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Expert Systems in Banking: Artificial Intelligence Application in Supporting Banking Decision-Making

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Abstract : This paper aims to evaluate the role of artificial intelligence in the bank lending process. A field study is conducted at the level of several banks. The article focuses on loan files of a commercial and productive nature. To achieve our goal, we utilized multiple expert systems: Sub expert system 1, Sub expert system 2 and the main expert system. Accordingly, the linguistic variables of the proposed expert systems were subsumed into qualitative variables and confirmation variables. To access the decision-making process for granting or denying the loan, the outputs of these variables of sub-expert systems 1 and 2 are fed as inputs to the main expert system**.** To achieve banking business success factors (quality and time), the expert systems improve the quality of banking service provided. It is performed by reducing the number and size of financial and non-financial errors and their ability to detect error cases. Additionally, unlike the human element, expert systems are characterized by their speed in executing the orders required of them in a few moments, which reduces the time required for decision-making.

Keywords: *Decision-making, expert system, qualitative variables, guarantee variables.*

1 Introduction

Since the fifties, decision support systems have been regarded as one of the most significant outcomes of technological advancements in artificial intelligence (AI) applications [1]. The systems are characterized by lower cost and more quality than those that preceded them. Furthermore, there is a growing need to direct AI applications toward management's needs in supporting decision-making and achieving effectiveness in this process. Accordingly, AI is a crucial and powerful technology for creating knowledge and ideas to improve the process of decision-making. It is a result of the confluence between the technical revolution in science systems, computer and automatic control on the one hand, and logic and mathematics on the other hand. AI applications have achieved decisions with advanced transformations [2].

From another side, cash lending is one of the critical responsibilities of a bank. Currently, as a monetary institution, there are many risks associated with the process of bank lending; one of its duties is to reduce the risk of lending [1]. Financial institutions and expert systems usually create a credit computation model. These systems aid in the loan collection assessment process to classify customer loans into bad credit or good credit. Bad credit is one in which timely loan repayment is not always possible, while good credit is paid on time [3].

A financial institution can gain a competitive advantage from the vast amount of collected knowledge and datasets. These datasets can be evaluated and effectively used to help the bank create a unique service that cannot be easily copied. Risks occur when the future outcome is not known. However, many possible outcomes can be expected with a level of certainty from knowledge of past or present events. Bank loans include different risks, such as credit risk, liquidity risk and interest rate risk. In liquidity risk, customers withdraw too much money at once. On the other hand, interest rate risk occurs when customers repay the loan. The interest rate will not be enough to recover the bank's money [4]. Therefore, the risks can be reduced.

Our work has been motivated by the study [5], where the researchers built an expert system in Islamic banks in the joint financing system to save time and effort and maximize profit. However, unlike [5], we used multiple expert systems and adopted linguistic variables (qualitative and quantitative) to use customers' information and make up for the deficiency of data. Eventually, to reach the bank's success and satisfy the

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borrowers through (reducing time and improving quality).

Therefore, we proposed this research to develop a system for the decision-making process of granting a loan. We seek to evaluate the role of expert systems in improving bank performance to achieve the essential success factors (quality and time). Therefore, this article proposes an expert system to guarantee the requirements for successful management in the current banking environment. In the design, multiple expert systems are utilized to determine whether the loan is granted or not. Furthermore, the system can determine whether the loan applicant has a bank account or credit to guarantee the repayment of the loan amount. We must mention that we collected data from different banks to obtain good knowledge.

Going forward, this article is structured as follows. Section 2 reviews some important efforts related to our work. Section 3 presents the utilized models and describes the modeling of our proposal. The performance of the proposal is evaluated in Section 5. Section 6 compares the main expert system decision against the decision maker of granting loans. Finally, we conclude this work in Section 6. The road map of this research is illustrated in Figure 1.

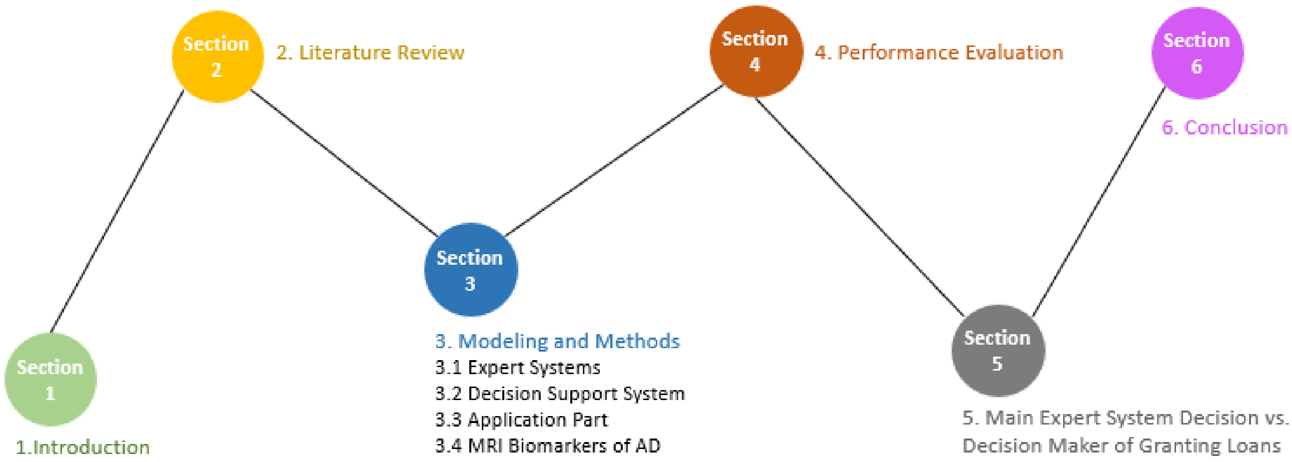

Fig. 1: The organization of the article.

2 Literature Review (Hypothesis Development)

In [6], Sudhakar and Reddy proposed the decision tree technique to assess a retail bank's credit risk. In the study, extensive information on the credit decision-making process has been provided. The system performed the following targets. Firstly, reduce the spent time and money on loan assessment. Secondly, using a decision tree, the system decreases threats faced by loan officials by supporting them with knowledge from historical loan data

Hamid and Ahmed [7] proposed a novel approach for grouping credit risk in the banking sector. The authors utilized data mining in their design. The model can predict the status of loans using data collected from banks. The models were developed using three algorithms: j48 bayesNet and Naïve Bayesian. The models were implemented and tested using the application “Weka”. The experiments revealed that the model achieved better accuracy. The paper focused on the following two points. Firstly, for different kinds of interference, the predicted behavior of five classifiers of credit risk prediction accuracy. Secondly, classifier ensembles can contribute to improving precision. Furthermore, the authors presented the results of four credit datasets. Furthermore, at various attribute noise levels, they compared each classifier’s performance on predictive correctness. The experimental assessment revealed that the ensemble of classifier algorithms enhanced prediction accuracy.

Srivastava et al. [8] proposed A prediction model based on Artificial Neural Networks (ANN). The research aimed to perform a loan nonpayment forecast and liken it to the Logistic Regression (LR) algorithm. On pre-documented data, the archetypal has been prepared to predict the debtor. Additionally, it made an effort to yield the most significant likely results.

Aslam et al. [9] utilized a Support Vector Machine (SVM) for loan nonpayment forecasting. The outcomes demonstrated that the SVM outperformed the counterparts’ throughput and arithmetical implementation methods. The accuracy of the model reached 81%. In the experiments, massive data were linked with various descriptive variables. To assess individual loan nonpayment in Kenya, a case study has been proposed by Obare et al. [10]. The authors utilized an LR model and an arithmetical examination procedure in their design. The arithmetical examination procedure is manipulated with the nonpayment of solitary loans as a characteristic of the debtor. The model achieved a precision of 0.7727 (0. 7333) in train (test) experiments. Similarly, the accuracy reached 0.8440 (0.8244) in train (test) experiments. Furthermore, the study's main limitation was a high level of false positives.

An all-inclusive investigation has been proposed by Tariq et al. [11]. The authors deployed a procedure to envisage the loan nonpayment and used KDD, CRISP-DM, and SEMMA in the model. The superlative scheme has been built on specific constraints, which are carefully selected, and elucidated. The reason was because of its momentous physiognomies concerning estimating the loan nonpayment in the fiscal subdivision. The model achieved precision reached 78%. Furthermore, the model flopped because its ROC score and zone weren't upright. Finally, to assess Loan Nonpayment, Kumar et al. [12] proposed a model-based ANN. The author recommended a basis to merge ANN employed to conjecture the nonpayment of loans. The prediction was performed regarding the fiscal and public particulars offered by the probable borrower.

3 Modeling and Methods

3.1 Expert Systems

An expert system is a piece of computer software that incorporates the skills and knowledge of a human professional in a particular area of difficulty. An area of AI study is called ESs. AI is centered on simulations that aim to mimic how the human brain approaches problems and learns. The expert system is a system that utilizes the undocumented knowledge of experts in such a way that even non-experts can use it. The inference engine and the knowledge base are the two fundamental parts of the expert system. The system mixes the user-provided input data with the data relationships for the inference engine. Then, using these data to establish facts, the inference engine applies rules to it to derive new facts. The inference engine can explain and troubleshoot. On the other hand, building a knowledge base entails acquiring information and identifying the relationships between them. A collection of IF-THEN rules is used to construct a knowledge base [13]. An expert system consists of components, each concerned with the decision-making process.

Fact Database: Includes all user-submitted inputs. It is a response to questions the inference engine asks indicative of specific circumstances or the user's knowledge of the problem.

Knowledge base: It is not just existing data or information but consists of the interrelationships, consequences and predictions of data and information. Therefore, the knowledge base is administrated by facts and rules. Knowledge engineering is used to obtain knowledge from experts and transforms that knowledge into facts and rules.

Inference engine: It links the two knowledge bases with the facts and data to infer and create variables and draw conclusions from them.

Interpretation mechanism: This stage is important for expert systems. It helps and explains how the system reached the decision and allows users to know why a particular question is being asked. Since the system is (based on rules), it can provide and explain to the user the rules used in the inference process. Consequently, it allows the user to make sure and judge the reliability of the decision.

User Interface: It allows customers and users to enter their data and get answers and results to their inquiries [14].

3.2 Decision Support System

Decision support system (DSS) is a computerized information system used as a potential solution for this research problem. The success of every firm depends heavily on the DSS. It is considered a responsive and adaptable software system with a graphical user interface that assists decision-makers. Usually, people in organizations' authority positions put facts and key information inspired by different aspects. For example, unprocessed knowledge, user input, files, and data stored in a knowledge base. These details can be used to: 1) identify a recurrent trend and pattern and 2) Make decisions to tackle issues [15]. The DSSs comprise four fundamental parts [16]:

1. Data entry.
2. User knowledge/experience.
3. Outputs.
4. Decisions.

3.3 Application Part

As mentioned earlier, expert systems are information systems, and knowledge-based can be used in many domains. Furthermore, these systems are knowledge-based systems (KBIS). It is a relatively new subfield of computer-based systems (CBIS), which also is artificial intelligence-simulating computer systems.

3.3.1 Data collection

Data collection for this study was based on the method of a questionnaire for two government banks in the province of Kirkuk/ Iraq. Mainly, the data comprises two folds: 1) Information about loan applicants, and 2) the experience of the bank's loan decision-making officer. The main aim was to demonstrate the benefits of using expert systems in the banks. For available possible solutions, the decision-maker has multiple options regarding customer preferences as follows.

3.3.2 Selecting Language Variants

The construction process is required in designing the model and analyzing the data. Therefore, we need to identify the appropriate sources (data). The questionnaire helped us build the model, especially identifying the most critical variables. Therefore, the model has relied on important documents to serve our objectives as much as possible. When studying the loan file, selecting the most appropriate variables remains challenging. To express the model's ability to assist the decision-maker, the number of questionnaire variables has been selected carefully. The questionnaire comprises 12 variables.

It is essential to mention that the variables have not adjusted except after the field study conducted at the level of the two banks. We focused on looking at the loan files of the four branches of these banks. The branches are denoted as: Branch 1, 2, 3 and 4. They are classified as small and medium enterprises and characterized by a financial and commercial nature. It is important to understand how the loan application process is performed. Additionally, we need to know what data must be collected to perform the evaluation. When any customer applies for a loan, a set of factors or variables must be considered, including (quality and collateral). It depends on two factors: 1) the bank's ability to provide the loan amount and 2) the customer's ability to pay it back. The model design process comprises three stages.

1. Data collection: Selection of information and personal data for loan applicants.
2. Expert sub-systems: Evaluate the loan provider's data and determine the qualitative and guarantee variables for the expert sub-system 1 and 2.
3. Main expert System: This stage is dedicated to verifying the possibility of granting the loan. Here, the second stage's outputs are inputs to the main expert system.

Figure (2) shows how the design data flows so that the selected (12) variables are distributed between the expert sub-systems. In the diagram, The set of variables related to (X1, X2, X3, and X4) refers to the inputs of the expert sub-system 1. It is defined as follows:

1. X1: The age of the bank's activity.
2. X2: The bank's relationship with the borrower.
3. X3: The education qualification of the decision-maker.
4. X4: The experience of the decision-maker.

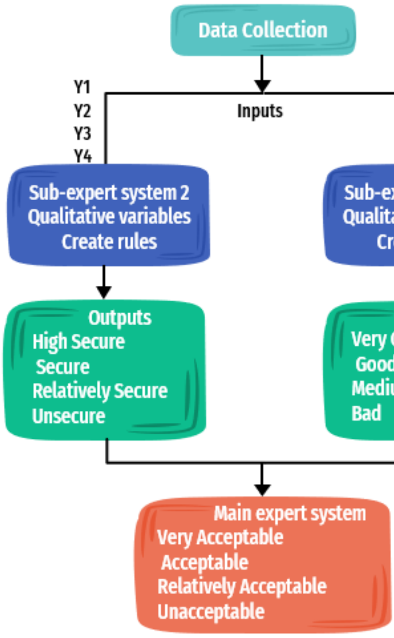

Fig. 2:The distribution of the proposed expert system model's main (linguistic) variables.

This step is required to determine the status of the borrower's capabilities to borrow. The outputs are as follows: "**Very good**", "**Good**", "**Medium**", and "**Bad**". Similar to above, for expert sub-system 2, the variables of (Y1, Y2, Y3, and Y4) indicate the inputs and are defined as follows:

1. Y1: The guarantee

2. Y2: The previous bank account.
3. Y3: The current bank account.
4. Y4: The entire guarantee.

These variables are needed to determine the characteristics of the loan taker, which could be: "**High Secure**, "**Secure**", "**Relatively Secure**", and "**Unsecure**". Finally, the outputs of sub-systems 1 and 2 are used as inputs to the main expert system. The main expert system is in charge of decision-making through the results obtained: very acceptable, acceptable, relatively acceptable, and unacceptable.

4 Performance Evaluation

The partial results associated with the sub-expert systems are presented by showing the number of guiding rules formulated to build the model. It is based on presenting all sub-units of the comprehensive expert system. Each expert sub-system displays its results by showing the number of guiding rules.-

Figure 3 shows the development of rules for the output of linguistic variables between the sub-expert systems 1 and 2. They are used as inputs of the main expert system. After utilizing the outputs of the sub-expert systems 1 and 2, the output of the main expert system is illustrated in Figure 4. Lastly, Figure 5 presents the output main expert system, sub-expert system 1, and sub-expert system 2.

Specifically, Figures (3, 4, and 5) show the partial results associated with the sub-expert systems. The number of guiding rules is formulated to build the model based on the presentation of all sub-units of the main expert system. For each sub-system, the results are displayed by clarifying the number of guiding rules (see Table 1). The graph for each output unit is according to the membership function. Note that the guiding rules of each sub-expert system output are digitally formed only, which indicates that it has performed at the level of all units of the expert systems.

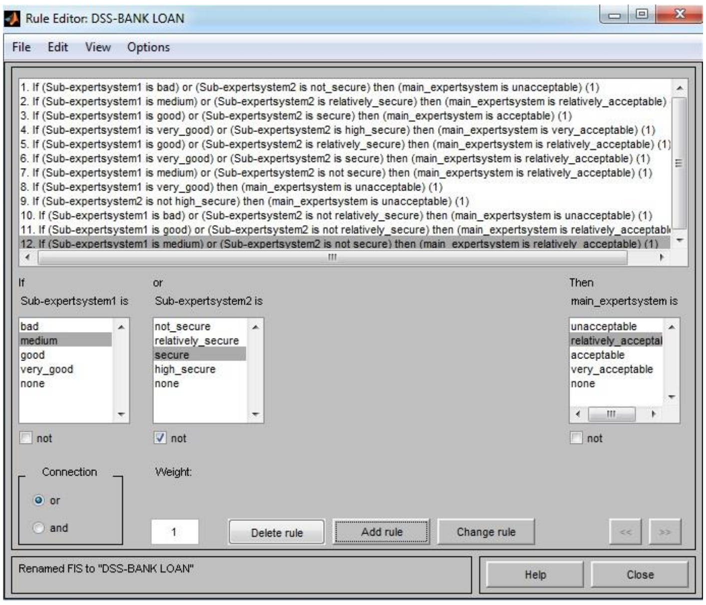

Fig. 3: Rules between sub-expert systems 1 and 2.

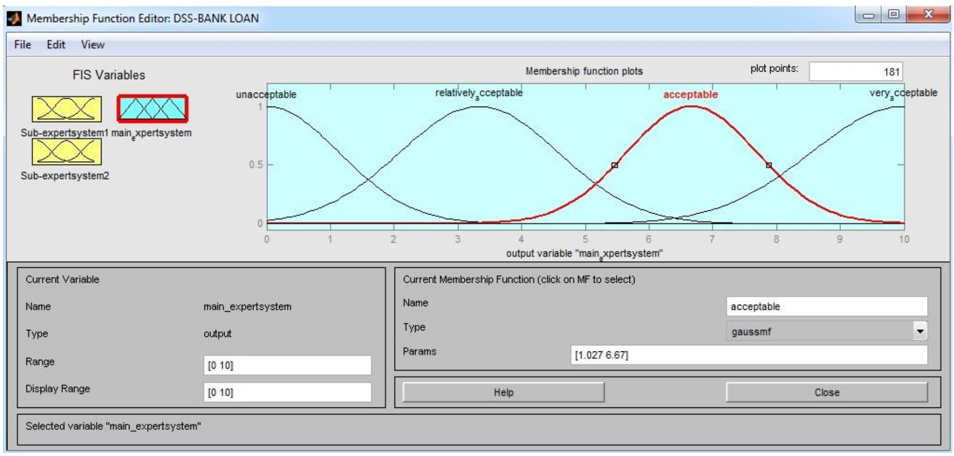

Fig. 4: The output of the main expert system.

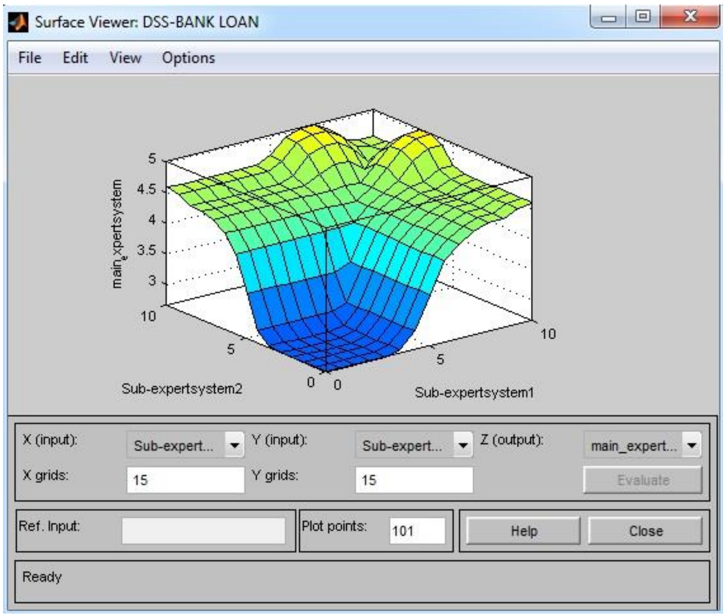

FiG. 5: The output of the expert systems.

Table 1: The rules of the sub-expert systems.

Sub- expert system1[Rules]	Sub- expert system2[Rules]
1 1 2 2 1 2 2 1 1, 3 (1) : 1	**2 1 3 3 1 2 3 2 3, 1 (1) : 1**
1 1 2 2 1 2 3 1 1, 3 (1) : 1	**2 1 3 3 1 2 2 3 3, 1 (1) : 1**
1 1 2 2 1 1 1 2 1, 3 (1) : 1	**2 2 2 2 2 2 3 3 3, 1 (1) : 1**
1 1 2 2 1 1 1 3 1, 3 (1) : 1	**2 2 2 2 1 2 3 3 3, 1 (1) : 1**
1 1 2 2 1 1 1 1 2, 3 (1) : 1	**2 2 3 2 1 2 3 3 3, 1 (1) : 1**
1 1 3 2 1 1 1 1 1, 3 (1) : 1	**2 2 2 3 1 2 3 3 3, 1 (1) : 1**
1 1 2 3 1 1 1 1 1, 3 (1) : 1	**2 2 2 3 2 1 3 3 3, 1 (1) : 1**
1 1 2 2 2 1 1 1 1, 3 (1) : 1	**2 2 3 2 2 1 3 3 3, 1 (1) : 1**
1 1 2 2 1 1 1 1 3, 3 (1) : 1	**2 2 2 2 2 1 3 3 3, 1 (1) : 1**
1 2 3 3 2 2 3 3 3, 1 (1) : 1	**2 2 3 2 2 2 1 3 3, 1 (1) : 1**
1 1 3 3 1 2 3 3 3, 1 (1) : 1	**2 2 3 2 2 2 3 2 3, 1 (1) : 1**
1 1 3 3 1 2 1 3 3, 1 (1) : 1	**2 2 2 2 2 2 3 2 3, 1 (1) : 1**

The database design used in the expert systems was based on the variables of the general guiding scheme. The scheme guides the selected two banks to: 1) Study the loan files from the credit official, and 2) Be in charge of decision-making. The database application for the four branches under study came after designing the model and ensuring it was correct. Furthermore, the validity of the results obtained regarding its ability to give positive results to the data that will be provided.

It should be noted that the nature of these branches' activity, subject to the study of loan files from the decision-making side, does not deviate from the financial and commercial framework. The branches can also be classified in size within small and medium enterprises based on the size of the invested capital or the loans provided.

Tables (2 and 3) list real numbers extracted from the financial documents (and other documents) and facts related to the loan files of the selected branches. It is worth mentioning that the coordination of the credit official or the decision-maker in these selected branches is crucial in assigning the numbers used and the methods by which the loan files are studied. It helps to determine the data required to cover all the selected variables.

Table 2: Database of the branches under study (Branches/Data real) (Non-financial variables X (borrower's potential for borrowing purposes).

Variable	Branch 1	Branch 2	Branch 3	Branch 4
X1	sarl:4	sarl:5	sarl:3	sarl:5
X2	strong 4	strong 4	strong 4	strong 4
X3	N/A	lic 5	lic 4	lic 5
X4	14 answ	13 answ	19 answ	17 answ

Table 3: Financial data Y (degree of loan safety).

Variable	Branch 1	Branch 2	Branch 3	Branch 4
Y1	N/A	23mda	10 mda	N/A
Y2	N/A	141 mda	13 mda	N/A
Y3	142 mda	155 mda	171 mda	157 mda
Y4	151 mda	156 mda	202 mda	187 mda

After applying the results extracted from the documents and financial statements of the loans of the four selected branches, Table (4) lists the results of outputs and the main expert system after. These results are represented in the outputs obtained from the expert sub-systems 1 and 2. Additionally, the results (produced by the main expert system) that express the decision-making process.

Table 4: The outputs of the main expert system.

Outputs	Branch 1	Branch 2	Branch 3	Branch 4
1	0.2614	0.2503	0.2161	0.2503
2	0.2215	0.2214	0.2215	0.2215
3	0.5001	0.5001	0.2830	0.2755
4	0.5005	0.5003	0.2830	0.2755
5	0.2217	0.2714	0.2714	0.2217
6	0.4203	0.4311	0.2778	0.2678
7	0.2218	0.2115	0.5014	0.2219
8	0.6411	0.4782	0.6422	0.6899
9	0.5000	0.5187	0.6255	0.4296
10	0.2118	0.2118	0.6865	0.2118
11	0.1553	0.1553	0.1553	0.1553
12	0.3744	0.3832	0.3822	0.3744

5 Main Expert System Decision vs. Decision Maker of Granting Loans

Table 5 shows the results from outputs 2 and 12 of the four branches. It shows the decision fields range between acceptance and rejection of the expert system 1 and 2. Table 6 demonstrates that the main expert system's results match the final decision of an official granting the decision within the banks, which is accepting the granting of loans.

As listed in Tables 5 and 6, the results of the main expert system were positive and identical to those of the four branches (credit officer or decision maker), especially through outputs 2 and 12. They are based on the results of sub-systems 1 and 2, represented by linguistic variables degree of loan safety (DLS) and borrower's potential for borrowing purposes (BPFBP). respectively, until the final decision-making results are reached through the main expert system.

Table 5: The results obtained from output 2 of the four branches and output 12.

Branches	Output 1	Output 2	Output 3	Output 4	Final Deci.
1	0.2614	0.2215	0.5001	0.5005	0.3734
2	0.2503	0.2214	0.2215	0.5003	0.3831
3	0.2161	0.2215	0.2830	0.2830	0.3831
4	0.2503	0.2215	0.2830	0.2755	0.3743

Table 6: The decision of the main expert system.

Branches	The decision of the main expert system	Officer loan decision
1	0.3734	Yes
2	0.3831	Yes
3	0.3831	Yes
4	0.3743	Yes

6 Conclusion

Expert systems are viewed as purely technical tools whose areas of use are limited only to aspects related to operational processes in the industry field. The expert systems relate to how to simulate the human brain in terms of its multiple functions reflected in the individual's life in general and economic institutions in particular. It is noticeable that the subject of expert systems has met with rapid development because of the period of its first inception, as it was able to sweep most of the economic activities of institutions of different sizes and objectives of their activities. The important economic advantage they provide has increased the popularity of using these systems, whether it is related to the time factor or the cost factor. Therefore, using expert systems is crucial in decision-making areas.

In this paper, we proposed expert systems for supporting banking decision-making. The results of the system were very positive, based on expert sub-systems 1 and 2 (degree of loan safety and borrower's potential for borrowing purposes). They were obtained from the inputs for the variables (X1, X2, X3, and X4) and (Y1, Y2, Y3, and Y4), respectively. The variables have been used for the decision-making of the main expert system. The results demonstrated the validation main expert system to utilize as a supporting basis for decision-making. The results of the sub-expert systems 1 and 2 came with a significant amount of vitality, which gives greater credibility to the main expert system.

Acknowledgment

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