*
	0.557	0.604		0.012	0.879	0.03	0.836	0.875	0.004	0.019	0.287	0.812	0.134	0.071	0.615	0.598	0.033
IBTSales	-0.041	0.005	-.101*	1	-0.002	.098*	-0.013	-0.005	0.007	.237**	.125**	.301**	0.042	-0.063	-0.02	-.090*	.466**
	0.305	0.898	0.012		0.962	0.014	0.754	0.898	0.864	0	0.002	0	0.297	0.114	0.623	0.025	0
CFOCL	0.034	-.096*	0.006	-0.002	1	0.008	0.008	0.003	0.023	0.045	0.023	-0.04	-0.007	0.048	0.021	0.005	0.006
	0.393	0.016	0.879	0.962		0.844	0.839	0.948	0.572	0.262	0.572	0.315	0.852	0.234	0.602	0.894	0.878
GrowIBT	-0.049	-0.021	-.087*	.098*	0.008	1	-0.008	-0.009	0.023	.109**	0.076	-0.008	0.011	0	-.201**	0.003	0.054
	0.221	0.594	0.03	0.014	0.844		0.848	0.828	0.563	0.006	0.059	0.85	0.783	0.993	0	0.949	0.176
DebtEqity	-0.029	-0.02	-0.008	-0.013	0.008	-0.01	1	-0.007	-0.008	-0.019	-0.017	-0.01	-0.034	.081*	-0.024	-0.056	-0.016
	0.471	0.625	0.836	0.754	0.839	0.848		0.863	0.839	0.637	0.676	0.811	0.4	0.043	0.549	0.159	0.686
AVR	.122**	0.02	-0.006	-0.005	0.003	-0.01	-0.007	1	-.117**	-0.02	0.051	-0.007	0.002	-0.059	-0.007	-0.001	0.017
	0.002	0.624	0.875	0.898	0.948	0.828	0.863		0.003	0.615	0.2	0.869	0.96	0.14	0.87	0.981	0.667
CATA	.087*	0.026	-.115**	0.007	0.023	0.023	-0.008	-.117**	1	0.019	-0.012	.098*	.114**	.141**	-.151**	0.052	-0.02
	0.029	0.517	0.004	0.864	0.572	0.563	0.839	0.003		0.635	0.76	0.015	0.004	0	0	0.197	0.626
EBITTA	0.076	-.105**	-.094*	.237**	0.045	.109**	-0.019	-0.02	0.019	1	.369**	-0.055	.083*	-0.06	0.017	-0.048	.141**
	0.059	0.008	0.019	0	0.262	0.006	0.637	0.615	0.635		0	0.17	0.038	0.132	0.671	0.23	0
LogEBITInt	0.047	-.091*	-0.043	.125**	0.023	0.076	-0.017	0.051	-0.012	.369**	1	-0.054	0.038	-.149**	0.012	0.006	0.037
	0.244	0.023	0.287	0.002	0.572	0.059	0.676	0.2	0.76	0		0.175	0.349	0	0.769	0.877	0.362
WCapSales	-0.047	0.063	-0.01	.301**	-0.04	-0.01	-0.01	-0.007	.098*	-0.055	-0.054	1	0.063	-0.069	-0.024	-0.009	.170**
	0.241	0.119	0.812	0	0.315	0.85	0.811	0.869	0.015	0.17	0.175		0.114	0.087	0.556	0.817	0
WCapTA	-0.041	.119**	-0.06	0.042	-0.007	0.011	-0.034	0.002	.114**	.083*	0.038	0.063	1	-.200**	.244**	-0.038	0.041
	0.306	0.003	0.134	0.297	0.852	0.783	0.4	0.96	0.004	0.038	0.349	0.114		0	0	0.344	0.304
TLTA	0.055	-.258**	0.072	-0.063	0.048	0	.081*	-0.059	.141**	-0.06	-.149**	-0.069	-.200**	1	-0.028	0.069	-0.078
	0.172	0	0.071	0.114	0.234	0.993	0.043	0.14	0	0.132	0	0.087	0		0.487	0.085	0.051
ITR	0.029	-0.039	-0.02	-0.02	0.021	-.201**	-0.024	-0.007	-.151**	0.017	0.012	-0.024	.244**	-0.028	1	-0.009	-0.039
	0.468	0.332	0.615	0.623	0.602	0	0.549	0.87	0	0.671	0.769	0.556	0	0.487		0.814	0.326
ROCE	-0.003	-0.02	-0.021	-.090*	0.005	0.003	-0.056	-0.001	0.052	-0.048	0.006	-0.009	-0.038	0.069	-0.009	1	-.126**
	0.944	0.61	0.598	0.025	0.894	0.949	0.159	0.981	0.197	0.23	0.877	0.817	0.344	0.085	0.814		0.002
NPM	0	0.021	-.085*	.466**	0.006	0.054	-0.016	0.017	-0.02	.141**	0.037	.170**	0.041	-0.078	-0.039	-.126**	1
	0.992	0.604	0.033	0	0.878	0.176	0.686	0.667	0.626	0	0.362	0	0.304	0.051	0.326	0.002	
VIF	1.054	1.124	1.05	1.461	1.014	1.078	1.014	1.042	1.149	1.266	1.207	1.152	1.175	1.207	1.171	1.032	1.305
Tolerance	0.949	0.89	0.953	0.684	0.986	0.928	0.986	0.96	0.87	0.79	0.828	0.868	0.851	0.829	0.854	0.969	0.766

Source: Collected from PROWESS and Computed using SPSS

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

6.3. Analysis of Logistic Regression

The results of the logit model, in respect of sample firms, are presented in **Table- 4.** The operating cash flow ratio of sample firm recorded the highest co-efficient value of 3.876, followed by return on capital employed (ROCE) at 1% significant level. However, the net income to sales, operating cash flow ratio, growth on net income, CA to TA, EBIT/TA, and working capital to sales and ROCE had significantly contributed to the financial distress prediction. The other variables did not contribute, at significant level, during the study period.

Table - 4(a) shows the results of the model summary of logistic regression. The Nagelkerke R Square implies that 53% of predictors could explain the model. **Table - 4(b)** reveals the results of Hosmer and Lemeshow Test. It is understood that the chi-square value was significant at 1% significant level, which implied that the overall model was fit in the case of sample firms.

Table 4: Results of Estimated Logit Model used for Sample Firms

	B	S.E.	Wald	Df	Sig.	Exp(B)
ATR	0.151	0.178	0.717	1	0.397	1.163
CR	-0.748	0.433	2.987	1	0.084	0.473
RE/TA	-0.19	0.365	0.27	1	0.604	0.827

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IBT/Sales	1.756	0.446	15.53	1	0	5.788
CFO/CL	**3.876**	1.543	6.309	1	0.012	48.245
Grow/IBT	0.814	0.371	4.818	1	0.028	2.258
Debt/Eqity	-0.07	0.142	0.243	1	0.622	0.933
Sales/AVR	-0.099	0.275	0.13	1	0.719	0.906
CA/TA	0.255	0.133	3.663	1	0.056	1.29
EBIT/TA	1.899	0.227	69.702	1	0	6.681
LogEBITInt	0.259	0.141	3.383	1	0.066	1.296
WCap/Sales	-4.91	2.011	5.964	1	0.015	0.007
WCap./TA	-0.051	0.097	0.276	1	0.6	0.95
TL/TA	-0.245	0.172	2.036	1	0.154	0.782
ITR	0.099	0.097	1.043	1	0.307	1.105
ROCE	0.273	0.104	6.846	1	0.009	1.314
NPM	-0.094	0.212	0.198	1	0.657	0.91
Constant	-1.107	0.256	18.771	1	0	0.33

Source: Collected from PROWESS and Computed using SPSS

Table 4(a): Model Summary used for sample firms

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	536.320a	0.4	0.536

Source: Collected from PROWESS and Computed using SPSS

Table 4(b): Hosmer and Lemeshow Test used for sample firms

Step	Chi-square	Df	Sig.
1	71.355	8	0

Source: Collected from PROWESS and Computed using SPSS

The results of the performance measures of the logit model are given in **Table -5**. It is clear that the accuracy of the model was at 85.6% while the error rate was at 14.4%. Besides the specificity of the model was at 89.9%, with precision of 86.2%, F-measure of 82.9% and Type 1 error of 15.9% & Type 11 of error17.5% during the study period.

Table 5: Prediction Results of Logit Model using Performance Measures

Performance Measure	**%**
Accuracy	**85.6**
Error	14.4
Sensitivity	79.9
Specificity	89.9
Precision	86.2
F Measure	82.9
Type 1 Error	15.98
Type 2 Error	17.51

Source: Collected from Prowess data and Computed Using SPSS 20.

6.4. Analysis of Kernal Models in Support Vector Machine (SVM)

Table - 6 depicts the results of the confusion matrix of different kernel models of Linear, Polynomial, and Radial Basis Function (RBF), in the Support Vector Machine Technique. It provides the results of redistribution, training, and testing data set. The analysis of above three models revealed that the polynomial model yielded the highest accuracy rate of 97.30%, followed by the RBF Model with 95.83% and the linear model with 86.20% (lowest accuracy rate), in the redistribution data set.

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Table 6: Confusion Matrix for Kernal Models in SVM

Scenarios	**Partition**	**Observed**	**Predicted**		
			Unsuccessful	Successful	Percent Correct
Linear	Redistribution	Unsuccessful	319	30	91.40%
		Successful	56	218	79.56%
		Overall	85.07%	87.90%	86.20%
	Training-66.67%	Unsuccessful	213	17	92.61%
		Successful	38	143	79.01%
		Overall %	84.86%	89.38%	86.62%
	Testing-33.33%	Unsuccessful	104	15	87.39%
		Successful	21	72	77.42%
		Overall	83.20%	82.76%	83.02%
Poly	Redistribution	Unsuccessful	343	6	98.28%
		Successful	10	234	95.90%
		Overall %	97.17%	97.50%	**97.30%**
	Training-66.67%	Unsuccessful	229	1	99.57%
		Non Unsuccessful	4	177	97.79%
		Overall %	98.28%	99.44%	98.78%
	Testing-33.33%	Unsuccessful	93	26	78.15%
		Successful	14	79	84.95%
		Overall %	86.92%	75.24%	81.13%
RBF	Redistribution	Unsuccessful	343	6	98.28%
		Successful	20	254	92.70%
		Overall %	94.49%	97.69%	95.83%
	Training-66.67%	Unsuccessful	229	1	99.57%
		Successful	17	68	80.00%
		Overall %	93.09%	98.55%	94.29%
	Testing-33.33%	Unsuccessful	113	6	94.96%
		Successful	25	68	73.12%
		Overall %	81.88%	91.89%	85.38%

Source: Collected from Prowess data and computed Using MATLAB

From the further assessment of performance measures, for predicting the outcomes for all models, in Support Vector Machine Technique (**Table -7)**, it was found that the polynomial model performed comparatively better than all other models, in terms of accuracy of 0.9730 (97%), error rate of 0.0270 (2%), sensitivity of 0.9590 (95.90%) and F-measure of 0.9669 (96.69%). But the RBF Model recorded 4.17% of error rate, 92.7% of sensitivity, **98.28%** of specificity, and 95.13% of F-measure. These results were closer to the polynomial model. Based on type 1 and type 2 errors, the RBF model gave the lowest type 1 error of 2.36%, followed by the Polynomial model with 2.56%, but the type 2 error polynomial model provided the lowest rate of 2.92% which was higher than the RBF model (5.83%). It was found that as per kernel function models of linear, polynomial and RBF models, the polynomial model gave the lowest error, highest rate of accuracy, sensitivity, specificity and F-measure. Hence the kernel model, the compared to Polynomial model yielded better accuracy rate as far as sample firms were concerned.

Table 7: Prediction Results for SVM Model using Kernal Functions of Redistributed data

Kernal Models	ACCURACY	ERROR	SENSI	SPEC	PRECISION	F MEASURE
Linear	0.8620	0.1380	0.7956	0.9140	0.8790	0.8352
Polynomial	**0.9730**	0.0270	0.9590	0.9828	0.9750	0.9669
RBF	0.9583	0.0417	0.9270	0.9828	0.9769	0.9513

Source: Collected from PROWESS and computed Using MATLAB

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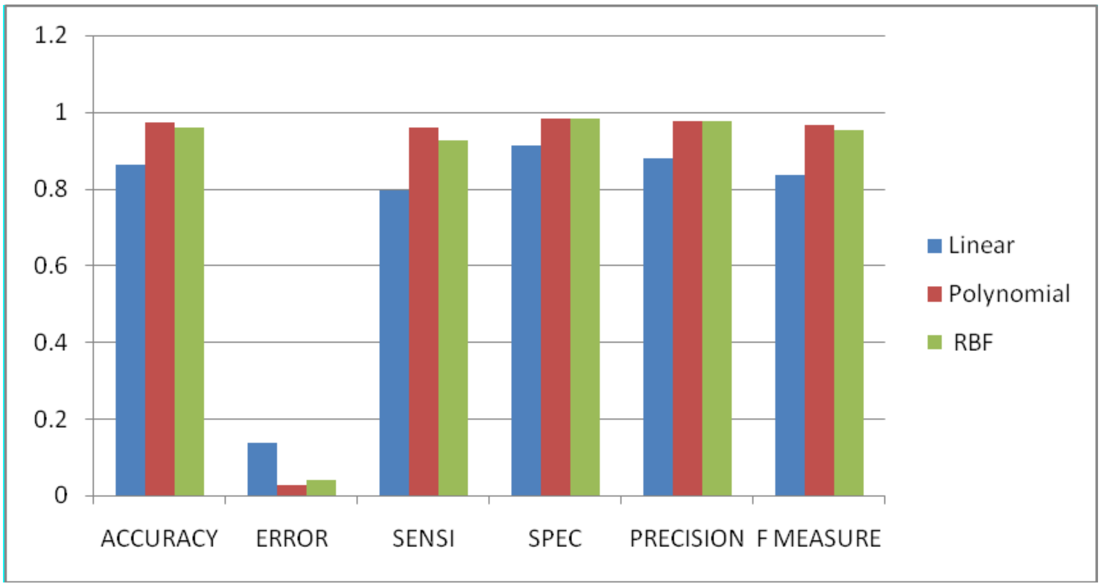
Chart -1 shown the comparative results of linear, polynomial and RBF –kernal models. It indicated that polynomial model provides highest accuracy level, sensivity, specificity, precision, F-measure with lowest error.

Chart -1: Comparative Performance of Kernal Model in SVM



Source: Computed from Table 7.

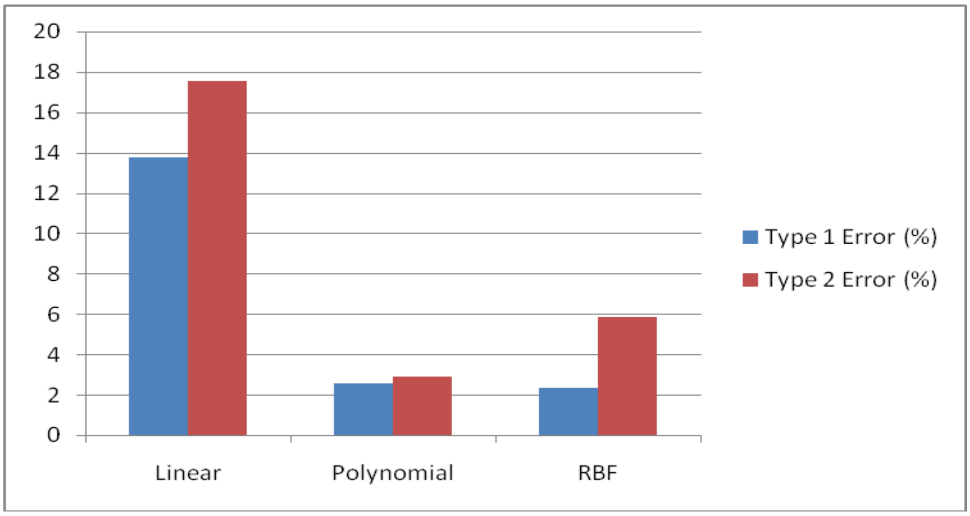
Table 8 demonstrated the results of Type 1 and Type 2 Errors of kernel models in SVM. The table expressed that RBF model provides the lowest Type 1 error followed by polynomial model. Chart-2 graphically expressed the above result. Polynomial model gives the lowest type 1 and type2 error.

Table 8: Percentage of Type 1 and Type 2 Errors in SVM model scenarios

Kernal Models	Type 1 Error (%)	Type 2 Error (%)
Linear	13.76	17.55
Polynomial	2.56	2.92
RBF	2.36	5.83

Source: Collected from PROWESS and computed Using MATLAB

Chart -2: Type 1 and Type 2 Error of Kernal Model in SVM



Source: Computed from Table 8

7. SUMMARY AND DISCUSSION

The study applied financial variables, under the traditional model of Logit model and Data mining techniques of SVM-Kernel functions model. The logit model yielded an accuracy rate of 85.55% while the SVM- Polynomial model reported 97.3% accuracy. Comparatively, the traditional model of Logit analysis reported the lowest accuracy rate and highest errors. The study revealed that the sample financial variables, namely, IBT on Sales, EBIT/Total Assets, Operating cash flow/ Current Liability ratio, Growth on Interest before tax, Working capital / Sales ratio, and Return on capital employed had significantly contributed to the prediction of financial distress of SME's, in listed BSE companies.

From these results, it could be concluded that the SVM Polynomial model was a more balanced and efficient model, based on better accuracy rate, reduced error rate, well-controlled type 1 and type 2 error rates, highest sensitivity and F-measure than other models.

REFERENCES

[1] Agrawal, K. (2015). "Default prediction using Piotrowski's F-score", Global Business Review, Vol. 16, No. 5_suppl, pp. 175S-186S.

[2] Alireza Mehrazin, Mohammad Taghipour, Omid froutan, Bashir Ghabdian & Hamid Soleimani (2013). "Radial Basis Function in Artificial Neural Network for Prediction of Bankruptcy", International Business Research; Vol. 6(8), pp. 121-128.

[3] Agostino Di Ciaccio and Giovanni Cialone (2019). "Insolvency Prediction Analysis of Italian Small Firms by Deep Learning", International Journal of Data Mining & Knowledge Management Process (IJDKP), Vol.9, No.6, pp.01-12.

[4] Behr, A. and Weinblat, J. (2017), "Default prediction using balance-sheet data: a comparison of models", The Journal of Risk Finance, Vol. 18 No. 5, pp. 523-540.

[5] Bagher Asgarnezhad Nouri, Milad Soltani (2016). "Designing a bankruptcy prediction model based on account, market, and macroeconomic variables (Case Study: Cyprus Stock Exchange)". Iranian Journal of Management Studies (IJMS), Vol. 9, No. 1, 2016 pp. 125-147.

[6] Ben Jabeur, S. (2017), "Bankruptcy prediction using partial least squares logistic regression", Journal of Retailing and Consumer Services, Vol. 36, pp. 197-202.

[7] Ben Chin Fook Yap, Dr. Shanmugam Munuswamy, Dr. Zulkifflee Bin Mohamed (2012), "Evaluating Company Failure in Malaysia Using Financial Ratios and Logistic Regression", Asian Journal of Finance & Accounting, Vol. 4, No. 1, pp-330-344.

[8] Ben Chin-Fook Yap, David Gun-Fie Yong and Wai-Ching Poon (2010). "How Well Do Financial Ratios and Multiple Discriminant Analysis Predict Company Failures in Malaysia", International Research Journal of Finance and Economics, Issue 54, pp.166-175.

[9] Chih-Chun Chen, Chun-Da Chen, Donald Lien (2020), "Financial distress prediction model: The effects of corporate governance indicators", Journal of forecasting, Vol.9, no.8, pp-1238-1252.

[10] Cultrera, L. and Bredart, X. (2016). "Bankruptcy prediction: the case of Belgian SMEs", Review of Accounting and Finance, Vol. 15 No. 1, pp. 101-119.

[11] David L. Olson, Dursun Delen, Yanyan Meng (2012). "Comparative analysis of data mining methods for bankruptcy prediction", Decision Support Systems 52 (2012), pp- 464–473.

[12] Dursun Delen, Cemil Kuzey, Ali Uyar (2013). "Measuring firm performance using financial ratios: A decision tree approach". Experts system with Applications, 40 (2013) 3970–3983

[13] Fang-Mei Tseng, Yi-Chung Hub (2010). "Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks", Expert Systems with Applications 37 (2010) 1846–1853.

[14] G.Ozdagoglu, A. Ozdagoglu, Y. Gumus and G. Kurt-Gumus (2017). "The application of data mining techniques in manipulated financial statement classification: The case of turkey", Journal of AI and Data Mining, Vol 5, No 1, pp-67-77.

[15] G.H. Muller, B.W. Steyn-Bruwer & W.D. Hamman (2009). "Predicting financial distress of companies listed on the JSE – A comparison of techniques", S.Afr.J.Bus.Management, 40(1), pp-21-32.

[16] Hamid Wagas, Rohani Md-Rus(2018). "Predicting financial distress: Applicability of O-score and logit model for Pakistani firms", Business, and Economic Horizons, vol.14, no.2, pp.389-401.

[17] Huong Giang Nguyen (2005). "Using Neutral Network in Predicting Corporate Failure", Journal of Social Sciences 1 (4): 199-202.

[18] Jae H. Mina, Young-Chan Lee (2005). "Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters", Expert Systems with Applications 28 (2005), PP-603–614.

[19] Jyoti Nair and Sachdeva (2018). "Financial Distress Indicators of Indian Manufacturing Companies– A Factor Analysis Approach", Global Journal for Research Analysis, Vol.7, No.3, pp. 66-69.

[20] Maryam Moharrampour, Sara Esfandiyari, Adib Asgarzadeh (2014). "Evaluating the Bankruptcy prediction models", Applied Mathematics in Engineering, Management, and Technology 2(3), pp-620-633.

[21] Mani Shehni Karamzadeh (2013). "Application and Comparison of Altman and Ohlson Models to Predict Bankruptcy of Companies". Research Journal of Applied Sciences, Engineering, and Technology 5(6): 2007-2011, 2013

[22] Nidhi Arora, JatinderKumar R. Saini (2014). "Bankruptcy Prediction of Financially Distressed Companies using Independent Component Analysis and Fuzzy Support Vector Machines", International Journal of Research in Computer and Communication Technology, Vol.3, No. 8, pp.924-931.

[23] Nur Adiana Hiau Abdullah.et all (2014). "Predictors of Financially Distressed Small and Medium-Sized Enterprises: A Case of Malaysia", IPEDR. 2014. V76. 18, pp-108-112.

[24] Ohlson, J.A. (1980). "Financial ratios and the probabilistic prediction of bankruptcy", Journal of Accounting Research, Vol. 18 No. 1, pp. 109-131.

[25] Rani, L. P. D., Verma, A., & Kharra, S. (2019). Discriminant analysis: An applied mathematical tool to Navarathna company's financial performance. *Journal of Engineering and Applied Sciences, 14*(3), 759–765.

[26] Rani, L. P. D., & Nagesweri, P. (2018). Analysis of financial parameters of private banks in India. *International Journal of Pure and Applied Mathematics, 119*(7), 2667–2679.

[27] Rani, L. P. D., & Jahahirdar, M. (2018). Developing a discriminant model for Indian FMCG sector: A tool to identify the sustainable performance of a company. *Research Journal of Applied Sciences, 13*(1), 54–58.

[28] Rani, L. P. D., & Das, P. (2018). Fortune Global 500 trend analysis – A comparative study between India and Britain. *International Journal of Scientific Research in Computer Science Applications and Management Studies, 7*(5).

[29] Rani, L. P. D., & Kowsalyadevi, S. (2014). A comparative analysis of HDFC Bank's financial performance before and after the acquisition with Centurion Bank of Punjab. *International Journal of Recent Research in Commerce, Economics, and Management, 1*(2), 34–37.

[30] Rani, L. P. D., & Kowsalyadevi, S. (2014). A study on the impact of employer branding in acquiring and retaining talent in the IT sector. *South Asian Academic Research Journals, 4*(11), 1–30.

[31] Rani, L. P. D., & Rajasekaran, D. (2014). A comparative study on financial betterment of LVB before and after the Internet banking chapter. *South Asian Academic Research Journals, 4*(11), 50–69.

[32] Rani, L. P. D. (2016). Employees' attitude towards health and safety measures at Jayasar Springs Private Limited, Namakkal. *International Journal of Recent Research in Commerce, Economics, and Management, 3*(1).

ISSN 2349-7807

International Journal of Recent Research in Commerce Economics and Management (IJRRCEM)
Vol. 12, Issue 3, pp: (21-31), Month: July - September 2025, Available at: www.paperpublications.org

[33] Ruibin Geng, Indranil Bose and Xi Chen (2015). "Prediction of financial distress: An empirical study of listed Chinese companies using data mining", European Journal of Operational Research, 241, pp. 236-247.

[34] Sajad Abdipour, Mojtaba Akbarpour and Amir Shams Koloukhi (2013). "In research of optimal model for predicting bankruptcy", Science Road Journal, 1(3), pp-31-41.

[35] Senthil Arasu B., Radhakrishna G.S., Sridevi P. and Thamaraiselvan N. (2019). "Business health characterization of listed Indian companies using data mining techniques", Int. J. Business Information Systems, Vol. 32, No. 3, pp-324-363, 2019.

[36] Senthil Arasu B., Radhakrishna G.S., Sridevi P. and Thamaraiselvan N. (2019), "Modeling Corporate Financial Distress using Financial and Non-financial variables: the case of Indian listed Companies", International Journal of Law and Management, Vol.61, No.3, pp. 457-484.