A COMPARATIVE STUDY OF GENETIC ALGORITHM AND NEURAL NETWORK MODEL IN BANKRUPTCY PREDICTION OF MANUFACTURING FIRMS IN NIGERIA

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Abstract
Previous studies have established the comparative accuracies of statistical failure models in Nigeria. However, the assumptions of these models often limit their practical application. The study, therefore, compares two models developed using AI techniques, the genetic algorithm (GA) and neural network on a sample of quoted manufacturing firms in Nigeria. This study adopts a quantitative approach and utilises a sample of sixty-six (66) companies listed on the Nigerian Stock Exchange (NSE), after excluding firms from the financial, natural, and oil & gas sectors. The study relied on secondary data from annual financial statements. The McNemar test was utilised to compare the accuracies of the two models. The model results showed a significant difference in the classification accuracies of the GA (96.94%; 97.85%) compared with the neural network (92.2%; 94.4%) models. In other words, the GA model outperformed the neural network model in corporate bankruptcy prediction. The inclusion of selected corporate governance variables also improved the accuracy of the models. The results demonstrate the practicality of using GA in a different context from prior western studies with different regulatory and institutional regimes.

Keywords: Bankruptcy, Genetic Algorithm, Neural Network, Corporate Governance.

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 (Mukkamala, Tilve, Sung, Ribeiro, & Vieira, 2006; Kim & Han, 2003; McKee & Lensberg, 2002).

In light of this, bankruptcy has remained a dominant topic of interest in accounting, auditing, and finance for the past three decades (Cheng, Chen, & Fu, 2006). And models have emerged from the 60’s till date (Altman, 1968; Adnan Aziz, & Dar, 2006). Past models are 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, recent studies have 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).

The techniques evolved along with advancements in computer systems, and are capable of providing better solutions for complex problems, such as bankruptcy prediction (Mukkamala, Tilve, Sung, Ribeiro, & Vieira, 2006). The popular ones include inductive learning methods, neural networks, support vector machines, genetic algorithms, among others (Alaka et al., 2018; Shin & Lee, 2002). Prior studies have employed Genetic Algorithms (GA) to develop hybrid models because of its capability in extracting optimal rules that can be integrated into any system and higher accuracy than individual models (Kirkos, 2015; Martin, Madhusudhnan, Lakshmi, & Venkatesan, 2011; Shin & Lee, 2002; Back, Laitinen, & Sere, 1996a,b).

The GAs have been applied in a wide range of applications (Shin & Han, 1999; Colin, 1994), such as trading systems (Deboeck, 1994), stock selection (Mahfoud & Mani, 1995), bankruptcy prediction (Shin & Lee, 2002), etc. The GA is an optimization tool that does not rely on any distributional assumptions about the variables (Kuri-Morales & Aldana-Bobadilla, 2013; Nanda & Pendharkar, 2001). Studies that utilise the GA, reports that in most instances it outperforms other techniques (Bateni & Asghari, 2016), and can handle the influence of human 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 were delisted voluntarily. Against this backdrop, the study develops a model using GA and compares it to a neural network model for bankruptcy prediction of Nigerian manufacturing firms.

1.2 Statement of the Problem

The obnoxious state of the Nigerian manufacturing sector has created a dire need for accurate prediction models for forecasting the failure outcomes of companies. Prior studies have 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), while few have investigated the manufacturing sector (Hur-Yagba, Okeji, & Ayuba, 2015; Ani & Ugwunta, 2012). Despite the success of traditional statistical models they are often subject to certain assumptions, such as linearity, normality, multicollinearity, among others (Dimitras, Zanakis, & Zopounidis, 1996; Back, Laitinen, & Sere, 1996a,b). 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). And, the 'high-dimensional' properties of data affect the classification accuracies of traditional statistical models (Zhang & Wu, 2011).

However, recently from the 90's there has been a heightened use and application of artificial intelligence to bankruptcy prediction problems, with Neural Networks (NNs) being among the first (Alaka et al., 2018; Atiya, 2001; Wilson & Sharda, 1994, Serrano-Cinca, 1993; Coats & Fant, 1993). Prior studies have confirmed the superiority of NNs to discriminant or logistic technique in the Nigerian context (Eriki & Udegbunam, 2013; Farinde, 2013), for banks (Yahaya, Nasiru, & Ebgejiogu, 2017; Farinde, 2013), investment interest rate (Enyindah & Onwuachu 2016), the stock market (Eriki & Udegbunam, 2013), and insurance companies (Ibiwoye, Ajibola, & Sogunro, 2012).

Studies have under-investigated the application of AI to the subject of bankruptcy prediction in Nigeria. The obvious lack of empiricism on the subject stemmed the researcher's interest in the subject. A recent study identifies the GA as a data mining technique that contributes to decision-making (Lin, Ke, & Tsai, 2017) and provides new insights into bankruptcy prediction (McKee & Lensberg, 2002). In addition, the inclusion of corporate governance variables in GA feature selection has been under-investigated. According to Brédart (2014b), studies should be directed to this under-investigated aspect of corporate bankruptcy. Thus, the addition of corporate governance variables may (or may not) improve the predictive power of bankruptcy models (Platt & Platt, 2012; Lajili, & Zéghal, 2010; Chang, 2009; Fich & Slezak, 2008; Donoher, 2004).

1.3 Objective of the Study

The broad objective of the study is to compare the predictive accuracy of genetic algorithm and neural network models in predicting corporate bankruptcy of Nigerian manufacturing firms. The study specifically examines the following:

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

1.4 Statement of Hypotheses

The hypotheses are stated in the alternate form as follows:

H_1: There is a significant comparative difference in the predictive accuracy of GA and the neural network model in predicting corporate bankruptcy.

H_2: The predictive accuracy of the GA model cannot be enhanced from inclusion of corporate governance variables.

2.0 Literature Review

2.1 Historical Perspective on Bankruptcy Prediction Models (BPMs)

The evolution of BPMs cannot be discussed without recourse to the studies by the Bureau of Business Research (BBR) (1930), Ramser and Foster (1931), Fitzpatrick (1932), Smith and Winakor (1935), Merwin (1942), Chudson (1945), Jackendoff (1962). Beaver (1966) is regarded as the pioneer in univariate analysis. The univariate analysis emphasizes 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 – a firm is classified as failing or non-failing. Despite its simplicity, 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).

Another limitation of the approach is 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). 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 the classification accuracy of the univariate model may be (much) lower when the model is used in a predictive context (i.e. 'ex-ante') (Balcaen & Ooghe, 2004a). The limitation of the approach led to the development of 'risk index', which includes different ratios (Tamari, 1966; Moses & Liao, 1987). The major drawback of this approach was its subjective nature 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). And, in the '80s logistic regression was introduced and applied by Ohlson (1980).

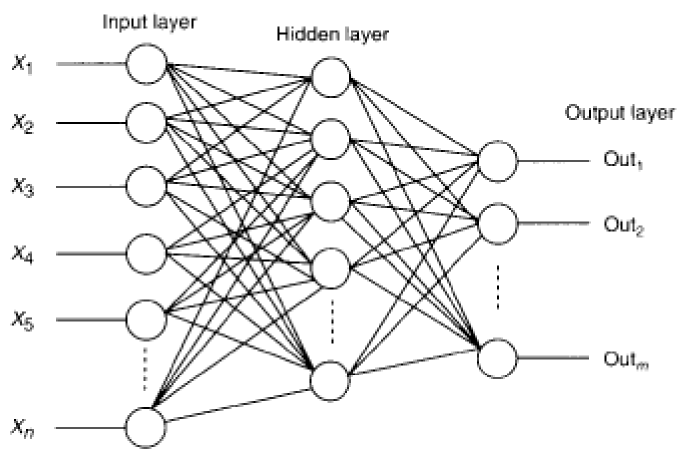
Broadly, bankruptcy prediction models are divided into parametric and non-parametric. Parametric models focus on symptoms of bankruptcy and could be univariate or multivariate (Adnan Aziz & Dar, 2006). The non-parametric models are mainly multivariate, based on machine learning which depends heavily 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). 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 models, 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; 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).

2.2 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 several simple, highly interconnected processing elements which process information by their dynamic state responses to external inputs" (Caudill, 1989; Hecht-Nielsen, 1988). NNs have the most practical effect in the following three areas: modelling and forecasting, signal processing, and expert systems (Lippmann, 1987). NNs learn and adapt from a data set, and can capture non-linear relationships between variables.

Figure 1: A Neural Network Architecture



Source: Back, Laitinen, and Sere (1996); Panda, Chakraborty, and Pal (2008)

Let $I_p = (I_{p1}, I_{p2}, \ldots, I_{pl})$, p = 1,2, . . . ,*N* be the *p*th pattern among *N* input patterns. Where w_{ji} and w_{kj} are connection weights between the *i*th input neuron to the *j*th hidden neuron, and the *j*th hidden neuron to the *k*th 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 $f(x) = 1/(1 + e^{-x})$.

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 process of working towards an appropriate mapping is also called 'convergence' (Coats & Fant, 1993). The method of neural networks is based on 'supervised' learning (Balcaen & Ooghe, 2004b).

There are several NNs methods, such as backpropagation (Dwyer, 1992), SOF-self organizing map (Alam, Booth, Lee, & Thordarson, 2000). However, the major 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 advantages include, first, NNs can analyse complex patterns quickly and with a high accuracy level (Shachmurove, 2002) and they can learn from examples, without any pre-programmed knowledge (Back, Laitinen, & Sere, 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; Tucker, 1996; Cybinski, 2000; Shachmurove, 2002). Thirdly, non-numeric data can easily be included in 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). NNs tolerate errors and missing values by making use of 'filling in the gaps'. In addition, NNs overcome the problem of autocorrelation, which frequently arises in time series data (Hawley, Johnson, & Raina, 1990; Cybinski, 2000). Fifthly, the NN technique can be considered user-friendly as it offers a clear 'failure/non-failure' output.

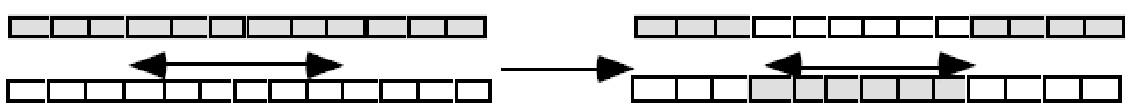
The application of NNs to bankruptcy prediction is linked to Messier and Hansen (1988), Odom and Sharda (1990), Coats and Fant (1993), Guan (1993), Tsukuda and Baba (1994), and Altman, Marco, and Varetto (1994). In predicting company failure, NNs are robust to smaller sample sizes and highly adaptable than many other techniques (Cybinski, 2000). However, 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). They are also 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 low generalizing ability.

2.3 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). GA is an evolutionary computing model based on stochastic, adaptive search methods for an optimal solution (Davalos, Leng, Feroz, & Cao, 2009). GA simulates Darwinian evolution and relies on bio-inspired operators; such as *mutation*, *crossover* and *selection* (Mitchell, 1998; Back, Laitinen, & Sere, 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 some 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* (Back, Laitinen, & Sere, 1996). Three genetic operators are mostly used in these algorithms: reproduction, crossover, and mutation (Etemadi, Rostamy, & Dehkordi, 2009).

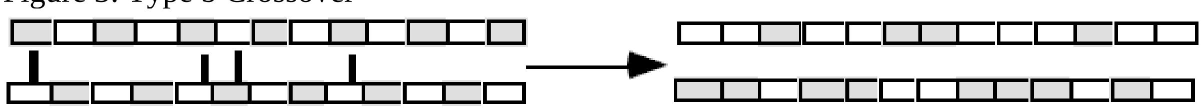
1. Reproduction: The reproduction operator simply chooses an individual in the current population and copies it without changes into the new population (Etemadi, Rostamy, & Dehkordi, 2009). It is a process in which strings are copied onto the next generation. Strings with a higher fitness value have 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 into 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, 1996a,b).
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, 1996a,b). This operator must ensure respect for the depth limits. If a condition is violated the too-large offspring is simply replaced by one of the parents. Other parameters specify the frequency with which internal or external points are selected as crossover points (Etemadi, Rostamy, & Dehkordi, 2009).

Figure 2: 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 3: 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. This operator aims to introduce 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

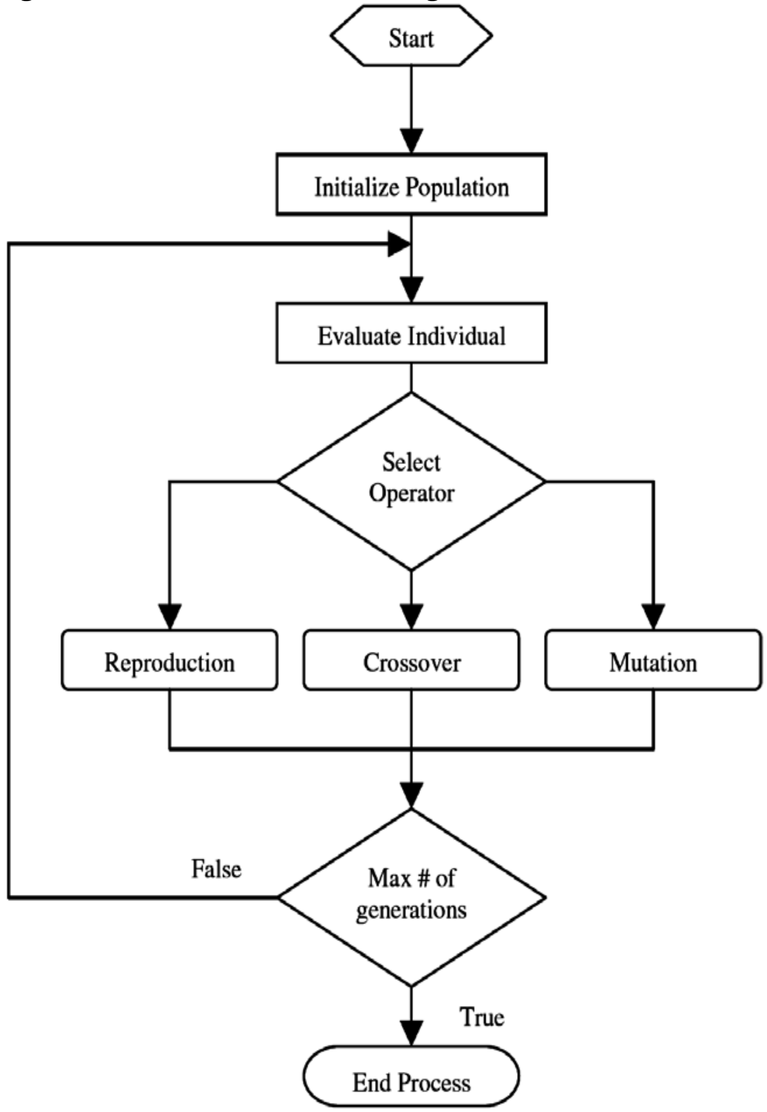
mutation is to be carried out, a new function node (not necessarily with the same arity) is chosen, and the original node together with its relative subtree is substituted by a new randomly generated subtree. A depth ramp is used to set bounds on size when generating the replacement subtree. Naturally, 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 4: 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 into any system (Kirkos, 2015; Martin, Madhusudhnan, Lakshmi, & Venkatesan, 2011; Shin & Lee, 2002; Back, Laitinen, & Sere, 1996a,b). 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 limitation of GAs includes the large number of parameters to be included which requires significant computational resources from a very large number of function calls (Schreyer, 2006).

Figure 5: 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.

2.4 Corporate Governance

Studies have shown that corporate governance plays 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; 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.

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

diversification of the expertise (Zahra & Pearce, 1989). 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 of technically unsophisticated firms.
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 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 four board committees greatly influence corporate activities: audit, executive, compensation, nomination committee. 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. **The 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 having just a female director on the board reduces the risk of bankruptcy by 20%. Studies have shown that the presence of women directors, instils new governance practices (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).
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 in bankruptcy (Eisenhardt, 1989).
6. **Board Independence.** From an agency perspective, a greater proportion of outside directors on boards acts as monitors in situations where conflict of interest may arise (Jackling & Johl, 2009). According to Weisbach (1988), independent directors are in a better position to monitor the actions of the CEO. 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.

Table 1: Major studies using Genetic Algorithm

Authors	Year	Method	Findings
Zelenkov, Fedorova, and Chekrizov	2017	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	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 outperform T1FLS
Chou, Hsieh, and Qiu	2017	They used a fuzzy clustering algorithm for the classifier design, which was compared with a backpropagation neural network. Experimental results based on one to four years of financial data before the occurrence of bankruptcy were used to evaluate the performance of the proposed model.	The proposed model performed significantly well.
Bateni and Asghari	2016	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	The study used a K-means clustering algorithm on a sample of 24 A-share companies listed in the Shanghai Stock Exchange and Shenzhen Stock Exchange.	The K-means clustering algorithm based on a genetic algorithm is more accurate than the traditional clustering algorithm.

Authors	**Year**	**Method**	**Findings**
Min	2016a	Applied four different learning algorithms to 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 confirmed that the model outperformed other models in the study.
Min	2016b	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	The 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	A comparison between GA and binary logistic regression.	The results showed that GA outperformed logistic regression.
Gordini	2014	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	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	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.
Gaspar-Cunha, Recio, Costa,	2014	They applied a multi-objective evolutionary algorithm,	The experimental results proved the utility of using

Authors	**Year**	**Method**	**Findings**
and Estébanez		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 self-adaptation of the classifier.
Poorzamani and Nooreddin	2013	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	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, and the type I error of GA is higher.
Kim and Kang	2012	They proposed a genetic algorithm-based coverage optimization technique to resolve multicollinearity problems.	The results indicate that the proposed coverage optimization algorithm can help to design a diverse and highly accurate

Authors	Year	Method	Findings
			classification system.
Jeong, Min, and Kim	2012	They applied a 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	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 a 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	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	They employed GA in predicting bankruptcy in Iran.	The results showed that GA can be used to predict bankruptcy in Iran.
Galveo, Becerra, and Abou-Seada	2002	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.

Authors	Year	Method	Findings
Shin and Lee	2002	Proposed a GA approach that can be applied to bankruptcy prediction modelling.	The preliminary results showed that the rule extraction approach using GAs for bankruptcy prediction modelling is effective.
McKee and Lensberg	2002	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	They developed GA which incorporates asymmetric Type I and Type II error costs. The model was compared with linear discriminant analysis (LDA), a 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	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	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: Empirical Literature Reviewed, 2019

3.1 Methodology

The study followed a quantitative approach and utilised 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.

3.2 Sample Size

The final sample comprised of sixty-six (66) companies selected via 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 number of firms classified by sectors included in the final sample is shown in table 1 below:

Table 1: Distribution of companies by sector

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 (2019)

3.3 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.

3.4 Methods of Data Analysis

3.4.1 Predictor Variables

The common approach in bankruptcy prediction studies is to review the literature and identify a large set of potential predictive financial and/or non-financial variables. The study applied a two-stage procedure for variable selection: first, 47 variables were selected from the literature. The selected variables were computed using information obtained from the annual reports of the companies. Secondly, the variables were subjected to an Exploratory Factor Analysis using Principal Component Analysis (PCA). This technique reduces the number of random variables under consideration (Davalos, Leng, Feroz, & Cao, 2009). EFA is 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 variances in the variables being used (Dunteman, 1989). The selected financial variables identified in the first stage, with their labels are shown in table 2 below:

Table 2: Financial ratios utilised in model development

Category	Ratio	Label
Index Activity	Net sales / Average net assets	R1
	Net sales / Average total fixed assets	R2
	Net sales / Average equity	R3
Index Cash flow	Cash Flow from Operations (CFO) / Sales	R4
	Cash Flow from Operations (CFO) / Total Assets	R5
	Cash Flow from Operations (CFO) / Current Liabilities or Cash Flow from Operations (CFO) – Dividends Paid / Current Liabilities	R6
	Cash Flow from Operations (CFO) / Long Term Debt or Cash Flow from Operations (CFO) – Dividends Paid / Long Term Debt	R7
	(CFO + Interest Paid + Taxes Paid) / Interest Paid	R8
	Cash Flow from Operations (CFO) / (CFO + Cash from *Investing Inflows* + Cash from *Financing Inflows*)	R9
	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
	Retention rate of earning reinvested (RR) x Return on Equity (ROE)	R18
	Dividends declared / Operating income after taxes	R19
	Retained earnings / Total assets	R20
Index Liquidity/Solvency	Current assets / Current liabilities	R21
	Current assets / Total assets	R22
	Current liabilities / Total assets	R23
	(Current assets – Inventory) / Current liabilities	R24
	(Current assets – Inventory) / Total assets	R25
	Net annual sales / Average receivables	R26
	Cost of goods sold / Average trade payables	R27
Index Leverage	Total liabilities / Total assets	R28
	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	Net profit / Total assets	R34
	Net profit / Equity	R35
	Gross profit / Net sales	R36

Category	**Ratio**	**Label**
	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
	Shareholders' equity / Total assets	R45
	Market Value of Equity/Book Value of Liability	R46
Index Contribution	Financial Expenses/Total Sales	R47

Source: Adnan Aziz and Dar (2006); Altman (1968); Bellovary, Giacomino, and Akers (2007); Etemadi, Rostamy, and Dehkordi (2009); Min (2016a,b,c)

Table 4: Corporate governance variables

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 Error Rates

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). The table shows the relationship among these three error rate types. The formula for each error rate is listed as follows:

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

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

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

Table 5: Relationship between Type I, II, & Total Error Rates

		Prediction		
		Normal	**Bankruptcy**	**Sum**
	Normal	Y_1	Y_2	Y_3
Actually	**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.

4.0 Data Analysis and Results

Table 6: 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, 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). 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).

The results showed 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). PCA with varimax orthogonal rotation was carried out to assess the underlying dimensions of the provided items for financial ratios (Delen, Kuzey, & Uyar, 2013). The rotation method used was Varimax with Kaiser Normalization:

1. **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.

2. **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.

3. **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.

4. **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.

5. **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.

6. **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.
7. **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.

8. **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.

9. **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.

10. **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.

11. **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.

12. **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.

13. **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.

14. **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 a high factor loadings value of 0.931 respectively.

15. **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.

16. **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.

4.1 Test of Hypotheses

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

H_2: The predictive accuracy of the GA model can be improved from inclusion of corporate governance variables.

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].

Table 7: 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 normalized importance of 53.1%. R39 and R34 had normalized importance of 39.0% and 32.5% respectively. The table below provides information on the neural network model developed with the addition of corporate governance variables. 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].

Table 8: 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 9: 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: RapidMiner Studio Version 7.6; SPSS Ver. 24.

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

Table 10: Parameters of the GA Operator

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 to tune its performance for different domains. Tournament selection is increasingly being used as a GA selection scheme because it satisfies all of the above criteria, and is therefore used in the study.

Table 11: 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 the inclusion of corporate governance variables".

4.2 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 statistically significant differences between the ratios. Studies mainly focus on measures of central tendencies, 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 in 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 that were 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 that 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 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, Gradient 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 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 the 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 backpropagation 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 the bankruptcy. In Taiwan, Cheng, Chen, and Fu (2006) compared the neural network model 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 ***second hypothesis*** showed that the predictive accuracy of the GA model can be improved from the inclusion of corporate 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. 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 can select the best set of predictive variables, then, search for the best neural network classifier and improve classification and generalization accuracies. This is in line with Varetto (1998) who identified GA as an effective instrument for insolvency diagnosis. In summary, the study established a significant difference in the predictive accuracy of the genetic algorithm compared with the neural network model in bankruptcy prediction. The techniques have different assumptions about the relationships between the independent variables (Back, Laitinen, & Sere, 1996a,b).

5.1 Conclusion and Recommendations

The study concludes that GA outperforms the 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 their predictive accuracy established in several studies. The inclusion of corporate governance variables slightly improved the accuracy of the GA model. 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. Based on these, the study recommends the following that 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. And, the use of an alternative model in benchmarking performance and accuracy.

Notably, a difference was found in the predictive accuracy of the models employed in the study. However, 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.

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