CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The issue of corporate bankruptcy has gained prominence in the business and finance literature. This follows from globalisation and intense competition which has restricted the profitability of most firms (Hajiamiri, Shahraki, & Barakati, 2014), making bankruptcy probable for non-adaptable firms (Balcaen & Ooghe, 2004a). As a result bankruptcy has remained a concern to various stakeholders, because of its contagious effect (Doumpos & Zopoudinis, 1999); and, ability to destabilize the economic system in various ways, such as: increasing unemployment and poverty level, depriving people, especially creditors of their legitimate earnings, intensifying the crime rate, reduction in the volume of tax earnings, and creates social and economic costs to a nation (Alifiah, 2014; Mbat & Eyo, 2013; Mukkamala, Tilve, Sung, Ribeiro, & Vieira, 2006; Charitou, Neophytou, & Charalambous, 2004; Kim & Han, 2003; McKee & Lensberg, 2002; Daubie & Meskens, 2002; Bickerdyke, Lattimore, & Madge, 1999; Zavgren, 1983).

In the light of this, bankruptcy has remained a dominant topic of interest in accounting, auditing, and finance for the past three decades (Wu, Tzeng, Goo, & Fang, 2007; Cheng, Chen, & Fu, 2006; Min, Lee, & Han, 2006; Salcedo-Sanz, Fernandez-Villacanas, Segovia-Vargas, & Bousono-Calzon, 2005).

Balcaen and Ooghe (2004a) documented six reasons for interest in corporate bankruptcy. First, the large costs associated with corporate failure, which prompted Governments to take corrective actions (Shumway, 2001). Second, the consequential negative downturn in the general economic environment following corporate collapses (Van Caillie & Dighaye, 2002; Tamari, 1966). Thirdly, public availability of corporate data which broadened research, and the evolution in techniques. Fourthly, the renewed interest on the subject of market imperfections and information asymmetry. Fifthly, the need for a more accurate assessment of the state of financial health of firms, and finally, the BASEL arrangements addressed issues of capital and risk. Therefore the extensive research on the development of bankruptcy prediction models is undoubtedly justified (Alaka, Oyedele, Owolabi, Kumar, Ajayi, Akinade, & Bilal, 2018; Hajiamiri, Shahraki, & Barakati, 2014; Alifiah, 2014; Etemadi, Rostamy, & Dehkordi, 2009; Mukkamala, Tilve, Sung, Ribeiro, & Vieira, 2006; Kim & Han, 2003; O'Leary, 1998). And models have emerged from the 60's till date (Altman, 1968; Adnan Aziz, & Dar, 2006).

Prior models were mainly statistical, with an average of sixty four percent of previous studies using such (Etemadi, Rostamy, & Dehkordi, 2009; Bellovary, Giacomino, & Akers, 2007; Adnan Aziz & Dar, 2006). However, the literature has transcended from the use of traditional statistical models to include other techniques which mainly depend on artificial intelligence (AI).

These techniques include decision trees, neural networks, support vector machines, rough sets, case based reasoning, Bayesian networks, among others (Ahn & Kim, 2009; Shin & Lee, 2002; Wilson & Sharda, 1994, Back, Laitinen, & Sere, 1994; Serrano-Cinca, Martin, & Gallizo, 1993). These techniques evolved along with advancements in computer systems, and were capable of providing better solutions for complex problems, such as bankruptcy prediction (Mukkamala, Tilve, Sung, Ribeiro, & Vieira, 2006). The most popular ones included the inductive learning methods, neural networks, support vector machines, genetic algorithms, among others, which often provided higher classification accuracies (Alaka et al., 2018; Shin & Lee, 2002; Shaw & Gentry, 1990; Messier & Hansen, 1988).

Recently attention has shifted to hybrid non-parametric models. Hybrid models combine several classification methods to achieve greater accuracy than individual models, while non-parametric techniques are suitable due to the specific features of financial information (Martin, Gayathri, Saranya, Gayathri, & Venkatesan, 2011; Ping & Yongheng, 2011). Studies usually employ Genetic Algorithms (GA) in developing hybrid models because of its capability in extracting optimal rules that can be integrated to any system (Kirkos, 2015; Martin, Gayathri, Saranya, Gayathri, & Venkatesan, 2011; Shin & Lee, 2002; Back, Laitinen, Sere, & van Wezel, 1996).

GA has demonstrated to be effective and robust in a wide range of applications (Shin & Han, 1999; Colin, 1994), such as trading system (Deboeck, 1994), stock selection (Mahfoud & Mani, 1995), bankruptcy prediction (Shin & Lee, 2002), among others. GA is a powerful tool for optimization of complex problems, does not rely on any distributional assumptions about the variables (Kuri-Morales & Aldana-Bobadilla, 2013; Nanda & Pendharkar, 2001).Studies which compared GA with other techniques show that it usually outperforms others (Bateni & Asghari, 2016), and could handle the influence of human expertise and intuition usually applied in selecting financial ratios for bankruptcy prediction models (Lakshmi, Martin, & Venkatesan, 2016).

The Nigerian manufacturing sector has experienced great shocks in recent years (Ani & Ugwunta, 2012). Between the period of Q1:2002 to Q3:2017, the Nigerian Stock Exchange delisted a total of 85 companies from its daily official list. 61 out of the 85 firms were delisted based on regulatory reasons; this constitutes 71.76 percent of the total number of companies delisted in the review period, while 13 of the firms delisted voluntarily. Thus, the Nigeria's manufacturing sector is entering a phase of major change (Ibrahim, 2017), coupled with the increase of economic globalization and evolution of information technology (Sai, Zhong, & Qu, 2007).

Presently, causes of corporate failures range from accidental factors (malfeasance, death of leader, fraud, disasters, litigation), market factors (loss of market share, failure of customers, inadequate products), financial threats (undercapitalization, cost of capital, default on payment, loan refusal), macroeconomic factors (decline in demand, increased competition, high interest rate), information and managerial problems (incompetence, prices), costs and production structures, and strategy failures (Sullivan, Warren, & Westbrook, 1998; Lussier, 1995).

Against this backdrop the study develops a hybrid model using GA for bankruptcy prediction of Nigeria manufacturing firms.

1.2 Statement of the Problem

The obnoxious state of the Nigerian manufacturing sector has created a dire need for accurate bankruptcy prediction models about the overall outlook of companies. This is precipitated on the overbearing consequences of corporate bankruptcy on key stakeholders. Prior studies have mainly focused on the banking sector, using traditional statistical models, such as discriminant and ratio analysis (Nwidobie, 2017; Egbunike & Ibeanuka, 2015; Ezejiofor, Nzewi, & Okoye, 2014; Pam, 2013; Ebiringa, 2011; Usman, 2005), while few have addressed the manufacturing sector (Hur-Yagba, & Okeji, Ayuba, 2015; Ani & Ugwunta, 2012). Other studies have also demonstrated the practicality of logistic regression (Egbunike & Ezeabasaili, 2013). Despite the success of traditional statistical models they often violate certain assumptions, such as linearity, normality, multicollinearity, among others (Hua, Wang, Xu, Zhang, & Liang, 2007; Dimitras, Zanakis, & Zopounidis, 1996; Back, Laitinen, Sere, & van Wezel, 1996). They are often inadequate in identifying and estimating key parameters which limit their application in the real world (Hawley, Johnson, & Raina, 1990; Zhu & Rohwer, 1996).

Secondly, the issue of time dimension limits the practicality of using previously developed models in present periods (Alaka et al., 2018). Bankruptcy prediction is a high-dimensional classification problem and most data distribution is non-Gaussian and exceptions are common (Zavgren, 1983).

The high-dimensional properties of data needed in model development also affect the classification accuracies of traditional statistical models (Zhang & Wu, 2011). Recent developments in artificial intelligence has widened its application to bankruptcy prediction problems, with the Neural Networks (NNs) being among the first (Alaka et al., 2018; Atiya, 2001; Wilson & Sharda, 1994, Serrano-Cinca, 1993; Coats & Fant, 1993; Udo, 1993).

Studies have addressed the issue of bankruptcy among firms quoted on the Nigeria Stock Exchange using four widely acknowledged methods: discriminant analysis (Babatunde, Akeju, & Malomo, 2017; Ani & Ugwunta, 2012), logistic regression, probit regression (Adeyeye & Migiro, 2015) and neural networks (Yahaya, Nasiru, & Ebgejiogu, 2017; Farinde, 2013; Eriki & Udegbunam, 2013). Studies have confirmed the superiority of NNs to discriminant and logistic approaches (Eriki & Udegbunam, 2013; Farinde, 2013), with prior studies in Nigeria, focused on banks (Yahaya, Nasiru, & Ebgejiogu, 2017; Farinde, 2013), interest rate on loan investment (Enyindah & Onwuachu 2016), stock market (Eriki & Udegbunam, 2013), and insurance companies (Ibiwoye, Ajibola, & Sogunro, 2012).

NNs possess certain limitations, such as; the difficulty in building models as a result of many parameters to be set by heuristics. Secondly, is the danger of overfitting, and its lack of explanation ability, i.e., the ‘*black box*’ problem, as users do not also easily comprehend the final rules which the models acquire (Shin & Lee, 2002). However, an overall better performance model can only be achieved from an informed integration of tools to form a hybrid model (Alaka et al., 2018). Studies have shown that hybrid models have higher classification accuracies (Alaka et al., 2018; Bartual, Garcia, Guijarro, & Moya, 2013; Chen, Ribeiro, Vieira, Duarte, & Neves, 2011). The GA has been proved effective in developing hybrid models (Sai, Zhong, & Qu, 2007). A recent survey identified GA as one of the present data mining techniques that contribute to business decision making (Lin, Ke, & Tsai, 2017) and can provide new insights into bankruptcy prediction (McKee & Lensberg, 2002).

Studies have underinvestigated the application of AI to the subject of bankruptcy prediction. In Nigeria application is limited to neural networks using feed forward and back propagation. The obvious lack of empiricism on the subject in developing countries stemmed the researcher’s interest on the subject.

Secondly, studies have questioned the reliability of models developed with only financial ratios, since there is doubt about the validity and reliability of the accounting information used for the ratios (Agarwal & Taffler, 2008). In addition, the relevance of particular ratios changes due to changes in the environment (Tsai, 2009). It may be worthwhile increasing the variety of explanatory variables to include corporate governance variables in developing prediction models (Ani & Ugwunta, 2012). Corporate governance structures are one of the prime causes of bankruptcy (Daily & Dalton, 1994; Gales & Kesner, 1994; Gilson, 1990; Hambrick & D'Aveni, 1988, 1992). Therefore the addition of corporate governance variables can improve the predictive power of bankruptcy models (Platt & Platt, 2012; Lajili, & Zéghal, 2010; Chang, 2009; Fich & Slezak, 2008; Donoher, 2004). However, the inclusion of corporate governance variables in GA selection and optimization process has been under-investigated. According to Brédart (2014b) studies should be directed to this under-investigated aspect of corporate bankruptcy.

Thirdly, in developing hybrid models GA has widely been applied in addition with other AI techniques (Min, Lee, & Han, 2006). This includes fuzzy logic and neural networks (Georgescu, 2017; Chou, Hsieh, & Qiu, 2017; Jeong, Min, & Kim, 2012; Esseghir, 2006); fuzzy Case Based Reasoning (CBR) method and Genetic Algorithms (Li & Ho, 2009); genetic-based support vector machines (GA-SVM) (Wu, Tzeng, Goo, & Fang, 2007; Min, Lee, & Han, 2006); Linear Genetic Programs (LGPs) (Mukkamala, Tilve, Sung, Ribeiro, & Vieira, 2006). Few studies have dealt with the integration of GA and Boosting Ensemble, such as the Gradient Decision Trees. One notable study is that of Sun and Hui (2006), applied decision tree and genetic algorithms for financial ratios' dynamic selection and financial distress prediction.

Fourthly, most models rely on profitability ratios from financial statements which are prepared on an accrual basis. Therefore, they are deemed to be prone to aggressive accounting. However, in contrast ratios based on cash flow information is deemed to be more immune to manipulations (Welc, 2017). The study therefore also placed emphasis on cash flow ratios classified.

1.3 Objective of the Study

The main objective of the study is to compare the predictive accuracies of four bankruptcy prediction models of Nigerian manufacturing firms. The study specifically addresses the following:

1. To compare the predictive accuracy of GA with the logit model in the prediction of corporate bankruptcy.
2. To compare the predictive accuracy of GA with the discriminant model in the prediction of corporate bankruptcy.
3. To compare the predictive accuracy of GA with neural network in the prediction of corporate bankruptcy.
4. To ascertain if the predictive accuracy of the GA model can be improved from inclusion of corporate governance variables.

1.4 Research Questions

This study is guided by the following research questions:

1. What is the predictive accuracy of GA compared with the logit model in the prediction of corporate bankruptcy?
2. What is the predictive accuracy of GA compared with the discriminant model in the prediction of corporate bankruptcy?
3. What is the predictive accuracy of GA compared with neural network in the prediction of corporate bankruptcy?
4. To what extent can the predictive accuracy of the GA model be improved from inclusion of corporate governance variables?

1.5 Statement of Hypotheses

The following hypotheses were formulated in line with the objectives and research questions above. The hypotheses are stated in there null form as follows:

H_{01}: There is no significant difference in the predictive accuracy of GA compared with the logit model in the prediction of corporate bankruptcy.

H_{02}: There is no significant difference in the predictive accuracy of GA compared with the discriminant model in the prediction of corporate bankruptcy.

H_{03}: There is no significant difference in the predictive accuracy of GA compared with neural network in the prediction of corporate bankruptcy.

H_{04}: The predictive accuracy of the GA model cannot be improved from inclusion of corporate governance variables.

1.6 Significance of the Study

The study theoretically contributes to an understanding of the implication of ensemble type on the classification accuracy of Genetic Algorithm Model. Boosting as an alternative to Bagging, reduces variance and bias therefore providing a means for the reduction of Type I errors, i.e., the misclassification of bankrupt firms as non-bankrupt. They provided a more robust decision model in bankruptcy classification.

The importance of bankruptcy prediction to various stakeholders provides a motivation for the study; the study will practically be beneficial to Government/Policy Makers (via its Agencies), Stockholders/Creditors, Management (Board of Directors), Auditors and Future Studies.

The Government is responsible for maintaining the stability of the economy, therefore findings of the study will enable the government and policy makers, through established agencies (like NSE, SEC, etc.) design systems for rating the performance of companies. This is very important as the number of bankrupt firms in a country, is often considered an index of the development and robustness of the economy.

The findings of the study will enable shareholders and creditors. Shareholders and creditors assess the firms where they have a vested interest in. Bankruptcy prediction models are regarded as tools for assessing the future performance of firms, if the employed tool gives a result closer to reality, the more sound the decision-basis is considered. Failure of such would impose great costs for investors and creditors. Bankruptcy prediction offers an opportunity to shareholders to make their decisions based on facts.

The findings of the study will be of benefit to the management of manufacturing firms, through the identification of the best set of predictors for corporate bankruptcy, they could see ratios that can easily be relied upon in checking for stability or weakness in the firms. It would also serve as a useful tool for planning and decision-making in firms, as managers are likely to face failure and increased risk without proper predictions. Predicting potential bankruptcy can enable corrective actions to be taken (*cf* Brabazon & Keenan, 2007).

The findings of the study will be of benefit to auditors in evaluating the going concern status of quoted firms on the Nigerian Stock Exchange. This becomes needful because auditors who have good knowledge of firms' situation, often fail to make an accurate judgement on firm's going concern status (*cf* Hopwood, McKeown, & Mutchler, 1994; McKee, 2003; Abdipoor, Nasseri, Akbarpour, Parsian, & Zamani, 2013).

The findings of this study will contribute to available literature on genetic algorithm and bankruptcy prediction. The study would thus serve as a source of vital and useful information and bank of knowledge for other researchers who may wish to embark on research from related perspectives. It is obvious that the work will provide them direction and guidance for their study.

1.7 Scope of the Study

The study is delimited to quoted manufacturing companies in Nigeria as at end of 2017. The duration of the study is from 2011 to 2017. The study in its content examines the application of genetic algorithm in developing a bankruptcy prediction model for manufacturing firms. The study also compares the performance of the GA model with two other traditional techniques, specifically the logit and discriminant methods. Thereafter the performance is compared with another conventional artificial intelligence technique the neural network. The study shall also investigate whether the performance of the GA model can be improved from addition of selected corporate governance variables.

1.8 Limitations of the Study

The general limitations of the study are as follows:

Firstly, authors have suggested that the use of existing models is limited by the conditions in which they are developed (Zelenkov, Fedorova, & Chekrizov, 2017). Therefore the development context of the GA model may limit its applicability to other sectors, more so the use of GA with different classification models would produce varying results.

Secondly, empirical data are assumed to be composed of a structural, replicable part and an idiosyncratic, nonreplicable part. The former is known as the signal, and the latter is known as the noise (Silver, 2012). Models that capture the entire signal and none of the noise provide the best possible predictions to unseen data from the same source. Overly simplistic models, however, fail to capture part of the signal; these models underfit the data and provide poor predictions. Overly complex models, on the other hand, mistake some of the noise for actual signal; these models overfit the data and again provide poor predictions. Thus, parsimony is essential because it helps discriminate the signal from the noise, allowing better prediction and generalization to new data (Vandekerckhove, Matzke, & Wagenmakers, 2015).

CHAPTER TWO

REVIEW OF RELATED LITERATURE

2.1 Conceptual Framework

2.1.1 Bankruptcy Prediction Models (BPMs)

The evolution of bankruptcy models cannot be discussed without recourse to the studies by the Bureau of Business Research (BBR) (1930), Ramser and Foster (1931), Fitzpatrick (1932), Winakor and Smith (1935), Merwin (1942), Chudson (1945), Jackendoff (1962). However, Beaver (1966) is regarded as the pioneer in univariate analysis. Univariate analysis places emphasis on a single factor/ratio and performs classification. Then based on the 'optimal cut off point' – the point at which the percentage of misclassifications is minimized – the firm is classified as failing or non-failing. Despite the simplicity of this approach, it was based on the assumption that the functional form of the relationship between a measure or ratio and the failure status is linear (Balcaen & Ooghe, 2004a). This assumption was often violated, where many ratios show a non-linear relationship with the failure status (Keasey & Watson, 1991).

Other disadvantages of the approach included, the *'inconsistency problem'*, as firm classification can only occur for one ratio at a time, which may give inconsistent and confusing classifications results for different ratios on the same firm (Altman, 1968; Zavgren, 1983).

Secondly, the difficultly in assessing the importance of any of the ratios in isolation, because most variables are highly correlated (Cybinski, 1998). Finally, the optimal cut-off points are chosen by 'trial and error' and on an 'ex post' basis, which means that the actual failure status of the companies in the sample is known (Bilderbeek, 1973). Consequently, the cut-off points may be sample specific and it is possible that the classification accuracy of the univariate model is (much) lower when the model is used in a predictive context (i.e. 'ex ante') (Balcaen & Ooghe, 2004a). The obvious limitation of the approach led to the development of risk index, which includes different ratios, generally accepted as measures of financial condition (Tamari, 1966; Moses & Liao, 1987). Despite the simplicity of the approach, its major drawback was the subjective nature applied in the development of the index.

The first *multivariate* study was conducted by Professor Edward Altman in 1968, which developed the Z score model based on discriminant analysis (Altman, 1968). Thereafter followed studies by Deakin (1972), Edminster (1972), Blum (1974), and Altman, Haldeman, & Narayanan, (1977), however Altman is considered the precursor in the transition from one dimensional to multidimensional statistical methods for predicting bankruptcy (Mączyńska & Zawadzki, 2006). Thereafter, in the 80's logistic regression was introduced and applied by Ohlson (1980).

Six problems were identified with the classical statistical methods, they include: assumptions on the dichotomous variable, the sampling method, stationarity assumptions and data instability, selection of independent variables, use of accounting information and the time dimension (Balcaen & Ooghe, 2004). Broadly, bankruptcy prediction models are divided into parametric and non-parametric. Parametric models focus on symptoms of bankruptcy and could be univariate or multivariate (Adnan Aziz & Dar, 2006). The most widely used parametric models are the logistic and multivariate discriminant analysis (MDA) (Fejér-Király, 2015). Other multivariate methods, such as cluster analysis, factor analysis, principal component analysis (Adeyeye, Fajembola, Olopete, & Adedeji, 2012), multidimensional scaling, probit analysis (Zmijewski, 1984), Fischer's LDA (Fisher 1936), and logit-probit (Zhang, Hu, Patuwo, & Indro, 1999; Zhang & Zhou, 2004; Sun, 2007), also developed.

The non-parametric models are mainly multivariate, based on machine learning which depend heavily and rule induction, and were introduced to improve upon the limitations of the classical statistical methods (Davalos, Leng, Feroz, & Cao, 2009; Andan & Dar, 2006; Varetto, 1998; Odom & Sharda, 1990). The most popular non-parametric models are artificial neural networks (ANN), hazard models, fuzzy models, genetic algorithms (GA) (Fejér-Király, 2015; Kiefer, 2014; Maghyereh & Awartani, 2014; Pradhan, Pathak, & Singh, 2013).

Others include: multivariate adaptive regression spines, fuzzy C-means clustering (Martin, Gayathri, Saranya, Gayathri, & Venkatesan, 2011) group method of data handling, counter propagation neural network and fuzzy adaptive resonance theory map (Ravisankar & Rav, 2010) classification and regression trees (Ioannidis, Pasiouras, & Zopounidis, 2010) k-Nearest neighbours (Ioannidis, Pasiouras, & Zopounidis, 2010) dynamic slacks based model (Wanke, Barros, & Faria, 2015) and geometric mean based boosting algorithm (Kim, Kang, & Kim, 2015).

Hybrid models are models in which several of the former models are combined (Fejér-Király, 2015; Davalos, Leng, Feroz, & Cao, 2009). They improve bankruptcy classification by combining the strengths of the different model, combining several classifiers into a multi-classifier model; can result in a classifier that outperforms single classifiers (Davalos, Leng, Feroz, & Cao, 2009; Kolter & Maloof, 2007; Kumar & Ravi, 2007; Zhou, Wu, & Tang, 2002; Opitz & Maclin, 1999; Olmeda & Fernandez, 1997). There are two types of multi-classifier models (Li & Sun, 2008); the hybrid model, which involves an optimizing model focused on manipulating the parameters for a classifier model that generates a classification (a class), and, a second type which combines the output of several classifiers into a single classifier, an ensemble (Lin & Mclean 2001; Jo & Han, 1996).

Ensembles perform better than single classifiers but are more time consuming to develop since the contribution of each classifier needs to be determined and in some cases, different combinations need to be tried (Li & Sun, 2008). According to Kouki and Elkhaldi (2011) hybrid models can be used as warning systems to help develop preventive strategies against bankruptcy and can be used as firm valuation techniques.

The various categories of prediction models and the main features are summarised in the tables below.

Table 2.1: Categories of prediction models

Model category	**Main features**
Statistical models	▪ Focus on symptoms of failure ▪ Drawn mainly from company accounts ▪ Could be univariate or multivariate (more common) in nature ▪ Follow classical standard modelling procedures
Artificially intelligent expert system models (AIES)	▪ Focus on symptoms of failure ▪ Drawn mainly from company accounts ▪ Usually, multivariate in nature ▪ Result of technological advancement and informational development ▪ Heavily depend on computer technology
Theoretical models	▪ Focus on qualitative causes of failure ▪ Drawn mainly from information that could satisfy the theoretical argument of firm failure proposed by the theory ▪ Multivariate in nature ▪ Usually employ a statistical technique to provide a quantitative support to the theoretical argument

Source: Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand?. *Corporate Governance: The International Journal of Business in Society*, *6*(1), 18-33.

Table 2.2: Different types of statistical prediction models

Models	**Main features**
Univariate (see Morris, 1998; Altman, 1993)	Traditionally focused on financial ratio analysis Underlying rationale: if financial ratios exhibit significant differences across the failing and non-failing firms then they can be used as predictive variables
Multiple discriminant analysis (MDA) (see Morris, 1998; Altman, 1993; Klecka, 1981)	MDA model is a linear combination (a bankruptcy score) of certain discriminatory variables Bankruptcy score is used to classify firms into bankrupt and non-bankrupt groups according to their individual characteristics
Linear probability model (LPM) (see Gujarati, 1998; Morris, 1998; Theodossiou, 1993; Maddala, 1983)	LPM expresses the probability of failure or success of a firm as a dichotomous dependent variable that is a linear function of a vector of explanatory variables Boundary values are obtained to distinguish between failing and non-failing firms
Logit model (see Gujarati, 1998; Morris, 1998; Theodossiou, 1993; Maddala, 1983)	Like LPM, Logit also expresses the probability of failure of a firm as a dichotomous dependent variable that is a function of a vector of explanatory variables The dichotomous dependent variable of a logit model, however, is the logarithm of the odds (probability) that an event (fail/not-fail) will occur Such a transformation of LPM is accomplished by replacing the LPM distribution with a logistic cumulative distribution function In application to bankruptcy, a probability of 0.5 implies an equal chance of company failure or non-failure. Therefore, where 0 indicates bankruptcy, the closer the estimate is to 1 the less the chance of the firm becoming bankrupt
Probit model (see Gujarati, 1998; Morris, 1998; Theodossiou, 1993; Maddala, 1983)	It is possible to substitute the normal cumulative distribution function, rather than logistic, to obtain the probit model Rest of the interpretations remain same as for the logit model

Source: Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand?. *Corporate Governance: The International Journal of Business in Society*, *6*(1), 18-33.

Table 2.2 cont'd: Different types of statistical prediction models

Cumulative sums (CUSUM) procedures (see Kahya & Theodossiou, 1999; Healy, 1987; Page, 1954)	CUSUM procedures are among the most powerful tools for detecting a shift in a distribution from one state to another In the case of bankruptcy prediction, the time series behaviour of the attribute variables for each of the failed and non-failed firms is estimated by a finite order VAR model The procedure, then, optimally determines the starting-point of the shift and provides a signal about the firm's deteriorating state as soon as possible thereafter The overall performance of the firm at any given point in time is assessed by a cumulative (dynamic) time-series performance score (a CUSUM score) As long as a firm's time-series performance scores are positive and greater than a specific sensitivity parameter, the CUSUM score is set to zero, indicating no change in the firm's financial condition. A negative score signals a change in the firm's condition
Partial adjustment processes (see Laitinen & Laitinen, 1998; Gujarati, 1998)	Partial adjustment models are a theoretic rationale of famous Koyck approach to estimate distributed-lag models Application of these models in bankruptcy prediction can best be explained by using cash management behaviour of the firms as an example, which refers to the management of cash by the firm from inflow to outflow, with failure being defined as the inability of the firm to pay financial obligations as they mature Elasticities of cash balances with respect to the motive factors will be smaller in absolute magnitude for a failing firm than for a similar healthy firm Also, the adjustment rate for a failing firm will exceed the rate for a healthy firm

Source: Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand?. *Corporate Governance: The International Journal of Business in Society*, *6*(1), 18-33.

Table 2.3: Different types of AIES models

Model	Main features
Recursively partitioned decision trees (an inductive learning model) (see Pompe & Feelders, 1997; Friedman, 1977)	▪ It is a form of supervised learning in which a program learns by generalising from examples (thereby mimicking the behaviour of many human experts) ▪ This kind of learning is exploited by decision tree procedures that use recursive partitioning decision rules to transform a ‘‘training’’ sample of data ▪ In bankruptcy classification the training sample is recursively partitioned into a decision tree in which the final nodes contain firms of only one type, bankrupt or healthy
Case-based reasoning (CBR) models (see Kolodner, 1993)	▪ CBR solves a new classification problem with the help of similar previously solved cases ▪ CBR programs can be applied directly to bankruptcy prediction by application of its typical four-stage procedure of (1) identification of a new problem, (2) retrieval of solved cases from a ‘‘case library’’, (3) adaptation of solved cases to provide a solution to the new problem, and (4) evaluation of the suggested solution and storage in the case library for future use
Neural networks (NN) (see Yang, Platt, & Platt, 1999; Coats & Fant, 1993; Salchenberger, Cinar, & Lash, 1992)	▪ Neural networks perform classification tasks in a way intended to emulate brain processes ▪ The ‘‘neurons’’ are nodes with weighted interconnections that are organized in layers. Each node in the input layer is a processing element that receives a variety of input signals from source objects (information about firms, in the case of bankruptcy prediction) and converts them into a single output signal. The latter is either: accepted as a classifying decision; or re-transmitted as an input signal to other nodes (possibly including itself) ▪ Signal processing continues until a classifying decision is reached (with some probability, the firm will fail) that satisfies pre-specified criteria

Source: Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand?. *Corporate Governance: The International Journal of Business in Society*, *6*(1), 18-33.

Table 2.3 cont'd: Different types of AIES models

Genetic algorithms (GA) (see Shin & Lee, 2002; Varetto, 1998)	▪ Based on the idea of genetic inheritance and Darwinian theory of natural evolution (survival of the fittest), GAs work as a stochastic search technique to find an optimal solution to a given problem from a large number of solutions ▪ GAs execute this search process in three phases: genetic representation and initialisation, selection, and genetic operation (crossover and mutation). The process continues until the actual population converges towards increasingly homogeneous strings ▪ In order to solve a classification problem like bankruptcy, researchers extract a set of rules or conditions using GAs. These conditions are associated with certain cut-off points. Based on these conditions, the model would predict whether or not a firm is likely to go bankrupt
Rough sets model (see Dimitras, Slowinski, Susmaga, & Zopounidis, 1999; Ziarko, 1993; Pawlak, 1982)	▪ The aim of rough sets theory is to classify objects using imprecise information ▪ In a rough sets model, knowledge about the objects is presented in an information table that, in effect, works like a decision table containing sets of condition and decision attributes that is used to derive the decision rules of the model by inductive learning principles. Every new object (for example, a firm) can then be classified (healthy or in financial distress) by matching their characteristics with the set of derived rules

Source: Adnan Aziz, M., & Dar, H. A. (2006). Predicting corporate bankruptcy: where we stand?. *Corporate Governance: The International Journal of Business in Society*, *6*(1), 18-33.

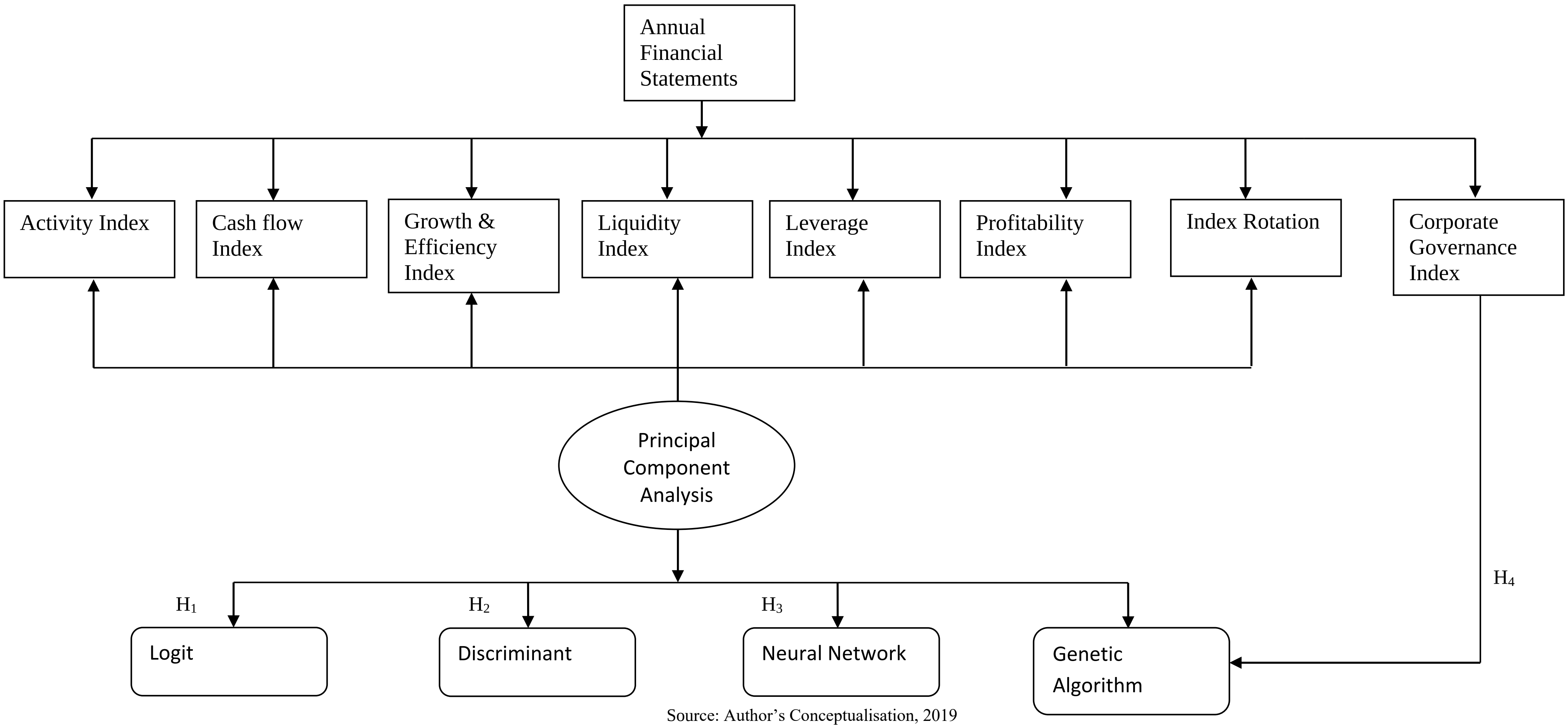
Table 2.4: A tabular framework of tools' performance in relation to important BPMs criteria

Tools category	Statistical		AI tools					
Important Criteria / Tools	**MDA**	**LR**	**ANN**	**SVM**	**RS**	**GA**	**DT**	**CBR**
Accuracy	Low	Mod.	V. High	V. High	High	High	Mod.	Low
Result transparency	Low	High	Low	Low	High	High	High	High
Can be Non-deterministic	No	No	No	No	Yes	Yes	Yes	Yes
Ability to use small Samples size	Low	Low	Low	V. high	high	NR	low	high
Data dispersion sensitivity	High	Normal	High	NR	NR	NR	NR	NR
Suitable variable selection	SW	SW	Any	Any	Any	Any	Any	Any
Multicollinearity Sensitivity	High	V. High	Low	Low	Low	Low	Low	Low
Sensitivity to outlier	Mod.	High	Mod.	Mod.	Mod.	Mod.	Mod.	Mod.
Variable type used	QN	Both	QN (both)	QN (both)	QL (both)	(both)	(both)	QL (both)
Variable relationship required	Linear	Logistic	Any	Any	Any	Any	Any	Linear
Other Assumptions to be satisfied	Many	Some	None	None	None	None	None	None
Overfitting possibility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Updatability	Poor	Poor	OK	-	Poor	OK/Good	Poor	Good
Ways to integrate to give hybrid	Few	Few	Many	Many	Many	Many	Many	Many
Output Mode	Cut-off	Binary	Binary	Binary	DR	DR	DR	DR

Note: All rankings are relative. NR: Not Reported SW: Stepwise V.: Very Mod: moderate QN: Quantitative QL: Qualitative DR: Decision rules.

Source: Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, *94*, 164-184. https://doi.org/10.1016/j.eswa.2017.10.040

Figure 2.1: Conceptual Framework



Source: Author's Conceptualisation, 2019

2.1.2 Logit Models

In statistics, the logit (or logistic) model is a statistical model that is usually applied to a binary dependent variable. The logit model creates a score (logit) for every firm. The logit score which implies the probability of failure, is presented as a value 0 or 1, where the failed status is usually coded as 1 and non-failed status as 0 (Salmistu, 2017). In logit analysis, the dichotomous dependent variable is simply the logarithm of the odds that a particular event (fail/non-fail) will occur (Adnan Aziz & Dar, 2006). Early application of logit model in bankruptcy prediction was by Ohlson (1980) on a sample of US companies. He used financial data from 1970 to 1976, which comprised 105 bankrupt and 2,058 non-bankrupt companies. Ratios used in the model were SIZE (logarithm of Total Assets/GNP Price Level Index), TLTA (Total Liabilities/Total Assets), WCTA (Working Capital/Total Assets), CLCA (Current Liabilities/Current Assets), OENEG (equals 1 if TL > TA and 0 otherwise), NITA (Net Income/Total Assets), FFOTL(Funds from Operations/Total Liabilities), INTWO (equals1 if Net Income < 0 for the last two years and 0 other-wise) and CHIN (change in Net Income).

The model is given by:

$$Z = \beta_0 + \beta_1 * \text{Size} + \beta_2 * \text{TLTA} + \beta_3 * \text{WCTA} + \beta_4 * \text{CLCA} + \beta_5 * \text{OENEG} + \beta_6 * \text{NITA} + \beta_7 * \text{FFOTL} + \beta_8 * \text{INTWO} + \beta_9 * \text{CHIN} + \varepsilon$$

This model with nine independent variables accurately predicted over 92% of bankrupt firms 2 years earlier. Another early application was by Zavgren (1985) who extended his time period from one to five years in advance. The accuracy rate of his model was about the same as Ohlson's 92% for one year prior to bankruptcy. Starting with the simple binary logit model, research progressed during the 1960s and 1970s to the multinomial logit (MNL) and nested logit models, the latter becoming the most popular of the generalized logit models (Train, 2003; Jones & Hensher, 2008; Klieštik, Kočišová, & Mišanková, 2015).

The difference between logistic and discriminant models is that logistic analysis requires logistic distribution (Lo, 1986). The logit model does not take into consideration what the MDA proposes: the normal distribution of the variables does not let the dummy variables be used; secondly, the variance and covariance matrix must be the same in the case of bankrupt and non-bankrupt firms & finally one of the weaknesses of the MDA is that it does not predict the probability of failure (Ohlson, 1980). The advantage of *logit model* is that it can handle both categorical and continuous variables, and the predictors do not have to be normally distributed, linearly related, or of equal variance within each group (Tabachnick & Fidell, 1996; Back, Laitinen, Sere, & van Wezel, 1996).

Table 2.5: Different logit models, strengths and challenges

	Classical MNL	Nested Logit	Mixed Logit	Latent Class-MNL
Major Strength	▪ Closed-form solution ▪ Provides one set of globally optimal parameter estimates ▪ Simple calculation ▪ Widely understood and used in practice ▪ Easy to interpret parameter estimates ▪ Easy to calculate probability outcomes ▪ Less demanding data quality requirements	▪ Closed-form solution ▪ Provides one set of globally optimal parameters ▪ Relatively easy to interpret ▪ Relatively easy to calculate probability outcomes ▪ Partially corrects for IID condition ▪ Incorporates firm-specific observed and unobserved heterogeneity to some extent (especially the covariance extension)	▪ Allows for complete relaxation of IID condition ▪ Avoids violation of the IIA condition ▪ High level of behavioural definition and richness allowed in model specification ▪ Includes additional estimates for random parameters, heterogeneity in means and decompositions in variances (these influences are effectively treated as "while noise" in basic models)	▪ Closed-form solution ▪ Semi-parametric specification ▪ Like mixed logit, this model form is free form, with many limiting statistical assumptions, such as homogeneity in variances and normality assumptions ▪ Incorporates firm-specific observed and unobserved heterogeneity through "latent class" constructs ▪ Less complex interpretation than mixed logit

Source: Kliештik, T., Kočišová, K., & Mišanková, M. (2015). Logit and probit model used for prediction of financial health of company. *Procedia Economics and finance*, *23*, 850-855.

Table 2.5: Different logit models, strengths and challenges

Major Challenges	▪ Highly restrictive error assumptions(IID condition) ▪ Violates the IIA assupmption ▪ Ignores firm-specific observed and unobserved heterogeneity which can lead to inferior model specification and spurious interpretation of model outputs ▪ Parameters are point estimates with little behavioural definition ▪ Often provide good aggregate fits but can be misleading given simple form of the model ▪ Tends to be less behaviourally responsive to changes in attribute levels	▪ Only partially corrects for IID condition ▪ Analytically very closely related to basic MNL model (thus shares many of the limitations of MNL) ▪ Does not capture potential sources of correlation across nests ▪ Judgement required in determining which alternatives can be appropriately partitioned into nests (nested logit requires well separated nests to reflect their correlation)	▪ Open-form solution (requires analytical integration and use of simalted maximum likelihood to estimate model parameters) ▪ Lack of a single set of globally optimal parameter estimates (i.e. due to the requirement for simalted maximum likelihood) ▪ Assumptions must be imposed for the distribution of unobserved influences ▪ Complex interpretation ▪ Model estimation can be time consuming due to computational intensity ▪ High quality data constraints	▪ Lacks flexibility in specification of firm-specific unobserved ▪ Model estimation can be time consuming due to computational intensity ▪ Assumption that manifest variables within latent classes are independent can be unrealistic ▪ High quality data constraints

Source: Kliеštik, T., Kočišová, K., & Mišanková, M. (2015). Logit and probit model used for prediction of financial health of company. *Procedia Economics and finance, 23*, 850-855.

2.1.3 Discriminant Models

Discriminant analysis is a technique that allows differentiating between two groups of objects with respect to several variables simultaneously (Adnan Aziz & Dar, 2006). Discriminant models in bankruptcy prediction classify companies into two groups: bankrupt and non-bankrupt companies. This classification is based on the companies' financial characteristics, which are determined using financial ratios that constitute the variables of the model. The MDA model is a linear combination of the discriminatory variables of the following form:

$$Z = \boldsymbol{\alpha} + \boldsymbol{\beta}_1 X_1 + \boldsymbol{\beta}_2 X_2 + \boldsymbol{\beta}_3 X_3 \ldots + \boldsymbol{\beta}_n X_n$$

Where Z is a transformed value (score) used to classify the object, α is a constant, β_n are discriminant coefficients, and X_n are values of independent discriminatory variables. The discriminant score allows the classification of the two groups (Fejér-Király, 2015). The two most frequently used methods in deriving the discriminant models are the *simultaneous (direct) method* and the *stepwise method.* The former is based on model construction by e.g. theoretical grounds, so that the model is ex ante defined and then used in discriminant analysis. The stepwise method selects a subset of variables to produce a good discrimination model using *forward selection*, *backward elimination*, or *stepwise selection* (Back, Laitinen, Sere, & van Wezel, 1996).

The first study to apply discriminant analysis was conducted by Altman (1968). The study developed a five-factor model to predict bankruptcy of manufacturing firms. The "Z-score", as it was called, predicted bankruptcy if the firm's score fell within a certain range.

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

Where:

X_1 - net working capital/total assets.
X_2 - retained earnings/total assets.
X_3 - EBIT/total assets.
X_4 - market value of common and preferred stock/book value of debt.
X_5 - sales/total assets.

In 1983, the model was modified

$$Z = 3.25 + 6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05\ X_4$$

Where:

X_1 - Working capital/ Total assets
X_2 - Retained earnings/ Total assets
X_3 - Earnings before taxes and interest/ Total assets
X_4 - Book value of equity/ Book value of total debt

Altman's Z-score model had high predictive ability for the initial sample one year before failure (95% accuracy). However, the model's predictive ability dropped off considerably from there with only 72% accuracy two years before failure, down to 48%, 29%, and 36% accuracy three, four, and five years before failure, respectively. The model's predictive ability when tested on a hold-out sample was 79%.

A major limitation of discriminant analysis is its restrictive assumption of normal distribution of each independent variable (Hamer, 1983). Other assumptions are (Etemadi, Rostamy, & Dehkordi, 2009):

- The predictors are not highly correlated with each other.
- The mean and variance of a given predictor are not correlated.
- The correlation between two predictors is constant across groups.

2.1.4 Neural Networks (NNs)

Neural networks are inspired by neurobiological systems. According to Robert Hecht-Nielsen, one of the earliest inventors of neurocomputers, NN is “a computing system made up of a number of simple, highly interconnected processing elements which process information by their dynamic state responses to external inputs” (Caudill, 1989; Hecht-Nielsen, 1988). Most types of NNs can be covered by the following definitions (Esseghir, 2006):

Definition 1:

A NN is a system composed of many simple processing elements operating in parallel whose function is determined by a network structure, connection strengths and the processing performed at computing elements or nodes (Widrow, 1988).

Definition 2:

NN is a massively parallel distributed processor that a natural propensity for storing experiential knowledge and making it available for use. It mimics the human brain in two aspects:

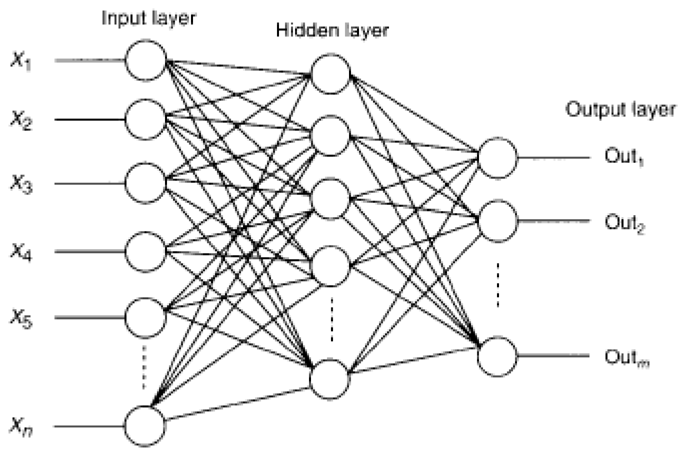
- Knowledge is acquired by the network through a learning process.
- Interneuron connection strengths known as synaptic weights are used to store the knowledge.

NNs have the most practical effect in the following three areas: modelling and forecasting, signal processing, and expert systems (Lippmann, 1987). The predictive ability of neural networks falls into the forecasting area. Predictive type problems relate to the auto associative memory of certain neural networks (Odom & Sharda, 1990). The method used for neural network prediction is called generalization (Dutta & Shekhar, 1989). Generalization is different from auto associative memory, in that once the network has been trained; new data is input for the network to predict the output. The application of NNs to bankruptcy prediction is linked to Messier and Hansen (1988), Odom and Sharda (1990), Raghupathi, Schkade, and Bapi (1991), Coats and Fant (1993), Guan (1993), Tsukuda and Baba (1994), and Altman, Marco, and Varetto (1994).

NNs are able to learn and adapt, from a data set, and they have the ability to capture non-linear relationships between variables. These features are the main advantages of these models (Lee & Choi, 2013). The analysis of neural network performs a classification; the neurons are nodes with weighted interconnections organized in layers.

In the input layer, each node receives information about the company's financial situation and converts into single output. This output is accepted as a classifying decision or re-transmitted till decision is accepted. The acceptance is based on pre-established criteria (Virág & Kristóf, 2005).

Figure 2.2: A Neural Network Architecture



Let $I_p = (I_{p1}, I_{p2}, \ldots, I_{pl})$, $p = 1,2, \ldots, N$ be the pth pattern among N input patterns. Where w_{ji} and w_{kj} are connection weights between the ith input neuron to the jth hidden neuron, and the jth hidden neuron to the kth output neuron, respectively (Panda, Chakraborty, & Pal, 2008).

Output from a neuron in the input layer is

$$O_{pi} = I_{pi}, \quad i = 1,2,\ldots,l$$

Output from a neuron in the hidden layer is

$$O_{pj} = f(NET_{pj}) = f\left(\sum_{i=0}^{1} w_{ji} o_{pi}\right), \quad j = 1,2,\ldots,m$$

Output from a neuron in the output layer is

$$O_{pk} = f(NET_{pk}) = f\left(\sum_{j=0}^{m} w_{kj} o_{pj}\right), \quad k = 1, 2, \ldots, n$$

Where *f*( ) is the sigmoid transfer function given by $f(x) = 1/(1 + e^{-x})$.

NN do not use any kind of 'pre-programmed knowledge base' (Hawley, Johnson, & Raina, 1990). The neurons of the network recognize meaningful patterns in the data. They process and transform the input – a vector of variables – by a vector of weights into one single output signal. The output signal of a neuron, in turn, is sent as an input signal to many other neurons and is possibly sent back to itself. As the signals are passed through the network via weighted interconnections between the neurons, the 'network knowledge' is stored (Hawley, Johnson, & Raina, 1990; Coats & Fant, 1993). The method of neural networks is based on 'supervised' learning (Balcaen & Ooghe, 2004b). The network is 'learned' or 'trained' on a 'training sample' of inputoutput pairs of data (and possibly a 'validation sample') and the appropriate, best possible sets of weights are determined on the basis of a training algorithm. This process of working towards an appropriate mapping is also called 'convergence' (Coats & Fant, 1993). Once a stable equilibrium configuration or mapping with acceptable error levels has been found, the learning phase (i.e. the weight adaptation mechanism) takes an end and the weightings are locked.

NNs contains many other methods: back propagation (Dwyer, 1992), SOF-self organizing map (Alam, Booth, Lee, & Thordarson, 2000). Their weakness lies in the fact that they cannot explain causal relationships among their variables (i.e., financial ratios), which constrains their application to management problems (Lee & Choi, 2013).

The neural network architecture consists of the following (Bapat & Nagale, 2014):

a) The input layer containing the predictors.
b) The hidden layer containing unobservable nodes, or units. The value of each hidden unit is some function of the predictors.
c) The output layer containing the responses. Since the history of bankruptcy is a categorical variable with two categories, it is recoded as two indicator variables.

NNs have several advantages: First, NNs are able to analyse complex patterns quickly and with a high accuracy level (Shachmurove, 2002) and they are able to learn from examples, without any pre-programmed knowledge (Back, Laitinen, Sere, & van Wezel, 1996). Secondly, they are not subject to the restrictive statistical assumptions of MDA. More in particular, no distributional assumptions are imposed and the input data do not need to conform to linearity (Coats & Fant, 1993; Zain, 1994; Tucker, 1996; Cybinski, 2000; Shachmurove, 2002).

Thirdly, non-numeric data can easily be included in a NN, because of the absence of the linearity constraint (Coats & Fant, 1993). Fourthly, NN is perfectly suited for pattern recognition and classification in unstructured environments with ‘noisy data’, which are incomplete or inconsistent (Hawley, Johnson, & Raina, 1990; Tucker, 1996; Shachmurove, 2002). The network tolerates data errors and missing values by making use of the context and ‘filling in the gaps’. Consequently, a NN is able to work with annual account data, which are often inconsistent and incomplete.

In addition, NNs overcome the problem of autocorrelation, which frequently arises in time series data (Hawley, Johnson, & Raina, 1990; Cybinski, 2000, 2001). Fifthly, the NN technique can be considered as user-friendly as it offers a clear ‘failure/non-failure’ output. Finally, when predicting company failure, neural networks generally seem to be more robust – especially when sample sizes are small – and more flexible than other methods (Cybinski, 2000).

Major drawbacks of NNs include: the ‘black box’ problem, as NN does not reveal the significance of each of the variables in the final classification and the derived weights can not be interpreted. They are also very sensitive to the ‘garbage in – garbage out’ problem. Consequently, one has to carefully select the variables that are included in the training samples and assure the quality of the data.

Thirdly, as a NN can be made to fit the data ‘like a glove’; it runs the risk of over-parametrization or over-fitting. This results in a sample-specific model with a low generalizing ability.

2.1.5 Genetic Algorithm (GA)

Genetic algorithm (GA) is a metaheuristic inspired by the process of natural selection and belongs to the larger class of Evolutionary Algorithms (EA). A GA model is an evolutionary computing model based on stochastic, adaptive search methods for an optimal solution (Davalos, Leng, Feroz, & Cao, 2009). The term is a coinage from two disciplines, *genetic* refers to a biological science, and *algorithm* is from computer science. An algorithm is a step-by-step procedure for accomplishing some specific task-sorting numbers, formatting text on a page, or diagnosing car problems (Forrest, 1993). GA simulates Darwinian evolution, and is commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators; such as mutation, crossover and selection (Mitchell, 1998; Back, Laitinen, Sere, & van Wezel, 1996; Goldberg, 1989; Holland, 1975).

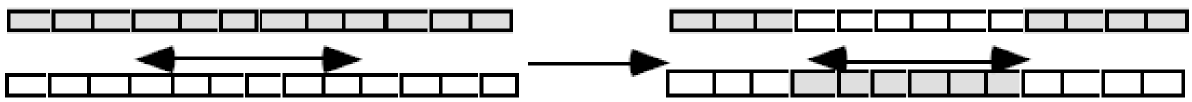
It maintains a population of chromosomes, where a chromosome is a candidate-solution to the problem we want to solve. Chromosomes are often called *strings* in a genetic algorithm context. A string in its turn, consists of a number of genes, which may take some number of values, called alleles. The genetic algorithm terms for genes and alleles are *features* and *values*.

Associated with each string is a *fitness value*, which determines how 'good' a string is. The fitness value is determined by a *fitness function*, which we can think of as some measure of profit or goodness that we want to maximise (Back, Laitinen, Sere, & van Wezel, 1996). Three genetic operators are mostly used in these algorithms: reproduction, crossover, and mutation (Etemadi, Rostamy, & Dehkordi, 2009).

1. Reproduction: The reproduction operator simply chooses an individual in the current population and copies it without changes into the new population (Etemadi, Rostamy, & Dehkordi, 2009). It is a process in which strings are copied onto the next generation. Strings with a higher fitness value have more chance of making it to the next generation. Different schemes can be used to determine which strings survive into the next generation. A frequently used method is *roulette wheel selection*, where a roulette wheel is divided in a number of slots, one for each string. The slots are sized according to the fitness of the strings. Hence, when we spin the wheel, the best strings are the most likely to be selected. Another well-known method is *ranking*. Here, the strings are sorted by their fitness value, and each string is assigned an offspring count that is determined solely by its rank (Back, Laitinen, Sere, & van Wezel, 1996).
2. Crossover: Two parent individuals are selected and a subtree is picked on each one. Then crossover swaps the nodes and their relative sub-trees from one parent to the other. That is a part of one string is combined

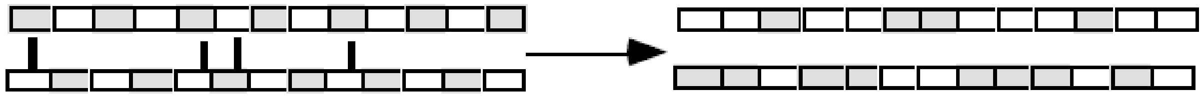
with a part of another string. This way, it combines the good parts of one string with the good parts of another string, yielding an even better string after the operation. This operation takes two strings, the parents, and produces two new ones, the offspring (Back, Laitinen, Sere, & van Wezel, 1996). This operator must ensure the respect of the depth limits. If a condition is violated the too-large offspring is simply replaced by one of the parents. There are other parameters that specify the frequency with which internal or external points are selected as crossover points (Etemadi, Rostamy, & Dehkordi, 2009).

Figure 2.3: Type a Crossover



Source: Back, B., Laitinen, T., Sere, K., & van Wezel, M. (1996). Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms. *Turku Centre for Computer Science Technical Report*, *40*, 1-18.

Figure 2.4: Type b Crossover



Source: Back, B., Laitinen, T., Sere, K., & van Wezel, M. (1996). Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms. *Turku Centre for Computer Science Technical Report*, *40*, 1-18.

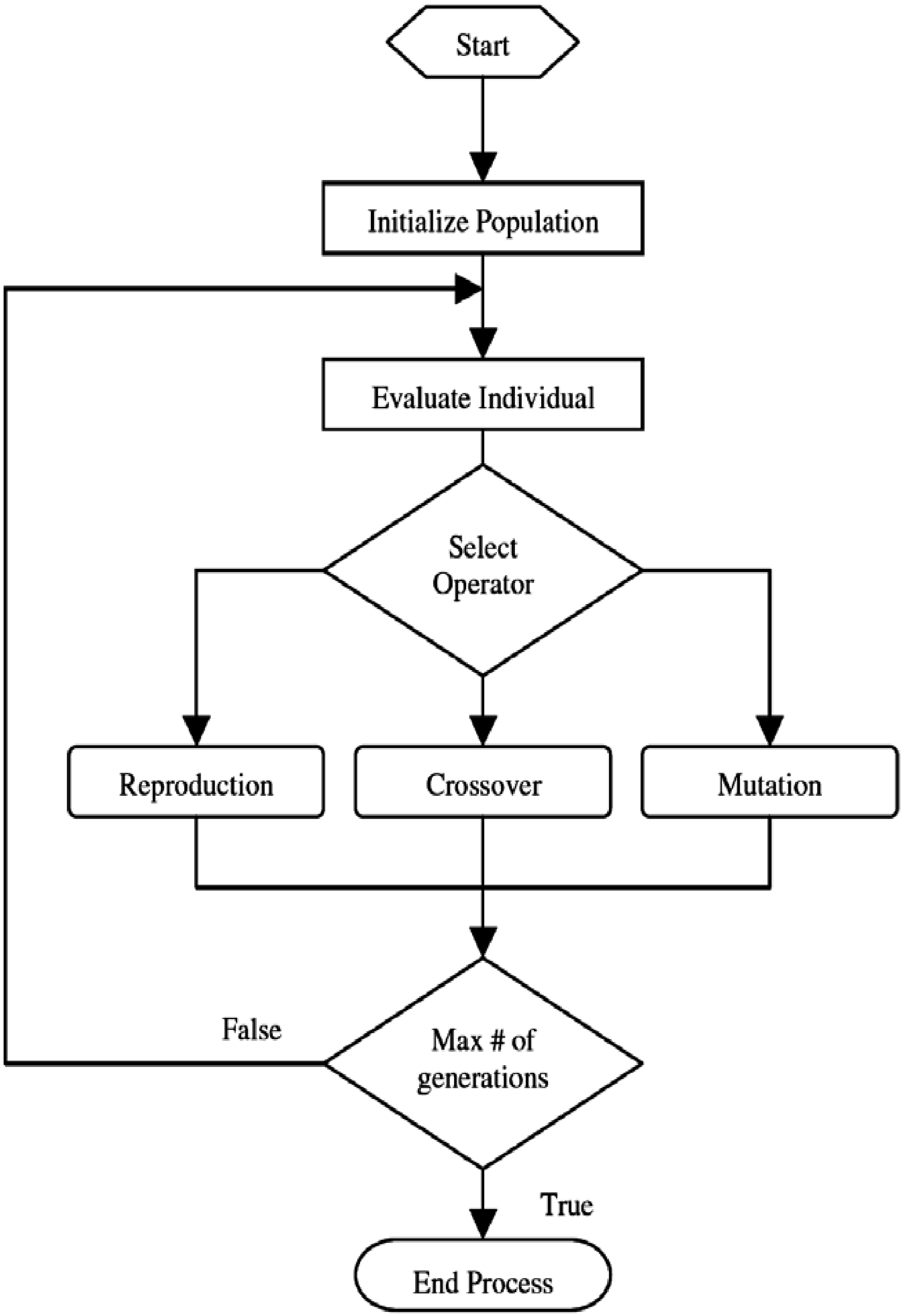
3. Mutation: In mutation, a randomly selected gene in a string takes a new value. The aim of this operator is to introduce a new genetic material in the population, or at least prevent the loss of it. Under mutation, a gene can get a value that did not occur in the population before, or that has been lost due to reproduction. The mutation operator can be applied to either a function node or a terminal node. A node in the tree is randomly selected. If the chosen node is a terminal it is simply replaced by another terminal. If it is a function and point mutation is to be performed, it is replaced by a new function with the same arity. If, instead, tree mutation is to be carried out, a new function node (not necessarily with the same arity) is chosen, and the original node together with its relative subtree is substituted by a new randomly generated subtree. A depth ramp is used to set bounds on size when generating the replacement subtree. Naturally it is to check that this replacement does not violate the depth limit. If this happens mutation just reproduces the original tree into the new generation. Further parameters specify the probability with which internal or external points are selected as mutation points.

Figure 2.5: Mutation

Source: Back, B., Laitinen, T., Sere, K., & van Wezel, M. (1996). Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms. *Turku Centre for Computer Science Technical Report*, *40*, 1-18.

These three operators (*reproduction*, *crossover*, and *mutation*) usually determine the performance of GA in problem solving (Etemadi, Rostamy, & Dehkordi, 2009). Its wide applicability stems from the fact that GAs are capable of extracting optimal rules that can be integrated to any system (Kirkos, 2015; Martin, Gayathri, Saranya, Gayathri, & Venkatesan, 2011; Shin & Lee, 2002; Back, Laitinen, Sere, & van Wezel, 1996). Moreover, in GAs the nature of the optimization model does not need to be known (Schreyer, 2006), and does not rely on any distributional assumptions about the variables (Kuri-Morales & Aldana-Bobadilla, 2013; Nanda & Pendharkar, 2001). The optimization model and its constraints do not have to be continuous or even real values (Schreyer, 2006).

Figure 2.6: Overview of Genetic Algorithm



Source: Etemadi, H., Rostamy, A. A. A., & Dehkordi, H. F. (2009). A genetic programming model for bankruptcy prediction: Empirical evidence from Iran. *Expert Systems with Applications*, *36*(2), 3199-3207.

GAs can be used to find an optimal or near-optimal solution for such factor: (i) as the coefficients of a function, (ii) the architecture parameters for a neural network, (iii) the variables to use in a parametric model, or (iv) the variables, cutoff values, and relational operators of *if-then* rules (Mahfoud & Mani, 1995). The obvious limitations of GAs, ranges from the large number of parameters included; which require significant computational resources from very large number of function calls (Schreyer, 2006).

2.1.6 Corporate Failure Prediction

Corporate failure prediction has remained an important research topic in accounting and finance for the last three decades (Hajiamiri, Shahraki, & Barakati, 2014; Salcedo-Sanz, Fernandez-Villacanas, Segovia-Vargas, & Bousono-Calzon, 2005). A company is said to be insolvent or under financial distress if it is unable to pay its debts as they become due, which is aggravated if the value of the firm's assets is lower than its liabilities (Galveo, Becerra, & Abou-Seada, 2002). The word *failure* is often used to describe bankruptcy in the accounting and finance literature. Beaver (1966) defined failure as the inability of a firm to pay its financial obligations as they mature – a definition similar to the definition of default presented above. Altman (1968) and Ohlson (1980) on the other hand used the term failure in a legal perspective on companies that have filed for bankruptcy.

However, Skogsvik (1990) extended the use to include not only legal bankruptcy but also with composition agreements, voluntary shut-downs of primary production activities and receipt of substantial subsidies from the state. Investors use bankruptcy prediction to avoid the risk of losing their capital, and in businesses, managers can also prevent bankruptcy if they are informed about bankruptcy risk in time (Zebardast, Javid, & Taherinia, 2014). The literature, presents three types of corporate failure:

1. A corporate body with low or negative returns (Berryman, 1982).
2. A corporate body that is technically insolvent (Bedeian, 1987).
3. A corporate body that is bankrupt (Baird & Rasmussen, 2002; Berryman, 1982).

Some of the causes of corporate failure in the literature include (Mbat & Eyo, 2013), (1) Managerial inefficiency and ineffectiveness, (2) Socio-cultural factors, (3) Economic instability, and (4) Public policy. The effects include (Mbat & Eyo, 2013): (1) Increase in the level of unemployment, (2) Decrease in standard of living, (3) Underutilization of resources, (4) Increase in crime level, (5) Instability of the banking system due to inability to pay back borrowed funds, and (6) Instability of the financial markets where short to medium and long-term funds were sourced and corporate failure makes it impossible to meet such obligations.

Causes of bankruptcy in manufacturing firms could be (1) decrease of profit generation ability; (2) insufficient operating capital and loss its ability to pay interest, (3) lack of managing relationship with customers, (4) relatively lower human resource quality (Zhou & Elhag, 2007). Blazy and Combier (1997) cited in Du Jardin (2010) synthesized some of the major causes of bankruptcy:

- Accidental causes: malfeasance, death of the leader, fraud, disasters, litigation…;
- Market problems: loss of market share, failure of customers, inadequate products…;
- Financial threats: under-capitalization, cost of capital, default on payment, loan refusal…;
- Information and managerial problems: incompetency, prices and stocks, inadequate organization…;
- Macroeconomic factors of fragility: declining demand, increased competition, credit rationing, high interest rates…;
- Costs and production structure: excessive labour costs, over- or under-investment, sudden loss of a supplier, inadequate production process…;
- Strategy: failures of major projects, acceptance of unprofitable markets.

2.1.7 Bankruptcy Features (Variables)

A classification model's accuracy can be affected by the particular features used, the number of features (variables) used, and dynamic factors that determine the relevance of the features (Ko & Lin, 2006). Seventy nine percent of studies used financial ratios as predicting variable (Hossary, 2006). However, the literature documents the absence of a theoretical basis for selecting variables, as to which variables are better and why they are better (Cochran, Darrat, & Elkhal, 2006; Back, Laitinen, & Sere, 1996a; Ohlson 1980). Altman (1968) showed that financial ratios of bankrupt companies and non-bankrupt companies are significantly different. The Bureau of Business Research (BBR) found eight ratios considered good indicators of the inherent weakness of a firm: Working Capital to Total Assets, Surplus and Reserves to Total Assets, Net Worth to Fixed Assets, Fixed Assets to Total Assets, Current Ratio, Net Worth to Total Assets, Sales to Total Assets, and Cash to Total Assets (Bellovary, Giacomino, & Akers, 2007). FitzPatrick (1932) reported two significant ratios: Net Worth to Debt and Net Profits to Net Worth.

Smith and Winakor (1935) identified Working Capital to Total Assets as a far better predictor of financial problems than both Cash to Total Assets and Current Ratio. They also found that the Current Assets to Total Assets ratio dropped as the firm approached bankruptcy. Merwin (1942) found three ratios that were significant indicators of business failure - Net Working Capital to Total Assets, the Current Ratio, and Net Worth to Total Debt.

Beaver (1966) found the following ratios useful for distinguishing between bankrupt and non-bankrupt companies: Cash flow/Total debt, Net income/Total assets, Total debt/Total assets, Working capital/Total assets, Current assets/Current liabilities, and, No credit interval = (Quick assets – Current liabilities)/ (Operating costs – Depreciation). Jackendoff (1962) showed that two ratios: Current Ratio and Net Working Capital to Total Assets are higher for profitable firms than for unprofitable firms. Also, profitable firms had lower Debt-to-Worth ratios than unprofitable firms. Chan, Tam, and Cheung (2005) in Hong Kong identified the following factors of business failure as: operating profit margin, return on equity, return on asset, total asset turnover, quick ratio, earning per share and debt ratio. Huang (2009) in Taiwan indicated that the determining factors of business failure, among others, are asset volatility, book leverage ratio and the price-to-earnings (P/E) ratio.

Garkaz and Abdollahi (2010) revealed the following ratios: ratio of operational income to sale; ratio of total debts of total assets; current assets to current debts; sale to current assets and interest cost to gross profit. The literature identifies the most dominant financial ratios to be in four categories (Edum-Fotwe, Price, & Thorpe, 1996): (1) Liquidity (2) Profitability (3) Leverage and (4) Activity. The number of factors considered in most studies ranges from one to fifty-seven (Bellovary, Giacomino, & Akers, 2007). Table 2.4 presents 42 ratios found in five or more studies on bankruptcy.

Table 2.6: Factors included in five or more studies

	Factor/Consideration	Number of Studies that Include
1	Net income / Total assets	54
2	Current ratio	51
3	Working capital/Total assets	45
4	Retained earnings / Total assets	42
5	Earnings before interest and taxes / Total assets	35
6	Sales / Total assets	32
7	Quick ratio	30
8	Total debt / Total assets	27
9	Current assets / Total assets	26
10	Net income / Net worth	23
11	Total liabilities / Total assets	19
12	Cash / Total assets	18
13	Market value of equity / Book value of total debt	16
14	Cash flow from operations / Total assets	15
15	Cash flow from operations / Total liabilities	14
16	Current liabilities / Total assets	13
17	Cash flow from operations / Total debt	12
18	Quick assets / Total assets	11
19	Current assets / Sales	10
20	Earnings before interest and taxes / Interest	10
21	Inventory / Sales	10
22	Operating income / Total assets	10
23	Cash flow from operations / Sales	9
24	Net income / Sales	9
25	Long-term debt / Total assets	8
26	Net worth / Total assets	8
27	Total debt / Net worth	8
28	Total liabilities / Net worth	8
29	Cash / Current liabilities	7
30	Cash flow from operations / Current liabilities	7
31	Working capital/Sales	7
32	Capital/Assets	6
33	Net sales / Total assets	6
34	Net worth / Total liabilities	6
35	No-credit interval	6
36	Total assets (log)	6
37	Cash flow (using net income) / Debt	5
38	Cash flow from operations	5
39	Operating expenses / Operating income	5
40	Quick assets / Sales	5
41	Sales / Inventory	5
42	Working capital/Net worth	5

Source: Bellovary, J., Giacomino, D., & Akers, M. D. (2007). A Review of Bankruptcy Prediction Studies: 1930-Present. *Journal of Financial Education, 33,* 1-42.

2.1.8 Corporate Governance Variables

Studies have shown that corporate governance play a role in the financial distress of a company (Brédart, 2014b; Platt & Platt, 2012; Lajili, & Zéghal, 2010; Chang, 2009; Fich & Slezak, 2008; Donoher, 2004; Daily & Dalton, 1994; Gales & Kesner, 1994; Hambrick & D'Aveni, 1992, 1988; Gilson, 1990). According to Fich and Slezak (2008) the influence of governance can be twofold: (1) Poor governance can facilitate accounting manipulation and distort the components of the prediction model, and (2) the ability to manage the firm during periods of distress may depend on the governance structure. In general, Boards perform two main functions, namely monitoring and contracting (Kumar & Sivaramakrishnan, 2008), and has a fiduciary duty to protect the interest of the shareholders (Adams, Hermalin, & Weisbach, 2010).

1. **Board Size.** From an agency theory, the argument in favour of a larger number of directors is that the increase raises their disciplinary control over the CEO. From a resource dependence perspective, it implies more external links (Goodstein, Gautam, & Boeker, 1994) and a diversification of the expertise (Zahra & Pearce, 1989). Studies by Chaganti, Mahajan, and Sharma (1985), Hambrick and D'Aveni (1992), Gales and Kesner (1994), carried out on paired samples, report that companies that have filed for bankruptcy protection chapter are characterized by a smaller number of directors. Fich and Slezak (2008) find a positive relationship between board size and bankruptcy probability. For each additional director, the risk of bankruptcy increases by 25–38 percent depending on whether the Z-score or the Interest Coverage Ratio (ICR) was the initial indicator of distress. Darrat,

Gray, Park, and Wu (2016) find that having larger boards reduces the risk of bankruptcy only for complex firms.

2. **Board Ownership.** Increased ownership positions by inside directors, however, reduce the bankruptcy hazard (Fich & Slezak, 2008). Darrat, Gray, Park, and Wu (2016) find that the proportion of inside directors on the board is inversely associated with the risk of bankruptcy in firms that require more specialist knowledge and that the reverse is true in technically unsophisticated firms. Executive ownership is associated with greater corporate focus, indicating that the severity of the managerial risk aversion problem may be reduced through higher equity stakes (Denis, Denis, & Sarin, 1997).
3. **Board Structure.** Board monitoring is not only a function of the composition of the board as a whole but also of the structure and composition of the board's subcommittees. According to Chen and Wu (2016) Board committees provide benefits (specialization, efficiency, and accountability benefits) and costs (information segregation). Kesner (1988) maintains that most important board decisions originate at the committee level, and Vance (1983) argues that there are four board committees that greatly influence corporate activities: audit, executive, compensation, nomination committee. Board committees provide three benefits. First, committees-through the process of decentralization-can allow for knowledge specialization (De Kluyver, 2009), which benefits firms because the monitoring and advising tasks of boards are complex and require firm-specific knowledge (Kim, Mauldin, & Patro, 2014). Second, specialization through committees can allow for a more efficient task allocation to directors, leading to task-division

efficiency. Third, committees can increase the accountability of the board to the firm by reducing individual free-riding and enabling outside directors to perform their monitoring duties more effectively through greater separation from management. Adams, Ragunathan, and Tumarkin (2015) find that 52% of board activity in S&P 1500 firms takes place at the committee level after the implementation of Sarbanes-Oxley.

4. **Proportion of Women on the Board.** Boards with high female representation experience a 53% higher return on equity, a 66% higher return on invested capital and a 42% higher return on sales (Joy, Carter, Wagner, & Narayanan, 2007). One study documents that by having just a female director on the board reduces the risk of bankruptcy by 20%. According to Bart and McQueen (2013) women were more consistent in making fair decisions when competing interests are at stake. While other studies have shown that when women directors are appointed, boards adopt new governance practices earlier (such as director training, board evaluations, director succession planning structures) (Singh & Vinnicombe, 2002), become more civilised and sensitive to other perspectives (Fondas & Sassalos, 2000), reduce 'game playing' (Singh, 2008) and ask more questions rather than nodding through decisions (Konrad, Kramer, & Erkut, 2008). Carter, Simkins, and Simpson (2003) found evidence of a significant positive relationship between board diversity and firm value. On the contrary, Rose (2007) showed no association between the proportion of woman on the Board and firm performance.

5. **CEO Duality.** Holding the role of both CEO and chairman of the board of directors makes evaluating managers more difficult and increases agency costs and

entrenchment risks (Fama & Jensen, 1983; Lipton & Lorsch, 1992; Jensen, 1993). This is because the board, being in principle the organ in charge of controlling the actions of the managers, is headed by the very object of this overseeing (Brédart, 2014b). That is the reason why OECD (Note 1) (2004) recommends separating the two functions. CEO duality unifies the decision-making process (Anderson & Anthony, 1986; Brickley, Coles, & Jarrell, 1997) which as per agency perspective, may lead to risk taking that may result into bankruptcy (Eisenhardt, 1989).

6. **Board Independence.** From an agency perspective, a greater proportion of outside directors on boards act to monitor independently in situations where conflict of interest between the shareholders and managers occurs (Jackling & Johl, 2009). According to Weisbach (1988) independent directors are in a better position to monitor the actions of the CEO. He states that as a result of their position in the firm and the existence of possible inherent contracts with the CEO, internal directors would not be as fair as independent ones. Studies by Daily, Dalton, and Cannella (2003), Elloumi and Gueyie (2001), and Hambrick and D'Aveni (1992) find that firms with a large proportion of independent directors show less likelihood to file for bankruptcy. Fich and Slezak (2008) observed that smaller boards with more independent or outside directors are more effective at avoiding bankruptcy. If the board size remains constant, each additional independent director cuts the bankruptcy risk by approximately half. Contrary opinion was rendered by Aglietta and Reberioux (2004), when they opined that independent directors are characterized by a more superficial understanding of the specificities of the company.

2.2 Theoretical Framework

The study is anchored on three theories; first, the theory of '*natural selection*' which explains the behaviour of the Genetic Algorithm Model during development. It explains the process the model uses in selecting individual ratios for crossover, mutation and reproduction. The theory of '*anthropomorphism*' involves the process of inductive inference whereby people attribute to machines distinctively human characteristics, such as the capacity for rational thought and conscious feeling. The next is *Agency theory*, which explains the information asymmetry between principals and agent. Agents act on behalf of principals in the conduct of company affairs. However, agents in a bid to maximize their own wealth; may face the dilemma of acting against the interests of their principals.

2.2.1 Theory of Natural Selection

This theory has its roots in the works of Charles Darwin and has evolved to become relevant in soft computing. In 1859, Charles Darwin set out his theory of evolution by natural selection as an explanation for adaptation and speciation. He defined natural selection as the "principle by which each slight variation [of a trait], if useful, is preserved" (Darwin, 1859). According to Darwin:

> If during the long course of ages and under varying conditions of life, organic beings vary at all in the several parts of their organisation, and I think this cannot be disputed; if there be, owing to the high geometrical powers of increase of each species, at some age, season, or year, a severe struggle for life, and this certainly cannot be disputed; then, considering the infinite complexity of the relations of all organic beings to each other and to their conditions of existence, causing an infinite diversity in structure, constitution, and habits, to be advantageous to them, I think it would be a most extraordinary fact if no variation ever had occurred useful to each being's own welfare, in the same way as so many variations have occurred useful to man. But if variations useful to any organic being do occur, assuredly individuals thus characterised will

> have the best chance of being preserved in the struggle for life; and from the strong principle of inheritance they will tend to produce offspring similarly characterised. This principle of preservation, I have called, for the sake of brevity, Natural Selection.

According to Back, Laitinen, Sere, and van Wezel (1996) genetic algorithm is a global search procedure that mimics the mechanics of natural selection and natural genetics. In genetic algorithms, selection operates on strings of binary digits stored in the computer's memory, and over time, the functionality of these strings evolves in much the same way that natural populations of individuals evolve (Forrest, 1993).

Assumptions of the Theory of Natural Selection

The theory of natural selection relies on several assumptions, such as (Crawford, 1998; Cosmides, Tooby, & Barkow, 1992):

1. All species are capable of over producing offspring.
2. The size of populations of individuals tends to remain relatively stable over time.
3. Resources for supporting individuals are limited.

   Inference 1: A struggle for existence among individuals ensues.

4. Individuals differ on traits (i.e. adaptions) that enable them to survive and reproduce.
5. At least some of the variation in these traits is inheritable.

   Inference 2: There is differential production or survival of offspring by genentically different members of the populations which is, by definition, natural selection.

   Inference 3: Through many generations, evolution of traits that are more adaptive than others will occur through natural selection.

2.2.2 Theory of Anthropomorphism

Anthropomorphism is derived from the Greek words *anthrōpos* (meaning "human") and *morphē* (meaning "shape" or "form"), anthropomorphism involves more than simply attributing life to the nonliving (i.e., animism) (Epley, Waytz, & Cacioppo, 2007). Anthropomorphism is a process of inductive inference whereby people attribute to nonhumans distinctively human characteristics, particularly the capacity for rational thought (agency) and conscious feeling (experience) (Gray, Gray, & Wegner, 2007). These nonhuman agents may include anything that acts with apparent independence, including nonhuman animals, natural forces, religious deities, and mechanical or electronic devices (Epley, Waytz, & Cacioppo, 2007). The Oxford Dictionary (Soanes & Stevenson, 2005) simply puts it, as the "attribution of human characteristics or behaviour to a god, animal, or object" (p. 66). The basic cognitive operations that perform such inferences should be no different for anthropomorphic inferences than for any other inductive inferences (Epley, Waytz, & Cacioppo, 2007). These basic cognitive operations include the acquisition of knowledge, the activation or elicitation of stored knowledge, and the application of activated knowledge to a given target (Higgins, 1996). One important theoretical determinant of trust in any nonhuman agent is anthropomorphism (Waytz, Cacioppo, & Epley, 2010).

Assumptions of the Theory of Anthropomorphism

The extent to which people anthropomorphize is determined by three major parts of the inductive process (Epley, Waytz, & Cacioppo, 2007):

i. the likelihood of activating, either chronically or situationally, knowledge about humans when making inferences about nonhuman agents;

ii. the likelihood of correcting or adjusting anthropomorphic representations to accommodate nonanthropomorphic knowledge about nonhuman agents; and
iii. the likelihood of applying activated and possibly corrected anthropomorphic representations to nonhuman agents.

2.2.3 Agency Theory

The accounting and finance literature has widely used agency theory to explain the information asymmetry between principals (shareholders) and agent (management). A company consists of a set of linked contracts between the owners of economic resources (the principals) and managers (the agents) who are charged with using and controlling these resources (Sarens & Abdolmohhammadi, 2007). The assumption of agency theory is that principals and agents act rationally and use contracting to maximize their wealth. A consequence of this is the moral hazard issue (Sarens & Abdolmohhammadi, 2007). Jensen and Meckling (1976) opine that moral hazard constitutes a situation where to maximize their own wealth; agents may face the dilemma of acting against the interests of their principals. Since principals do not have access to all available information at the time a decision is being made by an agent, they are unable to determine whether the agent’s actions are in the best interest of the firm. To reduce the likelihood of the moral hazard, principals and agents engage in contracting to achieve optimality, including the establishment of monitoring processes such as auditing.

Jensen and Meckling (1976) define the agency relationship in terms of “a contract under which one or more persons (the principal(s) engage another person (the agent) to perform some service on their behalf which involves delegating some decision-making authority to the agent”. In agency theory, agents have more information than principals and this information asymmetry adversely affects the principals’ ability to monitor whether or not their interests are being properly served by the agents (Jensen & Meckling, 1976). In her assessment and review of agency theory, Eisenhardt (1989) outlines two streams of agency theory that have developed over time: Principal-agent and positivist.

Eisenhardt (1989) further explained that agency problem arises when "(a) the desires or goals of the principal and agent conflict and (b) it is difficult or expensive for the principal to verify what the agent is actually doing”. The problem is that the principal is unable to verify that the agent is behaving appropriately. The agency problem arises primarily from the principals' desire to maximize shareholder wealth and the self-interested agents attempt to expropriate funds.

Assumptions of the Agency Theory

The theory relies on several assumptions; which includes the following as stated below:

1. There is a divergence of interest between the shareholders and managers with both parties seeking to maximise their own interest. Shareholders are interested in maximizing wealth while managers may succumb to self-interest and, unless restricted from doing otherwise, would be interested in protecting and enhancing his pay and perks;
2. Information asymmetry – The managers often have a greater access to information on the entity's position vis-a-vis shareholders;
3. The Board has a fiduciary relationship with the shareholders;
4. The agency problem results in agency costs. For example, monitoring costs, e.g., cost of audit, etc. and 'bonding costs'.

2.3 Empirical Review

2.3.1 Studies on Genetic Algorithm (GA)

Zelenkov, Fedorova, and Chekrizov (2017) proposed a two-step classification method based on genetic algorithm for bankruptcy forecasting. The model was tested on a balanced set of data, which included 912 observations of Russian companies (456 bankrupts and 456 successful) and 55 features (financial ratios and macro/micro business environment factors). The proposed model showed accuracy (0.934) value among tested models. It found bankrupts (recall = 0.953) and not bankrupts (precision = 0.910) than other tested models. The model showed that excluding features that were significant for less than 50% of the classifiers in the ensemble improved the all performance metrics (accuracy = 0.951, precision = 0.932, recall = 0.965). The authors however trained classifiers of various models; this process was random before combining into the voting ensemble. The authors failed to anchor the work on a theory.

Georgescu (2017) used genetic algorithms to evolve interval type-2 fuzzy logic systems (IT2FLS) for bankruptcy prediction. The shape of type-2 membership functions, the parameters giving their spread and location in the fuzzy partitions and the set of fuzzy rules are evolved at the same time by encoding all together into the chromosome representation. The enhanced Karnik–Mendel algorithms are used for the centroid type-reduction and defuzzification stage. The performance is evaluated by benchmarking IT2FLSs against type-1 FLSs. The experimental setup consists of evolving 100 configurations for both the T1FLS and IT2FLS and comparing their in-sample and out-of-sample average accuracy. The experiments confirm that representing and capturing uncertainty with more degrees of freedom allows IT2FLSs to outperform T1FLS, especially in terms of generalizability. The study used fuzzy logic which requires experimentation and experience based on the knowledge of the researcher.

Chou, Hsieh, and Qiu (2017) developed a hybrid model using genetic algorithm (GA) and fuzzy logic based fitness functions for key ratio selection. In the experiments, two financial ratio sets were selected, one extracted from suggestions of other studies and the other obtained by using the GA toolbox in SAS statistical software package. They used a fuzzy clustering algorithm for the classifier design, which was compared with back propagation neural network. They also compared the developed hybrid model with other models. However, the fuzzy clustering algorithm requires a high degree of computational time and sensitivity to noise.

The study by Bateni and Asghari (2016) compared the performance of logit and genetic algorithm (GA) prediction models. GA was used to classify 174 bankrupt and non-bankrupt Iranian firms listed in Tehran stock exchange for the period 2006–2014. Genetic model achieved 95 and 93.5% accuracy rates in training and test samples, respectively; while the logit model recorded 77 and 75% accuracy rates in training and test samples. The results showed that GA model outperformed the logit model. The authors did not provide a theoretical premise for the study.

Hou (2016) employed K-means clustering algorithm based on genetic algorithm in bankruptcy prediction. The sample included 24 A-share companies listed in Shanghai

Stock Exchange and Shenzhen Stock Exchange. The study found that K-means clustering algorithm based on genetic algorithm was more accurate than traditional clustering algorithm. The study also applied rough sets to further evaluate the accuracy of clustering. The study failed to provide a link to theory, moreover, in K-means clustering algorithm it is difficult to predict the number of clusters (K-value), and the order of the data has an impact on the final results.

Min (2016a) developed a method for optimizing the heterogeneous random subspace ensemble model and used genetic algorithm to optimize its classifier subsets. The data included 1,800 externally non-audited firms that filed for bankruptcy (900 cases) or non-bankruptcy (900 cases). Initially, 134 financial ratios were investigated based on literature review and basic methods. From these, 75 financial ratios were selected based on independent-samples t-test of each financial ratio as an input variable and bankruptcy or non-bankruptcy as output variable. Finally, 24 financial ratios were selected using logistic regression backward selection. The study applied four different learning algorithms to the heterogeneous random subspace ensemble: k-nearest neighbour (KNN), decision tree (DT), logistic regression (Logit), and support vector machines with RBF kernel (SVM-rbf). The experimental results showed that the proposed model (genetic algorithm-based heterogeneous random m subspace model) outperformed other models. One disadvantage of this method is that to reach the best prediction accuracy with these algorithms, the computation time for both training and testing grows infeasibly large.

Min (2016b) proposed and developed a new hybrid ensemble model that integrates bagging and random subspace method using genetic algorithm. The proposed model was applied to bankruptcy prediction on a sample of Korean companies. The performance of the proposed model was compared with other models in the study. The experimental results showed that the proposed model performed better than other models such as the single classifier, the original ensemble model and the simple hybrid model. The proposed model required a computational large amount of resources.

Min (2016c) proposed the integration of instance selection and bagging ensemble using genetic algorithms to improve the performance of the model. Genetic algorithm was used to select optimal or near-optimal instances to be used as input data by the bagging model. The proposed model was applied to a bankruptcy-prediction problem using real dataset of Korean companies. The data comprised 1800 firms that had not been externally audited and that filed for bankruptcy (900 cases) or did not (900 cases). Initially, 134 financial ratios were selected through literature review and basic methods. Next, 75 financial ratios (input variable) were selected using independent-sample t-tests comparing bankrupt and non-bankrupt firms (output variable) in terms of each financial ratio. Finally, 14 financial ratios were selected using logistic regression forward-selection method. The results showed that the proposed model outperformed other models. The study failed to link the study to any theory, and was mainly descriptive in nature.

Szebenyi (2014) applied genetic programming in bankruptcy prediction on a sample of Hungarian accommodation provider firms. The study investigated whether outperforms a binary logistic regression. Logistic regression was performed using SPSS while in case of genetic programming, python was used. The results revealed that genetic programming is capable of bankruptcy prediction, and it can outperform a logistic regression. The study had no theoretical premise for evaluating the models.

Gordini (2014) evaluated the use of Genetic Algorithms (GA) in small enterprise default prediction modeling. He applied GAs to a sample of 6,200 Italian small enterprises three years and one year prior to bankruptcy. The study employed multiple discriminant analysis and logistic regression to benchmark GAs. The results show that the best prediction results were obtained using GAs. The firms included in the sample were small enterprises, though the study used two traditional statistical models for benchmarking.

Zebardast, Javid, and Taherinia (2014) predicted bankruptcy of firms listed on Tehran Stock Exchange using artificial neural network and genetic algorithm. They also compared the performance of both models. The sample comprised 42 bankrupt and 84 non-bankrupt companies from the period 2006 to 2011. The variables used in the study were 7 financial ratios. They found that artificial neural network model, i.e., multi-layer neural network with a hidden layer using train LM method achieved a precision of 95.5% in training stage and 80.5% in testing stage and 91.2% on the whole. The genetic algorithm model gained 86.7% precision in training stage and 86.5% in testing stage, while its overall precision was equal to 86.5%. The study however selected firms for inclusion in the sample in a random manner and performed no validation for the results.

Hajiamiri, Shahraki, and Barakati (2014) examined bankruptcy predicition using genetic algorithm in Iran. The sample comprised 70 pairs of bankrupt and non-bankrupt companies from 2001 to 2011. They independent variables for the study comprised 5 financial ratios. The results indicated that genetic algorithm correctly predicted the bankruptcy of companies two years before the base year, one year before the base year and the base year at accuracies of 96.44, 97.94 and 95.53, respectively. The study however used only five financial ratios, and performed no validation for the results.

Gaspar-Cunha, Recio, Costa, and Estébanez (2014) proposed a self-adaptive Multi-Objective Evolutionary Algorithm feature selection (MOEA) for bankruptcy prediction. The MOEA used in the study is the Reduced Pareto Set Genetic Algorithm (RPSGA). They used four datasets; Industrial French Companies' Data, from the years 2005 and 2006, obtained from the DIANE database; German Credit Data and Australian Credit Data, both publicly accessible at the UCI Machine Learning Repository. Each candidate solution generated by the RPSGA was externally evaluated by SVM and the result returned to the RPSGA to be used as fitness function. The results proved the efficacy of the MOEA in bankruptcy classification. The external evaluation of results by the SVM would increase the computation time of the model and therefore suitable in experimental designs mainly. The study also did not provide any theoretical premise for the study.

Poorzamani and Nooreddin (2013) developed a non-linear genetic algorithm model for bankruptcy prediction of companies' listed in Tehran Stock Exchange. They utilised information for the period 1992 to 2011. They used neural network patterns (ANN) and principal component analysis with Non-Linear Genetic Algorithm (PCA+NON-LIN) for model development. The neural networks showed a classification of the firms in training, hold-out, and total sample into financially healthy and distressed firms with accuracy of 100%, 95.83% and 99.19%. The PCA+NON-LIN showed a classification accuracy of 89%, 79.17%, and 87.10%. They used a non-linear genetic algorithm, a variant of genetic algorithm in model development. The study was also devoid of any theoretical framework.

Salehi and Rostami (2013) compared Support Vector Machine and Genetic Algorithm. The population of the study comprised companies listed in Tehran Stock Exchange. The sample included 158 companies, selected based on article 141 of the Commercial Code Tehran. The results showed that genetic algorithm compared to support vector machine had higher accuracy of prediction and smaller type II error in three years t, t-1 and t-2. Secondly, genetic algorithm and support vector machine models were compared based on 9 variables selected among 56 initial independent variables from the first stage. In year's t and t-1, support vector machine outperformed genetic algorithm, and its type I and II errors are less. However, in year t-2 the prediction accuracy and type I error of genetic algorithm was higher. The models were built based on type I & II errors, which are usually difficult in implementation.

Kim and Kang (2012) proposed a genetic algorithm-based coverage optimization technique for the bankruptcy prediction. The applied the model on a sample of Korean firms. The results indicate that the proposed coverage optimization algorithm can help to design a diverse and highly accurate classification system. The performance of the proposed model however depends on the coverage optimization technique, and the study lacked a theoretical premise.

Jeong, Min, and Kim (2012) applied a generalized additive model (GAM) for input variable selection for a neural network model. Grid search method and genetic algorithm were sequentially implemented to fine-tune the number of hidden nodes and the value of the weight decay parameters. The suggested approach is used to predict the probability that a firm may apply for bankruptcy, and its performance is compared with the results of existing bankruptcy forecasting models such as case-based reasoning, the decision tree, the GAM, the generalized linear model, the multivariate discriminant analysis, and the support vector machine. The empirical results indicated that the proposed model significantly outperformed the other models. The study was devoid of any theoretical premise for the variables selection and theoretical framework.

Zhang and Wu (2011) proposed a novel method based on wrapper-based feature selection. They used a novel genetic ant colony algorithm (GACA) as the search method, and the rule-based model was employed as classifier. Stratified K-fold cross validation method was taken as the statistical resampling to reduce overfitting. Simulations take 1,000 runs of each algorithm on the dataset of 800 corporations during the period 2006-2008. The results of the training subset show that the GACA had 84.3% success rate, while GA had only 48.8% and ACA had 22.1% success rate. The results on test subset demonstrate that the mean misclassification error of GACA is only 7.79%, less than that of GA (19.31%) and ACA (23.89%). The average computation time of GACA is only 0.564s compared to GA (1.203s) and ACA (1.109s). One big disadvantage of wrappers is the computational inefficiency which becomes more apparent as the feature space grows. Therefore the proposed model may lead to inefficiencies. Also, the genetic ant colony algorithm (GACA) is a variant of GA.

The study by Martin, Madhusudhnan, Lakshmi, and Venkatesan (2011) employed genetic algorithm to find the non-linear relationship between financial ratios which have more impact in three bankruptcy models. The three bankruptcy models are Altman, Edmister and Deakin model. Genetic algorithm was applied in the three instances to find most impactful ratios. The Altman model showed the best result, with a threshold value of 98%. They used genetic algorithm in selecting the most impactful ratios for application in prior models, therefore GA was not actually used in the bankruptcy prediction.

Garkaz and Abdollahi (2010) employed genetic algorithm for bankruptcy prediction in Iran. The literature review revealed the following ratios of interest, ratio of operational income to sale, ratio of total debts of total assets; current assets to current debts; sale to current assets and interest cost to gross profit. The independent t-test showed that there was a meaningful difference between the average of these ratios of bankrupted group with that of non-bankrupt one. The results further showed that genetic algorithm can be used to predict bankruptcy in Iran. They developed an overly simplistic model which may not be widely applicable, especially in other contexts.

Kim, Kim, and Kang (2010) proposed a genetic algorithm-based optimization technique of SVM ensemble to solve multicollinearity problem. The studied a sample of Korean firms. The results showed that the proposed model can improve the performance of SVM ensemble. However, the combination of GA and SVM ensemble may increase the computational time of the system and therefore prove difficult in development.

Etemadi, Rostamy, and Dehkordi (2009) investigated the application of genetic programming for bankruptcy prediction in Iran. Genetic programming (GP) was applied to classify 144 bankrupt and non-bankrupt Iranian firms listed in Tehran stock exchange (TSE). They employed multiple discriminant analysis (MDA) to benchmark the genetic programming model. The GP model achieved 94% and 90% accuracy rates in training and holdout samples, respectively; while MDA model achieved only 77% and 73% accuracy rates in training and holdout samples, respectively. McNemar test showed that GP outperformed MDA in corporate bankruptcy prediction. The study used a statistical procedure in comparing performance of the models, however, they used a variant of genetic algorithm, i.e. genetic programming.

Davalos, Leng, Feroz, and Cao (2009) developed an adaptive, rule-based model for bankruptcy classification of firms subject to the SEC's Accounting and Auditing Enforcement Release (AAER). They used an evolutionary computing method, genetic algorithm (GA), to generate an optimal set of if-then (comprehensible) rules for bankruptcy classification of AAER firms. They employed bagging to improve the generalisation accuracy and developed a doubly controlled fitness function for the GA model. They assessed the accuracy performance of the GA classifier by comparing it to four classifiers: decision trees (C4.5), artificial neural network (MLP), linear discriminant analysis (LDA), and multinomial logistic regression (MLR). They found that the GA model correctly classifies bankrupt AAER firms better than other models. The GA model performed better when Type I errors were included. The models were robust, however, there was no theoretical framework guiding the study.

Min and Jeong (2009) proposed a method for bankruptcy prediction based on Genetic Algorithms. The sample comprised virtual companies. Genetic Algorithms was used to calculate the feature weights and values of variables for the cases. Classification was performed by calculating the distances among an observation firm and the representative firms. They found that firms' indicative of bankruptcy had a higher value for the ratio of current liabilities to total assets than non-bankrupt firms, while ratios of break-even point and the employment cost were higher for non-bankrupt firms. The model developed may be limited in practicability as the context of its development was virtual firms.

Li and Ho (2009) proposed a fuzzy Case Based Reasoning (CBR) method combined with Genetic Algorithm. GA with classification accuracy as a fitness function was used to calculate the weights of the features. The chromosomes contained 6 genes, each of which was a measure of a corresponding input variable. The results after model training showed that the most significant feature were current ratio followed by net operation cycle and sales. The proposed model is limited in practicability, as case based reasoning is not too popular in bankruptcy prediction studies. The study failed to anchor the work on a theory.

Wu, Tzeng, Goo, and Fang (2007) proposed a genetic-based support vector machine (GA-SVM) model. The model was tested on the prediction of financial distress in Taiwan. They also compared the model with other models: DA, logit, probit, NN and SVM. The size of the matched sample was 88 firms, which included 22 failed firms and 66 non-failed firms. In the simulated sample, the total sample size was 44 companies, which included 22 failed firms and 22 non-failed firms. The holdout sample comprised all corporations listed on the TSE and OTC market from 2001 to 2002. The experimental result showed that the GA-SVM model outperformed other models in terms of predictive accuracy. The study was not anchored on any theory and the use of a holdout sample may limit accuracy.

Esseghir (2006) proposed a new hybrid model based on genetic algorithms and artificial neural networks. They used data from Tunisian firms one year prior to bankruptcy, which consisted of 88 firms, 38 bankrupt and 50 non-bankrupt firms. The study employed 30 ratios and a binary variable representing the firm’s state (0: non-bankrupt, 1: bankrupt). The study found that an evolutionary classifier based on feature selection and evolutionary learning techniques outperformed ANNs using back propagation. The study had no theoretical premise, despite comparing the performance of the models.

Sun and Hui (2006) applied decision tree and genetic algorithms for financial distress prediction. Genetic algorithm was used to optimize the financial ratios, to ensure the decision tree model has a good balance between accuracy and generalization. The results showed that the model's predictive accuracy for the training and validation samples were respectively 94.67% and 93.75%. The proposed model was not compared with any other model on the same dataset to benchmark performance.

Mukkamala, Tilve, Sung, Ribeiro, and Vieira (2006) applied several techniques in bankruptcy prediction of medium-sized private companies. Financial data was obtained from Diane, a large database containing financial statements of French companies. Classification accuracy was evaluated for Linear Genetic Programs (LGPs), Classification and Regression Tress (CART), TreeNet, and Random Forests, Multilayer Perceptron (using Back Propogation), Hidden Layer Learning Vector Quantization and several gradient descent methods, conjugate gradient methods, the LevenbergMarquardt algorithm (LM), the Resilient Backpropogation Algorithm (Rprop), and One Step Secant Method. They analysed two datasets, balanced and an unbalanced datasets. They found that LGPs performed best on a balanced dataset. They studied data from privately owned firms which are usually smaller than publicly listed firms, moreover, they compared several approaches which increases the computation time in real life problems.

Min, Lee, and Han (2006) studied the integration of GA and SVM. The study proposed a method for improving SVM performance in two aspects: feature subset selection and parameter optimization. The GA was used to optimize both feature subset and parameters of SVM simultaneously for bankruptcy prediction. The proposed model was not compared with any other model on the same dataset in order to benchmark performance.

Abdelwahed and Amir (2005) proposed a new hybrid model (EBM: evolutionary bankruptcy model) based on genetic algorithms and artificial neural networks. They conducted experiments to see if the model is capable of: selecting the best set of predictive variables, then, searching for the best neural network classifier and improving classification and generalization accuracies. They show that EBM is satisfactory for bankruptcy prediction in terms of predictive accuracy and adaptability. The study was not anchored on any theory and used an experimental design approach.

Salcedo-Sanz, Fernandez-Villacanas, Segovia-Vargas, and Bousono-Calzon (2005) applied genetic programming for prediction of insolvency in non-life insurance companies in Spain. The data consisted of Spanish non-life insurance firms between 1983 and 1994. In each period, 72 firms (36 failed and 36 non-failed) were selected. As a control measure, a failed firm is matched with a non-failed one in terms of size (premiums volume). In addition, each firm is described by 21 financial ratios, from a detailed analysis of variables used in previous bankruptcy studies for non-life insurance. After adjusting for other income, the variables were reduced to 19. They compared the results of the model with that of support vector machine and a rough set approach. They confirm the suitability of genetic programming as a decision-support method. The model developed may be limited in practicability as the context of its development was insurance firms. More so, one disadvantage of rough set is its dependence on complete information systems i.e., the absence of missing values.

Galveo, Becerra, and Abou-Seada (2002) applied genetic algorithm in variable selection for financial distress. They used financial data from 29 failed and 31 non-failed British corporations from the period 1997 to 2000. They used twenty eight financial ratios extracted from the financial statements. The model based on ratios selected by the genetic algorithm compared favourably with a model using ratios from bankruptcy literature. The study failed to provide any basis for comparison, and was not directed by any theory.

Shin and Lee (2002) proposed a GA approach for application in bankruptcy prediction modeling. The preliminary results showed that rule extraction approach using GAs for bankruptcy prediction modeling is effective. The overly simplistic nature of the model may not provide high accuracy in all instances.

McKee and Lensberg (2002) developed a hybrid approach, using genetic programming algorithm and variables from a rough sets model derived in bankruptcy prediction. They used data from 291 U.S. public companies for the period 1991 to

1997. The genetic programming model developed in the study had accuracy of 80% on the validation sample as compared to the original rough sets model which was 67% accurate. The variables used in the study were selected from a prior study, one disadvantage of rough sets include the sensitivity to outliers and the initial cluster.

Nanda and Pendharkar (2001) developed and tested a genetic algorithm (GA) based approach that incorporates the asymmetric Type I and Type II error costs. They used simulated and real-life bankruptcy data, to compare the results of the proposed approach with three linear approaches: linear discriminant analysis (LDA), goal programming approach, and a GA-based classification approach that does not incorporate the asymmetric misclassification costs. The results showed that the proposed model, which incorporated Type I and Type II error costs, results in lower misclassification costs when compared to LDA and GA approaches that do not incorporate misclassification costs. The introduction of Type I and II error costs presents more complexity in building models.

Varetto (1998) applied genetic algorithm in the analysis of insolvency risk. The study compared linear discriminant analysis (LDA) and genetic algorithm (GA). The study was carried out in Turin, Italy, and analysed 1920 unsound and 1920 sound industrial Italian companies from 1982–1995. The GA experiments were oriented along two different lines: the genetic generation of linear functions and the genetic generation of scores based on rules. The two experiments proved GA to be an effective instrument for insolvency diagnosis, despite that LDA have superior results compared with those from GA. The study was not anchored on a theory.

Back, Laitinen, Sere, and van Wezel (1996) studied three alternative techniques-linear discriminant analysis, logit analysis and genetic algorithms- for selecting predictors of neural networks in failure prediction. Data was collected from annual financial statements of 37 randomly selected failed companies and non-failed companies in Finland. Each failure occurred between 1986 and 1989. The time period was not the same for each firm, but the financial statements of matched pairs are always from the same calendar years. The firms in the sample were from different industries, but mainly the manufacturing sector. The study found that the best prediction results were achieved using genetic algorithms. The study is mainly descriptive in nature and not anchored on any theory. Moreover, they used a random process in selecting sub-samples

2.3.2 Studies on Logit Models

Brîndescu-Olariu (2017) proposed a model for bankruptcy prediction using logistic regression. The population consisted of all companies from the Timis County with annual sales of over 10,000 lei (aprox. 2,200 Euro). The study used a paired sample that included all companies in 2010 that went bankrupt by the end of 2012. The duration of the study was from 2007 to 2010. The results classified companies under one of the following three risk classes: high bankruptcy risk, for estimated bankruptcy probabilities of 0.5 or more; average bankruptcy risk, for estimated bankruptcy probabilities between 0.3 and 0.5; and, low bankruptcy risk, for probabilities less than 0.3. The study failed to show the overall classification accuracy of the proposed logisitic regression model and focused mainly on medium sized firms.

Salmistu (2017) developed a model for bankruptcy for Estonian construction companies. The sample included 7,160 companies, which included 7,083 non-bankrupt and 77 bankrupt firms. The total number of observed annual reports was 13,902; i.e, 13,825 for non-bankrupt firms and 77 for bankrupt firms. The study selected financial ratios used in prior studies in model development. The proposed model showed an overall classification accuracy of 68.4%.

Welc (2017) compared the accuracy of bankruptcy predictions from EBITDA-based and cash flow-based liabilities-coverage ratios on a sample of firms listed on the Warsaw Stock Exchange, Poland. The sample comprised 92 companies, which filed for bankruptcy between the beginning of 2009 and the end of the first half of 2016. The analysis was conducted in four steps: First, medians of four liabilities coverage ratios within both sub-samples were compared and the statistical significance of differences checked. Then, four univariate logit models for bankruptcy prediction were estimated, each with one liability-coverage ratio as the only explanatory variable. In the third step the estimated logit models have been evaluated in terms of their in-sample prediction accuracy. Finally, on the ground of the estimated models the safety thresholds for liabilities-coverage ratios have been simulated. The study found that the logit models with only one ratio used as an explanatory variable is capable of identifying bankrupt firms (with one-period-ahead forecast horizon) in about 66-76% of cases. However, the study focused mainly on liabilities coverage ratios from the vast array of bankruptcy predictors.

Brédart (2014a) applied logit regression for bankruptcy prediction for U.S. companies. The sample comprised 870 firms quoted on Amex, Nasdaq and the NYSE from January 2000 to December 2012. The study used a matched-pair sample of US quoted firms with half of the sample filing for chapter 11 (reorganization procedure) of the United States Bankruptcy Code and conducted logit regression analysis. The results showed that profitability, liquidity and solvency had a negative impact on financial distress probability. The overall prediction accuracy of the model is 83.82%.

Bartual, Garcia, Guijarro, and Moya (2013) used logistic regression to predict corporate failure of Spanish manufacturing companies. They selected 2,783 companies, of which 736 were identified as insolvent (26.5% of the sample). Financial variables were obtained from balance sheets and the income statements of the firms.

The model correctly assessed risk in 88.1% of the cases, while the naïve model had a success rate of 73.5%.

Lundqvist and Strand (2013) examined the effect of different financial ratios and whether including industry differences can increase the accuracy of a prediction model. They estimated models using logistic regression for each year, with and without interaction terms accounting for industry effects. These were analyzed and tested on a holdout sample for their classification abilities. They analysed 311,930 annual reports from non-bankrupt companies and 5,257 annual reports from bankrupt companies, covering the period 2006 to 2011. The study found that bankruptcy prediction ability of financial ratios varies between years. However, only in some cases, significant differences between industries were found. The overall classification ability was not significantly increased when including the industry effects but using some specified cut-off values, a marginal increase was found.

Zaghdoudi (2013) developed a model for Tunisian bank using logistic regression. The model takes into account microeconomic factors. The study was based on annual data spanning 8 years, from 2002 to 2010 for the 14 universal Tunisian banks. They used 18 ratios which represent different indicators of banking vulnerability measure. The ratios are regrouped into five groups, liquidity, management, activity, profitability and vulnerability. The results obtained using our provisional model show that a bank's ability to repay its debt, the coefficient of banking operations, bank profitability per employee and leverage financial ratio has a negative impact on the probability of failure. The study focused on the banking sectors, as such may limit generalizability of results.

Ahmadi, Soleimani, Vaghfi, and Salimi (2012) examined the application of logit model to bankruptcy prediction of firms in Iran. They selected a sample of 49 bankrupt companies and 49 non-bankrupt companies for the years 2005 to 2007. They used 19 financial ratios. The study showed that variables of net profit to total assets ratio, ratio of retained earnings to total assets and debt ratio were more powerful to predict corporate bankruptcy in Iran.

Han, Kang, Kim, and Yi (2012) developed a model for bankruptcy prediction of Korean firms using logit regression. The study also included equity market inputs and macro-economic variables as predictors. They found that the effect of market value of equity in computing total assets is not significant. They compared the model with a Merton-type structural model and found that the model had a higher prediction power in distinguishing distressed firms from healthy firms.

Hassani and Parsadmehr (2012) developed a logit model for forecasting financial crisis in Tehran Stock Exchange. The population included all companies listed in Tehran Stock Exchange during 2002 to 2009; productive firms were selected as the sample. The companies were classified into two solvent and insolvent groups using the presupposition of article 141 of Commercial Code. Variables were selected from the literature. Next, they checked for difference between the variables (financial ratios) of the two groups. They found that variables of debt to equity ratio, net profit to net sales ratio and working capital to assets were significant. The results showed that using the test data, the forecast strength of the model is 81.49%, its degree of sensitivity is 96.12% and its degree of identification is 67.48%.

Hauser and Booth (2011) applied a robust logistic regression to predict bankruptcy. They used data from 2006 and 2007, and a three-fold cross validation scheme to compare classification and prediction of bankrupt firms using the Bianco and Yohai (BY) estimator versus maximum likelihood (ML) logistic regression. The results showed that the BY logistic regression better classified firms in the training and testing set. Using an out of sample test, the BY robust logistic regression correctly predicts bankruptcy for Lehman Brothers; however, the ML logistic regression never predicted bankruptcy for Lehman Brothers with either 2006 or 2007 data.

Zhou and Elhag (2007) applied logit analysis in bankruptcy prediction. They employed Logit analysis with forward stepwise regression to construct predictive models. They selected 100 samples from database AMADEUS (Analyse Major Database for European Sources), from 2000 to 2005. A total of 23 variables were chosen from financial statement of each sample firm in four groups. They developed a four-variable logit model for bankruptcy prediction, the overall prediction accuracy of the model was 81% with cut-off point 0.7, while type I error is 92% and type II error is 70%. Also the t test showed that the bankrupt group had lower profitability before failure, and there is a significant difference in operating efficiency ratio.

Kim and Gu (2006) developed logit models for predicting bankruptcy in the U.S. The sample comprised 16 U.S. hospitality firms that went bankrupt between 1999 and 2004 and 16 non-bankrupt firms. They estimated logit models for predicting bankruptcy up to 2 years in advance. The logit models, resulting from forward stepwise selection procedures, correctly predicted 91% and 84% of bankruptcy cases for years 1 and 2. The context of development may limit applicability to other sectors.

Darayseh, Waples, and Tsoukalas (2003) developed a logit model for bankruptcy prediction using macroeconomic variables and financial ratios. They studied a group of 110 manufacturing firms that went bankrupt between 1990 and 1997 matched by 110 non-bankrupt firms according to total assets and industry classification. Their estimated model could make correct predictions for 87.82% and 89.50% of the in-sample and holdout samples for 1 year prior to bankruptcy. They included macroeconomic varaibles which may have different impact on different sectors.

Low, Nor, and Yatim (2001) applied logistic regression in bankruptcy prediction. The sample consisted of 26 distressed companies selected from 9 industries, and 42 companies randomly selected non-distressed companies. They selected 11 financial ratios from prior studies. They tested the predictive ability of the model on a holdout sample, and showed that the overall accuracy rate for the estimation and holdout samples are 82.4% and 90% respectively.

2.3.3 Studies on Discriminant Models

Barreda, Kageyama, Singh, and Zubieta (2017) studied bankruptcy prediction of hospitality firms in the U.S. They compared the accuracy of logit and discriminant analysis (MDA) models on samples of bankrupt and non-bankrupt firms for the period 1992–2010. They used financial variables as predictors. The results showed that the MDA model outperformed the Logit model in overall bankruptcy prediction. The sample was limited to firms in the hospitality industry; which limits the applicability of the model to other sectors.

Yahaya, Nasiru, and Ebgejiogu (2017) applied discriminant analysis for insolvency prediction in Nigeria. They sample comprised companies that filed for receivership or failed from 1996 to 2012. They collected data from 15 failed and 13 non-failed companies. Financial ratios were employed as variables. They found that the most significant factors in bank insolvency are: retained earning to total asset, earning before interest tax to total asset and the market value of equity to total liability. They also found that failed companies were also less profitable, less liquid and had lower asset quality. The sample was limited to firms in the banking industry; which limits the applicability of the model to other sectors.

Nwidobie (2017) employed Altman's Z score for bankruptcy assessment of Nigerian banks. They used a two-stage sampling technique, the first stage involved the six CBN declared unsound banks in 2011 and second stage four of the banks were selected. He used secondary data to compute ratios. The results showed that there were marginal improvements in the financial status of the sampled banks between 2010-2013 but they were still in a bankrupt position with Union Bank Plc, Wema Bank Plc, Keystone Bank Ltd and Mainstreet Bank Ltd having a Zscore of -0.56, 0.417, 1.5 and 0.45 respectively at 2013, all below the minimum threshold of 2.675 for classification of a bank as sound and non-bankrupt. The study focused on the banking industry; which limits the generalizability of the results.

Babatunde, Akeju, and Malomo (2017) applied the Z-score model for bankruptcy prediction of quoted manufacturing companies in Nigeria. The sample comprised 10 manufacturing companies quoted on the Nigeria Stock Exchange (NSE) for 2015 financial year. The secondary data was analysed using Altman’s Z-score model. The study proved the efficacy of the Z-score model in identifying companies with deteriorating performance in Nigeria. The study used a small sample size, there is need for a wider investigation.

Mihalovič (2016) compared the performance of multiple discriminant analysis and logit models in bankruptcy prediction in Slovak Republic. The sample comprised 236 firms operating in Slovakia, divided into two groups – failed and non-failed firms. The discriminant model had a total accuracy of 64.41% on the test data and the logit analysis had a total of 68.64% on the test data. The results showed that the logit model outperformed the classification accuracy of the discriminant model.

Slefendorfas (2016) developed a bankruptcy prediction model for private limited companies of Lithuania. The sample comprised 145 companies (73 already bankrupt and 72 still operating). The study used multivariate discriminant analysis stepwise method. 156 different financial ratios were selected as primary input data by using correlation and Mann – Whitney U test techniques. The results showed that 89% of companies were classified correctly.

Situm (2015) investigated the potential of a specific trend, defined as the relative change of accounting ratios for two consecutive years, to improve the classification accuracy and model performance of insolvency prediction models based on multivariate discriminant analysis. The sample comprised Austrian firms from different industries from the period 2010 to 2012. Based on a review of 230 papers related to insolvency prediction, 23 potential variables were selected for analysis. The results showed that the trend could not be exploited to improve early detection of corporate crises and insolvencies.

Adeyeye and Migiro (2015) developed an integrated prediction model using PCA and three statistical models DA, logit and probit models in Nigeria. The sample comprised 21 banks out of the total 24 Deposit Money Banks (DMBs) quoted on the Nigerian Stock Exchange over a 23 year-period from 1993 to 2010. 11 financial ratios for both failed banks and non-failed banks were computed using data from annual financial reports of individual banks. The results showed that discriminant analysis (95.2), logit (90.24) and probit (89.02) models are good predictors of financial health. They found that key variables of significance to the performance of a bank were variables that measure profitability, liquidity, credit risk and capital adequacy. The study focused on the banking industry; which limits the generalizability of the results.

Adeyeye and Oloyede (2014) applied an enhanced discriminant model, which combined principal component analysis (PCA) and discriminant analysis (DA) to forecast bank failure in Nigeria. The sample comprised 21 banks out of the 24 banks operating as Deposit Money Banks in Nigeria from 2007 to 2009. The results showed that the overall classification accuracy of the model is 95.2 per cent. The discriminant model correctly predicted the financial status of about 20 banks out of the 21 banks. The model accurately predicted the status of 6 out of 7 failed banks included in the model. The model was developed using data from the banking industry; which limits the generalizability of the results.

Mosionek-Schweda (2014) applied discriminant models for bankruptcy prediction of companies listed on NewConnect. Discriminant analysis was used to analyse the status of four firms removed from trading on NewConnect due to bankruptcy. The analysis was based on three models: Altman's model for emerging markets, Z7 INEPAN model developed in the Polish Academy of Sciences and E. Mączyńska's model, developed by Polish scientists. The results confirm the efficacy of the models in assessing the financial condition of firms in Poland. The study however used models developed specifically for Polish firms (according to P. Antonowicz's research), this limits there applicability to other countries.

Unegbu and Adefila (2013) examined the efficacy of Z-Score and operating cash flow models for corporate insolvency prediction in Nigeria. They assessed the predictive ability of the two models across industries. They tested sixty-two corporate financial statements. They found that Z-Score predictive ability across services and merchandising sectors is very poor but very strong on manufacturing and oil services, while operating cash flow model is more effective in predicting accurately service and merchandising sectors. The predictive efficacy of the two models significantly varies as the year comes closer to the year of corporate failure.

Pam (2013) applied the Z score model to examine the state of health of Nigerian banks. The sample comprised two failed and two non-failed banks over a period of five years, from 1999 to 2003. The results showed that the Z scores of the two non-failed banks were below 1.80 indicating ill-health. The Z score of a bank classified as ‘failed’ was found to be above 3.00.

Serrano-Cinca and GutiéRrez-Nieto (2013) used partial least square discriminant analysis for the prediction of the 2008 USA banking crisis. They compared the performance of this technique to the performance of 8 algorithms widely used in bankruptcy prediction. In terms of accuracy, precision, *F*-score, Type I error and Type II error, results are similar; no algorithm outperforms the other. The results were analyzed using contingency tables, correlations, cluster analysis and dimensionality reduction techniques. The PLS-DA results obtained were very close to those obtained by linear discriminant analysis and support vector machine.

Islam, Semeen, and Farah (2013) applied discriminant analysis to firms in Bangladesh. The sample comprised 31 entreprises traded on the Dhaka Stock Exchange (DSE) between the years 2009 and 2011. 24 ratios listed under liquidity, solvency, activity and profitability were selected. The study found that each ratio (variable) had a significant effect on the financial health of a firm, liquidity ratios was the first, while profitability was the second, solvency and activity were also important.

Ani and Ugwunta (2012) employed ratio analysis and multi discriminant analysis in predicting business failure in Nigeria. They sample comprised eleven firms in the manufacturing, oil marketing and conglomerate sector for a five year period. The result showed that discriminant analysis is a veritable tool for the health status of Nigerian firms. The study however randomly selected firms included in the sample.

Wang and Campbell (2010) examined the accuracy of Z score for prediction in China. The sample comprised 42 delisted firms (16 manufacturing companies) and 42 (16 manufacturing companies) matching nondelisted Chinese publicly listed companies from September 2000 to September 2008. They tested three Z-score variations: Altman's original model, a re-estimated model for which the coefficients in Altman's model were recalculated, and a revised model which used different variables. The results showed that all three models were significant. However, the re-estimated model had higher prediction accuracy for predicting non-failed firms, but Altman's model has higher prediction accuracy for predicting failed firms. The revised Z-score model had higher prediction accuracy compared with both the reestimated model and Altman's original model.

Gu (2002) applied discriminant model for bankruptcy prediction of U.S. restaurant firms. The model achieved a 92-percent accuracy rate in classifying the in-sample firms into bankrupt and non-bankrupt groups. The *jackknife* cross-validation accuracy rate was 89 percent. The *ex-post* classification of out-of-sample restaurants, mainly non-bankrupt firms, was 80 percent correct.

Lennox (1999) compared the performance of three bankruptcy prediction models, multiple discriminant analysis, logit and probit models for U.K. companies. The study sought to identify bankrupt companies in the United Kingdom. They compared the performance of the three models in predicting bankruptcy and showed that the probit and logit models outperformed the discriminant model.

2.3.4 Studies on Neural Networks

Yahaya, Nasiru, and Ebgejiogu (2017) applied a feed forward back propagation neural network to predict insolvency. The sample comprised 15 failed and 13 non-failed companies. They used secondary data collected from 1996 to 2012. Financial ratios were used as independent variables. The results showed that the neural network correctly classified approximately 89 percent. The neural network model was applied on a sample of banks which limits the generalizability of the results.

Enyindah and Onwuachu (2016) applied a back propagation neural network for the prediction of interest rate on loan investment in Nigerian banks. They collected data from Imo State Microfinance Bank at Owerri, Imo State, Nigeria from 16/02/2009 to 17/04/2014. The input variables were twelve. They forecasted interest rate on loan investment in three areas which included commerce, education, and rent/housing. The simulation was done using Matlab 2008. The results showed a Mean Squared Error values 3.99104e-6 in the Training, 3.597228e-5 in the validation and 9.9464314e-6 in the testing, thus confirming a minimal amount of error.

Bapat and Nagale (2014) compared the performance of three bankruptcy prediction models, the multiple discriminant analysis, logistic regression and neural network for listed companies in India. The sample comprised 50 bankrupt and 50 non-bankrupt companies, and the holdout sample comprised 22 bankrupt and 22 non-bankrupt companies over the period 1991 to 2013. The models were developed, over three years prior to bankruptcy using financial ratios. The results of multiple discriminant analysis on the holdout sample showed that the accuracy rate fall from 70.45 per cent one year prior to bankruptcy to 61.36 per cent for years two and three prior. The results of logistic regression on the holdout sample showed that the accuracy rate fall from 75.00 per cent one year prior to bankruptcy to 59.09 per cent two years prior to bankruptcy and 61.36 per cent for the third year prior to bankruptcy. The results of neural network on the holdout sample showed that the accuracy rate falls from 77.27 per cent one year prior to bankruptcy to 63.64 per cent two years prior to bankruptcy and then rises to 65.91 per cent for third year prior to bankruptcy. Thus, the study proved that neural network had the highest classification accuracy for all the three years prior to bankruptcy.

Eriki and Udegbunam (2013) compared neural network with multiple discriminant analysis in predicting corporate distress in the Nigerian stock market. The studied forty four firms listed on the Nigerian Stock Market between 1987 and 2006. The results showed that the neural network outperformed the discriminant analysis technique.

Farinde (2013) applied neural network for distress prediction in Nigeria. The sample comprised thirty quoted banks that had published Annual Reports for the year preceding consolidation (2004). The study used the Multilayer Perceptron Neural Network Analysis. He further analyzed the reforms by the Central Bank of Nigeria using published Annual Reports of twenty quoted banks for the year 2008 and 2011. Discriminant analysis was used to benchmark the performance of the neural network. The study found that both approaches were useful in the prediction of corporate bankruptcy for Nigerian banks.

Ibiwoye, Ajibola, and Sogunro (2012) constructed an insolvency prediction model based on artificial neural network. The sample comprised registered insurance companies in Nigeria. They used 26 financial information and ratios used in prior bankruptcy studies. The data consisted of four years prior failure. As a control measure (training data set), a failed insurer was matched with a successful insurer in terms of size and accounting years, that is, asset size, number of branches, age, and charter status. They used total assets/total liability as a measure of liquidity ratio in the study as the springboard for determining the threshold of solvency from the ANN simulation. When they raised the threshold of solvency in the industry to 5 as a result of creative accounting (i.e. gross manipulation of accounting figures), they found that the graph of the ANN simulation model falls completely below the threshold. This confirms the insolvency of the insurance companies under consideration.

Kouki and Elkhaldi (2011) compared the performance of three bankruptcy prediction models, constructed using multivariate discriminate analysis, logit model and neural network on a sample of Tunisian firms. They used a sample of 60 failing and performing firms, during a period of three years before bankruptcy (2000-2002). They found that neural network was the most powerful at a very short term horizon. However, multivariate discriminate analysis and logit regression were powerful at a medium horizon of two and three years before bankruptcy.

Tseng and Hu (2010) compared the performance of four bankruptcy prediction models, logit, quadratic interval logit, neural and fuzzy neural networks on a sample of bankrupt and non-bankrupt firms in England. The average hit ratio of four methods range from 91.15% to 77.05%. The original classification accuracy and the validation test results indicate that the Radial Basis Function Network (RBFN) outperformed the other models.

Chen and Du (2009) applied the back propagation neural network and K-Means clustering algorithm for bankruptcy prediction in Taiwan. The sample comprised 68 firms listed on the Taiwanese Stock Exchange from 1999 January - October, 2006. They matched 34 bankrupt firms with 34 non-bankrupt firms. They selected 37 (33 financial ratios and 4 non-financial ratios). The results showed that the accuracy rate (non-factor analysis) with the BPN model is better than with the clustering model.

Lin (2009) compared the predictive ability of four distress prediction models, the Multiple Discriminant analysis (MDA), logit, probit, and artificial neural networks (ANNs) in Taiwan. He used a dataset of matched sample of failed and non-failed Taiwan public industrial firms from 1998 to 2005. The models were validated using within sample test and out-of-the-sample test, respectively. The results showed that probit model had the best and stable performance. However, if the data does not satisfy the assumptions of the statistical approach, then ANN achieves higher prediction accuracy.

Sookhanaphibarn, Polsiri, Choensawat, and Lin (2007) applied neural networks for bankruptcy prediction in Thailand. They used data sets of 41 Thai financial institutions for the period 1993 to 2003. They computed 30 financial variables and seven ownership variables to develop the models. They used principal component analysis to reduce the number of variables. They examined the performance of three neural networks: Learning Vector Quantization, Probabilistic Neural Network, and Feedforward Network with Back Propagation Learning. They found that Learning Vector Quantization (LVQ) outperformed the other two models in terms of predictive accuracy and bias. Probabilistic Neural Network (PNN) provided consistent results every running time but its accuracy is lowest. Feed Forward Network with Back Propagation Learning provided superior accuracy results but had a bias considerably higher than that of the other two methods.

Cheng, Chen, and Fu (2006) compared neural network with logit analysis for distress prediction in Taiwan. They used the radial basis function network to construct the neural network model. The sample comprised 192 firms listed on the Taiwan Stock Exchange, composed of firms which have incurred financial distress during the period from 1996 to 2004. They compared the performance of the proposed RBFN to logit analysis, and showed that the RBFN showed superior results.

Hsieh, Liu, and Hsieh (2006) proposed a hybrid neural network models for bankruptcy prediction in Taiwan. The models are, a MDA model integrated with financial ratios, a MDA model integrated with financial ratios and intellectual capital ratios, a MDA-assisted neural network model integrated with financial ratios, and a MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios. The experimental samples in the study consisted of bankruptcy cases reported in R.O.C. from 2002 through 2005. They employed 75 enterprises as experimental samples, while 80 financial ratios and 12 intellectual capital ratios were used as input variables. They compared the performance of the models with MDA model integrated with financial ratios as a benchmark. The results show that the MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios have accuracy of 89% which was highest.

Odom and Sharda (1990) compared the predictive ability of neural network and multivariate discriminant analysis models in bankruptcy risk prediction. They used the same financial ratios that Altman used in his 1968 study. The sample of firms from which the ratios were obtained consisted of firms that went bankrupt between 1975 and 1982. The sample, obtained from Moody's Industrial Manuals, consisted of a total of 129 firms, 65 of which went bankrupt during the period and 64 non-bankrupt firms matched on industry and year. Two subsamples were developed from this sample of 129 firms. The fist (training) subsample of 74 firms data (38 bankrupt firms and 36 non-bankrupt firms) was used as the training set for both methods. The second subsample consisted of 55 firms (27 bankrupt firms and 28 non-bankrupt firms) and was used as the holdout sample. Data used for the bankrupt firms is from the last financial statements issued before the firms declared bankruptcy. The discriminant analysis method correctly classified 33 of the 38 bankrupt firms for a correct classification rate of 86.84% when using the training subsample. The neural network correctly predicted all 36 of the non-bankrupt firms in the training subsample as non-bankrupt. The trained network also correctly predicted all 38 of the bankrupt firms as bankrupt. The discriminant analysis method correctly predicted 89.29% of the non-bankrupt firms while the neural network predicted 82.14% correctly when trained with the 50/50 sample. Using the 80/20 sample, the discriminant analysis method correctly predicted 85.71% as compared to the neural networks correct prediction rate of 78.57%. However, when the 90/10 sample was used for training, the neural network did better correctly predicting 85.71% of the holdout subsample, while the discriminant analysis method predicted only 78.57%.

2.4 Summary of Empirical Review

2.4.1 Review summary (Genetic Algorithm)

Authors	Year	Title	Method	Findings
Zelenkov, Fedorova, and Chekrizov	2017	Two-step classification method based on genetic algorithm for bankruptcy forecasting.	Two-step classification method based on genetic algorithm. Classifiers of various models are trained at the first step and combined into the voting ensemble at the second step.	It found bankrupts (recall = 0.953) and not bankrupts (precision = 0.910) rather accurately than other tested models.
Georgescu	2017	Using genetic algorithms to evolve type-2 fuzzy logic systems for predicting bankruptcy.	The shape of type-2 membership functions, the parameters giving their spread and location in the fuzzy partitions and the set of fuzzy rules are evolved at the same time by encoding all together into the chromosome representation. The enhanced Karnik–Mendel algorithms are used for the centroid type-reduction and defuzzification stage.	The IT2FLSs by representing and capturing uncertainty with more degrees of freedom allows them to outpeform T1FLS
Chou, Hsieh, and Qiu	2017	Hybrid genetic algorithm and fuzzy clustering for bankruptcy prediction.	They used a fuzzy clustering algorithm for the classifier design, which was compared with back propagation neural network. Experimental results based on one to four years of financial data prior to the occurrence of bankruptcy were used to evaluate the performance of the proposed model.	The proposed model performed significantly well.
Bateni and Asghari	2016	Bankruptcy Prediction Using Logit and Genetic Algorithm Models: A Comparative Analysis.	A comparison of logit and GA models by identifying conditions under which a model performs better.	GA achieved 95 and 93.5 % accuracy rates in training and test samples, while logit achieved 77 and 75 % accuracy rates in training and test samples, respectively.
Hou	2016	Financial Distress Prediction of K-means Clustering Based on Genetic Algorithm and Rough Set Theory.	The study used K-means clustering algorithm on a sample of 24 A-share companies listed in Shanghai Stock Exchange and Shenzhen Stock Exchange.	The K-means clustering algorithm based on genetic algorithm is more accurate than the traditional clustering algorithm.

Source: Empricial Literature Reviewed, 2019

2.4.1 cont'd: Review summary (Genetic Algorithm)

Min	2016a	A genetic algorithm-based heterogeneous random subspace ensemble model for bankruptcy prediction.	Applied four different learning algorithms to heterogeneous random subspace ensemble: k-nearest neighbor (KNN), decision tree (DT), logistic regression (Logit), and support vector machines with RBF kernel (SVM-rbf).	The experimental results confirmed that the model outperformed other models in the study.
Min	2016b	Genetic Algorithm based Hybrid Ensemble Model.	Developed hybrid ensemble model that integrates bagging and random subspace method using genetic algorithm and compared the performance with other models.	The experimental results showed that the proposed model performed better than the other models.
Min	2016c	Integrating instance selection and bagging ensemble using a genetic algorithm.	Genetic algorithm was used to select optimal or near-optimal instances to be used as input data by the bagging model.	The results showed that the proposed model outperformed the other models.
Szebenyi	2014	Bankruptcy prediction using genetic programming - a case study of Hungarian accommodation provider firms.	A comparison between GA and binary logistic regression.	The results showed that GA outperformed logistic regression.
Gordini	2014	Genetic algorithms for small enterprises default prediction: Empirical evidence from Italy	The study employed multiple discriminant analysis and logistic regression (two main traditional techniques in default prediction modelling) to benchmark GA.	The results show that the best prediction results were obtained using GAs.
Zebardast, Javid, and Taherinia	2014	The use of artificial neural network in predicting bankruptcy and its comparison with genetic algorithm in firms accepted in Tehran Stock Exchange.	They predicted bankruptcy in firms accepted in TSE using artificial neural network (ANN) and genetic algorithm (GA).	The results of the two models were compared with each other. ANN achieved a precision of 91.2% on the whole. GA achieved 86.5% on the whole.
Hajiamiri, Shahraki, and Barakati	2014	Application of Genetic Algorithm in Development of Bankruptcy Predication Theory Case Study: Companies Listed on Tehran Stock Exchange.	They deployed GA to predict bankruptcy on a sample of companies listed on TSE	The results showed that GA correctly predicted the bankruptcy of companies two years before the base year, one year before the base year and the base year.

Source: Empricial Literature Reviewed, 2019

2.4.1 cont'd: Review summary (Genetic Algorithm)

Gaspar-Cunha, Recio, Costa, and Estébanez	2014	Self-Adaptive MOEA Feature Selection for Classification of Bankruptcy Prediction Data	They multi-objective evolutuinary algorithm, specifically the reduced Pareto Set Genetic Algorithm (RPSGA) on four datasets; Industrial French Companies' Data, from the years 2005 and 2006, German Credit Data and Australian Credit Data, both publicly accessible at the UCI Machine Learning Repository.	The experimental results proved the utility of using self-adaptation of the classifier.
Poorzamani and Nooreddin	2013	Applying Internal Analysis Data and Non-Linear Genetic Algorithm in Developing a Predicting Pattern of Financial Distress.	A comparison of neural network patterns (ANNs) and principal component analysis + Non-Linear Genetic Algorithm (PCA+Non-Lin) in predicting financial distress.	The ANNs showed a classification of the firms in training, hold-out, and total sample into financially healthy and distressed firms with a general accuracy of 100%, 95.83% and 99.19%, respectively, in the training, hold-out and total sample, while the PCA+Non-Lin showed a classification of the firms in training, hold-out and total samples into two groups of financially distressed and healthy firms with a general accuracy of 89%, 79.17%, and 87.10%, in the training, hold-out and total sample.
Salehi and Rostami	2013	Bankruptcy Prediction by Using Support Vector Machines and Genetic Algorithms.	A comparison of Support Vector Machine (SVM) and Genetic Algorithm (GA) and the accuracy of both in bankruptcy prediction.	GA had higher accuracy of prediction and smaller type II error in three years t, t-1 and t-2. In the second stage, GA and SVM are compared. In year's t and t-1, SVM outperformed GA, and its type I and II errors are less. However, GA outperformed SVM in year t-2, however and type I error of GA is higher.

Source: Empricial Literature Reviewed, 2019

2.4.1 cont'd: Review summary (Genetic Algorithm)

Kim and Kang	2012	Classifiers selection in ensembles using genetic algorithms for bankruptcy prediction.	They proposed a genetic algorithm-based coverage optimization technique for the purpose of resolving multicollinearity problem.	The results indicate that the proposed coverage optimization algorithm can help to design a diverse and highly accurate classification system.
Jeong, Min, and Kim	2012	A tuning method for the architecture of neural network models incorporating GAM and GA as applied to bankruptcy prediction.	They applied generalized additive model (GAM) for input variable selection. Grid search method and genetic algorithm are sequentially implemented to fine-tune the number of hidden nodes and the value of the weight decay parameters.	The empirical results showed that the tuned neural network model significantly outperforms other models (such as case-based reasoning, decision tree, the GAM, the generalized linear model, the multivariate discriminant analysis, and the support vector machine).
Zhang and Wu	2011	Bankruptcy Prediction by Genetic Ant Colony Algorithm.	They proposed a novel method based on wrapper-based feature selection and used a novel genetic ant colony algorithm (GACA) as the search method, and the rule-based model was employed as the classifier. Stratified K-fold cross validation method was taken as the statistical resampling to reduce overfitting. Simulations take 1,000 runs of each algorithm on the dataset of 800 corporations during the period 2006-2008.	The results of the training subset show that the GACA obtains 84.3% success rate, while GA obtains only 48.8% and ACA obtains 22.1% success rate. The results on test subset demonstrate that the mean misclassification error of GACA is only 7.79%, less than those of GA (19.31%) and ACA (23.89%). The average computation time of GACA is only 0.564s compared to the GA (1.203s) and ACA (1.109s).
Martin, Madhusudhnan, Lakshmi, and Venkatesan	2011	To Find Best Bankruptcy Model using Genetic Algorithm.	Used genetic algorithm to find the non-linear relationship between financial ratios which have more impact in three bankruptcy models. The three bankruptcy models are Altman, Edmister and Deakin model.	The Altman model had best result, with a threshold value of 98%.
Garkaz and Abdollahi	2010	The investigation of possibility of the use of genetic algorithm in predicting companies' bankruptcy.	They employed GA in predicting bankruptcy in Iran.	The results showed that GA can be used of predict bankruptcy in Iran.

Source: Empricial Literature Reviewed, 2019

2.4.1 cont'd: Review summary (Genetic Algorithm)

Kim, Kim, and Kang	2010	Optimizing SVM ensembles using genetic algorithms in bankruptcy prediction.	Proposed a genetic algorithm-based optimization technique of SVM ensemble to solve multicollinearity problem. The studied a sample of Korean firms.	Empirical results showed that the proposed model can improve the performance of SVM ensemble.
Etemadi, Rostamy, and Dehkordi	2009	A genetic programming model for bankruptcy prediction: Empirical evidence from Iran.	They investigated the application of genetic programming (GP), a variant of genetic algorithm, and employed multiple discriminant analysis (MDA) to benchmark the genetic programming model.	The GP model achieved 94% and 90% accuracy rates in training and holdout samples, respectively; while MDA model achieved only 77% and 73% accuracy rates in training and holdout samples, respectively.
Davalos, Leng, Feroz, and Cao	2009	Bankruptcy classification of firms investigated by the US Securities and Exchange Commission: an evolutionary adaptive ensemble model approach.	They used bagging to improve the model's generalisation accuracy and to develop a doubly controlled fitness function to guide the operations of the (GA) method.	They assess the accuracy of the GA classifier by comparing it to the four classifiers: decision trees (C4.5), artificial neural network (MLP), linear discriminant analysis (LDA), and multinomial logistic regression (MLR).They find that the GA model is able to classify bankrupt AAER firms better than other classification models. Overall, the GA model performed better when Type I errors are included in the assessment.
Min and Jeong	2009	A binary classification method for bankruptcy prediction.	They used Genetic Algorithms to calculate the feature weights and the values of the variables for the cases.	Firms' that were representative of bankruptcy had a higher value for the ratio of Current liabilities to Total assets than non-bankrupt firms, while ratios of Break-Even Point and the Employment Cost were higher for non-bankrupt firms
Li and Ho	2009	Predicting financial activity with evolutionary fuzzy case-based reasoning.	They proposed a fuzzy Case Based Reasoning (CBR) method combined with Genetic Algorithms.	The results identified the most significant feature as the Current ratio followed by Net operation cycle and Sales.
Wu, Tzeng, Goo, and Fang	2007	A real-valued genetic algorithm to optimize the parameters of support vector machine for predicting bankruptcy.	Proposed a genetic-based support vector machine (GA-SVM) model and also compared the accuracy of the model with that of DA, logit, probit, NN and SVM.	The results showed that the GA-SVM model performs the best predictive accuracy.

Source: Empricial Literature Reviewed, 2019

2.4.1 cont'd: Review summary (Genetic Algorithm)

Esseghir	2006	New evolutionary classifier based on Genetic Algorithms and neural networks: application to the bankruptcy forecasting problem.	Proposed a new hybrid model based on genetic algorithms and artificial neural networks.	The study found that an evolutionary classifier based on feature selection and evolutionary learning techniques outperforms ANNs using back propagation.
Sun and Hui	2006	An application of decision tree and genetic algorithms for financial ratios' dynamic selection and financial distress prediction.	Applied decision tree and genetic algorithms for financial ratios' dynamic selection and financial distress prediction	They found that genetic algorithm applied to optimize the financial ratios selected using decision tree has a good balance between accuracy and generalization. The model's predicitive accuracy for training samples and validation samples are 94.67% and 93.75%.
Mukkamala, Tilve, Sung, Ribeiro, and Vieira	2006	Computational intelligent techniques for financial distress detection.	They evaluated the classification accuracy for Linear Genetic Programs (LGPs), Classification and Regression Tress (CART), TreeNet, and Random Forests, Multilayer Perceptron (using Back Propogation), Hidden Layer Learning Vector Quantization and several gradient descent methods.	The results showed that TreeNet has the best performance accuracy on unbalanced dataset and LGPs performs the best on balanced dataset. Scaled Conjugate Gradient performs the best among the neural network training functions used for the balanced dataset; and Resilient Back Propagation performs the best among the training functions used for the unbalanced dataset.
Min, Lee, and Han	2006	Hybrid genetic algorithms and support vector machines for bankruptcy prediction.	Integrated GA and SVM. The study proposed a method for improving SVM performance in two aspects: feature subset selection and parameter optimization.	The GA was used to optimize both feature subset and parameters of SVM simultaneously for bankruptcy prediction.
Abdelwahed and Amir	2005	New evolutionary bankruptcy forecasting model based on genetic algorithms and neural networks.	They conducted experiments to investigate the predictive accuracy and adaptability of EBM (Evolutionary Bankruptcy Model).	The model is capable of selecting the best set of predictive variables, then, searching for the best neural network classifier and improving classification and generalization accuracies.

Source: Empricial Literature Reviewed, 2019

2.4.1 cont'd: Review summary (Genetic Algorithm)

Salcedo-Sanz, Fernandez-Villacanas, Segovia-Vargas, and Bousono-Calzon	2005	Genetic programming for the prediction of insolvency in non-life insurance companies.	Applied genetic programming for the prediction of insolvency in non-life insurance companies. They compared the results of the genetic algorithm with that of Support Vector Machine and Rough Set.	They confirm the suitability of genetic algorithm in insolvency of non-life insurance firms.
Galveo, Becerra, and Abou-Seada	2002	Variable selection for financial distress classification using a genetic algorithm.	They used financial data from 29 failed and 31 non-failed British corporations from the period 1997 to 2000.	The model based on ratios selected by the GA performed well.
Shin and Lee	2002	A genetic algorithm application in bankruptcy prediction modelling.	Proposed a GA approach which can be applied to bankruptcy prediction modeling.	The preliminary results showed that rule extraction approach using GAs for bankruptcy prediction modeling is effective.
McKee and Lensberg	2002	Genetic programming and rough sets: A hybrid approach to bankruptcy classification.	Developed a hybrid model using genetic programming algorithm with variables from a rough sets model derived in prior research to construct a bankruptcy prediction model.	The model had an accuracy of 80% on the validation sample when compared to the original rough sets model which was 67% accurate.
Nanda and Pendharkar	2001	Linear models for minimizing misclassification costs in bankruptcy prediction.	They developed GA which incorporates asymmetric Type I and Type II error costs. The model was compared with linear discriminant analysis (LDA), goal programming approach, and a GA-based classification approach.	The results showed that the proposed approach, incorporating Type I and Type II error costs, results in lower misclassification costs when compared to LDA and GA approaches that do not incorporate misclassification costs.
Varetto	1998	Genetic algorithms applications in the analysis of insolvency risk.	He compared Linear Discriminant Analysis (LDA) and Genetic Algorithm (GA).	The experiments showed GA to be a very effective instrument for insolvency diagnosis.
Back, Laitinen, Sere, and van Wezel	1996	Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms.	They compared three alternative techniques-linear discriminant analysis, logit analysis and genetic algorithms-that can be used to select predictors for neural networks in failure prediction.	The best prediction results were achieved using genetic algorithms.

Source: Empricial Literature Reviewed, 2019

2.4.2 Review summary (Logit and Discriminant Models)

Authors	Year	Title	Method	Findings
Barreda, Kageyama, Singh, and Zubieta	2017	Hospitality Bankruptcy in United States of America: A Multiple Discriminant Analysis-Logit Model Comparison.	They compared the accuracy of the Logit model and the Multiple Discriminant Analysis (MDA). They employed various key financial variables as predictors and contrasting samples of both bankrupt and non-bankrupt firms for the period 1992–2010 were used.	The results show that for the period 1992–2010, the MDA model outperformed the Logit model for overall bankruptcy prediction.
Yahaya, Nasiru, and Ebgejiogu	2017	Insolvency Prediction Model of Some Selected Nigerian Banks.	They used discriminant analysis to evaluate predictor variables used to predict insolvency. They used secondary data collected from companies that filed for receivership or failed from.	The result showed that the failed companies were also less profitable and less liquid and lower quality assets.
Nwidobie	2017	Altman's Z-Score Discriminant Analysis and Bankruptcy Assessment of Banks in Nigeria.	Employed Altman's Z score for bankruptcy assessment of Nigerian banks. The study used a two-stage sampling technique, which involved the six CBN declared unsound banks in 2011 and thereafter four of the unsound banks in 2011 were sampled.	The results showed that there are marginal improvements in the financial status of the sampled banks between 2010-2013 but they are still in a bankrupt position with Union Bank Plc, Wema Bank Plc, Keystone Bank Ltd and Mainstreet Bank Ltd having Z score below the minimum.
Brîndescu-Olariu	2017	Bankruptcy prediction logit model developed on Romanian paired sample.	Proposed a model using logistic regression. The testing was performed over the entire target population from the period 2007-2010.	The results recommended classifying companies under one of the following tree risk classes: high bankruptcy risk, for estimated bankruptcy probabilities of 0.5 or more; average bankruptcy risk, for estimated bankruptcy probabilities between 0.3 and 0.5; and, low bankruptcy risk, for estimated bankruptcy probabilities of less than 0.3.
Salmistu	2017	Bankruptcy prediction model in the example of Estonian construction companies.	Focused on Estonian construction companies and selected financial ratios from prior literature.	The composed model shows 68.4% overall classification accuracy and classifies correctly 74% of bankrupt companies one year prior to bankruptcy.

Source: Empricial Literature Reviewed, 2019

2.4.2 cont'd: Review summary (Logit and Discriminant Models)

Welc	2017	EBITDA vs. Cash Flows in Bankruptcy Prediction on the Polish Capital Market.	The study evaluated the accuracy of bankruptcy predictions generated by EBITDA-based and cash flow-based liabilities-coverage ratios on a sample of firms firms listed on the Warsaw Stock Exchange, from the Polish market.	The study found that the logit models with only one ratio used as an explanatory variable is capable of identifying bankrupt firms (with one-period-ahead forecast horizon) in about 66-76% of cases.
Babatunde, Akeju, and Malomo	2017	The effectiveness of Altman's z-score in predicting bankruptcy of quoted manufacturing companies in Nigeria.	Evaluated the effectiveness of Altman's z-score in predicting bankruptcy of quoted manufacturing companies in Nigeria. The sample comprised 10 manufacturing companies quoted on the Nigeria Stock Exchange (NSE) for 2015 financial year.	The study proves the effectiveness of the Z-score model in identifying companies with deteriorating performance in Nigeria.
Mihalovič	2016	Performance Comparison of Multiple Discriminant Analysis and Logit Models in Bankruptcy Prediction.	Compared performance of multiple discriminant analysis and logit models in bankruptcy prediction in Slovak Republic.	The results showed that the logit model outperformed the classification accuracy of the discriminant model. The discriminant analysis had a total accuracy of 64.41% on the test data and the logit analysis had a total of 68.64% on the test data.
Slefendorfas	2016	Bankruptcy prediction model for private limited companies of Lithuania.	Developed a bankruptcy prediction model for private limited companies of Lithuania. 145 companies (73 already bankrupt and 72 still operating) were chosen as sample and by using multivariate discriminant analysis stepwise method a linear function was created. 156 different financial ratios were selected as a primary input data by using correlation calculation between bankruptcy and still operating companies and Mann – Whitney U test techniques.	The results showed that 89% of companies were classified correctly, which states that the model is strong enough to predict bankruptcy probability for private limited companies operating in Lithuania in a sufficient accuracy.
Situm	2015	The Relevance of Trend Variables for the Prediction of Corporate Crises and Insolvencies.	Investigated the potential of a specific trend, to improve the classification accuracy and model performance of insolvency prediction models based on multivariate linear discriminant analysis.	The results showed that the respective trend can include information from both consecutive years, but this informational content could not be exploited to improve early detection of corporate crises and insolvencies.

Source: Empricial Literature Reviewed, 2019

2.4.2 cont'd: Review summary (Logit and Discriminant Models)

Adeyeye and Migiro	2015	An investigation on Nigerian banks' status using early-warning signal.	Developed an integrated early warning signal which utilises the PCA with three statistical models DA, logit and probit models to determine the health status of Nigerian banks. The sample comprised 21 banks out of the total 24 Deposit Money Banks (DMBs) quoted on the Nigerian Stock Exchange over a 23 year-period from 1993 to 2010.	The results show that discriminant analysis (95.2), logit (90.24) and probit (89.02) models are credible predictors of a bank's financial status.
Brédart	2014a	Bankruptcy prediction model: The case of the United States.	The study used logit regression to forecast corporate bankruptcy among US companies. The sample used in the study consisted of 870 firms originally quoted on the Amex, the Nasdaq and the NYSE from January 2000 to December 2012. The study used a matched-pair sample of US quoted firms with half of the sample filing for chapter 11 (reorganization procedure) of the United States Bankruptcy Code and conducted logit regression analysis.	The results showed that profitability had a negative impact on financial distress probability, a negative relationship between liquidity and the probability to file for a bankruptcy law, and solvency had a negative impact on financial distress probability. The overall prediction accuracy of the model is 83.82%.
Mosionek-Schweda (2014)	2014	The Use of Discriminant Analysis to Predict the Bankruptcy of Companies Listed on the NewConnect Market.	The analysis was based on three models: Altman's model for emerging markets, and two other models based on P. Antonowicz's research, Z7 INEPAN model developed in the Polish Academy of Sciences and E. Mączyńska's model, developed by Polish scientists and adapted to the Polish economy.	The results confirmed that these models are a valuable tool in assessing the financial condition of enterprises and allow for bankruptcy forecasting.
Bartual, Garcia, Guijarro, and Moya	2013	Default pre diction of Spanish companies. A logistic analysis.	Developed a model to predict corporate default for Spanish manufacturing companies applying logistic regression. They selected 2,783 companies, of which 736 were identified as insolvent (26.5% of the sample). The variables employed in the study were obtained from the balance sheets and the income statements of the companies.	The model correctly assessed credit risk in 88.1% of the cases, while the naïve model obtained a success rate of 73.5%; equal to the percentage of solvent firms in the sample. Thus, the model beats by almost 15% the results obtained by the naïve model.

Source: Empricial Literature Reviewed, 2019

2.4.2 cont'd: Review summary (Logit and Discriminant Models)

Lundqvist and Strand	2013	Bankruptcy Prediction with Financial Ratios-Examining Differences across Industries and Time.	Bankruptcy prediction models were estimated using logistic regression for each year, with and without interaction terms accounting for industry effects.	The study shows that the bankruptcy-prediction ability of different financial ratios varies between years. However, only in some cases, significant differences between industries were found.
Adeyeye and Oloyede	2014	Forecasting Bank Failure in Nigeria: An Application of Enhanced Discriminant Model.	They combined principal component analysis (CPA) and discriminant analysis (DA) to estimate bankruptcy. The data set of the analysis contains 11 bank-specific variables of 21 banks out of the 24 banks operating as deposit money banks in Nigeria between 2007 and 2009.	The discriminant model correctly predicted the financial status of about 20 banks out of 21 sampled banks respectively. The model accurately predicted the status of 6 banks out of 7 failed banks included in the model. Even the one not correctly predicted was appropriately identified as misclassified.
Unegbu and Adefila	2013	Efficacy Assessments of Z-Score and Operating Cash Flow Insolvency Predictive Models.	They examined and compared the efficacy of Z-Score and operating cash flow as corporate insolvency prediction models. The tools of analyses employed are ANOVA, Loglinear Analysis, Fredman ANOVA and Percentages.	Z-Score predictive ability across Services and Merchandising sectors is found to be very poor but very strong on Manufacturing and Oil Services, while Operating Cash Flow model is found to be more effective in predicting accurately Service and Merchandising Sectors. The predictive efficacy of the two models significantly varies as the year becomes closer to the year of corporate failure.
Pam	2013	Discriminant Analysis and the Prediction of Corporate Bankruptcy in the Banking Sector of Nigeria.	Investigated the potency of Multiple Discriminant Analysis Model (propounded by Altman, 1968) in ascertaining the state of health of banks in Nigeria. The sample of the study comprised two 'failed' and two non-failed banks within a five year period (1999-2003).	The study found that the Z Scores of the two non-failed banks were found to be below 1.80 indicating ill-health.
Serrano-Cinca and GutiéRrez-Nieto	2013	Partial least square discriminant analysis for bankruptcy prediction.	Used Partial Least Square Discriminant Analysis (PLS-DA) for the prediction of the 2008 USA banking crisis. They compared the performance of this technique to the performance of 8 algorithms widely used in bankruptcy prediction.	The PLS-DA results obtained were very close to those obtained by Linear Discriminant Analysis and Support Vector Machine. In terms of accuracy, precision, *F*-score, Type I error and Type II error, results are similar; no algorithm outperforms the others.

Source: Empricial Literature Reviewed, 2019

2.4.2 cont'd: Review summary (Logit and Discriminant Models)

Islam, Semeen, and Farah	2013	The Effects of Financial Ratios on Bankruptcy.	They studied 24 ratios listed under the title of liquidity, financial solvency, activity and profitability. The data were subjected to analysis using discriminant analysis.	The results of the study demonstrate that each ratio (variable) has a significant effect on the financial positions of enterprises with differing amounts
Zaghdoudi	2013	Bank failure prediction with logistic regression.	Developed a predictive model of Tunisian bank failures using binary logistic regression method. The specificity of our prediction model is that it takes into account microeconomic indicators of bank failures.	The results showed that a bank's ability to repay its debt, the coefficient of banking operations, bank profitability per employee and leverage financial ratio has a negative impact on the probability of failure.
Ani and Ugwunta	2012	Predicting Corporate Business Failure in the Nigerian Manufacturing Industry.	Employed discriminant analysis in predicting business failure in Nigeria. They employed secondary data for a five year period from eleven firms in the manufacturing, oil marketing and conglomerate sector of the Nigerian Stock Exchange.	The result revealed that multi discriminant analysis is a veritable tool for assessing the financial health of firms in Nigeria.
Ahmadi, Soleimani, Vaghfi, and Salimi	2012	Corporate bankruptcy prediction using a logit model: Evidence from listed companies of Iran.	Attempt to predict corporate bankruptcy prediction using Logit model. They used 19 financial ratios.	The results showed that the Logit model with variables of net profit to total assets ratio, the ratio of retained earnings to total assets and debt ratio have more power to predict corporate bankruptcy in Iran.
Han, Kang, Kim, and Yi	2012	Logit regression based bankruptcy prediction of Korean firms.	They developed a bankruptcy prediction model for Korean firms using logit regression. They also include equity market inputs and macro-economic variables.	They compared the model with a Merton-type structural model and find that the model demonstrates a higher prediction power in distinguishing distressed firms from healthy firms.
Hassani and Parsadmehr	2012	The presentation of financial crisis forecast pattern (Evidence from Tehran Stock Exchange).	Used logit model on firms in Tehran Stock Exchange. Variables were obtained from literature and Article 141 of the Commerce Law.	The results indicated that using the test data, the forecast strength of the model is 81.49%, its degree of sensitivity is 96.12% and its degree of identification is 67.48%.

Source: Empricial Literature Reviewed, 2019

2.4.2 cont'd: Review summary (Logit and Discriminant Models)

Hauser and Booth	2011	Predicting bankruptcy with robust logistic regression.	They used data from 2006 and 2007, and a three-fold cross validation scheme to compare the classification and prediction of bankrupt firms using the Bianco and Yohai (BY) estimator versus maximum likelihood (ML) logistic regression.	The provide evidence to support the BY robust logistic regression for improved classification of bankrupt firms.
Wang and Campbell	2010	Business failure prediction for publicly listed companies in China.	Studied data from Chinese publicly listed companies for the period of September 2000-September 2008. They tested the accuracy of the Altman's Z-score model in predicting failure of the companies. They studied a total of 42 delisted firms (16 manufacturing companies) along with 42 (16 manufacturing companies) matching nondelisted firms.	All three models were found to have significant predictive ability. The re-estimated model had higher prediction accuracy for predicting non-failed firms, but Altman's model has higher prediction accuracy for predicting failed firms. The revised Z-score model has a higher prediction accuracy compared with both the reestimated model and Altman's original model.
Zhou and Elhag	2007	Apply logit analysis in bankruptcy prediction.	They employed Logit analysis with forward stepwise regression to construct predictive models. A total of 23 variables were chosen from financial statement of each sample firm in four groups.	The Logit model predicted bankruptcy, with an overall prediction accuracy of the model was 81% with cut-off point 0.7, while type I error is 92% and type II error is 70%. The t test showed that the bankrupt group had lower profit generation ability before failure, and there is a significant difference in operating efficiency ratio.
Kim and Gu	2006	A logistic regression analysis for predicting bankruptcy in the hospitality industry.	They estimated logit models for predicting bankruptcy up to 2 years in advance using financial data of 16 U.S. hospitality firms that went bankrupt between 1999 and 2004 and 16 non-bankrupt matching firms.	The logit models, resulting from forward stepwise selection procedures, could correctly predict 91% and 84% of bankruptcy cases 1 and 2 years earlier, respectively.
Darayseh, Waples, and Tsoukalas	2003	Corporate failure for manufacturing industries using firms specifics and economic environment with logit analysis.	They developed a logit model for bankruptcy prediction using economic variables in combination with firm-wise financial ratios.	Their estimated model could make correct predictions for 87.82% and 89.50% of the in-sample and holdout samples for 1 year prior to bankruptcy.

Source: Empricial Literature Reviewed, 2019

2.4.2 cont'd: Review summary (Logit and Discriminant Models)

Gu	2002	Analyzing bankruptcy in the restaurant industry: A multiple discriminant model.	Developed a multiple discriminant model for analyzing US restaurant firm bankruptcy. The model achieved a 92-percent accuracy rate in classifying the in-sample firms into bankrupt and non-bankrupt groups. The *jackknife* cross-validation accuracy rate was 89 percent.	The *ex-post* classification of out-of-sample restaurants, mainly non-bankrupt firms, was 80 percent correct. The model suggests that restaurant firms with low earnings before interests and taxes and high total liabilities are more likely to be bankruptcy candidates.
Low, Nor, and Yatim	2001	Predicting corporate financial distress using the logit model: The case of Malaysia.	They developed a model using an estimation sample consisting of both distressed and non-distressed companies. They selected 11 financial ratios from prior studies.	They tested the predictive ability of the model on a holdout sample, and showed that the overall accuracy rate for the estimation and holdout samples are 82.4% and 90% respectively.
Lennox	1999	Identifying failing companies: A re-evaluation of the logit, probit, and DA approaches.	The study compared the performance of the three models in predicting bankruptcy.	The results showed that the probit and logit models outperformed the discriminant model.

Source: Empricial Literature Reviewed, 2019

2.4.3 Review summary (Neural Network Models)

Authors	Year	Title	Method	Findings
Yahaya, Nasiru, and Ebgejiogu	2017	Insolvency Prediction Model of Some Selected Nigerian Banks.	Applied a feed forward back propagation neural network to predict insolvency. They used secondary data collected from companies that filed for receivership or failed from 1996-2012.	The result of the feed-forward back propagation neural network showed that the percentage correctly classified is approximately 89 percent.
Enyindah and Onwuachu	2016	A Neural Network Approach to Financial Forecasting.	Developed a back propagation neural network for the prediction of interest rate on loan investment in Nigerian banks. Simulation was done using Matlab 2008.	The results confirmed the efficacy of neural network model for the prediction of interest rate on loan investment.
Bapat and Nagale	2014	Comparison of bankruptcy prediction models: evidence from India.	Compared the performance of three bankruptcy prediction models, the multiple discriminant analysis, logistic regression and neural network for listed companies in India. The prediction models were developed, over three years prior to bankruptcy using financial ratios.	The results of showed that neural network performed much better one year prior to bankruptcy.
Eriki and Udegbunam	2013	Predicting corporate distress in the Nigerian stock market: Neural network versus multiple discriminant analysis.	Compared the performance of neural network with discriminant analysis, and performance obtainable by mere guesswork. The studied forty four firms listed on the Nigerian Stock Market between 1987 and 2006.	The results show that, while both the neural network and the discriminant analysis techniques performed better than guess work, the neural network out performs the discriminant analysis technique.
Farinde	2013		Applied neural network for statistical prediction of likely distress in Nigeria's banking sector. They used the Multilayer Perceptron Neural Network Analysis and Discriminant analysis used to benchmark the performance of the neural network.	The study confirmed the utility of both approaches in the prediction of corporate bankruptcy for Nigerian banks.

Source: Empricial Literature Reviewed, 2019

2.4.3 cont'd: Review summary (Neural Network Models)

Ibiwoye, Ajibola, and Sogunro	2012	Artificial neural network model for predicting insurance insolvency.	Used artificial neural network approach to evaluate the insolvency of insurance companies. They used total assets/total liability as a measure of liquidity ratio in the study as the springboard for determining the threshold of solvency from the ANN simulation.	They raised the threshold of solvency in the industry to 5 as a result of creative accounting (i.e. gross manipulation of accounting figures), and found that the graph of the ANN simulation model falls completely below the threshold.
Kouki and Elkhaldi	2011	Toward a predicting model of firm bankruptcy: evidence from the Tunisian context.	Compared the performance of three bankruptcy prediction models, the multivariate discriminate analysis, logit model and neural network on a sample of Tunisian firms.	They found that neural network was the most powerful at a very short term horizon. However, multivariate discriminate analysis and logit regression were powerful at a medium horizon of two and three years before bankruptcy.
Tseng and Hu	2010	Comparing four bankruptcy prediction models: Logit, quadratic interval logit, neural and fuzzy neural networks.	Compared the performance of four bankruptcy prediction models, the logit, quadratic interval logit, neural and fuzzy neural networks on a sample of bankrupt and non-bankrupt firms in England.	The average hit ratio of four methods range from 91.15% to 77.05%. The original classification accuracy and the validation test results indicate that the Radial Basis Function Network (RBFN) outperformed the other models.
Chen and Du	2009	Using neural networks and data mining techniques for the financial distress prediction model.	Studied a sample of 68 Taiwan firms listed on the Taiwanese Stock Exchange. They selected 37 (33 financial ratios and 4 non-financial ratios) variables and categorized them as six major types: earning ability, financial structure ability, management efficiency ability, management performance, debt-repaying ability, and non-financial factors. They employed Back Propagation Neural Network and K Means Clustering Algorithm.	The results showed that the accuracy rate (non-factor analysis) with the BPN model is better than with the clustering model, with the exception of the past 8 seasons. The accuracy rates (1st factor analysis) with the BPN model are all better than with the clustering model. The accuracy rate (2nd factor analysis) with the BPN model is better than with the clustering model, with the exception over the past 6 seasons.

Source: Empricial Literature Reviewed, 2019

2.4.3 cont'd: Review summary (Neural Network Models)

Lin	2009	A cross model study of corporate financial distress prediction in Taiwan: Multiple discriminant analysis, logit, probit and neural networks models.	Examined the predictive ability of four financial distress prediction models (Multiple discriminate analysis (MDA), logit, probit, and artificial neural networks (ANNs)) for public industrial firms in Taiwan. The final models are validated using within sample test and out-of-the-sample test, respectively.	The results indicated that the probit, logit, and ANN models used in the study achieved higher prediction accuracy and possess the ability of generalization. The probit model possesses the best and stable performance. However, if the data does not satisfy the assumptions of the statistical approach, then the ANN approach would achieve higher prediction accuracy.
Sookhanaphibarn, Polsiri, Choensawat, and Lin	2007	Application of neural networks to business bankruptcy analysis in Thailand.	Applied neural networks (Learning Vector Quantization, Probabilistic Neural Network, and Feedforward Network with Back Propagation Learning) for bankruptcy prediction in Thailand. They used data sets of 41 Thai financial institutions for the period 1993-2003. They computed 30 financial variables and seven ownership variables to develop the models. They used principal component analysis to reduce the number of variables, the obtained features were fed into neural networks as input data.	The study found that among the three models, Learning Vector Quantization (LVQ) outperforms the other two models when considering both prediction accuracy and bias. Probabilistic Neural Network (PNN) provided consistent results every running time but its accuracy is lowest. Feed Forward Network with Back Propagation Learning provided superior accuracy results but had a bias considerably higher than that of the other two methods.
Cheng, Chen, and Fu	2006	Financial distress prediction by a radial basis function network with logit analysis learning.	Compared neural network with logit analysis for financial distress prediction model. The radial basis function network (RBFN) was adopted to construct the neural network prediction model.	They results showed that the performance of the RBFN outperformed the logit model.

Source: Empricial Literature Reviewed, 2019

2.4.3 cont'd: Review summary (Neural Network Models)

Hsieh, Liu, and Hsieh	2006	Hybrid Neural Network Bankruptcy Prediction: An Integration of Financial Ratios, Intellectual Capital Ratios, MDA, and Neural Network Learning.	Proposed a hybrid neural network models for bankruptcy prediction in Taiwan. The models are: MDA model integrated with financial ratios, MDA model integrated with financial ratios and intellectual capital ratios, MDA-assisted neural network model integrated with financial ratios, and a MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios	The results show that the MDA-assisted neural network model integrated with financial ratios and intellectual capital ratios have accuracy of 89% which was higher than the others.
Odom and Sharda	1990	A neural networks model for bankruptcy prediction.	Compared the predictive ability of neural network and multivariate discriminant analysis models in bankruptcy risk prediction. They choose the same financial ratios that Altman used in his 1968 study.	Using the 80/20 sample, the discriminant analysis method correctly predicted 85.71% as compared to the neural networks correct prediction rate of 78.57%. However, when the 90/10 sample was used for training, the neural network did better correctly predicting 85.71% of the holdout subsample, while the discriminant analysis method predicted only 78.57%.

Source: Empricial Literature Reviewed, 2019

2.5 Gap in the Literature

The first and obvious gap is the paucity of studies on hybrid models in developing economies, which is premised on the lack of empiricism on the subject of AI in the prediction of bankruptcy in developing countries. Prior studies have extensively used Logit or Multiple Discriminant Analysis.

Secondly, in developing hybrid models GA has widely been applied in addition with other AI techniques (Min, Lee, & Han, 2006). For instance, studies have developed hybrid systems using GA and fuzzy logic systems and neural networks (Georgescu, 2017; Chou, Hsieh, & Qiu, 2017; Jeong, Min, & Kim, 2012; Esseghir, 2006); fuzzy Case Based Reasoning (CBR) method and Genetic Algorithms (Li & Ho, 2009); genetic-based support vector machines (GA-SVM) (Wu, Tzeng, Goo, & Fang, 2007; Min, Lee, & Han, 2006); Linear Genetic Programs (LGPs) (Mukkamala, Tilve, Sung, Ribeiro, & Vieira, 2006). Few studies have dealt with the integration of GA and Decision Trees.

Thirdly, studies conducted in Nigeria have placed less emphasis on cash flow ratios. Majorly, the studies focus on ratios in categories that are computed from the Statement of Financial Position and Statement of Comprehensive Income which are prepared on an accrual basis. Therefore, they are deemed to be prone to aggressive accounting.

Fourthly, studies have questioned the reliability of models developed primarily with financial ratios, since there is doubt about the validity and reliability of the accounting information used for the ratios (Agarwal & Taffler, 2008). In addition, the relevance of particular ratios changes due to changes in the environment (Tsai, 2009). Therefore scholars have suggested the inclusion of corporate governance variables in developing the prediction models (Ani & Ugwunta, 2012). Few studies have dealt with this issue in Nigera; therefore a basis for investigating the inclusion of corporate governance variables.

CHAPTER THREE

METHODOLOGY

3.1 Research Design

The study used a quantitative approach, which emphasize objective measurements and statistical, mathematical, or numerical analysis of data collected from annual financial statements and their manipulation using computational techniques (Babbie, 2010, Muijs, 2010). The quantitative research design adopted is the ex post facto research design. According to Kerlinger and Rint (1986) in the context of social science research an 'ex-post facto' investigation seeks to reveal possible relationships by observing an existing condition or state of affairs and searching back in time for plausible contributing factors. Ex post facto research is a systematic empirical inquiry in which the scientist does not have direct control of independent variables because their manifestations have already occurred or because they are inherently not manipulated. Inferences about relations among variables are made, without direct intervention, from co-commitment variation of independent and dependent variables. Independent variables are studied in retrospect for seeking possible and plausible relations and the likely effects that the changes in independent variables produce on a single or a set of dependent variables.

3.2 Population of the Study

The population of the study comprised quoted manufacturing firms on the Nigerian Stock Exchange (NSE) as at end of 2017 financial year-end. The number of firms included in the various sectors on the Nigerian Stock Exchange that constituted the population of the study is shown in the table below:

Table 3.1: Number of firms by sector

S/No	Sector	Number of firms
1	Agriculture	5
2	Consumer Goods	22
3	Conglomerates	6
4	Financial Services	57
5	Health Care	11
6	ICT	7
7	Industrial Goods	15
8	Natural Resources	4
9	Oil & Gas	12
10	Services	25
	Total	**164**

Source: The Nigerian Stock Exchange Website (2017)

3.3 Sample Size of the Study

The study was limited to sixty-six (66) companies determined using purposive sampling technique; the decision was premised on the classification of the firms as manufacturing (based on the nature and description of activities) as shown on the Nigerian Stock Exchange (NSE) website. The companies under the various sectors are shown in Appendix I.

Table 3.2: Firms from the various sectors included in the sample

S/No	Sector	Number of firms
1	Agriculture	5
2	Consumer Goods	22
3	Conglomerates	6
4	Health Care	11
5	ICT	7
6	Industrial Goods	15
	Total	**66**

Source: The Nigerian Stock Exchange Website (2017)

The sample percentage with respect to the population is approximately 40% of the entire quoted companies on the Nigerian Stock Exchange.

3.4 Sources of Data

The data utilised for the study were drawn from secondary sources. The sources included the (1) annual financial reports and accounts of the individual companies downloaded from the websites of the companies and (2) the Nigerian Stock Exchange (NSE) Fact Book. The Statement of Financial Position provided information on assets and liabilities; the Statement of Comprehensive Income provided information on revenue and expenses; and the Statement of Cash Flows provided information on Operating, Investing and Financing Activities (see Appendix II, III).

3.5 Methods of Data Analysis

3.5.1 Predictor Variables

The most common approach to bankruptcy prediction is to review the literature to identify a large set of potential predictive financial and/or non-financial variables (Lensberg, Eilifsen, & McKee 2006). Failure analysis using financial ratios is very important for several reasons (Odom & Sharda, 1990).

First, management can use it to identify potential problems that need attention (Siegel, 1981). Second, investors use ratios to evaluate a firm. Last, auditors use it as a tool in going-concern evaluation (Altman, 1982). The study applied a two stage procedure for variable selection: first, 47 variables were selected from among the bankruptcy literature. The selected variables were computed using information obtained from annual reports and accounts of the companies.

Secondly, the 47 variables were subjected to Exploratory Factor Analysis using Principal Component Analysis (PCA). This is one of data reduction technique used in several studies in selecting the most significant variables. This dimension reduction technique, which involves reducing the number of random variables under consideration (Davalos, Leng, Feroz, & Cao, 2009), to a smaller set of uncorrelated components helps deal with the issue of multicollinearity of variables. The 47 variables identified in the first procedure, with their labels are shown in the table below:

Table 3.3: Categories of selected ratios

Category	Ratio	Formula	Label
Index Activity	Total asset turnover	Net sales / Average net assets	R1
	Fixed asset turnover	Net sales / Average total fixed assets	R2
	Equity turnover	Net sales / Average equity	R3
Index Cash flow	Cash flow ratio	Cash Flow from Operations (CFO) / Sales	R4
	Asset efficiency ratio	Cash Flow from Operations (CFO) / Total Assets	R5
	Current Liability Coverage Ratio	Cash Flow from Operations (CFO) / Current Liabilities or Cash Flow from Operations (CFO) – Dividends Paid / Current Liabilities	R6
	Long Term Debt Coverage Ratio	Cash Flow from Operations (CFO) / Long Term Debt or Cash Flow from Operations (CFO) – Dividends Paid / Long Term Debt	R7
	Interest Coverage Ratio	(CFO + Interest Paid + Taxes Paid) / Interest Paid	R8
	Cash Generating Power Ratio	Cash Flow from Operations (CFO) / (CFO + Cash from *Investing Inflows* + Cash from *Financing Inflows*)	R9
	External Financing Index Ratio	Cash from Financing / Cash Flow from Operations (CFO)	R10
		Financial Debt/Cash Flow	R11
Index Growth/Efficiency		Total sales / Shareholders funds	R12
		Total Sales/Total Assets	R13
		Operating cash flow / Total assets	R14
		Operating cash flow / Total sales	R15
		EBIT/Total Sales	R16
		Value Added/Total Sales	R17
	Sustainable growth rate	Retention rate of earning reinvested (RR) x Return on Equity (ROE)	R18
	RR (retention rate)	Dividends declared / Operating income after taxes	R19
		Retained earnings / Total assets	R20
Index Liquidity/Solvency	Current ratio	Current assets / Current liabilities	R21
	Current assets to total assets	Current assets / Total assets	R22
	Current liabilities to total assets	Current liabilities / Total assets	R23
	Quick ratio	(Current assets – Inventory) / Current liabilities	R24
		(Current assets – Inventory) / Total assets	R25
	Receivables turnover	Net annual sales / Average receivables	R26
	Payables turnover	Cost of goods sold / Average trade payables	R27

Source: Bellovary, Giacomino, and Akers (2007); Du Jardin (2010); Van Greuning, Scott, and Terblanche (2011).

Table 3.3 (Cont'd): Categories of Selected Ratios

Index Leverage	Debt ratio	Total liabilities / Total assets	R28
	Debt to worth	Total liabilities / Shareholders' equity	R29
		Long Term Debt/Total Assets	R30
		Long Term Debt/Shareholder Funds	R31
		Shareholder Funds/Total Assets	R32
		Net Op. Work. Capital/Total Assets	R33
Index Profitability	Return on asset	Net profit / Total assets	R34
	Return on equity	Net profit / Equity	R35
	Gross profit margin	Gross profit / Net sales	R36
	Net profit margin	Net profit / Net sales	R37
		Profit before Tax/Shareholder Funds	R38
		EBIT/Total Assets	R39
Index Rotation		Current assets / Total sales	R40
		Net op. working capital / Total sales	R41
		Accounts receivable / Total sales	R42
		Accounts payable / Total sales	R43
		Inventory / Total sales	R44
	Equity ratio	Shareholders' equity / Total assets	R45
		Market Value of Equity/Book Value of Liability	R46
Index Contribution		Financial Expenses/Total Sales	R47

Source: Bellovary, Giacomino, and Akers (2007); Du Jardin (2010); Van Greuning, Scott, and Terblanche (2011).

Table 3.4: Corporate governance variables

Corporate Governance	Board Size	This is measured as the total number of directors sitting on the board as at the financial year end.	CG1
	Board Ownership	This is measured as the proportion of shares held by the board of directors, i.e., $\frac{\text{Capital Held by Board of Directors}}{\text{Total Capital}}$	CG2
	Board Structure	This is measured as the number of sub-committees present within the board as at financial year end.	CG3
	Proportion of Women on the Board	This is measured as the number of women sitting on the board as at the financial year end, i.e., $\frac{\text{No. of Women on Board of Directors}}{\text{No. of Directors}}$	CG4
	CEO Duality	CEO duality occurs when the Chief Executive Officer (CEO) also holds the position of Chairman of Board at the same time.	CG5
	Proportion of Non-Executive Directors	This is measured as the number of non-executive directors sitting on the board as at the financial year end, i.e., $\frac{\text{No. of Non-Executive Directors on Board}}{\text{No. of Directors}}$	CG6

Source: Darrat, Gray, Park, and Wu (2016); Chen and Wu (2016); Brédart (2014b); De Kluyver (2009); Jackling and Johl (2009); Fich and Slezak (2008); Rose (2007); Carter, Simkins, and Simpson (2003).

3.5.2 Test of Normality

Normality implies that the distribution of the test is normally distributed (or bell-shaped) with 0 mean, with 1 standard deviation and a symmetric bell shaped curve. Most multivariate models assume that the data are normally distributed. Failure to consider the characteristics of the distribution can lead to faulty interpretations of statistical findings (Marczyk, DeMatteo, & Festinger, 2005). Therefore the normality of the input variables must be tested before these models can be applied (Wu, Tzeng, Goo, & Fang, 2007).

The study employed the Kolmogorov–Smirnov test (KS) and Shapiro–Wilk test to determine the distribution of the financial ratios.

The Kolmogorov–Smirnov test statistic 'D' is calculated as follows:

D = max [Cum Obser. Freq – Cum Expect. Freq]

The largest difference (irrespective of sign) between observed cumulative frequency and expected cumulative frequency.

The critical value at the 5% level is given by:

$$D \text{ (at 5\%)} = \frac{1.36}{\sqrt{Q}}$$

where Q is the number of quadrats

If $D_n < D_n^{\alpha}$, the theoretical distribution is acceptable

If $D_n \geq D_n^{\alpha}$, the theoretical distribution is rejected

The Shapiro-Wilk test statistic 'W' is calculated as follows:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

Where:

x_i are the ordered random sample values

a_i are constants generated from the covariances, variances and means of the sample (size n) from a normally distributed sample.

3.5.3 Principal Components Analysis

The study employed PCA for dimension reduction. PCA determines which vector is significant in the data set (Delen, Kuzey, & Uyar, 2013). Assuming that X_{mxn} is a data matrix, it is a dimensional vector sample in terms of its degree of variance (a higher degree of variance indicates greater significance). Singular value decomposition (SVD) is employed to transform the data set X_{mxn} into an ordered series of eigenvectors and eigenvalues. The covariance matrix *S* is obtained for the given data set to produce eigenvectors. The covariance matrix is defined as:

$$S_{nxn} = \left(\frac{1}{n}\right) X^T X$$

where, $\mathbf{X}_{mxn} = U_{mxn}\, S_{mxn} V_{nxn}{}^T$, $U^T U = I_{mxm}$ and $V^T V = I_{nxn}$ (**I**: Identity matrix, **U** and **V**: Orthogonal).

$\lambda_1, \lambda_2, \ldots, \lambda_n$ are the eigenvalues of the covariance matrix and **S**, $\lambda_1 \geqslant \lambda_2 \cdots \geqslant \lambda_n \geqslant 0$ are sorted in order.

The proportion of variance between the eigenvectors and the data set is obtained by dividing the eigenvalues to the total sum of the eigenvalues (Delen, Kuzey, & Uyar, 2013). Eigenvectors are mutually orthogonal to the exiting set of axes. It reduces the sum of squared error distance between the data points and their projections on the component axis. Different degrees of variance are attributed to each eigenvector. The *m* eigenvectors correspond to the largest m eigenvalues of *S*, which represent the greatest degree of variance. The first principal component has the highest degree of variance; the second principal component has the second highest degree of variance, and so forth (Kantardzic, 2003).

3.5.4 Logistic Regression (LR)

LR is a "conditional probability model which uses the non-linear maximum log-likelihood technique to estimate the probability of firm failure under the assumption of a logistic distribution" (Jackson & Wood, 2013). The LR function, constructed after variable selection, is as follows:

$$P_1(V_i) = 1/[1 + \exp - (b_0 + b_1V_{i1} + b_2V_{i2} + \ldots\ldots + b_nV_{in})] = 1/[1 + \exp - (D_i)]$$

Where: $P_1(V_i)$ = probability of failure given the vector of attributes; V_i;

V_{ij} = value of attribute or variable j (j = 1, 2, ….., n) for firm i;

b_j = coefficient for attribute j; b_0 = intercept; D_i = logit of firm i.

The dependent variable P_1 is expressed in binary form (0,1) (Boritz & Kennedy, 1995). The only restriction considers that the dependent variable, Y, takes only two values. Logit analysis incorporates non-linear effects, and uses the logistical cumulative function in predicting a bankruptcy. The logit function may be increasing or decreasing but its value is always between zero and one (Valášková, Gavláková & Dengov, 2014). One of the biggest disadvantages of the logistic analysis is the problem of multi-collinearity between the variables. This problem was tackled using the PCA approach described previously (*cf* Fejér-Király, 2015).

3.5.5 Discriminant Analysis (MDA)

Discriminant analysis derives the linear combinations from an equation that takes the following form:

$$Z = w_1x_1 + w_2x_2 + \ldots + w_nx_n$$

Where:

Z = discriminant score
w_i (i=1, 2, ... ,n) = discriminant weights
x_i (i=1, 2, ... ,n) = independent variables, the financial ratios

Thus, each firm receives a single composite discriminant score which is then compared to a cut-off value, which determines to which group the company belongs to.

First, create cross-products matrices for between-group differences and within groups differences, $SS_{total} = SS_{bg} + SS_{wg}$.

The determinants are calculated for these matrices and used to calculate a test statistic – either Wilks' Lambda or Pillai's Trace. Wilks' Lambda follows the equation:

$$\Lambda = \left| \frac{S_{wg}}{S_{bg} + S_{wg}} \right|$$

Next an F ratio is calculated as in MANOVA:

$$F_{approximate}(df_1, df_2) = \left(\frac{1-y}{y} \right) \left(\frac{df_2}{df_1} \right)$$

For cases where n is equal in all groups:

$y = \Lambda^{1/s}$ $p = \#$ **of predictor variables**

$$s = \sqrt{\frac{p^2 (df_{effect})^2 - 4}{p^2 + (df_{effect})^2 - 5}}$$ df_{error} **= number of groups times (n-1): k(n - 1)**

$$df_1 = p(df_{effect})$$

$$df_2 = s\left[(df_{error}) - \frac{p - df_{effect} + 1}{2}\right] - \left[\frac{p(df_{effect}) - 2}{2}\right]$$

df_{effect} **= number of groups minus one (k - 1)**

For unequal n between groups, this is modified only by changing the df $_{error}$ to equal the number of data points in all groups minus the number of groups (N – k). If the experimental F exceeds a critical F, then the experimental groups can be distinguished based on the predictor variables. The number of discriminant functions used in the analysis is equal to the number of predictor variables or the degrees of freedom, whichever is smaller. The discriminant function score for the ith function is:

$D_i = d_{i1}Z_1 + d_{i2}Z_2 + \ldots + d_{ip}Z_p$

Where z = the score on each predictor, and d_i= discriminant function coefficient. The discriminant function score for a case can be produced with raw scores and unstandardized discriminant function scores. The discriminant function coefficients are, by definition, chosen to maximize differences between groups.

The mean over all the discriminant function coefficients is zero, with a SD equal to one. The mean discriminant function coefficient can be calculated for each group – these group means are called Centroids, which are created in the reduced space created by the discriminant function reduced from the initial predictor variables. Differences in the location of these centroids show the dimensions along which the groups differ. Once the discriminant functions are determined groups are differentiated, the utility of these functions can be examined via their ability to correctly classify each data point to their a priori groups. Classification functions are derived from the linear discriminant functions to achieve this purpose. Different classification functions are used and equations exist that are best suited for equal or unequal samples in each group. For cases with an equal sample size for each group the classification function coefficient (C_j) is equal to the sum of: $C_j = c_{j0} + c_{j1}x_1 + c_{j2}x_2 + ... + c_{jp}x_p$ for the jth group, j = 1...k, x = raw scores of each predictor, c_{jo} = a constant. If W = within-group variance-covariance matirix, and M = column matrix of means for group j, then the constant $c_{jo} = (-1/2)\ C_jM_j$. For unequal sample size in each group:

$$C_j = c_{jo} + \sum_{i=1}^{p} c_{ij}x_i + \ln\left(n_j / N \right)$$

n_j = size in group j, N = total sample size.

3.5.6 Neural Network (NN)

The study implemented NN, using the Multilayer Perceptron (MLP) option in SPSS Ver. 24. NN consists of a large number of processing elements, *neurons*, and connections between them. It implements some *function f* that maps a set of given input values *x* to some output values *y: y = f(x)*. A neural network tries to find the best possible approximation of the function *f*. This approximation is coded in the neurons of the network using *weights* that are associated with each neuron (Back, Laitinen, Sere, & van Wezel, 1996).A formal *neuron* is the basic element of any neural network. A neuron is a simple processing element that as inputs takes an *n*-dimensional vector $[x_1, ..., x_n]^T$, extended with a constant component x0 = 1.

The neuron forms the weighted sum $w^T x = w_0 + S_{1 \le i \le n} w_i x_i$,

Where $x = [1, x_1, ... , x_n]^T$ and where $w = [w_0, ..., w_n]^T$ is the *weight vector* which is stored in the neuron. Such a neuron can classify *n*-dimensional vectors into two different classes when the weights are determined so that y = 1 for class 1 vectors and y = -1 for class 2 vectors. The weights of a neural network are *learned* using an iterative procedure during which examples of correct input-output associations are shown to the network and the weights get modified so that the network starts to mimic this desirable input-output behaviour. The procedure produces a predictive model for one or more dependent (target) variables based on the values of the predictor variables. *MLP* allows for more complex relationships at the possible cost of increasing the training and scoring time.

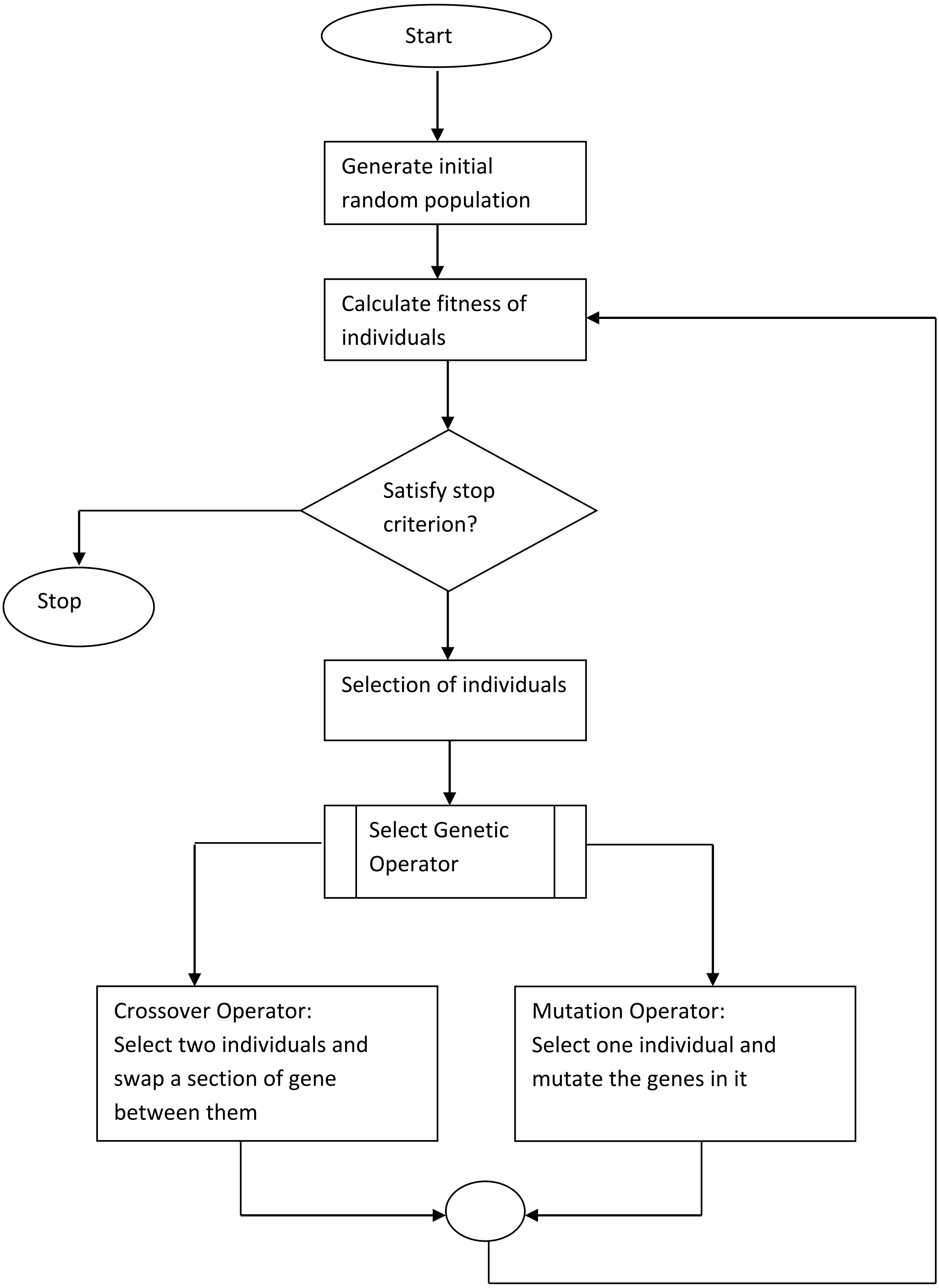
3.5.7 Genetic Algorithm

The GA is a nested function in the form:

$$p[t+1] = r(s(f(p[t])))$$

Where p[t] is the current population of solutions in generation t, f (.) is the fitness function that measures the solution quality of each member of the current population, s (.) is a function that selects members based on their fitness value to generate the next population, r (.) is a reproduction function that uses crossover and mutation operators to generate the next population from the selected ones (Brabazon & Keenan, 2007).

Figure 3.1: Genetic Algorithm Flowchart



Source: Ab Wahab, M. N., Nefti-Meziani, S., & Atyabi, A. (2015). A comprehensive review of swarm optimization algorithms. *PLoS One*, *10*(5), e0122827.

3.6 Validation Method

There is a need for an appropriate validation method when developing and testing bankruptcy prediction models (Jones, 1987). The study employed a *cross-validation* scheme. Cross-validation is a technique to evaluate predictive models by partitioning the original sample into a training set to train the model, and a test set to evaluate it. This technique is recommended since it eliminates variability in samples and minimizes the effect of bias (Han & Camber, 2000; Zhang, Hu, Patuwo, & Indro, 1999; Tam & Kiang, 1992). In k-fold cross-validation, the original sample is randomly partitioned into k equal size subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k-1 subsamples are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds can then be averaged (or otherwise combined) to produce a single estimation. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once.

3.7 Robustness Check

The robustness check involved evaluating the *Sensitivity* and *Specificity* of the models. Sensitivity refers to the ability of the model to predict a financial distress event correctly, while Specificity deals with the ability of the model to predict a non-financial distress event correctly (Tinoco & Wilson, 2013).

Three types of *error rates* are usually estimated in bankruptcy prediction, to examine the accuracy of a prediction model: Type I Error Rate, Type II Error Rate, and Total Error Rate (Chen & Du, 2009). Type I errors are the misclassification of bankrupt firms as non-bankrupt. Type II errors are the reverse-non-bankrupt firms misclassified as bankrupt firms. It is generally agreed upon that Type I errors are more costly than Type II errors for several reasons including loss of business (audit clients), damage to a firm's reputation, and potential lawsuits/court costs (Koh, 1987). Table 3.4 shows the relationship among these three error rate types. The formula for each error rate is listed as follows: Y_2

$$\text{Type I Error Rate} = \frac{Y_2}{Y_3}$$

$$\text{Type II Error Rate} = \frac{Y_4}{Y_6}$$

$$\text{Total Error Rate} = \frac{(Y_2 + Y_4)}{Y_9}$$

Table 3.5: Relationship between Type I, II, & Total Error Rates

		Prediction		
		Normal	**Bankruptcy**	**Sum**
Actually	**Normal**	Y_1	Y_2	Y_3
	Bankruptcy	Y_4	Y_5	Y_6
	Sum	Y_7	Y_8	Y_9

Source: Chen, W. S., & Du, Y. K. (2009). Using neural networks and data mining techniques for the financial distress prediction model. *Expert systems with applications*, *36*(2), 4075-4086.

3.8 Description of Process in RapidMiner Studio

The Cross Validation Operator is a nested Operator. It has two subprocesses: a Training subprocess and a Testing subprocess. The Training subprocess is used for training a model. The trained model is then applied in the Testing subprocess. The performance of the model is measured during the Testing phase. The input DataSet is partitioned into *k* subsets of equal size. Of the *k* subsets, a single subset is retained as the test data set (i.e. input of the Testing subprocess). The remaining *k–1* subsets are used as training data set (i.e. input of the Training subprocess). The cross validation process is then repeated *k* times, with each of the *k* subsets used exactly once as the test data. The *k* results from the *k* iterations are averaged (or otherwise combined) to produce a single estimation. The value *k* can be adjusted using the *number of folds* parameter (RapidMiner Studio, Operator Reference Guide).

CHAPTER FOUR

DATA PRESENTATION AND ANALYSIS

4.1 Data Presentation

The number of firms included in the sample was sixty-six manufacturing firms. A total of fourty seven (47) ratios was computed for each firm and six (6) corporate vaiables. The average values (Mean) of the financial ratios and the corporate variables are shown in the tables below (Table 4.1 and 4.2). The next table presents the average Z scores of the firms included in the sample (Table 4.3).

Table 4.1: Average of selected bankruptcy features

Name of company	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
7-up bottling	1.05	0.61	13.54	0.09	0.08	0.20	0.85	9,121,742,252.00	0.17	-2.97
A.G Levent	0.65	0.38	0.93	0.10	0.06	7.83	0.46	2,019,277,501.00	-36.64	-0.34
Afrik Pharmaceutical Plc.	0.18	0.09	0.18	0.35	0.11	0.17	0.26	18,930,577,400.00	0.12	-47.78
ARBICO PLC	2.39	0.60	0.54	0.46	0.33	0.97	0.82	2,201,036,242.00	0.59	-79.71
Austin laza plc	0.28	0.27	1.57	0.73	0.22	8.26	1.81	6,568,992,531.00	-2.81	-9.64
Berger Paints Nig. Plc.	0.78	0.55	0.86	0.53	0.44	1.52	7.08	1,401,310,160.00	1.59	0.15
Beta Glass	0.65	0.46	0.71	0.17	0.15	0.45	0.72	5,715,588,881.00	1.69	2.43
Cadbury Nigeria Plc	0.79	0.45	0.82	0.15	0.14	0.30	1.33	5,506,479,339.00	2.04	-1.44
CAP plc	2.85	1.26	2.60	0.35	0.62	1.17	14.52	4,387,654,408.00	1.24	1.79
CCNN PLC	0.64	0.57	0.32	5.97	5.52	2.94	65.68	120,916,506,600.00	1.93	-2.54
Champion Breweries Nig. Plc.	-0.01	0.23	0.31	1.12	0.31	0.43	20.67	3,644,941,667.00	2.26	-0.01
CHAMS Plc.	0.20	0.11	0.40	0.45	0.09	0.25	78.15	1,107,468,651.00	4.80	-1.09
Chellarams Plc	-9.15	1.27	4.56	0.52	1.17	1.48	28.48	14,459,956,880.00	25.88	-0.36
Computer Warehouse (CWG)	2.90	2.15	1.61	0.47	0.77	0.50	2.52	7,611,509,936.00	0.46	-1.51
Courteville Biz sol. Plc.	-11.62	2.98	3.84	0.61	7.03	20.16	243.76	41,537,745,020.00	-2.36	-0.42
Cutix Plc.	0.95	0.77	1.31	7.82	1.04	46.43	135.19	32,970,657,830.00	1.07	-0.25
Dangote Cement Plc	61.30	41.35	74.24	0.24	0.23	1.14	1.16	72,822,468,790.00	5.06	-0.17
Dangote Flour Mills Nig. Plc	4.21	1.10	-14.94	0.67	0.47	0.62	3.41	19,913,092,370.00	18.09	0.09
Dangote Sugar Refinery Plc	4.98	3.00	5.53	0.36	2.29	6.35	40.04	171,967,242,400.00	0.06	-0.45
DN Tyre and Rubber Plc.	0.32	0.23	0.62	0.08	0.03	0.31	0.07	8,710,000.15	1.49	0.43
E-Transact Plc.	1.77	1.02	1.48	0.22	0.17	0.42	0.03	3,061,659,400.00	0.00	-92.73
Eko Corp Plc.	0.33	0.30	0.47	0.02	0.01	0.08	0.04	54,315,787.58	3.06	-0.26
Ellah Lakes Plc.	0.03	0.02	0.05	-0.59	-0.02	-4.88	-0.02	-15,060,090.00	3.94	-3.77
Evans Medical Plc.	0.41	0.39	0.70	1.62	0.66	19.20	0.90	51,513,469,000.00	0.88	-0.12
Fidson Healthcare Plc.	0.53	0.48	5.03	0.10	0.05	0.28	3.54	1,941,915,111.00	0.91	0.71
First Aluminium Plc.	0.89	0.60	1.11	0.09	0.08	0.23	0.76	1,132,449,401.00	15.38	-3.99
Flour mill of Nigeria Plc.	2.12	0.99	3.38	0.64	0.80	2.03	55.54	194,101,869,100.00	-0.52	0.01
FTN Cocoa processors Plc.	0.11	0.06	0.14	36.80	0.54	7.21	7.06	11,366,891,250.00	0.60	-2.40

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 cont'd: Average of selected bankruptcy features

Name of company	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Glaxo Smithkline Consumer Nig. Plc	0.42	0.65	1.32	0.51	0.58	0.94	7.71	12,457,311,400.00	0.62	-0.42
Golden guinea brew. Plc	1.73	0.51	0.26	5.80	5.57	21.49	1.63	78,737,824,010.00	0.62	-38.88
Greif Nig. Plc.	-0.07	1.12	3.14	0.64	1.69	0.10	49.32	2,821,597,334.00	0.23	-15.78
Guiness Nig. Plc	1.31	0.67	1.60	0.65	0.67	1.71	3.08	78,708,211,510.00	1.65	-0.78
Honeywell Flour Mill Plc.	1.16	0.56	1.46	0.70	0.61	1.34	3.46	30,732,901,630.00	0.98	0.07
International Breweries Plc.	0.89	0.75	6.19	1.68	1.30	30.92	30.73	49,054,584,730.00	9.30	-0.99
JOHN HOLT Plc.	-0.22	0.27	0.32	0.52	0.17	0.30	1.48	2,383,875,000.00	-0.91	-3.57
Lafarge Africa Plc	0.61	0.40	0.56	0.46	0.17	0.60	0.56	31,049,131,260.00	0.21	-0.17
Livestock Feeds Plc.	8.06	1.67	5.14	0.44	1.48	1.65	52.10	2,454,757,376.00	0.99	-9.89
May & Baker Nig. Plc.	-0.16	0.68	1.72	0.59	0.50	0.36	0.53	3,974,809,172.00	2.26	-0.40
MCNICHOLS Plc.	1.82	1.23	2.28	0.13	0.16	0.61	1.84	69,505,413,000.00	0.80	-0.21
Meyer Plc.	0.13	0.09	0.33	-0.01	0.00	0.00	0.00	32,321,250.16	0.09	-8.53
Morison Industries Plc.	0.13	0.10	0.28	18.29	0.66	8.97	3.78	7,247,365,845.00	2.07	-92,573.60
Multi-Trex Integrated plc.	-0.19	3.74	3.66	4.85	5.74	1.21	667.14	79,252,051,250.00	0.36	-5.67
Nasco Allied Industries	-0.01	1.46	1.13	0.56	0.68	0.20	7.89	63,531,166,290.00	-1.47	-2.27
NCR Nig. Plc.	1.24	0.72	16.57	0.58	0.74	2.49	38.75	69,671,391,470.00	1.27	-0.16
Neimeth Int. Pharm. Plc.	0.61	0.42	0.63	0.58	0.18	0.60	4.11	1,888,310,376.00	-2.38	-0.46
Nestle Nig. Plc.	0.85	0.68	1.65	0.56	0.53	35.11	3.18	75,801,436,890.00	1.66	-0.23
Nig-Germ Chemical plc.	1.32	0.62	2.19	2.59	0.97	2.36	561.06	51,213,629,330.00	2.09	-3.17
Nig. Enamelware Plc.	0.03	1.01	0.37	35.10	74.67	13.19	26.82	317,472,484,000.00	3.41	-0.14
Nigerian Breweries Plc.	1.12	0.67	1.55	0.61	0.64	1.72	2.49	165,702,699,500.00	2.70	-0.26
Northern Nigeria Flour Mills Plc.	2.40	1.03	3.65	0.64	0.80	2.03	168.82	194,101,869,100.00	-0.52	0.01
Okomu Oil Palm Plc	1.18	0.54	1.50	1.37	0.74	2.71	9.66	27,382,342,990.00	-10.38	-0.01
Omatek Ventures	0.09	0.07	0.18	-0.97	-0.03	-0.04	0.01	-142,787,143.50	1.09	-0.04
Paint and Coating Manufacturing Plc.	0.33	2.48	1.07	0.57	1.02	0.48	7.31	1,259,290,257.00	5.39	-0.21
Pharma-deko plc.	0.44	0.33	11.92	-0.10	-0.05	-0.26	1.54	638,524,902.30	0.04	-0.33
Portland Paint&Product Plc	-1.50	17.59	0.95	3.91	32.95	11.55	59.98	48,979,558,630.00	0.30	-0.64
Premier Paints Plc.	0.44	0.36	2.95	0.12	0.03	0.04	0.09	219,361,381.50	-0.30	10.94

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 cont'd: Average of selected bankruptcy features

Name of company	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Presco Plc	1.03	0.45	7.56	0.18	0.04	0.19	1.76	2,995,189,635.00	1.14	1.26
PZ CUSSONS NIG. PLC.	1.19	0.75	1.14	0.62	0.67	2.09	10.61	43,935,631,450.00	0.56	-0.46
SCOA Plc.	0.89	0.40	1.63	0.61	0.41	1.23	26.22	284,433,748.70	0.23	-6.33
Transactional Corporation of Nig. Plc.	0.21	0.16	0.36	0.52	0.11	0.55	0.44	18,918,128,760.00	-0.19	-2.33
Tripple Gee and Company Plc.	0.40	0.36	0.57	0.09	0.03	0.60	0.46	122,883,800.20	-1,039.56	0.70
UACN	-1.03	0.48	1.74	0.46	0.22	1.27	2.96	33,273,232,400.00	-0.15	-1.29
Unilever Nig. Plc.	3.49	0.94	3.98	0.41	0.64	1.02	5.05	25,835,712,130.00	0.68	0.80
Union diagonistic&Clinicals	1.04	0.48	1.08	0.98	1.89	1.40	0.55	4,120,978,850.00	1.25	-0.84
Union Dicon Salt Plc.	-0.14	1.19	-0.12	0.02	0.10	0.01	0.09	24,697,000.50	2.01	0.05
VITAFOAM	-0.21	0.97	3.19	0.47	0.74	1.23	8.70	8,155,957,376.00	1.19	-0.14

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20
7-up bottling	-0.73	22.81	1.01	0.08	0.09	0.16	0.17	11.66	7.88	0.00
A.G Levent	-47.38	1.46	0.59	0.06	0.10	0.07	0.25	0.01	0.06	0.14
Afrik Pharmaceutical Plc.	-0.01	0.40	0.14	0.11	0.35	16.16	1.89	0.47	0.92	0.04
ARBICO PLC	-9.95	28.84	2.76	0.33	0.46	1.67	0.19	3.91	-2.79	-0.98
Austin laza plc	1.99	1.41	0.72	0.22	0.73	10.96	0.51	0.13	0.27	-0.01
Berger Paints Nig. Plc.	0.20	1.24	0.80	0.44	0.53	0.13	0.41	0.19	2.98	0.47
Beta Glass	1.37	1.01	1.45	0.15	0.17	0.51	0.24	0.01	0.12	1.31
Cadbury Nigeria Plc	2.43	1.39	0.83	0.14	0.15	0.15	0.33	0.01	0.03	1.21
CAP plc	0.16	3.90	1.78	0.62	0.35	0.61	0.50	1.11	1.85	0.35
CCNN PLC	1.18	0.65	0.87	5.52	5.97	0.23	0.15	0.00	1.80	0.21
Champion Breweries Nig. Plc.	0.49	0.48	0.31	0.31	1.12	-0.01	0.03	-1.09	3.80	-0.87
CHAMS Plc.	-0.05	0.69	0.16	0.09	0.45	4.18	0.43	-0.27	-8.87	-0.20
Chellarams Plc	15.80	10.91	1.90	1.17	0.52	0.14	0.13	0.10	3.37	0.03
Computer Warehouse (CWG)	0.11	4.67	1.94	0.77	0.47	2.03	0.97	5.83	7.47	0.08
Courteville Biz sol. Plc.	-4.45	9.97	8.07	7.03	0.61	0.09	0.38	12.12	1,218.83	0.11
Cutix Plc.	-0.29	2.22	0.85	1.04	7.82	1.01	0.19	0.05	0.40	0.08
Dangote Cement Plc	4.44	286.90	161.08	0.23	0.24	0.54	0.61	0.02	0.28	232.55
Dangote Flour Mills Nig. Plc	8.26	-22.67	1.54	0.47	0.67	-0.13	0.12	-0.03	0.27	-0.05
Dangote Sugar Refinery Plc	-0.15	9.18	4.61	2.29	0.36	0.12	0.15	0.19	1.30	0.44
DN Tyre and Rubber Plc.	3.86	1.62	0.36	0.03	0.08	4.39	0.25	-0.03	0.00	-0.38
E-Transact Plc.	-0.22	1.67	1.10	0.17	0.22	0.62	2.68	9.19	115.49	-0.02
Eko Corp Plc.	116.98	0.56	0.42	0.01	0.02	0.00	0.14	0.00	0.00	0.06
Ellah Lakes Plc.	-211.59	0.10	0.05	-0.02	-0.59	-1.23	0.37	0.00	-0.06	-0.10
Evans Medical Plc.	2.16	0.96	0.54	0.66	1.62	9.13	7.94	1.30	3.08	0.01
Fidson Healthcare Plc.	0.84	11.42	1.00	0.05	0.10	0.11	0.24	0.00	0.00	0.07
First Aluminium Plc.	14.86	1.67	0.89	0.08	0.09	0.10	0.04	0.62	0.25	-0.18
Flour mill of Nigeria Plc.	-5.03	4.01	1.13	0.80	0.64	0.18	0.13	0.30	3.72	0.06
FTN Cocoa processors Plc.	3.18	0.36	0.09	0.54	36.80	-1.35	-0.45	0.00	0.00	-0.19

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20
Glaxo Smithkline Consumer Nig. Plc	0.02	1.90	0.94	0.58	0.51	0.15	0.45	0.15	0.86	0.48
Golden guinea brew. Plc	-10.14	172.22	0.93	5.57	5.80	12.90	-3.32	-0.18	224.58	-0.01
Greif Nig. Plc.	-0.08	6.71	2.16	1.69	0.64	4.76	4.05	0.06	0.31	0.29
Guiness Nig. Plc	2.85	2.33	0.87	0.67	0.65	0.28	0.40	0.57	3.37	0.27
Honeywell Flour Mill Plc.	2.19	2.05	0.77	0.61	0.70	0.22	0.21	0.23	2.05	0.13
International Breweries Plc.	5.72	17.02	1.91	1.30	1.68	1.17	0.29	17.94	12.01	0.06
JOHN HOLT Plc.	3.25	0.50	0.27	0.17	0.52	0.28	0.28	-0.10	-1.97	-0.01
Lafarge Africa Plc	-2.19	0.77	0.45	0.17	0.46	0.20	0.30	0.02	0.38	0.56
Livestock Feeds Plc.	-0.08	2,151.03	2.61	1.48	0.44	0.07	0.10	0.17	0.83	0.00
May & Baker Nig. Plc.	2.93	2.26	0.86	0.50	0.59	0.59	0.37	0.02	-0.12	0.13
MCNICHOLS Plc.	0.39	2.51	1.45	0.16	0.13	0.30	0.07	0.86	4.37	-0.48
Meyer Plc.	13.27	0.86	0.25	0.00	-0.01	0.55	0.25	1.04	12.53	0.09
Morison Industries Plc.	-3.31	0.37	0.21	0.66	18.29	6.04	0.33	0.70	12.50	0.08
Multi-Trex Integrated plc.	-1.68	8.81	6.74	5.74	4.85	5.70	-0.27	0.04	-8.82	-0.01
Nasco Allied Industries	0.48	3.25	1.02	0.68	0.56	4.74	0.36	0.86	3.11	0.37
NCR Nig. Plc.	3.31	130.03	1.06	0.74	0.58	0.04	0.12	0.04	0.05	0.02
Neimeth Int. Pharm. Plc.	-4.76	0.84	0.56	0.18	0.58	0.64	0.36	0.04	-0.40	-0.22
Nestle Nig. Plc.	0.61	2.66	1.00	0.53	0.56	0.29	0.44	0.04	0.31	0.24
Nig-Germ Chemical plc.	0.19	3.29	0.92	0.97	2.59	0.34	1.66	0.04	0.16	0.03
Nig. Enamelware Plc.	10.07	1.03	1.68	74.67	35.10	44.60	0.14	0.96	10.73	0.65
Nigerian Breweries Plc.	1.46	2.19	0.99	0.64	0.61	0.22	0.49	0.27	1.88	0.30
Northern Nigeria Flour Mills Plc.	0.10	4.13	1.13	0.80	0.64	0.17	0.13	0.31	74.97	0.06
Okomu Oil Palm Plc	-3.14	1.60	0.78	0.74	1.37	1.46	0.21	0.52	0.67	0.30
Omatek Ventures	-189.42	38.84	0.12	-0.03	-0.97	0.38	1.12	0.00	0.01	-0.30
Paint and Coating Manufacturing Plc.	260.71	1.40	1.75	1.02	0.57	0.25	0.80	0.02	0.41	0.19
Pharma-deko plc.	-0.14	18.29	0.57	-0.05	-0.10	-0.14	0.71	1.35	-6.81	-0.03
Portland Paint&Product Plc	-0.19	2.51	28.90	32.95	3.91	1.05	0.24	-0.02	-5.78	0.34
Premier Paints Plc.	-22.52	-16.77	0.64	0.03	0.12	4.55	0.29	0.31	2.83	-0.52

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20
Presco Plc	-7.04	11.43	0.69	0.04	0.18	0.33	0.40	0.20	0.33	0.26
PZ CUSSONS NIG. PLC.	-0.21	1.69	1.05	0.67	0.62	0.12	0.26	0.22	3.83	0.43
SCOA Plc.	0.16	4.16	0.53	0.41	0.61	-0.18	0.27	0.06	2.64	0.22
Transactional Corporation of Nig. Plc.	-1.82	0.44	0.21	0.11	0.52	1.06	0.64	0.09	1.73	0.03
Tripple Gee and Company Plc.	-2,719.07	0.73	0.46	0.03	0.09	0.07	0.25	0.00	0.26	0.08
UACN	0.16	1.35	0.56	0.22	0.46	0.32	0.24	0.36	2.26	0.01
Unilever Nig. Plc.	0.13	5.79	1.32	0.64	0.41	0.16	0.35	0.88	2.58	0.16
Union diagonistic&Clinicals	-2.13	1.72	1.95	1.89	0.98	7.30	0.16	0.00	31.82	-1.07
Union Dicon Salt Plc.	-632.05	-0.19	1.74	0.10	0.02	-2.37	-1.49	0.00	-0.02	-2.53
VITAFOAM	-0.83	4.94	1.40	0.74	0.47	0.13	0.33	0.26	106.94	0.23

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R21	R22	R23	R24	R25(WC/TA)	R26	R27	R28	R29	R30
7-up bottling	0.64	0.22	0.35	0.33	-0.12	80.83	93.46	0.46	5.30	0.12
A.G Levent	69.67	0.43	0.39	38.22	0.04	5.37	2.23	0.51	1.24	0.12
Afrik Pharmaceutical Plc.	0.31	0.24	0.46	0.38	-0.22	2.49	0.43	0.61	10.53	0.15
ARBICO PLC	1.52	2.24	1.44	-5.03	0.80	0.65	1.31	3.25	40.93	1.80
Austin laza plc	18.88	0.20	0.02	7.48	0.18	17.96	3.75	0.12	0.21	0.10
Berger Paints Nig. Plc.	1.82	0.51	0.29	1.26	0.22	6.95	1.97	0.36	0.56	0.07
Beta Glass	2.53	1.58	0.58	1.46	1.00	1.69	3.95	0.89	0.65	0.31
Cadbury Nigeria Plc	1.36	0.66	0.51	0.91	0.15	3.49	1.08	0.65	1.21	0.14
CAP plc	1.69	0.90	0.53	1.25	0.36	10.12	1.93	0.59	1.28	0.05
CCNN PLC	1.34	1.62	1.17	0.06	0.45	16.65	2.00	1.62	0.83	0.45
Champion Breweries Nig. Plc.	0.43	0.15	0.80	0.32	-0.65	3.53	0.56	0.93	1.59	0.13
CHAMS Plc.	1.34	0.45	0.26	1.14	0.19	0.35	0.38	0.27	1.40	0.00
Chellarams Plc	0.97	0.73	0.77	0.53	-0.04	16.42	4.16	0.88	5.91	0.11
Computer Warehouse (CWG)	1,335.61	0.51	0.21	986.99	0.31	405.89	396.60	0.61	1.03	0.41
Courteville Biz sol. Plc.	1.36	0.55	0.37	0.75	0.18	18.80	27.81	0.68	0.86	0.31
Cutix Plc.	1.44	0.21	0.16	0.78	0.05	12.31	10.83	0.30	0.80	0.14
Dangote Cement Plc	0.76	0.17	0.23	-16.62	-0.06	3,157.11	10.68	0.43	0.70	0.20
Dangote Flour Mills Nig. Plc	0.79	0.50	0.65	0.64	-0.15	16.95	5.67	0.83	-0.68	0.18
Dangote Sugar Refinery Plc	4.20	0.66	0.40	2.79	0.26	12.78	9.24	0.46	0.83	0.06
DN Tyre and Rubber Plc.	0.86	0.16	0.19	-1.63	-0.03	6.16	1.83	0.51	2.41	0.32
E-Transact Plc.	2.10	0.71	0.35	1.95	0.36	4.89	0.04	7.38	10.27	7.04
Eko Corp Plc.	0.64	0.08	0.09	0.70	-0.01	1.66	3.37	0.37	0.53	0.27
Ellah Lakes Plc.	11.59	0.04	0.00	2.37	0.04	9.72	6.28	2.53	5.42	2.52
Evans Medical Plc.	0.71	0.12	0.12	-1.38	0.00	33.75	2.04	1.85	1.96	1.74
Fidson Healthcare Plc.	1.25	0.11	0.16	0.18	-0.05	15.47	24.15	0.25	0.83	0.09
First Aluminium Plc.	0.96	0.32	0.33	-0.18	-0.02	12.06	4.52	0.43	0.81	0.10
Flour mill of Nigeria Plc.	0.96	0.40	0.43	0.50	-0.03	26.51	12.51	0.68	2.40	0.24
FTN Cocoa processors Plc.	0.65	0.12	0.27	0.32	-0.15	0.89	0.17	0.69	1.97	0.42

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30
Glaxo Smithkline Consumer Nig. Plc	1.31	0.63	0.91	0.88	-0.27	3.33	1.26	0.97	1.95	0.06
Golden guinea brew. Plc	0.82	0.37	0.42	-2.29	-0.05	35.50	-2.87	3.63	0.45	3.21
Greif Nig. Plc.	0.69	12.27	26.24	0.65	-13.98	9.29	-22.94	30.59	88.33	4.35
Guiness Nig. Plc	0.89	0.37	0.42	0.57	-0.05	4.52	1.74	0.66	1.98	0.24
Honeywell Flour Mill Plc.	0.73	0.34	0.45	0.49	-0.12	6.20	2.51	0.67	1.93	0.22
International Breweries Plc.	2.28	0.18	0.18	-4.80	0.00	2.19	49.58	0.27	1.88	0.09
JOHN HOLT Plc.	0.49	0.20	0.48	0.39	-0.28	5.21	7.12	0.72	1.27	0.24
Lafarge Africa Plc	1.05	0.25	0.27	0.66	-0.02	9.43	1.16	0.58	0.82	0.30
Livestock Feeds Plc.	1.00	0.81	0.84	-1.43	-0.03	13.85	3.16	0.86	566.11	0.03
May & Baker Nig. Plc.	1.23	2.03	1.67	0.54	0.37	6.54	3.15	2.84	7.19	1.18
MCNICHOLS Plc.	0.95	0.26	0.27	0.29	-0.01	3,487.89	1,946.01	0.36	0.64	0.09
Meyer Plc.	0.57	0.09	0.16	-22.24	-0.07	1.44	0.51	0.47	1.61	0.31
Morison Industries Plc.	2.09	0.49	0.21	-1.21	0.27	1.39	4.53	0.68	1.73	0.46
Multi-Trex Integrated plc.	1.08	15.03	17.39	1.06	-2.36	2.97	-146.76	25.61	30.71	8.22
Nasco Allied Industries	1.07	2.70	2.74	0.87	-0.04	8.91	2.92	3.26	10.80	0.51
NCR Nig. Plc.	1.01	0.47	0.41	0.05	0.06	1.13	36.47	0.59	43.01	0.17
Neimeth Int. Pharm. Plc.	2.10	0.93	0.36	-17.53	0.57	0.15	2.20	0.44	0.85	0.09
Nestle Nig. Plc.	51.28	0.38	0.18	40.30	0.19	4.05	3.20	0.35	0.77	0.17
Nig-Germ Chemical plc.	2.22	0.82	0.37	2.20	0.45	7.14	2.36	0.42	1.47	0.01
Nig. Enamelware Plc.	1.18	9.03	8.70	-13.64	0.33	274.36	1.69	10.42	5.98	1.73
Nigerian Breweries Plc.	0.73	0.22	0.36	0.38	-0.13	3.42	1.52	0.60	1.30	0.24
Northern Nigeria Flour Mills Plc.	0.96	0.40	0.43	0.50	-0.03	26.51	12.51	0.55	2.01	0.12
Okomu Oil Palm Plc	1.17	0.55	0.59	0.71	-0.03	11.44	24.20	0.69	1.44	0.10
Omatek Ventures	3.05	0.39	0.14	1.46	0.25	0.66	0.91	0.55	163.80	0.41
Paint and Coating Manufacturing Plc.	3.59	6.53	3.83	1.87	2.69	1.38	0.66	42.53	20.18	38.70
Pharma-deko plc.	0.58	0.15	0.27	0.32	-0.12	1,707.62	122.79	0.29	1.72	0.02
Portland Paint&Product Plc	1.60	6.39	8.67	1.04	-2.29	6.48	43.20	9.21	0.96	0.54
Premier Paints Plc.	0.16	0.47	6.73	0.12	-6.26	5.11	0.22	18.28	-17.11	11.55

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R21	R22	R23	R24	R25	R26	R27	R28	R29	R30
PZ CUSSONS NIG. PLC.	2.10	0.66	0.32	0.88	0.34	3.93	2.35	0.38	0.61	0.06
SCOA Plc.	1.44	0.46	0.33	-1.58	0.13	42.33	28.22	0.36	0.93	0.03
Transactional Corporation of Nig. Plc.	1.17	0.23	0.21	1.10	0.03	2.07	0.68	0.49	1.03	0.28
Tripple Gee and Company Plc.	1.61	0.15	0.08	0.98	0.07	7.90	7.27	0.20	0.31	0.12
UACN	1.16	0.23	0.15	0.54	0.08	4,399.68	2,830.77	0.21	0.67	0.06
Unilever Nig. Plc.	0.72	0.46	0.64	0.27	-0.18	2.24	1.23	0.76	3.51	0.12
Union diagonistic&Clinicals	28.46	12.55	8.56	28.13	3.98	2.37	0.15	14.60	18.84	6.04
Union Dicon Salt Plc.	0.02	0.23	10.81	0.02	-10.58	10.35	0.14	16.02	-1.32	5.22
VITAFOAM	1.03	0.64	0.62	0.35	0.02	7.72	1.93	0.70	2.49	0.08

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R31	R32	R33	R34	R35	R36	R37	R38	R39(EBIT/TA)	R40
7-up bottling	0.99	0.17	-0.12	0.15	2.69	0.17	0.14	2.91	0.18	0.10
A.G Levent	0.30	0.42	0.04	-0.01	-0.06	0.25	-0.02	-0.03	0.04	0.35
Afrik Pharmaceutical Plc.	1.71	0.33	-0.22	0.19	3.34	1.18	9.23	3.44	0.21	3.11
ARBICO PLC	21.66	0.04	0.80	-0.01	-0.47	0.19	-0.03	9.15	0.94	10.45
Austin laza plc	0.19	0.73	0.18	4.00	4.18	0.51	9.96	4.76	5.07	0.67
Berger Paints Nig. Plc.	0.11	0.65	0.22	0.07	0.10	0.41	0.08	0.15	0.10	0.20
Beta Glass	0.25	1.56	1.00	0.24	0.14	0.24	0.14	0.28	0.56	0.37
Cadbury Nigeria Plc	0.27	0.54	0.15	0.08	0.13	0.33	0.08	0.16	0.14	0.30
CAP plc	0.12	0.47	0.36	0.42	0.93	0.50	0.24	1.22	1.07	0.14
CCNN PLC	0.12	5.70	0.45	0.05	0.07	0.15	0.06	0.11	0.20	52.23
Champion Breweries Nig. Plc.	0.40	0.43	-0.65	-0.05	-0.15	0.03	-0.26	-0.14	0.02	0.15
CHAMS Plc.	0.01	0.25	0.19	-0.02	3.28	0.43	4.10	3.29	-0.01	0.37
Chellarams Plc	0.90	0.21	-0.04	0.01	0.07	0.13	0.01	0.36	0.28	0.17
Computer Warehouse (CWG)	0.83	0.45	0.31	1.07	3.23	0.97	0.85	8.27	4.02	0.23
Courteville Biz sol. Plc.	0.39	0.68	0.18	0.01	0.02	0.39	0.01	0.03	0.14	0.07
Cutix Plc.	0.22	0.74	0.05	0.18	0.25	0.19	0.23	1.08	0.51	0.40
Dangote Cement Plc	0.33	0.62	-0.06	0.24	0.37	0.61	0.32	1.60	0.97	0.04
Dangote Flour Mills Nig. Plc	0.41	0.34	-0.15	-0.03	0.65	0.12	-0.04	0.84	-0.07	0.11
Dangote Sugar Refinery Plc	0.11	0.50	0.26	0.13	0.24	0.15	0.08	0.32	0.20	0.12
DN Tyre and Rubber Plc.	1.68	0.18	-0.03	0.11	2.01	0.27	4.40	2.02	0.08	0.90
E-Transact Plc.	9.73	0.67	0.36	0.13	0.21	2.68	0.13	0.21	0.66	0.06
Eko Corp Plc.	0.35	0.81	-0.01	0.02	0.01	0.14	-0.01	0.01	0.02	0.01
Ellah Lakes Plc.	5.42	0.49	0.04	-0.02	-0.03	0.38	-1.23	-0.03	-0.02	0.82
Evans Medical Plc.	1.88	1.67	0.00	1.93	0.96	7.94	9.05	0.96	1.96	0.09
Fidson Healthcare Plc.	0.33	0.31	-0.05	0.03	-0.18	0.24	0.05	0.51	0.08	0.06
First Aluminium Plc.	0.19	0.54	-0.02	-0.01	-0.02	0.04	-0.07	0.05	0.07	0.68
Flour mill of Nigeria Plc.	0.86	0.29	-0.03	0.03	0.12	0.13	0.03	0.61	0.21	0.17
FTN Cocoa processors Plc.	1.17	0.64	-0.15	-0.11	-0.27	-0.45	-3.51	-0.27	-0.06	1.58

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40
Glaxo Smithkline Consumer Nig. Plc	0.13	0.51	-0.27	0.10	0.19	0.45	0.11	0.27	0.14	0.36
Golden guinea brew. Plc	0.42	11.13	-0.05	-0.01	0.00	-2.90	-0.01	0.63	10.83	2.70
Greif Nig. Plc.	14.74	0.40	-13.98	4.60	15.24	4.05	2.03	41.46	12.64	0.08
Guiness Nig. Plc	0.73	0.35	-0.05	0.08	0.20	0.40	0.07	0.56	0.28	0.20
Honeywell Flour Mill Plc.	0.63	0.38	-0.12	0.05	0.13	0.21	0.06	0.40	0.18	0.14
International Breweries Plc.	0.56	0.98	0.00	0.13	0.90	0.29	0.09	3.02	1.49	0.17
JOHN HOLT Plc.	0.40	0.81	-0.28	0.00	0.02	0.28	0.03	0.04	0.06	0.18
Lafarge Africa Plc	0.42	0.84	-0.02	0.05	0.08	0.30	0.11	0.10	0.09	0.23
Livestock Feeds Plc.	18.97	0.29	-0.03	0.07	57.05	0.10	0.02	76.01	0.17	0.74
May & Baker Nig. Plc.	2.97	0.39	0.37	0.06	0.14	0.37	0.06	1.14	0.50	1.38
MCNICHOLS Plc.	0.16	0.56	-0.01	0.11	0.19	0.07	0.09	0.53	0.29	0.17
Meyer Plc.	0.95	1.32	-0.07	0.05	0.08	0.25	0.52	0.08	0.06	9.93
Morison Industries Plc.	1.35	1.28	0.27	-0.07	-0.04	0.33	0.09	0.52	2.33	5.06
Multi-Trex Integrated plc.	10.46	9.56	-2.36	0.46	0.06	-0.27	3.18	0.09	0.84	0.73
Nasco Allied Industries	1.66	0.32	-0.04	0.40	1.29	0.36	0.40	1.79	5.32	0.47
NCR Nig. Plc.	12.30	0.16	0.06	0.04	5.54	0.12	0.03	5.58	0.04	0.29
Neimeth Int. Pharm. Plc.	0.17	0.59	0.57	-0.02	-0.07	0.36	-0.51	-0.05	0.76	15.42
Nestle Nig. Plc.	0.40	0.44	0.19	0.14	0.34	0.44	0.14	0.57	0.30	0.09
Nig-Germ Chemical plc.	0.03	0.30	0.45	0.09	0.32	1.66	0.21	0.32	0.32	0.02
Nig. Enamelware Plc.	0.23	67.06	0.33	1.32	0.66	0.14	0.61	1.73	97.37	0.14
Nigerian Breweries Plc.	0.53	0.45	-0.13	0.14	0.31	0.49	0.14	0.44	0.23	0.11
Northern Nigeria Flour Mills Plc.	0.41	0.27	-0.03	0.02	0.07	0.13	0.02	0.56	0.20	0.17
Okomu Oil Palm Plc	0.21	0.50	-0.03	0.51	1.24	0.21	1.41	1.28	0.53	0.26
Omatek Ventures	134.94	0.39	0.25	0.02	10.03	1.12	0.17	9.69	0.03	3.76
Paint and Coating Manufacturing Plc.	17.83	1.39	2.69	0.14	0.08	0.80	0.07	0.28	0.29	3.37
Pharma-deko plc.	0.07	0.27	-0.12	-0.03	-0.20	0.71	-0.20	0.85	0.00	0.15
Portland Paint&Product Plc	0.07	23.55	-2.29	49.48	2.38	0.24	0.85	2.90	52.67	0.22
Premier Paints Plc.	-3.67	6.76	-6.26	0.21	2.01	0.30	3.63	1.74	0.43	0.09

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R31	R32	R33	R34	R35	R36	R37	R38	R39	R40
PZ CUSSONS NIG. PLC.	0.09	0.62	0.34	0.07	0.10	0.26	0.06	0.19	0.13	0.34
SCOA Plc.	0.07	0.24	0.13	0.01	0.11	0.27	0.02	0.17	-0.14	1.76
Transactional Corporation of Nig. Plc.	0.60	0.51	0.03	0.03	0.05	0.64	0.15	0.29	0.19	0.07
Tripple Gee and Company Plc.	0.19	0.63	0.07	0.02	0.03	0.25	0.03	0.03	0.03	0.07
UACN	0.18	0.45	0.08	0.07	0.16	0.24	0.11	0.34	0.14	0.16
Unilever Nig. Plc.	0.57	0.27	-0.18	0.10	0.41	0.35	0.08	0.64	0.21	0.19
Union diagonistic&Clinicals	7.28	2.14	3.98	-0.33	-0.68	0.16	-0.53	10.70	38.75	0.22
Union Dicon Salt Plc.	-0.42	-12.17	-10.58	-0.70	0.09	-1.49	-2.37	0.09	-0.68	0.00
VITAFOAM	0.29	0.28	0.02	0.02	0.08	0.33	0.01	0.30	0.19	0.30

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R41	R42	R43	R44	R45(BOE/TA)	R46MVE/BVL	R47
7-up bottling	-0.11	11.18	0.11	0.10	0.17	0.46	0.02
A.G Levent	0.07	0.20	0.43	0.35	0.42	1.67	0.07
Afrik Pharmaceutical Plc.	-12.79	0.36	1.10	3.11	0.33	0.38	0.60
ARBICO PLC	0.40	88.66	0.47	10.45	0.04	-0.01	1.35
Austin laza plc	1.02	0.41	2.07	0.67	0.73	10.07	0.82
Berger Paints Nig. Plc.	0.27	0.11	0.22	0.20	0.65	2.59	0.01
Beta Glass	0.59	1.35	0.36	0.37	1.56	2.27	0.24
Cadbury Nigeria Plc	0.24	0.40	0.48	0.30	0.54	1.40	0.05
CAP plc	0.21	0.07	0.24	0.14	0.47	1.22	0.30
CCNN PLC	0.53	0.07	1.07	52.23	5.70	5.08	0.01
Champion Breweries Nig. Plc.	-2.54	0.25	2.71	0.15	0.43	1.68	0.23
CHAMS Plc.	0.40	2.29	1.06	0.37	0.25	1.38	0.06
Chellarams Plc	-0.03	0.17	0.13	0.17	0.21	0.49	0.10
Computer Warehouse (CWG)	0.36	-33.49	1.42	0.23	0.45	124.35	0.01
Courteville Biz sol. Plc.	0.03	0.16	0.12	0.07	0.68	29.49	0.05
Cutix Plc.	0.07	0.13	0.07	0.40	0.74	23.62	0.35
Dangote Cement Plc	-0.06	0.01	0.32	0.04	0.62	511.33	0.01
Dangote Flour Mills Nig. Plc	-0.16	0.11	0.53	0.11	0.34	0.59	-0.24
Dangote Sugar Refinery Plc	0.13	0.13	0.33	0.12	0.50	2.77	0.01
DN Tyre and Rubber Plc.	-0.06	1.79	0.27	0.90	0.18	1.36	-0.03
E-Transact Plc.	0.38	0.32	0.98	0.06	0.67	0.62	0.49
Eko Corp Plc.	-0.06	0.21	0.23	0.01	0.81	2.40	0.00
Ellah Lakes Plc.	0.98	0.01	0.12	0.82	0.49	0.99	0.01
Evans Medical Plc.	-0.01	0.01	0.13	0.09	1.67	2.32	0.08
Fidson Healthcare Plc.	-0.11	0.17	0.21	0.06	0.31	14.70	0.03
First Aluminium Plc.	-0.05	0.08	0.19	0.68	0.54	1.86	0.07
Flour mill of Nigeria Plc.	-0.05	0.04	0.11	0.17	0.29	0.56	0.04
FTN Cocoa processors Plc.	-1.64	5.55	148.76	1.58	0.64	2.60	2.09

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R41	R42	R43	R44	R45	R46	R47
Glaxo Smithkline Consumer Nig. Plc	-0.09	0.28	0.49	0.36	0.51	1.28	0.00
Golden guinea brew. Plc	-0.05	0.06	3.85	2.70	11.13	2.51	1.47
Greif Nig. Plc.	-10.06	0.56	1.81	0.08	0.40	0.19	-0.05
Guiness Nig. Plc	-0.10	0.25	0.39	0.20	0.35	0.81	0.08
Honeywell Flour Mill Plc.	-0.27	0.21	0.25	0.14	0.38	0.80	0.05
International Breweries Plc.	-0.04	1.33	0.20	0.17	0.98	11.10	0.04
JOHN HOLT Plc.	-1.03	0.14	1.06	0.18	0.81	1.53	0.14
Lafarge Africa Plc	-0.03	0.16	0.80	0.23	0.84	2.28	0.05
Livestock Feeds Plc.	0.01	1.58	0.24	0.74	0.29	0.67	0.03
May & Baker Nig. Plc.	0.40	0.23	0.37	1.38	0.39	0.40	0.06
MCNICHOLS Plc.	0.00	0.09	0.21	0.17	0.56	1.89	0.01
Meyer Plc.	-0.26	1.40	6.48	9.93	1.32	5.82	0.02
Morison Industries Plc.	1.58	25.07	0.53	5.06	1.12	2.08	0.03
Multi-Trex Integrated plc.	-1.14	4.00	0.14	0.73	9.56	2.63	2.41
Nasco Allied Industries	-0.06	0.21	0.30	0.47	0.32	0.45	4.20
NCR Nig. Plc.	0.14	0.69	0.31	0.29	0.16	1.14	0.00
Neimeth Int. Pharm. Plc.	2.24	7.34	0.62	15.42	0.59	1.74	1.11
Nestle Nig. Plc.	0.16	0.25	0.19	0.09	0.44	2.50	0.04
Nig-Germ Chemical plc.	1.18	-0.39	0.08	0.02	0.30	1.12	0.13
Nig. Enamelware Plc.	0.18	0.51	1.28	0.14	67.06	44.67	43.10
Nigerian Breweries Plc.	-0.13	0.21	0.27	0.11	0.45	1.27	0.03
Northern Nigeria Flour Mills Plc.	-0.05	0.04	0.11	0.17	0.27	0.68	0.04
Okomu Oil Palm Plc	-0.02	0.54	0.05	0.26	0.50	2.04	0.02
Omatek Ventures	4.27	3.08	0.97	3.76	0.39	1.61	0.22
Paint and Coating Manufacturing Plc.	4.55	0.87	1.23	3.37	1.39	1.78	0.02
Pharma-deko plc.	-1.72	8.90	1.32	0.15	0.27	1.88	0.02
Portland Paint&Product Plc	0.23	0.16	0.45	0.22	23.55	17.00	0.03
Premier Paints Plc.	-14.18	0.16	20.41	0.09	6.76	2.33	0.88

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.1 (Cont'd): Average of selected bankruptcy features

Name of company	R41	R42	R43	R44	R45	R46	R47
Presco Plc	-0.16	0.40	0.18	0.60	0.30	0.81	0.03
PZ CUSSONS NIG. PLC.	0.33	0.20	0.26	0.34	0.62	2.48	0.01
SCOA Plc.	0.24	-176.16	0.36	1.76	0.24	17.16	-0.24
Transactional Corporation of Nig. Plc.	0.17	0.54	0.43	0.07	0.51	1.40	0.13
Tripple Gee and Company Plc.	0.12	0.08	0.06	0.07	0.63	86.87	0.03
UACN	0.15	-0.01	0.15	0.16	0.45	1,601.32	0.11
Unilever Nig. Plc.	-0.15	0.72	0.43	0.19	0.27	0.49	0.04
Union diagonistic&Clinicals	12.29	2.66	11.47	0.22	2.14	0.81	0.87
Union Dicon Salt Plc.	-51.47	0.27	49.10	0.00	-12.17	-1.26	0.00
VITAFOAM	0.01	0.11	0.26	0.30	0.28	0.68	0.07

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.2: Corporate governance variables of the studied firms

COMPANY	Board size	WD	NED	BC	Ceo Duality	BO
7-up bottling	10.00	0.00	8.00	4.00	1.00	0.00
A.G Levent	8.00	0.00	4.50	2.75	1.00	0.00
Afrik Pharmaceutical Plc.	5.00	0.00	1.50	2.25	0.00	0.00
ARBICO PLC	7.00	1.00	4.00	3.00	0.00	0.00
Austin laza plc	13.00	1.00	10.88	5.63	0.00	0.00
Berger Paints Nig. Plc.	6.00	0.00	3.00	2.00	1.00	0.12
Beta Glass	9.00	0.00	8.00	4.00	1.00	0.00
Cadbury Nigeria Plc	7.00	2.00	5.00	3.00	1.00	0.01
CAP plc	7.50	1.00	4.00	3.63	0.63	0.01
CCNN PLC	9.00	1.00	4.00	3.00	0.00	0.00
Champion Breweries Nig. Plc.	8.00	1.00	4.00	5.00	1.00	0.02
CHAMS Plc.	5.00	0.00	2.00	3.00	0.00	0.00
Chellarams Plc	7.00	0.00	5.00	2.50	0.00	0.03
Computer Warehouse (CWG)	8.00	1.00	4.00	2.00	1.00	0.91
Courteville Biz sol. Plc.	7.50	0.00	4.00	3.00	1.00	0.04
Cutix Plc.	7.00	1.00	4.00	3.00	0.00	0.00
Dangote Cement Plc	13.00	1.00	11.00	4.00	1.00	0.00
Dangote Flour Mills Nig. Plc	6.00	2.00	4.00	3.00	1.00	0.06
Dangote Sugar Refinery Plc	9.00	2.00	7.00	5.00	1.00	0.05
DN Tyre and Rubber Plc.	5.00	0.00	2.00	2.00	0.00	0.00
E-Transact Plc.	8.00	0.00	4.00	3.00	0.00	0.00
Eko Corp Plc.	6.00	0.00	3.00	3.00	0.00	0.00
Ellah Lakes Plc.	9.00	2.00	4.00	2.00	0.00	0.00
Evans Medical Plc.	11.00	1.00	4.00	2.00	1.00	0.04
Fidson Healthcare Plc.	8.00	3.00	4.00	4.00	1.00	0.17
First Aluminium Plc.	8.00	2.00	4.00	3.00	1.00	0.00
Flour mill of Nigeria Plc.	13.00	3.00	8.00	4.00	1.00	0.00
FTN Cocoa processors Plc.	6.00	0.00	4.00	2.00	0.00	0.04
Glaxo Smithkline Consumer Nig. Plc	9.00	1.00	7.00	6.00	1.00	0.03
Golden guinea brew. Plc	4.50	0.00	1.50	2.25	0.00	0.00
Greif Nig. Plc.	5.25	0.00	3.00	3.00	1.00	0.00
Guiness Nig. Plc	12.00	2.00	8.00	2.00	1.00	0.00
Honeywell Flour Mill Plc.	9.00	0.00	5.00	3.00	1.00	0.23
International Breweries Plc.	8.00	5.00	5.00	3.00	1.00	0.12
JOHN HOLT Plc.	6.00	0.00	4.00	2.00	0.00	0.00
Lafarge Africa Plc	6.00	2.00	4.00	4.00	1.00	0.00
Livestock Feeds Plc.	9.00	0.00	5.00	2.00	1.00	0.00
May & Baker Nig. Plc.	9.00	1.00	5.00	3.00	0.00	0.00
MCNICHOLS Plc.	6.00	1.00	4.00	3.00	0.00	0.00
Meyer Plc.	7.00	1.00	5.00	3.00	0.00	0.00
Morison Industries Plc.	8.00	0.63	4.63	3.00	0.00	0.23
Multi-Trex Integrated plc.	7.00	1.00	3.38	3.00	1.00	0.13
Nasco Allied Industries	10.00	4.00	6.13	3.00	1.00	0.04
NCR Nig. Plc.	5.00	0.00	3.00	3.00	1.00	0.01
Neimeth Int. Pharm. Plc.	11.00	0.00	8.00	3.00	0.00	0.53
Nestle Nig. Plc.	15.75	1.00	6.00	4.00	1.00	0.00
Nig-Germ Chemical plc.	5.00	0.00	4.00	3.00	0.00	0.00
Nig. Enamelware Plc.	6.00	0.00	4.00	3.00	0.00	0.01
Nigerian Breweries Plc.	15.00	2.00	8.00	4.00	1.00	0.00
Northern Nigeria Flour Mills Plc.	13.00	3.00	8.00	4.00	1.00	0.00
Okomu Oil Palm Plc	10.00	0.00	5.00	3.00	0.00	0.19
Omatek Ventures	11.00	1.00	5.00	3.00	1.00	0.24

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.2 cont'd: Corporate governance variables of the studied firms

COMPANY	Board size	WD	NED	BC	Ceo Duality	BO
Paint and Coating Manufacturing Plc.	7.00	0.00	3.00	2.00	0.00	0.98
Pharma-deko plc.	10.00	3.00	7.00	3.00	1.00	0.12
Portland Paint&Product Plc	6.00	0.00	4.00	3.00	1.00	0.00
Premier Paints Plc.	9.00	0.00	6.00	3.00	1.00	0.14
Presco Plc	10.00	1.00	5.25	3.00	0.00	0.15
PZ CUSSONS NIG. PLC.	12.00	3.00	2.00	3.00	1.00	0.01
SCOA Plc.	8.00	0.00	4.00	3.00	1.00	0.00
Transactional Corporation of Nig. Plc.	14.00	0.00	0.00	4.00	1.00	1.32
Tripple Gee and Company Plc.	7.00	1.00	3.00	3.00	0.00	0.00
UACN	8.00	1.00	5.00	2.00	1.00	0.02
Unilever Nig. Plc.	9.00	2.00	5.00	4.00	1.00	0.00
Union diagonistic&Clinicals	6.00	0.00	2.00	3.00	0.00	0.71
Union Dicon Salt Plc.	8.00	0.00	6.00	2.00	1.00	9.88
VITAFOAM	11.00	1.00	6.00	3.00	0.00	0.14

Source: Annual Financial Reports of the Companies (2011-2017)

Table 4.3: Z score variables of the studied companies

	0.012(X1)	0.014(X2)	0.033(X3)	0.006(X4)	0.999(X5)	Z
7-up bottling	0.00	0.00	0.01	0.00	1.01	1.02
A.G Leventis	0.00	0.00	0.00	0.01	0.59	0.60
Afrik Pharmaceutical Plc.	0.00	0.00	0.01	0.00	0.11	0.11
ARBICO PLC	0.01	-0.01	0.03	0.00	2.76	2.78
Austin laza plc.	0.00	0.00	0.17	0.06	0.72	0.95
Berger Paints Nig. Plc.	0.00	0.01	0.00	0.02	0.80	0.83
Beta Glass	0.01	0.02	0.02	0.01	1.45	1.51
Cadbury Nigeria Plc.	0.00	0.02	0.00	0.01	0.83	0.86
CAP plc.	0.00	0.00	0.04	0.01	1.78	1.83
CCNN PLC	0.01	0.00	0.01	0.03	0.87	0.92
Champion Breweries Nig. Plc.	-0.01	-0.01	0.00	0.01	0.31	0.30
CHAMS Plc.	0.00	0.00	0.00	0.01	0.16	0.17
Chellarams Plc.	0.00	0.00	0.01	0.00	1.90	1.91
Computer Warehouse (CWG)	0.00	0.00	0.13	0.75	1.94	2.82
Courteville Biz sol. Plc.	0.00	0.00	0.00	0.18	8.06	8.25
Cutix Plc.	0.00	0.00	0.02	0.14	0.85	1.01
Dangote Cement Plc.	0.00	3.26	0.03	3.07	160.92	167.27
Dangote Flour Mills Nig. Plc.	0.00	0.00	0.00	0.00	1.54	1.54
Dangote Sugar Refinery Plc.	0.00	0.01	0.01	0.02	4.61	4.64
DN Tyre and Rubber Plc.	0.00	-0.01	0.00	0.01	0.36	0.37
E-Transact Plc.	0.00	0.00	0.00	0.01	1.30	1.32
E-Transact Plc.	0.00	0.00	0.02	0.00	1.10	1.13
Eko Corp Plc.	0.00	0.00	0.00	0.01	0.42	0.44
Ellah Lakes Plc.	0.00	0.00	0.00	0.01	0.03	0.03
Evans Medical Plc.	0.00	0.00	0.06	0.01	0.47	0.55
Fidson Healthcare Plc.	0.00	0.00	0.00	0.09	1.00	1.09
First Aluminium Plc.	0.00	0.00	0.00	0.01	0.89	0.90
Flour mill of Nigeria Plc.	0.00	0.00	0.01	0.00	1.13	1.14
FTN Cocoa processors Plc.	0.00	0.00	0.00	0.02	0.09	0.10
Glaxo Smith Kline Consumer Nig. Plc.	0.00	0.01	0.00	0.01	0.93	0.95
Golden guinea brew. Plc.	0.00	0.00	0.36	0.02	0.81	1.18
Greif Nig. Plc.	-0.17	0.00	0.42	0.00	2.15	2.41
Guinness Nig. Plc.	0.00	0.00	0.01	0.00	0.87	0.88
Honeywell Flour Mill Plc.	0.00	0.00	0.01	0.00	0.77	0.78
International Breweries Plc.	0.00	0.00	0.05	0.07	1.90	2.02
JOHN HOLT Plc.	0.00	0.00	0.00	0.01	0.27	0.28
Lafarge Africa Plc.	0.00	0.01	0.00	0.01	0.45	0.48
Livestock Feeds Plc.	0.00	0.00	0.01	0.00	2.61	2.62
May & Baker Nig. Plc.	0.00	0.00	0.02	0.00	0.86	0.89
MCNICHOLS Plc.	0.00	-0.01	0.01	0.01	1.45	1.47
Meyer Plc.	0.00	0.00	0.00	0.03	0.25	0.29
Morison Industries Plc.	0.00	0.00	0.07	0.01	0.19	0.27
Multi-Trex Integrated plc.	-0.03	0.00	0.03	0.02	6.74	6.75
Nasco Allied Industries	0.00	0.01	0.18	0.00	1.02	1.20
NCR Nig. Plc.	0.00	0.00	0.00	0.01	1.06	1.07
Neimeth Int. Pharm. Plc.	0.01	0.00	0.02	0.01	0.56	0.60
Nestle Nig. Plc.	0.00	0.00	0.01	0.02	1.00	1.03
Nig-Germ Chemical plc.	0.01	0.00	0.01	0.01	0.92	0.95
Nig. Enamelware Plc.	0.00	0.01	3.21	0.27	1.68	5.17
Nigerian Breweries Plc.	0.00	0.00	0.01	0.01	0.99	1.01
Northern Nigeria Flour Mills Plc.	0.00	0.00	0.01	0.00	1.13	1.14
Okomu Oil Palm Plc.	0.00	0.00	0.02	0.01	0.78	0.82
Omatek Ventures	0.00	0.00	0.00	0.01	0.11	0.12

Source: Author’s computation (2018)

Table 4.3 cont'd: Z score variables of the studied companies

	0.012(X1)	0.014(X2)	0.033(X3)	0.006(X4)	0.999(X5)	Z
Paint and Coating Manufacturing Plc.	0.03	0.00	0.01	0.01	1.75	1.80
Pharma-deko plc.	0.00	0.00	0.00	0.01	0.57	0.58
Portland Paint&Product Plc	-0.03	0.00	1.74	0.10	28.87	30.69
Premier Paints Plc.	-0.08	-0.01	0.01	0.01	0.64	0.59
Presco Plc	0.00	0.00	0.00	0.00	0.69	0.70
PZ CUSSONS NIG. PLC.	0.00	0.01	0.00	0.01	1.04	1.07
SCOA Plc.	0.00	0.00	0.00	0.08	0.46	0.54
Transactional Corporation of Nig. Plc.	0.00	0.00	0.01	0.01	0.21	0.23
Tripple Gee and Company Plc.	0.00	0.00	0.00	0.26	0.23	0.49
UACN	0.00	0.00	0.00	9.61	0.49	10.10
Unilever Nig. Plc.	0.00	0.00	0.01	0.00	1.32	1.33
Union diagonistic&Clinicals	0.05	-0.01	1.28	0.00	1.95	3.27
Union Dicon Salt Plc.	-0.13	-0.04	-0.02	-0.01	1.74	1.55
VITAFOAM	0.00	0.00	0.01	0.00	1.40	1.41

Source: Author's computation (2018)

Note: The Altman's Z-score indicates how close or far a firm is from bankruptcy. The Z-score was computed as follows: $Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$,

Where: X1 = working capital/total assets,

X2 = retained earnings/total assets,

X3 = earnings before interest and taxes/total assets,

X4 = market value equity/book value of total liabilities,

X5 = sales/total assets and

Z = overall index

4.2 Factor Analysis

The first procedure involved performing an Exploratory Factor Analysis (EFA). EFA is often used to gather information (explore) the interrelationships among a set of variables (Pallant, 2007). The EFA technique employed is the Principal Component Analysis (PCA). PCA decomposes a given data into a set of linear components within the data. It indicates how a variable contributes to that component, with all of the variance in the variables being used (Dunteman, 1989). Therefore, the purpose of PCA stage of the analysis is to determine factors that can convey the essential information in a larger set of variables (McNamara & Duncan, 1995) and to at least reduce multicollinearity problems which make it difficult to make any statistical inferences (Issah & Antwi, 2017). PCA also compresses data by reducing the number of dimensions and keeps only those characteristics of the data sets that contribute most to its variance without losing much of information (Andreica, Andreica, & Andreica, 2009; Abassi & Taffler, 1982).

In order to perform PCA, it is crucial to establish the suitability of the data size. According to Tabachnick and Fidell (2007) it is “comforting to have at least 300 cases for factor analysis” (p. 613). Both the KMO (Kaiser–Meyer–Olkin Measure of Sampling Adequacy) Index and Bartlett’s Test of Sphericity were used to check the adequacy of sample size. The KMO index represents the ratio of the squared correlation between variables to the squared partial correlation between variables.

The values of KMO range between 0 and 1. Any value close to 1 indicates that the patterns of correlation are compact, and therefore the analysis should result in distinct and reliable factors (Field, 2005). It is considered to be an adequate sample size if the obtained KMO value lies between 0.5 and 1. The KMO test results are presented in the table below:

Table 4.4: KMO and Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.666
Bartlett's Test of Sphericity	Approx. Chi-Square	2532.055
	Df	595
	Sig.	.000

Source: SPSS Ver. 24

The KMO Index value is 66.6%; therefore the sample size of the data set in this study is adequate for use in factor analysis. In addition, the Bartlett's Test of Sphericity signifies whether the R-matrix is an identity matrix, i.e., whether the population correlation matrix resembles an identity matrix (Delen, Kuzey, & Uyar, 2013). If there is an identity matrix, every variable correlates poorly with all the other variables, which means correlation coefficients are close to zero, leaving them perfectly independent from each other. It should be significant at $p < 0.05$; the value obtained is highly significant at $p < 0.01$. This result indicated that the correlation coefficient matrix is not an identity matrix. PCA determines which vector is significant in the data set (Delen, Kuzey, & Uyar, 2013; Field, 2005). The table below shows the total variance explained by the extracted components:

Table 4.5: Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.499	15.954	15.954	7.499	15.954	15.954	7.074	15.052	15.052
2	4.343	9.241	25.196	4.343	9.241	25.196	4.013	8.538	23.589
3	4.031	8.576	33.772	4.031	8.576	33.772	3.514	7.476	31.065
4	3.611	7.683	41.455	3.611	7.683	41.455	2.759	5.870	36.935
5	2.418	5.144	46.599	2.418	5.144	46.599	2.474	5.264	42.200
6	2.251	4.790	51.389	2.251	4.790	51.389	2.113	4.495	46.695
7	2.037	4.334	55.723	2.037	4.334	55.723	2.080	4.424	51.119
8	1.969	4.189	59.912	1.969	4.189	59.912	2.061	4.385	55.504
9	1.859	3.956	63.868	1.859	3.956	63.868	2.039	4.339	59.843
10	1.764	3.752	67.620	1.764	3.752	67.620	2.006	4.267	64.111
11	1.538	3.272	70.893	1.538	3.272	70.893	1.986	4.225	68.336
12	1.436	3.056	73.949	1.436	3.056	73.949	1.836	3.906	72.242
13	1.305	2.776	76.725	1.305	2.776	76.725	1.476	3.140	75.382
14	1.186	2.523	79.248	1.186	2.523	79.248	1.408	2.996	78.378
15	1.122	2.388	81.636	1.122	2.388	81.636	1.341	2.853	81.231
16	1.109	2.360	83.996	1.109	2.360	83.996	1.300	2.765	83.996
17	.997	2.121	86.117						
18	.961	2.044	88.162						
19	.921	1.960	90.121						
20	.912	1.940	92.061						
~	~	~	~						
45	-3.612E-17	-7.684E-17	100.000						
46	-2.199E-16	-4.678E-16	100.000						
47	-2.881E-16	-6.131E-16	100.000						

Source: SPSS Ver. 24

The table shows that the first sixteen factors explained a relatively large amount of variance (Cumulative 83.996%); SPSS by default extracted all factors with eigenvalues greater than 1. The eigenvalue of a factor represents the amount of the total variance explained by that factor (Pallant, 2007). The table shows the factor loadings of the components. PCA with varimax orthogonal rotation was carried out to assess the underlying dimensions of the provided items for financial ratios (Delen, Kuzey, & Uyar, 2013). Orthogonal rotation results in solutions that are easier to interpret and to report (Tabachnick & Fidell, 2007). The communalities of the extracted components are shown in Table 4.5. Communality is the proportion of a common variance within a variable. It is the amount of variance in each variable that could be explained by the retained factors is represented by the communalities after extraction (Field, 2005).

Table 4.6: Communalities

	Initial	Extraction
R1	1.000	.935
R2	1.000	.958
R3	1.000	.937
R4	1.000	.938
R5	1.000	.966
R6	1.000	.389
R7	1.000	.588
R8	1.000	.575
R9	1.000	.992
R10	1.000	.032
R11	1.000	.992
R12	1.000	.943
R13(Sales/TA)	1.000	.989
R14	1.000	.966
R15	1.000	.938
R16(EBIT/TS)	1.000	.916
R17	1.000	.994
R18	1.000	.691
R19	1.000	.718
R20(RE/TA)	1.000	.983
R21	1.000	.993
R22	1.000	.871
R23	1.000	.890
R24	1.000	.992
R25(WC/TA)	1.000	.961
R26	1.000	.890
R27	1.000	.934
R28	1.000	.974
R29	1.000	.992
R30	1.000	.901
R31	1.000	.184
R32	1.000	.920
R33	1.000	.961
R34	1.000	.673
R35	1.000	.985
R36	1.000	.994
R37	1.000	.843
R38	1.000	.968
R39(EBIT/TA)	1.000	.773
R40	1.000	.980
R41	1.000	.832
R42	1.000	.085
R43	1.000	.882
R44	1.000	.980
R45(BOE/TA)	1.000	.920
R46MVE/BVL	1.000	.859
R47	1.000	.804
Extraction Method: Principal Component Analysis.		

Source: SPSS Ver. 24

The rotation method used was Varimax with Kaiser Normalization (See Appendix IV)

Factor 1: The first factor was the most significant, explaining 15.954% of the total variance. Nine ratios: R5, R14, R45, R32, R47, R4, R15, R16, and R39 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.969, 0.969, 0.952, 0.952, 0.866, 0.803, 0.803, 0.739 and 0.660 respectively.

Factor 2: The second factor was significant, explaining 9.241% of the total variance. Four ratios: R29, R35, R38, and R12 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.996, 0.990, 0.981, and 0.960 respectively.

Factor 3: The third factor was significant, explaining 8.576% of the total variance. Four ratios: R3, R2, R1, and R26 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.948, 0.942, 0.936, and 0.739 respectively.

Factor 4: The fourth factor was significant, explaining 7.683% of the total variance. Three ratios: R25, R33, and R41 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.942, 0.942, and 0.873 respectively.

Factor 5: The fifth factor was significant, explaining 5.144% of the total variance. Four ratios: R28, R30, R23, and R22 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.958, 0.940, 0.524, and 0.561 respectively.

Factor 6: The sixth factor was significant, explaining 4.790% of the total variance. Three ratios: R26, R27, and R46 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.582, 0.958, and 0.915 respectively.

Factor 7: The seventh factor was significant, explaining 4.334% of the total variance. Four ratios: R39, R34, R23, and R22 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.549, 0.771, 0.668, and 0.636 respectively.

Factor 8: The eighth factor was significant, explaining 4.189% of the total variance. Two ratios: R17 and R36 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.989 and 0.989 respectively.

Factor 9: The ninth factor was significant, explaining 3.956% of the total variance. Two ratios: R40 and R44 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.985 and 0.985 respectively.

Factor 10: The tenth factor was significant, explaining 3.752% of the total variance. Two ratios: R21 and R24 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.994 and 0.993 respectively.

Factor 11: The eleventh factor was significant, explaining 3.272% of the total variance. Two ratios: R9 and R11 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.996 and 0.996 respectively.

Factor 12: The twelfth factor was significant, explaining 3.056% of the total variance. Two ratios: R13 and R20 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.916 and 0.906 respectively.

Factor 13: The thirteenth factor was significant, explaining 2.776% of the total variance. Two ratios: R19 and R18 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.841 and 0.830 respectively.

Factor 14: The fourteenth factor was significant, explaining 2.523% of the total variance. One ratio: R43 was loaded under this factor. The loaded variable was positive, having high factor loadings value of 0.931 respectively.

Factor 15: The fifteenth factor was significant, explaining 2.388% of the total variance. Two ratios: R16 and R37 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.589 and 0.908 respectively.

Factor 16: The sixteenth factor was significant, explaining 2.360% of the total variance. Three ratios: R7, R8, and R6 were loaded under this factor. The loaded variables were all positive, having high factor loadings values of 0.736, 0.585, and 0.532 respectively.

4.3 Comparison of Bankrupt vs Non-Bankrupt Firms

The t statistic was used to check for statistical significant difference between the ratios for Bankrupt and Non-Bankrupt firms. The t statistic showed a total of fifteen financial ratios statistically significant between the two groups. The ratios are: R5 ($p<.05$); R8 ($p<.05$); R14 ($p<.05$); R16 ($p<.05$); R17 ($p<.05$); R22 ($p<.05$); R23 ($p<.05$); R25 ($p<.10$); R28 ($p<.05$); R32 ($p<.05$); R34 ($p<.05$); R36 ($p<.05$); R37 ($p<.05$); R38 ($p<.10$); R39 ($p<.05$); R45 ($p<.05$); and R47 ($p<.05$); with the exception of R25 and R38; all the ratios were statistically signinifant at 5%. The t statistic was re-calculated using the Altman's Z score for classification, the results showed that previous variables were significant with the exception of R8; R17; R36; and R37.

4.4 Test of Hypotheses

4.4.1 Hypothesis One

H_1: There is a significant difference in the predictive accuracy of GA compared with the logit model in the prediction of corporate bankruptcy

Table 4.7: Coefficients of the Logit model

	Coefficient	*Std. Error*	*z*	*p-value*	
Const	-3.81807	0.194718	-19.6082	<0.00001	***
R5	-0.030458	0.0267571	-1.1383	0.25499	
R16	0.122194	0.0618435	1.9759	0.04817	**
R22	-0.00914575	0.0529382	-0.1728	0.86284	
R23	0.0183518	0.0276975	0.6626	0.50760	
R28	0.0201262	0.0198029	1.0163	0.30947	
R32	-319.26	313.909	-1.0170	0.30913	
R34	6.43318	0.952049	6.7572	<0.00001	***
R39	-0.203157	0.0491371	-4.1345	0.00004	***
R45	319.308	313.915	1.0172	0.30907	
R47	0.229774	0.0994051	2.3115	0.02081	**

Mean dependent var	0.132576	S.D. dependent var	0.339437
McFadden R-squared	0.638410	Adjusted R-squared	0.585162
Log-likelihood	-74.69805	Akaike criterion	171.3961
Schwarz criterion	218.3562	Hannan-Quinn	189.7800

Source: Gretl; SPSS Ver. 24.

Note: The Logit model omitted R14 and R25 due to exact collinearity

The Logit model showed significant values for R16, R34, R39 and R47, the McFadden R-squared value was 0.638410; the Adjusted R-squared value was 0.585162; and Likelihood ratio test: Chi-square(10) = 263.768 [0.0000].

Table 4.8: Coefficients of the Logit model with corporate governance

	Coefficient	*Std. Error*	*z*	*p-value*	
const	-4.80606	1.32766	-3.6200	0.00029	***
R5	-0.035581	0.0266247	-1.3364	0.18142	
R16	0.14096	0.0775371	1.8180	0.06907	*
R22	-0.0131732	0.0638362	-0.2064	0.83651	
R23	0.00537709	0.0303616	0.1771	0.85943	
R28	0.02846	0.0224684	1.2667	0.20528	
R32	-319.184	321.353	-0.9932	0.32059	
R34	6.65728	1.06178	6.2699	<0.00001	***
R39	-0.215411	0.0537039	-4.0111	0.00006	***
R45	319.237	321.358	0.9934	0.32052	
R47	0.237695	0.105993	2.2425	0.02493	**
Boardsize	0.0029477	0.0837205	0.0352	0.97191	
BC	0.213039	0.197708	1.0775	0.28124	
CeoDuality	0.462726	0.522808	0.8851	0.37611	
BO	-0.0260821	0.130042	-0.2006	0.84104	
PNED	-0.168952	1.55139	-0.1089	0.91328	
PWD	0.246004	1.70323	0.1444	0.88516	

Mean dependent var	0.132576	S.D. dependent var	0.339437
McFadden R-squared	0.647416	Adjusted R-squared	0.565124
Log-likelihood	-72.83762	Akaike criterion	179.6752
Schwarz criterion	252.2499	Hannan-Quinn	208.0867

Source: Gretl; SPSS Ver. 24.

Note: The Logit model omitted R14 and R25 due to exact collinearity
The Logit model with corporate governance variables also showed significant values for R16, R34, R39 and R47, the McFadden R-squared value was 0.647416; the Adjusted R-squared value was 0.565124; and Likelihood ratio test: Chi-square(16) = 269.489 [0.0000].

Table 4.9: Comparison of logit and genetic algorithm model

	Model	Model + Corporate Governance
Logit model	93.4%	93.6%
Genetic algorithm	96.94%	97.85%

Source: Gretl; RapidMiner Studio Version 7.6; SPSS Ver. 24.

4.4.2 Hypothesis Two

H_1: There is a significant difference in the predictive accuracy of GA compared with the discriminant model in the prediction of corporate bankruptcy

Table 4.10: Standardized canonical discriminant function coefficients

	Function 1
R5	-.344
R16	.046
R22	.201
R23	.191
R28	.197
R32	.411
R34	.461
R36	.214
R37	.590
R39	-.235
R47	.453

Source: SPSS Ver. 24.

Note: The disciromінant analysis indicated that three variables failed the **Tolerance Test** (R14; R25; and, R45); the first two variables were also rejected in the logit model for exact collinearity.

The **discriminant** command in SPSS performs canonical linear discriminant analysis which is the classical form of discriminant analysis.

Table 4.11: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.455[a]	100.0	100.0	.559

a. First 1 canonical discriminant functions were used in the analysis.

Source: SPSS Ver. 24.

The Eigenvalue shows the eigenvalues of the matrix product of the inverse of the within-group sums-of-squares and cross-product matrix and the between-groups sums-of-squares and cross-product matrix. Eigenvalues are related to the canonical correlations and describe how much discriminating ability a function possesses. Thus, the first function possess a .455 discriminating ability (the % of variance explained by the first function is 100%; i.e. accounts for 100% of the discriminating ability of the discriminating variables).

Table 4.12: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.687	195.278	11	.000

Source: SPSS Ver. 24.

The WIlks' Lambda value is .687; the Chi-square statistic is 195.278; the Chi-square tests that the canonical correlation of the given function is equal to zero. In other words, the null hypothesis is that the function, and all functions that follow, have no discriminating ability. The p-value of the Chi-square statistic is less than .05; therefore the null hypothesis that the function's canonical correlation is equal to zero is rejected.

Table 4.13: Standardized canonical discriminant function coefficients (Model + Corporate Governance)

	Function
	1
R5	-.379
R16	.107
R22	.228
R23	.151
R28	.205
R32	.442
R34	.454
R36	.194
R37	.577
R39	-.228
R47	.414
Board size	.044
BC	-.074
Ceo Duality	.143
BO	-.002
PNED	.031
PWD	.006

Source: SPSS Ver. 24.

Note: The discirominant analysis (corporate governance variables inclusive) indicated that the following three variables failed the **Tolerance Test** (R14; R25; and, R45).

Table 4.14: Eigenvalues (Model + Corporate Governance)

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.466[a]	100.0	100.0	.564

a. First 1 canonical discriminant functions were used in the analysis.

Source: SPSS Ver. 24.

The first function possess a .466 discriminating ability (and the % of variance explained by the first function is 100%; the canonical correlation value is .564).

Table 4.15: Wilks' Lambda (Model + Corporate Governance)

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.682	197.845	17	.000

Source: SPSS Ver. 24.

The WIlks' Lambda value is .682; the Chi-square statistic is 197.845; the p-value of the Chi-square statistic is less than .05; therefore the null hypothesis that the function's canonical correlation is equal to zero is rejected.

Table 4.16: Comparison of discriminant and genetic algorithm model

	Model	Model + Corporate Governance
Discriminant model	91.1%	90.9%
Discriminant model (cross validated)	90.3%	90.3%
Genetic algorithm	96.94%	97.85%

Source: Gretl; RapidMiner Studio Version 7.6; SPSS Ver. 24.

4.4.3 Hypothesis Three

H_1: There is a significant difference in the predictive accuracy of GA compared with neural network using in the prediction of corporate bankruptcy

Network Information:

Neural network using Multilayer Perceptron (MLP) was performed using the Statistical Package for Social Sciences Version 24.

Input layer: The input layer had 12 factors (R5: R14; R16; R22; R23; R25; R28; R32; R34; R39; R45; and R47). Number of units in the input layer was 12. Rescaling method for covariates: Standardized

Hidden layer: Hidden layer(s) of a neural network contains unobservable units. The value of each hidden unit is some function of the predictors; the exact form of the function depends in part upon the network type. Number of hidden layers 1; Number of units in hidden layer 9; Activation function-Hyperbolic tangent.

Output layer: Number of units 2; Activation function-Softmax: Error function-Cross entropy. The network diagram is shown in Appendix VI.

Table 4.17: Model summary for neural network

Training	Cross Entropy Error	56.882
	Percent Incorrect Predictions	6.8%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.73
Testing	Cross Entropy Error	34.022
	Percent Incorrect Predictions	10.5%

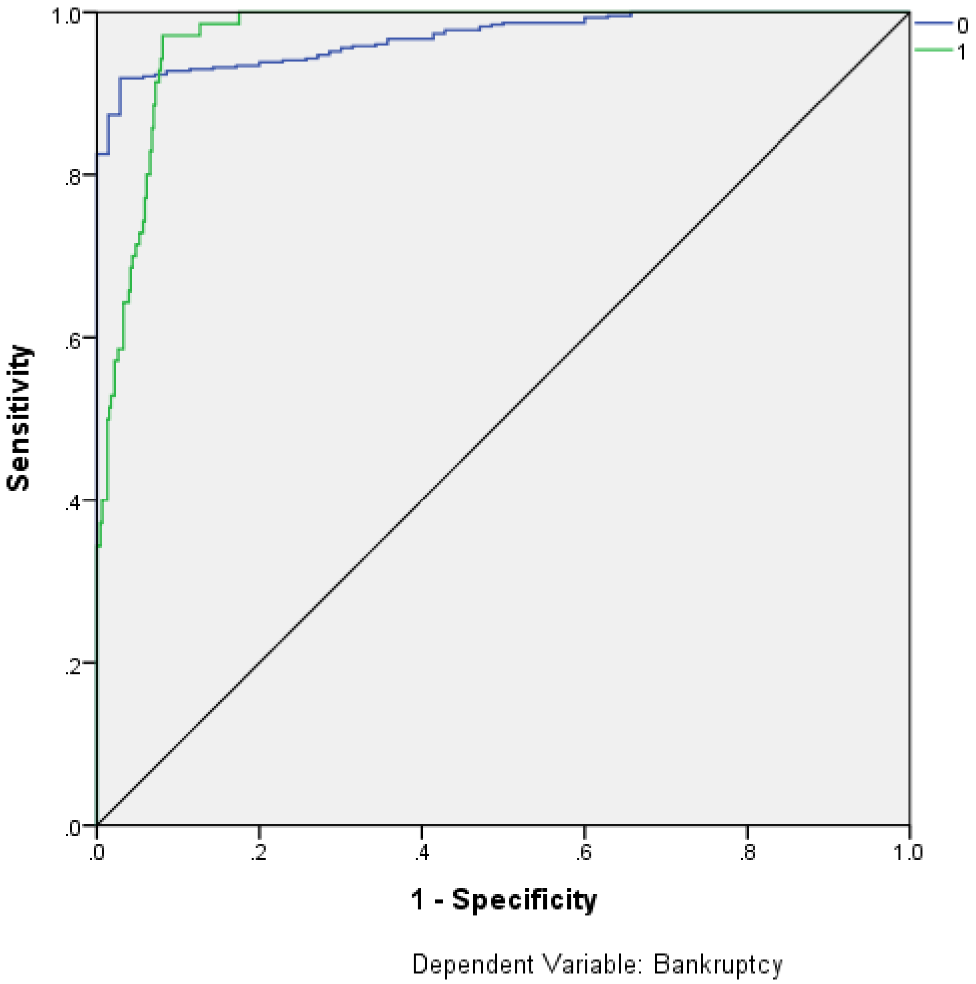
Dependent Variable: Bankruptcy

a. Error computations are based on the testing sample.

Source: SPSS Ver. 24.

The percentage of incorrect predictions at the training phase was 6.8%; while that at the testing phase was 10.5% [The neural network partitioned the data between (70.0%) training and (30.0%) testing]. The figure below shows the ROC:

Figure 4.1: ROC Chart



Source: SPSS Ver. 24.

The ROC curve gives a visual display of the *sensitivity* and *specificity* for all possible cutoffs in a single plot, and this chart is based on the combined training and testing samples. The chart displays two curves, one for the category Bankrupt and one for the category *Non-Bankrupt*.

Table 4.18: Area under the curve

		Area
Bankruptcy	Bankrupt	.970
	Non-Bankrupt	.970

Source: SPSS Ver. 24.

The area under the curve gives a numerical summary of the ROC curve, and the values in the table represent, for each category, the probability that the predicted pseudo-probability of being in that category is higher for a randomly chosen case in that category than for a randomly chosen case not in that category.

Table 4.19: Independent variable importance

	Importance	Normalized Importance
R5	.028	9.4%
R14	.096	32.5%
R16	.076	25.6%
R22	.059	20.0%
R23	.028	9.4%
R25	.041	13.7%
R28	.034	11.6%
R32	.036	12.0%
R34	.297	100.0%
R39	.116	39.0%
R45	.158	53.1%
R47	.031	10.4%

Source: SPSS Ver. 24.

The table shows the importance and normalized importance of each factor in the neural network model; R34 (100%) had the largest normalized importance, following this was R45 with a normalized importance of 53.1%. R39 and R34 had normalized importance of 39.0% and 32.5% respectively.

The following tables provide information on the neural network model developed with corporate governance variables:

Input layer: The input layer had 18 factors (R5: R14; R16; R22; R23; R25; R28; R32; R34; R39; R45; and R47 [Board size; Board structure; CEO duality; Board ownership; Proportion of women directors; Proportion of non-executive directors]). Number of units in the input layer was 18. Rescaling method for covariates: Standardized

Hidden layer: Hidden layer(s) of a neural network contains unobservable units. The value of each hidden unit is some function of the predictors; the exact form of the function depends in part upon the network type. Number of hidden layers 1; Number of units in hidden layer 8; Activation function-Hyperbolic tangent.

Output layer: Number of units 2; Activation function-Softmax: Error function-Cross entropy. The network diagram is shown in Appendix VII.

Table 4.20: Model summary for neural network (Model + Corporate Governance)

Training	Cross Entropy Error	37.111
	Percent Incorrect Predictions	4.3%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.60
Testing	Cross Entropy Error	25.197
	Percent Incorrect Predictions	5.6%

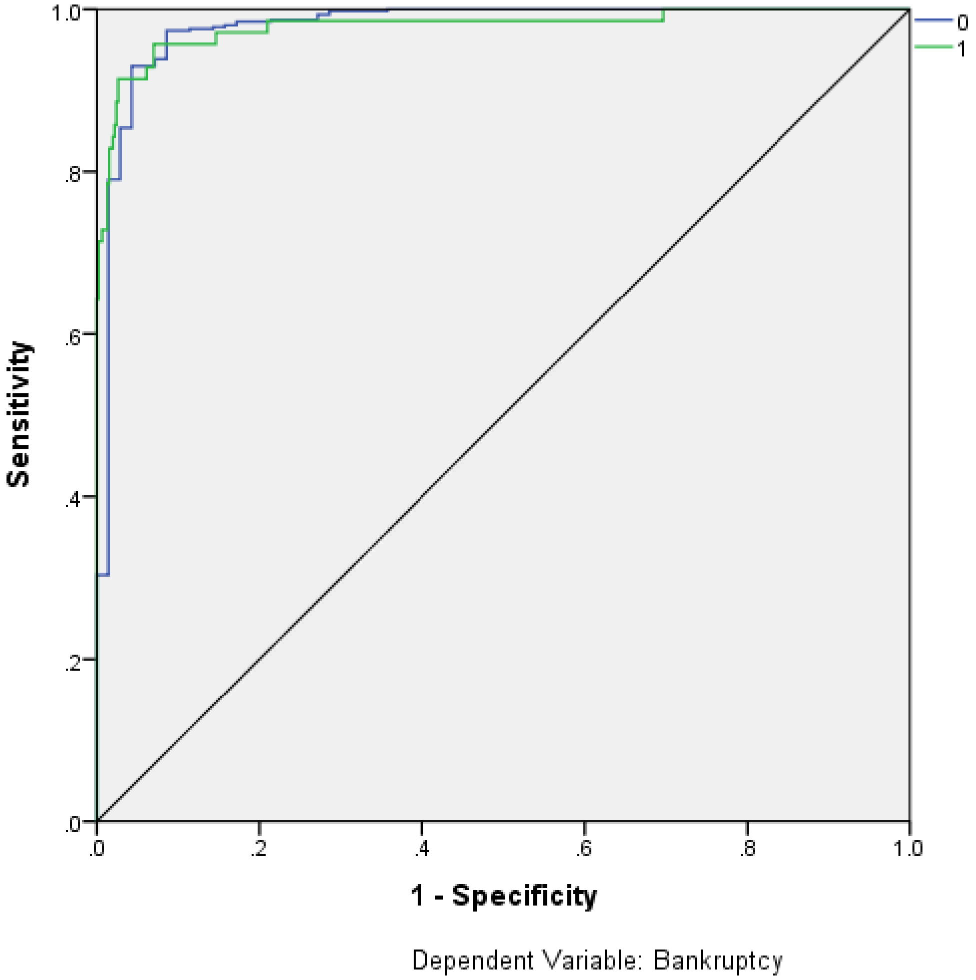
Dependent Variable: Bankruptcy

a. Error computations are based on the testing sample.

Source: SPSS Ver. 24.

The percentage of incorrect predictions at the training phase was 4.3%; while that at the testing phase was 5.6% [The neural network partitioned the data between (70.0%) training and (30.0%) testing]. The figure below shows the ROC:

Figure 4.2: ROC Chart (Model + Corporate governance)



Source: SPSS Ver. 24.

Table 4.21: Area under the curve

		Area
Bankruptcy	Bankrupt	.978
	Non-Bankrupt	.978

Source: SPSS Ver. 24.

The area under the curve showed slight increment when the corporate governance variables were to the neural network model.

Table 4.22: Independent variable importance

	Importance	Normalized Importance
Board size	.039	21.7%
BC	.036	20.0%
Ceo Duality	.022	12.1%
BO	.040	22.5%
PNED	.047	26.3%
PWD	.027	15.2%
R5	.056	31.1%
R14	.044	24.6%
R16	.094	52.8%
R22	.052	29.0%
R23	.044	24.5%
R25	.067	37.4%
R28	.030	16.7%
R32	.097	54.4%
R34	.179	100.0%
R39	.036	20.1%
R45	.051	28.4%
R47	.040	22.5%

Source: SPSS Ver. 24.

The table shows the importance and normalized importance of each factor in the neural network model; R34 (100%) had the largest normalized importance, next was R32 with a normalized importance of 54.4%. Following this was R16 with a value of of 52.8% and R25 with a normalized importance value of 37.4%.

Table 4.23: Comparison of neural network and genetic algorithm model

	Model	Model + Corporate Governance
Neural network [training]	94.4%	95.7%
Neural network [testing]	92.2%	94.4%
Genetic algorithm	96.94%	97.85%

Source: Gretl; RapidMiner Studio Version 7.6; SPSS Ver. 24.

4.4.4 Hypothesis Four

H_1: The predictive accuracy of the GA model can be improved from inclusion of corporate governance variables.

The Genetic Algorithm was developed with the aid of RapidMiner Studio Version 7.6. The parameters of the operators are described below:

Table 4.24: Parameters of the Operators:

Optimize by generation (YAGGA)	
Maximal fitness:	Infinity
Population size:	5
Maximum number:	30
Tournament size:	0.25
Start temperature:	1.0
p initialize:	0.5
p cross over:	0.5
The operator used the heuristic mutation probability	
Cross validation	
Number of folds:	5
Sampling type:	automatic
Gradient Boosted Tress	
Number of trees:	20
Maximal depth:	5
Min rows:	10
Min split improvement:	0
Number of bins:	20
Learning rate:	0.1
Sample rate:	1.0

Source: RapidMiner Studio Version 7.6

Note: Many selection schemes are available for GAs, each with different characteristics. An ideal selection scheme would be, simple to code, and efficient for both nonparallel and parallel architectures. Furthermore, a selection scheme should be able to adjust its selection pressure so as to tune its performance for different domains (Miller & Goldberg, 1995). Tournament selection is increasingly being used as a GA selection scheme because it satisfies all of the above criteria, and therefore used in the study.

Table 4.25: Result of Genetic Algorithm Model

accuracy:	96.94% +/- 2.70%	(mikro: 96.94%)
classification_error:	3.06% +/- 2.70%	(mikro: 3.06%)
spearman_rho:	0.627 +/- 0.124	(mikro: 3.135)
kendall_tau:	0.627 +/- 0.124	(mikro: 3.135)
absolute_error:	0.160 +/- 0.019	(mikro: 0.160 +/- 0.220)
relative_error:	16.04% +/- 1.88%	(mikro: 16.04% +/- 22.03%)
relative_error_lenient:	16.04% +/- 1.88%	(mikro: 16.04% +/- 22.03%)
relative_error_strict:	61.72% +/- 25.08%	(mikro: 61.76% +/- 255.95%)
normalized_absolute_error:	0.185 +/- 0.023	(mikro: 0.185)
root_mean_squared_error:	0.271 +/- 0.024	(mikro: 0.273 +/- 0.000)
root_relative_squared_error:	0.313 +/- 0.029	(mikro: 0.314)
squared_error:	0.074 +/- 0.013	(mikro: 0.074 +/- 0.171)
correlation:	0.627 +/- 0.124	(mikro: 0.627)
squared_correlation:	0.409 +/- 0.139	(mikro: 0.393)
cross-entropy:	0.354 +/- 0.061	(mikro: 0.354)
margin:	0.056 +/- 0.017	(mikro: 0.056)
soft_margin_loss:	0.160 +/- 0.019	(mikro: 0.160)
logistic_loss:	0.364 +/- 0.007	(mikro: 0.364)
Model with corporate governance		
accuracy	97.85% +/- 2.48%	(mikro: 97.85%)
classification_error:	2.15% +/- 2.48%	(mikro: 2.15%)

Source: RapidMiner Studio Version 7.6

The table above showed that the GA model had an accuracy of 96.94%; and a classification error of 3.06% before the inclusion of corporate governance variables; thereafter the classification accuracy slightly rose to 97.85%; and a classification error of 2.15% after the inclusion of corporate governance variables, the null hypothesis is therefore rejected and the alternate accepted. That the “predictive accuracy of the GA model can be improved from inclusion of corporate governance variables”.

4.5 DISCUSSION OF FINDINGS

Studies have used parametric procedures to establish the statistical significance of ratios between bankrupt and non-bankrupt firms. This study employed the t statistics to check for statistical significant difference between the ratios. Studies mainly focus on measures of central tendency, such as the mean, median. Welc (2017) in Poland compared the statistical significance of differences between medians of bankrupt and non-bankrupt firms. In contrast, Slefendorfas (2016) employed correlation and Mann – Whitney U test to select input data.

This study found the following ratios significant in explaining bankrupt and non-bankrupt firms: R5 (Cash Flow from Operations (CFO) / Total Assets); R8 ((CFO + Interest Paid + Taxes Paid) / Interest Paid); R14 (Operating cash flow / Total assets); R16 (EBIT/Total Sales); R17 (Value Added/Total Sales); R22 (Current assets / Total assets); R23 (Current liabilities / Total assets); R25 ((Current assets − Inventory) / Total assets); R28 (Total liabilities / Total assets); R32 (Shareholder Funds/Total Assets); R34 (Net profit / Total assets); R36 (Gross profit / Net sales); R37 (Net profit / Net sales); R38 (Profit before Tax/Shareholder Funds); R39 (EBIT/Total Assets); R45 (Shareholders' equity / Total assets); and R47 (Financial Expenses/Total Sales); thus, 2 cash flow ratios, 3 growth ratios, 3 liquidity ratios, 2 leverage ratios, 5 profitability ratios, 1 for rotation and 1 for index contribution. Thus the profitability ratios were more sensitive to financial distress than any other ratio. Also, of worth mentioning are the liquidity and growth ratios which also had 3 ratios each that were sensitive for each category.

Similarly, studies have shown the dominance of profitability ratios in assessing corporate bankruptcy. For instance, Brédart (2014a) on a sample of U.S. firms showed that profitability, liquidity and solvency were all significant is assessing financial distress probability. In Slovakia, Mihalovič (2016) showed that the most significant predictors were net income to total assets, current ratio and current liabilities to total assets. Ahmadi, Soleimani, Vaghfi, and Salimi (2012) on a sample of firms in Iran showed that variables of net profit to total assets ratio, ratio of retained earnings to total assets and debt ratio were more powerful in bankruptcy prediction. Also, Hassani and Parsadmehr (2012) on a sample of firms in Iran found that variables of debt to equity ratio, net profit to net sales ratio and working capital to assets as significant. Zhou and Elhag (2007) showed that bankrupt firms had lower profitability before failure, and a significant difference in operating efficiency ratio. Islam, Semeen, and Farah (2013) on a sample of firms in Bangladesh, reported that liquidity ratios ranked first before profitability ratios.

Studies done in the banking sector also show similar results. For instance, Yahaya, Nasiru, and Ebgejiogu (2017) in Nigeria found that failed companies were less profitable, less liquid and had lower asset quality. However, the study by Lundqvist and Strand (2013) showed that the predictive ability of ratios varies between years; and in some instances, significant differences between industries occur.

The classification of firms was done using Altman’s Z score model, this is in line with studies which confirm its efficacy. Recently the study by Babatunde, Akeju, and Malomo (2017) on a sample of manufacturing firms in Nigeria, proved that the Z-score model was capable of identifying companies with deteriorating performance. Similarly, Unegbu and Adefila (2013) found that the predictive ability of the Z score model is very strong for manufacturing firms. In China, Wang and Campbell (2010) showed that the Altman’s model has higher prediction accuracy for predicting failed firms. While another recent study by Nwidobie (2017), established the suitability of Altman’s Z score model for the banking industry. The Genetic Algorithm model was developed using a Boosting Ensemble, Gradien Boosted Decision Trees, in contrast, the study by Davalos, Leng, Feroz, and Cao (2009) used bagging to improve the model's generalisation accuracy and to develop a doubly controlled fitness function to guide the operations of the (GA) method.

The ***first hypothesis*** showed that logit model had an accuracy of 93.4% and 93.6% when corporate governance variables were added as explanatory variables. The overall accuracy was far greater than most of the studies reviewed, for instance, the study by Salmistu (2017) for construction companies in Estonia showed an overall classification accuracy of 68.4%. Welc (2017) for firms listed on the Warsaw Stock Exchange, Poland found that logit models with only one ratio as explanatory variable was capable of identifying bankrupt firms in about 66-76% of cases. Brédart (2014a) for firms in U.S. showed an overall prediction accuracy of 83.82%. While in Spain, Bartual, Garcia, Guijarro, and Moya (2013) using logistic regression predicted 88.1% of the cases, while the naïve model had accuracy of 73.5%. The study by Hassani and Parsadmehr (2012) in Iran showed forecast strength of 81.49%, degree of sensitivity is 96.12% and degree of identification as 67.48%. Zhou and Elhag (2007) using data from AMADEUS (Analyse Major Database for European Sources), developed a four-variable logit model with overall prediction accuracy of 81% with cut-off point 0.7. However, Kim and Gu (2006) using data from U.S. hospitality firms reported that there logit models, developed using forward stepwise selection procedures, correctly predicted 91% and 84% of bankruptcy cases for years 1 and 2.

The study by Darayseh, Waples, and Tsoukalas (2003) which combined both macroeconomic and financial variables reported that the model could make correct predictions for 87.82% and 89.50% of the in-sample and holdout samples for 1 year prior to bankruptcy. Similarly, Low, Nor, and Yatim (2001) showed that there model had overall accuracy for the estimation and holdout samples as 82.4% and 90% respectively. While, the study by Han, Kang, Kim, and Yi (2012) on a sample of Korean firms found that there proposed logit model outperformed a Merton-type structural model with a higher prediction power.

The ***second hypothesis*** showed that the discriminant model had an accuracy of 91.1% and 90.9% when corporate governance variables were added. The logit model with overall accuracy of 93.4% and 93.6% therefore outperformed the discriminant model in classification. This is similar to the findings of Mihalovič (2016) in Slovak Republic, where the discriminant model had a total accuracy of 64.41% and the logit analysis a total of 68.64% on the test data. Similarly, Lennox (1999) on a sample of companies in the U.K., showed that the logit model outperformed the discriminant model. In contrast, Barreda, Kageyama, Singh, and Zubieta (2017) on a sample of hospitality firms in U.S showed that MDA outperformed logit in bankruptcy prediction.

The MDA model however showed a high discriminating power of 90% and above for the studied manufacturing firms. This is line with prior studies, for instance by Ani and Ugwunta (2012) confirmed that discriminant analysis has a high predictive ability in assessing financial health of manufacturing, oil marketing and conglomerate sector of Nigerian firms. Gu (2002) on a sample of U.S. restaurant firms, showed a 92-percent accuracy rate in classifying the firms into bankrupt and non-bankrupt groups. The study by Adeyeye and Migiro (2015) on a sample of Nigerian banks showed that discriminant analysis had an overall accuracy of 95.2%. A similar model developed in Lithuania by Slefendorfas (2016) on a sample of manufacturing firms showed an accuracy of 89%.

The ***third hypothesis*** showed that the neural network (MLP) had an accuracy of 94.4% and 95.7% when corporate governance variables were added. Thus, the neural network model outperformed both the logit and discriminant models. In India, the study by Bapat and Nagale (2014) which compared the performance of multiple discriminant analysis, logistic regression and neural network proved that neural network had highest classification accuracy when compared with multiple discriminant analysis and logistic regression. Another study, by Eriki and Udegbunam (2013) in Nigeria, which compared the performance of neural network and multiple discriminant analysis, showed that neural network outperformed discriminant analysis technique for corporate distress prediction.

Yahaya, Nasiru, and Ebgejiogu (2017) using a feed forward back propagation neural network showed an accuracy of approximately 89 percent. Chen and Du (2009) applied the back propagation neural network and K-Means clustering algorithm for bankruptcy prediction in Taiwan. The results showed that the accuracy rate (non-factor analysis) with the BPN model is better than the clustering model.

Kouki and Elkhaldi (2011) compared the performance of multivariate discriminate analysis, logit model and neural network on a sample of Tunisian firms and found that neural network is the most powerful at a very short term horizon. As the firm approaches bankruptcy neural networks were more likely to detect. The study also showed that multivariate discriminate analysis and logit regression were also effective at a medium horizon of two and three years before bankruptcy. In Taiwan, Cheng, Chen, and Fu (2006) compared neural network with logit analysis showed that the radial basis function network outperformed the logit model. The study by Lin (2009) observed that if the data does not satisfy the assumptions of the statistical approach, then artificial neural networks achieve higher prediction accuracy. Multilayer Perceptron (MLP) neural network has been used also in prior studies and proved effective. For instance, Farinde (2013) applied MLP neural network for Nigeria banks and found that it had a significant predictive ability in distress prediction of Nigerian banks.

In contrast, the study by Tseng and Hu (2010) which compared the performance of four models, logit, quadratic interval logit, neural and fuzzy neural reported that the Radial Basis Function neural network outperformed the other models.

The ***fourth hypothesis*** showed that the predictive accuracy of the GA model can be improved from inclusion ocorporate governance variables. The GA model had an accuracy of 96.94%; and a classification error of 3.06% before the inclusion of corporate governance variables; thereafter the classification accuracy slightly rose to 97.85%; and a classification error of 2.15% after the inclusion of corporate governance variables. More so, GA was efficient in determining the best set of predictors for corporate bankruptcy. The study by Hajiamiri, Shahraki, and Barakati (2014) found that GA is highly effective in predicting financial bankruptcy, to the extent it managed to correctly predict the financial bankruptcy of companies two years before the base year, one year before the base year and the base year at accuracies of 96.44, 97.94 and 95.53, respectively. The proposed model by Abdelwahed and Amir (2005) the EBM (Evolutionary Bankruptcy Model) based on genetic algorithms and artificial neural networks showed that the EBM is able of: selecting the best set of predictive variables, then, searching for the best neural network classifier and improving classification and generalization accuracies. This is line with Varetto (1998) whom identified GA as an effective instrument for insolvency diagnosis.

In summary, the study established a significant difference in the predictive accuracy of genetic algorithm compared with the logit, discriminant and neural network models in bankruptcy prediction. The three alternative techniques have different assumptions about the relationships between the independent variables (Back, Laitinen, Sere, & van Wezel, 1996).

Etemadi, Rostamy, and Dehkordi (2009) used GP model and achieved 94% and 90% accuracy rates in training and holdout samples, respectively; while MDA model achieved only 77% and 73% accuracy rates in training and holdout samples, respectively. The models used in the study achieved higher prediction accuracy and possess the ability of generalization when compared with those of Altman, Ohlson, and Zmijewski.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Findings

The study makes the following empirical findings:

1. There is a significant difference in the predictive accuracy of GA compared with the logit model in the prediction of corporate bankruptcy;
2. There is a significant difference in the predictive accuracy of GA compared with the discriminant model in the prediction of corporate bankruptcy;
3. There is a significant difference in the predictive accuracy of GA compared with neural network in the prediction of corporate bankruptcy; and,
4. The predictive accuracy of the GA model can be improved from inclusion of corporate governance variables.

5.2 Conclusion

The study concludes that GA outperforms Logit, Discriminant and Neural Network models for bankruptcy prediction of Nigerian manufacturing firms. The literature has identified an abundance of techniques following studies by Beaver and Altman; however these models differ in their predictive accuracy. More recently, machine learning techniques such as Support Vector Machines (SVM), Neural Networks (NN), Genetic Algorithm (GA), among others have been employed and there predictive accuracy established in several studies. The inclusion of corporate governance variables slightly improved the accuracy of the GA model.

5.3 Contribution to Knowledge

This study contributes to the bankruptcy prediction literature by demonstrating the practicality of a machine learning technique, namely the Genetic Algorithm in the Nigerian context. Prior studies have extensively used Logit or Multiple Discriminant Analysis. The overall performance of the hybrid model was found by informed integration of tools (Alaka et al., 2018). Few studies have dealt with the integration of GA and Decision Trees. The Genetic Algorithm model was integrated with an ensemble method, namely boosting. Boosting adaptively changes the training set based on the accuracy of the previous classifiers. Boosting concentrates on the instances misclassified by the previous classifier. The weight of examples misclassified by the base classifier is increased, while the weight of examples correctly classified is decreased (Freund & Schapire, 1996).

Secondly, in developing the GA model, the study applied Gradient Boosting, specifically Gradient Boosted Decision Trees. Gradient boosting is a sequential classifier and therefore reduces variance and bias. By sequentially applying weak classification algorithms to the incrementally changed data, a series of decision trees are created that produce an ensemble of weak prediction models. While boosting trees increases their accuracy, it also decreases speed and human interpretability. However, gradient boosting method generalizes tree boosting to minimize these issues.

Thirdly, the study also placed emphasis on the inclusion of cash flow ratios. The rationale behind cash flow information is that cash inadequacy, resulting in default on debt obligations, is the main reason for business failure or bankruptcy proceeding (Bhandari, 2014). Majorly, other categories of ratios take into account mainly numbers from financial statements which are prepared on an accrual basis. Therefore, they are deemed to be prone to aggressive accounting. However, in contrast ratios based on cash flow information is deemed to be more immune to manipulations (Welc, 2017). Theoretically, cash flow-based ratios should be more reliable than profit-based ratios. The study therefore considers a vast array of ratios classified under the cash flow category. Researchers have found that various cash flow-based ratios are statistically significant predictors of the forthcoming bankruptcy (Ohlson, 1980; Gentry, Newbold, & Whitford, 1985; Casey & Bartczak, 1985; Ward & Foster, 1997; Bhandari & Iyer, 2013; Unegbu & Adefila, 2013; Khan & Guruli, 2015). Inaddition, the study also adds another category of ratios, namely growth ratios, which are capable of measuring the growth potential of firms.

Fourthly, the inclusion of corporate governance variables also sheds light on the influence of governance variables in bankruptcy prediction. The study, therefore selects in addition to financial ratios, corporate governance variables from a wide array of studies thereby increasing the chances of selecting more optimal predictors over there least optimal counterparts.

Studies have shown a decline in accuracy of the original Altman's Model and Ohlson's Model when used in time periods other than those used to originally develop the models (Wu, Gaunt & Gray, 2010; Grice & Ingram, 2001; Grice & Dugan, 2001). The authors document evidence to show that both models were sensitive to time periods. Therefore, the present study restricted the application of the Z score model to classification, and developed three models the Principal Component Analysis with logit (PCA+logit); Principal Component Analysis with Discriminant Analysis (PCA+MDA); and, Principal Component Analysis with Neural Network (PCA+NN).

5.4 Recommendations

The study makes the following recommendations:

1. The deployment of GA in determining the best set of predictors: GA has demonstrated its efficacy in determining the best set of predictors, the study therefore recommends that future models for particular industries could be built using GA.

2. The use of an alternative model in benchmarking performance and accuracy: A difference was found in the predictive accuracy of several models employed in the study. The study therefore recommends the use of an alternative model, such as;

a. The logit model in benchmarking the performance of a genetic algorithm classifier. However, the use of logisitic regression for benchmarking should involve a comparison of the Bianco and Yohai (BY) estimator and the Maximum Likelihood (ML). Hauser and Booth (2011) recommend that Bianco and Yohai (BY) estimator should be used as a robustness check on Maximum Likelihood (ML) logistic regression. If a difference exists, then BY robust logistic regression should be used as the primary classifier.
b. The discriminant model can also be utilised to evaluate the performance of a genetic algorithm classifier. Multiple discriminant model can also be developed for classification of different classes of firms in line with the original classification by Altman.

3. Establishing the reliability and relevance of a model prior to use: The relevance and reliability of a model should be tested prior to deployment, this would help minimize Type I errors, which is the misclassification of bankrupt firms as non-bankrupt. They are more costly than Type II errors. The use of a training, testing and validation dataset is suggested for several reasons, such as; improving classification accuracy, etc.

5.5 Suggestions for Further Studies

The application of GA could also be extended to other sectors, such as the service sector (banks and insurance companies); also other less investigated sectors, such as the Financial Services, Oil & Gas and Natural Resources could also serve as areas for further investigation. Therefore the proposed model could be evaluated using other datasets. Another question concerns the selection of ratios for inclusion in the model, authors have suggested that indicators of the macro environment and firm size contain important information (Zelenkov, Fedorova, & Chekrizov, 2017); future studies can therefore also consider factors external to the entity as well as corporate governance variables.

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APPENDIX I: Names, ticker and sector of quoted manufacturing included in the sample

S/No	Company Name	Ticker	sector
1	ELLAH LAKES PLC.	ELLAHLAKES	AGRICULTURE
2	FTN COCOA PROCESSORS PLC[RST]	FTNCOCOA	AGRICULTURE
3	LIVESTOCK FEEDS PLC.	LIVESTOCK	AGRICULTURE
4	OKOMU OIL PALM PLC.	OKOMUOIL	AGRICULTURE
5	PRESCO PLC	PRESCO	AGRICULTURE
6	A.G. LEVENTIS NIGERIA PLC.[BMF]	AGLEVENT	CONGLOMERATES
7	CHELLARAMS PLC.[BLS]	CHELLARAM	CONGLOMERATES
8	JOHN HOLT PLC.	JOHNHOLT	CONGLOMERATES
9	S C O A NIG. PLC.	SCOA	CONGLOMERATES
10	TRANSNATIONAL CORPORATION OF NIGERIA PLC	TRANSCORP	CONGLOMERATES
11	U A C N PLC.	UACN	CONGLOMERATES
12	7-UP BOTTLING COMP. PLC.	7UP	CONSUMER GOODS
13	CADBURY NIGERIA PLC.	CADBURY	CONSUMER GOODS
14	CHAMPION BREW. PLC.	CHAMPION	CONSUMER GOODS
15	DANGOTE FLOUR MILLS PLC	DANGFLOUR	CONSUMER GOODS
16	DANGOTE SUGAR REFINERY PLC	DANGSUGAR	CONSUMER GOODS
17	DN TYRE & RUBBER PLC[DIP]	DUNLOP	CONSUMER GOODS
18	FLOUR MILLS NIG. PLC.	FLOURMILL	CONSUMER GOODS
19	GOLDEN GUINEA BREW. PLC.[MRS]	GOLDBREW	CONSUMER GOODS
20	GUINNESS NIG PLC	GUINNESS	CONSUMER GOODS
21	HONEYWELL FLOUR MILL PLC	HONYFLOUR	CONSUMER GOODS
22	INTERNATIONAL BREWERIES PLC.	INTBREW	CONSUMER GOODS
23	MCNICHOLS PLC	MCNICHOLS	CONSUMER GOODS
24	MULTI-TREX INTEGRATED FOODS PLC[BLS]	MULTITREX	CONSUMER GOODS
25	N NIG. FLOUR MILLS PLC.	NNFM	CONSUMER GOODS
26	NASCON ALLIED INDUSTRIES PLC	NASCON	CONSUMER GOODS
27	NESTLE NIGERIA PLC.	NESTLE	CONSUMER GOODS
28	NIGERIAN BREW. PLC.	NB	CONSUMER GOODS
29	NIGERIAN ENAMELWARE PLC.	ENAMELWA	CONSUMER GOODS
30	P Z CUSSONS NIGERIA PLC.	PZ	CONSUMER GOODS
31	UNILEVER NIGERIA PLC.	UNILEVER	CONSUMER GOODS
32	UNION DICON SALT PLC.[BRS]	UNIONDICON	CONSUMER GOODS
33	VITAFOAM NIG PLC.	VITAFOAM	CONSUMER GOODS
34	AFRIK PHARMACEUTICALS PLC.[DIP]	AFRIK	HEALTHCARE
35	EKOCORP PLC.[BMF]	EKOCORP	HEALTHCARE
36	EVANS MEDICAL PLC.[DIP]	EVANSMED	HEALTHCARE
37	FIDSON HEALTHCARE PLC	FIDSON	HEALTHCARE
38	GLAXO SMITHKLINE CONSUMER NIG. PLC.	GLAXOSMITH	HEALTHCARE
39	MAY & BAKER NIGERIA PLC.	MAYBAKER	HEALTHCARE
40	MORISON INDUSTRIES PLC.	MORISON	HEALTHCARE
41	NEIMETH INTERNATIONAL PHARMACEUTICALS PLC	NEIMETH	HEALTHCARE
42	NIGERIA-GERMAN CHEMICALS PLC.[MRS]	NIG-GERMAN	HEALTHCARE
43	PHARMA-DEKO PLC.	PHARMDEKO	HEALTHCARE
44	UNION DIAGNOSTIC & CLINICAL SERVICES PLC[MRF]	UNIONDAC	HEALTHCARE
45	CHAMS PLC	CHAMS	ICT
46	COURTEVILLE BUSINESS SOLUTIONS PLC	COURTVILLE	ICT
47	CWG PLC	CWG	ICT
48	E-TRANZACT INTERNATIONAL PLC[BLS]	ETRANZACT	ICT
49	NCR (NIGERIA) PLC.	NCR	ICT
50	OMATEK VENTURES PLC[MRF]	OMATEK	ICT

Source: Nigerian Stock Exchange Website

APPENDIX I: Names, ticker and sector of quoted manufacturing included in the sample

S/No	Company Name	Ticker	sector
51	TRIPPLE GEE AND COMPANY PLC.	TRIPPLEG	ICT
52	AFRICAN PAINTS (NIGERIA) PLC.[DIP]	AFRPAINTS	INDUSTRIAL GOODS
53	AUSTIN LAZ & COMPANY PLC[MRF]	AUSTINLAZ	INDUSTRIAL GOODS
54	BERGER PAINTS PLC	BERGER	INDUSTRIAL GOODS
55	BETA GLASS PLC.	BETAGLAS	INDUSTRIAL GOODS
56	CAP PLC	CAP	INDUSTRIAL GOODS
57	CEMENT CO. OF NORTH.NIG. PLC	CCNN	INDUSTRIAL GOODS
58	CUTIX PLC.	CUTIX	INDUSTRIAL GOODS
59	DANGOTE CEMENT PLC	DANGCEM	INDUSTRIAL GOODS
60	FIRST ALUMINIUM NIGERIA PLC	FIRSTALUM	INDUSTRIAL GOODS
61	GREIF NIGERIA PLC	VANLEER	INDUSTRIAL GOODS
62	LAFARGE AFRICA PLC.	WAPCO	INDUSTRIAL GOODS
63	MEYER PLC.	MEYER	INDUSTRIAL GOODS
64	PAINTS AND COATINGS MANUFACTURES PLC[DIP]	PAINTCOM	INDUSTRIAL GOODS
65	PORTLAND PAINTS & PRODUCTS NIGERIA PLC	PORTPAINT	INDUSTRIAL GOODS
66	PREMIER PAINTS PLC.[MRF]	PREMPAINTS	INDUSTRIAL GOODS

Source: Nigerian Stock Exchange Website