

## Automation of Credit Worthiness Appraisal for Small Businesses

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### Abstract

*Using two analytical approaches, the decision matrix credit grading model and the rule-based evidence tree nodal analytical model this paper developed an Expert System (ES) framework for the automation of credit worthiness appraisal for small businesses. The framework provides an interface for inputting data which is pre-analyzed and entered into a three level grading rule based expert system. The result is exported back into the Management Information System (MIS) and forms are drawn up as and when needed based on a combined system recommendation. This paper is not a substitute to the traditional Know Your Borrower (KYB) analysis but serve as an additional aid to credit processing officers in financial institutions for risk assessment and loan package completion processes. Implementation of the ES will be of immense benefit to the banking and finance industries as the focus will be to achieve an effective automated integrated system for credit application, evaluation and processing.*

Keywords: Expert System, Credit Worthiness, Risk Assessment, Information System, Automation.

## 1. Introduction

Generally, commercial credit lending is an essential service in the financial sector; one that is to be managed and not avoided since credit lending is as much a pivotal banking management activity as is deposit mobilization. The worry though is whether a prospective borrower or a borrower will default or pay back, hence the reason why credit risk management is considered by many to be an actual science.

The process of commercial credit evaluation is one that requires a great deal of expertise. (Fletcher, Freundlich, Kolodziejcki, Schoder, & Ronen, 2000) shortlists at least nine steps, primarily manually driven as an existing approach to the credit process. These are traditionally undertaken by a credit officer who is adequately trained. A number of analytical financial techniques are employed in line with a co-ordinated system in the credit appraisal process with a view to assessing the borrower's business and financial position during and after the application period and as such credit score and rates are given to determine whether to grant credit to a consumer (Koh, 2015), or not for the purpose of security of transactions (Gupta, Mittal, & Bhalla, 2010). In addition to decisions on personal loan applications, financial institutions now make use of credit scores to help set credit limits, manage existing accounts, and forecast the profitability of consumers and customers (Lucas, 2000a).

Anderson (1984) posits and rightly so that this is a classification problem as the main goal is to assign credit to applicants classifiable as either good or bank. The credit officer is thus a risk manager whose evaluation can dictate loan sanctioning motions or outright loan refusal to a lender. Recent times has witnessed rising non-performance of credit portfolios which is in part responsible for the financial distress the banking sector is facing currently, thus ascertaining of credit risks viz a viz credit risks identification, grading and management is a primal factor for which a system must be established. Even with highly trained personnel and under prescribed guidelines, inconsistencies may result from the very subjective nature of the process, and no matter how clear the guidelines, the decision making process involves an extremely wide range of possible decisions often requiring a great deal of experience; not minding the difficulty in attaining or recruiting such expertise, well trained and experienced credit officers cannot still shortchange the usually long turnaround time for loan application packages, this time being the essential commodity to which credit trading is itself deemed essential. Thus, the present personnel element of the process for determining credit can be very inefficient. Such decisions as may also be made by an officer could therefore be conservative resulting in loss of business. Conversely poor decisions are sometimes made which result in loan loss. Therefore, this paper this paper creates an alternative automated system for apprising the Credit Worthiness of Small Businesses. The system incorporates these decisions that seldom prove impossible especially when a credit applicant falls within what is called the marginal or watchlist range.

A useful method for easing this process, reducing demand on staff, while also taking care of the myriad of decisions that may crop up is an intelligent automation system; one that will assimilate data, apply reasoning mechanisms and emulate the thought processes of a credit officer for commercial credit analyses and assessment. This paper is not a substitute to the traditional Know

Your Borrower (KYB) analysis but serve as an additional aid to a credit officer in the risk assessment and loan package completion process.

## **2. Literature Review**

Marrison (2002) has it that the main activity of bank management is not deposit mobilization but credit lending and (Lahsasna, Aion, & Wah, 2008) reiterated that credit risk decisions are key determinants for success of financial institutions as poor evaluation of credit risk can cause money loss (Gouveau & Goncalves, 2007). Furthermore (Angelini, Di Tollo, & Roli, 2008) emphasizes that risks continue to provide a major threat to successful lending despite advancements in credit evaluation techniques and portfolio diversification. It must therefore be clearly established at this point that a conservative credit officer can lose business faster than any gutsy deposit mobilizing officer (closer) can get business, while on the converse a speedy but not necessarily poor evaluation can cause the weight of the business loss to lie on the credit officer. This is thus a necessary dilemma to which a positive leaning would give an edge to the financial institution at hand.

The lending process which has thus far been painted as an all-important but risky process has also been suggested by (Treacy & Carey, 2000) to involve a wide range of possible decisions which can often require a great deal of experience. Cost, efficiency of information gathering, consistency of ratings produced, nature of banks' business, staff incentives and uses to be made of internal ratings are factors to consider. The thalamus of such rigorous processes is none other than the credit worthiness appraisal process itself.

Agu (1998) has described credit worthiness as a function of both ability and willingness to repay loans. For the purpose of security of transactions, agencies usually give credit rating/grade the main goal of which is to assign credit to applicants (Gupta, Mittal, & Bhalla, 2010). (Koh, Tan, & Goh, 2006) defined credit scoring quite simply as a method used by credit providers to determine whether to grant credit to consumers. This is a process often analytical and evaluative in nature undertaken for the purpose of estimating the credit worthiness of an individual, corporation or even a country. The obligor's overall credit history if any must also be taken into consideration. The main issue faced by any lender is to ascertain if a prospective borrower is likely to repay the loan or not. It's important for a lender to assess the probability that a borrower will fail to pay back, that is, assess the risk of default. In the United States, lenders use rating as an index of the risk of default (Martin, 2006). When credit rating is poor upon evaluation, it indicates a high risk of defaulting on a loan, and thus may lead to high interest rates or an outright refusal of loan by the creditor or lender. (Njoku & Odii, 1991) used regression analysis to identify factors that significantly influence repayment. The result revealed that amount borrowed, loan period, business size, business output, value of asset and interest on loan largely influence repayments. (Ezeh, 2003) also shows that the nearer a borrower's home or business to a credit lending institution the greater the probability that the obligor will be classified as credit worthy. Amongst the nine steps proffered by (Fletcher, Freundlich, Kolodziejwski, Schoder, & Ronen, 2000) as the then existing framework for commercial credit evaluation, management information systems were found to be crucial. (Petersen & Rajan, 2002), however conclude that due to newer and more impersonal ways of communication that distance now matters very little in the lending evaluation process. The paper later cited this development to come from systematic changes which they attributed to improvements in lender productivity. The evidence they claimed indicates substantial development of the financial sector, even in areas such as small business lending. (Wenner, 1995) also studied means of improvement of information transfer and loan repayment

performance through group credit and after considering effects of membership screening on composite delinquency states using dependent variables of a polynomial logit model of the third rank; results showed that variables such as screening, visit, frequency of inspection, etc. all contributed to the likelihood of repayment. It was thus found that individuals who belonged to groups were less likely to be delinquent. This was accrued to additional information obtained from groups screened which yielded informational efficiency gain.

The importance of information in the issue of Credit Rating in Banking Institutions cannot be over emphasized. (Analide, 2011), postulated that the decision mechanism from client history information can help evaluate client credit risk. Information was viewed as an asset relying less on technology but in truth, one cannot but argue a case of synonymous misconstruction, an antithetical irony-if one could. It was soon affirmed that statistical analysis and deterministic systems are the most commonly used classification systems. The importance of technology in the issue of Credit Rating in Banking Institutions cannot be over emphasized. The scoring model captures the relationship between the historical information and future credit performance. This can be represented as follows:

$$f(x_1, x_2, x_3, x_m) = y_n$$

where  $f$  is the credit scoring function that maps between the customer features  $(x_1, x_2, x_3, x_m)$  and his creditworthiness  $y_n$ .  $f$  is a function which predicts the value of  $y_i$ , that is, the creditworthiness of customer  $i$  by knowing the  $x_1, x_2, x_3, x_m$ , which denote the customer features such as income and age (Lahsasna, Aionon, & Wah, 2008). Technology has in fact become a part of our everyday lives as almost all our daily activities has an aspect of technology playing active roles. As a result, so many sectors have adopted technology practices and the lending institutions, for example, the banks cannot be left behind. The role of information systems even in the banking industries cannot be overlooked as information systems are vital for managing both company and customer activities so as to yield effective and efficient production. Therefore, because credit rating evaluation is one of the many important activities in the banking industry it is indeed in need of information system (Osamor, Wiwuga, Osamor, & Musa, 2013). Information is important but without a processing system, it is useless. This processing system is what is referred to as an Expert System (ES) an application of Artificial Intelligence technique which has proven to be a useful method for assisting with the decision making process such as that necessary for loan analysis. Many techniques have been explored, applied and tested for automation of the lending process.

A number of different approaches using expert systems have been taken in dealing with either the credit recommendation or the decision type of problem as applied to loan analysis. These approaches include decision trees and evidence trees. Other approaches deal with loan analysis on a case-specific 'frame base' process and others in a procedural rule-based analysis, such as a series of rules. An existing expert system for credit evaluation was built by (Castillo & Melin, 1993); a rule-based approach that utilizes a series of questions for which the user answers yes or no. There were some drawbacks mainly in the system's inflexibility. It also had no graphical interfaces with which to ease understanding of the loan application process.

Huang, etel (2004), had introduced an AI based learning technique called the support vector machine. The methodology was to review and compare back propagation network is against the AI based support vector machine. Accuracy of prediction for both systems was found to be 80%. (Ong, Huang, & Tzeng, 2005) made use of genetic programming to build a credit scoring model,

This procedure as compared to Artificial Neural Networks (ANN) a most commonly used soft computing credit scoring model yielded more flexible results and with better accuracy. Hybrid models have also been explored. (Huang, Chen, & Wang, 2007) identified and resolved credit scoring problems via Neural networks and Genetic Algorithm. An attempt was made to resolve reasons for the negative classification of some rejected applicants based on ANN models and then further attempt was made to re-assign them to preferably acceptable classes using the inverse classification technique prior. (Tsai & Wu, 2008), posits that Multi-Layer Perceptron trained by Back-Propagation Neural Networks is the most commonly used technique for financial decision making problems. They compared credit scoring performance of single classifiers against that of multiple classifiers. It was seen that in terms of prediction accuracy and with three datasets used, multiple classifiers only perform better in one dataset. By the result obtained, they concluded that it is better to consider the three-classifier architecture for an optimal financial decision.

### **3. Methodology**

Using two analytical approaches, the decision matrix credit grading model and the rule-based evidence tree nodal analytical model this paper developed an Expert System (ES) framework for the automation of credit worthiness appraisal for small businesses. In this research, existing systems are compared with the proposed system. Processes of loan qualification based on rules consisting of loan payment history, available credit, account age, medical records, crime records, business structure, amount to be borrowed etc., are examined. An expert system is proposed to assist with the analysis and evaluation of loan applications. Furthermore, a system is provided for inputting data from the user end of a loan application, such data as is needed for support of the automation process.

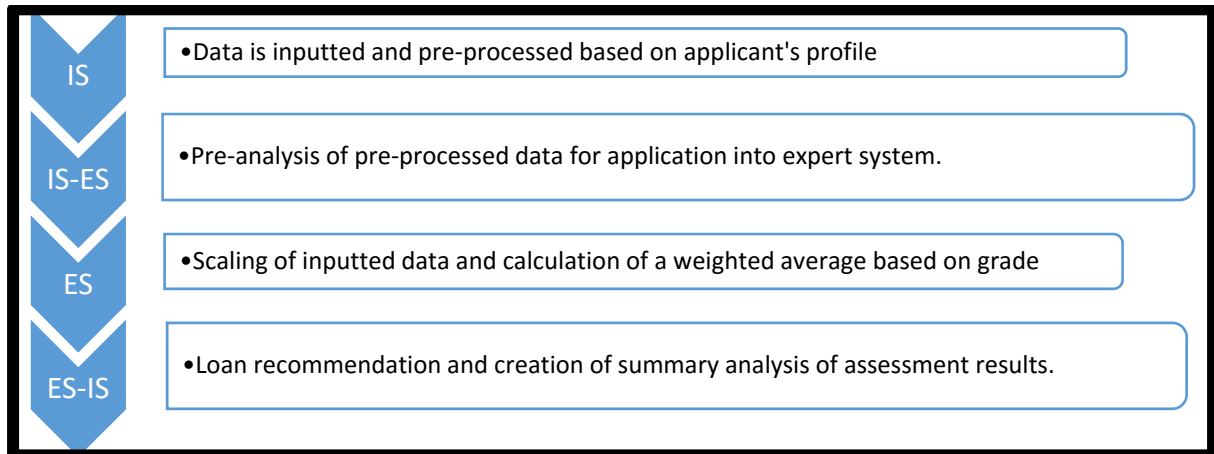
This system will also automatically transmit the inputted data to an expert analysis system for the operation of a loan, analysis, evaluation and decision assessment model. Credit rating is done by consideration of a combination of several factors to which weights are attached for different factors. A summary narrative of the key positive and negative weights involved in the assessment model is also provided automatically. A loan decision recommendation is also generated automatically as well as alternative analyses for such a decision. Forms are printed as and when needed and the final validation process window will then be presented to the credit officer in charge for evaluation. In all, this system can be condensed into three major subsystems;

- i. A database management subsystem that manages and collects data via electronic access
- ii. A user data entry and reporting subsystem
- iii. A support expert system that applies a rule base and employs an inference engine for use in credit requests analysis. The major concern for this paper will be the framework for the formation of the expert system.

For the user data collection window, A user friendly graphical interface is used, specific weights for the assessment factors, tags, flags, rules applied, explanatory boxes etc., are presented with ease of understanding. It is far much easier to grade a script than to write one. The system would be able to present to the credit officer, the specific factors involved in a credit decision, relative weights assigned and how the information provided by the applicant affects the process. The officer can thus identify specific weaknesses and strengths, and use the information for making the final decision. This is kind of a double check system because

the system itself simulates the thought process of a credit officer, much like a human, it considers the pros and cons based on answers to 'no' 'yes' questions and figures provided by the applicant which it then goes ahead to authenticate thanks to the MIS. This it does by entering and importing via links with databases data relating to a loan application into a data management system.

Two analytical approaches were considered for use in the expert system namely the decision matrix credit grading model and the rule-based evidence tree nodal analytical model. The latter was subsequently adopted. The chart below outlines the major steps for the expert system analysis and assessment model.



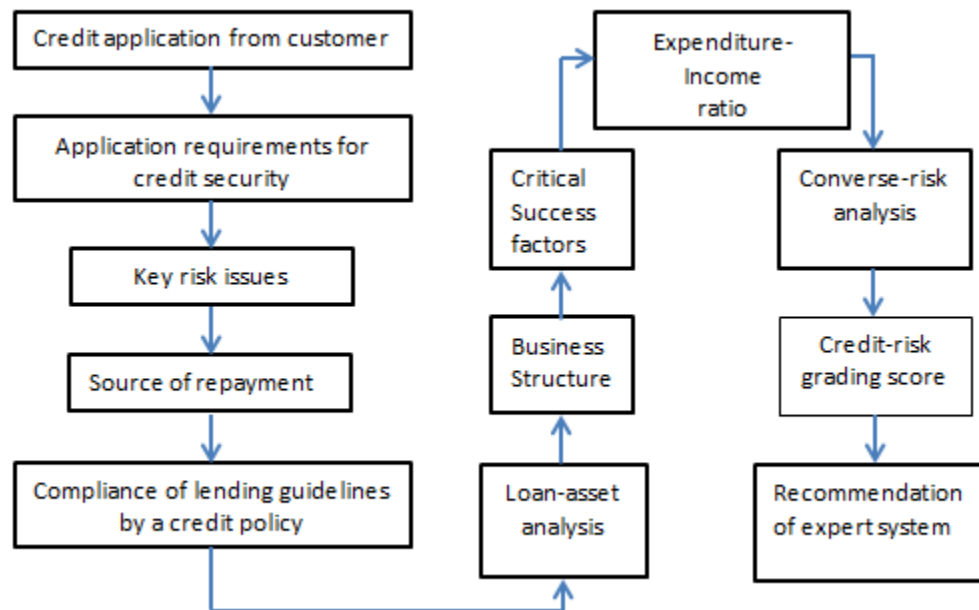
**Figure 3. 1:** Expert system process chart

Source: Author

The expert system cannot function independently. Normally the procedure can be different for bank customers and unknown persons. A lot of data has to be gathered from unknown persons since with a customer, transaction history can help a lot with loan decisions. This is why we have weighted averages for which specific factors are scaled and then weighted before post analysis of the loan application begins.

For the credit rating, the attached proposed weights are as follows Business Structure/Size (7%), Payment history (9%), Credit owed (7%), Available credit(4%), Age of account (3%), Proximity to Obligor's place of business (3%), Medical Records (7%), Amount requested as credit (4%), Collaterals provision (22%), Purpose for Loan (3%), Loan –asset ratio(4%), Expenditure-income (2%), Education (4%), Other factors (21%). From the information in the credit assessment report, the lender is then tasked with decision based on credit rating produced by the expert system. Of course, the expert system would make a recommendation for three major stages stemming from the grading stage. There is a pre-acceptance stage whereby the application is deemed acceptable, unacceptable or conditionally acceptable and if the condition is met for acceptance or the loan was accepted, the expert system would continue interacting with the MIS for grading the loan as performing, non-performing, or as marginally performing during each post assessment period as scheduled by the credit officer. Despite this credit worthy credit approval process, loans may still become troubled. The system should thus be equipped with analysis of markers or tracers of deteriorating credit performance to ensure quick action to protect the institution's

interest. There are so many symptoms of marginally performing loans and thus if the concerns exist such as breach of loan terms or adverse market news that will warrant more caution, a risk grading process was further adapted into the expert system as represented below;



**Figure 3. 2:** Adapted credit grading process showing key assessment criteria

Source: Author

Assets (RoA), the system however generates a slip containing the list of non-performing loans, thus a central database for all loan applications is seen to evolve to accommodate such tasks as afore listed. Commercially available software may be used to develop some aspects of the system including a user interface consisting of windows based format such as may include

- i) The Hypertext Mark-up Language (HTML) for coding in use for production of the credit form, user interface and customer application form.
- ii) Sybase SQL server from Sybase which is used as Data Base Management System (DBMS) for storage and manipulation.
- iii) Hypertext Pre-Processor (PHP) for interaction as a middleware between the DBMS and the front end/reporting application. There could be others like Brightware Inc's ART Enterprise for building the assessment model, performing loan analysis and display via a graphical interface of assessment result. The rule base for the assessment is contained in this third compartment.

#### 4. Results and Discussion

So far, an automated and integrated lending process has been considered. A browser based delivery process for the purpose of full automation and integration of processes involved in the conduction of a lending business through real-time collection of user information, workflow automation, processing and portfolio management was considered. This is to meet small business lending requirements based on an efficient rating system which according to (Loffler, 2004), should be more timely so as to result in a better discrimination between high-risk and low-risk issues, also more stable as to result in fewer governance rule-triggered transactions leading to lower transaction costs. This work provides a framework for such a system part of which is adapted from some basic principles from the adhoc system for loan evaluation the requirements of which have been stated. The algorithm developed for the lending process workflow for the proposed system is shown in figures 4.1 and 4.2.

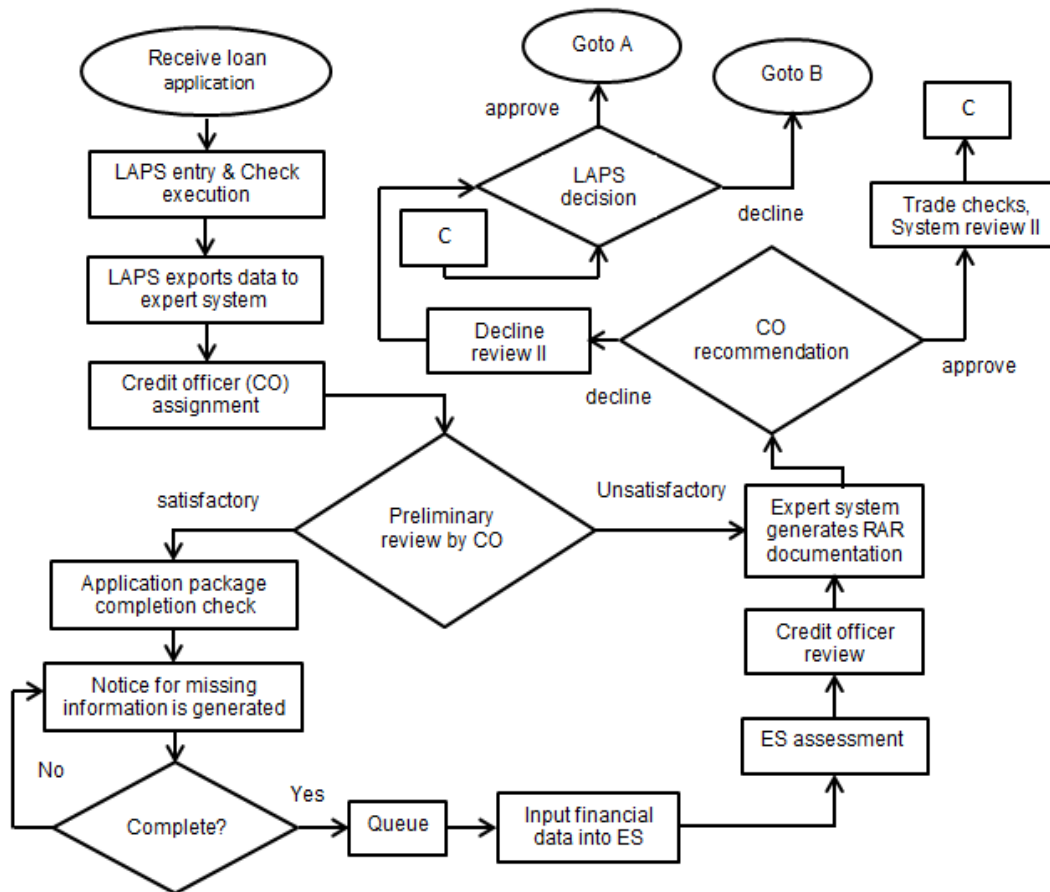


Figure 4. 1: ES workflow algorithm. Source: Author

There are basically three (3) main components

- i) An Applications Origination components (AOC) - For processing an application comprising: entering applicant data into a processing system; organizing the applicant data into formatted data by the processing system generating preliminary results by

- the processing system; forwarding the preliminary results to an expert analysis system comprised of an evidence tree;
- ii) A Loan Accounting and Processing System component (LAPS); accessing a central database based on several databases to obtain additional data; generating second results by the expert system based upon the formatted data, preliminary results and the additional data using the evidence tree containing a plurality of nodes and factors and at least one of the following techniques: propagating a value from a first node or a first factor to a second node; propagating a weighted value from a third node
- iii) A Portfolio Management / Network Management (PMNM) component ;exporting the results from the processing system; and producing documents necessary for a financial transaction portfolio by the processing system wherein some of the results from the expert analysis system are contained in the documents.

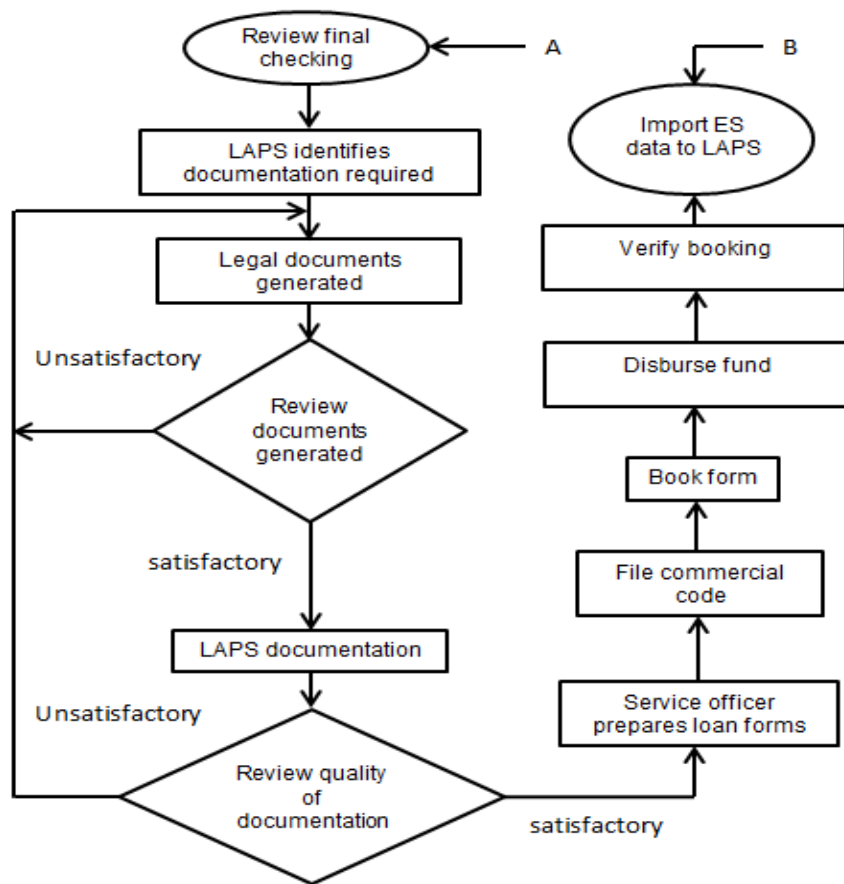
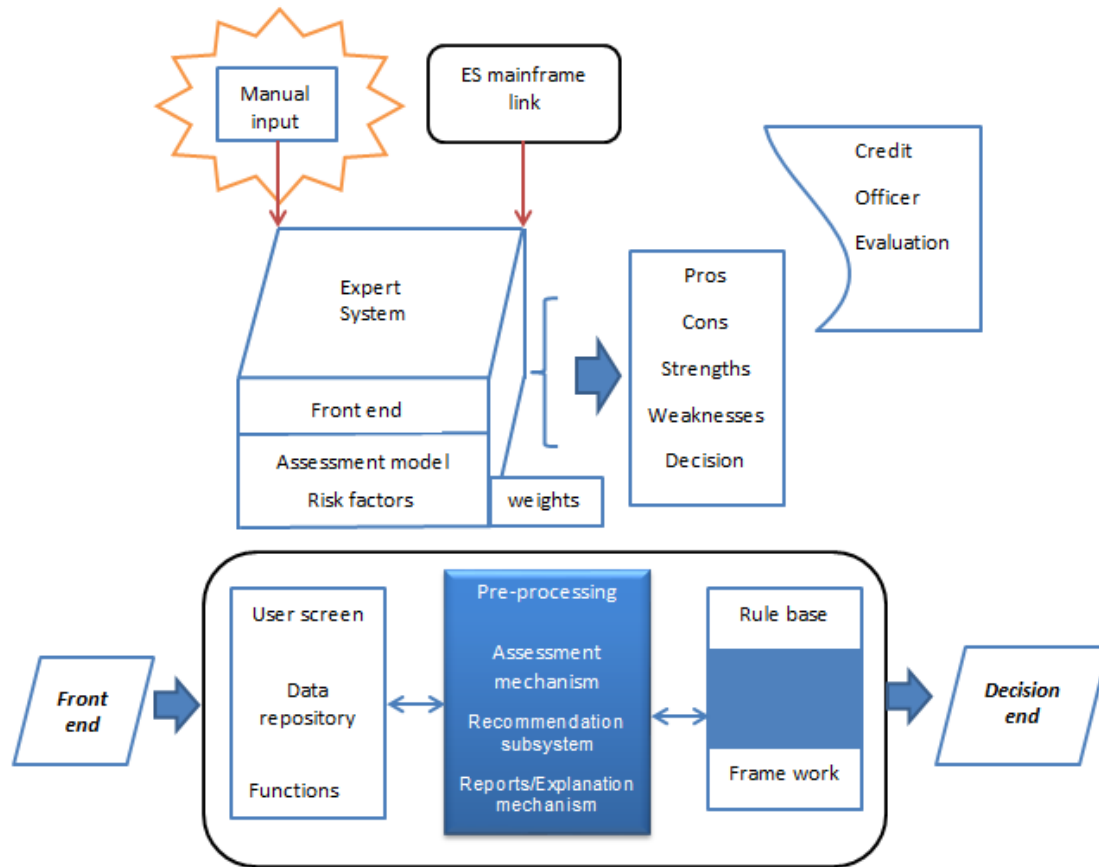


Figure 4. 2: ES workflow algorithm, Source: Author

The user is also allowed to determine basis of decision at time of that decision; enter new data without distorting the old for certain kinds of information at all times.

A schematic overview is presented in figure to further digest the system embodiments



**Figure 4. 3:** ES framework embodiments, Source; Author

This proposed system will ensure efficient approval or disapproval of loan applications by small businesses. A portfolio management component is also included and coupled with issuance and compliance to constructed rules from combinations of factors earlier discussed for prediction of credit worthiness. The framework should provide a timelier, more stable, high risk management system for loan application and processing. It is expected that by adapting this system framework, which is essentially a moderately portable framework for a rule-based evidence tree analytical network, with an explanation mechanism, and an input-output (I-O) facility, a secure robust but simple to navigate multi-faceted system will emerge for the purpose of providing an automated integrated loan/credit application processing system.

## 5. Conclusion

There is no doubt that there is a big need for an automated system for credit approval for all businesses small, medium or large. A lot of systems have also been proposed, designed, and implemented to that end. This present work put together a lot of evolving ideas from both the adhoc system for credit evaluation and some automated systems in different countries and a conclusion was derived. This is one towards a general approach for adoption of an openly accessible LAP system with multi-review platforms. Implementation of such a system will be of immense benefit to the banking and finance industries as the focus will be to achieve an effective automated integrated system for credit application, evaluation and processing.

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