ENHANCED RECESSION FORECASTING USING ARTIFICIAL NEURAL NETWORK ALGORITHM

BY

NDUBUISI JUSTICE EZIRIM (B. Tech.)

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CERTIFICATION

This is to certify that this work "**Enhanced Recession Forecasting using Artificial Neural Network Algorithm**" was carried out by Ndubuisi Justice Ezirim with Registration Number 20144914818 in partial fulfilment for the award of degree of Master of Science (M.Sc) in Information Management Technology, in the Department of Information Management Technology, Federal University of Technology Owerri.

Prof. G. E. Nworuh Supervisor	25/10/18 Date
Engr. Dr. O.C. Nwokonkwo HOD, IMT	29/11/18 Date
Prof. C. C. Ibe Dean, SMAT	5/12/18 Date
Prof. (Mrs.) Nnenna N. Oti (Dean, PGS)	Date
Prof. T. O. Oyebisi External Examiner	Date

DEDICATION

To Jehovah the Grand creator, the giver of life and every good and perfect present, who made it possible for me not to give up despite the travails and exigencies of this academic endeavor. To my parents Mr. and Mrs. Damian Ndubuisi Robinson, my siblings, my dear, beautiful wife and favorite field service partner.

And especially to my beloved daughter Nneoma Pearl Ezirim.

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ABSTRACT

Recession is a global concern, as nations, industries and individuals are affected. Application of machine learning in finance is not novel, it strength in this field is shown in this thesis. Several literature on the use of artificial neural network and key financial indicators were "x-rayed" with the peculiar nature of the Nigerian state at the background. From the thirty one variables initially taken from the Central bank of Nigeria statistics portal and the Nigerian Bureau of Statistics and subjected to a genetic algorithm, twelve most correlated variables to economic growth from four sectors were used. These were used to train and test the Neural Network algorithm and then compared with known regression and generalized linear model results. Findings from this study revealed that Artificial Neural Network outperformed the other models in terms of speed of prediction, robustness of algorithm and accuracy. The algorithm developed is able to make monthly recession forecasts after being trained and tested with Data from 2010 to 2017. The performance of the neural network far outweighed the Regression and the Generalized Linear model as its Mean Square Error was approximately 4 while the generalized neural network was 25 and was 14 for the regression model.

KEYWORDS: Artificial Neural Network, model, recession probability, performance indicators, machine learning.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the Study

Neural networks are state-of-the-art, trainable algorithms that emulate certain major aspects in the functioning of the human brain. This gives them a unique, self-training ability, the ability to formalize unclassified information and, most importantly, the ability to make forecasts based on the historical information they have at their disposal (Roghani, 2015). An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems function. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems (Aleksander and Morton, 1995). ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is also true of ANNs as well (Roghani, 2015).

Hardesty (2017), notes that neural nets are a means of doing machine learning, in which a computer learns to perform some task by analyzing training examples. Usually, the examples have been hand-labeled in advance. Modeled loosely on the human brain, a neural net consists of thousands or even millions of simple processing nodes that are densely interconnected.

Artificial neural networks are forecasting methods that are based on simple mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors. Guoqiang, Eddy and Hu (2008), adds that interest in using artificial neural networks

(ANNs) for forecasting has led to a tremendous surge in research activities in the past decade. While ANNs provide a great deal of promise, they also embody much uncertainty.

Simple mathematical models cannot be used to describe exactly certain processes due to their higher complexity (Jorge, Mariana and Pedro, 2010). In fact, most economic or financial interactions cannot be elucidated by a simple stepwise algorithm or a precise formula, particularly when the data are complex or noisy. ANNs allows an accurate description of those kind of complex processes, offering new advantages over traditional algorithms as the possibility of a model, prediction and optimize results (Jorge et al., 2010).

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions (Aleksander and Morton, 1995).

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly (Jiménez et al., 2008).

Kasabov (1996) on the other hand adds that conventional computers use a cognitive approach to problem solving; the way the problem is to be solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency.

According to Jack (1999), neural networks offer a number of advantages, including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms.

The field of neural network technology has been extensively studied in the last decade. This has led to considerable research on its use in various scientific applications and to the development of a diverse range of business applications. Consequently, an increasing amount of application efforts have concentrated on their development in the finance sector (Bo and Yakup, 1998).

Roghani (2015), adds that neural networks have been used increasingly in a variety of business applications, including forecasting and marketing research solutions. In some areas, such as fraud detection or risk assessment, they are the indisputable leaders. The major fields in which neural networks have found application are financial operations, enterprise planning, trading, business analytics and product maintenance. Neural networks can also be applied gainfully to recession probability forecasting using correct recession predictors.

The International Monetary Fund (IMF), states that "Global recessions seem to occur over a cycle lasting between eight and 10 years. A global annual real GDP growth of 3.0 percent or less in their view was "...equivalent to a global recession." By this measure, six periods since 1970 qualify: 1974–1975, 1980–1983, 1990–1993, 1998, 2001–2002, and 2008–2009. During what IMF in April 2002 termed the past three global recessions of the last three decades, global per capita output growth was zero or negative, and IMF argued—at that time—that because of the opposite being found for 2001, the economic state in this year by itself did not qualify as a *global recession* (Lall, 2008).

In April 2009, IMF changed their Global recession definition to:

- *A decline in annual per-capita real World GDP (purchasing power parity weighted), backed up by a decline or worsening for one or more of the seven other global macroeconomic indicators: Industrial production, trade, capital flows, oil consumption, unemployment rate, per-capita investment, and per-capita consumption* (Davis, 2009; WHO,2009).

By this new definition, a total of four global recessions took place since World War II: 1975, 1982, 1991 and 2009. All of them only lasted one year, although the third would have lasted three years (1991–93).

A significant decline in economic activity spread across an economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales is recession (NBER, 2016). One of the main causes of financial recession is failure of policymakers in tighten regulations and the dishonesty of financial institutions (Stiglitz, 2008). Many economists agree that the main factor that leads to financial crisis is liberalization of financial markets and lack of control and regulations over the financial institutions and their activities towards risk taking (Dudovskiy, 2013). Tropeano (2010) adds that the roots of the financial crisis and the main causes that lead to recession were low interest rates that encouraged excessive borrowing by the investors.

Afe (2016) adduces the dangers of an economy that is largely based on oil revenue. The drop in Oil prices from about $100 per barrel to less per barrel portends lots of ills for the Nigerian economy that is largely based on Oil generated revenue. This dependence coupled with the huge cost of running and maintaining our political structure was always a recipe for disaster.

Macroeconomic indicators such as GDP (gross domestic product), investment spending, capacity utilization, household income, business profits, and inflation fall, while bankruptcies and the unemployment rate rise. Recessions generally occur when there is a widespread drop in spending (an adverse demand shock). This may be triggered by various events, such as a financial crisis, an external trade shock, an adverse supply shock or the bursting of an economic bubble (Afe, 2016).

1.2 Statement of Problem

The prediction of the start of next recession is important to central bankers, investors and government policy makers who make their current decisions and planning based on the prediction of the economy in the future. However this prediction has so far been found to be difficult because financial and economic data are mostly non-linear, non-stationary and noisy. It is rare for economists, particularly those at an investment banks, to forecast a recession. For a start, it is difficult to get it right; a recession is by definition is a change in trend and economists tend to extrapolate from past ones.

Economists are good at measuring the past but inconsistent at forecasting future events, particularly recessions. That's because recessions are not caused merely by concrete changes in the markets. Gross domestic product is usually sustained by prolong fiscal expansion which when limited by high level of public debt forces economies to surrender their monetary policy sovereignty. Prediction of recessions is an important as well an arduous job that requires careful model selection and underlying estimation algorithms. Extensive empirical research reveals that business cycle fluctuations are asymmetric thus requiring a novel paradigm.

Application of artificial neural networks in recession probability forecasting is not novel but its application is primarily done mostly using time series data. Recession in developing nations adopts a different measurement metrics compared to developed nations with advanced data collection techniques. Focus on leading indicators — statistics about economic variables that may have preceded recessions are often used to appraise recession, with the goal of prediction. These kinds of correlations can sometimes be useful in forecasting, but they provide little understanding of why major changes are taking place. Leading indicators don't usually address ultimate causes, nor do econometric models that try to predict events. Ah-Hin and You-Beng (2016) notes that the main approach in the literature focuses on finding the recession probability as a function of time, and use the probability to predict recession. As the recession variable will take the value of one if there is recession and zero otherwise, the mean of the binary variable exceeding half becomes an indication that the economy will tend to go towards recession.

Many analysts, however, arbitrarily narrow their focus to a small set of candidate variables, a prior, to find a best model specification. Therefore, logically, the model so chosen can only be the best within the limited combinations of variables that were examined. Since a broader, larger number of economic indicators exist every month and quarter, a better approach would be to examine a large set of indicators in order to find a best model globally. This would allow the data to speak for itself without the prior bias of the analysts to limit results to expected outcomes. While it is impossible to incorporate all possible variables, it becomes imperative to examine the best model that can subsist while encompassing a large number of data set and predictors; especially in developing countries where the data collated are not as qualitative and quantitative as those of developed countries. In applying machine learning's artificial neural network a broader set of predictors that are available is utilized in the modeling process together with recession probability time function to achieve more sensitive forecasts (Ah-Hin and You-Beng, 2016).

1.3 Aim and Objectives of the Study

The aim of this study is to design and implement an improved artificial neural network algorithm for recession probability forecasting. To achieve this aim, the specific objectives would be:

1. To identify leading financial and economic indicators that precursors recession in zdeveloping countries and identify performance indicators of a forecast model or algorithm

2. To evaluate an existing statistical/economic model using the identified precursors.

3. To design, implement and test run the enhanced artificial neural network for recession probability forecasting.

4. To evaluate the enhanced machine learning system based on the identified performance indicators.

1.4 Research Questions

In relation to the specific objectives of this study, the following research questions serves to guide this study.

1. What are the key performance measures for making a recession forecast?
2. To what extent does the existing statistical or economic model not measure up with identified performance indicators?
3. To what extent have the novel artificial neural network (ANN) modeled the relationship between the leading indicators and the probability of a future recession?
4. To what extent have the novel artificial neural network (ANN) performed to measure up with required standard of performance indicators?
5. What policy recommendations can be made?

1.5 Scope of Study

This study utilizes financial and economic indicators used in predicting the current recession in Nigeria. Data from several sectors of the economy like inflation, Gross Domestic Product (GDP), Oil and non-oil sectors, were used to make forecasts but using Artificial neural network with a view to comparing prediction of ANN with the statistical method used and thus make early warning of economic contraction which usually precursors a recession.

1.6 Limitation of Study

Artificial neural networks are algorithms that can be used to perform nonlinear statistical modeling and provide a new alternative to logistic regression, the most commonly used method for developing predictive models for dichotomous outcomes. Given the following strengths: the advantage of requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithm a study of this nature would be expected to use multiple training algorithm. But this thesis would not employ multiple training algorithms or detect all possible interaction between all the economic and financial predictors. Also because of the "black box" nature of ANN and it being prone to over fitting which can make it produce unreliable predictions multiple trainings were not done.

1.7 Significance of the Study

Recent research activities in artificial neural networks (ANNs) have shown that ANNs have powerful pattern classification and pattern recognition capabilities. Currently, ANNs are being used for a wide variety of tasks in many different fields of business, industry and science (Widrow et al., 1994). One major application area of ANNs is forecasting (Sharda, 1994). ANNs provide an attractive alternative tool for both forecasting researchers and practitioners. Several distinguishing features of ANNs make them valuable and attractive for forecasting. Global economies are usually guided by economic and financial performance indicators which are supposed to be timely, accurate and being amenable to sensitivity analysis so as to guide post budget policy thrust and prevent economic contraction. Hence the thesis would be useful first to government and its agencies for advance economic contraction warnings, to the academic as a contribution to the existing body of knowledge and to the private and non-governmental organizations.

1.8 Organization of Thesis

Chapter one introduces the Artificial Neural Network and recession, established the research focus in its statement of problem, showed the significance, scope and relevant objectives including research questions. The chapter two dealt with the body of literature existing on the subject, provided conceptual, theoretical and empirical frame works relevant to this thesis. The methodology adopted, data, analysis procedure performance indicators to be measured are found in the third chapter. While in chapter four the results and analysis of the proposed enhanced machine learning algorithm for recession probability forecasting. Final chapters would include summary of the findings, conclusion relevant recommendation and contribution to knowledge.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Conceptual Framework

2.1.1 Historical Development of Artificial Neural Networks

In 1986, the modern era of neural networks was ushered in by the derivation of back propagation. In the short ten years since the rewriting of parallel distributed processing (Rumelhart and McClelland, 1986), an enormous amount of literature has been written on the topic of neural networks.

The history of neural networks can be traced back to the work of trying to model the neuron. The first model of a neuron was by physiologists, McCulloch and Pitts (1943). The model they created had two inputs and a single output. McCulloch and Pitts noted that a neuron would not activate if only one of the inputs was active. The weights for each input were equal, and the output was binary. Until the inputs summed up to a certain threshold level, the output would remain zero. The McCulloch and Pitts' neuron has become known today as a logic circuit.

The perceptron was developed as the next model of the neuron by Rosenblatt (1958); he randomly interconnected the perceptrons and used trial and error to randomly change the weights in order to achieve "learning. According to Anderson and Rosenfeld, (1987), McCulloch and Pitts' neuron is a much better model for the electrochemical process that goes on inside the neuron than the perceptron, which is the basis for the modern day field of neural networks. The electrochemical process of a neuron works like a voltage-to-frequency translator (Anderson and Rosenfeld, 1987). The inputs to the neuron cause a chemical reaction such that, when the chemicals build to a certain threshold, the neuron discharges. As higher inputs come into the neuron, the neuron then fires at a higher frequency, but the magnitude of the output from the neuron is the same.

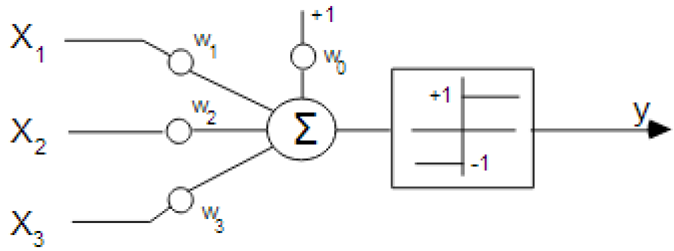


Figure 2.1: Schematics of the perceptron

Selfridge (1958) brought the idea of the weight space to the perceptron. Rosenblatt adjusted the weights in a trial-and-error method but Selfridge adjusted the weights by randomly choosing a direction vector. If the performance did not improve, the weights were returned to their previous values, and a new random direction vector was chosen. Selfridge referred to this process as climbing the hill, this today is referred to as “gradient decent” as it generally tends to reduce the error squared between the response elicited and the desired response.

Widrow and Hoff (1960) developed a mathematical method for adapting the weights. Assuming that a desired response existed, a gradient search method was implemented, which was based on minimizing the error squared. This algorithm became known as Least Mean Squared, LMS whose application has been extensive these last few years. This gradient search method provided a mathematical method for finding an answer that minimized the error. The learning process was not a trial-and-error process anymore. Although the computational time decreased with Selfridge's work, the LMS method decreased the amount of computational time even more, which made use of perceptrons feasible.

At the peak of neural network research in the 1960’s, the newspapers were agog with articles promising that robots could think because it seems that the perceptron could solve any problem. But Minsky and Papert, (1969) in their book “Perceptrons”, fizzled out the research on neural networks when it demonstrated that perceptron's could only solve linearly separable problems. It notes that a perceptron is a single node thus in order to solve an n-separable problem, n-1 nodes are needed. A perceptron could then only solve a 2-separable problem, or a linearly separable problem.

Werbos (1974) was first to develop the back propagation algorithm. It was then independently rediscovered by Parker (1985) and by Rumelhart and McClelland (1986), simultaneously. Back propagation is a generalization of the Widrow-Hoff LMS algorithm and allowed perceptrons to be trained in a multi-layer configuration, thus an n-1 node neural network could be constructed and trained. The weights are adjusted based on the error between the output and some known desired output. The birth of backward propagation reenergized research in Neural Networking.

In backward propagation, the weights are adjusted backwards through the neural network, starting with the output layer and working through each hidden layer until the input layer is reached. The back propagation algorithm changes the schematic of the perceptron by using a sigmoidal function as the squashing function. Earlier versions of the perceptron used a signum function. The advantage of the sigmoidal function over the signum function is that the sigmoidal function is differentiable. This permits the back propagation algorithm to transfer the gradient information through the nonlinear squashing function, allowing the neural network to converge to a local minimum.

Neural Networks have been applied successfully in engineering, medical science, business and economics because of their pattern recognition ability. Kuan and White (1994) discussed neural networks and their applications in economics. Swanson and White (1995, 1997 a, 1997) found usefulness of neural network models in economic time series data pertaining to interest rate unemployment rate and GNP among others. Hutchinson et al. (1994) employed neural networks in option pricing, and Garcia and Gencay (2000), and Qi and Midala (1999) in stock market predictions. Similarly, Vishwakerma (1995), and Qi (2001) used neural networks for business cycle turning points and recessions, respectively.

The scores of literature considered portends an array of machine learning theories, algorithms and models which highlights the applicability of machine learning to recession probability forecasting. This study builds from its conceptual framework thus:

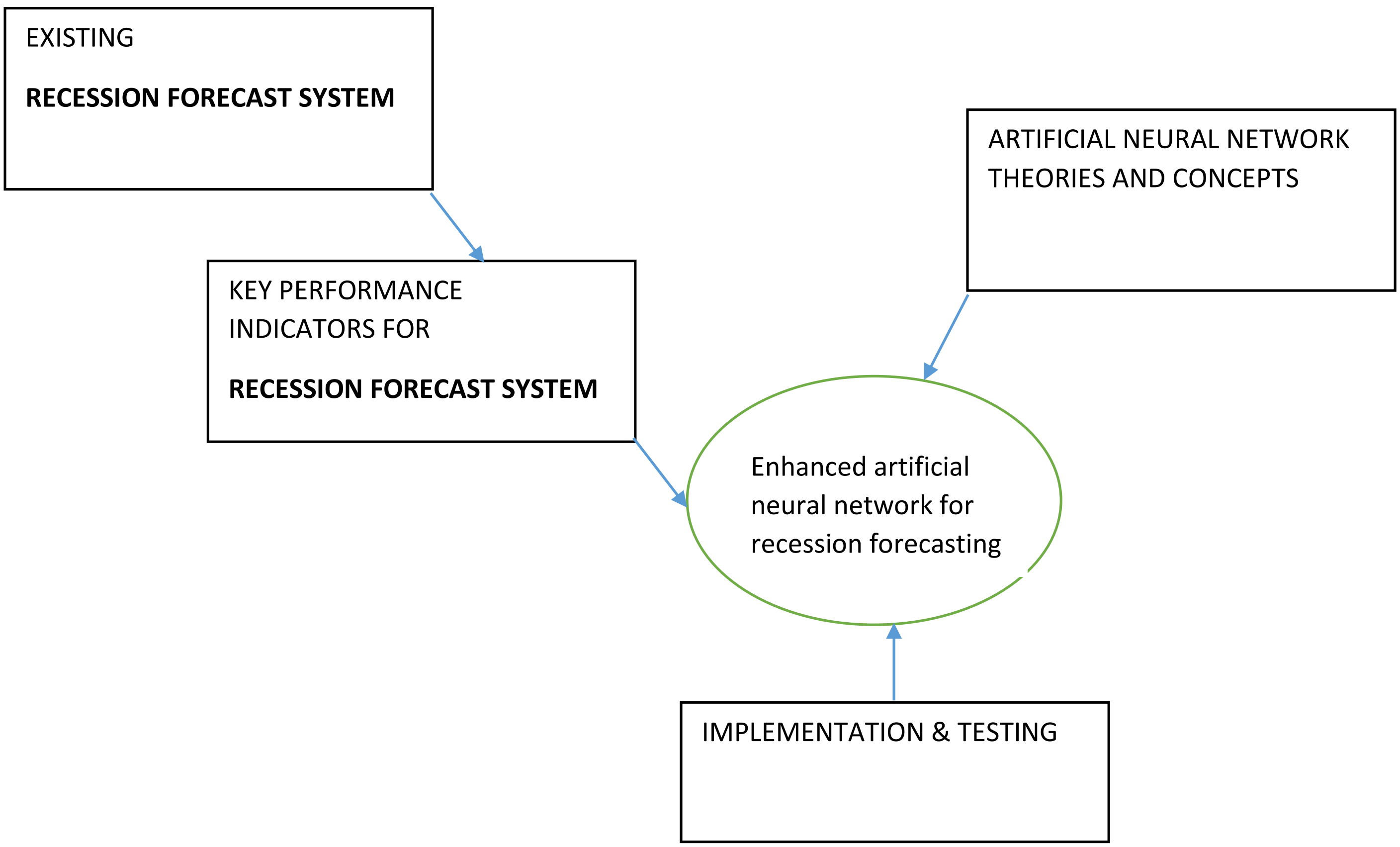


Figure 2.2 Conceptual Framework of the study

The aim of this study is designing an improved machine learning algorithm for quick recession forecasting, this is achievable through identifying probable performance indicators. The concept provides for enhancing the existing system, on this premise the improved algorithm would exist.

2.1.2 Key Recession Indicators

2.1.2.1 Consumer Price Index

Limam (2015) studied the association between Consumers Price Index and GDP and provided empirical evidences from Ordinary Least Square (OLS) and Granger Causality Test Model that a positive and significant relationship between the GDP and CPI and also that a unidirectional causality running from Inflation to economic growth. The influence of inflation on the economic growth has been a debatable issue among economists in both theoretical and empirical sides.

Mallik and Chowdhury (2001) their study concluded with two basic outcomes: First, the empirical finding revealed positive and significant relationship between inflation and economic growth of Bangladesh, Pakistan, India and Sri Lanka. Second, the possibility of inflation to fluctuate in growth is greater than that of growth to fluctuate in inflation.

Gokal and Hanif (2004) employed diverse economic theories in order to discover the linkages between inflation and economic growth of Fiji. The findings revealed a scrawny negative relationship exists between CPI and GDP. The causality test indicates a one-way run from GDP to inflation.

Shahzad (2011) recognized a positive and significant correlation between inflation and economic growth in Pakistan. While Iqbal and Nawaz (2009) conclude that 6 percent level of inflation is better for economic growth and above 6 percent has negative and significant correlation with economic growth. Umaru and Zubairu (2012) documented that all variable under investigation were stationary. Granger Causality test indicated that GDP grange cause inflation and not vice versa. The findings exposed a positive effect between economic growth and inflation through encouraging productivity and output level and by development of total factor productivity.

2.1.2.2 Fuel Pump Price

It is a common knowledge today that fuel scarcity worsens inflation and poverty in Nigeria and many workers will lose their jobs as companies will find it difficult to cope. Arinze (2011) itemized the effect as follows:

i. Fuel crisis paralyzed social and economic activities, it brings about socio-economic unrest which result in increase in transport fare, sky rocketing of market prices and prices of building materials.

ii. High rate of inflation: this leads to increased spending both by government and private individuals. Fuel scarcity creates inflation in both public and private life with a consequent increase in prices of goods and services.

iii. Excessive corruption and mismanagement: Fuel crisis bring about corruption by both government and private individual. Corruption however, discourages foreign direct investment.

iv. Retardation in economic growth: It slows down the pace of economic development because of its negative impact on the socio-economic life of the people.

Olorunfemi (2012) predicted that inflation rate would fluctuate between 13 and 14 per cent for most part of 2012. An investment and research firm, Renaissance Capital said it expected inflation to rise from a projected 10 per cent to between 13 and 14 per cent between January and March and average about 15 per cent for the year, 2012. It, however, said that should the government be persuaded to phase the removal of petrol subsidy as a means of easing the burden of price increases, then the increase in inflation could be lesser than 15 per cent for the year. The inflation rate had been a source of worry for the Central Bank of Nigeria, which struggled throughout 2011 to reduce the figure to a single digit rate. Nigeria’s inflation rates experienced a wavy flow for most parts of

2011, from January till December 2011. Although, the National Bureau of Statistics attributed the development to the upward and downward movement in the prices of food items, it also linked the movement to increase in the price of kerosene across the country.

Ocheni, (2015) adds that the inflationary figure for January 2011 was 12.1 per cent as against 11.8 per cent recorded in December 2010. This, according to the NBS, was due to hike in the price of kerosene experienced across the country and increase in the prices of some household items and building materials. In the month of February, inflation declined to 11.1 per cent. As the country was trying to regain its balance, the rate yet increased to 12.8 per cent in March, the highest in the year, as a result of the major determinant, according to the monthly release by NBS. April inflation rate was put at 11.3 per cent which was slightly lower than the 12.8 recorded in March. There was a huge jump again in May from 11.3 per cent recorded earlier to 12.4 per cent. The statistical data in May revealed that the percentage increase which was higher than the corresponding level a year ago was as a result of the planting season in the country. In June, the inflation reduced to 10.2 per cent as against the corresponding month which was 12.4 per cent (Ocheni, 2015).

Onwuka, Chiekezie & Igweze (2013) asserted that the causes of price instability is attributed to scarcity caused by refinery maintenance and rehabilitation problem, low capacity utilization, supply, and demand inequality. The political change that Nigeria went through, which turned over the administration and endured a lingering economic down turn is enough reason to cause price instability of oil products in Nigeria. The author opined that trailing oil products prices down to crude oil prices has revealed that the instability in the prices of oil products was due to cost of refining, storing, transporting distributing and inefficiencies in the process.

Ayadi (2005) stated that the single most important issue confronting a growing number of world economies today is the price of oil and its attendant consequences on economic output. He notes that several studies have investigated the effect of oil price shocks on levels of gross domestic product. He focused his paper primarily on the relationship between oil price changes and economic development via industrial production. A vector auto regression model was employed on some macroeconomic variables from 1980 through 2004. The results indicate that oil price changes affect real exchange rates, which, in turn, affect industrial production. However, this indirect effect of oil prices on industrial production is not statistically significant. Therefore, the implication of the results presented in this paper is that an increase in oil prices does not lead to an increase in industrial production in Nigeria. Farzanegan and Markwardt (2009), stated that due to the high dependence on oil revenues, oil price fluctuations had a special impact on the Iranian economy. Unexpectedly, the authors noted that they could not identify a significant impact of oil price fluctuation on real government expenditures. Furthermore, the response of inflation to any kind of oil price shocks is significant and positive.

2.1.2.3 Money supply (M1)

Economists differ on the effect of money supply on economic growth. While some agreed that variation in the quantity of money is the most important determinant of economic growth, and that countries that devote more time to studying the behaviour of aggregate money supply rarely experience much variation in their economic activities (Handler 1997). Steve (1997) and Domigo (2001), explain that there may not be possibility of economic growth without an appropriate level of money supply, credit and appropriate financial conditions in general.

Ikhide and Alawode (1993) while evaluating the effect of Structural Adjustment Programme (SAP) concluded that reducing money stock through increased interest rates would lower gross National product. Thus, the notion that stock of money varies with economic activities applies to the Nigerian economy (Laidler 1993).

2.1.2.4. Broad Money (M2)

The study of Chude and Chude (2016) evaluated the effect of money supply within the institutional framework and basic theoretical model on economic growth of Nigeria for the periods 1987 to 2010. The study used secondary data obtained main stream publications of central bank of Nigeria. The findings based on the empirical analysis albeit, support that aggregate money supply is positively related to economic growth. This in turn suggests that efforts should be made by government to ensure appropriate policy mix for harmony and proper coordination of economic policies and greater attention directed to M2.

Chuku (2009) worked on measuring the effects of monetary policy innovations in Nigeria. He found evidence that monetary innovations carried out on the quantity-based nominal anchor (M2) has modest effects on output and prices with a very fast speed of adjustment. The study concludes that manipulation of the quantity of money (M2) in the economy is the most influential instrument for monetary policy implementation. He recommends that central bankers should place more emphasis on the use of the quantity-based nominal anchor rather than the price-based nominal anchors.

2.1.2.5 All Share Index

Popoola (2014) opined that the stock market promotes economic growth and development, his results indicated that there is a positive relationship between economic growth and the stock market development variables. He established positive links between the stock market development and economic growth, and suggests the pursuit of policies geared towards rapid development of the stock market.

Olowe (2008) credits the Nigerian All-share Index to favourably compete with that of the developed economies around the globe. Ime (2013) notes that the performance of the Nigeria Stock market and its capitalization with other world stock markets using All-share index and the Dow-Jone representing the world markets and the New York stock market index in particular for the year ended 2003 showed that out of 98 world economics, Nigeria was ranked 31st representing 55 percent (55%).

2.1.2.6 Exchange Rate

Exchange rates and the choice of the exchange rate regime retain a centre stage in the post crisis environment especially for emerging economies (Klein and Shambaugh 2010; Rose 2011; Ghosh et al. 2014). There is a relatively large body of literature suggesting a correlation between the real exchange rate and GDP growth.

Hausmann et al. (2005) demonstrate that rapid growth accelerations are often correlated with real exchange rate depreciations. Rodrik (2008) Önds that the growth acceleration takes place, on average, after ten years of steady increase in undervaluation in developing countries. Di Nino et al. (2011) also conclude that there is a positive relationship between undervaluation and economic growth for a panel dataset covering the period 1861-2011.

2.1.2.7 Export

The conclusion from the literature is that the effects of exports on economic growth is transmitted through their impact on economies of scale, including improving allocation of resources, enhancing greater inflows of FDI and technology transfers, improving managerial and workers' skills, enhancing capital formation, enhancing job creation, and enhancing productive capacity of the economy (About-Stait 2005, Konya, 2004).

Depending on the econometric model, data frequency, and the country or region studied, export is causing growth, growth is causing export, there is bidirectional causality, and there is no causality (Konya 2004). The link between export and growth may also depend on the level of the country's economic development (About-Stait 2005). Chen (2007) in a study on Taiwan used the Granger causality test, Vector Error Correction (VECM), and the Bounds testing methodology to investigate the link between export and economic growth, and find empirical evidence in support of a bidirectional causality between export and economic growth.

2.1.2.8 Import

Yuhong et al. (2010) did co-integration analyses with the data of import, export and economic, and the results suggests that growth of import greatly promoted economic growth of China. The findings of Afaf and Majeed (2015) clarified that import and GDP are found stationary at the first differences. Therefore, the variables were found to be integrated of order one. The co-integration test confirmed that GDP and import are co-integrated, indicating an existence of long run equilibrium relationship between all the variables under study as confirmed by the Johansen (1998) co-integration test results. The error correction models test confirmed that there exist short run causality between GDP and imports.

2.1.2.9 Crude Oil Price

Olomola (2006) studied the effect of oil price shock on aggregate economic activities in Nigeria, the findings showed that while oil price significantly influenced exchange rate, it did not have significant effect on output and inflation in Nigeria. He thus concluded that an increase in the price of oil results in wealth effects which appreciates the exchange rate.

Aliyu (2009), assessed the impact of oil price shock and real exchange rate volatility on the real gross domestic product, the result of the long-run analysis indicated that a 10.0 percent increase in crude oil prices increased the real GDP by 7.72 percent, similarly a 10.0 percent appreciation in exchange rate increased GDP by 0.35 percent. The short-run dynamics was found to be influenced by the long-run equilibrium condition. He recommended the diversification of the economy and infrastructural diversification.

2.1.2.10 Lending Rate

Udoka and Ayingang (2012) investigated the effect of lending rate fluctuation on the economic growth of Nigeria, their findings revealed that there existed an inverse relationship between interest rate and economic growth in Nigeria, meaning that increase in lending rate will decrease GDP of the country, thus retarding growth of the real sector. Obamuyi and Olorunfemi (2011) examined the implications of financial reform and lending rate behavior on the economic growth in Nigeria and revealed that financial reform and interest rates have significant impact on economic growth in Nigeria; also, results implied that the interest rate behavior is important for economic growth.

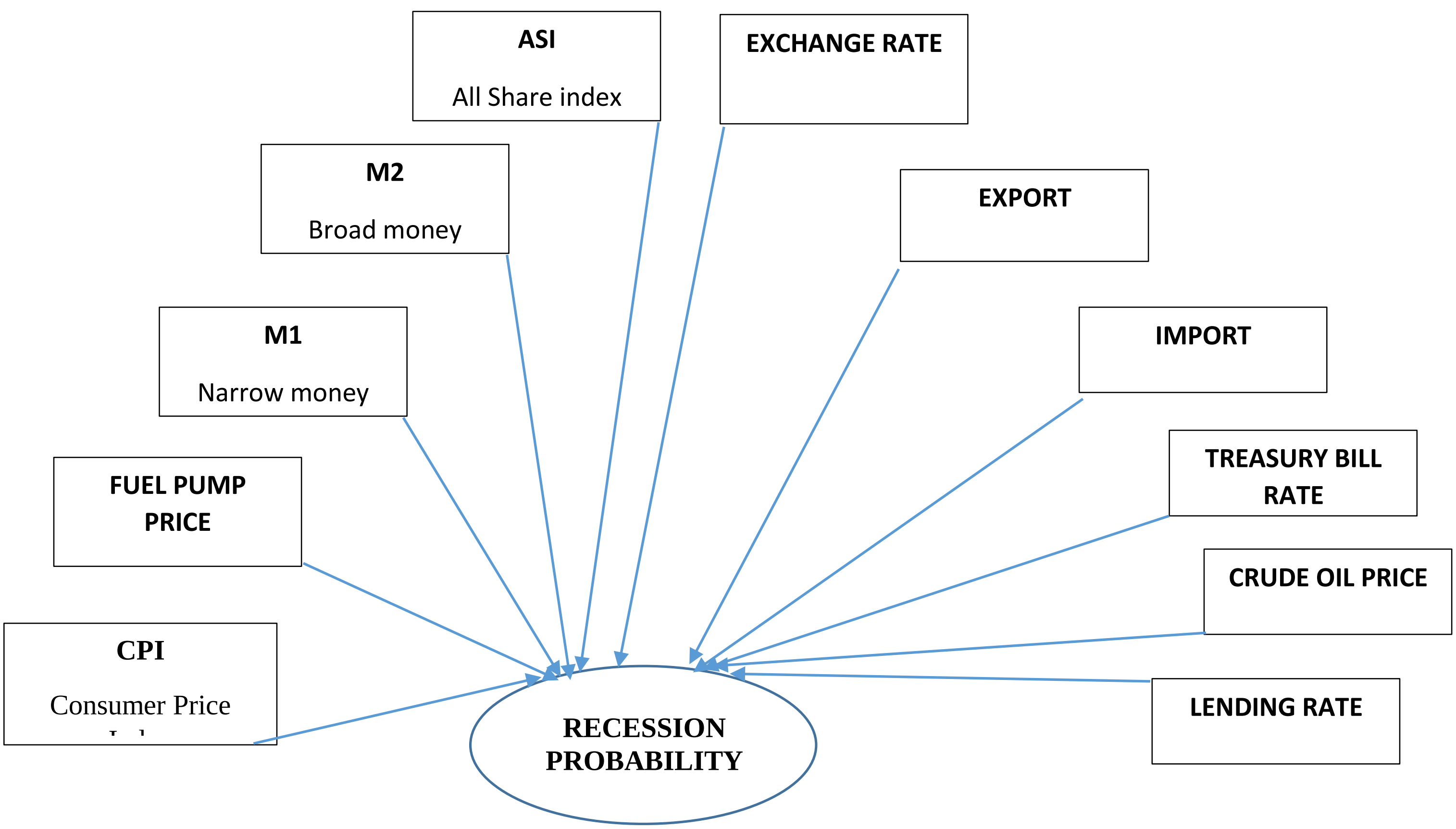


Figure 2.3: model for recession forecasting in Nigeria

2.2 Theoretical Framework

Certain concepts form the basis of Artificial Neural Networks, these are the basic building blocks. Processing of artificial neural networks hinges on the following: Network Topology, Adjustments of Weights or Learning, Activation Functions.

2.2.1 Theories, Concepts, Model Approach and Technology

A neural network consists of nodes (input nodes and neurons, or input nodes and computation nodes), synaptic connections, and functional connections. As far as connection types are concerned, there are two types of neural networks, i.e., feed forward network and feedback network. Feedforward networks are functional mapping networks and usually used for pattern recognition, function approximation and prediction (Haykin, 1994; Yan and Zhang, 2000; Fecit, 2003). Feedback neural networks are used as association memorizers and optimization tools. In a feed forward network, every neuron receives the inputs from the last layer and yields outputs for the next layer and there is not any feedback. A feedback network can be redrawn as an undigraph in which each connection is bidirectional.

In a feedback neural network all nodes are computation nodes, and each node has ($n-1$) inputs and one output if the total number of nodes is n. There are two phases in the workflow of a neural network:

(1) **Learning phase.** The states of all computation nodes are constant and the connection weights can be adjusted through learning process.

(2) **Working phase.** Connection weights are constant during this phase and the states of computation nodes change to achieve stable states.

2.2.2 Architecture of Artificial Neural Networks

2.2.2.1. The Neuron

The neuron is the basic building block of the neural network. A neuron is a communication conduit that both accepts input and produces output. The neuron receives its input either from other neurons or the user program. Similarly, the neuron sends its output to other neurons or the user program (Chakravarthy, 2011).

a. One-input neuron

The architecture of a one-input neuron is indicated in figure 2.4. The mathematical expression of the one-input neuron is

$$y = f(wx + b) \qquad \text{eqn. 1}$$

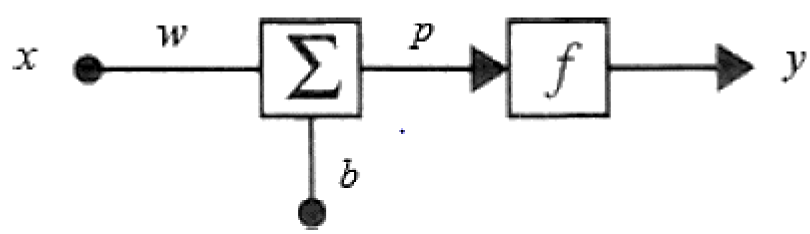


Figure 2.4: schematics of one-input neuron

where *w* = the weight of input *x*; *b* = bias; *y* = output; *f* = transfer function. In this expression, the output of accumulator, $p = wx+b$, is also called net input of transfer function *f* . Addition of a bias, *b*, can increase the adaptability of neurons and neural networks.

b. Multiple-input neuron

The architecture of a multiple-input neuron is indicated in Figure 2.5. The mathematical expression of the multiple-input neuron is

$y = f\sum(w_{1i}x_i + b)$ eqn. 2

where w_{1i} = the connection weight of source neuron i to target neuron 1,

$i = 1, 2, \ldots, n$; b = bias; y = output; f = transfer function.

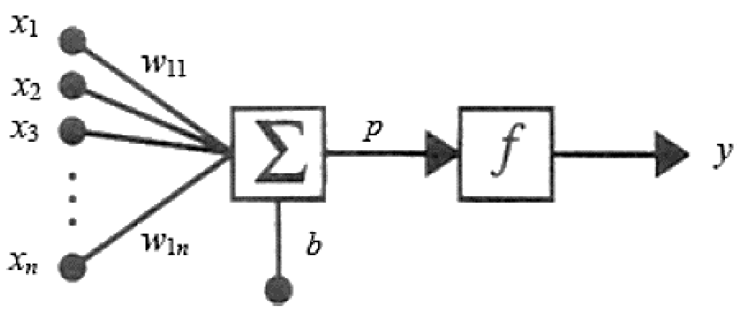


Figure 2.5: schematics of a Multiple-input neuron. There are *n* inputs for the neuron

The architecture of the multiple-input neuron (*n* inputs) can be briefly represented by a simpler illustration, as indicated in Figure 2.6.

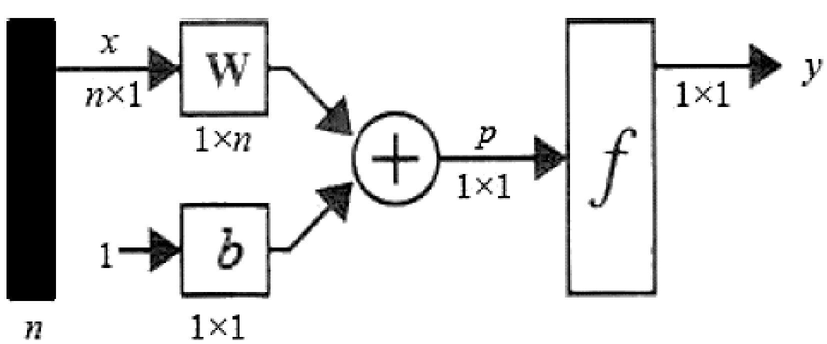


Figure 2.6: The simpler representation of a multiple-input neuron.

In this representation x is a $n \times 1$ input vector; w is the $1 \times n$ weight vector; b, p and y are scalar constant and variables.

2.2.2.2. Types of Artificial Neural Networks

There are four basic types of Neural Networks shown below in figure 2.7:

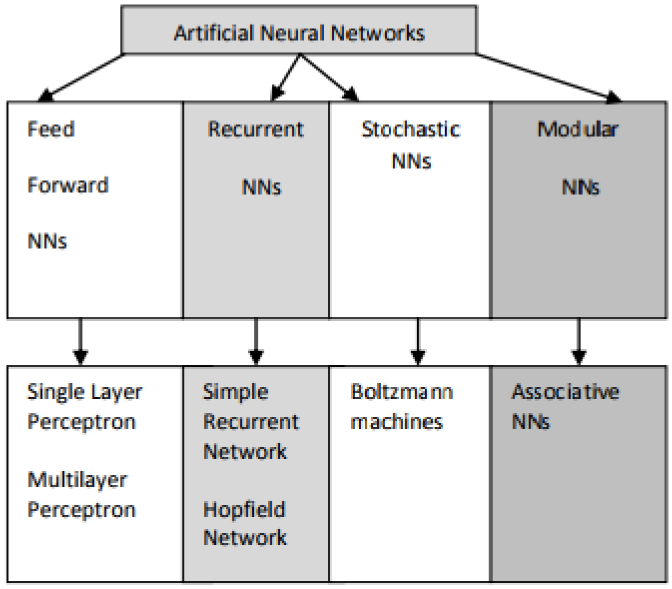


Figure 2.7: Taxonomy of neural network architectures

1. Feed-forward Neural Networks

These are the first and simplest type of ANNs. In these networks, the information moves in only one direction, forward from the input nodes, through the hidden nodes and to the output nodes (Sibanda and Pretoriu, 2012). There are no cycles or loops in the network. Examples of feed-forward NNs are one or single layer perceptron (SLP) and multi-layer perceptron (MLP).

a. One-layer feed forward neural network

A neuron with multiple inputs is not enough to generate a neural network. In a neural network there are generally several neurons operated in parallel (Hagan et al., 1996). A set of neurons xoperated in parallel form a layer (Figure 2.8). Inputs are fed directly to the outputs via a series of weights. The sum of the products of the weights and inputs is calculated in each node, and if the value is above some threshold, the neuron fires and takes the activated value, otherwise it takes the deactivated value. Neurons with this kind of activation function are also called McCulloch-Pitts neurons or threshold neurons. These networks were described by Warren McCulloch and Walter Pitts in the 1940s (Graben and Wright, 2011). The mathematical expression of one-layer feedforward neural networks with s neurons is

$y = f(wx + b)$

where $x \in R^n, y \in R^s, b \in R^s, and\ w = (w_{ij}) s \times n.$

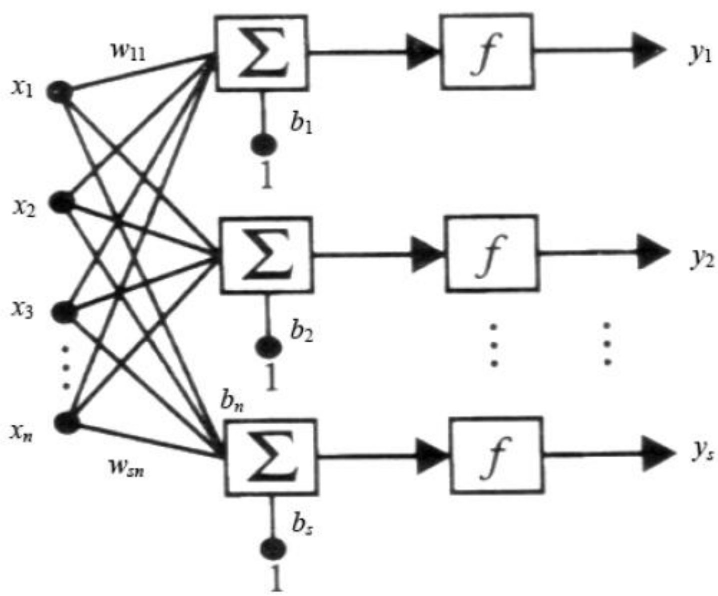


Figure 2.8. A one-layer feedforward network with *s* neurons. Each neuron has *n* inputs.

The architecture of one-layer feedforward networks with *s* neurons is briefly represented by a simpler illustration, as indicated in Fig. 2.8.

The number of neurons in a one-layer feedforward neural network is completely dependent on the number of network outputs. This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents (Chakravarthy, 2011).

2.2.2.3. Multilayer feedforward neural network

MLPs consist of multiple layers of computational units, interconnected in a feed-forward way (Calcagno et al., 2010). MLPs use a variety of learning techniques, the most popular being back-propagation, where the output values are compared with the correct answer to compute the value of some predefined error-function. The error is then fed back through the network and using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. A general method for non-linear optimization called gradient descent is applied to adjust the weights. In a multilayer feedforward neural network, each layer has its bias vector, net input vector, weight vector, and output vector. The layer with its output as the network output is output layer and the remaining layers are hidden layers as seen in Figure 2.9. A multilayer feedforward neural network, such as the network using sigmoid transfer function in the first layer and linear transfer function in the second layer, may arbitrarily approximate most functions (Hagan *et al.*,1996).

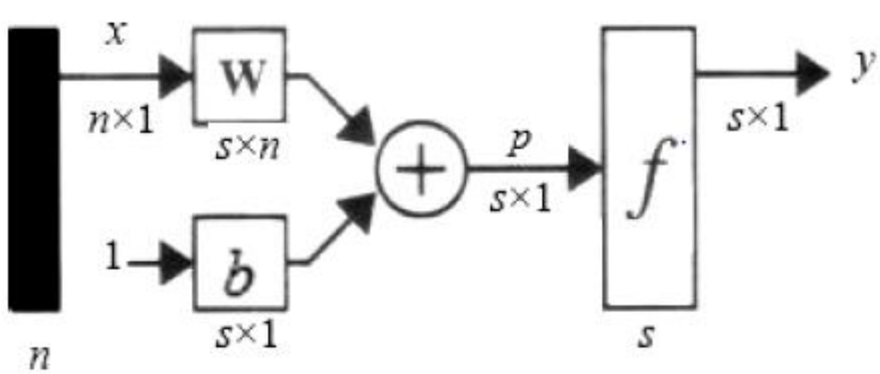


Figure 2.9. The simpler representation of a one-layer feedforward network with *s* neurons.

In this representation x is $n \times 1$ input vector; w is the $s \times n$ weight matrix; b, p and y are

$s \times 1$ vector

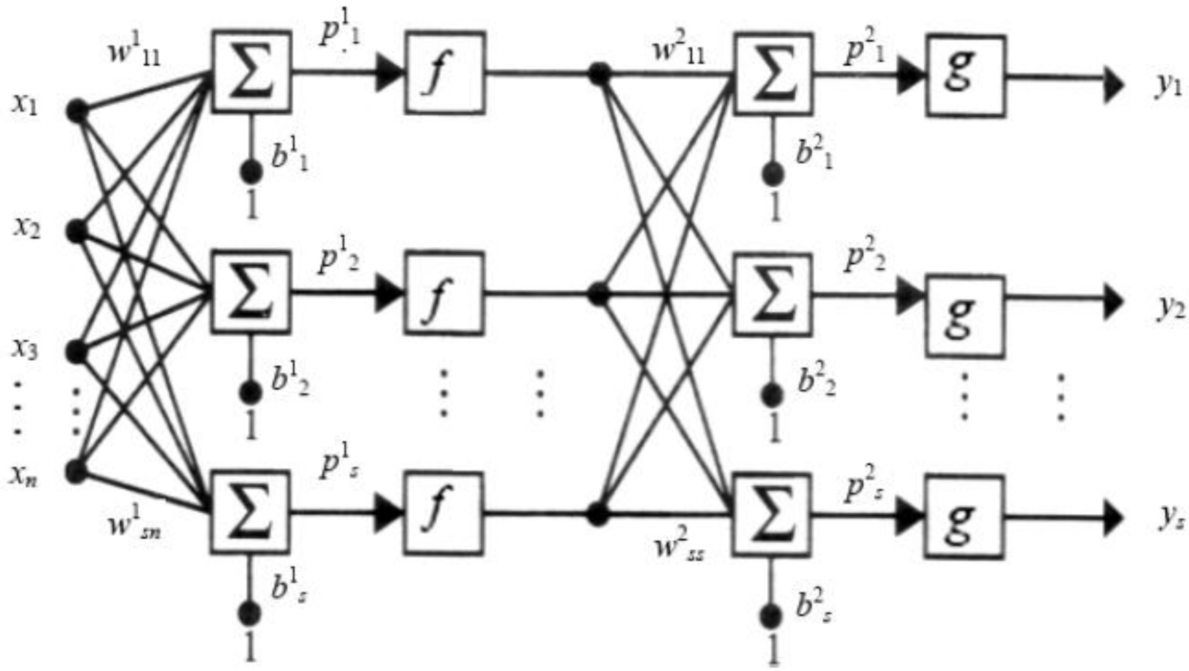


Figure 2.10: A two-layer feedforward neural network with s neurons in each layer. Each neuron of the first layer receives n inputs.

A two-layer feedforward neural network, as indicated in Fig. 2.10, is represented by the following equation:

$$y = g(w^2 f(w^1 x + b^1) + b^2)$$

where $x \in R^n, y \in R^s,\ b_1 \in R^s,\ b_2 \in R^s,$

$$w_1 = (w_{1ij}) s \times n, and$$

$$w_2 = (w_{2ij}) s \times s.$$

As for the number of layers, two or three layers are enough in most cases. There is not any reasonable algorithm or rule to determine the number of hidden neurons in a multilayer feedforward neural network.

2.2.3 Recurrent Networks

Unlike feed-forward networks, recurrent neural (RN) networks are models with a bi-directional data flow. While a feed-forward network propagates data linearly from input to output, RN, propagate data from later processing stages to earlier stages (Bitzer and Kiebel, 2012).

2.2.3.1 Simple Recurrent Network (SRN)

An SRN is a variation of the MLP. It is sometimes called an “Elman network” due to its invention by Jeff Elman. A three layer network is used, with the addition of a set of context units fixed with weights of one. At each step, the input is propagated in a standard feed-forward fashion, and then a back-propagation learning rule is applied. SRN can be used for sequence-prediction that is beyond the power of a standard MLP (Sibandar and Pretoriu, 2012).

In a fully recurrent network, every neuron receives inputs from every other neuron in the network. These networks are not arranged in layers. Usually only a subset of the neurons receive external inputs in addition to the inputs from all the other neurons, and another disjunct subset of neurons report their output externally as well as sending it to all the neurons (Sibandar and Pretoriu, 2012). These distinctive inputs and outputs perform the function of the input and output layers of a feed-forward or simple recurrent network, and also join all the other neurons in the recurrent processing.

2.2.4 Hopfield Network

The Hopfield is a recurrent neural network in which all connections are symmetrical. This network was invented by John Hopfield in 1982 (Dong et al., 2011). The Hopfield guarantees that its dynamics will converge (Pajares et al., 2010).

2.2.5 Stochastic Neural Networks

A stochastic neural network differs from a regular neural network in the fact that it introduces random variations into the network (Su et al., 2011). Boltzmann machines is an example of a stochastic neural network.

2.2.6 Modular Neural Networks

A modular neural network is a neural network characterized by a series of independent neural networks moderated by some intermediary (Pandey, 2012). Each independent neural network serves as a module and operates on separate inputs to accomplish some subtask of the task the network intends to perform (Azam, 2000)). The intermediary takes the outputs of each module and processes them to produce the output of the network as a whole. The intermediary accepts the modules‟ outputs but not respond to, nor otherwise signal, the modules. The modules do not interact with each other. One of the benefits of a modular neural network is the ability to reduce a large neural network to smaller, more manageable components (Azam, 2000). Examples of modular neural networks include committee of machines (CoM) and associative neural networks (ASNN).

2.2.6.1 Committee of machines (CoM)

CoM is a collection of different neural networks that together decide and vote on a given example, hoping that errors would cancel as there are several experts (Bettebghor et al., 2011). This gives a much better result compared to other neural network models. CoM is similar to the general machine learning bagging method, except that the necessary variety of machines in the committee is obtained by training from different random starting weights rather than training on different randomly selected subsets of the training data (Bettebghor et al., 2011).

2.2.6.2 Associative Neural Network (ASNN)

This is an extension of the CoM that goes beyond simple/weighted average of different models. ASNN represents a combination of feed-forward neural networks and the k-nearest neighbor technique (kNN) (Sivaram et. al. 2011). It uses the correlation between ensemble response as a measure of distance amid the analyzed cases for the kNN. This corrects the bias of the neural network ensemble.

2.2.7 Neuron Connection Weights

Neurons are usually connected together. These connections are not equal, and can be assigned individual weights (Chakravarthy, 2011). These weights gives the neural network the ability to recognize certain patterns. Adjust the weights, and the neural network will recognize a different pattern. Adjustment of these weights is a very important operation. The process of training is by adjusting the individual weights between each of the individual neurons until the desired output is achieved (Chakravarthy, 2011).

2.2.8 Transfer Function

The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories: linear (or ramp), threshold and sigmoid. For linear units, the output activity is proportional to the total weighted output. For threshold a unit, the output is set at one of two levels, depending on whether the total input is greater than or less than some threshold value. For sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered rough approximations.

2.2.9 Recursive Neural Network

A recursive network is a feedback neural network in which some of the net outputs are redirected to inputs. Recursive networks are more powerful than feedforward networks. A recursive network contains one or more time-delay modules that form the network feedback. Figure 2.11 illustrates the architecture of a recursive neural network.

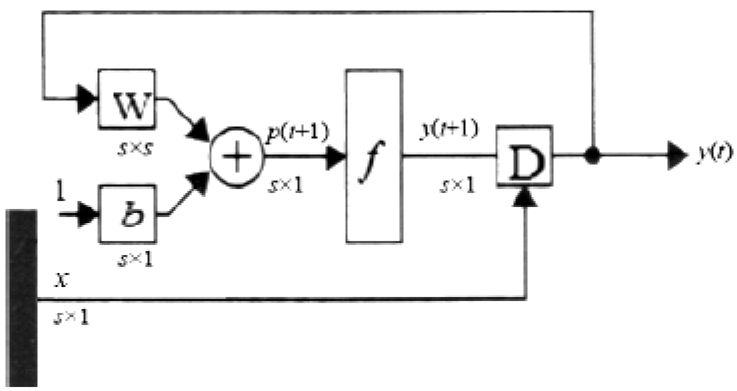


Figure 2.11: A Recursive Neural Network

2.2.10 Learning Process, Methods and Algorithms of Artificial Neural Networks

2.2.10.1. The Learning Process

Two general paradigms sums up the memory pattern and response of a neural net:

i. Associative mapping in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units (Chakravarthy, 2011). The associative mapping can generally be broken down into two mechanisms:

  a. Auto-association: an input pattern is associated with itself and the states of input and output units coincide. This is used to provide pattern completion, i.e. to produce a pattern whenever a portion of it or a distorted pattern is presented. In the second case, the network actually stores pairs of patterns building an association between two sets of patterns.

b. hetero-association: is related to two recall mechanisms:

   Nearest-neighbor recall, where the output pattern produced corresponds to the input pattern stored, which is closest to the pattern presented, and Interpolative recall, where the output pattern is a similarity dependent interpolation of the patterns stored corresponding to the pattern presented. Yet another paradigm, which is a variant associative mapping, is classification, i.e. when there is a fixed set of categories into which the input patterns are to be classified (Chakravarthy, 2011).

ii. Regularity detection in which units learn to respond to particular properties of the input patterns. Whereas in associative mapping the network stores the relationships among patterns, in regularity detection the response of each unit has a particular 'meaning'. This type of learning mechanism is essential for feature discovery and knowledge representation.

2.2.10.2 Learning Methods

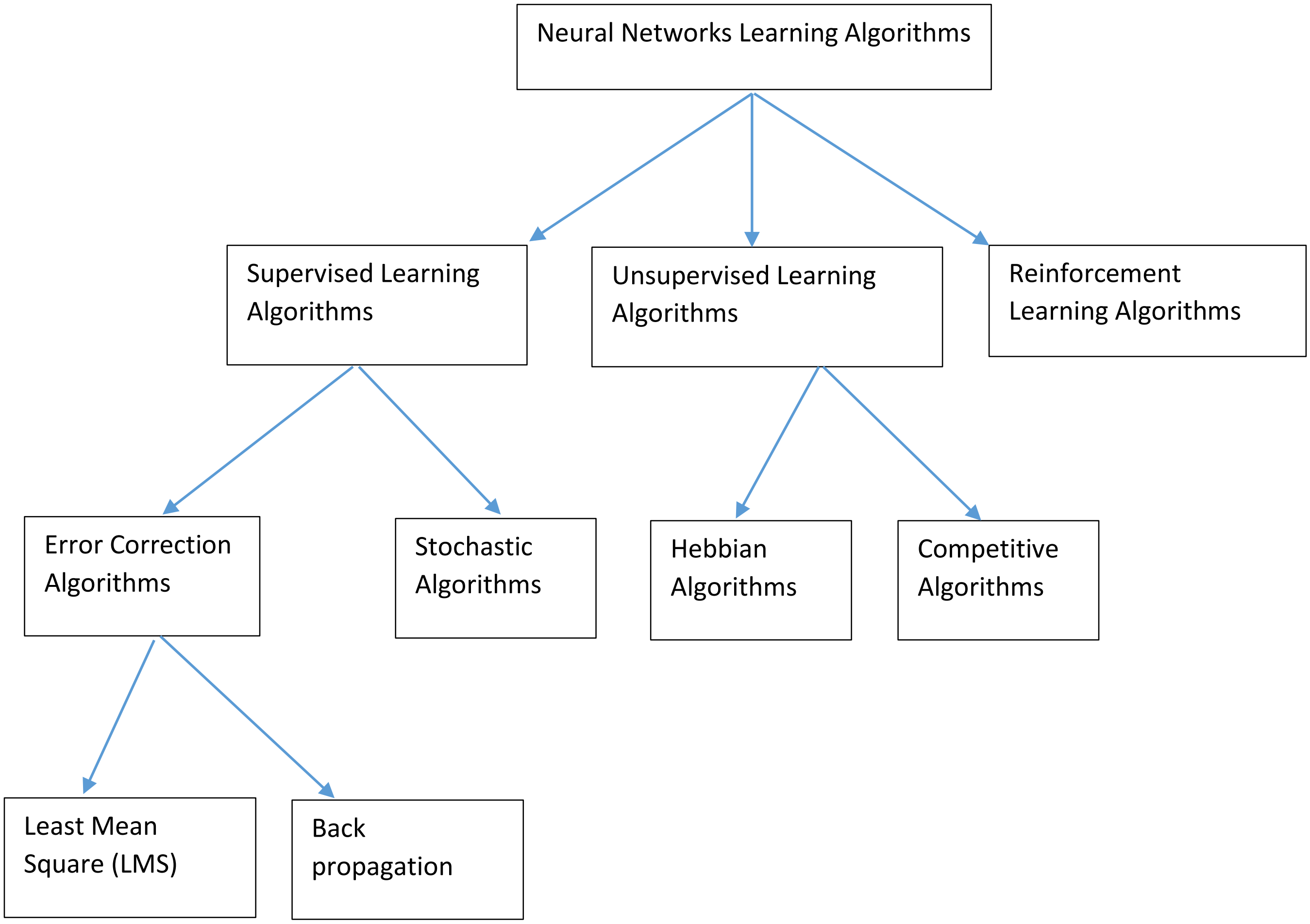


Figure 2.11: Neural Network Algorithms learning methods

1. **Supervised Machine Learning**

As seen in Figure 2.11 in supervised machine learning, a set of training samples and neural network adjusts its connection weights according to the difference between given outputs and actual outputs; incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error correction learning, reinforcement learning and stochastic learning. An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights which minimizes the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

Kotsiantis (2007) described supervised machine learning as the search for algorithms that reason from externally supplied instances to produce general hypotheses, which then make predictions about future instances. In other words, the goal of supervised learning is to build a concise model of the distribution of class labels in terms of predictor features. The resulting classifier is then used to assign class labels to the testing instances where the values of the predictor features are known, but the value of the class label is unknown. Every instance in any dataset used by machine learning algorithms is represented using the same set of features. The features may be continuous, categorical or binary. If instances are given with known labels (the corresponding correct outputs) then the learning is called supervised (Kotsiantis, 2007). The process of applying supervised ML to a real-world problem is described in Figure 2.12.

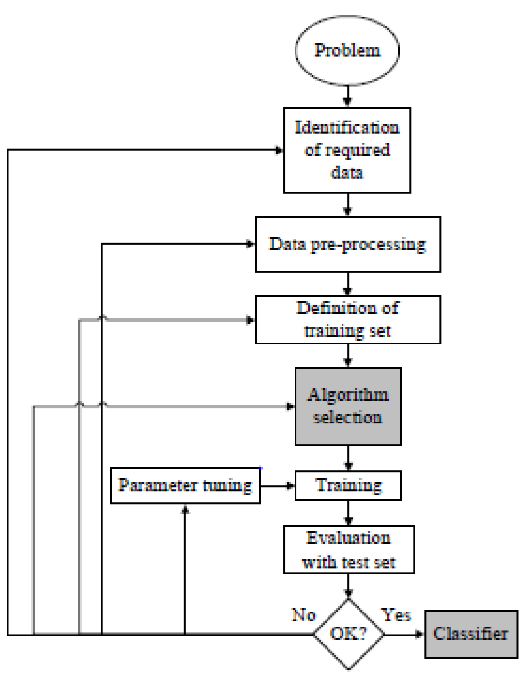


Figure 2.12: Flowchart of supervised Machine learning

The first step is collecting the dataset. If a requisite expert is available, then s/he could suggest which fields (attributes, features) are the most informative. If not, then the simplest method is that of "brute-force," which means measuring everything available in the hope that the right (informative, relevant) features can be isolated. However, a dataset collected by the "brute-force" method is not directly suitable for induction. It contains in most cases noise and missing feature values, and therefore requires significant pre-processing (Zhang et al., 2002).

The second step is the data preparation and data preprocessing. Depending on the circumstances, researchers have a number of methods to choose from to handle missing data (Batista and Monard, 2003). Hodge and Austin (2004) have recently introduced a survey of contemporary techniques for outlier (noise) detection. Noise is principally handled by instance selection.

These researchers have identified the techniques' advantages and disadvantages. Instance selection is not only used to handle noise but to cope with the infeasibility of learning from very large datasets. Instance selection in these datasets is an optimization problem that attempts to maintain the mining quality while minimizing the sample size (Liu and Motoda, 2001). It reduces data and enables a artificial neural networks algorithm to function and work effectively with very large datasets. There is a variety of procedures for sampling instances from a large dataset (Reinartz, 2002).

Feature subset selection is the process of identifying and removing as many irrelevant and redundant features as possible (Yu & Liu, 2004). This reduces the dimensionality of the data and enables artificial neural networks algorithms to operate faster and more effectively. The fact that many features depend on one another often unduly influences the accuracy of supervised ML classification models. The choice of which specific learning algorithm we should use is a critical step. The classifier's evaluation is most often based on prediction accuracy (the percentage of correct prediction divided by the total number of predictions).

There are at least three techniques which are used to calculate a classifier's accuracy. One technique is to split the training set by using two-thirds for training and the other third for estimating performance. In another technique, known as cross-validation, the training set is divided into mutually exclusive and equal-sized subsets and for each subset the classifier is trained on the union of all the other subsets. The average of the error rate of each subset is therefore an estimate of the error rate of the classifier. Leave-one-out validation is a special case of cross validation. All test subsets consist of a single instance. This type of validation is, of course, more expensive computationally, but useful when the most accurate estimate of a classifier's error rate is required. Supervised classification is one of the tasks most frequently carried out by so-called Intelligent Systems. Thus, a large number of techniques have been developed based on Artificial Intelligence (Logical/Symbolic techniques), Perceptron-based techniques and Statistics (Bayesian Networks, Instance-based techniques).

2. Unsupervised Learning Algorithm

Unsupervised learning studies how systems can learn to represent particular input patterns in a way that reflects the statistical structure of the overall collection of input patterns. By contrast with supervised learning or reinforcement learning, there are no explicit target outputs or environmental evaluations associated with each input; rather the unsupervised learner brings to bear prior biases as to what aspects of the structure of the input should be captured in the output.

Neural network adjusts connection weights according to statistical information carried by environmental data (Yan and Zhang, 2000), which is a self-organizing process; uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. Paradigms of unsupervised learning are Hebbian learning and competitive learning.A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas unsupervised learning is performed on-line.

Unsupervised learning methods have to work with the observed input patterns xi, which are often assumed to be independent samples from an underlying unknown probability distribution P_I [x], and some explicit or implicit a priori information as to what is important.

K-means (Bishop, 1995) and (Tapas, 2002) is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. k new centroids as barycenter's of the clusters resulting from the previous step recalculated. Then these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop it may be noticed that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more. Finally, this algorithm aims at minimizing an objective function, in this case a squared error function.

The basic step of k-means clustering is uncomplicated. Firstly, the number of cluster K was determined and the centre of these clusters was assumed then any random object can be taken as the initial centre or the first K objects in sequence can also serve as the initial centre. Then the K means algorithm will do the three steps below until convergence.

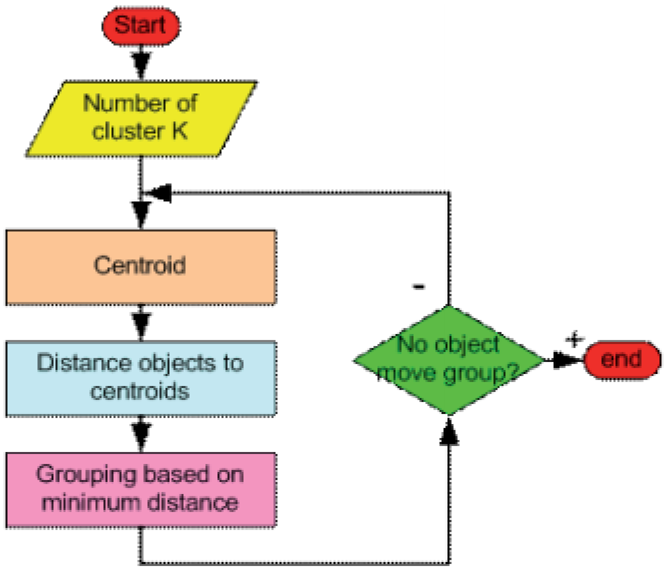


Figure 2.13: K-means clustering flow chart

1. Determine the centre coordinate

2. Determine the distance of each object to the centre

3. Group the object based on minimum distance

2.2.11 The Back Propagation Algorithm

The best-known example of a neural network training algorithm is back propagation (Haykin, 1994), (Patterson, 1996), (Fausett, 1994). Modern second-order algorithms such as conjugate gradient descent and Levenberg-Marquardt (see Bishop, 1995; Shepherd, 1997) (both included in ST Neural Networks) are substantially faster (e.g., an order of magnitude faster) for many problems, but back propagation still has advantages in some circumstances, and is the easiest algorithm to understand. In back propagation, the gradient vector of the error surface is calculated.. A sequence of such moves (slowing as we near the bottom) will eventually find a minimum of some sort. The difficult part is to decide how large the steps should be. Large steps may converge more quickly, but may also overstep the solution or (if the error surface is very eccentric) go off in the wrong direction. A classic example of this in neural network training is where the algorithm progresses very slowly along a steep, narrow, valley, bouncing from one side across to the other. In contrast, very small steps may go in the correct direction, but they also require a large number of iterations. In practice, the step size is proportional to the slope (so that the algorithm settles down in a minimum) and to a special constant: the learning rate. The correct setting for the learning rate is application-dependent, and is typically chosen by experiment; it may also be time-varying, getting smaller as the algorithm progresses.

All learning methods used for adaptive neural networks can be classified into three major categories:

2.2.12 Learning Algorithms In ANN

Three kinds of learning algorithms are used in neural networks (Yang and Zhang, 2000)

1. **Hebb learning law.** The strength of connection between two neurons is expected to increase if the activation of the two neurons is synchronous and decrease if the activation is asynchronous,

2. Error correction learning law

3. **Reinforcement learning.** In this learning system the external environment yields evaluation to network output and neural network adjusts its connection weights through reinforcing those actions encouraged by external environment. It is a learning method between supervised and unsupervised learning.

2.2.13 Training a Neural Network

A neuron that receives information from outside of the network is called an input layer. A neuron that contains the network's predictions or classifications is called the output layer. Neurons that are found between the input and output layers form the hidden layer. The transfer function is usually a log function, a sigmoid function, or a hyperbolic tangent and scales all of the information coming into the neuron. The sigmoid curve is often used as a transfer function because it introduces non-linearity into the network's calculations. The sigmoid function has the additional benefit of having an extremely simple derivative function, as required for back-propagation errors through a feed-forward neural network.

As values are sent from one layer to the next, a weight is assigned to each interconnecting line and is multiplied by the values. Each neuron on the hidden layer sums all inputs, and the combined input is modified by the function. The output value of the transfer function is generally passed directly to all neurons in the next layer, again with a weight assigned to each value. Values of the interconnecting weights predetermine the neural network's computation reaction to any arbitrary input pattern. As information is passed forward from the inputs towards the outputs, interconnecting weights are adjusted by a back-propagation algorithm during the learning phase so that known outputs will best match predicted outputs.

As stated above, back-propagation is the most common algorithm used to train NNs due to its ability to generalize well on a wide variety of problems. It is a feed-forward, fully interconnected, supervised network. It builds models that classify patterns or make predictions according to patterns of inputs and outputs it has learned.

Training of a NN is the procedure by which the values for the individual weights are determined such that the relationship the network is modeling is accurately resolved. By varying the weights through all possible values, and by plotting the errors in the three-dimensional space, an error surface is developed as shown in Fig. 2.13.

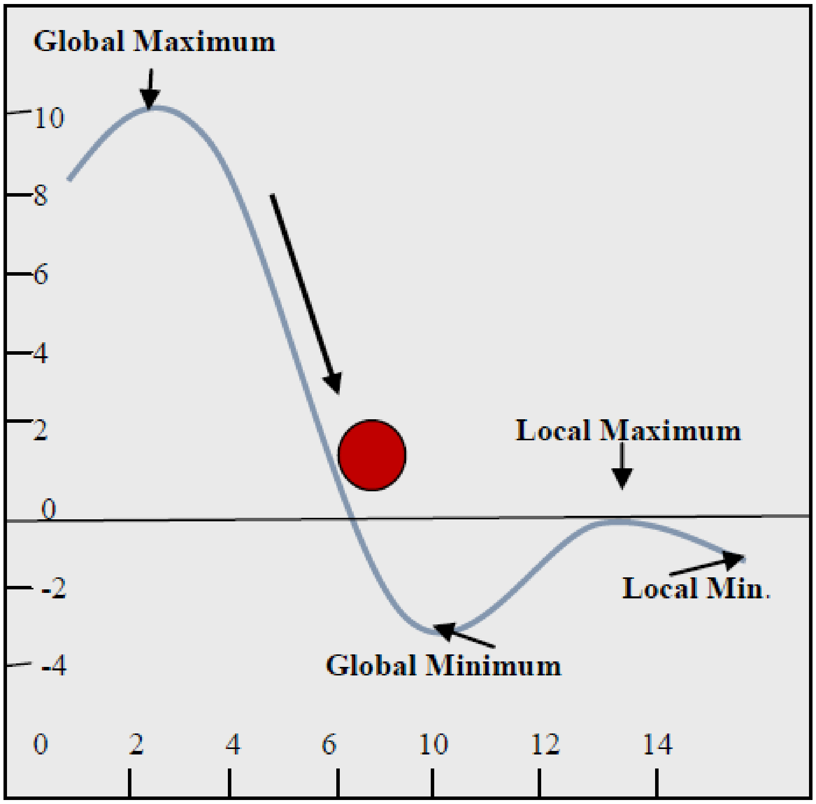


Figure 2.14: Three dimensional error plot of a neural network

The objective of training a neural network is to find the combination of weights which will result in the smallest error. In practice, it is not possible to plot such a surface due to the multitude of weights and hence it is more relevant to find the minimum point of the error. One possible technique is to use a procedure known as gradient descent. The back-propagation training algorithm uses this procedure to attempt to locate the global minimum of the error surface. The back-propagation algorithm is the most computationally straightforward algorithm for training the multilayer perceptron. Back-propagation has been shown to perform adequately in many applications. A great number of applications discussed in this paper used back-propagation to train NNs.

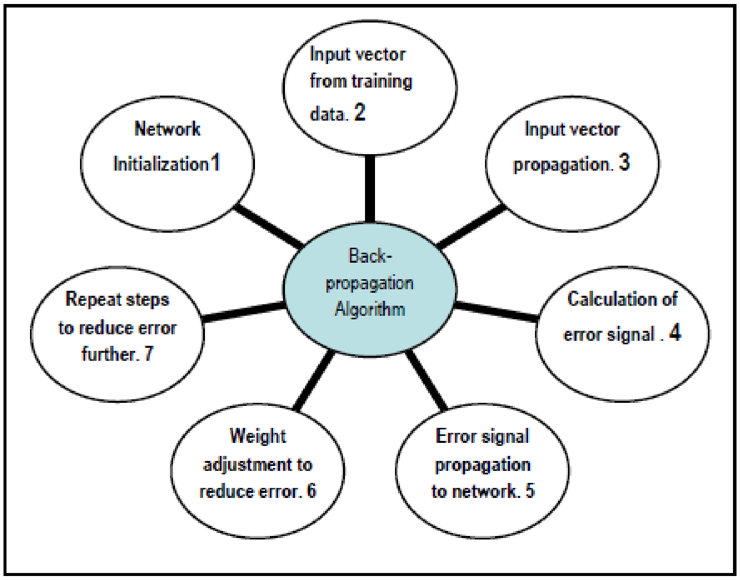


Figure 2.15: Backpropagation Algorithm

Fig. 2.15 shows a back-propagation algorithm also known as on-line training whereby the network weights are adapted after each pattern has been presented (Reuter et. al. 2010). The alternative is known as batch training, where the summed error for all patterns is used to update the weights. In practice, many thousands of training iterations will be required before the network error reaches a satisfactory level as determined by the problem being addressed. Training should be stopped when the performance of the NN on the independent test data reaches a maximum.

The error surface in Fig. 2.15 contains more than one minimum. It is important that the training algorithm does not become trapped in a local minimum. The back-propagation algorithm contains two adjustable parameters, a learning rate and a momentum term, which can assist the training process in avoiding this. The learning rate determines the step size taken during the iterative gradient descent learning process. If this is too large then the network error will change erratically due to large weight changes, with the possibility of jumping over the global minima. Conversely, if the learning rate is too small then training will take a long time. The momentum term is used to assist the gradient descent process if it becomes stuck in a local minimum. By adding a proportion of the previous weight change to the current weight change it is possible that the weights can escape the local minimum.

2.3 Empirical Framework

Artificial Neural Networks are increasingly finding applications in expertise orientation and the development of applications for a problem-oriented domain (Liao et al., 2012). This present work simulates a model for forecasting Recession Probability in order to improve an existing system and identify the several performance indicators that a machine learning system should be evaluated on with to ascertain its efficiency. The performance indicators are also the major characteristics the existing system do not possess which makes the system a weak one. Several scholars have explored the application of Artificial Neural Networks for series of research analysis and to provide solutions to myriad of problems confronting human race (Alhassan and Lawal, 2015). Model evaluation performance of some scholar was based on specific criteria but the present work established not only one criterion but identify the key performance indicators of a model of Artificial Neural Networks.

Gopal and Chandra (2012) in providing valuable information for accurately predicting the hydrological behavior of watershed which is critical for the planning, land use, design of civil projects and water resources management used Artificial Neural Net. Hydrologic systems include, to a large extent, stochastic components and are often non-linear and non-stationary. In spite of high adaptability of Artificial Neural Network (ANN) in modelling hydrologic time series, often signals are highly non-stationary and exhibit seasonal irregularity. In such cases, prediction accuracy of ANN suffers for want of pre-processing of data. In this study, different data pre-processing techniques are presented to deal with irregularity components that exist in hydrologic time series data of the Brahmaputra basin within India at the Pancharatna gauging station using daily time unit and their properties are evaluated by performing one step ahead flow forecasting using ANN. The model results were evaluated by using Root mean square error (RMSE) and Mean absolute percentage error (MAPE) and it was found that Logarithm based pre-processing technique provides better forecasting performance among various pre-processing techniques. The results indicate that detecting non-stationary nature and selecting an appropriate pre-processing technique is highly beneficial in improving the prediction performance of ANN model. Recession probability is stochastic, non-stationary and exhibit seasonal irregularities thus requiring a logarithm based preprocessing technique for better forecasting performance, this present work tries to use logarithm based preprocessing technique.

Hasan et al., (2014) presents an artificial neural network approach for forecasting electric energy consumption. For effective planning and operation of power systems, optimal forecasting tools are needed for energy operators to maximize profit and also to provide maximum satisfaction to energy consumers. Monthly data for electric energy consumed in the Gaza strip was collected from year 1994 to 2013. Data were trained and the proposed model was validated using 2-Fold and K-Fold cross validation techniques. The model has been tested with actual energy consumption data and yields satisfactory performance. Validation is essential to ensure data and model serve the desired purpose, 2 –fold validation would be used for the data to be used in this work.

Mohammad**,** Hamidreza and Mojtaba (2015) in evaluation of the forecasting efficiency of artificial neural network models and SARIMA in terms of their ability to predict hydrostatic levels using error evaluation criteria used data on hydrostatic level of 13 wells present in Birjand plain as one of the sub-basins of Lut Desert which utilized a 16-year statistical period of 1997-2013 on a monthly basis. In this study, to determine the effect of the most significant factors on the groundwater level, Feed Forward Back Propagation Neural Networks with Levenberg Marquardt training functions were used. The training of a selective network based on the available information includes adjustment of the weight values and biases or initial constant values, in order to minimize the error between observed and calculated output (Mohammad et al., 2015). The algorithm was based on an error correction learning rule. Back-propagation learning rule was used for training of feed-forward multilayer networks, which are commonly called multilayer perception networks. Similar to quasi-Newton methods, Levenberg-Marquardt algorithm seeks to reduce calculations using non-calculation of Hissin Matrix, and it operates very faster than other algorithms. Artificial neural network model of the data was divided into three parts including test, training and validation, and in 16-year statistical period, 70% of data are used for training (the most important part of the model), 15 percent for the test, and 15 percent for validation.

Mohammad et al., (2015), notes that R^2 of the data simulated by using feed-forward neural network models was higher than that of time series (SARIMA), and RMSE and MAE in the neural network model was less than that of SARIMA model. In general, both feed-forward neural network model and SARIMA time series had a high correlation with actual data of the hydrostatic level of the wells, and had absolute error and quantitative standard. However, feed-forward neural networks are more efficient in predicting hydrostatic level. The data of this research would use 70% of the data to train, 15% to test and 15% to validate as well as extrapolate and compare R^2, RMSE and MAPE of the extrapolated data to further test the validity of recession probability forecasts.

The works of Akram, Ziad and Eyad (2011) focused on the network parameters needed in order to get the optimal architecture of the network. Many examples were tested and they showed that using one hidden layer with the number of neurons equal to the square of the number of inputs will lead to optimal neural network by mean of reducing the number of training stages (number of training iterations) and thus the processing time needed to train the network. Akram et al., (2011) established that the optimal neural network is the network that can reach the goals in minimum number of training iterations and minimum time of training.

Neural Networks have been used in a number of disciplines including business, and economics. In this context, Kuan and White (1994), Swanson and White (1995, 1997a, 1997b), Hutchinson, Lo, and Poggio (1994), Garcia and Gencay (2000), Gencay (1998), and Qi and Madala (1999), Gencay (1999) employed neural networks in business and economics. Although neural networks have demonstrated some success in financial and economics applications, only a few studies, for example Vishwakarma (1995), Qi (2001), Kiani (2005), and Kiani, Bidarkota, and Kastens (2005) employed neural networks in business cycles. Estrella and Mishken (1998) employed nonlinear time series models to predict USA business cycles regimes. However, Qi (2001) successfully used neural networks to predict USA recessions using data from Estrella and Mishken (1998) study and came up with similar results.

Interest rates are commonly used as predictors of future economic conditions as measured by industrial production, real gross domestic product and real total business sales (RTBS), as well as through the prediction of recessions in the economy as used in the work of Josepha, Larrainb and Eshwar (2011). Recession forecasting is mainly characterized by “probit categorical analysis”, and there appears to be hardly any neural network research in this area. Josepha et al., (2011) contributed to the recession forecasting literature by using interest rate spreads (the difference between the average yields on 10 year U.S. Treasury bonds and on 3 month U.S. Treasury bills) to forecast the 2007 to 2009 recession with neural network models referenced against regression models. They showed that neural network models out-performed regression models as evidenced by their R-squared and mean square error performance metrics. Unlike other studies, the change in interest rates is used to compute the interest rate spread. The targeted variable is RTBS. The interest rate spread variable was used to generate three input variables comprising 23, 26, and 29 month leads respectively over RTBS.

Many recent research studies like Wheelock and Wohar (2009), Berk and van Bergeijk (1998), and Plosser and Rouwenhorst (1993) independently reveal that the spread does play a significant role in anticipating real economic growth as exemplified by real gross domestic product (real GDP), real total business sales (RTBS), and industrial production, among others; and that the spread can also forecast inflation and consumption. Most importantly, while the spread's ability to forecast these variables, particularly output growth, has diminished somewhat over the years, its ability in forecasting recessions has remained remarkably stable. This research includes interest rate spread as a predictor using the Nigerian context for recession probability forecasting.

Kiani and Kastens (2006) employed artificial neural networks using macro-financial variables to predict recessions. They modeled the relationship between indicator variables and recessions to 10 periods into the future and used a procedure that penalizes a misclassified recession more than a misclassified non-recession. Their results revealed that among the 16 models that were constructed from 9 indicator variables and their combinations, the indicator variables Spread, 3-year bond rates, 10-year bond rates, monetary base, industrial production were candidates variables for predicting recessions ranging to 10 periods in the future. However, most indicator variables became candidate for predicting recessions when misclassified recessions are penalized more heavily than misclassified non-recessions.

Ross (2013) explored the ability of Support Vector Regression (SVR) and feedforward neural networks to predict the 2008 Great Recession when trained only on macroeconomic data from 1978 to 2005. Their performance was compared to that of a standard ARIMA model taken from recent economic literature. To estimate the input-output relationship between various macroeconomic indicators and US quarterly GDP, and to select which indicators improve this estimation. Leading economic indicators (LEIs), such as the value of the S&P 500, Number of weekly initial jobless claims, Velocity of M2 money supply, Number of new private building permits, The Consumer Sentiment Index, published by the University of Michigan,. The results demonstrate that SVR can make use of relationships between LEIs to produce models with predictive power greater than that of the simple ARIMA models that have been so popular among econometricians.

Although in general, neural networks are well-suited to estimate the solutions to time series problems, the sparseness of this dataset causes the behavior of neural networks to be largely erratic and substantially influenced by initial randomization. Even if neural networks can theoretically provide better fits than SVR or ARIMA, the reproducibility of their behavior is harmed by the small size of the training set. Tkacz and Hu (2010), who explored the application of neural networks to predict the GDP of Canada, also note that small training sets deteriorate the performance of neural networks, and they surmise that at least 300 observations are needed to achieve results better than those of traditional linear regression models. The constraint of sparse data to Artificial Neural nets would be highly considered to better the forecasting ability of this research.

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

3.1 Preamble

Research Methodology typically encompasses concepts such as paradigms, theoretical models, phases and quantitative or qualitative techniques (Irny and Rose, 2005). It comprises the theoretical analysis of the body of methods and principles associated with a branch of knowledge. A research method is a systematic plan for conducting research, it does not set out to provide solutions, but it offers the theoretical underpinning for understanding which method, set of methods, or best practices that can be applied to a specific case.

Researchers draw on a variety of both qualitative and quantitative research methods, including experiments, survey research, participant observation, and secondary data. Quantitative methods aim to classify features, count them, and create statistical models to test hypotheses and explain observations. Qualitative methods aim for a complete, detailed description of observations, including the context of events and circumstances.

Methodology implies more than simply the methods intended for use to collect data. It is often necessary to include a consideration of the concepts and theories which underlie the methods to be used in carrying out and concluding a research. Forecasting is the process of making predictions of the future based on past and present data and most commonly by analysis of trends (Armstrong et al., 2013). A common place example might be estimation of some variable of interest at some specified future date. Prediction is a similar to forecasting, but more general term. Both might refer to formal statistical methods employing time series, cross-sectional or longitudinal data, or alternatively to less formal judgmental methods. The generality of steps, data, analysis and results generation procedures embodies the research methods in this field.

Forecasting techniques can be categorized in two broad categories: quantitative and qualitative. The techniques in the quantitative category include mathematical models such as: moving average, straight-line projection, exponential smoothing, regression, trend-line analysis, simulation, life-cycle analysis, decomposition, Box-Jenkins, expert systems, and neural network. The techniques in the qualitative category include subjective or intuitive models such as jury or executive opinion, sales force composite, and customer expectations (Kress, 1985; Mentzer and Kahn, 1995).

Along with qualitative and quantitative, forecasting models can be categorized as time-series, causal, or judgmental. A time-series model uses past data as the basis for estimating future results. The models that fall into this category include decomposition, moving average, exponential smoothing, and Box-Jenkins. The premise of a causal model is that a particular outcome is directly influenced by some other predictable factor. These techniques include regression models. Judgmental techniques are often called subjective because they rely on intuition, opinions, and probability to derive the forecast. These techniques include expert opinion, Delphi, sales force composite, customer expectations (customer surveys), and simulation (Kress, 1985; Wilson & Keating, 1994).

Central to forecasting and prediction are risk and uncertainty notes Armstrong et al. (2013); it is generally considered good practice to indicate the degree of uncertainty attaching to forecasts. In any case, the data must be up to date in order for the forecast to be as accurate as possible. Forecasting or prediction can adopt either a qualitative or quantitative methodology.

3.1.1 Qualitative Forecasting / Prediction

According to Lie, (2009) qualitative forecasting techniques are subjective, based on the opinion and judgment of consumers, experts; they are appropriate when past data are not available. They are usually applied to intermediate or long-range decisions. The techniques in the qualitative category include subjective or intuitive models such as

Jury of executive opinion consists of combining top executives' views concerning future sales.

Sales force composite combines the individual forecasts of sales people.

Customer expectations (customer surveys) use customers' expectations as the basis for the forecast. The data are typically gathered by a customer survey by the sales force.

Delphi model is similar to jury of executive opinion in taking advantage of the wisdom of experts. However, it has the additional advantage of anonymity among participants.

Naïve model assumes that the next period will be identical to the present. The forecast is based on the most recent observation of data (Kress, 1995; Mentzer & Kahn, 1995).

The Delphi Technique

The Delphi Technique is a structured communication technique or method, originally developed as a systematic, interactive forecasting method which relies on a panel of experts (Grisham, 2009). Delphi is based on the principle that forecasts (or decisions) from a structured group of individuals are more accurate than those from unstructured groups. (Rowe and Wright, 2001). According to Buckley (1994) one clear use of the Delphi technique is when the issue under investigation does not lend itself to precise analytical techniques, but can benefit greatly from subjective judgments on a collective basis.

3.1.2 Quantitative forecasting

Quantitative forecasting models are used to forecast future data as a function of past data. They are appropriate to use when past numerical data are available and when it is reasonable to assume that some of the patterns in the data are expected to continue into the future. These methods are usually applied to short- or intermediate-range decisions and include:

Regression Analysis: statically relates sales to one or more explanatory (independent) variables. Explanatory variables may be marketing decisions (price changes, for instance), competitive information, economic data, or any other variable related to sales.

Exponential smoothing makes an exponentially smoothed weighted average of past sales, trends, and seasonality to derive a forecast.

Moving average takes an average of a specified number of past observations to make a forecast. As new observations become available, they are used in the forecast and the oldest observations are dropped.

Box-Jenkins uses the auto correlative structure of sales data to develop an autoregressive moving average forecast from past sales and forecast errors.

Trend line analysis fits a line to the sales data by minimizing the squared error between the line and actual past sales values. This line is then projected into the future as the forecast.

Decomposition breaks the sales data into seasonal, cyclical, trend and noise components and projects each into the future.

Straight-line projection is a visual extrapolation of the past data, which is projected into the future as the forecast.

Life-cycle analysis bases the forecast upon whether the product is judged to be in the introduction, growth, maturity, or decline stage of the life cycle.

Simulation uses the computer to model the forces, which affect sales: customers, marketing plans, competitors, flow of goods, etc. The simulation model is a mathematical replication of the actual corporation.

• *Expert systems* use the knowledge of one or more forecasting experts to develop decision rules to arrive at a forecast.

• *Neural networks* look for patterns in previous history

Quantitative forecasting methods are categorized as simple and weighted N-Period moving averages, simple exponential smoothing, poisson process model based forecasting (Mahmud et. al., 2016) and multiplicative seasonal indexes. These can be implemented using

1. Time series methods (Weighted moving average, Autoregressive moving average (ARMA) and Autoregressive integrated moving average (ARIMA) using Box- Jenkins)
2. Causal / econometric forecasting methods (Regression analysis and Autoregressive moving average with exogenous inputs (ARMAX)) (Ellis, 2008)
3. Artificial intelligence methods (Artificial neural networks and support vector machine)

Nowadays neural models are enjoying resurgence and there is a substantial amount of research in the area of neural networks, because of their ability to represent nonlinear relationships, useful in making function approximation, forecasting, and recognizing patterns. An artificial neural network is a computational-based, nonlinear empirical model, inspired on the biological neural networks. ANN can "learn" complex dynamic behaviors of physical systems. An ANN acts as a black box and learns to predict the value of specific output variables given sufficient input information.

3.2 Methodology Adopted

Since recession probability forecasting is based majorly on historical data about economic indicators, the quantitative technique is adopted. Artificial Neural Networks methodology is adopted for this research. Due to imprecision and uncertainties in predicting real world problems, artificial neural network (ANN) techniques have become increasingly useful for modeling and optimization. Various Artificial Neural Network techniques such as Generalized Regression Neural Networks (GRNN), Feed Forward Neural Networks (FFNN) and Radial Basis Neural Networks (RBNN) have been evaluated based on their performance and the Feed Forward Neural Networks would be used to forecast recession probability given the Nigerian context as it better forecasts recession with the peculiar nature of the Nigerian state.

Unlike classical Artificial Intelligence (AI) systems that are aimed at directly emulating rational and logical reasoning, ANN's are targeted at reproducing the causal processing mechanisms that give results to intelligence as a developing property of complex systems. Practically, ANN provides accurate approximation of both linear and non-linear functions.

The Three Layer Feed forward network is adopted for this present study.

Let $f = the\ underlying\ linear\ or\ non\ linear\ function$

Through which a vector of causal or explanatory variables $X = (x_1 \ldots x_n)$ relates to the dependent variable y,

i.e $y = f(X)$

then f can be approximated by a three-layer feed forward Neural Network thus:

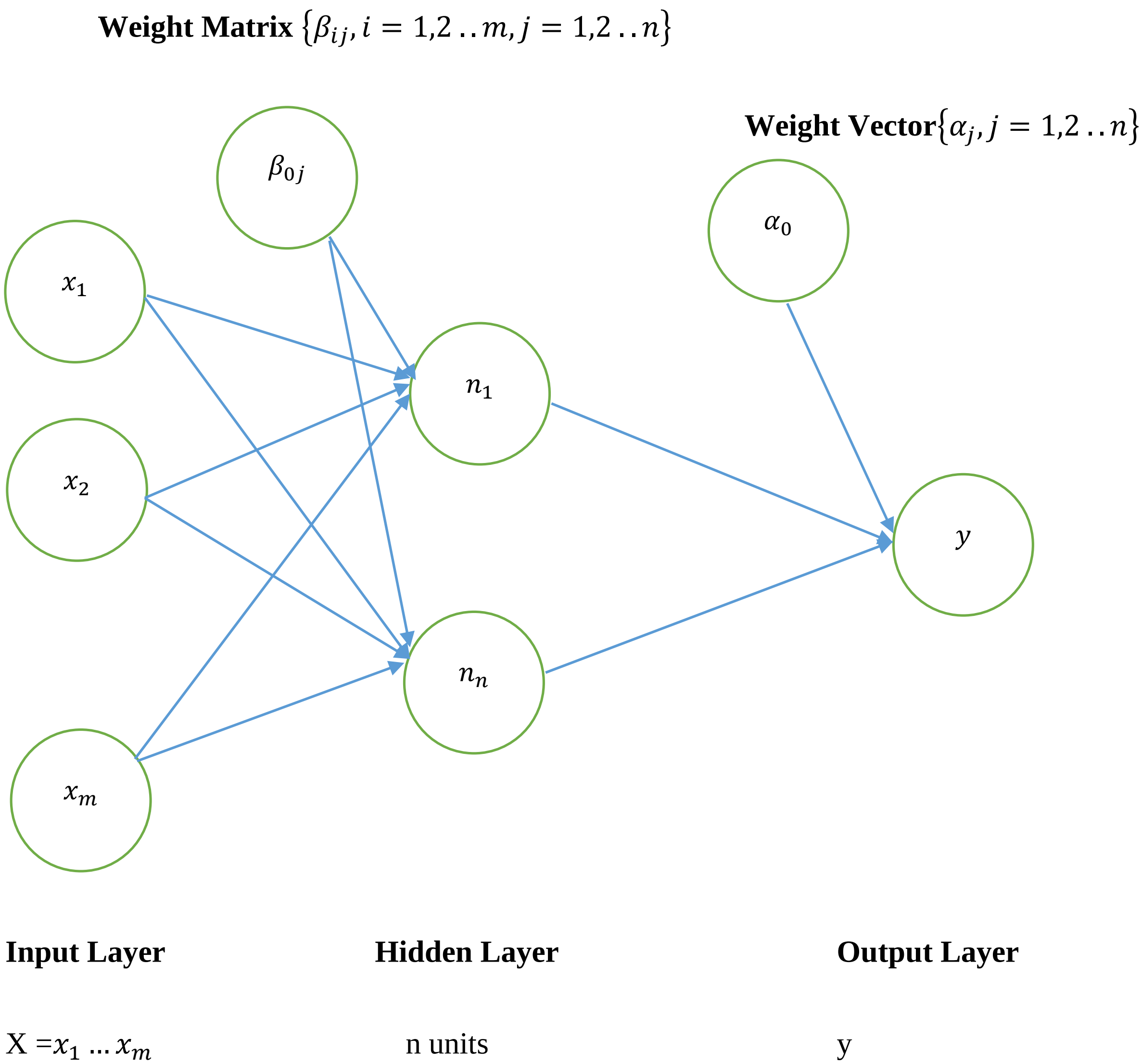


Figure 3.1 Three Layer Neural Network model

This ANN model can be written as two layers of logistic function thus:

$$f(x) = g\left[\alpha_0 + \sum_{j=1}^{n} \alpha_j\, g\left(\sum_{i=1}^{m} \beta_{ij}\, x_i + \beta_{0j}\right)\right] + \varepsilon$$

Where

n = the number of hidden layer

m = the number of explanatory variables (i.e the number of macroeconomic variables)

g = logistic transfer function defined thus as: $g(a) = \frac{1}{(1+e^{-a})}$

$\{\alpha_j, j = 1,2\,..n\}$ = a vector of parameters from the hidden layer to the output layer units

$\{\beta_{ij}, i = 1,2\,..m, j = 1,2\,..n\}$ = Matrix of parameters from the input units to the hidden layer

ε = error term

Despite the presence of noise or incomplete information, it is possible for neurons to learn the behaviour or trends and consequently, make useful conclusions. Usually, a neural network is trained to perform a specific function by adjusting weight values between elements as seen in Fig. 2(a).

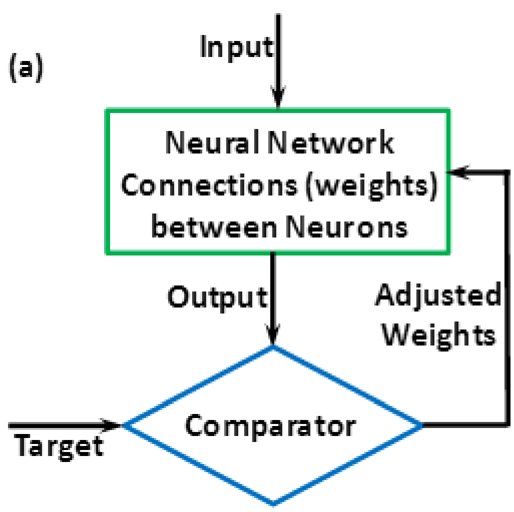


Figure 3.2: Process Diagram for a Neural Network Algorithm

The neural network function is mainly determined by the connections between the elements (Khamis et. Al., 2011). By observing the data, it is possible for the ANN to make accurate predictions. Unlike other forecasting approach, the ANN technique has the ability to predict future trends with theoretically poor, but rich data set.

3.2.1 The Model Process

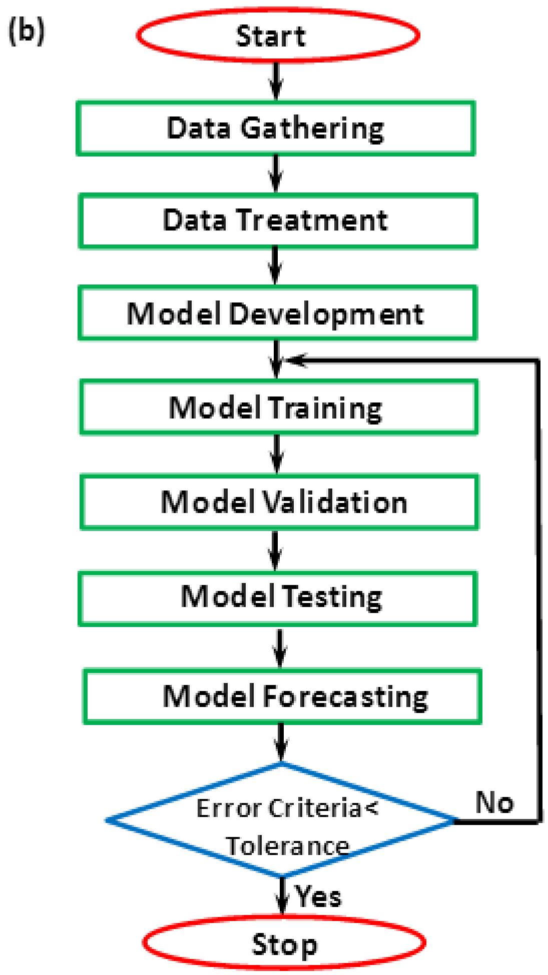


Figure 3.2 b: Flow Chart of Artificial Neural Network Model Process
Source: Park et al., (1999)

The implementation of the ANN model can be described using the flow chart in Fig. 3.2(b). Historical monthly data on economic indicators have been gathered, based on the gathered data, and this study will develop a forecast model that predicts recession. Using the ANN technique, training and learning procedures are fundamental in forecasting future events. The training of feed forward networks is usually carried out in a supervised manner. With a set of data to be trained (usually extracted from the historical data), it is possible to derive an efficient forecast model. The proper selection of inputs for ANN training plays a vital role to the success of the training process. On the other hand, the learning process involves providing both input and output data, the network processes the input and compares the resulting output with desired result. The system then adjusts the weights which acts as a control for error minimization. In order to minimize error, the process is repeated until a satisfactory criterion for convergence is attained. The knowledge acquired by the ANN via the learning process is tested by applying it to a new data set that has not been used before, called the testing set.

It should now be possible that the network is able to make generalizations and provide accurate result for new data. Due to insufficient information, some networks do not converge. It is also noteworthy that over-training the ANN can seriously deteriorate forecasts. Also, if the ANN is fed with redundant or inaccurate information, it may destabilize the system.

Training and learning process should be thorough in order to achieve good results. To accurately forecast, it is imperative to consider all possible factors that influence recession, which is not feasible in reality.

3.2.2 Steps

(1) Gather data;

(2) Select Dependent Variable - what is the model trying to predict and what is to be optimised?

(3) Data preprocessing stage 1 (cleansing and identifying appropriate predictors);

(4) ANN selection - select an appropriate network type and training algorithm;

(5) Data preprocessing stage 2 (standardize the data and split into appropriate training, test and validation sets);

(6) Network training - train the network(s) with the processed data sets;

(7) Evaluation - using appropriate error measures to interpret the results.

3.3 Data Collection

Data collection involves collecting and measuring data on several variables of interest, following an established systematic fashion that enables one to answer stated research questions, test hypotheses, and evaluate outcomes. There are a variety of techniques that can be used to collect data in a quantitative research study. However, all of them are geared towards numerical collection. The data collection component of research is common to all fields of study including physical and social sciences, humanities, business among others. While methods vary by discipline, the emphasis on ensuring accurate and honest collection remains the same (Knatterud, 1998). The data used for analysis were collected from Nigeria Bureau of Statistics, Central Bank of Nigeria, interview, questionnaire and from observation.

3.3.1 Characteristics of the Population

According to the World Bank (2017) population estimate, Nigeria's 186 million can be considered as part of the population for this study, but specifically bankers (commercial and developmental), discount houses, stock brokers, government and its agencies would fit the characteristic of the population of choice. Nigeria being a developing nation accurate records could not be obtained from the Bureau of Labour and statistics, because of the bureaucracy involved on obtaining such information .

3.3.2 Sampling Design and Procedure

Sample size determination is the act of choosing the number of observations or replicates to include in a statistical sample. The sample size is an important feature of any empirical study in which the goal is to make inferences about a population from a sample. A sample is a subset of people, items, or events from a larger population that one collects and analyzes to make inferences. To represent the population well, a sample should be randomly collected and adequately large (Minitab, 2016).

Sample sizes may be chosen in several different ways:

- experience – for example, include those items readily available or convenient to collect. A choice of small sample sizes, though sometimes necessary, can result in wide confidence intervals or risks of errors in statistical hypothesis testing.
- using a target variance for an estimate to be derived from the sample eventually obtained
- using a target for the power of a statistical test to be applied once the sample is collected.
- using a confidence level determines how accurate a result will turn out with lower chances of error.

In other to estimate the required sample size as the population is not determined, the confidence level would be used which is estimated using the margin of error times the standard error. At 95% confidence level the margin of error is 1.96 times the standard error which is

$$M.E = z\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

Where

ME is the desired margin of error (set at 4%)

z is the z-score, e.g. 1.645 for a 90% confidence interval, 1.96 for a 90% confidence interval, 2.58 for a 99% confidence interval.

$\hat{p}$ is our prior judgment of the correct value of p (which if unknown assumed to be 0.5) n is the sample size (to be found)

$$0.04 = 1.96\sqrt{\frac{0.5(0.5)}{n}}$$

$$\frac{0.5\ x\ 0.5}{n} = \left(\frac{0.04}{1.96}\right)^2$$

$$\frac{0.5\ x\ 0.5}{n} = (0.02041)^2$$

$$\frac{0.5\ x\ 0.5}{n} = 0.0004165$$

$$n \approx 596$$

3.3.3 Data Collection Instruments

Data collection instruments are the means used in collecting data that is the tool used in data collection such as interviews and questionnaire.

1. **Interview:** Some managers of the company were interviewed. The results support the need to embarking on this project. Sample questions used are referenced at the appendix F.

2. **Questionnaire:** copies of the questionnaire were administered to decision makers of various finance and discount houses for information gathering are referenced at appendix F.

3.4 Model Analysis Procedures

The performance of ANN models in training and testing stages are compared with the observed values to identify the best fit forecasting model. For this purpose, some performance criteria such as Mean Square Error (MSE), Root Mean Square Error (RMSE) isolated from literature would be used to examine the model. Questionnaire would be used to identify the problems with the existing forecasting methods with a view to finding user perceptions with the current forecasting method.

3.4.1 Performance Indicators for Existing System

Accuracy: The accuracy of a model is an indicator of its ability to predict future observations. The most basic indicator is the proportion of observations of the test set correctly classified by the model. Similarly, the error rate is calculated as the ratio between the number of errors and the number of cases examined (Clemente et al., 2017).

A popular and important criterion used for performance analysis is the MSE. It is used to relay concepts of bias, precision and accuracy in statistical estimation. Here, the difference between the estimated and the actual value is used to get the error, the average of the square of the error gives an expression for MSE. The MSE criterion is expressed as.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \qquad \text{eqn 3.1}$$

Where

Yi is the actual data and yi is the forecasted data. The RMSE is a quadratic scoring rule which measures the average magnitude of the error. The RMSE criterion is expressed in Equation (3.1). RMSE usually provides a relatively high weight to large errors due to the fact that averaging is carried out after errors are squared. This makes this criterion an important tool when large errors are specifically undesired.

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \qquad \text{eqn 3.2}$$

The MAE measures the average error function for forecasts and actual data with polarity elimination. Equation (3.2) gives the expression for the MAE criterion used. The MAE is a linear score which implies that all the individual differences are weighted equally in the average.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y}_i|$$

eqn 3.3

MAPE, on the other hand, measures the size of the error in percentage (%) terms. It is calculated as the average of the unsigned percentage error. Equation (3.3) gives the expression for the MAPE criterion used.

Speed: Speed of artificial neural networks process is an important economic goal (Skalak, 2002). In this present work results are to be generated in real- time in order to close the gap of the existing system. The ability for the model to process its input in order to produce its output in a real time to quarterly is expression of the timeliness and speed of the model.

Visualization: The main objective of data visualization is the overall idea about artificial neural networks model. In artificial neural networks most of the times retrieving data from repositories which innately hidden is a difficult task for a user, so this visualization of the artificial neural networks helps to provide high levels of understanding and trust. Data visualization is to let the user understand what is going on (Fayyad et al., 2001).

The visualization tool used in the course of study is Dashboard. Dashboard is self-explanatory.

Robustness: Robust is characteristic describing a model's, test's or system's ability to effectively perform while its variables or assumptions are altered. A robust concept can operate without failure under a variety of conditions. Robustness can relate to both economic and statistical concepts. For statistics, a test is claimed as robust if it still provides insight to a problem despite having its assumptions altered or violated. In financial markets that continue to perform despite alterations in market conditions in general, being robust means system can handle variability and remain effective.

Validation: Validation techniques are employed to tackle fundamental problems in pattern recognition (model selection and performance estimation). In this study, 2-Fold and K-Fold cross validation techniques were employed and the validation set was only used as part of training and not part of the test set. The test set will be used to evaluate how well the learning algorithm works as a whole.

Consistency: this characteristic is measured using goodness of fit and explained variation to ascertain a models prediction closeness to real data and forecast.

3.4.2 Performance Indicators for the Proposed System

To evaluate the accuracy of the ANN approach in forecasting, they include: mean squared error (MSE) and root mean squared error (RMSE) will be estimated along with perceptions of user experience with the proposed neural network forecast.

Questionnaires would be administered to the same responded to elicit their perception of the algorithms output.

CHAPTER FOUR

4.0 RESULT AND DISCUSSION

4.1 Data Presentation and Model Analysis

4.1.1 Data Presentation

After data collection, the researcher must prepare the data to be analyzed. Organizing the data correctly saves a lot of time and prevent mistakes. This can be accomplished by spot-checking a random assortment of participant data groups, but this method is not as effective as re-entering the data a second time and searching for discrepancies. This method is particularly easy to do when using numerical data because the researcher can simply use the database program to sum the columns of the spreadsheet and then look for differences in the totals. The components of data preparation include data recovery, profiling, cleansing, validation and transformation; it often also involves pulling together data from different internal systems and external sources (Rouse, 2017). Data collected for preparation in this study are of two categories; the primary and the secondary data.

Primary Data: For the purpose of this study relevant observations were collected through personal interviews, observation and questionnaires 596 copies of questionnaire were distributed to commercial bank and central bank staff, stock brokers and staff of NBS Owerri. 370 copies of questionnaire were returned due to several factors, representing approximately 62% response rate.

Secondary Data: principally collected from CBN’s Website and NBS statistics database.

4.1.2 Analysis of the Existing System

Questionnaires were distributed to ascertain the performance of the existing forecasting method used in Nigeria and to form a yardstick for performance evaluation of the existing and proposed forecasting methods. This was done using the delphi method.

The questionnaire received from the three groups of independent evaluators are spread, thus:

1. Finance and I.T professionals 105
2. Finance and economic consumers 121
3. Independent evaluators 144

Table 4.1 Likert scale for responses on degree of perception				
Very Low	Low	Neutral	High	Very High
1	2	3	4	5

Assessment by Finance and I.T professionals (105)

Table 4.2: Control Matrix for Finance and I.T professionals						
Performance indicator	**Very low**	**low**	**Neutral**	**High**	**Very high**	**Ranking**
Accuracy	0	68	25	8	4	2
Visualization	67	11	19	0	8	1
Consistency	26	14	50	9	6	3
Robustness	49	0	8	26	22	1
Validation	61	27	17	0	0	1
Speed	90	9	6	0	0	1

Table 4.2 identifies four weak performance indicators with the traditional forecasting method used in Nigeria for recession forecast. These are poor visualization, not robust, poor validation and low speed of forecast as it takes three (3) to six (6) months to make a forecast after consecutive quarters have been compared.

Assessment by Finance and Economic Consumers (121)

Table 1: Control Matrix for Finance and economic consumers						
Performance indicator	**Very low**	**low**	**Neutral**	**high**	**Very high**	**Ranking**
Accuracy	44	55	0	22	0	2
Visualization	60	12	39	10	0	1
Consistency	60	43	18	0	0	1
Robustness	14	74	0	30	3	2
Validation	56	29	27	15	0	1
Speed	79	31	11	0	0	1

From Table 4.3 Consumers of recession forecasts agree to a large extent with professionals as to the degree of poor visualization, validation and speed but they also associated low consistency with the way the forecast are made.

Assessment by independent evaluators (144)

Table 2: Control Matrix for independent evaluators						
Performance indicator	**Very low**	**low**	**Neutral**	**high**	**Very high**	**Ranking**
Accuracy	100	39	0	5	0	1
Visualization	91	36	17	0	0	1
Consistency	132	12	0	0	0	1
Robustness	77	29	36	2	0	1
Validation	22	69	40	23	0	2
Speed	55	32	29	18	10	1

The Independent respondents surveyed affirmed the low visualization, validation and low speed of the existing forecast system and went further to rate accuracy and robustness as being equally poor.

Inference on the Existing System

The three category of evaluators agree on the poor level of speed of prediction, robustness, and validation and somewhat on accuracy and visualization of the existing methods of recession forecasting in Nigeria. This thus expose the weakness of the existing system

Recession forecasting by quarter comparism

Table 4.5: Existing Forecast Method based on GDP quarters comparism

Quarterly	Gdp	DATE	gdpNormalized	growth rate	SIGN
2010 Quarter 1	12,583,478.33	1/1/2010	0.23807762	351,052.34	Base Year
2010 Quarter 2	12,934,530.67	4/1/2010	0.552894189	1,369,907.77	+
2010 Quarter 3	14,304,438.44	7/1/2010	0.279583055	485,378.30	-
2010 Quarter 4	14,789,816.74	10/1/2010	-0.284163283	-1,339,100.06	-
2011 Quarter 1	13,450,716.68	1/1/2011	0.224470609	307,015.34	+
2011 Quarter 2	13,757,732.02	4/1/2011	0.457718795	1,061,887.24	+
2011 Quarter 3	14,819,619.26	7/1/2011	0.334576011	663,354.55	-
2011 Quarter 4	15,482,973.81	10/1/2011	-0.354726721	-1,567,467.78	-
2012 Quarter 1	13,915,506.03	1/1/2012	0.255532303	407,541.74	+
2012 Quarter 2	14,323,047.77	4/1/2012	0.538210714	1,322,386.96	+
2012 Quarter 3	15,645,434.73	7/1/2012	0.253347135	400,469.78	-
2012 Quarter 4	16,045,904.51	10/1/2012	-0.337119143	-1,510,483.56	-
2013 Quarter 1	14,535,420.95	1/1/2013	0.303055296	561,342.60	+
2013 Quarter 2	15,096,763.55	4/1/2013	0.549093959	1,357,608.91	+
2013 Quarter 3	16,454,372.46	7/1/2013	0.339037141	677,792.31	-
2013 Quarter 4	17,132,164.77	10/1/2013	-0.393664919	-1,693,485.27	-
2014 Quarter 1	15,438,679.50	1/1/2014	0.329195951	645,942.81	+
2014 Quarter 2	16,084,622.31	4/1/2014	0.560494581	1,394,505.27	+
2014 Quarter 3	17,479,127.58	7/1/2014	0.337009101	671,228.87	-
2014 Quarter 4	18,150,356.45	10/1/2014	-0.519198396	-2,099,755.07	-
2015 Quarter 1	16,050,601.38	1/1/2015	0.25713868	412,740.53	+
2015 Quarter 2	16,463,341.91	4/1/2015	0.597075157	1,512,892.68	+
2015 Quarter 3	17,976,234.59	7/1/2015	0.301873371	557,517.48	-
2015 Quarter 4	18,533,752.07	10/1/2015	-0.67069098	-2,590,037.53	-
2016 Quarter 1	15,943,714.54	1/1/2016	0.214524989	274,827.87	+
2016 Quarter 2	16,218,542.41	4/1/2016	0.542694882	1,336,899.28	+
2016 Quarter 3	17,555,441.69	7/1/2016	0.332951046	658,095.60	-
2016 Quarter 4	18,213,537.29	10/1/2016	-0.616782635	-2,415,571.46	-
2017 Quarter 1	15,797,965.83	1/1/2017	0.287118067	509,764.21	+
2017 Quarter 2	16,307,730.04	4/1/2017	-4.909326574	-16,307,730.04	-

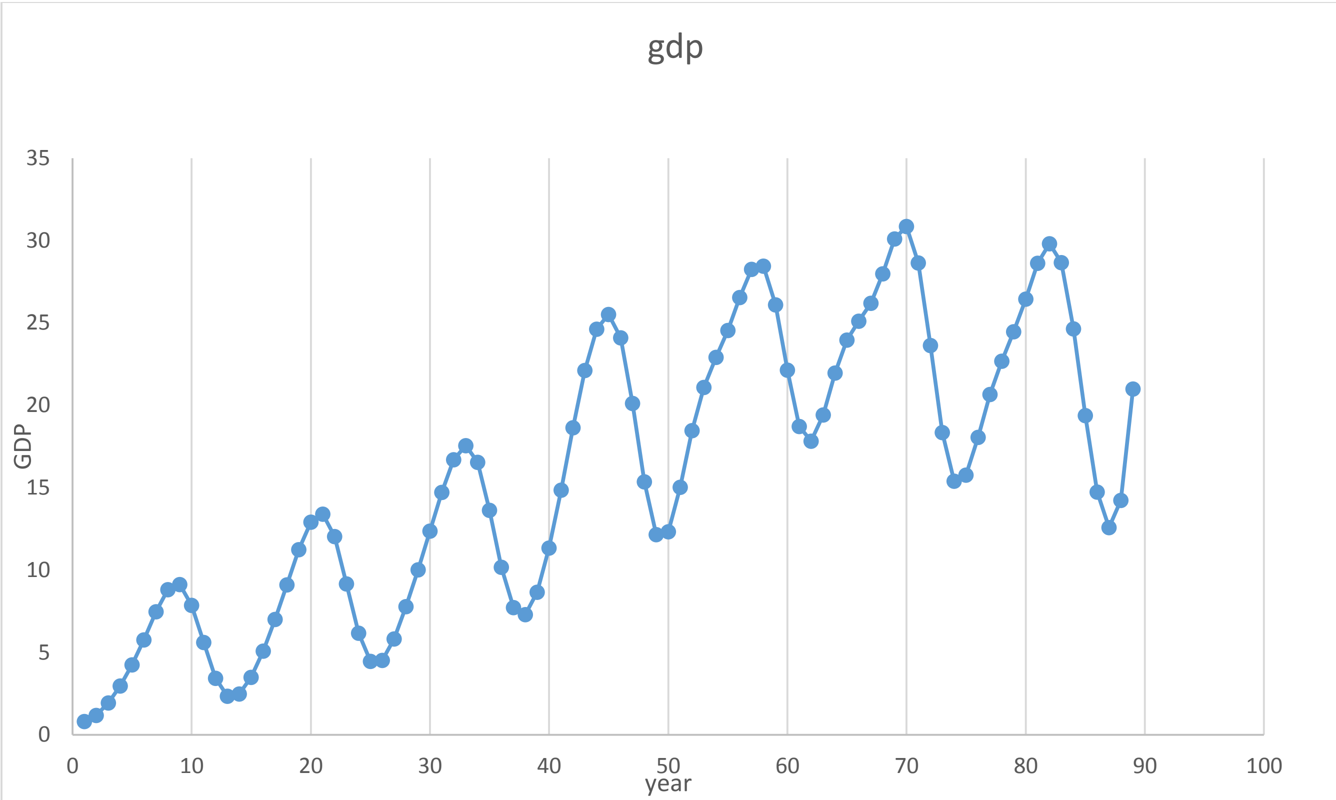


Figure 4.1: Plot of GDP forecast from 2010 - 2017

Problems with the Existing System

1. **The time Lag:** at least a quarter between leading, coincident and lagging indicators makes it hard to stall recession and performance of policy cannot be ascertained quickly.
2. The existing system is not robust and this poses difficulty in data exploratory analysis and manipulation.
3. Accessibility and visualization are greatly limited with the existing system
4. The difficulty in accessing the system for information retrieval and the existing system seems to be difficult to be used for data analysis.

4.2 Modelling with Tools/Environment

The improved Neural Network algorithm used in the prediction of recession probability was done using R studio and r

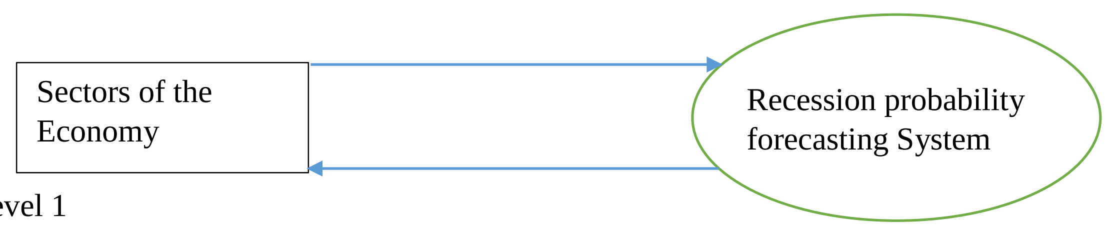
4.2.1 Logical System Model

Logical system design describes an abstract representation of the data flows, inputs and outputs of the *system*. This is often conducted via modelling, using an over-abstract (and sometimes graphical) model of the actual *system*. In the context of systems, *designs* are included *(Ulrich and* Eppinger, *2000)*.

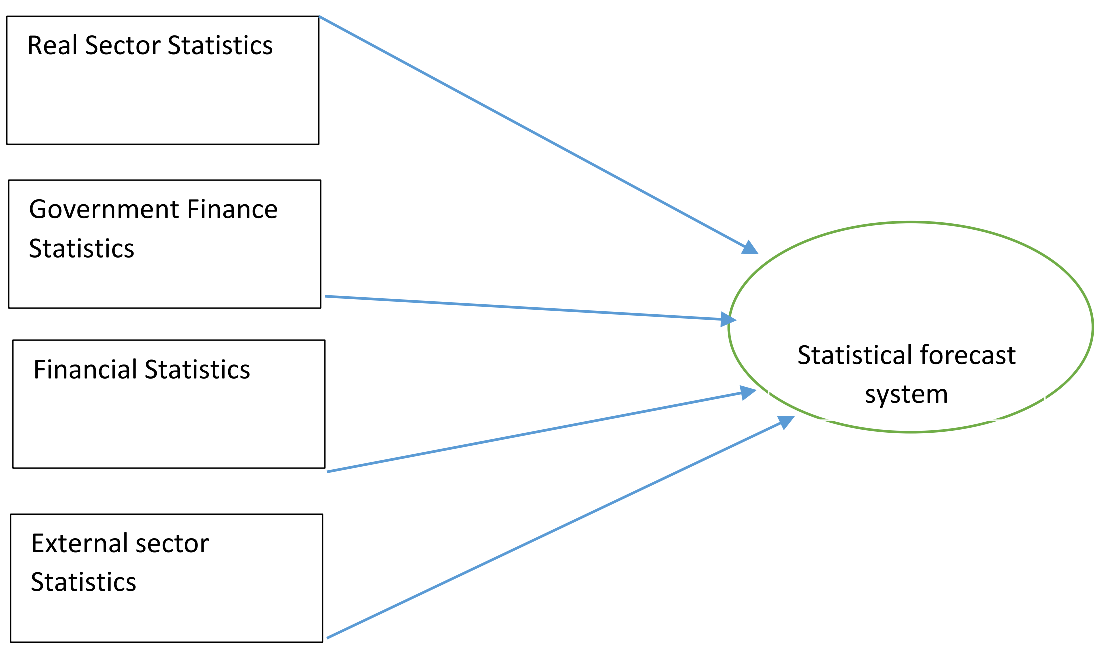
4.2.1.1 Data Flow Diagram of the Existing System

Level 0

Relevant Leading and coincident indicators that precursor recession are collected from relevant arms and agencies of government, stored and compared quarterly for recession probability.



Level 1



4.2.2 Physical System Models

The screenshot of the Input/output design of the proposed system is presented in this section.

4.2.2.1 Input Design

After the dataset have been loaded into the system, the preprocessing operation (feature selection and reduction) starts. The dataset had 40 features but was reduced to the 12 most highly correlated features to Nigeria economic growth and this was generated from the application of Genetic Algorithm on the entire dataset after a ten-fold cross validation.

Table 4.6 Output from the Genetic Algorithm on choice of features fed into the Neural Network

Features Selected	Correlation to GDP
Consumer Price Index	100%
Fuel Pump Price	
Narrow Money (M1)	100%
Broad Money (M2)	
All Share Index	
Exchange Rate	100%
Export	
Import	
Treasury Bill Rate	
Crude Oil	
Lending Rate	

From table 4.6 the selected eleven features with 90 observation were split into training and test sets. Generalized linear model and neural networks were applied to both data sets. The training set consisted of 75% of randomly selected data points while the remaining 25% for the test/ validation set was also randomly picked to avoid bias.

4.2.2.2 Output

The trained system was tested with 25% of the randomly selected data points. The result of the system is shown below:

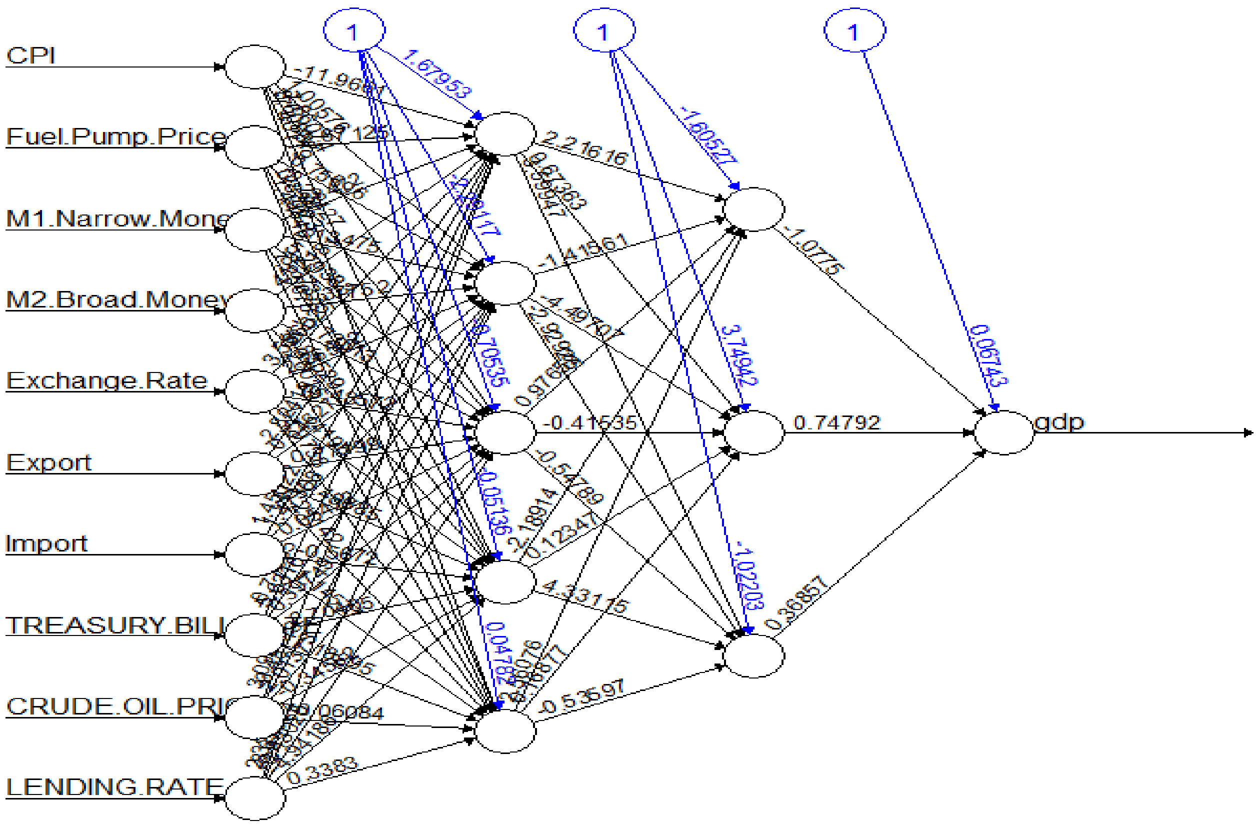


Figure 4.2. Plot of Neural Networks

The neural network diagram shows the relationship between the input variables or features to Economic Growth. Biases or exogenous factors are indicated by the Blue lines are external factors not captured with the features like civil unrest in the oil rich Niger delta, oil theft e.t.c. The hidden layers are not defined, as they function like a blackbox, through which the algorithm after training use to generate its predictive output.

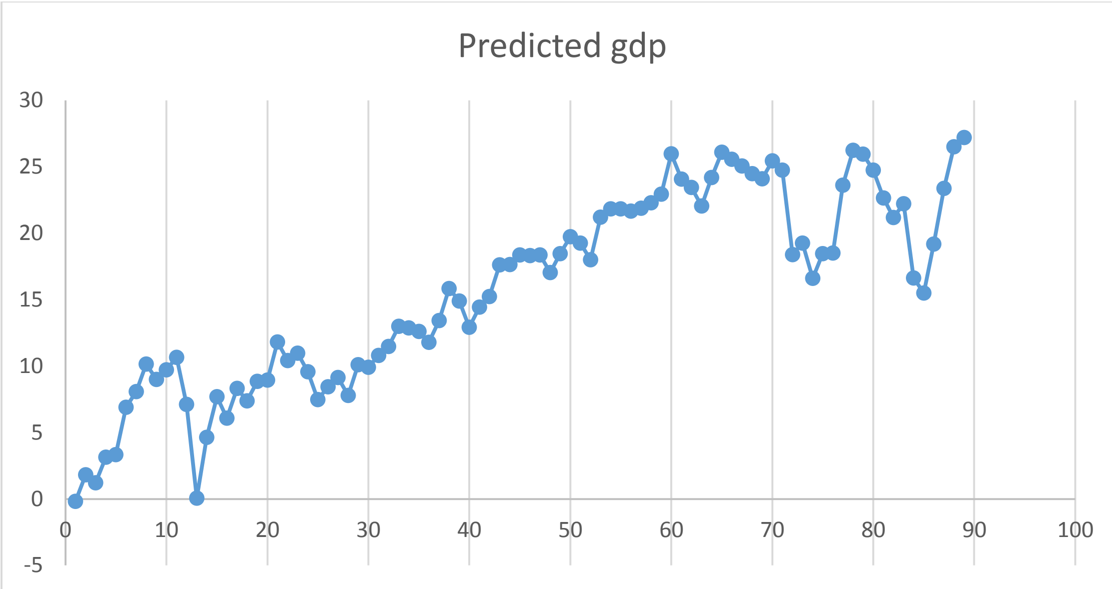


Figure 4.4 Predicted GDP

4.3 System Requirements

4.3.1 Hardware Requirements

The Enhanced Neural Network algorithm was designed to function with the following minimum hardware specification requirements:

1. Dual core series processor
2. RAM (Random Access Memory) 1GB
3. 15'' colour monitor, preferably a flat screen monitor for space management and to avoid excess radiation on the eye of the user.

4.3.2 Software Requirements

R is a language and environment for statistical computing and graphics. It compiles and runs on a wide variety of UNIX platforms, Windows and MacOS. R provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering …) and graphical techniques, and is highly extensible.

RStudio is a free and open-source integrated development environment (IDE) for R.

Operating System: any version of Microsoft Windows operating system (windows NT/2000/ME/XP/Vista/7/8), any version of Linux, and any version of Macintosh will enable one to run this system comfortably.

Anti-virus/Anti-spyware Software: Any good anti-virus software consisting of Norton's, Avira, among others, that will protect the system against malicious attacks is useful.

4.3.3 Data Requirements

The data required for this algorithm were sourced online from the Central Bank of Nigeria Statistics Database. To be amenable for use with this algorithm they were preprocessed using spline function interpolation for the GDP data and normalized or scaled.

4.4 Implementation and Testing

4.4.1 Implementation

To implement this algorithm R studio was used which has R programming language at its core. R studio is written in C++ and Qt framework which is a cross-platform application framework that is used for developing application software that can be run on various software and hardware platforms with little or no change in the underlying codebase, while still being a native application with native capabilities and speed. It provides a simple user interface for this algorithm design.

Coding: This is the actual programming for implementing the designs in this work. It consists of the major modules such as:

Preprocessor: this interpolates GDP data for sync with other variables to be used in recession prediction

Dataframe Object Creation: creates a placeholder for the preprocessed data being read into the algorithm.

Test / Train Data Split: The variables of interest are randomly divided into two groups in a ratio of 75% to 25%. 75% for the Training Set and 25% for test set or validation.

4.4.1 Implementation

Coding: This is the actual programming for implementing the designs in this work. It consist of the major modules such as:

1. Database Module: This is to establish the connection between the front end and back end of the system development.
2. CSS module: This codes is used for interface layout design and arrangement.
3. Java script module: This is used for validation and events automation that links the functional programs.
4. Image module: This contents the images or pictures that displays on the system interface.
5. Menu Listing: Program listing of the modules 1 to 6 above and other files can be seen at the appendix

4.4.2 Testing

Testing is an important part of every software development. This is done to verify if the system achieves the goal set for it. It involves the execution of a software component or system to evaluate one or more properties of interest. There are various phases of testing done in this proposed system. However, the tests performed include (Eleven40 pro theme, 2016):

1. **Unit Testing**

This testing method checks individual units of source code for errors or repeated entities. It also used to test sets of one or more program modules together with associated control data, usage procedures, and operating procedures to determine if they are fit for use Kolawa (2007).

2. **Integration Testing**

Integration testing is a software testing in which individual software modules are combined and tested as a group Ould and Unwin (1986). It is usually done after unit testing and before validation testing. Integration testing takes modules that have been unit tested, groups them in larger aggregates and applies tests defined in an integration test plan to those aggregates. This serves as its input. The output is the integrated system ready for system testing. The purpose of integration testing is to detect any inconsistencies between the software units that are integrated together (called assemblages) or between any of the assemblages and the hardware.

3. **System Testing**

System Testing is testing conducted on a complete, integrated system to evaluate the system's compliance with its specified requirements. System testing is a more limited type of testing; it seeks to detect defects both within the "inter – assemblages" and also within the system as a whole IEEE Standard Computer Dictionary (1990). Here, the system testing was carried out and also achieved.

4.5 Result Discussions

What are key performance measures for making a recession forecast?

Recession forecasting has been carried out using various indicators from different parts of the world as shown in literature. From the literature review as well as the results of analyses carried out, several performance indicators were identified for evaluation of a recession forecasting model. The performance indicators identified were: accuracy, visualization, consistency, robustness, speed (response in time), reliability.

GDP growth rate is usually done by comparing consecutive quarter's growth and asserting if there is a positive or negative growth, this is cumbersome time consuming and provides a post mortem approach to solving the problems recession can cause.

The accuracy of prediction can be validated by how many corrects forecasts exist and how far predictions are from real values (error rate). Thus with the variable of choice it is possible to predict the economy at any instant of time precisely monthly.

To what extent does the existing statistical or economic model not measure up with identified performance indicators?

The accuracy of most statistical models falls below that of artificial neural networks as shown by the classification rate of the ANN model implemented in this study. From the results of this study the Mean Square Errors (MSE) were approximately 14 for the Neural Network, 25 for the generalized neural network and 24 for the regression thus its observed that the forecasting accuracy level of the ANN model compared with that of the ARIMA model is quite significant. It can be argued that both models achieved good forecast performance judging from the forecast error of both models which are quite low. This finding agrees with the work of Sterba and Hilovska, (2010). However, the performance of ANN model is better than ARIMA model in terms of forecasting accuracy on many occasions from the test data. Results show that the ANN model is better than the ARIMA model for prediction. We also observed that the pattern of ARIMA model is directional, while ANN model is toward value forecasting. This finding also agrees with the work of (Lahane, 2008). Statistical test was carried out, which also showed that there is no significant difference between the actual and predicted values of the two models as the values of ANN and ARIMA are close. Notwithstanding, ANN is still better.

To what extent have the novel artificial neural network (ANN) modeled the relationship between the leading indicators and the probability of a future recession?

The Improved artificial neural network used twelve leading and coincident variables to forecast recession probability in Nigeria. GDP was first interpolated from quarterly to monthly to be able to train the neural network to forecast monthly GDP thus making the probability monthly instead of quarterly. The relationship between the indicators of choice are peculiar to the Nigerian scenario as it includes the prices of dollars and premium motor spirit.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of Findings

Recession probability forecasting using an improved artificial neural network provided a formal basis for recession prediction in the Nigerian contest employing machine learning. Existing literature identified different indicators for the prediction of recession which are different from country to country and specific, some indicators are in Nigeria while others are not captured. The dynamic nature of nation states makes it peculiar as an entity and thrives on models typical of the internal workings of the state as an entity. Nigeria is peculiar in it share of variables both exogenous and endogenous.

The use of genetic algorithm helped in selecting the indicators that correlate the most to recession in Nigeria, thus making modelling with such selected variable a step towards making accurate forecasts even with .other statistical models as exemplified with the Generalized Linear Model and the Regression.

Mean Square error appreciably helped in checking the validity of the predictions by the Neural Network as compared with GLM and Regression.

5.2 Conclusion

From the course of this thesis, several literature were reviewed in other to identify best practices with implementing machine learning that makes artificial neural networks algorithm a powerful tool to be used for carrying out probability forecasts that will achieve good result to support decision making in financial services sector. The performance indicators identified in this study are accuracy, speed (monthly), visualization, robustness, validation and consistency. Furthermore, in the study the identified performance indicators were assessed and measured against existing system method use for recession probability forecasting. The findings shows several countries adopt or use different leading, coincident and lagging indicators in forecasting a recession, for the Nigerian nation the following were used; consumer price index, fuel pump price, Narrow Money (M1), Broad money (M2), All Share index, Exchange rate, Export, Import, Treasury bill rate, crude oil price and lending rates.

The enhanced system was developed which proves to be stronger than the existing system. The improved artificial neural network developed is able to make recession probability forecast on a monthly basis instead of waiting for quarterly comparism as is obtained from the various agencies of government charged with the responsibility of forecasting recession. The training and test data used for model exploratory analysis range from 2010 to 2017**.**

5.3 Knowledge Contribution

Previous studies on recession in Nigeria were purely statistical and quarterly, this thesis has been able to forecast recession monthly.

5.4 Recommendations

The following recommendations are made based on the findings of this research:

i. Most financial players are aware of the dangers of bad financial indexes and the damage that can arise from late or poor financial information, they are aware of the long wait to be able to forecast a recession. This makes it imperative to bridge the knowledge gap and competitive market space they find themselves by deploying machine learning systems able to forecast recession at least on a monthly basis.

ii. Governments and its agencies should change their existing manual approach in favour of a more current monthly recession forecasting system.

iii. There should be a central data system that would feed the machine learning system with relevant indicators to be able to create early warning system to enable decision makers enact policies on time.

iv. A web-based system should be created for easy collection of these variables and onward analysis.

5.5 Areas for Further Research

There should be growing and concerted efforts towards daily early warning recession forecasting system that can be fed daily financial indicators and predict the tread of the economy.

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APPENDIX A

INPUT DATA FOR THE SIMULATION

CPI	Fuel. Pump. Price	M1. Narrow. Money	M2. Broad. Money	Exchange. Rate	Export	Import	TREASURY .BILL.RATE	CRUDE. OIL. PRICE	LENDING. RATE	Gdp
103.13	65	5571270	10446374	153.55	869237	742224.7	7.58	77.6	18.82	0.82
105.04	65	5274242	10792645	152.08	933643	638266	6.75	75.1	18.74	1.18
104.9	65	5332750	11023313	151.85	1024761	765741.9	6.6	80.3	19.03	1.94
105.72	65	5255891	10972488	152	1134119	578830.5	2.63	85.3	19.05	2.97
105.68	65	5422502	10759315	153.26	890504.6	640987.6	2.94	77.5	18.77	4.25
108.76	65	4958350	10845498	153.87	977726.4	655407.1	2.29	75.8	17.65	5.77
109.94	65	4917990	10941435	152.41	995138.1	638303.6	1.63	77.2	17.4	7.47
111.87	65	5018270	11520645	152.23	853635.6	707287.3	1.2	78.7	16.89	8.81
112.38	65	5043289	11224790	153.85	1115777	845816.1	1.04	79.5	16.66	9.13
112.72	65	4966454	11224607	153.98	1104088	620035.2	2.33	84.4	16.16	7.87
112.77	65	4800717	11142651	153.13	940334.5	705119.3	3.72	86.7	16.11	5.61
114.22	65	4640919	11525530	154.57	1172511	625955.3	14.27	92.8	15.74	3.44
115.59	65	6771581	11561526	156.13	1229190	862663.2	14.53	98	15.77	2.35
116.7	65	5773222	11595668	155.11	1157635	652256.6	15	106.6	15.75	2.48
118.3	65	5798198	11653624	157.09	1189597	890600.9	8.92	116.6	15.81	3.5
117.66	65	6002260	11898957	157.05	1567176	843384.7	7.41	124.5	15.75	5.08
118.73	65	5871232	11986235	158.05	1249850	801042.7	7.08	118.4	15.81	7
119.89	65	5868318	12172097	158.32	1449185	830344.3	8.2	117	15.76	9.11
120.27	65	5637265	12389275	163.71	1233996	1119639	8.63	117.9	15.84	11.24
122.27	65	5551087	12508015	163.1	1318765	1188719	9.52	112	15.82	12.91
124	65	5616622	12618080	158.23	1021378	1063679	8.27	115.7	15.87	13.4
124.6	65	5424517	12172500	161.25	1398834	785311.8	7.09	113.1	16.49	12.03
124.65	65	5389130	12210412	160.35	1200196	1194695	7.49	113.9	16.82	9.16
125.97	65	5567075	13303495	163.3	1220865	763527.6	11.77	111.5	16.75	6.18
130.19	97	6826905	13755293	164.62	1332248	685173.6	12.6	113.81	16.92	4.47
130.55	97	6420603	13153787	160.85	1412883	876445.7	12.94	121.87	17.11	4.53
132.63	97	6522940	13270974	159.41	1387260	1319775	12.75	128	17.27	5.82
132.8	97	6668824	13304784	159.37	1500589	1033264	14.26	122.62	16.9	7.79
133.8	97	6534504	13603139	159.67	1168388	925711.2	13.86	113.08	16.98	10.02
135.34	97	6599395	13483059	163.43	1096707	799791	14.08	98.06	16.93	12.37
135.66	97	6403788	13392426	163.32	1196963	686629.8	13.34	104.62	16.96	14.72
136.57	97	6244358	13770062	162.24	1406320	719992.1	13.92	113.76	16.53	16.69
137.95	97	6392455	14065267	159.8	1167092	467266.7	14.49	114.36	16.37	17.55
139.17	97	6542100	14399299	159	1099532	749415.2	14.76	108.92	16.48	16.55
140.01	97	6880644	15062730	159.32	1052250	779186.8	14.85	111.05	16.51	13.63
141.06	97	7420946	15483848	159.26	1319095	723905.9	10.97	114.49	16.54	10.17

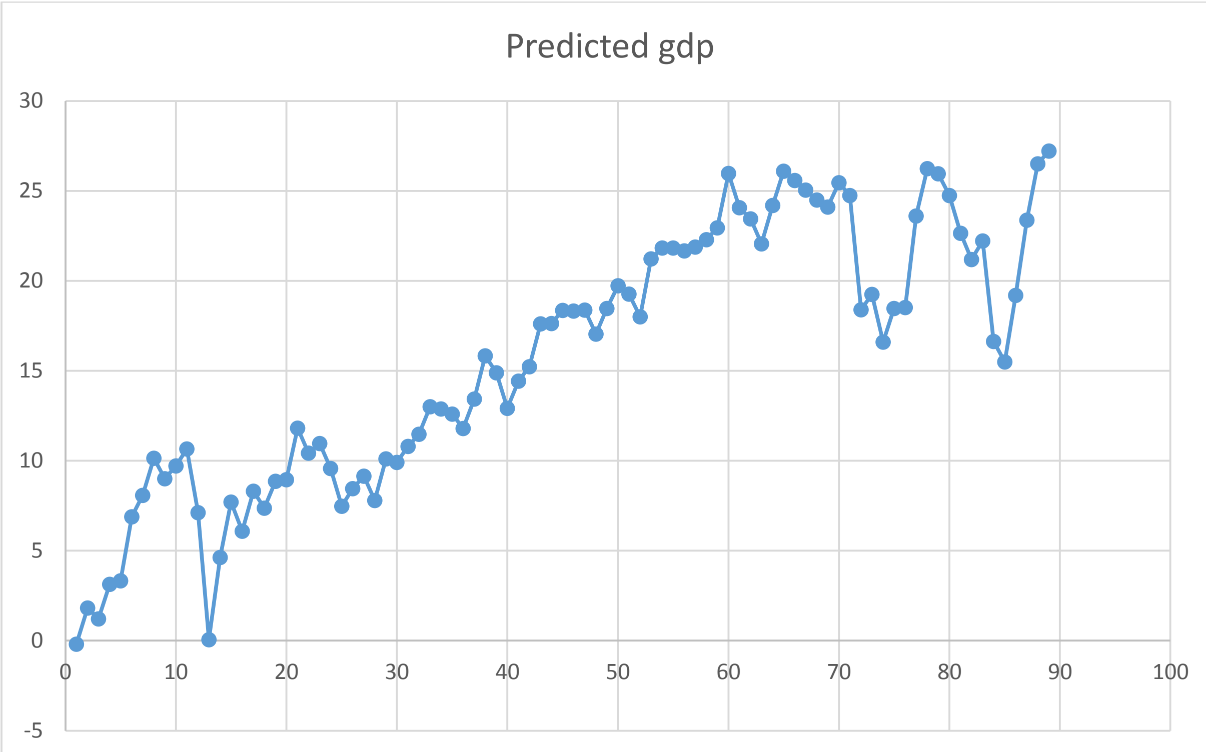
141.94	97	7078746	15308393	159.12	1296337	701136	10.8	115.24	16.57	7.72
143	97	6914399	15547625	158.7	1058931	778134.2	10.8	118.81	16.56	7.3
144.02	97	6938532	15669169	159.8	1248219	696015.5	10.91	112.79	16.61	8.65
144.82	97	6776177	15634382	159.81	1701638	811089.9	11.3	105.55	16.65	11.33
145.79	97	6744555	15424053	159.57	1430792	1028297	11.56	106	16.66	14.85
146.65	97	6939549	15593173	160.98	1254802	690024	11.6	106.06	16.56	18.64
147.44	97	6522553	14811430	162.43	1149973	821352.6	10.64	109.78	16.47	22.11
147.81	97	6270342	14619449	162.28	1321140	775297	10.41	107.84	16.55	24.63
148.92	97	6293477	14362451	163.14	1243363	817988.6	10.17	113.59	16.76	25.52
150.04	97	6460005	14529508	165	1174748	747973.8	9.9	112.29	17.1	24.1
151.11	97	6378039	14734883	167.14	1164829	865357.4	11.17	111.14	17.17	20.12
152.29	97	7032839	15688964	171.4	1217242	706759.2	10.8	112.75	17.01	15.36
153.26	97	6782016	15493690	171.71	1221928	743598.3	9.82	110.19	16.95	12.15
154.03	97	6739404	15424175	169.45	1062006	878897.7	9.83	110.83	16.93	12.33
155.23	97	6930692	15738908	171.52	1174558	828151.6	9.75	109.47	16.69	15.02
156.19	97	7153673	16041029	170.25	1366031	1000041	9.95	110.41	16.7	18.46
157.41	97	6990318	16156594	166.85	1030685	910584.5	9.88	111.9	16.5	21.09
158.62	97	6830528	16171623	167.17	1132897	857712.8	9.98	114.6	16.5	22.91
159.65	97	6989261	16669201	167.71	1098281	852901.6	10.13	109.63	16.44	24.55
160.42	97	6727525	16375439	170.36	1141071	724465.8	11.26	102.33	16.6	26.55
161.31	97	6860613	16814451	168.64	1065494	766825.7	11.92	98.27	16.44	28.25
162.13	97	6754212	16558084	169.43	941486.5	847751.3	11.82	83.5	16.48	28.44
163.09	97	6678249	16696664	175.85	904199.6	1225255	10.81	80.42	16.47	26.09
164.44	97	6919549	18927787	188.45	821854.8	902595.3	4.57	63.28	15.88	22.14
165.77	97	7118512	18975001	196.13	706159.1	828383	5.62	48.81	16.86	18.71
166.9	87	6729928	18871259	213.03	768244.8	735598	9.11	58.09	16.77	17.82
168.42	87	6994086	19142526	222.93	746259.4	1033741	10.36	56.69	16.9	19.42
169.71	87	6844753	19267593	210.7	892291	712818.8	10	57.45	15.95	21.97
171.58	87	6669647	19193976	219.55	710661.6	901231.7	10	65.08	16.08	23.96
173.17	87	6542392	18811429	218.98	760617	870972.9	9.95	62.06	17.24	25.1
174.37	87	6471057	18424703	237.15	725430	965772.1	10.03	57.01	17.3	26.19
175.4	87	6969592	18491572	216.64	662663.6	1004861	10.23	47.09	17.29	27.99
176.46	87	7148593	18718003	222.68	708442.5	755069	10.77	48.08	17.02	30.09
177.2	87	6689646	18204396	224.98	775713.1	695809.6	10.88	48.9	16.84	30.85
178.37	87	6980497	18367239	232.4	637983.8	953394.5	11.2	44.82	16.98	28.64
180.15	87	8571701	20029831	258.3	614151.8	795235.9	13.96	37.8	16.96	23.64
181.71	86.5	8250773	19799458	289.78	484441.2	647176.9	13.99	30.66	16.54	18.35
185.89	86.5	9066713	20620803	329.83	475713.8	563053.8	13.96	31.7	16.72	15.39
189.94	86.5	9040818	20470436	320.93	533607.2	612485.2	14	37.76	16.82	15.76
192.99	86.5	9136068	20727909	320.71	665217.8	850021.6	14.93	41.6	16.77	18.05
198.3	145	9391866	20721908	336.93	595746	678996.3	12.34	47.01	16.13	20.66

201.7	145	9125933	21684965	351.82	658268.9	978795.9	8.32	48.46	16.78	22.68
204.23	145	9230931	22182188	364.47	719339.6	807662	8.04	45.92	17.14	24.46
206.29	145	9125897	21647325	396.15	894532.4	941347.8	7.27	46.15	17.18	26.45
207.96	145	9937237	22121330	431.1	787785.3	862238.3	5.53	47.43	17.09	28.63
209.68	145	10023617	22275513	462.03	961533.3	898323.7	4.91	51	17.1	29.8
211.33	145	10429541	22382915	415.36	1077991	843885.2	4.12	45.25	17.06	28.66
213.56	145	11068107	23388333	455.26	981435.9	796380	13.35	53.48	17.09	24.65
215.72	145	10983299	23096527	493.29	1096731	763846.5	13.46	55.01	16.91	19.37
218.95	145	10057955	22210955	494.7	1002213	872347.3	13.5	46.39	17.13	14.74
222.71	145	10234532	22304268	429.48	941264.9	912542.1	13.5	52.13	17.43	12.58
226.27	145	9815679	21768241	392.89	1165747	941941.4	13.58	52.94	17.44	14.24
230.53	145	10257331	22047771	384.48	1106627	924980.1	13.6	50.57	17.58	21

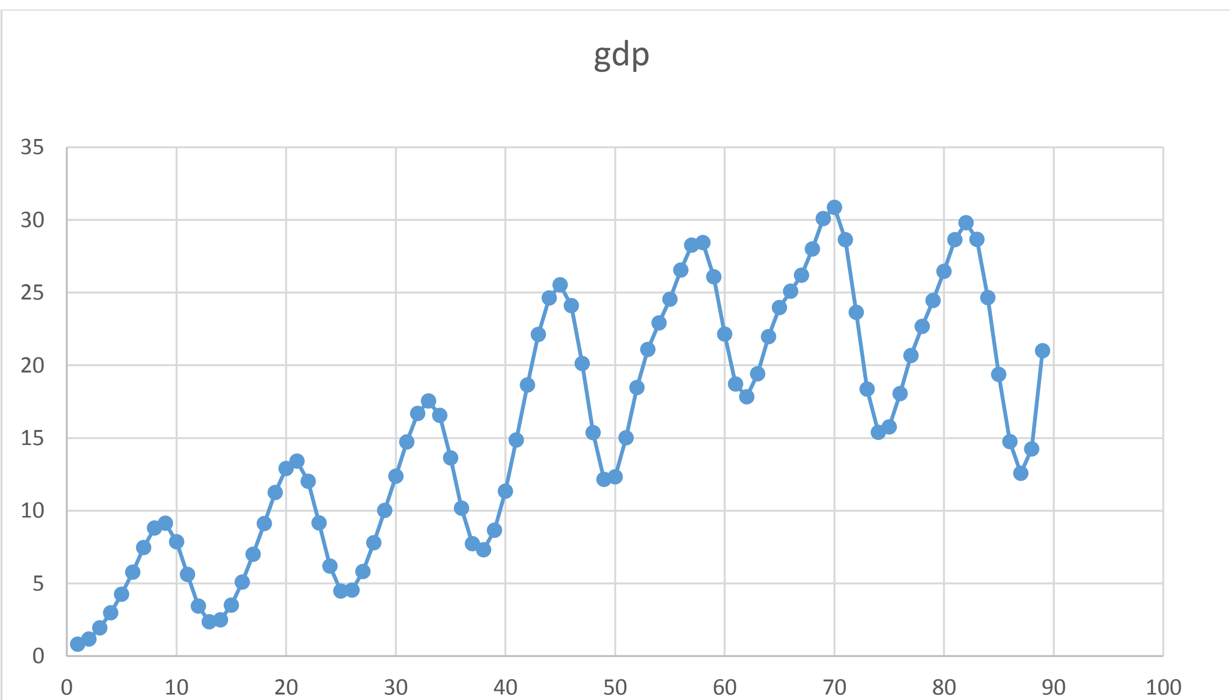
FEATURED DATA BEFORE SELECTION BY GENETIC ALGORITHM

FINANCIAL STATISTICS	Sectoral Analysis of Deposit Money Banks Credit (N Million)
	Principal Financial Ratios of Deposit Money Banks
	Monthly Monetary Authority Account (Naira Million)
	Commercial & Non Interest Banks Analytical Balance Sheet (Naira Million)
	Merchant Banks Analytical Balance Sheet (Naira Million)
	Payment Systems Statistics
	Capital Market Activities
	DMBs Deposit Categories (Naira Million)
	Discount Houses Comparative Statement of Assets & Liabilities (Naira Million)
	Monetary Survey - Monthly (Naira Million)
	Sectoral Analysis of Deposit Money Banks Credit (2015 To Date)
	Money Market Rates
EXTERNAL SECTOR STATISTICS	Balance of bayment
	International investment position
	Interntional Reserves
	External Trade Statistics
	Foreign xchange
	Other sectors
REAL SECTOR STATISTICS	GDP
	CPI
	others
GOVERNMENT FINANCIAL STATISTICS	Federation Account Operations (Naira Billion)
	Federally Collected Revenue Distributions (Naira Billion)
	Summary of General Government Finances (Naira Billion)
	Functional Classification of Federal Government Recurrent Expenditure (Naira Billion)

APPENDIX B



Predicted gdp
30
25
20
15
10
5
0
-5
0
10
20
30
40
50
60
70
80
90
100



gdp
35
30
25
20
15
10
5
0
0
10
20
30
40
50
60
70
80
90
100

APPENDIX C
SUMMARY OUTPUT

Multiple R	
R Square	
Adjusted R Square	
Standard Error	
Observations	

ANOVA

	F	*Significance F*
Regression	131.126	1.64697E-44
Residual		
Total		

	P-value	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	#N/A	#N/A	#N/A	#N/A	#N/A
CPI	0.000154	0.192749643	0.579016	0.19275	0.579016
Fuel.Pump.Price	0.416627	-0.057555878	0.13763	-0.05756	0.13763
M1.Narrow.Money	0.018055	-6.19336E-06	-6E-07	-6.2E-06	-6E-07
M2.Broad.Money	0.566973	-1.15936E-06	2.1E-06	-1.2E-06	2.1E-06
Exchange.Rate	0.015896	-0.083747394	-0.00891	-0.08375	-0.00891
Export	0.217566	-1.27812E-05	2.95E-06	-1.3E-05	2.95E-06
Import	0.88578	-7.48923E-06	6.48E-06	-7.5E-06	6.48E-06
TREASURY.BILL.RATE	0.026789	-0.763880324	-0.04789	-0.76388	-0.04789
CRUDE.OIL.PRICE	0.336842	-0.049342992	0.142455	-0.04934	0.142455
LENDING.RATE	0.001175	-1.468289408	-0.37732	-1.46829	-0.37732

FIRST ASSESSMENT QUESTIONAIRE

QUESTIONNAIRE FOR EVUALUATION OF EFFECTS OF PERFORMANCE INDICATORS IN HISTORICAL DATA ANALYSIS FOR RECESSION FORECASTS

Note: Select all that applies where necessary.

SECTION A

1. Highest Level of Education:

WASC/GCE [ ] OND [ ] NCE [ ] HND [ ] B.Sc [ ] MSc [ ] Ph.D [ ]

2. What is the Name of your Organization?

3. What is your Job Tittle?

4. Years of Experience?

5. Roles considered are (a) **Information Professionals (IP):** these are people who are knowledgeable in artificial intelligence

(b) Finance/Economic Consumers (F/EC): these are people who use the Economic growth indicators for planning, advice or forecasts.

Independent Experts (IE): these are experts that have appropriate amount of practical or academic experience in the practices of forecasting.

Kindly tick* [X] *in any of the box below to identify the category of your role

IP [ ] IC [ ] IE [ ]

SECTION B

With to respect to the method (either Manual or Automated) been used by your organization in carrying out data analysis on historical sales records, kindly rate the following performance indicators below.

Please rate the following performance indicators. Kindly mark* [X] *in box below to identify your answer.

Using a scale ranging from 1 to 5 where 1= extremely low , 2= low , 3= Neutral , 4= High and 5= Extremely High.

8. Does Government Agencies in Nigeria always have an accurate historical data for Economic growth performance analysis; such as historical data of past Thirty six years that can be used for Recession forecasting?

1	2	3	4	5

9. Are the result generated from data analysis of these historical data easy to interpret?

1	2	3	4	5

10. Does presentation quality such as the use of pie chart, line graph and histogram etc affect information use for decision making in your experience?

1	2	3	4	5

11. Are these historical data such as for the past twenty six year's easy to obtain or access for business performance evaluation?

1	2	3	4	5

12. Is your present system very robust in the sense that it can adjust to any change such as change in figure and still produce an accurate result?

1	2	3	4	5

13. How long can it take the present method you are acquitted with for historical data analysis to respond to requested information such as a request of five years sales records?

Less than 5mins ☐ greater than 5mins less/equal to 20mins ☐ 30 mins time ☐

45mins time ☐ One hour or more ☐

MSE.lm	24.9275754464836
MSE.nn	22.0312090165829

APPENDIX D

SECOND ASSEMENT QUESTIONNAIRE

QUESTIONNAIRE FOR EVUALUATION OF EFFECTS OF PERFORMANCE INDICATORS.

SECTION A

1. Highest Level of Education:

WASC/GCE [ ] OND [ ] NCE [ ] HND [ ] B.Sc [ ] MSc [ ] Ph.D [ ]

2. What is the Name of your Organization?

3. What is your Job Tittle?

4. Years of Experience?

5. Roles considered are (a) **Information Professionals (IP):** these are people who are knowledgeable in artificial intelligence

(b) Finance/Economic Consumers (F/EC): these are people who use the Economic growth indicators for planning, advice or forecasts.

Kindly tick* [X] *in any of the box below to identify the category of your role

IP [ ] IC [ ]

SECTION B

Using a scale ranging from 1 to 5 where 1= extremely unimportant, 2= Unimportant, 3= Somewhat Important, 4=Important and 5= extremely important.

Please rate the following performance indicators with respect to its performance in this new model. Kindly mark* [X] *in box below to identify your answer.

PERFORMANCE INDICATORS	**1**	**2**	**3**	**4**	**5**
Presentation quality(visualization/understanding)					
Accessibility					
Easy to Use					
Precision					
Robustness					
	1hr	**45mins**	**30mins**	**20mis**	**5mins**
Speed (Response in time)					

Spline Interpolation

```
mydata = read.csv("gdpnow.csv", header = TRUE)

head(mydata)

tail(mydata)

library(zoo)

gdp = mydata[c("qvar","gdp")]

head(gdp)

gdp2 = data.frame(gdp2=spline(gdp, method="fmm")$y)

head(gdp2)

plot.ts(mydata$gdp)

gdptimeseries<-ts(mydata$gdp, frequency = 4, start = c(2010,1))


plot.ts(gdptimeseries)

plot(mydata$qvar,mydata$gdp,lwd="2", col="red", xlab="year",ylab="Realgdp", main="GDP plots from
2010-2017")
```

ARTIFICIAL NUERAL NETWORK

```
# Set a seed

set.seed(500)

data <- read.table("C:/Users/justice/Downloads/analysis GDP/cleaned4.txt", header = TRUE)

# Check that no data is missing

apply(data,2,function(x) sum(is.na(x)))

plot(data$gdp)

library(ggplot2)

ggplot(data, aes(Date, gdp)) + geom_line() +

  scale_x_date(format = "%b-%Y") + xlab("months") + ylab("GDP")


# Train-test random splitting for linear model

index <- sample(1:nrow(data),round(0.75*nrow(data)))
```

```
train <- data[index,]
test <- data[-index,]
# Fitting linear model
lm.fit <- glm(gdp~., data=train)
summary(lm.fit)

# Predicted data from lm
pr.lm <- predict(lm.fit,test)

# Test MSE
MSE.lm <- sum((pr.lm - test$gdp)^2)/nrow(test)
# Neural net fitting

# Scaling data for the NN
maxs <- apply(data, 2, max)
mins <- apply(data, 2, min)
scaled <- as.data.frame(scale(data, center = mins, scale = maxs - mins))

# Train-test split
train_ <- scaled[index,]
test_ <- scaled[-index,]

# NN training
library(neuralnet)
n <- names(train_)
f <- as.formula(paste("gdp ~", paste(n[!n %in% "gdp"], collapse = " + ")))
nn <- neuralnet(f,data=train_,hidden=c(5,3),linear.output=T)

# Visual plot of the model
```

```
plot(nn)
# Predict
pr.nn <- compute(nn,test_[,1:10])

# Results from NN are normalized (scaled)
# Descaling for comparison
pr.nn_ <- pr.nn$net.result*(max(data$gdp)-min(data$gdp))+min(data$gdp)
test.r <- (test_$gdp)*(max(data$gdp)-min(data$gdp))+min(data$gdp)
# Calculating MSE
MSE.nn <- sum((test.r - pr.nn_)^2)/nrow(test_)

# Compare the two MSEs
print(paste(MSE.lm,MSE.nn))

# Plot predictions
par(mfrow=c(1,2))

plot(test$gdp,pr.nn_,col='red',main='Real vs predicted NN',pch=18,cex=0.7)
abline(0,1,lwd=2)
legend('bottomright',legend='NN',pch=18,col='red', bty='n')

plot(test$gdp,pr.lm,col='blue',main='Real vs predicted lm',pch=18, cex=0.7)
abline(0,1,lwd=2)
legend('bottomright',legend='LM',pch=18,col='blue', bty='n', cex=.95)

# Compare predictions on the same plot
plot(test$gdp,pr.nn_,col='red',main='Real vs predicted NN',pch=18,cex=0.7)
points(test$gdp,pr.lm,col='blue',pch=18,cex=0.7)
abline(0,1,lwd=2)
```

```
legend('bottomright',legend=c('NN','LM'),pch=18,col=c('red','blue'))

#-------------------------------------------------------------------------------
# Cross validating

library(boot)
set.seed(200)

# Linear model cross validation
lm.fit <- glm(gdp~.,data=data)
cv.glm(data,lm.fit,K=10)$delta[1]
CODE
# Neural net cross validation
set.seed(450)
cv.error <- NULL
k <- 10

# Initialize progress bar
install.packages("plyr")
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)

for(i in 1:k){
  index <- sample(1:nrow(data),round(0.9*nrow(data)))
  train.cv <- scaled[index,]
  test.cv <- scaled[-index,]

  nn <- neuralnet(f,data=train.cv,hidden=c(5,2),linear.output=T)
```

```
  pr.nn <- compute(nn,test.cv[,1:11])
  pr.nn <- pr.nn$net.result*(max(data$gdp)-min(data$gdp))+min(data$gdp)

  test.cv.r <- (test.cv$gdp)*(max(data$gdp)-min(data$gdp))+min(data$gdp)

  cv.error[i] <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)

  pbar$step()
}

# Average MSE
mean(cv.error)

# MSE vector from CV
cv.error

# Visual plot of CV results
boxplot(cv.error,xlab='MSE CV',col='cyan',
        border='blue',names='CV error (MSE)',
        main='CV error (MSE) for NN',horizontal=TRUE)
```