Financial Ratios and Corporate Failure: Evidence from Nigerian Listed Manufacturing Firms

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Abstract

This paper examines the effectiveness of financial ratios in predicting corporate failure among listed manufacturing firms in Nigeria. The paper utilized secondary data collected from annual reports of the sampled firms for the period 2012 – 2018. Twenty firms were selected through a non-probabilistic sampling technique in the form of convenience sampling technique. The sample firms consist of ten failed and ten Non-failed firms. The analysis was performed using the multiple discriminant analysis models run on SPSS version 21. Six financial ratios out of the eighteen earlier selected as predictors of failure emerge as the best predictors. Specifically, the findings of the study reveals that Earnings Before Interest and Tax to Total Assets (EBITA), Working Capital to Total Assets (WCTA), Current Liabilities to Total Assets (CLTA), Market Value of Equity to Book Value of Debt (MVEBVD) contributed most in predicting corporate failure. Cross-validation test shows 76.4% prediction accuracy of the discriminant function model. The study concluded that, univariate descriptive analysis is crucial in generating the most significant single failure predictor to predict the possibility of failure or to provide a warning signal for imminent failure. Based on the findings, the study recommends management to compute financial ratios regularly and made use of by listed manufacturing firms in Nigeria in assessing their financial health and sound decision making. Policymakers and regulatory authorities such as Central Bank of Nigeria and the Nigerian Stock Exchange should develop an early warning system sign of corporate failure to avoid corporate failure.

Keywords: *Financial Ratios, Corporate Failure, Corporate Bankruptcy, Corporate Distress, Multiple Discriminant Function.*

1. Background of the Study

The global financial crisis caused numerous companies with historically strong financial standing to go out of business because they were caught off guard and could not meet their financial obligations **(**Umar, 2018**).** This has bring to the fore the reasons behind the collapse of firms and the need to take timely failure preventive action as a precautionary measure. Despite the popularity of the topic, corporate failure problem remains a topical issue, finding the most accurate and reliable method for predicting firm failure remains a contestable issue. Corporate failure has been a core concern for users of financial statement such as investors, banks, credit rating agencies, auditors, regulators and underwriters. It has also gained considerable attention from practitioners and academicians since the1960s (Scorlat & Delcea, 2011). Failure is the inability of a firm to pay its financial obligations as they mature (Ani & Ugwunta, 2012). This motivates researchers to find a tool to detect unfavorable symptoms before an entity fails.

Besides outright failure, few business organizations utilize over fifty percent of their installed capacities in Nigeria. The reasons for this ugly development range from exchange rate problems, inflation, government unstable policies and other disequilibria in the macro-economy. The capacity under-utilization snowballs into very adverse business times for most manufacturing companies and those who failed to monitor the early warning signals eventually go under. Signs of potential financial distress are generally evident in a ratio analysis long before the firm actual fails, and researchers use ratio analysis to predict the probability that a given firm will fail (Uchenna & Okelue, 2012).

The paper is precipitated by the dire consequences of business failure with colossal cost implication evidenced by the loss of jobs, decline in the gross domestic product, declining overall standard of living, general social disequilibrium in the polity and in the macro-economy. All these consequences have been witnessed in Nigeria in the past decades. It, therefore, becomes imperative to ascertain if ratio analysis is sure ways of predicting failing Corporations so that the above-mentioned consequences can be averted if noticed.

The Manufacturers Association of Nigeria (MAN) declared that over 920 manufacturing companies closed down between 1999 and 2018 of the Civilian rule and rendered thousands of people jobless (African Vanguard, 2019). The high exit rate was blamed on the tough operating environment, unstable electricity, high-interest rate and exchange rate misalignment, smuggling, high cost of energy to power Firm generators, high taxation and levies. These events have a negative influence, both socially and economically on the manufacturing companies in particular and the country at large. Outside the shores of this country, companies such as Global Crossing, Enron, Adelphia and WorldCom are now infamous names representing massive failure.

Besides, the existing empirical literature evidenced that since 1960s, several studies were conducted to examine the corporate failure prediction from different countries of the world. For instance the studies of Altman & Lavelle, (1981) in Canada; Izan, (1984) in Australia; Charitou et al, (2004) in UK; Micha, (1984) in France; Altman et al, (1995) in Korea; Xu-Zhang, (2008) in Japan; Bidin, (1988) in Malaysia; Eljelly & Mansour, (2001) in Sudan; Bandyopadhyay, (2006) in India; Ugurlu & Aksoy, (2006) in Turkey; and Etemadi, et. al., (2008) in Iran; Moscalu & Vitila, (2012) in Romania; Mary, (2013) in USA.

However, most of the studies on financial ratios and corporate failure predictions in Nigeria concentrate on banks. For example the study of Maishanu (2004), Unuofe and Egbunike (2014), Yahaya, Nasiru and Ebgejiogu (2017). Though there are few studies on manufacturing firms despite the important role the sector plays in the economic development of the country. Empirical studies testified the effectiveness of financial ratios in predicting corporate failure. For example, a financially distressed firm can be separated from the non-failed firms in the year before the declaration of the failure at an accurate rate of better than 94% examining financial ratios (Altman, 1986). Based on the foregoing, this study is set to examine the effectiveness of financial ratios in predicting corporate failure among listed manufacturing firms in Nigeria. Other specific objectives are (i) To examine the extent to which financial ratios predict corporate failure among Listed Manufacturing Firms in Nigeria (ii) To determine the extent to which financial ratios distinguish Failed from Non-Failed Firms among Listed Nigerian Manufacturing Firms in Nigeria.

2. Literature Review

2.1 The Concept of Corporate Failure

A number of 'failure' definitions are used in the literature. For instance, Altman & Holchkiss (2006), defined 'failure' as existing when the realized rate of return on invested capital is significantly and continually lower than prevailing rates on similar investments. Beaver, (1966) defines **'failure'** as the inability of a firm to pay its financial obligations as they mature. Researchers identify distressed companies based on several financial dimension's "Financial distress" conditions are represented by business restructuring or reorganization (Routledge & Gadenne, 2000), failure to pay annual listing fees (Jone & Roll, 1987), Liquidation and acquisition (Coats & Fant, 1993).

The success or failure of any business is as a result of the interaction of two sets of main factors. Firstly, the performance of a company is affected by external factors, which are beyond the control of business managers. The growth rate of the economy, inflation, exchange rates, interest rates, preferences, attitudes and changing activities, environmental conditions clearly affect the profitability of a business and its market power (Sharma & Mahajan, 1980). The other set of main factors affecting the performance of a business entity is the set of internal factors, which are the factors existing in the company and under control. Among the factors related to a company are: insufficient equity to finance growth and excessive use of leverage, failures in location selection, inability to meet customer expectations and excessive fixed assets investments.

Similarly, it is possible to classify financial failure as a result of bad management that resembles internal reasons of financial distress (Wruk, 1990). Poor management alone can cause economic failure. Therefore, the performance fall resulting from internal causes and excessive leverage can be considered as managerial incompetence (Whiteaker, 1999). Commonly accepted financial indicators of impending failure include low profitability related to assets and commitments, low equity returns, dividend and capital, poor liquidity, high gearing and the high variability of income. Itodo (2010) assert that during the course of managing a corporation, there are bound to be a lot of obstacle within and outside the environment. The attending effects of these problems and obstacles lead to failure. It is always important for entrepreneurs to observe and monitor the symptoms of corporate failure, because they serve as indices which portend that something is going wrong within the enterprise or consequently the imminent failure of the corporation. The symptoms include deterioration of working capital, a decline in sales, high debt-equity ratio and decline in profit. In determining the symptoms of corporate failure, Hooks, (1994) highlights: declining turnover, undercapitalization, persistent liquidity deficiency, high debt ratio and accumulated losses. These symptoms are very important in developing an early warning model for predicting corporate failure for the identification of possible failure (Bovenzi, Morino & Mcfadden, 1983).

2.2 Theoretical Review

Several theories are used in explaining the study of financial ratios and corporate failure, some of which include: the Notional theory, the Cash flow theory, the Merton theory, the Gambler's ruin theory and the Entropy theory. However this study is underpin by the Notional theory, Cash flow theory and the Entropy theory. On the other hand, the Notional theory emanates from the perception of financial ratio's indicators of firms heath when the firms' indicators are 'good' it is perceived as healthy, if otherwise, it is perceived as unhealthy and at risk of bankruptcy. Besides, the Cash flow theory is the theory that can best be explained within the framework of a cash flow. According to Maishanu, (2004) the firms is viewed as a reservoir of liquid assets, which is supplied by inflows and drained by outflows. The reservoir servers as a cushion or buffer against variations in the flows. Finally, the Entropy theory is one way of identifying financial distress by examining the structural changes in the statement of financial position of the company. Thus, companies try to maintain equilibrium in their financial structure.

3. Research Methodology

The cross-sectional research design was adopted to ensure a satisfactory level of validity and reliability. Data are sourced from the Firm's annual reports extracted from NSE Factbook. The data covered a period spanning from 2012 – 2018. Multiple discriminant Analysis was employed in analyzing the data in line with the study model. Twenty (20) Manufacturing Firms consisting of ten (10) Failed firms and ten (10) Non-Failed were selected as a sample for the study. The selection of the firms is based on the availability of data for the period (2012- 2018). The paper focus on eighteen (18) financial ratios grouped under the leverage; liquidity, profitability and turnover ratios. This is consistent with Abdul Rashid and Qaiser (2011).

3.1 Model Specification

Multi Discriminate Analysis (MDA) Model determines a set of discriminate coefficient and transforms individual variable values to a single discriminate score or Di –value were specified to classify the sample firms into two groups, failed and non-failed companies.

$$Di = \acute{\alpha} + \beta_1 X_1 + \beta_2 X_2 + \text{------------------} + \beta_n X_n$$

Where:

'Di' discriminate Score (predicted score), '$\beta_1\beta_2$----------------------βn' Discriminate Coefficients of independent variables, 'X_1, X_2-------------------------- X_n' independent variables (predictors), n = the number of independent variables and $\acute{\alpha}$ = Constant. The Discriminate Score (D) is taken to estimate the failure character of the company. The Lower the value of Di, the greater is the firm's failure probability and vice versa. The dependent variable (D) is the discriminate score that forecasts the failure probability of the Company. This variable takes the value '0' or '1' for any firm observation. In this paper, value "0" has been assigned to failed firms and value "1" for non-fail firms while estimating the model. The paper further employs eighteen financial ratios as independent variables.

4.0 Result and Discussion

4.1 Results

Table 4.1: Robust Tests of Equality of Group Means

Variable	Walks Lambda	F	Df1	Df2	Sig.
OCFTD	.824	29.424	1	138	.000
CLTA	.956	6.418	1	138	.012
EBITNCA	.807	32.900	1	138	.000
EBITL	.696	60.350	1	138	.000
TLEQ	.991	1.285	1	138	.259
MVEBVD	.984	2.279	1	138	.133
CACL	1.000	.001	1	138	.977
LQACL	1.000	.013	1	138	.911
WCTA	1.000	.014	1	138	.905
EBITS	.836	26.994	1	138	.000
EBITA	.799	34.631	1	138	.000
EAITS	.888	17.490	1	138	.000
EAITA	.831	28.050	1	138	.000
RETA	.862	22.096	1	138	.000
SNCA	.911	13.433	1	138	.000
EXSAL	.956	6.408	1	138	.000
SATA	.848	24.688	1	138	.000
WCS	1.000	.000	1	138	.983

Source: SPSS Output, 2019.

Table 4.1 provides strong statistical evidence of significant difference between means of Failed and Non-Failed Firms groups for all independent variables i.e. 18 financial ratios, the result shows that Earnings Before Interest Tax to Total Liability (EBITL), Earnings Before Interest and Total to Total Assets (EBITA), Earnings Before Interest to Non-Current Assets (EBITNCA), Operating Cash flow to Total Debt (OCFTD), Earnings After Interest and Tax to Total Assets (EAITA), Retained Earnings to Total Assets (RETA), Earnings After Interest and Tax to Sales (EAITS), Sales to Non-Current Assets (SNCA), Current Liability to Total Assets (CLTA), Expenses to Sales (EXSAL), Earnings Before Interest and Tax to Sales (EBITS) and Sales to Total Assets (SATA) ratios have a less wilks Lambda value and highest F- value and less sig. value.

Table 4.2 Eigenvalues

Function	Eigenvalue	%of Variance	Cumulative%	Canonical Correlation
1	.886[a]	100.0	100.0	.685

a. The first 1 canonical discriminate functions were used in the analysis.

Source: SPSS Output, 2019

Table 4.2 shows the canonical correlation which is the multiple correlations between the predictors and the discriminate function. With only one function it provides an index of overall model fit explain (r^2). A canonical correlation of 0.685^2 suggested the model explains 46.92% of the variation in the grouping variable i.e. whether Failed or Non- Failed Firms. The higher the correlation value, the better the function that discriminates. The value 1.00 is perfect. Here the correlation of 0.685 is comparatively high.

Table 4.3 Wilks Lambda

Test Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.530	85.618	6	.000

Source: SPSS Output, 2019

Table 4.3 shows the Wilks lambda which indicates the significance of the discriminate function. Indicates a highly significant function (P<.000) and provides the proportion of total variability not explained, i.e. it is the converse of the squared canonical correlation. So we have 0.530 or 53% unexplained.

Table 4.4 Standardized Canonical Discriminate Function Coefficient

	Function
	1
CLTA	.422
EBITL	-1.449
MVEBVD	.356
WCTA	.516
EBITA	.815
SATA	-.589

Source: SPSS Output, 2019

Table 4.4 provides an index of the importance of each predictor like the standardized regression coefficients (beta) do in multiple regression. The sign indicates the direction of the relationship. Earnings Before Interest and Tax to Total Assets (EBITA) discriminated the most with the highest discriminate magnitude 0.815 followed by Working Capital to Total Assets (WCTA) with 0.516, Total Liability to Total Assets (TLTA) with 0.422, Market Value of Equity to Book Value of Debt (MVEBVD) with 0.356, Sales to Total Assets (SATA) with -0.589, Earnings Before Interest Tax to Total Liability (EBITL) with -1.449 that discriminating the least.

Table 4.5 Canonical Discriminate Function Coefficients

	Function
	1
CLTA	1.633
EBITL	-7.162
MVEBVD	4.300
WCTA	1.972
EBITA	5.504
SATA	-1.435
(Constant)	.694
Unstandardized coefficients	

Source: SPSS Output, 2019

Table 4.5 shows the canonical discriminate function coefficients, the discriminate function can be arranged as follows: D = .694 + 1.633 (TLTA) - 7.162 (EBITL) + 4.300 (MVEBVD) + 1.972 (WCTA) + 5.504 (EBITA) - 1.435 (SATA). The discriminate function coefficients "b" or standardized form beta both indicate the partial contribution of each variable to the discriminate function controlling for all other variables in the equation.

Table 4.6 Functions at Group Centroids

Group(ID)	Function
	1
Failed	-.934
Non-failed	.934
Unstandardized canonical discriminate functions evaluated at group means	

Source: SPSS Output, 2019

Table 4.6 shows that failed firms have a means of -0.934 while non-failed firms produce a means of 0. 934. Cases with a score near to a centroid are predicted as belonging to that group. The cut -off point of failed and non-failed group centroid is zero, which suggests that the movement of Firm with the D = value below zero is approaching towards failure. At last, the firm having D= value -0.934 classified as 'failed' and the firm having a D= value 0.934 classified as 'non- Failed'.

Table 4.7 Classification Results

Classification Results[c]		Failed or Non-Failed	Predicted Group Membership Failed(0)	Non-failed(1)	Total
Original	Count	Failed(0)	57	13	70
		Non-failed(1)	14	56	70
	%	Failed(0)	81.4	18.6	100.0
		Non-failed(1)	20.0	80.0	100.0
Cross-Validated	Count	Failed(0)	56	14	70
		Non-failed(1)	19	51	70
	%	Failed(0)	80.0	20.0	100.0
		Non-failed(1)	27.1	72.9	100.0

Source: SPSS Output, 2019. a. 80.7% of original grouped cases correctly classified. b. cross-validation is done only for those cases in the analysis. In cross-validation, each is classified by the functions derived from all cases other than that case. c. 76.4% of cross-validated grouped cases correctly classified.

Table 4.7 shows that the overall model classification accuracy is 80.7%, which is an average of the correct classification of the dependent variable, Failed firms (0) at 81.4% and 80% for dependent variable, Non-Failed (1). This is almost similar to the model classification accuracy of 76.4% obtained from cross-validation. The cross-validation is an average of 80% and 72.9% for DV (0) and DV (1) respectively. This overall predictive accuracy of the discriminate function (80.7% for original 76.4% for cross-validation) is called the 'hit ratio' and is acceptable when compared to the 50% probability that a firm would fail based on chance (when two samples of failed and Non-failed firms being compared are equal, there is a 50% chance of picking either a failed or non- failed firm).

Table 4.8 Classification Process Summary

Processed		140
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		140

Source: SPSS Output, 2019

Table 4.8 shows The Classification Processing Summary which gives a summary of the total cases that have been processed successfully based on the analysis. In case, any observation is not processed the reason for the same is highlighted. The table shows that all the 140 observations have been processed successfully.

Table 4.9 Prior Probabilities for Groups

Variable	Prior	Cases Used in Analysis Unweighted	Weighted
Failed	.500	70	70.000
Non-Failed	.500	70	70.000
Total	1.000	140	140.000

Source: SPSS Output, 2019.

Table 4.9 shows the prior probabilities which gives the number of observations used in the analysis and the distribution of the observations into groups used as a starting point in the analysis. It gives the weighted value which is further used in the calculation of the centroid value

Table 4.10 Variables in the Analysis

Step		Tolerance	F to Remove	Wilks' Lambda
1	EBITL	1.000	60.350	
2	EBITL	.999	48.714	.848
	SATA	.999	15.323	.696
3	EBITL	.195	26.977	.718
	SATA	.978	17.439	.676
	EBITA	.193	6.086	.626
4	EBITL	.186	30.486	.711
	SATA	.960	13.817	.639
	EBITA	.193	6.268	.607
	WCTA	.841	4.453	.599
5	EBITL	.181	33.615	.697
	SATA	.952	14.811	.619
	EBITA	.189	7.713	.589
	WCTA	.811	6.156	.583
	MVEBVD	.937	5.442	.580
6	EBITL	.180	28.649	.645
	SATA	.826	20.649	.613
	EBITA	.188	8.271	.563
	WCTA	.639	11.535	.576
	MVEBVD	.901	7.549	.560
	CLTA	.577	6.730	.557

Source: SPSS Output, 2019

Table 4.10 shows that six steps were taken, with each one including another variable and therefore these six were included in the variables in the Analysis and Wilks Lambda tables because each was adding some predictive power to the function.

Table 4.11 Variable Entered/Removed[a,b,c,d]

Step	Entered	Wilks' Lambda Statistic	df1	df2	df3	Exact F Statistic	df1	df2	Sig.
1	EBITL	.696	1	1	138.000	60.350	1	138.000	.000
2	SATA	.626	2	1	138.000	40.969	2	137.000	.000
3	EBITA	.599	3	1	138.000	30.355	3	136.000	.000
4	WCTA	.580	4	1	138.000	24.457	4	135.000	.000
5	MVEBVD	.557	5	1	138.000	21.298	5	134.000	.000
6	CLTA	.530	6	1	138.000	19.629	6	133.000	.000

Source: SPSS Output, 2019. At each step, the variable that minimizes the overall Wilks' Lambda is entered. a. The maximum number of steps is 36. b. The minimum partial F to enter is 3.84. c. The maximum partial F to remove is 2.71. d. F level, tolerance, or VIN insufficient for further computation.

Table 4.11 shows that out of eighteen (18) financial ratios, only six (6) ratios namely Current Liability to Total Assets (CLTA), Earnings Before Interest and Tax to Total Liability (EBITL), Market Value of Equity to Book Value of Debt (MVEBVD), Working Capital to Total Assets (WCTA), Earnings Before Interest and Tax to Total Assets (EBITA) and Sales to Total Assets (SATA) are highly significant at 5% significance level in the analysis. Among these six ratios, Earnings Before Interest and Tax to Total Assets (EBITA) discriminate the most with sig value of 000. Thus this result shows that the null hypothesis is rejected in favor of alternate hypothesis which stated that financial ratios significantly predict corporate failure of Listed Manufacturing Firms in Nigeria.

Table 4.12: Wilks Lambda

Step	Number of Variables	Lambda	df1	df2	df3	Exact F Statistic	df1	df2	Sig.
1	1	.696	1	1	138	60.350	1	138.000	.000
2	2	.626	2	1	138	40.969	2	137.000	.000
3	3	.599	3	1	138	30.355	3	136.000	.000
4	4	.580	4	1	138	24.457	4	135.000	.000
5	5	.557	5	1	138	21.298	5	134.000	.000
6	6	.530	6	1	138	19.629	6	133.000	.000

Source: SPSS Output, 2019.

Table 4.12 reveals that all the predictors add some predictive power to the discriminate function as all are significant with P<.000. Thus the model is a good fit for the data with just six predictor variables. Therefore, the Null hypothesis stand rejected in favor of the alternate hypothesis which stated that financial ratios significantly distinguish Failed from Non-Failed manufacturing firms in Nigeria.

4.2 Discussion of Findings

The Descriptive univariate statistics as well as Multi-Discriminate Analysis was used in the data presentation and analysis. The result of the descriptive univariate test of the variable indicates that the Failed Firms have higher Turnover ratios i.e. EXSAL, SATA, WCS and lower SNCA and lower leverage ratios. That is lower OCFTD, TLEQ, EBITNCA, EBITL and higher MVEBVD. Also, higher Liquidity ratios: CACL, WCTA and lower LQACL. Finally, the results exert Poor/Negative Profitability ratios (EBITS, EBITA, EAITS, EAITA, RETA). Thus, the Univariate result shows that Failed Firms differs significantly from Non-Failed. This result coincided with the findings of Chung, et al., (2008) where its reveals that failed firms have less profitability ratios and, higher turnover ratios. Nonetheless, the results contradicted the suggestion that, failed firm equally characterize with less liquidity ratios and higher leverage ratios. Furthermore, the finding is consistent with the studies of Wruk (1990), Haniffa and Cook (2002), Zororo (2006) and Hlahla (2010). The studies indicates that companies are more likely to fail if they suffers depleting profit, high leverage and liquidity ratios.

However, for discriminate analysis it is very important to meet optimal conditions and the main assumptions to prevent the misclassification problem. The key assumptions of discriminate analysis include multivariate normality, homogeneity of variance-covariance matrices and non-multicollinearity. Discriminate analysis is found to be relatively robust to violation of multivariate normality, if the violation is not caused by outliers and robust to the violation of homogeneity of variance-covariance matrices if the sample sizes are larger or equal across groups.

The Multi Discriminate Analysis examined the Eigen value and Wilks Lambda statistics in order to identify the importance of discriminate functions used in the analysis and presented in Tables 4.2 and 4.3 respectively. Eigen value is calculated as .0886 indicating that the dependent variable is explained by discriminate function and differentiates effectively the Failed from Non-Failed Firms. In addition, the square value of canonical correlation in Table 4.2 indicates that the discriminate function explains 46.9% of variance of dependent variable. Table 4.3 Shows the Wilks Lambda Statistical value of 0.530, which is statistically significant at 1% level of significance.

Table 4.4 Present Standardized Canonical Discriminate function Coefficients. The Standardized coefficients of the variables indicate that the most efficient variable for separating the failed and non-failed firms is EBITA, the other efficient variables are:

WCTA, TLTA, MVEBVD, SATA and EBITL respectively. Table 4.5 shows the Unstandardized Canonical discriminate function coefficients. The coefficients was used in developing a discriminate model for predicting Corporate Failure. Thus, the findings from the Multi-Discriminate Analysis concurs with the studies of Dimitries *et al* (1996), Abdulrashid and Qeaser (2011), Puagwatama and Gunawa'adana (2005), Yap and Munuswamy (2012), Almansur (2014), Libby (1975) and Johnson (2002). Specifically, the finding coincides with five out of six ratios developed by Altman, (1968) for predicting Corporate Bankruptcy. These ratios are: WCTA, RETA, EBITA, MVEBVD and SATA. Furthermore, From Table 4.7, the classification results of discriminate analysis was presented to review the success of accuracy prediction of the model. The results exerted that the discriminate model classifies correctly 81.4% of Failed Firms Cases and 80.0% of Non-Failed firms. Additionally, total classification success of the model is 80.7%. While the Cross Validation test shows that the discriminate model classifies correctly 80% of Failed Firms Cases and 72.9% of Non- Failed Cases. The overall success of the model is 76.5%.

5. Conclusion and Recommendations

In view of the foregoing, this study therefore, concludes that univariate statistical test is crucial in generating the most significant single failure, predicting the possibility of failure and/or to provide a warning signal of eminent failure. Financial ratios are related to each other and a combination of financial ratios will be more effective in prediction of failure than a single failure predictor. The cross validation prediction accuracy of 76.4% clearly indicates the reliability of the model.

Accordingly, the study recommends management to compute financial ratios regularly and made use of by Nigerian listed Firms in assessing their financial performance and decision making. Similarly, in computing the financial ratios, emphasis should not be laid on only the traditional ratios analysis, but also the current development in ratio analysis (the multivariate and univariate models of ratios analysis). Moreover, in assessing the likelihood of corporate failure, a more detailed analysis need to be carried out, which include the quantitative as well as the qualitative technique. Finally, policy makers as well as the regulatory authorities should develop early warning systems to avoid eminent corporate failure among manufacturing firms in Nigeria.

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