AN ARTIFICIAL NEURAL NETWORK-BASED EXPERT SYSTEM FOR LOAN APPLICATION EVALUATION AT KENYA COMMERCIAL BANK

BY

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MOI UNIVERSITY

DECLARATION

Declaration by the Candidate

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ABSTRACT

A number of manual loan application evaluation models that use traditional judgmental methods have been used and continue to be used by commercial banks in Kenya. These systems however have shortcomings like more time taken to process loan applications and inconsistency in decision making by bank officials due to a variation of information provided by different customers. Some customers who are dissatisfied by this mode of processing loan applications subsequently moving to other banks or seek other financing modes. This poses a potential loss of business to a competitor commercial bank. The aim of this study was to analyze the current loan evaluation system at KCB with a view to design and develop an ANN architecture-based expert system for evaluating loans at the bank. The objectives of the study were: to find out the types of loans KCB offers to its clients; to examine the current systems used by KCB to evaluate loan applications; to determine the challenges faced when evaluating loan applications; to recommend suitable systems for improving the evaluation of loan applications; to design and develop an intelligent system that will improve loan applications evaluation process. This study was based on the expert system theory and the neural network architecture. Data were collected from information rich sources at KCB which involved sixteen respondents. The expert system was developed based on ANN architecture and modeled using the evolutionary development model. The neural network system was built using the back propagation algorithm. The developed expert system helps to fairly and uniformly evaluate loan applications efficiently and is considered an improvement to current loan evaluation processing. This system is recommended for use in Kenya Commercial Bank.

DEDICATION

This thesis is dedicated to my parents Nick Juma and Janet Orawo; and my siblings Victor Juma, Walter Juma, and Loice Juma.

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
ANN	Artificial Neural Networks
CBK	Central Bank of Kenya
ES	Expert System
IS	Information System
IT	Information Technology
KCB	Kenya Commercial Bank
LEN	Loan Evaluation Network
MU	Moi University
NCST	National Council for Science and Technology
OLTP	On-line Transaction Processing
SBA	Small Business Administration
SWOT	Strength, Weakness, Opportunity and Strength

CHAPTER ONE

INTRODUCTION AND BACKGROUND INFORMATION

1.1 Introduction

The chapter provides introduction and background information to the study. The issues covered in this chapter include: global trends in financial information systems, the rise of neuro-computing, application areas for neural networks and background information to Kenya Commercial Bank (KCB). The chapter also provides the statement of the problem; aim and objectives of the study; research questions; assumptions of the study; significance; scope and limitations of the study and operational definitions of terms used.

1.2 Conceptual Setting

According to Finlay and Dix (1996), AI is concerned with building machines that can do something and respond appropriately, and adapt their reaction to the demands of the prevailing circumstances. Such machines display behavior only described as intelligence in human beings. There are a number of areas that that are useful to look at in AI, among them language understanding, problem solving and planning, expert decision making, game playing, and robotics (Finlay and Dix, 1996).

According to Franz (2013) neural networks are a proven, widely used technology to solve complex classification problems. Loosely modeled after the human brain, neural networks are interconnected networks of independent processors that by changing their connections (known as training), learn the solution to a problem. More recently, the development of neural networks, modeled on the human brain has been argued by some

people as the basis for legitimate machine intelligence and learning (Finlay and Dix, 1996).

In the fiscal environment, every organization setup has the aspect of financial gain as a push factor. To reduce losses and improve on gains, various organizations have put in place systems that enable them to improve their services. Organizations have adopted intelligent systems to help them achieve some of these objectives. The recent upsurge in research activities into Artificial Intelligence (AI) has proven that artificial neural networks have powerful pattern classification and prediction capabilities. ANNs have been successfully used for a variety of tasks in many fields of business, industry, and science (Zhang, 2003).

Zhang (2003) acknowledges that ANNs have fast become a standard class of quantitative modeling tools for researchers and practitioners. Interest in neural networks is evident from the growth in the number of papers published in journals of diverse scientific disciplines. This author concludes that ANNs are known to perform well in data –rich, knowledge poor situations and are mostly used to uncover complex relationships in data and permit forecasting based on those relationships.

Desouza (2002) advises that financial institutions that allow for credit and loans should ensure that the transaction would be successfully completed by repayment of the loan. He notes that risk can never be eliminated, but must be reduced to a minimum or some acceptable value. The scoring point method, multivariate discriminate analysis, and simple trend studies of financial performance are the most common methods used for determination of credit worthiness (Desouza, 2012). He continues to say that credit risk

or bankruptcy prediction is a pattern classification problem. Hence, recently we have seen a number of ANN- based applications used in this domain.

A study of ANN incorporating the back propagation algorithm that simulated bank credit decisions in Poland is presented (Desouza, 2002). The study used data from 75 companies that applied for credit from 1994 to 1997, ranging in amounts from $140 to $1600 per month. The ANN decision errors were found to be significantly lower than those generated by other conventionally programmed computer mechanisms.

Liptak (2006) acknowledges that currently, neural network technology is the most progressive of the Artificial Intelligence (AI) systems. The author goes on to say that neural networks have made an unusual rapid transition from laboratory experiments into the marketplace, overtaking other better-established technologies like real time technologies. They are mostly used under human supervision or integrated with Expert Systems (ESs) and fuzzy logic systems (Liptak, 2006).

1.2.1 Application of Neural Networks

Neural networks could imitate and perfect a credit manager's evaluation and decision process to control loss and guide business expansion. Neuro-computing involves processing information by means of changing the states of networks formed by interconnecting extremely large numbers of simple processing elements (Green, 2005). As noted in Sivanandam (2006) the majority of information processing today is carried out by digital computers. This has led to the widely held misperception that information processing is dependent on digital computers. The author further says that in cybernetics and other disciplines that form the basis of information science, information processing

originates with living creatures in their struggle to survive in their environments, and the information being processed by computers today accounts for only a small part. Because of this, people have begun to consider the possibility of information processing devices that differ from conventional computers.

Sivanandam (2006) observes that research is now being carried out that is aimed at the development of an information processing device that mimics the structures and operating principles found in the information processing systems possessed by humans and other living creatures. It is therefore recommended that Information Systems (ISs) should adapt the processing operation in the human nervous system to build new types of advanced parallel information processing device. A large volume of data to be processed and progress in Information Technology (IT) has also raised the need for parallel information processing.

1.2.1.1 Role of Neural Networks in Classification

According to Zhang (2000) classification is one of the most often encountered decision making problems of humans. This happens when a classification problem arises and an object needs to be set aside into a predetermined group based on a number of attributes that have been identified. Finlay (2012) notes that classification models predict which behaviour someone is likely to exhibit. Examples include, response models that predict the likelihood someone responds to a mailing and credit scoring models that predict the likelihood that someone repays a loan.

Many problems in science, medicine, industry, and business can be treated as classification problems. Examples include credit scoring, banking and prediction, quality

control, and speech recognition (Zhang 2000). In the same light, Widrow, Rumelhard, and Lehr (1994) note that neural networks have been effectively applied to various real world classification problems in industry, business, and science.

Zhang (2000) argues that neural networks have emerged as a vital tool for classification and the vast research into neural networks is a promising alternative to existing conventional methods.

1.2.2 Background of KCB Financial Facility

KCB is the pre-eminent regional bank providing access to banking services to over 100 million people in East Africa (KCB Strategic document, 2010). Established in 1896 along the East African coastline, KCB has grown from a simple outfit to a world-class operation. KCB is a Financial Services Provider Headquartered in Nairobi, Kenya. It is among the three largest banks in Kenya with assets of more than 223 billion shillings and shareholders capital valued at 40.9 billion shillings (KCB Strategic document, 2010). The other two are Barclays Bank of Kenya and Standard Chartered Bank of Kenya. KCB is listed on the Nairobi Stock Exchange with the Government of Kenya owning 17.74% of the company and 82.26% being owned by institutional and private investors, (KCB Strategic document, 2010).

Even though KCB made "super-profits", it turned out that most of the loans were made to ill-advised ventures, politically connected individuals, and companies that were actually non-performing and were thus written off by the new management in subsequent years. The provisioning and write-offs of these loans severely affected KCB's capital base. As part of a recovery program to increase public confidence in the bank, KCB launched a

successful Rights Issue in 2004 to bolster its capital to meet the Central Bank of Kenya's (CBK) requirements, and in 2008 to support the bank in growing its business and finance regionally, and lastly in 2010 to facilitate the banks longer strategy of consolidating the business in its markets, meeting growth needs and to grow profitability, (KCB Strategic document, 2010).

1.3 Statement of the Problem

Finance is the pillar of every organization and capital is needed in every aspect of running an organization. Banks need a strong capital base that should rise as the business grows. Since a major service that banks offer to their customers are loans, there is need for efficient systems that will save banks from advancing loans to unworthy recipients that may lead to increased bad debts. Green (2005) argues that lenders earn the majority of their revenue from loan interests and that their primary job is to make and collect good loans.

Inadequate credit scoring management systems in banks have led to a major risk of customers defaulting on loans. Although various credit scoring models have emerged for use in the banking sector since time immemorial, the range of risks have become more and more sophisticated. Demand for accurate, faster, efficient, and unbiased evaluation of loan applications while still retaining profitability has called for novel and sturdy solutions. All these issues if not addressed would lead to loss of customers to the competition, long turnaround time for credit scoring thus dissatisfied customers, and inefficient credit scoring system that would award loans haphazardly.

In view of the foregoing, this study sought to evaluate the existing system at KCB with a view of designing and developing a more powerful, robust, and efficient system that met the demands of all cadres of loan applications. This study carried out an examination of the types of loans evaluated at KCB and the current system used to evaluate loan applications. It took into consideration ways that could be used to mitigate the credit scoring problems. This involved design and development of an ANN-based expert system for use in loan application evaluation at KCB bank.

1.4 Aim of the Study

The aim of this study was to analyze the current loan application evaluation system at KCB with a view to design and develop an ANN architecture-based Expert system for evaluating loans application at the bank.

1.5 Objectives of the Study

The objectives of this study were to;

i) Find out the types of loans KCB offers to its clients.

ii) Examine the current systems used by KCB to evaluate loan applications.

iii) Determine the challenges faced when evaluating loan applications.

iv) Recommend suitable systems for improving the evaluation of loan applications.

v) Design and develop a system that will improve evaluation of loan applications process.

1.6 Research Questions

i) What types of loans does KCB offer to its clients?

ii) What are the current systems being used by KCB to evaluate loan applications?

iii) What are the challenges experienced in assessing loan applications?

iv) Which is the most suitable system for improving the evaluation of loan applications?

v) How can a neural network based expert system be used to improve loan application evaluation at KCB?

1.7 Assumptions of the Study

The study assumptions were:

(i) The system in place at KCB does not adequately satisfy demands for loan applications' evaluation.

(ii) Loans have occasionally been offered to ineligible loanees and denied others who deserve them.

(iii) Putting in place of ANN ES will immensely improve the bank's competitiveness in offering loans to its clients and will make the process of evaluating loan applications more cost-effective.

1.8 Significance of the Study

By undertaking this study, the researcher envisaged to design and develop a robust system that efficiently assisted KCB in evaluating loan applications. The adoption of the system would improve efficiency and ensure that KCB extends its lending services to only creditworthy clients in a quick and timely manner. This would in turn enhance customer satisfaction and give the bank a competitive advantage. The findings were useful in generating and furthering knowledge on composite applications of AI ideas, in this case ANN and ESs.

1.9 Scope of the Study

This study covered the loan applications evaluation process at KCB. Thus, the process on loan awards was not studied. This study also specifically sought to investigate evaluation of applications for business loans only. Business loans applications were evaluated because it is this category of loans that require rigorous process of analysis before loans are extended to the clients. Finally, this study was confined to KCB Head Office in Nairobi.

The study did not include bank clients as respondents because they were not directly involved with the systems used in the bank. This system targeted the bank's retail credit manager, senior credit analysts, OLTP administrators, financial analysts, credit analysts, and office automation and enterprise solutions personnel.

1.10 Limitations of the Study

KCB took a long time in granting permission to conduct this study because it involved studying systems in the bank. Most systems in banks are sensitive and risk averse especially when exposed to outsiders. Creating of interview schedules was tricky and time consuming. It involved slotting the interviewees for different time slots which were sometimes not honored as the interview schedule sometimes ran concurrently with meetings and other activities in the bank.

1.11 Summary

Effective loan application evaluation systems cannot be overemphasized. Banks need steady growth and strong capital base to stay profitable in business. This chapter has described in detail the background of the study including the background information at

KCB facility. This information formed the basis by which the researcher formulated research hypothesis and gave an insight into the area of business loans in the bank. This chapter also covered the conceptual setting, aims and objectives of the study, and significance of the study.

1.11 Operational Definition of Terms

- **Artificial Neural Network (ANN).** A computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computing.
- **Business loans.** A bank loan granted for use in a business.
- **Corporate client.** A large company or group that is recognized as an entity.
- **Criteria.** A specific combination of values associated with data elements that permit one to select a subset of entries that meet one's needs.
- **Expert System (ES).** Computer program that uses a direct encoding of human knowledge to help solve complex problems, such as loan applications appraisal. Also called a knowledge-Based System.
- **Individual client.** A person who forms niche of people who loans can be awarded to.
- **Loan approval.** Formal authorization to get a loan from a bank.
- **Loan award.** The act of granting of loan to a client.
- **Loan evaluation.** Process of appraising a loan through consideration of predetermined criteria.

- **Loan.** A financial transaction in which one party who is the lender agrees to give another party who is the borrower a certain amount of money with the expectation of total repayment.
- **Training.** Refers to comparison of input fed into a neural system to expected output and involves adjust this input until it is closely or similar to the target output.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents the theoretical framework and review of literature related to the study. The researcher examined in depth literature about neural networks and expert systems and how they have been applied in the business field especially the financial services sector specifically for loan application evaluation.

2.2 Theoretical Framework

A theoretical framework is the foundation in which the entire research project is based (Sekaran and Bougie, 2010). It is a logically developed, described, and elaborated network of associations among constructs relevant to the problem situation in a research study. Munhall and Chenail (2008) describe the importance of a theoretical approach to a phenomenon-logical research and specifically point out that a theory used before data collection could influence researcher's findings and perceptions. Therefore, the expert system theory and ANN architecture discussed below served as a foundation for the study and a guide for modeling the system. It also connected the researcher to existing knowledge in the area of expert systems and neural networks and their application to loan processing.

2.2.1 Expert System Theory

The neural network architecture was used to inform this study in implementation of the expert system. An expert system is a computer program that performs a task normally done by a human expert (Gallant, 1995). Tyler (2007) notes that expert systems are a particular type of knowledge-based systems and their name come from two sources; one,

they are able to learn by themselves; and the other, that the knowledge they manage comes from experts consultation. An expert system therefore mimics the decision-making ability of a human expert. The outcome of this study was a system built on the two meanings. This ANN based expert system was built as a system that learns by itself and used data that had been acquired from experts who carried out loan evaluation at KCB. Many expert systems applications are characterized by uncertainty or the need to carry out reasoning in the absence of a clear formulation of complete knowledge about the problem domain (Mohan, 2013). This is the reason why the study used an expert system to automate the process of loan application evaluation. Some of the issues raised (Mohan, 2013) that one must understand to be able to build successful expert systems include; how reasoning can be carried out despite uncertainty associated with problem parameters; how inference engines of rule-based systems work; how interaction with the environment can be used to evolve knowledge; and how knowledge may be augmented by learning algorithms among others.

Gallant (1995) observes that expert systems are the biggest success story for artificial intelligence and many and perhaps thousands of companies use them for complex tasks such as configuring computers and for simpler tasks such as routing telephone requests. The author goes on to identify other applications that include process control, stock trading, scheduling, tax preparation, prediction, medical diagnosis and military uses.

Mohan (2013), and (Tyler, 2007) identify three major components of an expert system; the knowledge base, the inference engine and an interactive graphic user interface or the working memory. The knowledge base is often static and only changes when it needs to

be updated with newly acquired knowledge. The inference engine is the operational component which verifies the consistency of the knowledge base and extracts consequences from already formulated symbolic formulae.

When coming up with the knowledge base, symbolic formulae are constructed by translating information acquired from an expert into symbols that can best be understood and used by the system. These symbols are a set of propositional logic formulae, called production rules (Tyler, 2007). A further step involves transferring of the rules, potential facts, and integrity constraints into polynomial.

To communicate with users, Mohan (2013) identifies three kinds of interfaces needed in an expert system; developer interface, expert interface, and the user interface. The author advises that it is important to separate the interfaces for the sake of protection against modification of the knowledge base by mistake or malice.

Figure 1 shows a typical connectionist expert system as illustrated in (Gallant, 1995)

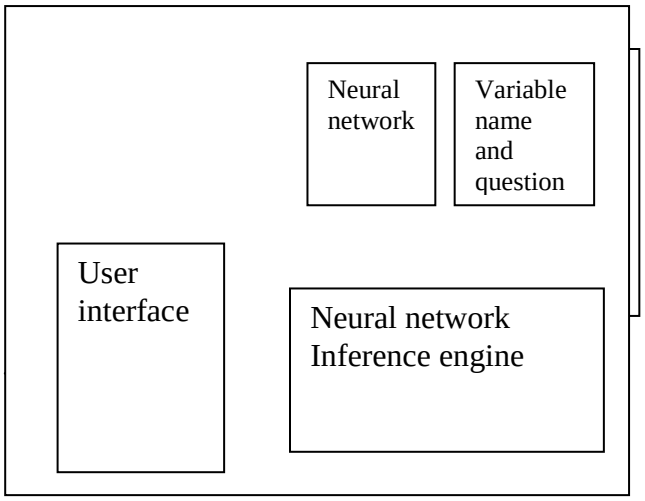

***Figure 1: Connectionist Expert System, Gallant (1995*)**

Figure 1 is a multi-layer perceptron with symbolic aspect related to the domain knowledge. It is a system that combines the domain expert knowledge with neural training. It consists of an expert system implemented throughout a multi-layer perceptron. In this approach, knowledge is incorporated into a neural network in different ways; by setting the topology; by setting weights and bias values; by pre-wiring or pruning connections, and by choosing the adequate learning procedure for the system.

2.3 Review of Related Literature

A survey of the literature was done and those related directly to the research were brought out in this section. The review was done under headings pertinent to the study.

2.3.1 The Biological Foundation of Neural Computing

Many researchers have made use of the potential of computers and the efficiency of computational models to elaborate 'biological computational models' and reach a better understanding of the structure and behaviour of both pyramidal neurons which are believed to be involved in learning and memory processes (Leray, Fernandez, Porto, Fuenzalida, & Buno, 2004).

Rabunal and Dorado (2006) posit that these models have provided a better understanding of the causes and factors that are involved in the specific functioning of biological circuit. The present study was inspired by these new progresses in artificial neural networks and expert systems.

Artificial neural networks are mathematical inventions inspired by observations made in the study of biological systems (Priddy and Keller, 2007). It can be described as mapping

an input space to an output space. Priddy and Keller (2007) observe that the human body is made up of vast array of living cells, where cells are interconnected in a way that allows them to communicate pain, or to actuate fibers or tissues. These specialized communication cells that experience cold, heat, and other sensations are called neurons. Similarly, (Bosque, 2002) notes that in the human body, there are some neurons that are also connected with a nervous terminal (eyes, medulla and nerves) which activate the corresponding actions.

Priddy and Keller (2007) note that when a neuron's potential exceeds a threshold, the neuron fires creating an action potential that flows down the axons to the synapses and other neurons. A cell is caused to fire when the voltage across the membrane becomes too large thus creating a spike that travels down the axon to other neurons and cells. Therefore, if the motivation on a cell is low it takes a long time to make the cell fire and the vice versa is true.

Further, Priddy and Keller (2007) note that man-made neural networks mimic this potential through weighted interconnections and threshold terms that allow the artificial neurons to fire more rapidly just as a biological cell can be biased to fire more rapidly through the introduction of adrenaline which is the bias in an artificial neuron. Bosque (2002) notes as follows, "If we have a substitute of neurons, and we apply between them a similar mechanism of interaction to the one used by the human brain, some of the abstract brain functions will be duplicated or simulated."

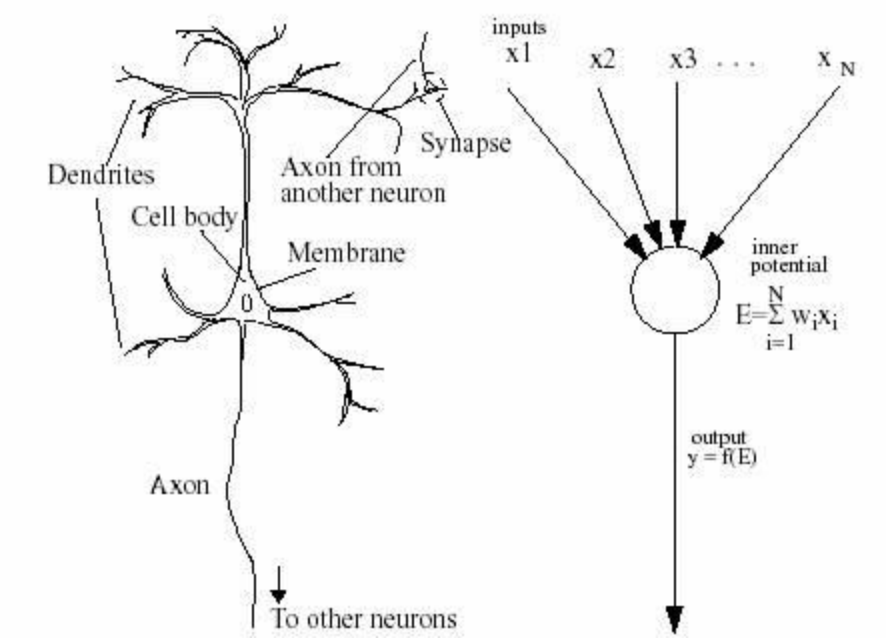

Figure 2: Diagram of a Biological Neuron and an Artificial Neuron, Muehlauser (2011)

Figure 2 shows inputs from other neurons and corresponding output in both the biological and artificial neurons. Neurons send signals to other neurons by sending an action potential down the axon. This is modeled through the use of a transfer function that mimics the firing rate of the neuron.

2.3.2. ANN as an Aspect of Artificial Intelligence

According to Kamruzzaman, Begg, and Sarker (2006), ANNs have attracted increasing attentions in recent years for solving many real world problems. ANNs have been successfully applied in solving many complex problems where traditional problem solving methods have failed or proved insufficient. He goes on to say that with significant advances in processing power, neural networks research has been able to address problems that were often tackled by using simplified assumptions in the past.

ANNs are one of the most common data mining tools, and they have attracted the attention of researchers from various industries such as business, medicine and engineering. Neural networks have a wide array of applications. They are particularly useful for the tasks of classification, prediction, and clustering. They try to emulate biological neurological systems. In other words, they try to mimic the way the human brain functions and processes information (Haav and Kalja, 2002).

Neural net models are composed of many processing elements or nodes, operating in parallel and connected by links with variable weights. The models are specified by the net topology, node characteristics, and learning rules. Therefore, they are not models of the brain, rather they are models inspired by the brain. Some of the main characteristics of ANNs are pattern recognition, the ability to reconstruct an incomplete pattern, the ability to self-reorganize and learn, and the resistance to fuzzy or noisy input.

2.3.3. ANNs and their Business Applications with Relation to Loans Processing

Gallant (1995) is quick to point out that not all expert system problems are suitable for a neural network approach. The most suitable problems are those that seek to classify inputs into smaller groups, for example, medical diagnosis in specialized domains, fault detection, process control, and credit and loan application.

While there is an increasing need to be able to effectively evaluate loan applications in credit facilities in banks, there has been no proper and standard way of doing this as banks have constantly been affected negatively because of the many loans they have had to write off and which cannot be recovered from their clients.

Bidgoli (1998) is of the view that neural computing is one of the new multidisciplinary research fields that have grown because of the study of the brain and its potential for solving poorly structured business problems. Neural networks are capable of performing tasks that conventional computers find difficult like learning from patterns that have been formed over time. In some cases large databases exist that include truth data concerning profiles of good and bad loan candidates. By giving the neuro-computer examples of loans that defaulted and those that did not, the hope is that the computer will extract the pertinent information about lending money.

2.3.4. Criteria for Evaluating Bank Loan Applications

Loan application evaluation involves taking into consideration given standard values for measuring qualification. There are traditional 5C's that can be considered, namely: Capacity, Capital, Collateral, Credit and Character (Green, 2005). Green further notes that based on the information provided and confirmed, lenders have a responsibility to make lending decisions that are consistent with the parameters and limitations of their institution and with the principles of prudent lending. Stretching these principles beyond their limitations is not good business and carries enormous risks that are not worth taking. Green (2005) says that most denied loan requests lack a key ingredient that would make the lender confident that the funds could be repaid from the operations of the business. Lenders test each loan application against elementary lending criteria to determine the strength of the proposed deal. He further adds that there is no magic formula or defined minimum standard of these criteria for the borrower to attain.

In order to consider the loan request seriously, the lender has to be comfortable with the combined subjective strength of these criteria. If the borrower has an acute weakness in one of these criteria, then that deficiency may or may not be overcome with a stronger position in one of the remaining criteria.

These five categories of elementary lending criteria include capacity, capital, collateral, credit and character. Green (2005) calls them the 5Cs of lending. The first criterion is capacity; the lender attempts to determine whether the borrower has the qualification, wherewithal or capacity to borrow the sum requested. Capital is the second lending criterion; when lenders are asked to be involved in a transaction, they must quantify the adequacy of the borrower's investment. The lender will always limit its leverage in a deal and require the borrower to have a meaningful amount of capital at risk, thereby ensuring the owner's commitment to the venture and reducing the lender's exposure to loss.

The third lending criterion is collateral; this criterion quantifies the borrower's ability to support the loan request with tangible assets that will guarantee the loan by providing a secondary source of repayment. The fourth lending criterion is concerned with credit; the lender must evaluate the applicant's previous experience as a borrower. Studying the borrower's credit history discloses whether the business or the owners have paid previous borrowings as agreed.

The fifth and final lending criterion is character; character may be the most important assessment the lender can make about the loan applicant. Regardless of the positive attributes of the borrower's capacity, capital, collateral and credit. If the borrower does

not demonstrate integrity and appear trustworthy to the lender, any proposal will be refused.

From the 5Cs example of the lending criteria as used in banks for loan application appraisal, it is not easy to look at these criteria combined in a quick but thorough way because each application needs thorough scrutiny and use of good judgment. Therefore, this means that the staffs have to take a while to process the applications. This has also meant that clients have had to wait for a long time (see section 2.3.5) before they are finally awarded loans.

Given that good judgment is what helps the banking staff to come up with decisions about who to award loans, it is possible that the judgment may vary from one loan evaluator to another and totally different judgment is arrived at for every loan applied for. This may be as result of bias and errors during the process of loan evaluation much as the set of criteria be the same.

2.3.5. Customer Dissatisfaction

Customer satisfaction is generally defined as a feeling or judgment by customers towards products or services after they have used them (Jamal and Naser, 2003). According to Weil and Maher (2005), reducing the time from the placement of a customer order to customer delivery can increase output, customer satisfaction and profits. Customer satisfaction increases with the shorter processing time and the cost per every loan application goes down, and thus the company processes many loans in a month. The authors propose that customer response time can be reduced by identifying activities that

consume most resources, for example, verification of required credit, employment, and other information which often delay loan applications.

Achieving customer satisfaction is highly targeted by firms as it leads to improved profits, word of mouth, and less marketing expenditure (Yeung, Ging, & Ennew, 2002). According to (Wiele et al., 2002; Yeung et al., 2002; Anderson et al., 1994) in (Al-Hawari and Ward, 2006), many empirical studies in the literature have found a positive relationship between customer satisfaction and financial performance. In the same light, (Al-Hawari and Ward, 2006) note that in an automated banking service context, customer satisfaction is positively related to financial performance. This shows that technologies used in the banking sector have a positive impact on performance of the firms.

2.3.6 System Modeling Techniques

This section reviewed the various system modeling techniques that were considered appropriate for this study. The techniques reviewed here were the ANN architecture as linked to expert systems theory and the evolutionary software process model. A model is used to investigate a system or phenomenon that is too complex to deal with directly. An important class of models is represented by computational models which are implemented as algorithms, (Fum, Missier, & Stocco, 2007).

It is important to note that it is only the ANN architecture that does not follow in the way other expert system architecture are developed (Mohan, 2013), and this called for the evolutionary software model when developing the system which brought out the idea of neurons and nodes, and the way data is transmitted among them so as to reach a threshold and the iterations involved. The ANN based ES also involves training which fits well

with evolutionary software development process. This study was conducted as an effort to deal with loan evaluation system challenge experienced at KCB. The weaknesses and strengths existing in ANN architecture and expert system model were explored (see section 2.3.6.1) and researcher came up with an ANN based expert system as detailed in the next paragraphs.

2.3.6.1. Strength and Weaknesses of ANN Architecture and Expert System Model

A major limitation of neural network systems is that they always have to find out how to solve a problem by themselves and this makes their operation unpredictable as compared to conventional machines that use conventional approach to problem solving thus very predictable (Stergiou and Siganos, 2013).

However, Stergiou and Siganos go on to say that neural networks have been known to work well as they can do things that we don't know exactly how to do because they do parallel processing analogous to the way a human brain does. Similarly, Maharana (2013) notes that neural network learns and does not need to be programmed like conventional computers that cannot do without algorithms and when an element of the neural network fails, it can continue without a problem because of their parallel nature of processing. On the other hand, expert systems mainly involve a very narrow range of codified domain and cannot be generally adopted at managing the highly sophisticated sensory inputs. However, they are good at handling a specific area of knowledge in depth, (MBA Official, 2013).

2.3.6.2. Evolutionary Software Process Model

Mall (2009) observes that the evolutionary approach is suitable for large problems which can be decomposed into a set of modules for incremental development and delivery. This model is also used widely for object oriented development projects. He proceeds to give some of the advantages of this model as; user gets a chance to experiment with partially developed software much before the complete version of the system is released thus accuracy in eliciting user requirements, core modules of the system get tested thoroughly, thereby reducing chances of error in the final product. Objective of evolutionary software process model is to work with customers and to evolve a system from an initial outline specification (Sommerville, 2015). An evolutionary software process model illustrated by Sommerville is presented in Figure 3.

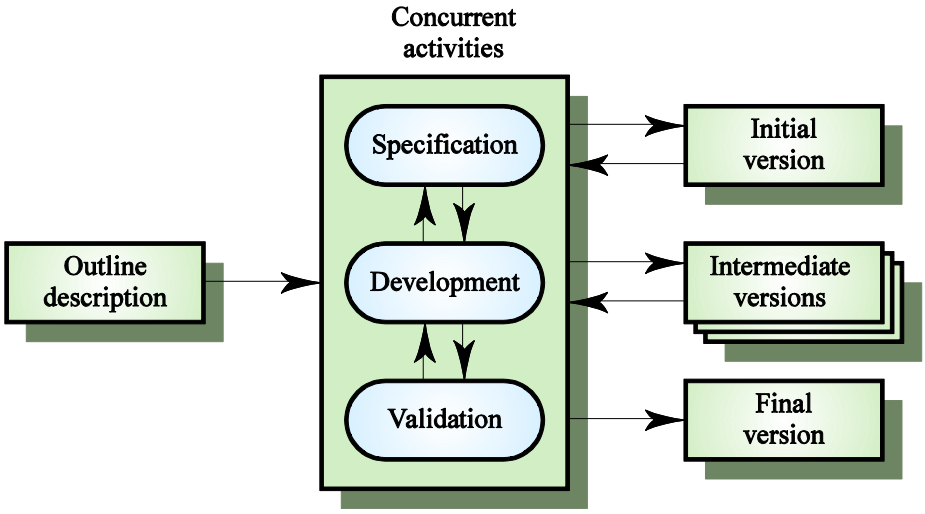

Figure 3: Evolutionary Process Model, Sommerville (2015)

2.3.6.3 Expert System Model and ANNs

Artificial neural networks can be combined with expert systems to produce powerful systems, (Jain and Jain, 1997). These integrated systems can also involve database and other technologies to produce the best solutions to complex problems. Expert systems and ANNs have unique and to a large extent complimentary features. Expert systems provide a logical, symbolic approach while neural networks use numeric and associative processing to mimic models of biological systems (Jain and Jain, 1997).

A common characteristic of neural networks is the ability to classify streams of input data without the explicit knowledge of rules. ANNs can also use arbitrary patterns of weights to represent the memory of categories, (Jain and Jain, 1997). Similarly, Khosrowpour (1995) gives Table 1 comparing ANN and expert systems;

Table 1: Comparison of ANN and Expert Systems

Characteristic	**Expert systems**	**Neural networks**
Approach	Symbolic	Numeric
Reasoning	Logical	Associative
Operations	Mechanical	Biological-like
Explanation	Available	Not available
Processing	Sequential	Parallel
System	Closed	Self-organizing
Validation and verification	Slow, difficult	Fast
Driven by	Knowledge	Data
Maintenance	Difficult	Easy

Together, (Jain and Jain, 1997) the network of neurons can store information that can be recalled in order to interpret and classify future inputs to the network. Since knowledge is represented as numeric weights, the rules and reasoning process in neural networks are not readily explainable in terms of the particular values of the weights and accurate performance can be demonstrated using carefully chosen test data sets (Jain and Jain, 1997). The knowledge bases in the system that the researcher developed came out as the weights, rules and logic stored in the neurons of neural networks.

Neural networks have the potential to provide some of the human characteristics of problem solving that are difficult to simulate using the logical, analytical techniques of expert system and software technologies (Jain and Jain, 1997). Neural networks can analyze large quantities of data to establish patterns and characteristics in situations of uncertainty and can make sense of incomplete or noisy data. These capabilities have so far proven difficult for traditional symbolic or logic-based approaches.

While knowledge engineers have to feed expert data to a knowledge base of an expert system which is totally relied on for differencing; this implies that no inferences can be made out of data that is not in the expert system knowledge base. A neural network on the other hand just needs to have a bit of input data and will learn patterns from the little data fed into it to come up with an output.

2.3.6.4. Artificial Neural Network

According to Turban (1995), the development process for an ANN application has nine steps, as summarized in the data flow diagram shown in Figure 4.

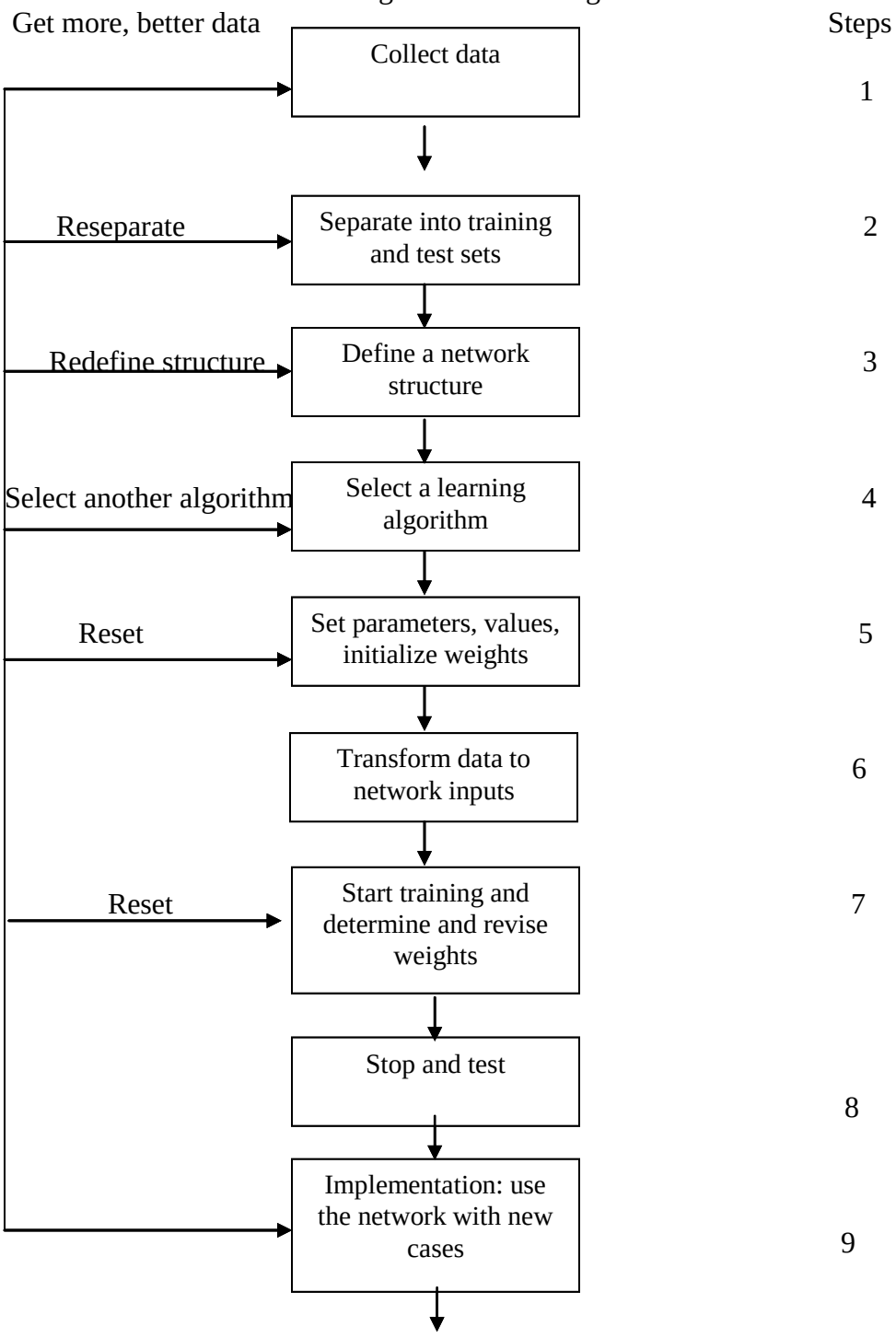

Figure 4: The Development Process for an ANN Application, Turban (1995)

2.3.6.5. ES Based on ANN Architecture

Expert systems ensure that interpretations are consistent and comply with the tenets of scientific methods. The rules used in expert systems are explicit and can be spelt out in enough detail and encoded into a computer system easily and through use of a knowledge base.

The expert system assists in reasoning constructs rather than simply learning of the machine's reasoning; rules that operate the expert system are derived from a number of sources which in the case of this study are the set of criteria used. These rules are then coded and incorporated as part of the system.

Gallant (1995) identifies some problems with conventional expert systems as follows; constructing and debugging the knowledge base can be difficult and expensive because of getting a human expert who is able to express his or her knowledge using if-then rules; conventional expert systems occur with statistical or pattern recognition domains. On the other hand, neural networks are more appealing for expert systems because it can take advantage of a learning algorithm to construct knowledge bases; also, neural networks are more suited for numerical or statistical tasks.

The researcher came up with the model illustrated in figure 5. In this conceptual model, the ANN fits into the expert system and is linked by the knowledge base that is common to both the ANN as well as experts system. The ANN based expert system in this study had no explanation subsystem like many expert systems and the data collected was presented to the knowledge engineer for pre-processing into numeric representation.

Neural networks can learn complex non-linear relationships even when the input information is noisy and less precise (Khosrowpour, 1995). He goes on to say that, neural networks can be applied to problems in areas where data is multivariable with a high degree of interdependence between attribute; where data is incomplete or in cases where many hypothesis are to be pursued in parallel and with the requirement of high computational rates.

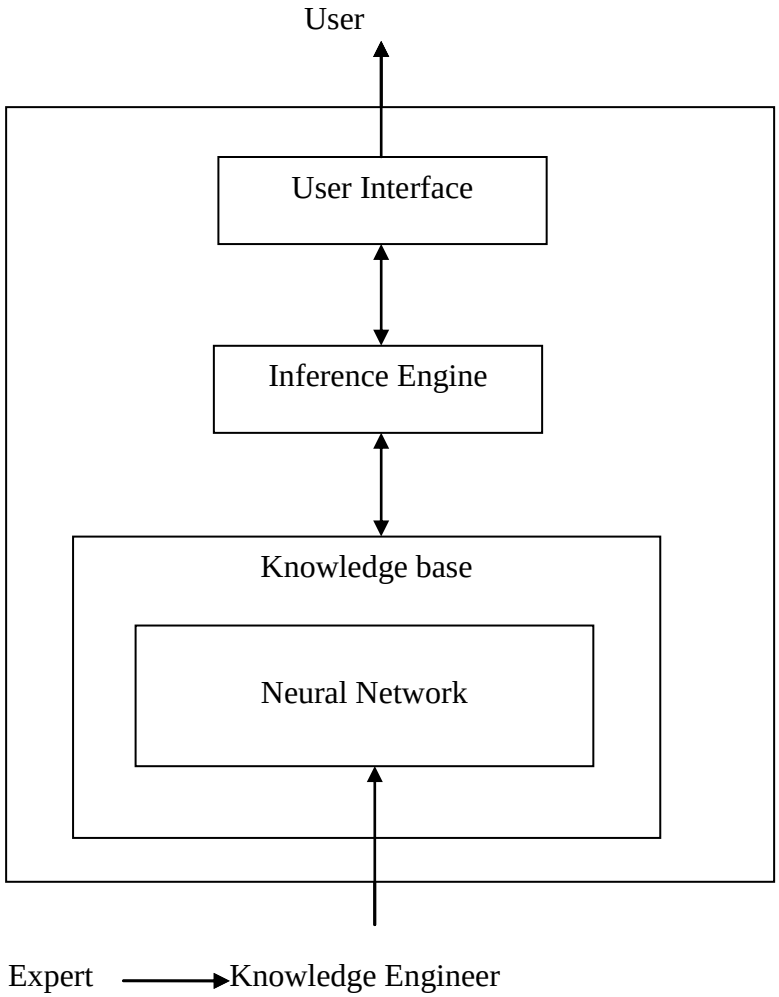

Figure 5: ANN Based Expert System Model, Researcher, (2012)

The conceptual model in Figure 5 shows the neural network as part of the larger expert system and it has a knowledge base that contains the weights, rules, and logic. The knowledge base came in where the criteria from the data sources were systemized and rules used to produce results. The knowledge engineer decodes the data obtained from an expert and the data is numerically presented for storage into the knowledge base of the neural network. This data consists of training and test cases, rules, weights and reasoning processes.

2.4 Summary

This chapter expansively reviewed literature related to the study. It thoroughly scrutinized the literature pertinent to the topic under study. The topics covered included; biological foundation of neural computing, ANN as an aspect of artificial intelligence, ANN and their business application with relation to loan processing, criteria for evaluating bank loan applications, customer dissatisfaction, system modeling techniques, strengths and weaknesses of ANN architecture versus Expert system model, evolutionary software process model, expert system model and ANN, artificial neural network, ES based on ANN architecture. The expert system theory and evolutionary software model was used to develop the system in Chapter 5.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses the research design and methodology adopted by the study, study population, sampling methods, procedure for data collection, validity and reliability of the research instruments, ethical considerations, data presentation and analysis. Kothari (2004) defines research methodology as a systematic way to solve a problem. It is the science of studying how research is done scientifically. He goes on to say that in research methodology, we study the various steps that are generally adopted by a researcher in studying a research problem along with the logic behind them.

3.2 Research Design

Kothari (2004) defines research design as the arrangement of conditions for collection and analysis of data in a manner that aims to combine relevance to the research purpose with economy in procedure. Kothari further asserts that research design is needed because it facilitates the smooth sailing of the various research operations thereby making research as efficient as possible thus yielding maximal information with minimal expenditure of effort, time, and money.

This study adopted qualitative case study research design for data collection and experimental research design for the expert system development as indicated in the following sections of this chapter.

3.2.1 Qualitative Methodology

The study adopted the qualitative methodology. According to Mugenda and Mugenda (2003), qualitative research includes design techniques and measures that do not produce discrete numerical data. They note that in this type of research, data is in the form of words rather than numbers and that these words are often grouped into categories.

The researcher adopted qualitative methodology because of its inherent attributes and benefits. Qualitative approach provides rich data about real life situations and is able to make sense of behaviour and understand behaviour in context (Cresswell, 2013). In other words, this type of research allows the researcher to describe and analyze well the behaviour involved such as attitudes and opinions of respondents in their natural setting. This type of research also proves suitable for use in a case study research design as the researcher is able to do an in-depth examination of a particular case before generalization to others.

Brown and Baker (2007) state that qualitative research:

(i) Has an interpretive character, aimed at discovering the meaning events have for the individuals who experience them and the interpretations of those meanings by the researcher.

(ii) Has an emergent (as opposed to predetermine) design, and researchers focus on emerging process as well as the outcomes or product of research.

(iii) Is judged using special criteria for trustfulness.

(iv) Makes use of the natural setting as the source of data meaning the researcher attempts to observe, describe and interpret settings as they are.

(v) Reports are descriptive, incorporating expressive language and the "presence of voice in the text."

(vi) Pays attention to the idiosyncratic as well as the pervasive seeking and uniqueness of each case.

(vii) Predominantly use inductive data analysis.

(viii) Acts as the "human instrument" of data collection.

3.2.2. Case Study

Case study research design was considered the most appropriate for this study. Oso and Onen (2009) refer to a case study as an intensive, descriptive, and holistic analysis of a single entity: the bounded case. Supporting this, Mugenda and Mugenda (2003) define a case study as an in-depth investigation of an individual, group, institution or phenomenon.

KCB bank was chosen over other banks because as of December 2010, it was among the three largest commercial banks in Kenya with assets of more than US$2.65 billion and shareholders capital valued at US$486 million. Also in its history, it had faced a major blow by having to write of huge credit which could not be recovered over a period of time and it managed to recover and make profits again, (KCB Strategic document, 2010).

Most case studies are based on the premise that a case can be located that is typical of many other cases. Mugenda and Mugenda (2003) continue to say that the primary purpose of the case study is to determine factors and relationships among the factors that have resulted in the behaviour under study. The investigation therefore made a detailed

examination of a single case involving KCB. This provided in depth data for solution development.

KCB Headquarters was chosen as an entity for the case study because processing and evaluation of loans took place at the Headquarters, loan evaluation in the KCB bank is centralized in the Headquarters at Nairobi. The researcher therefore thoroughly examined the processes involved in loan evaluation at KCB Headquarters.

This study adopted case study research design as it enabled the researcher to exhaustively study a single unit, KCB Headquarters, which represents many other units that are similar in characteristics to it before generalization.

Also, KCB branches are scattered in East Africa and the time frame for carrying out this research required that a case study be used. Through case study research design, the researcher studied an entity in depth and gathered data leading to development of a system. Kothari (2004) says that a case study method is a technique by which individual factor whether it is an institution or just an episode in the life of an individual or a group is analyzed in its relationship to any other in the group.

3.3. Population of the Study

According to Gay, Mills, and Airasian (2014), a population is described as the group to which the study can be generalized. The target population of this study was 53 loan evaluation staff at KCB Headquarters, Nairobi, Kenya. KCB Head Office was selected because the volume of business generated by the head office is bigger than the rest of the branches and so by undertaking the research there it gave an opportunity to investigate

the various aspects of business loan evaluation. Also, all business loan applications are ultimately rated at the Head office. Finally, considering all the KCB branches both in Kenya and the rest of East Africa, what happens in one center is virtually a duplication of what happens in the other centers, only that the headquarters branch has more rating done from the other branches of the business loans.

Table 2 shows that the study population constituted of 53 loan evaluation staff consisting of 1 (1.8868%) Retail Credit Unit Manager, the 8 (15.0943%) Senior Credit Analysts, 8 (15.0943%) Online Transaction Processing (OLTP) Administrators, 13 (24.5283%) Credit analysts, 13 (24.5283%) Financial Analysts, and 10 (18.8679%) Office automation and enterprise solutions personnel.

Table 2: Study Population (N =53), Research Data, (2011)

Category of Staff	**Number**	**Percentage**
Retail Credit Unit Manager	1	1.8868
Senior Credit Analysts	8	15.0943
Online Transaction Processing (OLTP) Administrators	8	15.0943
Financial Analysts	13	24.5283
Credit Analysts	13	24.5283
Office Automation and Enterprise solutions personnel	10	18.8679
Total	**53**	**100**

The criterion for the selection of the targeted persons was based on their role as loan evaluation staff with valuable information of the current system used at KCB for loans evaluation as well as their suggestions for improving the system. The data from these

respondents was considered useful for the purposes of training and testing the proposed system.

3.4. Sampling Method

Kombo and Tromp (2006) refer to sampling design as that part of the research plan that indicates how cases are to be selected for the study. Orodho and Kombo (2002) define sampling as the process of selecting a number of individuals or objects from a population such that the selected group contains elements representative of the characteristics found in the entire group.

According to Saravannel (1992), a sample is composed of some fraction or part of the total number of elements or units in a defined population. From the targeted study population of 160 KCB branches as at December 2009, the researcher using purposive sampling selected to study KCB Headquarters, Nairobi.

The targeted population of staff at KCB Headquarters was 53 as shown in Table 2. From this number, the researcher selected a sample population of 16. This was 30.1887 percent of the targeted population. According to Mugenda and Mugenda (2003) a sample size of 30 percent is considered representative for a research. Sampling was adopted in this study because the population studied is big but was well covered through a sample. Through a small sample, the costs of undertaking the study were reduced.

The study employed the non-probability sampling design because it is the most appropriate for a qualitative study with focus on in-depth information. Non-probability sampling strategies commonly used are purposive, convenience quota and snowball

sampling (Babbie, 2013). According to Patton (2002), the power of non-probability sampling is that it provides a researcher with the opportunity to select a sample that provides in depth information.

Purposive sampling technique was used to select the sample population. Gerrish and Lacey (2010) define purposive sample as one where people from a pre-specified group are purposely sought out and sampled. According to Oso and Onen (2009), the meaning of purposive sampling technique is that the researcher decides who to include in the sample. They go further to give its purpose as; used to collect focused information. In purposive sampling, researchers rely on their experience, ingenuity or previous research findings to select respondents who seem to be appropriate for the research project.

Kombo and Tromp (2006) note that the power of purposive sampling lies in selecting information rich cases for in-depth analysis related to the central issues being studied. These respondents were going to provide information about loans offered by KCB, systems currently used at KCB, and functionalities needed for an alternative system. Purposive sampling technique enabled researcher to comprehensively explore the universe and understand the audience chosen using purposive sampling technique. In addition, it also enabled use of good judgment in choosing the right subjects and meeting the right number of subjects for the purpose of this study.

3.4.1. Sample Size

Since the study sought to examine how business loans were evaluated at KCB, from the foregoing, it is clear that the study population constituted various stakeholders of the system in the bank. Table 3 summarizes the distribution of the sample population.

Table 3: Study Population Sample Size (N = 16), Research Data (2011)

Strata	Total population	Sampling Method used	Sample Size	Percentage %
Retail Credit Unit Manager	1	Census	1	6.25
Senior Credit Analysts	8	Purposive	2	12.5
Online Transaction Processing (OLTP) Administrators	8	Purposive	2	12.5
Financial Analysts	13	Purposive	4	25
Credit Analysts	13	Purposive	4	25
Office Automation and Enterprise solutions personnel	10	Purposive	3	18.75
Total	**53**		**16**	**100**

These stakeholders are described as follows:

i) **Retail Credit Unit Manager** This refers to manager of the whole of the retail credit unit of KCB. The Retail Credit Unit Manager acts like the team leader and helps direct the work of the retail credit team as a whole apart from participating in policy and decision making in the organization. Retail credit unit manager was purposively sampled as the only one from the target population.

ii) **Senior Credit Analysts** They are the ones responsible for planning, policy formulation and introduction of new products in the area of credit/loan management. This study targeted a sample of 2 Senior Credit Analysts. From the Senior Credit Analysts, the researcher derived detailed information on the processes undertaken during loan evaluation when KCB is able to judge who is creditworthy and who is not.

iii) **OLTP Administrators** This category of staff refers to the bank staffs who work with the current loans approval system. They are in charge of making sure that the online transaction processing system is up and running and maintain this system to ensure good working conditions. The study sample targeted 2 OLTP administrators. The OLTP administrators were involved in this study for the sole reason that they were the ones who mostly used the systems and understood them better.

iv) **Financial Analysts** These are an important part of the retail credit team. They are responsible for analyzing a number of financial documents from a client before passing them over to the credit analyst. Without the financial analysts, the retail credit team is incomplete. 4 Financial Analysts were targeted sample in this research.

v) **Credit Analysts** This staffs work directly under the Senior Credit Analyst. They are the ones who determine if a client really qualifies to be given a loan by looking at various parameters after taking over from the Financial Analysts and using already specified criteria. Targeted sample in this research were 4 Credit Analysts. The Credit Analysts were involved in this study as they are the ones who used pre-determined criteria to know which clients were creditworthy and those who were not.

vi) **Office Automation and Enterprise Solutions Personnel** These groups of staff are in charge of running systems in the organization. They manage, maintain and incorporate changes as needs arose. The researcher targeted a sample of 3 Office Automation and Enterprise Solutions Personnel. The

researcher involved the Office Automation and Enterprise Solutions Personnel in order to find out if there were any information systems already in place that assisted in evaluation of loans and how effective they were. The Office Automation and Enterprise solutions personnel are the ones in charge of running information systems in the organizations and IT in general could not exist in isolation.

3.5 Data Collection Methods

The researcher collected primary and secondary data. The researcher used open semi-structured face-to-face interviews to collect primary data. Interviews are considered as the main data collection method in qualitative research. They provide a situation where the participant's descriptions can be explored, illuminated, and gently probed. Secondary data was captured using secondary sources which were documents reviewed (see Appendices 2, 3 and 4). Documentary sources provided a great deal of information about loan application evaluation in KCB.

3.5.1 Interviews

Oso and Onen (2009) refer to interviews as person to person verbal communication in which one person or a group of persons asks the other questions intended to elicit information or opinions. Interviews allows the researcher to obtain information that cannot be directly observed, obtain historical information and also to gain control over the line of questioning. The researcher developed separate interview schedules for each category of respondents. A total of four interview schedules were used in data collection (see Appendices 1a, 1b, 1c and 1d). According to Kombo and Tromp (2006), the

advantages of this form of semi-structured interviews are flexibility because they consist of both open ended and closed-ended questions, in-depth information can be gathered using close-ended questions, and by using both open ended and closed-ended approach the researcher gets a complete and detailed understanding of the issues under research.

Use of interview was suitable for this study because it enabled the researcher to ask questions personally, probe further and thus, she was able to seek clarifications about the systems involved and the user needs. The training data was then derived from samples of applications obtained during the interview sessions with the Financial Analysts and Credit Analysts at the KCB.

Interviews have their own limitations and the researcher had to apply various strategies to ensure that these limitations could not impact on the final study findings. Personal interviews are expensive and time consuming to transcribe the responses. To counter this, the researcher confirmed appointments before visits and ensured that the same questions were asked to similar respondents. This ensured that the interviews were carried out within the limited time available for the interview. Another limitation was that the interviewer presence might have influenced the way questions were answered. To counter this, the researcher ensured that prospective respondents were provided with a convincing rationale for the study. The researcher constantly rephrased the responses to help confirm the responses.

The interview schedules were categorized into four for each of the four groups of respondents. The interview schedules were for Information Systems Manager, Advances Manager, Loan Officers, and System operators. All interviews were conducted in person

in the respondents' offices. The interviews lasted 25-30 minutes each. The interviewer transcribed the responses for further analysis.

3.5.2 Documentary Sources

Documentary analysis means the critical examination of public or private recorded information related to the issue under investigation (Oso and Onen, 2009). The researcher examined the documentary sources of KCB bank which included the KCB business credit application form, mockup cash flow statement, and a mockup financial statement analysis (see Appendices 2, 3, and 4). The researcher sought to get an overview of the technical and functional procedures followed in using the current systems and also examined trends registered for award and recovery of loans. These documentary sources gave an in-depth understanding of the matter that the study sought to investigate. Most importantly, the reviewed sources provided profound information that was used for training users of the system. Table 4 provides a summary guide for the documents reviewed at KCB and their significance.

Table 4: Document Review Guide Summary, Research Data (2011)

Name of document	Description of document	Information acquired from document
KCB Business Credit Application Form (Appendix 2)	A form that is used by the bank to elicit customer details.	-Customer details -Criteria for evaluating the credit worthiness
Mock up Cash flow Statement (Appendix 3)	This is a mockup cash flow statement that shows the cash flow of a business that is being considered for a loan award.	-Criteria for evaluating customer for loan.
Mock up Financial Statement Analysis (Appendix 4)	This document contains information that assists come with criteria used to evaluate a business for credit worthiness.	-Provides information about criteria that is used to evaluate a customer for loan.

3.6. Procedure for Data Collection

Data collection was conducted from the 5th to the 28th of January, 2009. An interview schedule was used to collect data. The researcher cleared all official channels by obtaining a research permit from the National Council for Science and Technology (see Appendix 7) and an introductory letter from the Head of Department of Information Technology at MU (see Appendix 6) to facilitate the commencement of the research. The researcher proceeded to make appointments with prospective respondents by first introducing herself, explaining the purpose of the study, giving an estimate of how long the interview would take and assuring them of anonymity and confidentiality issues.

Before the actual data collection started, a pilot study was conducted between 4th and 8th November, 2008. In this pilot study, the researcher mainly sought to address feasibility issues such as studying of systems at KCB and the extent of study that was permitted, availability of respondents, enlisting time of respondents, and the estimated cost of the study. This feasibility pilot study was important bearing in mind that KCB is a very sensitive institution that majorly deals with finances.

There were no major shortcomings faced in the carrying out of the interviews because the researcher and one of the interviewees drafted a programme showing the date and time to interview all the respondents. This programme was followed strictly and promptly by the researcher.

3.7. Validity and Reliability of the Research Instruments

Joppe (2000) defines reliability as the extent to which results are consistent over time and an accurate representation of the total population. Reliability was achieved by conducting short and as precise interviews as possible which were carried out at regular times of the day.

Validity is the accuracy and meaningfulness of inferences, which are based on the research results (Mugenda and Mugenda, 2003). It is the degree to which results obtained from the analysis of the data actually represent the phenomenon under study. Validity of this research was realized by piloting the instruments and making all necessary adjustments to ensure consistency and to ensure it addresses key data required as observed in the pilot study.

3.8. Data Analysis and System Modeling

Qualitative data analysis method was chosen for this research and data was summarized for use in the system design and development. This is also because the data analysis was not meant for making recommendations based on the data itself but for justifying the need for the proposed system and obtaining test cases datasets. A comprehensive data analysis and interpretation was not carried out and much time was spent on using relevant data for training the system. The data analysis was done simultaneously with data collection and general statements were made based on the training set used to train the system.

Most of the data obtained from documentary sources (Appendices 2, 3 and 4) have been used for modeling the training and test cases data for the system.

3.9 Systems Development Methodology

The system was developed following the documented procedures in section 2.3.6.4 and 2.3.6.5. The researcher used .NET programming language contained in the Visual Studio 2010 suite to implement the system. Systems analysis and design, including interpretation of user requirement was done using flow charts as detailed in Chapter 5.

3.10. Ethical Considerations

The Moi University Research Policy (2008) stresses on the need to strictly adhere to ethical guidelines that are laid down to proper conduct of researchers in carrying out of research. These areas cover plagiarism, fabrication and falsification of data. The researcher therefore took these ethical rules into consideration by doing the following:

(i) Ensuring that responses elicited from respondents remained anonymous. To protect respondents and also to enable them to respond well to interviews bearing in mind that the information they provided remained confidential.

(ii) Obtaining a research authorization (Appendix 7) and a research permit (Appendix 8) from the National Council for Science and Technology (NCST) before undertaking the research study.

(iii) Informed consent was sought from participants before the study was done.

(iv) Disseminating the results to the public by depositing a copy of this research study at Margaret Thatcher Library, fulfill requirements by depositing two copies of this thesis with NCST. Publish the study findings as a book by relevant publishers and as an article in a scientific journal.

3.11. Chapter Summary

This chapter has described in detail the methodology that was used in data gathering and analysis. It substantiates how the population for study was chosen, sample population and the sampling technique that was used to come up with the study sample at KCB bank. The study population comprised 53 loan evaluation staff. The researcher narrowed down to a sample size of 16 using a purposive sampling technique across the study population that consisted of Retail credit unit manager, Senior credit analysts, OLTP administrators, and Office automation and enterprise solutions personnel. In addition, this chapter has described the data collection methods and instruments. Interview schedules and documentary reviews were used to collect data at KCB after obtaining the legal research permits from KCB and NCST.

CHAPTER FOUR

DATA PRESENTATION AND SYSTEM ANALYSIS

4.1. Introduction

This chapter presents the analysis and interprets the research findings in line with the study objectives and research questions. The findings have been tabulated, analyzed and percentages recorded where applicable. The data have been analyzed using qualitative analysis method.

4.2. Response Rate

The population of the study comprised staff that works in the business retail loan section of the bank's credit management division. The population was homogeneous and worked under similar conditions. The researcher interviewed 16 actual respondents from the business retail loan section out of a potential 25.

Out of the 16 respondents interviewed, OLTP administrators, Information technology personnel dealing with office automation and enterprise solutions, Credit analysts, Senior credit analysts, the Retail credit unit manager, and the Financial analysts.

For simple flow of analysis, the data collected was grouped and presented under the following objectives:

(i) Types of loans offered by KCB to its clients.

(ii) Current systems used by KCB to evaluate loans.

(iii) Challenges faced when evaluating loan applications

(iv) Suitable system to improve evaluation of loan applications

(v) Design and development of a system that will improve evaluation of loan application process.

4.3 Types of Loans Offered by KCB to its Clients

Credit division of KCB is a very wide section that appraises both personal loans and business loans which are further divided into business retail loans and business corporate loans. The researcher studied in detail the appraisal of business retails loans. These are loans that go up to a maximum of 20 million Kenya shillings.

One of the objectives of this study was to find out the types of loans KCB offers to its clients. To achieve this objective, the Credit Analysts, Financial analysts, system administrators and the heads of the credit retail section were asked through use of interview schedules to identify the kind of loans that the bank offered to its clients. The researcher also did a thorough documentary review of the documents at KCB which included the KCB business credit application form, mockup cash flow statement, and a mockup financial statement analysis (see Appendices 2, 3, and 4) and came up with more or less the same kind of loans identified by the respondents as presented overleaf.

4.3.1 Categories of Loans KCB offers to its Clients

i) Small scale enterprise loans that target small loans to borrow primarily due to lack of tangible security.

ii) KCB Grace Loans which is tailor made for individual women entrepreneurs and women entrepreneurs in groups.

iii) Asset finance and insurance premium finance.

iv) Secured business loans

v) Secured overdrafts

vi) SME's loans (partially secured)

vii) Insurance premium finance

viii) Brookside loans

ix) Nairobi bottlers limited loans

x) Temporary overdrafts

All the respondents provided more or less the same answers to the type of loans offered at KCB. The response was 100 percent. This is especially because these are the already existing loans and the staff at the loan section knows them because they work with them every day. The types of loans remain fixed unless otherwise the bank comes up with some other types of loans to fulfill the needs of its clients.

4.4. Current Systems Used by KCB to Evaluate Loans

Another objective of this study was to examine the current systems used by KCB to evaluate loans applied for by its clients. This objective was met by asking the respondents to identify the business functionalities already integrated with IT, the loan appraisal activities already integrated with IT, the kind of system that is currently being used to appraise the loans, the variables taken into consideration when evaluating loans and the procedures involved in evaluating loans.

The business functionalities already integrated with IT included record keeping, tracking transactions and auditing, history purposes- especially for the 'know your customer' functions, lending, credit and risk management, and capturing of scanned loan applications.

The above question was answered by the Information technology personnel dealing with office automation and enterprise solutions. They identified the various business functionalities at KCB that have made use of IT. Over the years, these are the main business support areas that KCB has integrated with IT to make their work effective and efficient in the long run. KCB has continually emphasized on new technologies to gain a competitive edge.

The researcher narrowed down to the loan appraisal activities integrated with IT. This question was directed at the OLTP administrators, Information technology personnel dealing with office automation and enterprise solutions, financial analysts, and the credit analysts. The responses revealed that KCB had rolled out an online real-time system called Credit Quest from Harland Solutions, to assist in various loan operations at KCB. The modules included on the system are: credit manager, financial analyzer, project manager, risk assessment, report manager, table manager, and system maintenance.

The system's modules are fixed and each and every user group have their module for use, for example, the credit manager module is used by the credit managers, financial analysts, and sectional heads.

In the process of loan appraisal, the respondents all applied the seven set criteria abbreviated as CAMPARI.

i) **Character**-This criterion entails evaluating the integrity and trustworthiness of the business entity asking for the loan.

ii) **Ability**- This criterion involves looking at a business' skills or expertise for the job its involved in and the kind of employees it has employed, whether these employees have the required skills to be able to perform well.

iii) **Margin**- Margin criterion here refers to the interest rate at which the loan will be repaid; it should not be very high or very low but just good enough depending on the amount borrowed and the ability and time to repay it.

iv) **Purpose**- There is no lending, for instance, for speculative purposes, child trafficking, drugs, arms, money laundering and so on. Money is only lent for legal and transparent use.

v) **Amount**- This criterion demands that a realistic amount of money is borrowed by the client; this is evaluated by looking at the turnover of the business for instance.

vi) **Repayment**- This criterion involves the bank looking at the source of repayment of the loan borrowed by considering cash flows and other financial statements of the business.

vii) **Insurance**- Insurance here refers to security for example Land Title deed; it also refers to insurance that has been used to secure the property that the bank receives as security for its loans.

The procedure of loan appraisal from the time a client presents a request at the branch to the time it is granted or turned down, was clearly illustrated by the respondents, the researcher was actually taken through part of the process that takes place at the headquarters. In addition, a number of documents were available for the researcher to examine such as forms to be filled in by client for example, KCB business credit

application form. This form is subdivided into sections that are meant to elicit information from the client. The subsections include;

Part A: Details of the business

Part B: Credit request details

Part C: Existing facilities

Part D: Directors and shareholder/partners

Part E: Key person(s) in the business (e.g. proprietors, partners, directors etc.)

Part F: Associated accounts

Part G: Financial details

Part H: Security

The use of CAMPARI loan evaluation criteria implies that KCB has over the years used this measure as a major guideline in drawing a line between credit defaulters and credit-worthy clients. This has helped a great deal to reduce the instances of non recovery of debt in the bank.

On application of a business loan, an application form is completed by the client and further documents about the business asking for a loan is sought by the bank. The documents are scanned and printed or presented in a hard copy that is presented to the Branch Advances Manager. The Advances manager forwards the request to the Branch Manager who then sends them to the Head Office Advances Manager. The Advances Manager hands over the financial documents and business details to the Financial Analyst. The Financial Analyst's work entails assessment of Financial Statements such as

Cash flow statements, Profit and Loss accounts and Balance Sheet of the business entity in question.

The financial analysis process involves evaluating the financial performance of a company by generating ratios, Strength, Weakness, Opportunity, Strength (SWOT), gross gearing, leverage, current ratio, a company's financial trend over time, solvency and various criteria looked at in evaluation of loans such as Credit, Collateral, prior liens and so on.

The essence of the whole process of Financial Analysis is to enable the bank to know the financial position of the company that is borrowing a loan and thus know if it is creditworthy or it is a credit defaulter. After the rigorous process of appraising the financial status of the client, the Financial Analyst is in a position to approve a loan, decline approval or in some cases cancel the whole application for instance in a case where the client changes their mind not to take the loan anymore.

The system at KCB was partly automated, and the process of financial analysis was the part of it that was automated. The researcher therefore intended to pick up from where the system was not automated –for instance, picking up the ratios equating a certain value to them and simply assigning a 'yes' or 'no' recommendation unless otherwise the customer cancels or backs up from the offer.

The financial analysis process being an important part of the loan application evaluation process, the analyst still has to look out for certain values such as current ratio, liquidity ratio among other loan application evaluation criteria. For example, if leverage is <50

(less than 50) then *OK*. A system is therefore needed to combine these loan evaluation criteria by pulling them from the database then just giving a straightforward action. The researcher takes over from where the system ends for instance combining the ratios and vital values into a neural structured system and giving a recommended action. The system user does not have to consume a lot of time examining the determinant factors one by one and use judgment to know what action to take.

4.5 Challenges Faced when Evaluating Loan Applications

The third objective of this study aimed at determining the challenges faced by KCB when evaluating loans applied for by its clients. This objective was met by asking the respondents to point out the challenges faced when appraising loan applications.

Table 5: Summary of Respondent Views, Research Data (2011)

Category of respondents	**Challenges experienced**
2 OLTP administrators	Need for personnel with proficiency in IT Need for training of system users
3 Office Automation and Enterprise solutions personnel	Need for training of system users
4 credit analysts	Wrong accounting in business Information needed to appraise clients' requests is inadequate. Lack of inclusion for benchmarks
2 Senior credit analysts,	Skills gap in use of existing system

	Inadequate or lack of experience for system users Shortage of staff Questionable integrity of customers Political tussles Product knowledge challenges by staff System breakdown or slowness Questionable integrity of audited accounts Inability of clients to provide all required information Economic challenges
1 Retail credit unit manager	Bureaucracies involved in the process of loan appraisal is cumbersome as applications are tossed back and forth Lack of credit and/or computer skills Bandwidth slow with regard to system issues Inadequacy of reports needed for monitoring and decision making
4 financial analysts	2 out of 4 financial analyst said they experienced no problems the remaining posed lack of credit and/or computer skills as a major problem

The respondents provided a number of general challenges that affect the credit division, among the challenges provided, few cannot be avoided for example economic challenges and political challenges but they can only be kept in check. The system challenges can however be monitored by putting in place systems that address the challenges experienced for example, the benchmarks that guide in the appraisal of loans.

4.6 Design and Development of a System to Improve Loan Evaluation Process

Design and development of a system was also looked into by the researcher. In order to obtain the opinions and responses of the respondents, the researcher asked the employees about what they thought regarding the introduction of a new system to handle loan appraisal activities and the functionalities they would advocate for inclusion if at all an alternative system is to be embraced. These questions were directed to all the respondents regardless of their category.

These questions were also in line with the previous question on whether the respondents experienced challenges when using the system. If some experienced no challenges then that meant that they were comfortable and saw no need of a new system and thus no new functionality. Otherwise those who had a few problems here and there concerning the system in question meant that they needed a few more functionalities to make them comfortable when using the system. Ninety percent of the respondents supported the need of an alternative system just to include a few more functionalities and also to correct the problems being faced like lack of experience and need for training of system users.

4.6.1 Coded and Randomized Values

Scaling of these input data coded from mockup documents (see Appendices 2, 3 and 4) is done by the system with the aid of a sigmoid function so that they fall between the values 0 and 1.

Table 6: Scaled Inputs

Criteria	**Weights**			
Current ratio(ratio)	0.5	0.02	1.9	4.1
Liquidity ratio(ratio)	0.45	0.1	5	0.66
Creditor days (days)	7	55	30	40
Solvency ratio (%)	9%	23%	74%	68%
Collection period (days)	100	8	30	61
Stock turnover	1	90	65	13
Gearing ratio (%)	20	400	124	50
Profits/Interest cover (%)	2	1.1	10	51

Current ratio –This ratio reflects the Working Capital situation, it indicates the ability of a company to pay its short-term creditors from the realization of its current assets and without having to resort to selling its fixed assets to do so. Ideally the figure should always be greater than 1, which would indicate that there are sufficient assets available to pay liabilities, should the need arise. The higher the current ratio figures the better.

Liquidity ratio- This ratio indicates the ability of a company to pay its debts as they fall due. It is generally considered to be a more accurate assessment of a company's financial health than the current ratio as it excludes stock, thus reducing the risk of relying on a ratio that may include slow moving or redundant stock. The higher the ratio is over 0.4, the better.

Solvency ratio- This ratio measures if the total liabilities of a business (both secured and unsecured) are too high, indicating a possible over dependency on outside sources for long-term financial support. The higher the results of the solvency ratio are the better. Between 30% and 50% is good, below 30% is poor performance, above 50% is exceptional performance.

Collection period-This measures the length of time a company takes to collect its debts and is measured in days. In general terms the figure indicates the effectiveness of the company's credit control department in collecting monies outstanding. The lower the number of collection days the better. Below 40 days is good, above 40 days is worse.

Creditor days- This ratio measures the length of time it takes a company to pay its creditors. Generally the average figure is around 30 days. The lower the number of creditor days, the better. High number of days indicates worst performance.

Stock turnover- Measures the number of times a company converts its stock into sales during the year. Low figures are generally poor as they indicate excessively high or low moving stocks.

Profits/Assets-This is a useful indicator as to whether a business is using its assets well and getting the most value out of capital expenditure. Companies using their assets well will have a relatively high return, while those less well-run businesses will have a relatively low return. Above 6% is acceptable but below is not a good indication.

Gearing ratio-Gearing is a comparison between the amounts of borrowings a company has to its shareholders funds (net worth). The result of the calculation will show as a percentage the proportion of capital available within the company in relation to that owed to sources outside the company. Lower figures are more acceptable, showing that the company is predominantly financed by equity whilst high gearing shows an over reliance on borrowings for a significant proportion of the company's capital requirements. High gearing is significantly more dangerous at times of high or rising interest rates and also low profitability. A ratio of less than 100% is good but higher than that is bad.

4.7 Summary

This chapter has concentrated on the presentation, analysis and interpretation of the data that the researcher collected while on the field. Presentation, analysis, and interpretation was done under the objectives of the research study that are have been identified as types of loans KCB offers to its clients, the current systems used by KCB to evaluate loan applications, challenges faced when evaluating loan applications, suitable systems for improving the evaluation of loan applications, and design and development of a system that would improve evaluation of loan applications process. This chapter has thoroughly looked at the main issues that come up in evaluation of business retail loan application. It has further looked into the current systems used and finally come up with valid data that will form the basis of the next chapter.

CHAPTER FIVE

SYSTEM MODELLING

5.1 Introduction

This chapter looks at the logical as well as the physical design of the proposed system. It outlines the various functionalities that are included in the system.

5.2 Systems Engineering Process

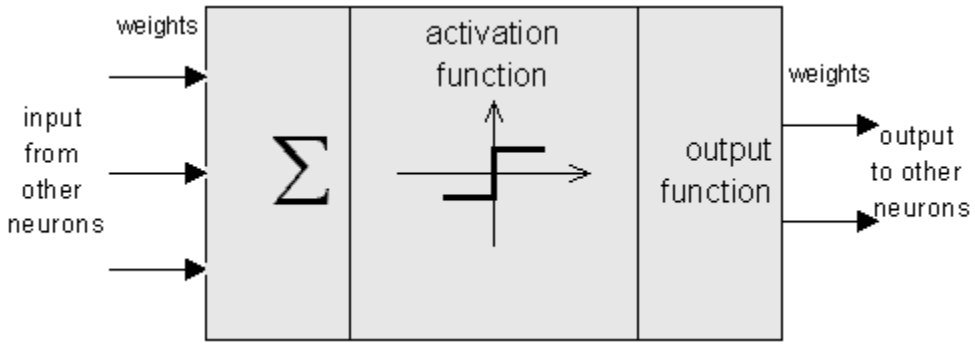

Figure 6: Idealized Neuron of a Neural Net, Froehlich (2013).

Figure 6 shows how similar the neural net is to the human brain. It is made up of neurons and connection where the neurons pass received information onto other subsequent neurons. Information (input) is sent to neurons which are then processed by a propagation function. The result is then compared to a threshold value given by the neuron's activation function. If the input exceeds threshold value, it fires, otherwise it is restrained. If input exceeds the threshold, it will make the target neuron to lead to an action. On the other hand if the threshold is not exceeded, then no action potential will be caused to the target neuron. Whichever way the input goes, there is no partial firing.

5.3 Neural Network Structure

The system developer used the hidden layer architecture. According to Turban (1995), hidden layer architecture is commonly used in complex practical applications that require one or more hidden layers between the input and output neurons and large number of weights.

The system under study had many objectives to be tested at the same time and this required some sort of parallelism. The system training was done on test cases of related loan evaluation criteria. There are various expert systems used in many fields which adopt the main architecture that has the inference engine, explanation mechanism, knowledge base and user interface but artificial neural networks are a unique kind of expert system as they only have a few of the mentioned features and they still perform well in and hazy decision making environments.

5.4. Collection of Data for Training the Network

The researcher had earlier conducted an information requirement exercise at KCB to determine requirements and went further to conduct a feasibility analysis for this research study project. The neural net system uses eight conditions as in Table 6 in section 4.6.1 necessary for gauging the qualification of a loan depending on the decision made by the system from available information presented by clients. After this, data was collected to be used for training and testing of the network.

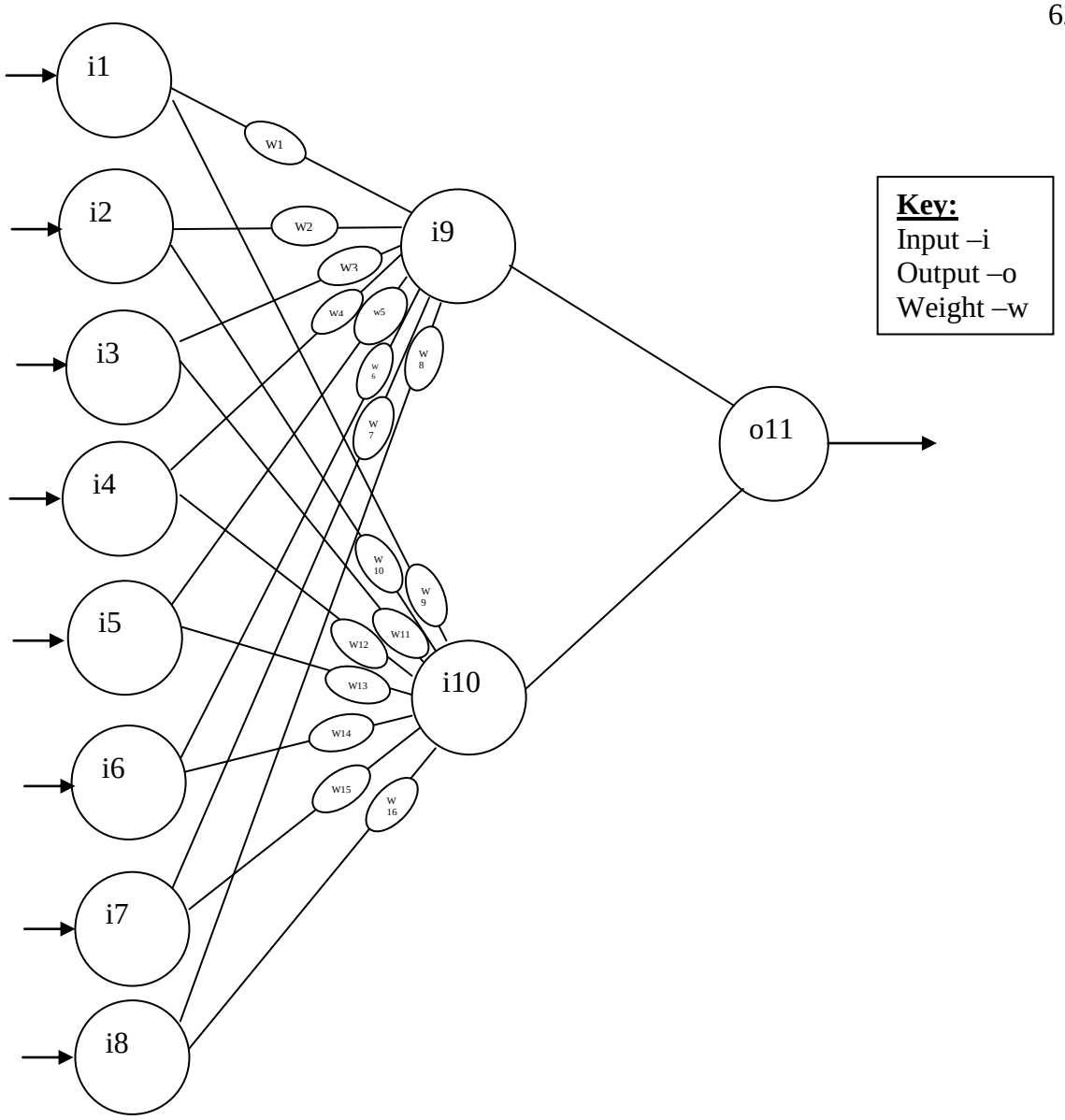

Figure 7: 3-Layer Back Propagation Network, Research Data (2011)

Inputs represented by i are:

i. Current ratio,

ii. Liquidity ratio,

iii. Creditor days,

iv. Solvency ratio,

v. Collection period,

vi. Stock turnover,

vii. Gearing ratio and

viii. Profits/Interest cover.

The neural network in Figure 7 is formed in three layers, called the input layer, hidden layer, and output layer. Each layer consists of one or more nodes, represented in Figure 7. The line below the nodes indicates the flow of information from one node to the next. In this particular type of neural network, the information flows only from the input to the output (from left-to-right). The nodes of the input layer are passive; this is to denote that they do not change the data. They receive a single value on their input, and duplicate the value to their multiple outputs. In contrast, the nodes of the hidden and output layer are active because they modify the data fed to them by the input nodes.

Variables in the input nodes hold data that has been drawn from conclusions in the coded data deduced from the field by observation of documentary sources and interviews.

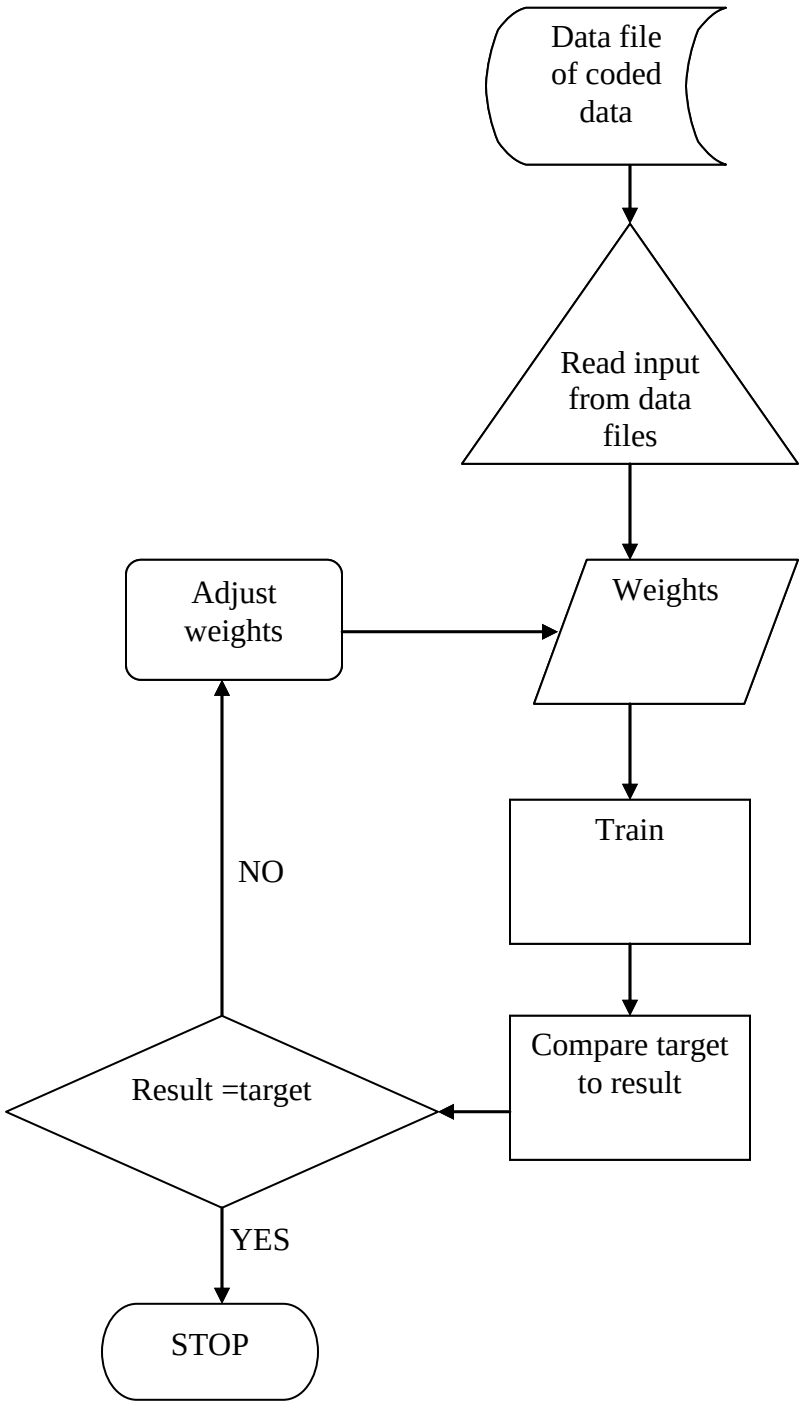

Figure 8: Process of ANN Based Expert System, Rabunal and Dorado (2006).

Figure 8 is a flow chart diagram of the process of information flow of an ANN based expert system. Data collected in this case the criteria are coded from manual documents provided by customers into a database. The neural network system then reads data that has been fed into the database. Weights of all the criteria in the database are then weighed against an already predetermined set of criteria weights. This process leads to adjusting of weights until either result is equal to target, in which case the process of training stops. If result obtained is not equal to target then the process is repeated from adjustment of weights forwards.

5.5 Back Propagation: Learning Algorithm

Back propagation is the type of algorithm that this system will use. According to Russell, Norvig, and Davis (2012), this method of neural net learning was first invented in 1969 by Bryson and Ho.

Froehlich (2013) notes that it is a supervised learning algorithm and is mainly used by Multi-Layer-Perceptrons to change the weights connected to the net's hidden neuron layer(s). Supervised learning uses a set of inputs for which the desired outputs are already known.

The back propagation algorithm uses a computed output error to change the weight values in backward direction. To obtain the net error, a forward propagation phase must have been done first so that while propagating in the forward direction, the neurons are activated using the sigmoid function shown in Figure 9.

The algorithm works as follows:

1. Execute the forward propagation phase for an input pattern and calculate the output error
2. Adjust all weight values of each weight matrix using the formula

Weight (old) + learning rate * output error * output (neurons i) * output (neurons i+1) * { 1 - output(neurons i+1) }

3. Go to step 1
4. End algorithm if all output patterns match the target patterns, else go to step 2.

5.6 Input Function: The Summation Function

$$in_i = \sum_j W_{j,i} a_j = \mathbf{W}_i \cdot \mathbf{a}_i$$

Figure 9: Sigmoid Function, Russel et al. (2012)

where,

in_i -implies weighted sum of inputs to unit *i*

$W_{j,i}$ –implies weight on the link from unit to unit *i*

W_i – implies weight from unit r to the output in a perceptron

a_i – the activation value of unit *i*

$\mathbf{a}_i$ – vector of activation values for the inputs to unit *i*

The formula in Figure 9 is used in the system to calculate the total weighted input which corresponds to the sum of the input activations multiplied by their weights.

a. Activation Function

The function in Figure 10 is referred to by some authors as the transformation or transfer function. After using the input function to find sum of weighted input, an activation function is used. This is done by applying the activation function, *g*, to the result of the input function. In this system, the researcher decided to use the sigmoid mathematical function to determine the threshold. According to Turban (1995), the purpose of the transformation is to modify the output levels to a reasonable value for example between zero and one.

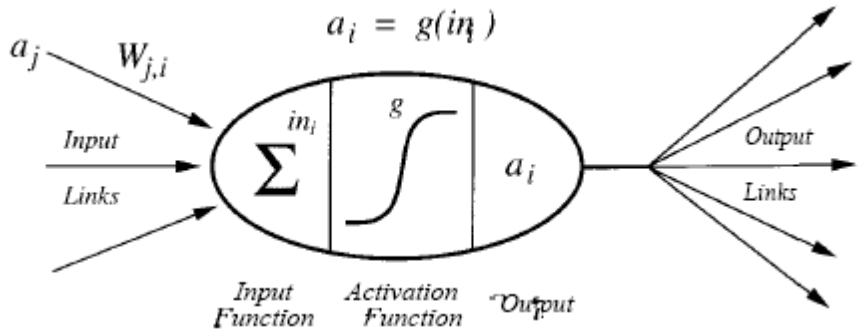

Figure 10: A Unit, Russel et al. (2012).

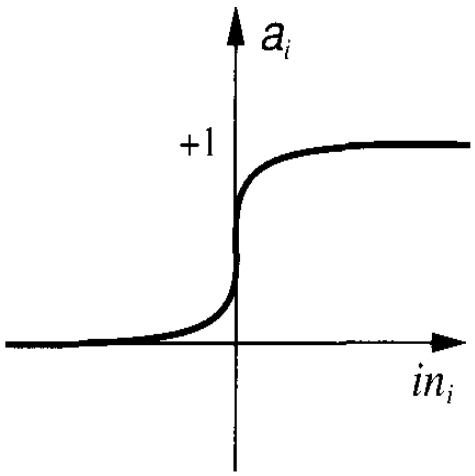

Figure 11: Sigmoid Function Representation for Threshold, Turban (1995).

Chong (2009) notes that the sigmoid curve is widely used as a transfer function because it has the effect of "squashing" the inputs into the range [0, 1]. This neural network system made use of the sigmoid function to squash the inputs into the range of 0 and 1.

The formula of **sigmoid activation** is:

$$f(x) = \frac{1}{1 + e^{-input}}$$

A derivative of the sigmoid function that will make it easier to calculate values is,

$$s'(x) = s(x)[1 - s(x)]$$

According to Chong (2009), there are three distinct functional operations that take place in a neural network neuron. First, the scalar input *p* is multiplied by the scalar weight *w* to form the product *wp*, again a scalar. Second, the weighted input *wp* is added to the scalar bias *b* to form the net input *n*. The bias shifts the function *f* to the left by an amount *b*. The bias is much like a weight, except that it has a constant input of 1. Finally, the net input is passed through the transfer function *f*, which produces the scalar output *a*. He further goes on to say that the names given to these three processes are: the weight function; the net input function and the transfer function. For many types of neural networks, the weight function is a product of a weight times the input. The most common net input function is the summation of the weighted inputs with the bias.

In essence, the activation function acts as a logic gate for which argument is based on. The threshold is compared to the weight that is the threshold, and then considering the sigmoid function used the neuron can fire or not depending on predetermined circumstances. The truth table *AND* is used as a logic gate where training values are initialized to match the *AND* truth table.

The neural network would definitely be more flexible if the sigmoid could be adjusted or centered on it based on a different value other than 0. For that purpose, this particular neural network made a provision for this bias by providing an extra input node that has an input value of 1 always. Current ratio was chosen to be the bias node since it is a condition that is considered first even before the rest when evaluating loan applications. When the value of the bias node is multiplied by the weights of the hidden layer, it

provides a bias (DC offset) to each sigmoid. In as much as this is a bias node, it is treated the same as the other nodes, except for the constant input.

5.7 Learning Rate

According to Turban (1995) learning rate refers to a parameter (*alpha*) that controls how fast the net learning will take place. The system developer set this learning rate to 0.25 for this particular system.

5.8 Training the Network

Turban (1995) notes that an ANN learns from its experiences and the process of learning involves three tasks, computation of outputs; comparison of outputs with desired target and adjustment of weights and repeat of the whole process

These three processes are illustrated as below;

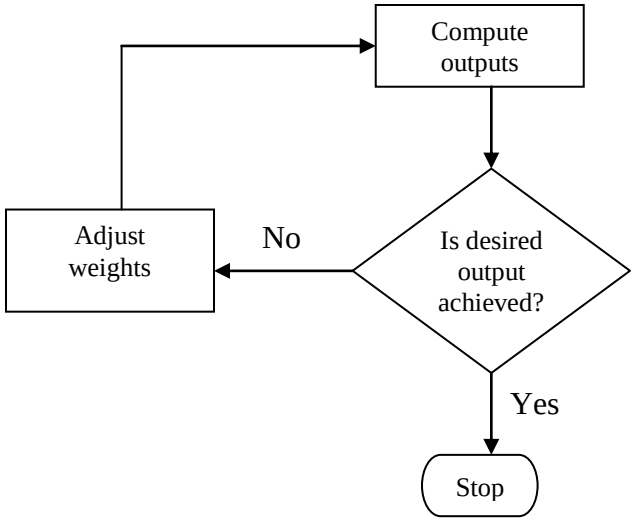

Figure 12: Process of Neural Network Learning, Turban (1995)

Learning process starts by setting the weights. The delta in this system comes as a difference between the actual output and the target. The main objective of training data here is to minimize the delta or to reduce it to zero by changing weights in the right direction.

Table 7: Training Cases for the Neural Network, Research Data (2011)

Criteria	Weights			
Current ratio(ratio)	0.5	0.02	1.9	4.1
Liquidity ratio(ratio)	0.45	0.1	5	0.66
Creditor days (days)	7	55	30	40
Solvency ratio (%)	9%	23%	74%	68%
Collection period (days)	100	8	30	61
Stock turnover	1	90	65	13
Gearing ratio (%)	20	400	124	50
Profits/Interest cover (%)	2	1.1	10	51

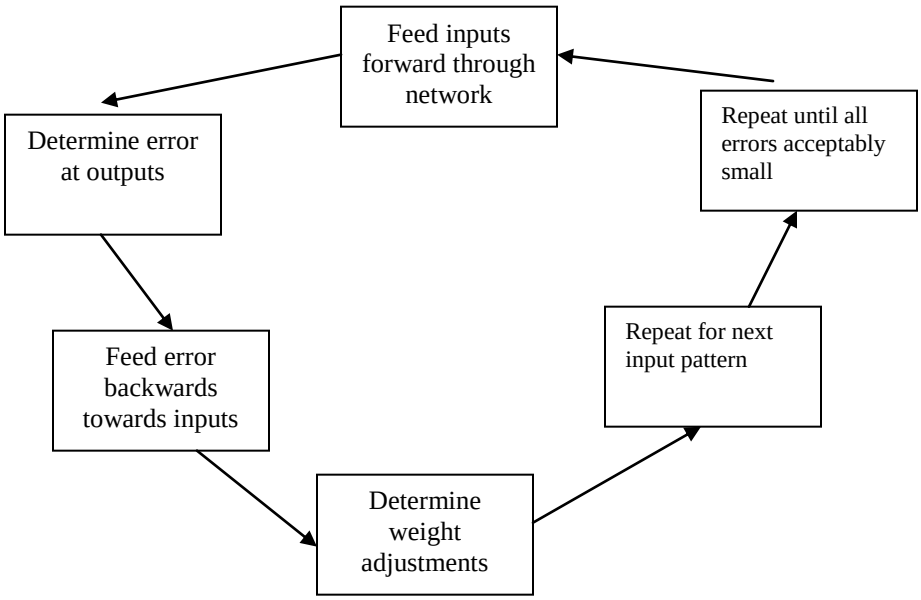

Figure 13: A cycle Diagram Representing the Processes of the Network

Figure 13 is a variation of Figure 12 above. It shows the processes that take place when the network is training and learning.

Using mock up test cases acquired from the bank, the researcher trained the neural network before testing. The mockup data was coded, (see table 7) then fed into the system and training done repeatedly till the threshold was reached.

5.8.1 The *Train ()* Network Function

To start training, the system is reset by clicking the 'Reset button' and then click the 'Run' button to run the network then see the output. *TrainOnce ()* is a function that has been coded in the system and it enables the network to call the Train function.

5.8.2 Testing of the Neural Network

Testing of the network involved validating of the neural networks functionality. After training the network with some training cases (see table 7), the test case were input into the system to see if the network had learned properly.

Table 8: Test Cases for the Neural Network, Research Data (2011)

Criteria	**Weight**			
Current ratio (ratio)	0.4	0.06	2.1	5.3
Liquidity ratio (ratio)	0.3	0.1	5	0.85
Creditor days (days)	3	40	20	2
Solvency ratio (%)	8	2	74	68
Collection period (days)	12	20	30	91
Stock turnover (%)	2	80	63	2
Gearing ratio (%)	30	500	125	80
Profits/Interest cover (%)	3	2.1	18	45

5.8.2.1 Input into System

Neural computing can process only numbers and therefore a problem involving qualitative values must be preprocessed to numeric equivalences before they can be treated by the artificial neural network (Turban, 1995).

Each input corresponds to a single attribute. In this case the attributes involved in the network include, current ratio, stock turnover, gearing ratio and profits/interest cover. The numeric values of either 1 or 0 assigned to these attributes which are the inputs to the network.

The coded data in form of ones and zeros are then input into the system using either mouse or keyboard. The system's interface and an inbuilt database have provision for text boxes that accept the coded data.

5.8.2.2 System Output Design

Output of the system will be in form of zero (0) and one (1) which will be interpreted as a bad loan and a good loan respectively. The numeric values will be displayed on the monitor arising from already processed data. In essence the function of the network is to compute the values that act as the output.

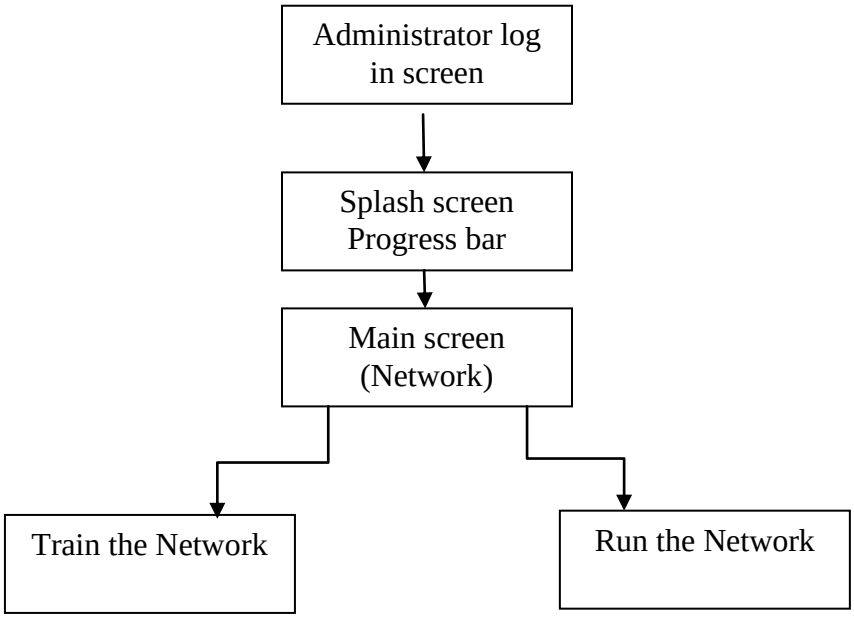

Figure 14: Graphical User Interface Flow Chart, Research Data (2011).

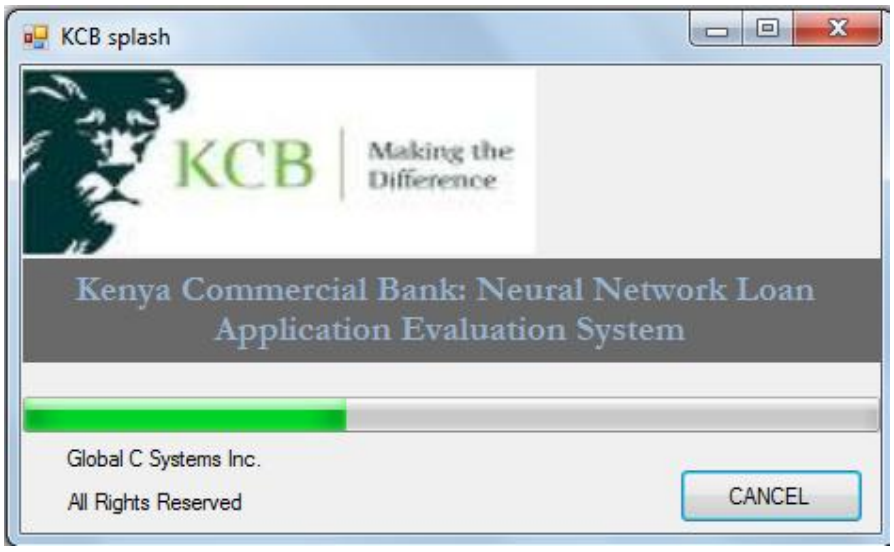

Figure 15: The Welcome Screen/Splash Screen and the Progress Bar

Figure 15 above is the welcome screen for the system and also acts as the splash screen. It tells the user that they are now welcome to start using the system.

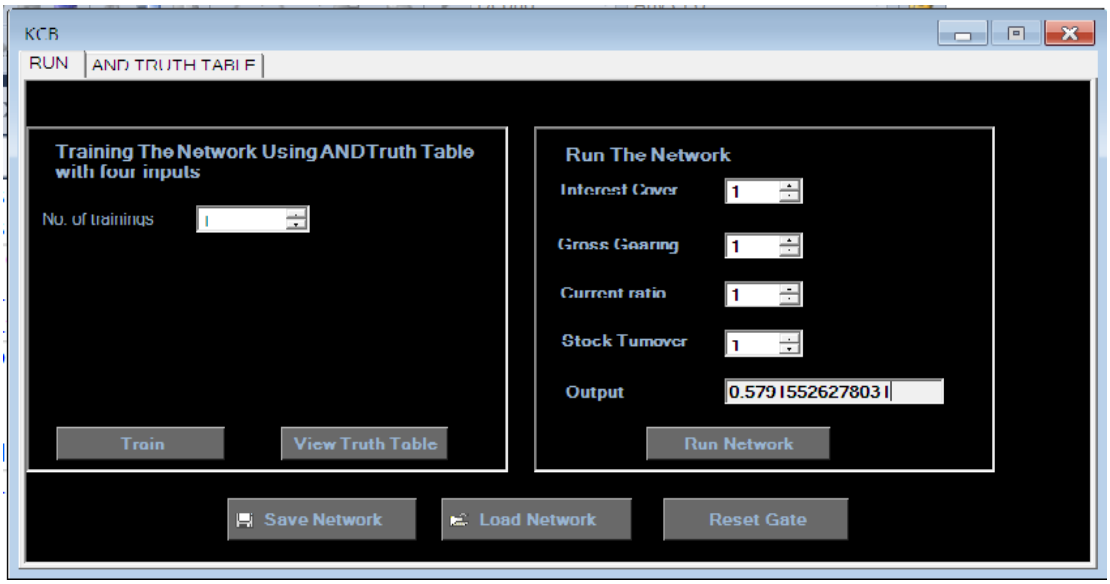

Figure 16: The Main Screen-Loan Evaluation Network (LEN)-Before Training, Research Data (2011)

Figure 16 shows the values of the criteria before training is done. With the current ratio /profits, interest cover, stock turnover and gearing ratio/gross gearing.

This screen shows the main screen before any training is done. It shows the number of trainings tab which allows selection of the number of trainings from the pull down menu. The training can then begin by pressing on the *Train* tab.

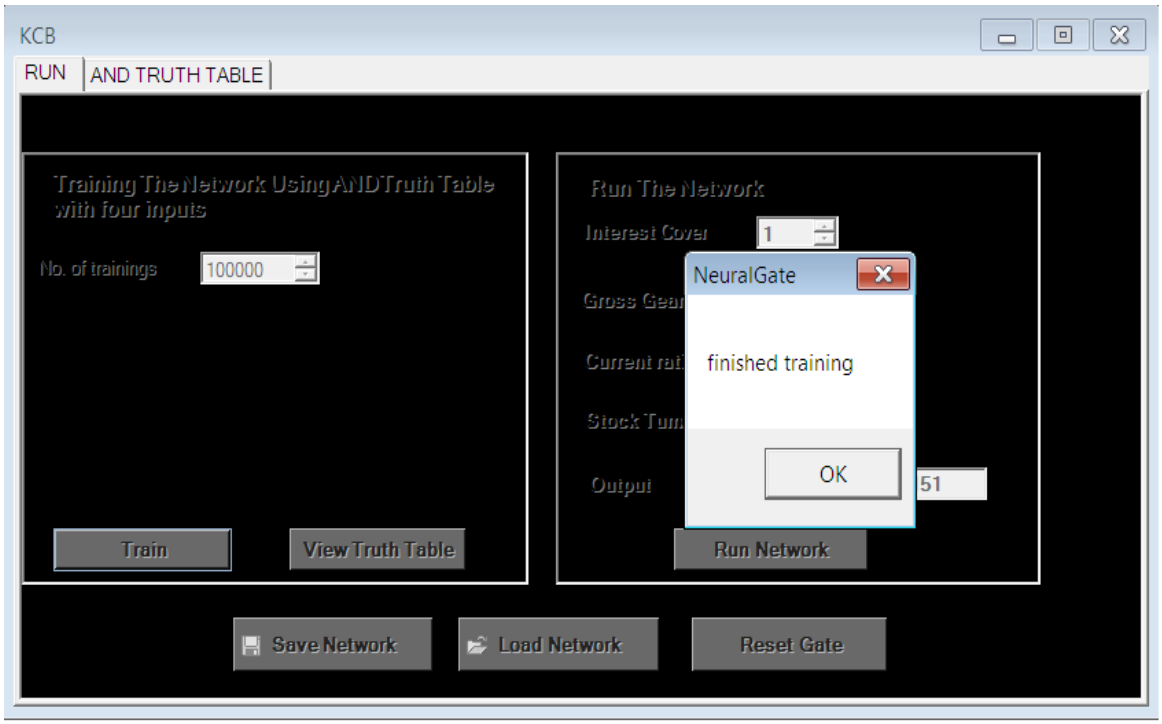

Figure 17: The Main Screen-LEN-During Training, Research Data (2011

Figure 17 illustrates the training of the network going on. The network is training 100,000 times then a dialog box pops up after the training to indicate training 100,000 times has been completed. This shows that the network undergoes training 100,000 times as keyed in so as to produce results and when it comes to an end, the dialogue box to show that training has finished pops up.

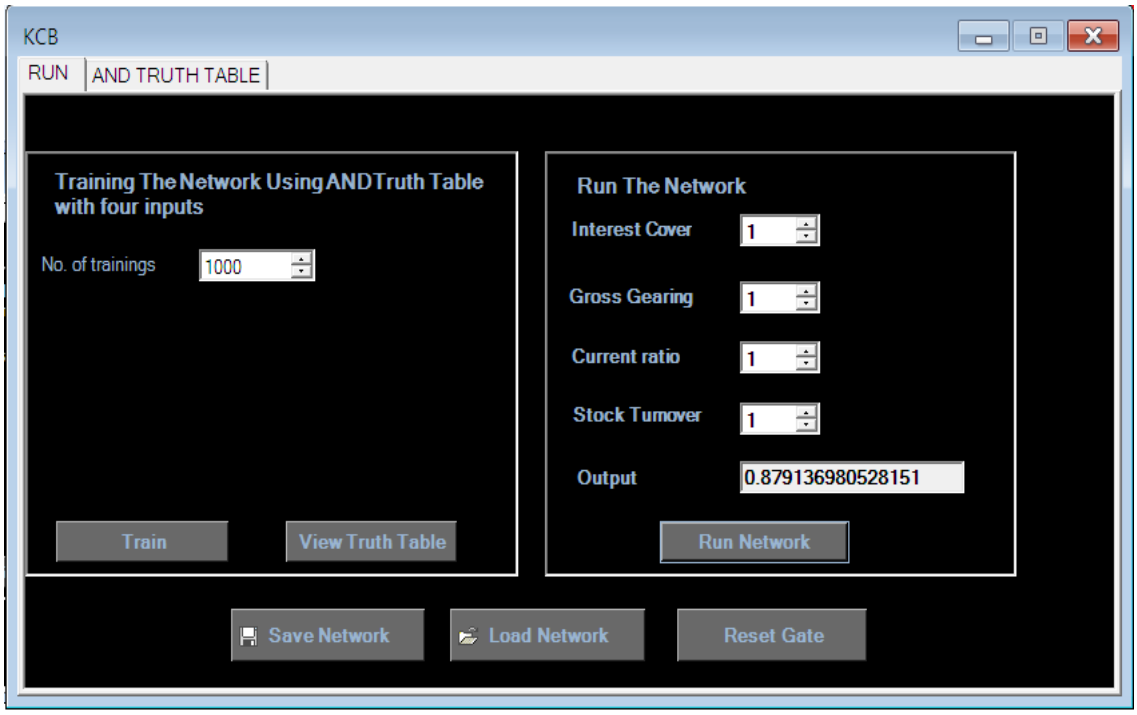

Figure 18: The Main Screen-LEN- after Training 1000 Times, Research Data (2011).

Figure 18 illustrates a screen of result after training 1000 times. Notice the Inputs are current ratio is 1, interest cover is 1, stock turnover is 1, and gearing ratio is also 1 giving a result of 0.879136980528151 which is drawing nearer to expected result which is 1 in the *AND* truth table shown in Figure 20.

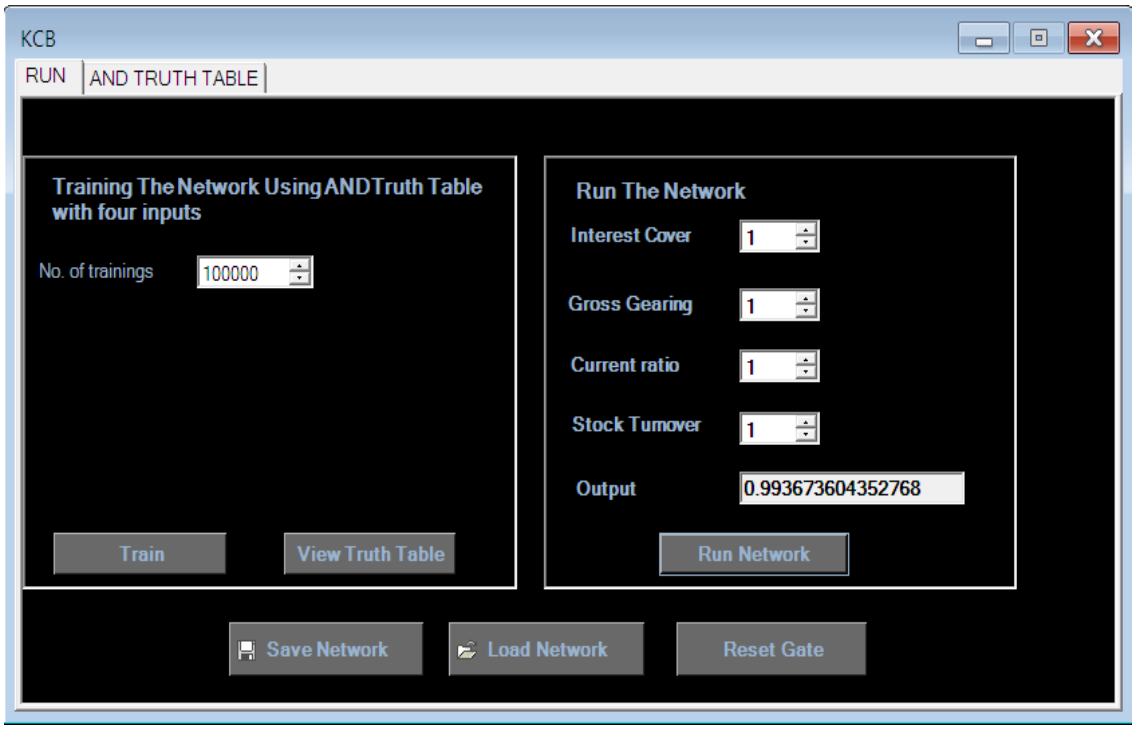

Figure 19: The Main Screen-LEN- Second Training
Source: Research Data (2011)

Figure 19 shows training again 100,000 times after getting results in the previous Figure 18. Notice the values of the criteria have not changed but because of this second training which has been done 100,000 times; we get a result that is now even closer to 1 which is, 0.993673604352768. This means that a customer that has the criteria combined in values of 1 qualifies for a loan. The more we train the more the output draws near to expected output. The inputs for the four criteria are all 1's which are drawn from the truth table (see Figure 20).

truth_table

ID	Interest_cover	Gross_gearing	Current_ratio	Stock_turnover	AND_OUTPU
1	1	1	1	1	1
2	1	1	1	0	0
3	1	1	0	1	0
4	1	1	0	0	0
5	1	0	1	1	0
6	1	0	1	0	0
7	1	0	0	1	0
8	1	0	0	0	0
9	0	1	1	1	0
10	0	1	1	0	0
11	0	1	0	1	0
12	0	1	0	0	0
13	0	0	1	1	0
14	0	0	1	0	0
15	0	0	0	1	0
16	0	0	0	0	0

Figure 20: The Main Screen-LEN-Truth Table Database
Source: Research Data (2011)

Figure 20 shows the database screen shot. It is derived from the *AND* truth table values, which in this case have 16 possible instances in permutation and combination. The neural network draws training values from this database for training.

5.9 System Set up and Installation

The proposed system will be integrated into already existing system at KCB that is used for business loan evaluation. Parallel integration is recommended to enable testing and debugging of the system if necessary. The functioning of the system will be facilitated by both the existing system and later the integration of this system into the existing system to ensure that important data is not lost during the implementation stage. This will only stop after the system is fully implemented and does not have bugs or problems.

CHAPTER SIX

SUMMARY OF MAJOR FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter provides a summary of the main findings of the study in light of the aim, objectives, research questions and assumptions of the study. This chapter also gave a conclusion and recommendations in relation to the topic under study.

6.2 Summary of Study Findings

This study examined the systems applied in evaluating loan applications at KCB. It intended to assess the strengths and weaknesses of the systems with an aim to designing and developing an ANN system to improve loan applications to curb shortcomings faced in appraisal of loan applications at KCB.

This study sought to analyze the current loan evaluation system at KCB with a view to design and develop an ANN architecture-based Expert system for evaluating loans at the bank.

This was intended to solve the problem of credit defaulting at KCB. It was therefore important for the bank to employ suitable software that provide some of the human characteristics of problem solving that are difficult to simulate using the logical, analytical techniques and other standard software technologies. Also the issue of delay of approval of loan was considered given that KCB is a big bank that has opened its doors to other east Africa countries. It was important that the clients got served efficiently,

effectively and on time to maintain its clientele base especially because of stiff competition. The research study had five objectives guided by the research questions below.

i) What types of loans does KCB offer to its clients?

ii) How are the current systems being used by KCB to evaluate loan applications?

iii) What are the challenges experienced in assessing loan applications?

iv) Which is the most suitable system for improving the evaluation of loan applications?

v) How can a neural network based expert system be developed to improve loan application evaluation at KCB?

Interviews, questionnaires and documentary sources were used to collect data in relation to above research questions. Documentary sources provided data used to test and train the neural network.

6.2.1 Summary of Study Findings in Relation to Research Questions

This section gives a summary of the study findings based on the research questions and data analysis in chapter 4.

6.2.1.1 Types of Loans Offered by KCB to its Clients

This study sought to identify the types of loans offered by KCB to its clients. The study revealed that the types of business loans offered were up to a maximum of 20 million Kenyan shillings. Documentary review resulted to identification of different categories of loans as detailed in Chapter 4 Section 4.3.1 which included small scale enterprise loans,

KCB grace loans, asset finance, secured business loans, SME loans, insurance premium finance, Brookside loans, Nairobi bottler's loans and temporary overdrafts. The staffs were very familiar with these loans and this is due to the fact that they processed these loans every day.

6.2.1.2 Current Systems Used by KCB to Evaluate Loans

The findings revealed that KCB had rolled out an online real-time system called Credit Quest from Harland Solutions to assist in various loan operations at KCB. The models included in the system are as listed in Chapter 4, Section 4.4. The system's modules are fixed and every user group had their own module for use. The findings also showed that loan appraisal criteria existed and was abbreviated as CAMPARI, for Character, Ability, Margin, Purpose, Amount, Repayment and Insurance as detailed in Section 4.4. The use of specific loan evaluation criteria CAMPARI implied that KCB has over the years used this measure as a major guideline to separate the credit defaulters from the credit worthy clients. The system at KCB was partly automated and, the process of financial analysis was the part that was automated.

6.2.1.3 Challenges Experienced when Evaluating Loan Applications

The study established that the interviewees across the board faced a myriad of challenges in loan evaluation that were more than often echoed by their colleagues. The findings indicated that wrong accounting in business, inadequate information to appraise clients' requests, lack of inclusion benchmarks and bureaucracy in the process of loan appraisal among others (see Section 4) were major challenges faced when evaluating loans. Among the challenges, a few cannot be avoided like political and economical challenges but

system challenges can be monitored by putting in place robust systems that include benchmarks to guide appraisal of loans.

6.2.1.4. Suitable System to Improve Evaluation of Loan Applications

The study indicated that the system users needed a system with a few more functionalities to make them comfortable when using the system. 90% of the respondents supported the need of an alternative system just to include a few more functions that include benchmarks for criteria for use in loan evaluation (see Section 4). This would result to more uniformity of loan evaluation in the credit unit. The study picked up from where the current system was not automated by picking up ratios, equating the ratios to a certain value and simply assigning ‘yes’ or ‘no’ recommendation unless otherwise the customer cancelled the loan quest. A neural network expert system was therefore needed to combine the criteria values by pulling them from the database and then just give a straightforward action.

6.2.1.5 Expert System to Improve Loan Evaluation at KCB

The study finally established that KCB needed a neural network based expert system to ease process of loan evaluation at KCB. The researcher therefore designed and developed (see Chapter 4 section 4.6 and Chapter 5) a neural network based expert system for use in loan evaluation at KCB. This involved software reuse and adoption of major DLL files from BrainNet Library which inspired the system development. BrainNet Library is free and open source and can be obtained from http://www.codeproject.com/Articles/14188/.

6.3 System Demonstration

During prototyping, the system was developed by involving three system users namely, financial analyst, credit analyst, and OLTP administrator. After the system was completed, it was demonstrated to two users to get their feedback in terms of functionality, appropriateness, ease of use, speed and efficiency. The expert users' comments are herein attached in Appendices 9(a) and 9(b).

6.4 Conclusions

The aim of this study was to analyze the current loan evaluation system at KCB with a view to design and develop an ANN architecture-based Expert system for evaluating loans at the bank. This aim has been successfully achieved. From the five sets of mock up training sets and five sets of mock up test sets obtained, the researcher established that 99 percent were able to give results similar to those given by human beings after the loan evaluation. Apart from adopting this system for use in the bank only, it can be used as a guide by clients who are looking forward to borrowing a loan from the bank to see if they can qualify before approaching the bank. The system can be customized and made available to customers for self assessment through mobile apps which can be accessed by prospective customers. The system can also be customized for use in other banks in both web platforms and mobile application platforms.

The developed system will enhance the operations of loans' department and ensure that only customers who are credit-worthy are awarded loans. Consequently this will reduce bad debts often posted by KCB and instead increase pre-tax profits during a financial review.

6.5 Recommendations

From the findings and conclusion of this study, the following are recommendations proposed in the use, adoption and maintenance of the system:

(i) Adoption of the System

The bank should consider adopting the system on a trial basis to see how it works in real life. The system's customized mobile app version can also be adopted and made available for use by customers for self assessment.

(ii) Policies Regarding Use of System

The bank may use the existing training policies for this system. This will ensure maximum exploitation and productivity from the system.

(iii) Frequent Re-Evaluation of User Requirements Versus System Performance

Frequent appraisal of system performance versus expectations should be done often to identify inadequacy or obsolescence before it takes toll on work performance by the staff. This involves holding system reviews with various system users and experts to find out if the system is meeting their expectation in carrying out their duties.

(iv) Recruitment of Qualified Staff and Retraining of Existing Staff

Competitive staff should be considered during recruitment to enable expertise in use and management of systems. Well trained staff should be absorbed to enable maximum exploitation of system. Already existing staff should be retrained to be able to better know how to use the system.

6.6 Suggestions for Further Research

i) A related research study should be conducted in other areas associated with financial transactions like risk mitigation in banks and insurance companies.

ii) The researcher proposes widening of this study to include more functionality like database integration which is not covered in this study so as to come up with a robust and more multifunctional system.

iii) Further study could consider including customers as respondents.

iv) The system's criteria can be widened by assigning each of the criteria used by the system some weight so that it doesn't have to use predetermined values of just one and zero that are used to denote a 'yes' and a 'no' respectively.

v) The system's customized mobile app version can be developed and made available for use by the bank and by customers for self assessment.

6.7 Dissemination of Research Findings

The findings of this study were disseminated to the public through presentation on the Second Annual Conference of the School of Information Sciences, Moi University in July 2009 and IST-Africa May 2013 Conference. The research was exposed to peer-review in the conference. This research content is also available in thesis form from the author, jjumacloy67@gmail.com and under Moi University custody.

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Appendix 1(a)

Interview Schedule for Information Systems Manager

i) What are the existing business functionalities already integrated with IT according to the KCB ICT strategy?

……

……

……

……

ii) What loan appraisal activities have you integrated with IT?

……

……

……

……

iii) What do you think about introduction of an alternative system to handle loan appraisal?

……

……

……

……

iv) What functionalities would you need to be included in the alternative system?

……

……

Appendix 1(b)

Interview Schedule for Advances Managers

i) What kinds of loan services do you offer your clients?

……

……

……

ii) What kind of system are you currently using to appraise loans applied for by clients?……

……

……

iii) What are the variables considered when evaluating loan applications?

……

……

……..

iv) What are the procedures involved in evaluation of the loans?

……

……

……

v) What are the challenges faced in evaluating loan applications?

……

……

……

What do you think about the introduction of an alternative system to handle loan appraisal?……

……

……

vi) What functionalities would you advocate for inclusion in the alternative system?

……

……

Appendix 1(c)

Interview Schedule for Loan Officers

i) What kind of system are you currently using to appraise loans applied for by clients?……

……

……

……..

ii) How effective does this system aid you in loan evaluation process?

……

……

……

iii) What are the challenges currently faced in using the current system?

……

……

……...

iv) What do you think about the introduction of an alternative system for loan appraisal activities?

……

……

……

…….

v) What functionalities do you advocate for inclusion in an alternative system to make the process of loan appraisal efficient and cost-effective?

……

……

……

……

Appendix 1(d)

Interview Schedule for System Operators

i) What loan appraisal activities have you integrated with IT?

……

……

……

ii) What do you think about introduction of an alternative system to handle loan appraisal?

……

……

……

iii) What functionalities would you need to be included in the alternative system?

……

……

……

Appendix 2 –KCB Business Credit Application Form

KCB Making the Difference

KCB BUSINESS CREDIT APPLICATION FORM

Branch:	**Application Date:**
Account Title:	**Account No:**
Business Name: (If different from A/C Title)	**Date Opened:**

A) DETAILS OF THE BUSINESS

Nature of Business: (Describe services or products offered)		
Date Started:	Registration No.	PIN No.
Ownership: Limited Company ☐ Partnership ☐ Sole Proprietorship ☐ Other ☐		
If response above is 'Other" please specify:		
Location of Business: (Street, Plot No. etc)		
Address: P.O. Box	Tel. No.	Town:
Email Address:		Fax No.
Manager: (Of the business on a day-to-day basis)		Experience: (years) (In the line of business)
No. Of Employees:	Business Premises: Owned ☐ Rented ☐	

(Please attach copy of Trade License)

B) CREDIT REQUEST DETAILS

Type of Facility	Existing Facility (Shs)	Now Applied For (Shs)	Purpose
1. Overdraft			
2. Loan			
3. Guarantees			
4. Letters of Credit			
5. Other (please specify)			

Total Cost of Project/Items to be Financed: (Shs).....

(Where applicable please attach documentary evidence of costs to be financed e.g. LPOs, Pro-forma Invoices etc.)

Source of Repayment: .....

Repayment Terms: .....

C) EXISTING FACILITIES

i) In KCB:

Nature of Facility	Branch	Limit/ Initial Amount Granted (Shs)	Outstanding Balance (Shs)	Repayment Per Month (Shs)

ii) In Other Banks/Institutions:

Nature of Facility	Branch	Limit/Initial Amount Granted (Shs)	Outstanding Balance (Shs)	Repayment Per Month (Shs)

D) DIRECTORS AND SHAREHOLDERS/PARTNERS

Directors	Shareholders	% age Shares
1) (MD)	1)	
2)	2)	
3)	3)	
4)		
5)		

E) KEY PERSON(S) IN THE BUSINESS(e.g. proprietor, partners, directors etc.)

Name:		ID/Passport No.
Nationality:		Age: (years)
P.O. Box No.	Town:	Telephone No.
Email Address:		Mobile No.
Designation:		Length of Period in Business: (years)
Qualification:		Marital Status:
Any Personal Account? Yes ☐	No ☐	If yes, indicate below:
A/C No.	Branch:	Bank:
Facilities Enjoyed:	Type:	Amount:

(If more than one key person, indicate details in a separate schedule)

F) ASSOCIATED ACCOUNTS

A/C Title	Bank/Branch	Type of Account	Facilities Enjoyed	Amount (Shs)

G) FINANCIAL DETAILS

Details for the Last 12 Months on :	From: ..... To :		As at last end-month date
Sales (p.a.)		Value of Stocks Held	
Cost of Goods Sold		Trade Debtors o/s	
Operating Expenses		Trade Creditors o/s	
Other Costs		Other Debts	
Net Profit (before tax)		Paid-up Capital	

Please Attach: 1) Audited Accounts for the last 3 years
2) Aged lists of current debtors and creditors

H) SECURITY

Nature of Security:	Property Title ☐	Quoted Shares ☐	Fixed Deposit ☐	Life Policy ☐	Other ☐

If you have ticked 'Other' above, specify nature of the security below:

Approximate Market Value: Shs.	Owned by:

If security is not owned by the applicant indicate the following details relating to the owner:

P.O. Box No.	Town	Tel. No.

If nature of security offered is 'Property Title' Indicate the following details:

Location of Property:	L.R. No. (Attach copy of Title document)
Nearest Major Town:	Size(in acres):

If the property is developed, describe nature of developments below:

Appendix 3 –Mock up Cash Flow Statement

Cashflow Statement

Test Invetsment Limited

Cash Flow Statement

Monetary Values in KES '000s	Valid 05/01/05 12/31/05 Other KLSA Panne Unqualif.	Valid 01/01/06 12/31/06 12 Months KLSA Panne Unqualif.	Valid 01/01/07 12/31/07 12 Months Explan.	Valid with warnings 01/01/08 06/30/08 6 Months
Profit Before Interest and Tax	9,720	10,513	18,232	
Depreciation	920	1,838	1,854	
Loss (profit) on Disposal	0		0	
Foreign Exchange loss(Income)			(19,996)	
WC Variation Stocks	(31,347)	(9,772)	(5,247)	
WC Variation Debtors	(251,994)	35,428	26,552	
WC Variation Payables	224,472	(29,387)	(84,088)	
Total W/Capital Variation	(58,869)	(3,731)	(62,783)	
Cash from Operations	**(48,229)**	**8,620**	**(62,693)**	
Interest Paid	(5,564)	(8,417)	(12,196)	
Tax Refunded(Paid)		(4,176)	62	
Operating Cashflow	**(53,793)**	**(3,973)**	**(74,827)**	
Purchase of Plant Property and Equipment	(11,343)	(221)	(1,409)	
Investments			0	
Investment in Subsidiary	(1)	(3,574)		
Proceeds from sale of Non Current Assets	0		746	
CASH SURPLUS OR DEFICIT	**(65,137)**	**(7,768)**	**(75,490)**	
Loans Received	73,000	4,000	50,000	
Overdraft			937	
Share capital issue			0	
Related Parties			20,503	
Cash	(27,863)	3,768	4,051	
Issue of Ordinary Shares	20,000			
TOTAL FINANCING	**65,137**	**7,768**	**75,491**	

Cash Flow Statement Notes

- The company generated positive cash flows from operations of Kes 8.6 million up from a deficit of Kes 48.2 million in 2005. Upon payment of interest and taxes the company had an operating deficit of Kes 4 million.
- The company went on and invested Kes 0.22 million on fixed assets and Kes 3.6 million in its South African and Ugandan subsidiaries. The resulted in an overall cash deficit of Kes 7.8 million. The cash deficit was financed by banking facilities.

Appendix 4 –Mock up Financial Statements Analysis

Financial Statements Analysis

Test Invetsment Limited

Monetary Values in KES '000s	12/31/05 Other Audited Company KLSA Panne Unqualif.	% Ann. Chg.	12/31/06 12 Months Audited Company KLSA Panne Unqualif.	% Ann. Chg.	12/31/07 12 Months Audited Company Explan.	% Ann. Chg.	06/30/08 6 Months Mgt Acc Company
Turnover	**296,841**	-8%	**408,256**	6%	**434,086**	-8%	**200,168**
Cost Of Sales	243,366	-10%	329,703	15%	379,850	-13%	164,363
Gross Profit	**53,475**	-2%	**78,553**	-31%	**54,236**	32%	**35,805**
Overheads	43,943	9%	71,615	27%	90,754	-3%	43,852
Operating Income	**9,532**	-51%	**6,938**	-626%	**-36,518**	56%	**-8,047**
Other Income	188	###	3,575	###	54,750	-19%	22,133
Profit before Interest & Tax	**9,720**	-28%	**10,513**	73%	**18,232**	55%	**14,086**
Finance Costs	4,288	63%	10,488	207%	32,192	-47%	8,509
Profit Before Tax	5,432	-100%	25	###	-13,960	180%	5,577
Gross Profit Margin	18.01%		19.24%		12.49%		17.89%
Earnings Capacity	**5.02%**		**1.63%**		**-20.73%**		**-7.52%**
Net Profit Margin	1.83%		0.01%		-3.22%		2.79%
Working Capital	**14,347**	-14%	**12,404**	67%	**20,675**	-67%	**6,899**
Current Ratio	1.05		1.05		1.09		1.03
Days Inventories	31		46		45		63
Days Debtors	76		102		52		162
Days Creditors	98		179		63		105
Years to Repay	5.12		11.27		-3.54		-8.20
Interest Cover	1.98		1.00		0.00		1.89
Interest Cover Cash Basis	0.00		1.02		0.00		0.00
Net Tangible Assets	**22,889**	-2%	**22,543**	-47%	**12,007**	46%	**17,586**
Non Current Directors' Loans (Liabilities)	**N/A**		**N/A**		**22,052**		**N/A**
Long Term Leverage	8.21%		9.95%		183.66%		0.00%
Short Term Leverage	1,303.70%		1,212.27%		1,987.03%		1,456.89%
Overall Leverage	1,311.91%		1,222.22%		2,170.69%		1,456.89%
Gross gearing	320.11%		346.88%		1,075.50%		750.01%
Adjusted Gross Gearing	320.11%		346.88%		379.15%		750.01%

Financial Spread Notes

(31/12/07, Samuel Mwangi Wachira)

Turnover and Profitability.

- Turnover rose by 6% in 2007 from Kes 408.256m to Kes 434.086m. The Gross Profit declined by 15% from 78.55m in 2006 to 54.42m in 2007 due to higher cost of sales.
- PBT rose by 73% to Kes 18.2m in 2007 from 10.5m in 2006. The growth was largely derived from other incomes mainly Sundry income and recharge of expenses. These rose from Kes 3.575m in 2006 to Kes 54.75m in 2007.

Appendix 5 –Budget

Items	**Quantity**	**Sub-total**
Internet Access	45 days @ 100	4500
Stationery:		
Pens	1 dozen	240
Fullscaps	2 reams @350	700
Printing paper	5 reams @ 350	1750
Tape recorder	1@1000	1000
Storage devices- Flashdisk	2 flashdisks@800	1600
-DVD-RW	3 DVDRW@ 40	120
Transport	5 days fieldwork @500	2500
	To and from Nairobi	4000
Printing, photocopying, binding	Printing @ 10000	10000
	Photocopying@ 5000	5000
	Binding@ 2500	2500
Data collection and analysis	@2000	2000
System development &equipment	@5000	5000
Communication charges	@1000	1000
Accomodation fees	9months@ 2000	18000
Subsistence	9months@4000	36000
Miscellenous	10000	10000
GRAND TOTAL		**105,910**

Appendix 6 –Introductory Letter

MOI UNIVERSITY
DEPARTMENT OF INFORMATION TECHNOLOGY

Tel. 053-43720,43620,43231
Fax No. 053-43047,43360
Telex No. MOIVERSITY 35047
Email: dit@mu.ac.ke

P.O. Box 3900
Eldoret
Kenya

Our Ref: IS/MPHIL/070/07

11th November 2008

The Chief Executive Officer,
Kenya Commercial Bank Ltd.,
Headquarters,
P.O. Box
Nairobi.

For: KENYA COMMERCIAL BANK LTD.
Divisional Director, Human Resources
16/12/08

Dear Sir/Madam,

RE: JUMA JANE AKELLO (IS/MPHIL/070/07)

The above named is a bona fide student of Moi University pursuing MPhil in Information Sciences (Information Technology) Degree at our Information Technology Department.

As a partial fulfillment of this degree, she will be required to conduct a research study. The title of her research is "***Artificial Neural Network Based Expert System for Loan Application Evaluation***"

We would be grateful if you could be kind enough to allow her to conduct her research study at Kenya Commercial Bank. Any assistance accorded to her will be highly appreciated.

Please do not hesitate to contact the undersigned for any further information.

Thank you.

Yours sincerely,

HEAD
DEPT. OF INFORMATION TECHNOLOGY

DR. D. GICHOYA
HEAD,
DEPARTMENT OF INFORMATION TECHNOLOGY

DC/cam

Appendix 7 –Research Authorization

NATIONAL COUNCIL FOR SCIENCE AND TECHNOLOGY

Telegrams: "SCIENCETECH", Nairobi
Telephone: 254-20-241331, 241349,
254-20- 311761, 241376,
Fax: 254-20- 213215
When replying please quote

P. O. Box 30623 –00100
NAIROBI- KENYA

REF: NCST/5/002/R/002-B/4 **18th December 2008**

Ms. Jane Juma Akelo
P.O. Box 3900
Eldoret

RE: RESEARCH AUTHORIZATION

Following your application for authority to carry out research on "**Artificial Neutral Network Based Expert System for Loan Application Evaluation: A Case Study of Kenya Commercial Bank (KCB) Headquarters, Nairobi**",

I am pleased to inform you that you have been authorized to conduct research at **Kenya Commercial Bank (KCB) Headquarter Offices in Nairobi** for a period ending **30th July, 2009**.

You are advised to report to Chief Executive Officer, Kenya Commercial Bank (KCB) before embarking on your research.

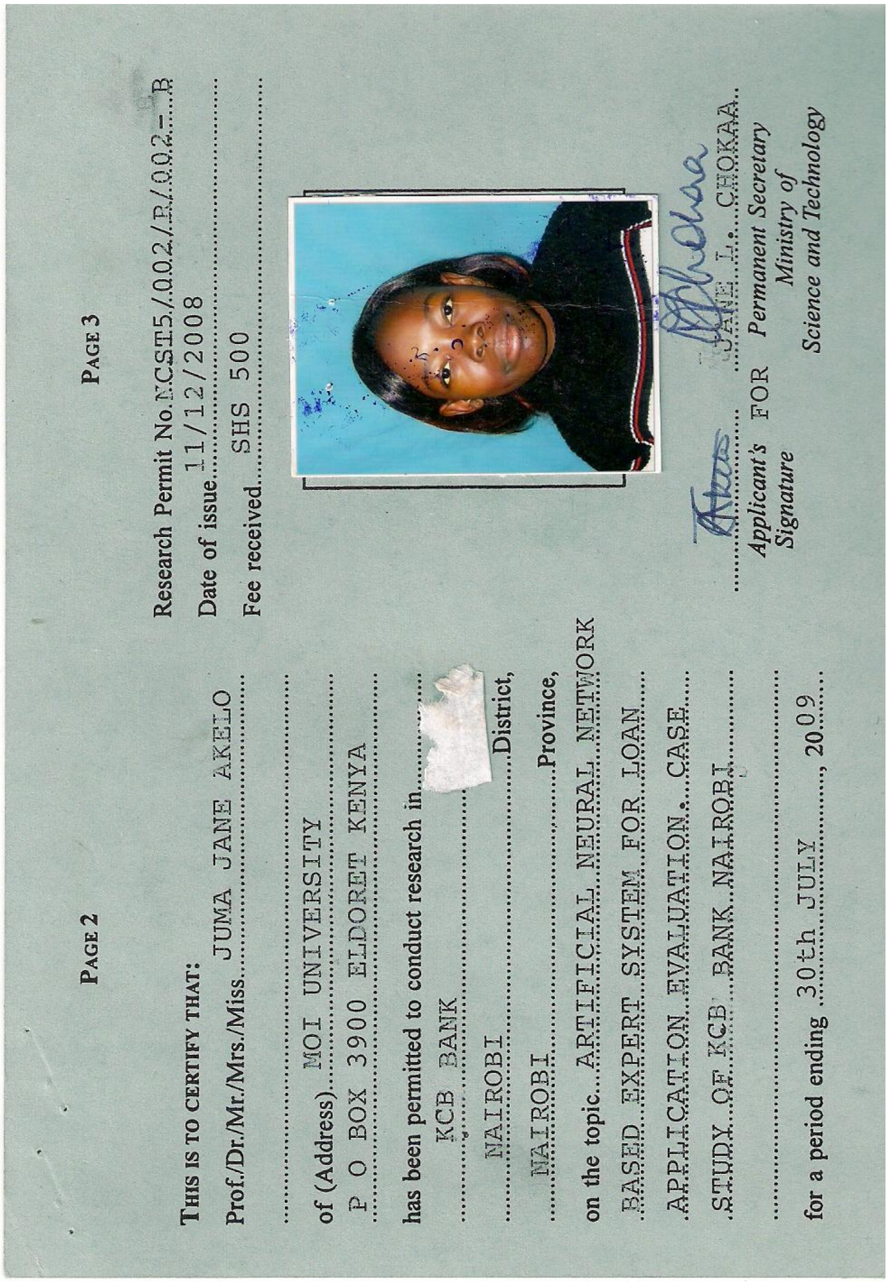
You are further advised to submit two copies of your research report to this office on completion of your research.

Jane L. Chokaa
FOR: EXECUTIVE SECRETARY

Copy to:

Chief Executive Officer
Kenya Commercial Bank (KCB)
P.O. Box, 46950-00100
Nairobi

Appendix 8 –Research Permit



PAGE 2

THIS IS TO CERTIFY THAT:

Prof./Dr./Mr./Mrs./Miss. JUMA JANE AKELO

of (Address) MOI UNIVERSITY

P O BOX 3900 ELDORET KENYA

has been permitted to conduct research in

KCB BANK

NAIROBI District,

NAIROBI Province,

on the topic ARTIFICIAL NEURAL NETWORK BASED EXPERT SYSTEM FOR LOAN APPLICATION EVALUATION. CASE STUDY OF KCB BANK NAIROBI

for a period ending 30th JULY, 2009.

PAGE 3

Research Permit No. NCST5/002/R/002 B

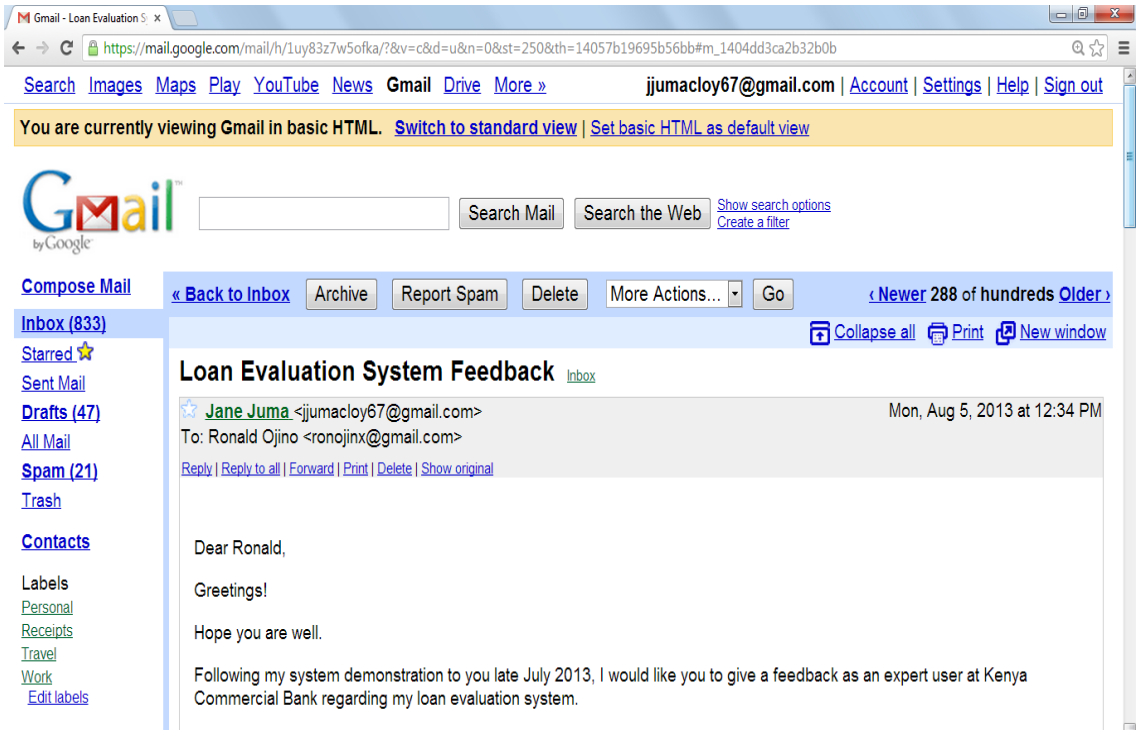
Date of issue 11/12/2008

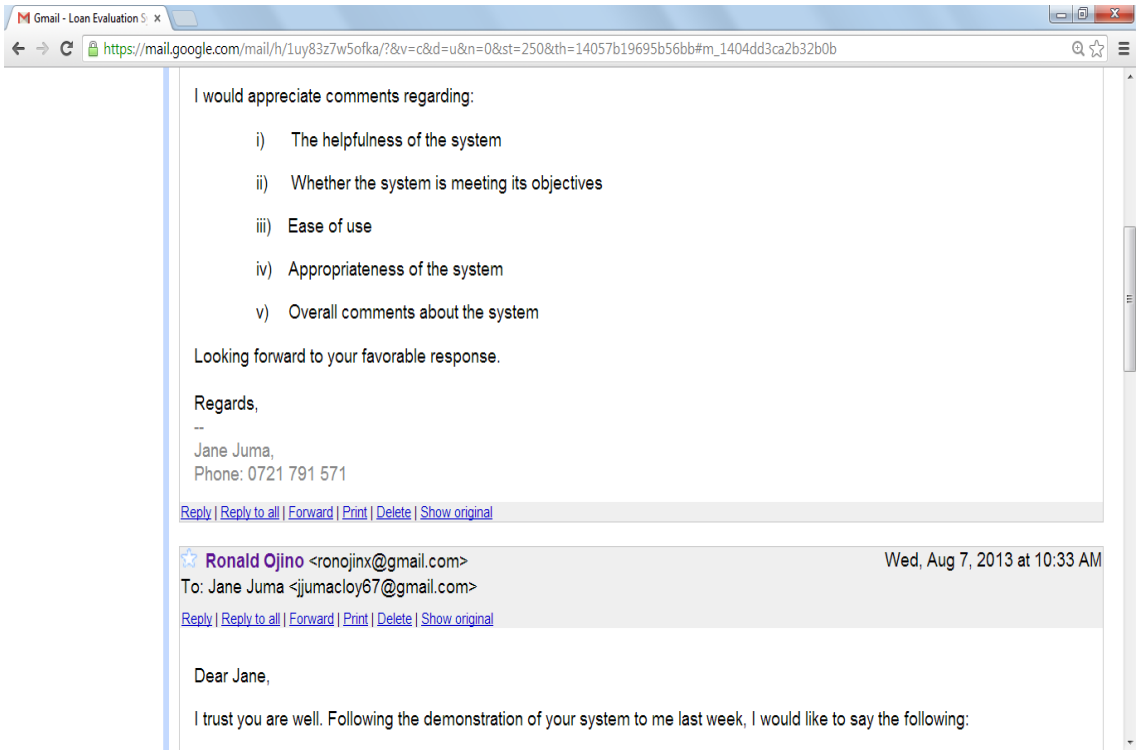
Fee received SHS 500

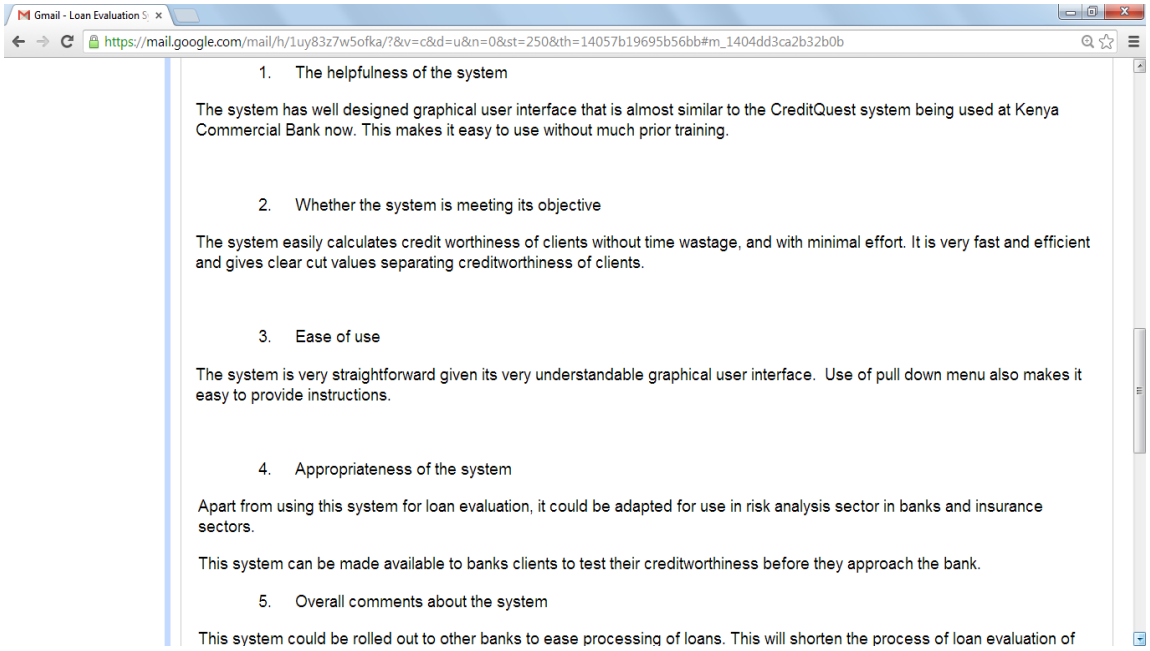
Applicant's Signature

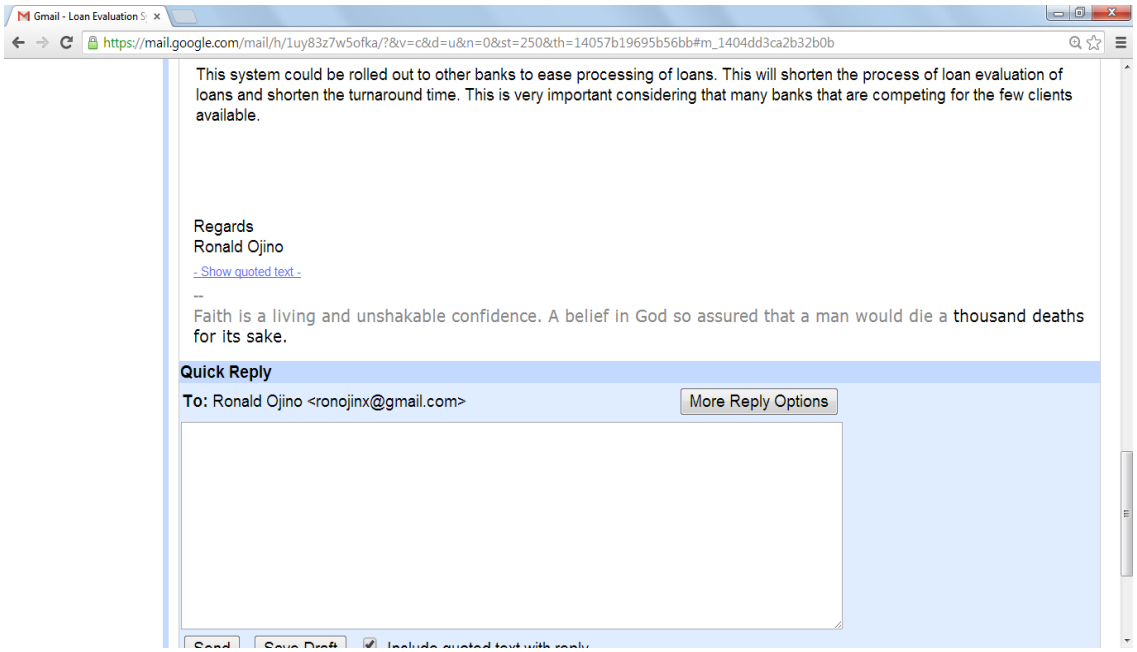
JANE L. CHOKAA FOR Permanent Secretary Ministry of Science and Technology

Appendix 9(a) –Feedback from KCB Expert 1

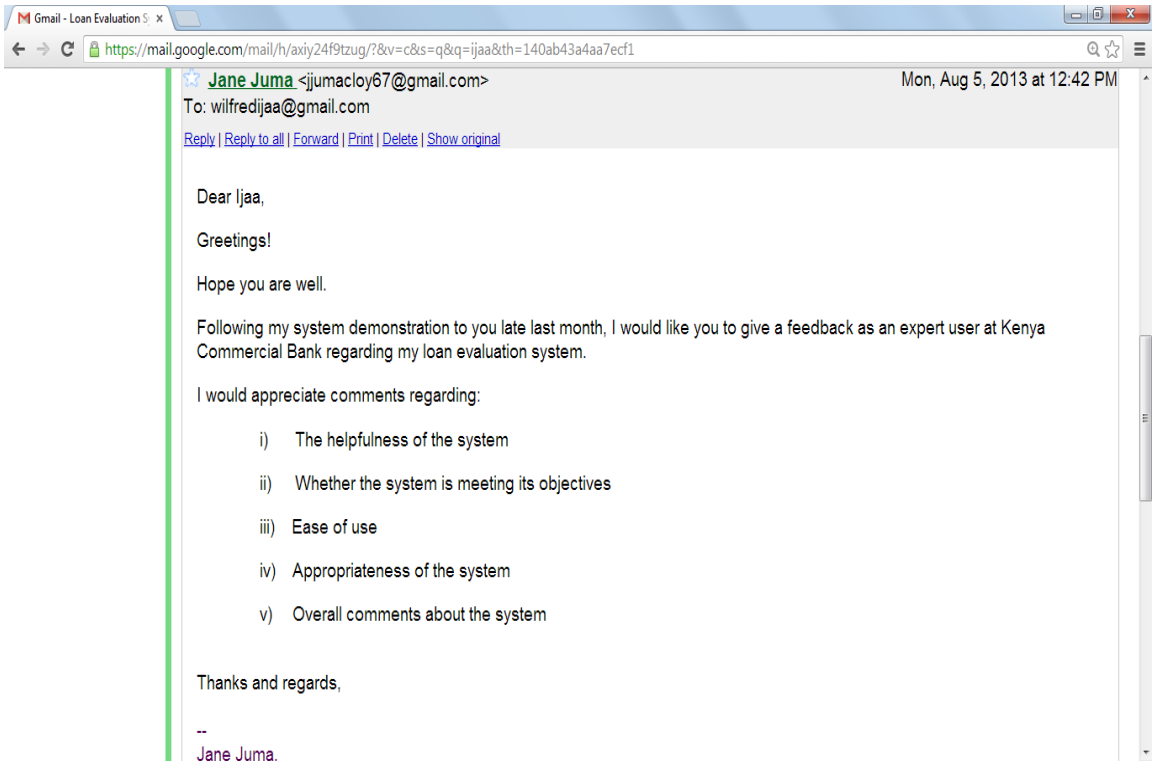





Gmail - Loan Evaluation S
https://mail.google.com/mail/h/1uy83z7w5ofka/?&v=c&d=u&n=0&st=250&th=14057b19695b56bb#m_1404dd3ca2b32b0b
1. The helpfulness of the system
The system has well designed graphical user interface that is almost similar to the CreditQuest system being used at Kenya Commercial Bank now. This makes it easy to use without much prior training.
2. Whether the system is meeting its objective
The system easily calculates credit worthiness of clients without time wastage, and with minimal effort. It is very fast and efficient and gives clear cut values separating creditworthiness of clients.
3. Ease of use
The system is very straightforward given its very understandable graphical user interface. Use of pull down menu also makes it easy to provide instructions.
4. Appropriateness of the system
Apart from using this system for loan evaluation, it could be adapted for use in risk analysis sector in banks and insurance sectors.
This system can be made available to banks clients to test their creditworthiness before they approach the bank.
5. Overall comments about the system
This system could be rolled out to other banks to ease processing of loans. This will shorten the process of loan evaluation of


Gmail - Loan Evaluation S
https://mail.google.com/mail/h/1uy83z7w5ofka/?&v=c&d=u&n=0&st=250&th=14057b19695b56bb#m_1404dd3ca2b32b0b
This system could be rolled out to other banks to ease processing of loans. This will shorten the process of loan evaluation of loans and shorten the turnaround time. This is very important considering that many banks that are competing for the few clients available.
Regards
Ronald Ojino
- Show quoted text -
--
Faith is a living and unshakable confidence. A belief in God so assured that a man would die a thousand deaths for its sake.
Quick Reply
To: Ronald Ojino <ronojinx@gmail.com>
More Reply Options

Appendix 9(b) –Feedback from KCB Expert 2



Gmail - Loan Evaluation S

https://mail.google.com/mail/h/axiy24f9tzug/?&v=c&s=q&q=ijaa&th=140ab43a4aa7ecf1

Jane Juma <jjumacloy67@gmail.com> Mon, Aug 5, 2013 at 12:42 PM

To: wilfredijaa@gmail.com

Reply | Reply to all | Forward | Print | Delete | Show original

Dear Ijaa,

Greetings!

Hope you are well.

Following my system demonstration to you late last month, I would like you to give a feedback as an expert user at Kenya Commercial Bank regarding my loan evaluation system.

I would appreciate comments regarding:

i) The helpfulness of the system

ii) Whether the system is meeting its objectives

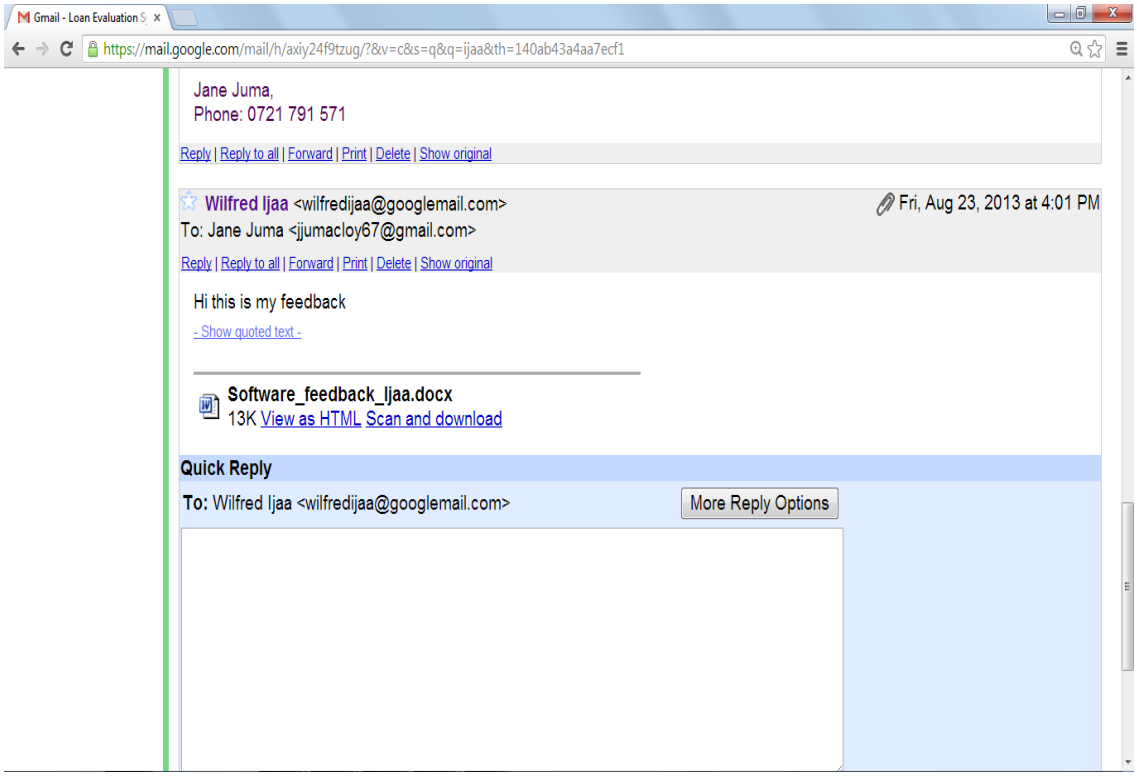
iii) Ease of use

iv) Appropriateness of the system

v) Overall comments about the system

Thanks and regards,

--
Jane Juma.



Gmail - Loan Evaluation S

https://mail.google.com/mail/h/axiy24f9tzug/?&v=c&s=q&q=ijaa&th=140ab43a4aa7ecf1

Jane Juma,
Phone: 0721 791 571

Reply | Reply to all | Forward | Print | Delete | Show original

Wilfred Ijaa <wilfredijaa@googlemail.com> Fri, Aug 23, 2013 at 4:01 PM

To: Jane Juma <jjumacloy67@gmail.com>

Reply | Reply to all | Forward | Print | Delete | Show original

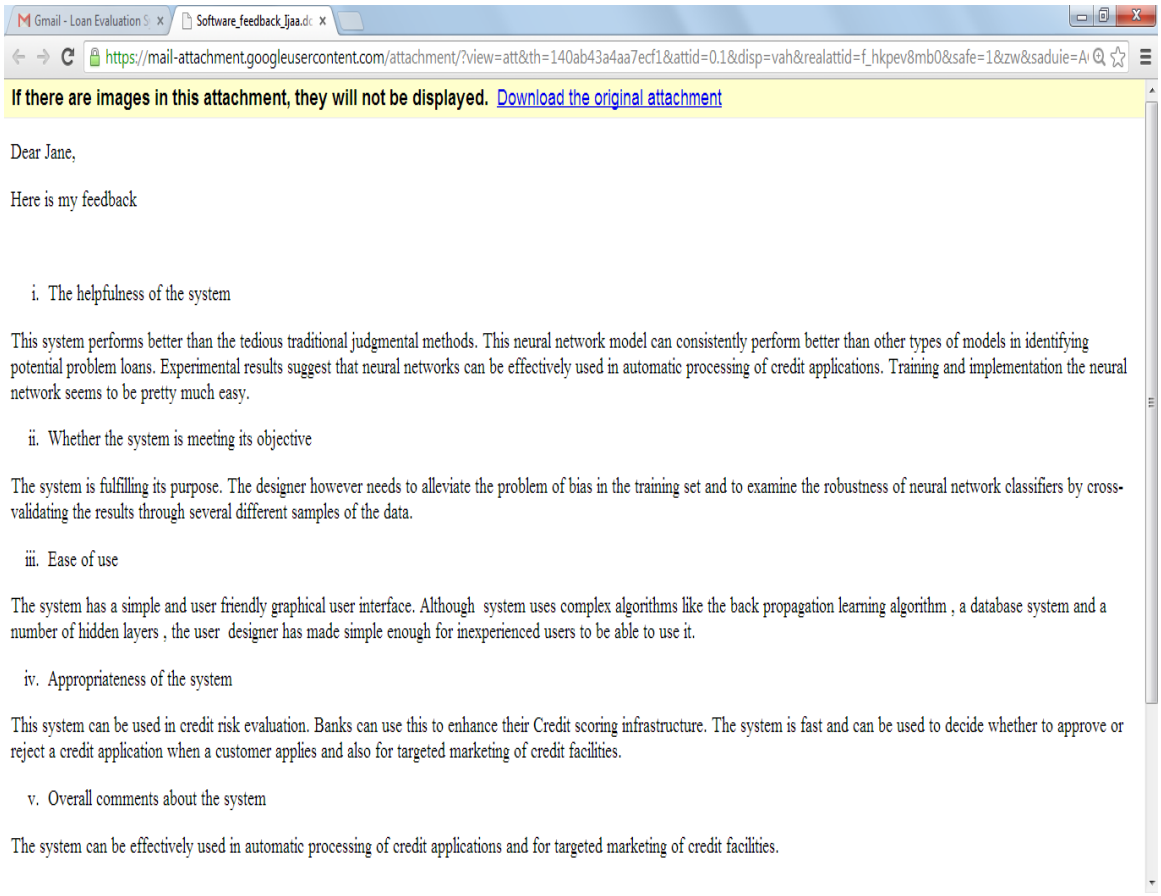
Hi this is my feedback

- Show quoted text -

Software_feedback_Ijaa.docx
13K View as HTML Scan and download

Quick Reply

To: Wilfred Ijaa <wilfredijaa@googlemail.com> More Reply Options


Gmail - Loan Evaluation S
Software_feedback_Ijaa.dc
https://mail-attachment.googleusercontent.com/attachment/?view=att&th=140ab43a4aa7ecf1&attid=0.1&disp=vah&realattid=f_hkpev8mb0&safe=1&zw&saduie=A
If there are images in this attachment, they will not be displayed. Download the original attachment
Dear Jane,
Here is my feedback
i. The helpfulness of the system
This system performs better than the tedious traditional judgmental methods. This neural network model can consistently perform better than other types of models in identifying potential problem loans. Experimental results suggest that neural networks can be effectively used in automatic processing of credit applications. Training and implementation the neural network seems to be pretty much easy.
ii. Whether the system is meeting its objective
The system is fulfilling its purpose. The designer however needs to alleviate the problem of bias in the training set and to examine the robustness of neural network classifiers by cross-validating the results through several different samples of the data.
iii. Ease of use
The system has a simple and user friendly graphical user interface. Although system uses complex algorithms like the back propagation learning algorithm , a database system and a number of hidden layers , the user designer has made simple enough for inexperienced users to be able to use it.
iv. Appropriateness of the system
This system can be used in credit risk evaluation. Banks can use this to enhance their Credit scoring infrastructure. The system is fast and can be used to decide whether to approve or reject a credit application when a customer applies and also for targeted marketing of credit facilities.
v. Overall comments about the system
The system can be effectively used in automatic processing of credit applications and for targeted marketing of credit facilities.