Designing a proper model and software program to evaluate and predict credit risk of small and medium-sized enterprises in commercial banks

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ABSTRACT

Globalization and, consequently, intensifying the competition between banks and financial institutions in domestic and foreign financial markets increase significantly the importance and requirement of strengthening and modifying systems in financial enterprises. Banks are no exception. Credit risk assessment is one of the most significant components of the granted facilities process. Small and medium enterprises are the majority of customers of commercial banks; hence, it is possible that designing a credit risk system considerably helps banks to manage credit risk.

This study aims to introduce a new approach to predict and assess the credit risk of small and medium-sized enterprises. To this end, we identified the indices effective on the credit risk of medium and small-sized enterprises and determined significant indices by selecting the feature. We selected 98 cases of medium and small-sized legal clients in the industrial sector for research data from one of the commercial banks during the years 2018-2020. We then implemented the logit regression models, artificial neural network, and hybrid model (fuzzy expert system, logit, and artificial neural network) in order to predict and assess customers' credit risk and also calculated the accuracy of the models. Ultimately, we have designed the program applying visual studio software. We calculated the customer using logit regression models, artificial neural network, and hybrid model according to the designed program by inserting each customer's information and we also determined credit rating and type of collateral of each customer based on customer risk.

Keywords:

Credit risk, Logit regression, Artificial neural network, Fuzzy expert system, Small and medium-sized enterprises.

1. Introduction

Profitability and increasing the shareholders' wealth is the most significant motivation of banks and financial institutions in granting facilities, and currently, the commercial banks' main income is earned through the place of granting facilities. If a credit risk system is not managed, banks cannot identify the credit risk level and determine the possible losses of non-repayment of loans, consequently, they will not be able to allocate their capital optimally, and hence, their profitability will experience a fundamental threat.

Credit risk is extremely significant among the risks that the banking system experiences. In other words, credit risk is an indispensable part of banking activities, whether traditional banking that operates in the form of interest containing loan agreements or Islamic banking that is active in the form of exchange and participatory contracts (Abolhassani and Hassani Moghadam, 2009)

Despite the innovations and reforms in the financial services sector, financial institutions experience failure mainly because of this type of risk. This is because usually, 80% of a bank balance sheet turns back to aspects of this type of risk. (Greening and Bratanovic, 2003)

Credit risk arises is originated because that the recipients of the facilities have no ability or inclination to meet their debts to the bank on time. Measuring this risk is highly significant among the risks that banks experience in their extensive operational field. Reducing and controlling risk are among the significant factors that are effective on the improvement of the lending process and consequently the performance of banks and play a key role in providing continually facilities and the survival of banks and financial institutions.

The importance of granting facilities in banking and its significant role in economic growth and employment growth has developed several various models to assess customers in terms of the credit who apply for facilities. But many of these models are classic and cannot assess completely and optimally. Consequently, the context of introducing more complex models such as artificial intelligence has been provided in this field. In general, there are extended techniques in the fields of statistics, mathematics, econometrics, and operational research in banks and credit institutions in the field of credit scoring, which are classified into two general categories:

A) Nonparametric credit scoring patterns such as mathematical planning, tree classification, nearest neighbors' algorithm, hierarchical analysis process, expert systems, artificial neural network, and genetic algorithm.

B) Parametric credit scoring patterns such as linear probability model, auditing analytic model, logit model, and Probit model. (Haji Kurd et al., 2016)

Consequently, the most previous studies in credit risk models have been focused in the form of two groups of traditional statistical methods (Altman, 1968) (Altman & sabato, 2007) (Banasik, Crook & Thomas, 2001) or artificial intelligence technologies (Angelini, Tollo & Roli, 2008). (Tsai & Wu, 2008) and recently, some studies such as (lin, 2009) (Kang et al, 2016) have utilized hybrid models to assess credit risk. The research results explain that hybrid models have high capacity and accuracy compared to the models alone in assessing credit risk.

Credit risk assessment based on applicants for small and medium-sized enterprises is a comparatively new technology that limited research has been conducted in foreign countries in recent years. To this end, banks are required to grant Facilities to these enterprises considering the emphasis of the Supreme Leader to support the production sector and also according to Article (80) of the Fifth Development Plan Law in Iran which approved the support and development of small and medium-sized enterprises. Accordingly, banks are not able to use the usual methods to manage innovatively the risk of this group of applicants and it is required to use new and creative innovative methods to assess the credibility and measure the risk of small and medium-sized enterprises. Additionally, it is required that these new and innovative ways be set in the context of simple and efficient credit processes to be attainable. Consequently, banks are required to have a model and system to verify, evaluate, and predict the amount of risk of small and medium-sized enterprises.

The credit risk assessment of medium and small-sized enterprises is significant for banks; hence, this study aims to present a model and software program to validate medium and small-sized enterprises based on logit regression methods, artificial neural network and hybrid model (fuzzy expert system, logit, Artificial neural network). The software program results in determining each customer's risk based on each of the implemented models, credit rating, and determining the type and percentage of customer collateral.

2-Theoretical Foundations and Literature Review

John Murray performed credit risk measurement and the rating on bonds in 1909, Moody's Institute was one of the oldest institutions that acted to rank bonds and founded in 1909. Some researchers regarded the high similarity of the granted bonds and facilities. Consequently, they studied the credit rating, i.e., measuring the risk of non-payment of initial capital and interest of the facility (Falah Shams, 2008)

Credit risk is the risk that the borrower cannot repay the initial money/principal and interest of the loan according to the terms set in the contract. In other words, according to this risk, repayments are either delayed or not collected at all. This issue produces problems in the bank's cash flow. (Parker, Parsaian, 1999)

Credit scoring models in classification are classified into parametric and non-parametric models. Models whose objective is to obtain and estimate parameters in order to classify customers, parametric models and models that calculate no parameter and aim to classify customers according to the relationships between variables are non-parametric models. The threshold is an issue that is required to be carefully considered in the case of parametric models; because all model results are based on this threshold. (Bridge and Disney, 2001)

Parametric credit scoring models include linear probability models, auditing analytic models or difference analysis models, and Logit and Probit models. Nonparametric credit scoring models include: artificial neural network method, genetic algorithm, mathematical programming, tree or decision tree classification model, nearest neighbors' patterns, analytic hierarchy process, and expert systems (Bridge and Disney 2001).

It is hard to examine the perfection of these methods in predicting default compared to each other because each one has its own disadvantages and advantages, and selecting each model depends on the applicants' business conditions and also the specific portfolio of banks. It is possible that two or more models be used in some cases to measure the credit risk of a bank or financial institution.

Myers and Forgy (1963) and Orgler (1971) applied the regression model in order to assess credit risk.

Wiginton introduced the logistic regression model in (1980). Siddiqi showed in (2005) that it is possible that estimating the probability of default to be observed for binary classification problems and hence, logistic regression can be regarded as a proper method to estimate credit risk, which the studies conducted by Abdou, et al (2007) and Crook et al. (2007) approved this issue.

Artificial intelligence methods have been applied in recent years as new technologies in order to assess credit risk.

Studies conducted by Huang in 2007 showed that artificial intelligence techniques determine credit ratings better than traditional methods.

The artificial neural network method is one of the artificial intelligence techniques that studies conducted by Angelini et al., 2008, Tsai and Wu, 2008; Khashman, 2011; Zhao et al., 2015; Soydaner and Kocadağlı, (2015) indicate that the artificial neural network method is a right method to assess credit risk.

Recently, hybrid models have been recommended for credit risk assessment, and conducted studies have revealed that hybrid models function better and higher than each method.

We introduce some foreign and domestic research in the following part that has been conducted about credit risk.

Wanga et al. (2020) conducted a study entitled Comparative evaluation of machine learning-based credit risk model based on five models including simple Bayesian model, logistic regression analysis, random forest, decision tree, and nearest neighbors' classification. Their research results explain that each classification has its own strengths and weaknesses and it is not possible to state with confidence which model is better. Notwithstanding, the results of this research explain that random forests perform better than others in terms of accuracy and precision.

Wang (2017) conducted a study entitled combined system with Filter Approach and multi-population genetic algorithm to select features in credit rating. The research results reveal that the accuracy of feature subsets obtained from HMPGA, MPGA, and GA is preferred to the three filter methods.

Kang Li et al. (2016) conducted a study entitled Financial Innovation: A combined credit debt model to lend to small and medium-sized enterprises. A combined model with a logistic regression approach and artificial neural networks has been presented in this research. The research results explain that the combined model of logistic regression and artificial neural network is more accurate than the models of artificial neural network or logistic regression.

Hamadani et al. (2013) conducted a study entitled A combined model based on genetic of simple Bayesian networks to rate credit. Computational results reveal that this approach is preferred in terms of accuracy of functional classification compared to earlier studies and has higher results.

Oreski et al. (2012) conducted a study entitled combined system with genetic algorithm and artificial neural networks and its application in retail credit risk assessment (2012). The research results indicate that the combined system is able to compete with a genetic algorithm and it is possible to be used as a feature selection method in order to discover the most significant features in determining default risk.

Ling Lin (2009) conducted research on a new two-stage hybrid method of credit risk in the banking industry. The research results indicate that the two-stage combined model performs better and has stronger predictive power compared to conventional methods (logistic regression, and artificial neural network approaches).

Rastegar and Eydi Gosh (2016) conducted a study entitled Credit risk modeling of bank customers applying a survival analysis model based on the spline method. The research results indicate that the Cox regression model is more effective than the spline-based logistic regression survival model.

Mohammadi and Johari (2019) conducted a study entitled Designing and developing a credit risk model in Iran's banking system using multilevel models applying the Logistic Regression Method. The research results reveal that the customers' level of credit risk at each level is different with the change of their business.

Haji Kurd et al. (2016) examined the credit risk related to legal customers applying the vector machine model. The research results indicate that the GA-SVM hybrid model performs better than the SVM model in identifying good and bad customers and predicting customers' credit risk.

The results achieved by a study conducted by Mirghafouri and Ashouri (2015) entitled Credit risk assessment of bank customers using parametric method (logistic regression) and a non-parametric method (division tree and regression) to create a credit mode show the non-parametric method has competitive accuracy compared to the parametric method in separating good and bad customers.

Taghavifard et al. (2014) presented a combined ranking model of genetic algorithm and fuzzy expert system and their results confirm that the classification accuracy of the combined model is higher than other compared methods.

Ebrahimi and Daryaber (2012) conducted a study entitled Credit risk management in the banking system using DEA approach, logistic regression and neural network and the results indicate that the neural network model has higher efficiency in predicting the credit risk related to legal clients and credit rating.

Mirzaei et al. (2011) identified the factors influencing credit risk using the logistic regression method for legal clients.

Tehrani and Fallah Shams (2005) conducted a study entitled Designing and explaining the credit risk model in Iran's banking system. The efficiency of possible linear models, logistics, and artificial neural networks has been examined to predict customers' credit risk. The research results reveal that the artificial neural network method is the most efficient and performs better.

3- Methodology

This study aims to design a suitable model and software program to predict and assess the credit risk of medium and small-sized enterprises in commercial banks.

Figure 1 shows the steps of conducting the research.

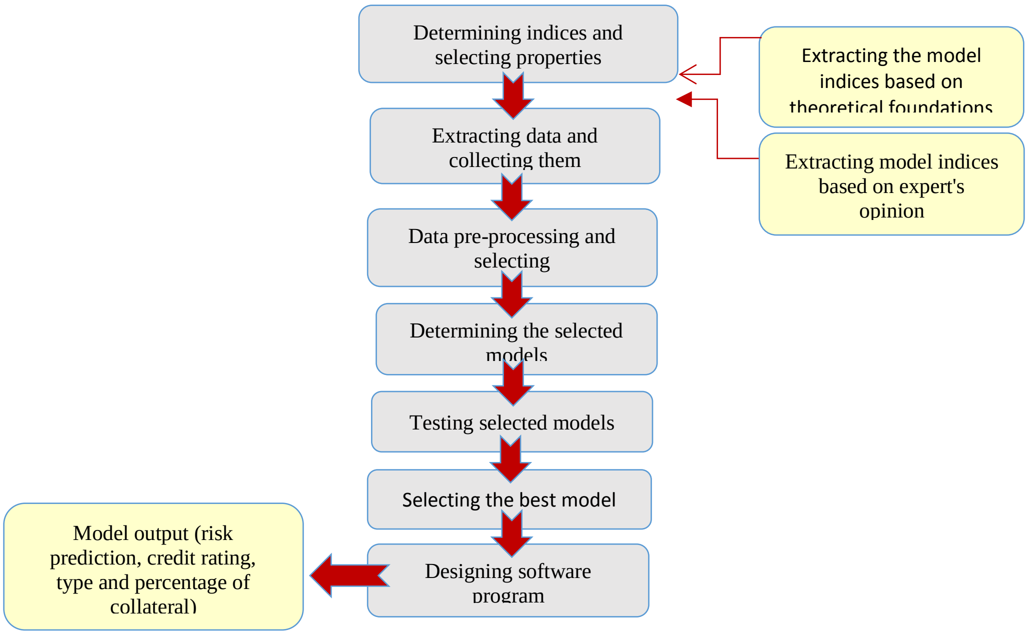

Figure1- Research steps

1-3- Selecting indices

First, in order to identify the effective indices in assessing the risk of credit customers, by studying the research literature and the background of domestic and foreign studies, all indices related to the credit risk of legal credit customers were identified and duplicate indices were removed. At this stage, 69 effective indices in assessing the risk of credit customers were determined from the research background. Then, in order to enrich the indices and select practical and important indices to make the model operational, eight credit experts were surveyed using the brainstorming technique. In selecting credit experts, two characteristics are considered, firstly, they must have at least twenty years of banking experience, and secondly, they must have worked in various credit positions in the field of credit for at least 12 years. Finally, 57 indices were selected by a survey of credit experts. If more accurate, comprehensive, and high-quality indices are selected, the output will be more accurate and efficient. Accordingly, to identify and select the most important and effective indices from the selected indices (57 indices), SPSS Modeler software was used to select the feature selection. The selected indices along with the data have been entered into the software and 9 indicators have been selected as the most important effective indicators in credit risk by feature selection. Table 1 shows the feature selection indices.

Table 1- Feature selection using SPSS Modeler software

Rank	Field	Value
1	Debt ratio	0.992252
2	Ownership ratio	0.992138
3	Asset turnover ratio	0.988844
4	operating costs	0.980067
5	Cash	0.952616
6	net sales	0.944028
7	ROA (Return on Assets)	0.937849
8	account average	0.932676
9	Net profit margin ratio	0.926848

2-3- Selecting data and preparing them

120 files of medium and small-sized legal credit customers have been selected from one of the commercial banks and their information has been extracted after determining the indices in order to implement the models. Medium and small-sized enterprises are selected based on two factors: the number of employees and the level of customer sales. Then, we deleted the outlier data using the Outliers Data technique and selected 98 files as the final data. Since the data did not have the same scale to enter the

software, consequently, we modified the indices for entering the software in order to make the data equal. Therefore, the data were prepared to be used in software models.

3-3- Implementing credit risk models

SPSS Modeler software has been used after selecting the significant indices and the data have been divided into two parts: testing and training. We tried in such a way to determine the percentage of test and training groups that over fitting errors to be avoided. Consequently, the best state for dividing the percentages was determined as 40% of the test group and 60% of the training group with several repetitions. The research samples show that 98 files are credit, 53 data were selected as training and 45 data were selected as the test group, and each model was implemented. Figure 2 shows the structure of the research model and the way that it is implemented.

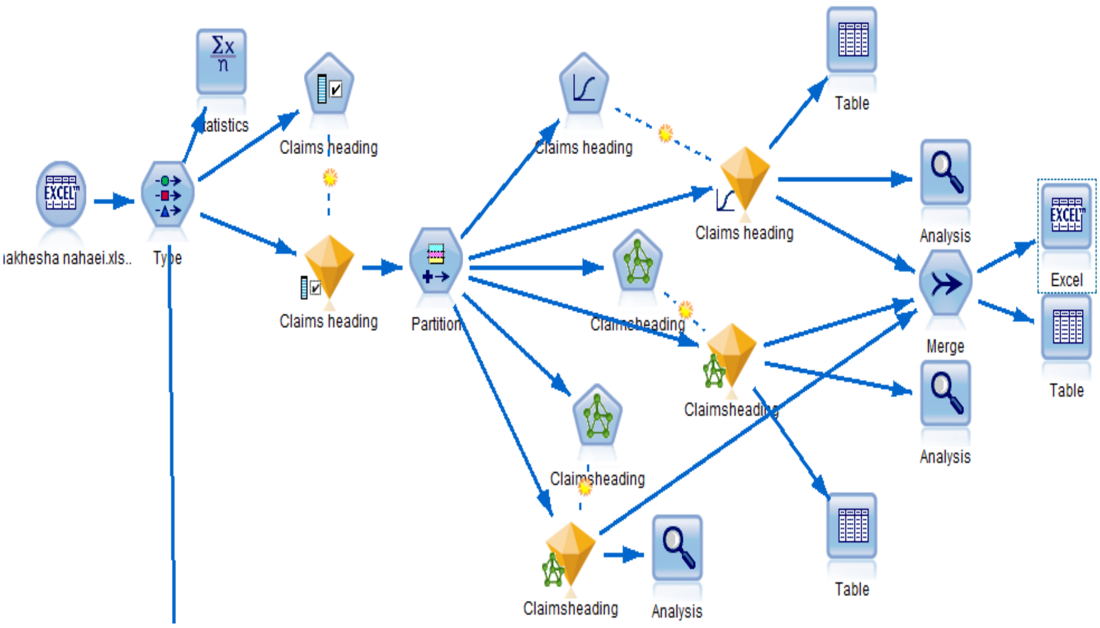

Figure 2- Research model structure

4-3- Logit regression model

Logistic regression is a statistical regression model for two-way dependent variables such as disease or health, death or life. It is possible to consider this model as a generalized linear model that applies the logit function as a link function and its error follows a polynomial distribution. Being two-way means occurring a random event in two possible situations. For example, purchasing or not purchasing, registering or not registering, going bankrupt or not going bankrupt, and etc. are variables that have only two positions and the total probability of each one will ultimately be one.

We have implemented the logit regression model with SPSS Modeler software with two groups of testing and training with the indices of the model selection in this research. The accuracy of the model is 71.7% in the training group and 60% in the test group, which has been shown in Table 2.

Table 2- Accuracy of a logit regression model with feature selection indices

Partition	1_Training	Percent	2_Testing	percent
Correct	38	71.7%	27	60%
Wrong	15	28.3%	18	40%
Total	53	100%	45	100%

5-3- Artificial neural network

The main philosophy of the artificial neural network is to model the processing features of the human brain in order to approximate conventional computational methods using the bioprocessing method. In other words, an artificial neural network is a method that learns the knowledge of the relationship between several data sets through training and stores them to use in similar cases. This processor operates in two ways similar to the human brain:

- Neural network learning is performed through training.
- Weighting similar to the information storage system occurs in the neural network of the human brain.

The model has been implemented using SPSS Modeler software with two groups of testing and training with feature selection indices in the artificial neural network method. Furthermore, the artificial neural network model has been implemented in two parts, including the artificial neural network with hidden layers and the combined neural network in order to achieve better results and higher accuracy.

The artificial neural network with two hidden layers has been performed with feature selection indices and the model accuracy was estimated to be 60.38% in the training group and 66.67% in the experimental group, which has been shown in table 3.

Table 3- Accuracy of the artificial neural network model with two hidden layers with feature selection indices (SPSS Modeler software)

Partition	1_Training	percent	2_Testing	percent
Correct	32	60.38%	30	66.67%
Wrong	21	39.62%	15	33.33%
Total	53	100%	45	100%

We have applied the combined artificial neural network model in order to achieve better results. Voting has been performed with consecutive repetitions of the neural network (10 neural networks are performed here) in this model and the model with the most votes and the best possible condition has been selected as the neural network model.

The accuracy of the model is 77.36% in the training group and is 64.44% in the test group in this method, which has higher accuracy compared to the artificial neural network method and has been shown in Table 4.

Table 4- Accuracy of the combined artificial neural network model with feature selection indices (SPSS Modeler software)

Partition	1_Training	percent	2_Testing	percent
Correct	41	77.36%	29	64.44%
Wrong	12	22.64%	16	35.56%
Total	53	100%	45	100%

6-3- Hybrid method (fuzzy expert system, logit regression, and artificial neural network)

Fuzzy expert systems are a kind of expert systems that apply fuzzy logic instead of dual value logic. In reality, fuzzy expert systems include a set of membership functions and rules that are totally applied for reasoning. Fuzzy systems are based on perceptions or rules, and a knowledge base is the core of a fuzzy system which involves fuzzy rules and is based on if-then rules.

```
RULE Rule1
        IF      y1 Low AND
                y2 Low AND
                r1 Low
        THEN    o1 VLow
ENDRULE

RULE Rule2
        IF      y1 High AND
                y2 High AND
                r1 High
        THEN    o1 VHigh
ENDRULE
```

In the hybrid method, Data Engine software is applied. The inputs of this software involve eight indicators. Five indicators involve the financial ratios in the feature selection indicators (Debt ratio, Ownership ratio, Asset turnover ratio, Return on Assets, Net profit margin ratio) and other three indicators involve the outputs of logit regression model, hidden two-layer artificial neural network model and hybrid neural network. Furthermore, model output is the customer risk (probability of default). To execute the model, variables and fuzzy functions, eight input indices and one output index are defined. Moreover, fuzzy membership functions are defined for each of the indicators, and an instance of the definition of fuzzy functions is indicated in Figure3.

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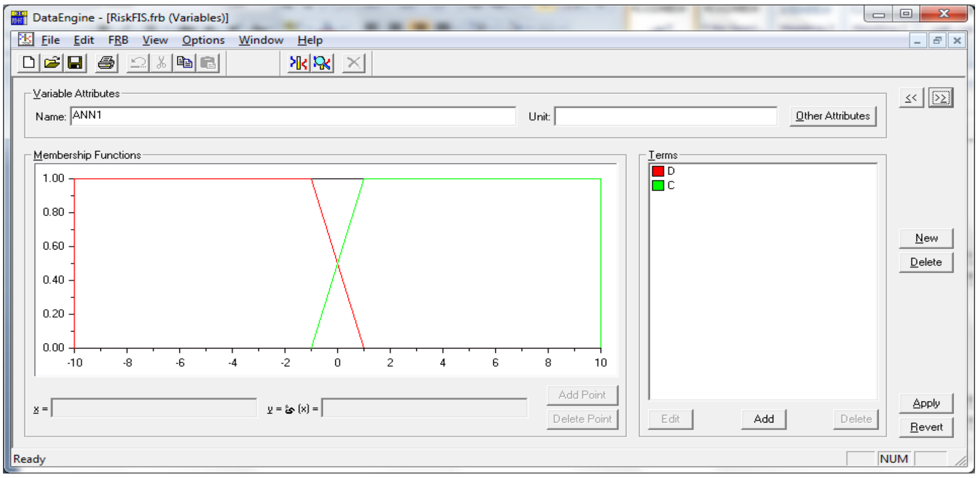

Figure-۳ Example of defining fuzzy functions

In every figure, the vertical axis is the membership of every word in fuzzy system. The horizontal axis shows the value of demanded index. Every variable has several words which are commonly low, medium, and high. Graph shapes indicate in which range the variable is low and in which range it is high.

The findings of hybrid model indicate that model accuracy is 82.4% in training group and 79.3% in test group. The findings provided from hybrid model reveal that this model has a higher accuracy compared to other implemented models.

Because the hybrid method applies a fuzzy expert system, one of the significant advantages of this method is its sensitivity analysis. Applying sensitivity analysis charts, it is possible to determine the effect of every indicators on customer's credit status and guide the customer to reduce risk and improve credit status. In other words, if the customer's risk is high, it can aid customer with sensitivity analysis that if he strengthens some of his indicators or financial ratios, he can decrease his risk, and this is one of the strengths of this method.

4- Result

1-4- Comparing implemented models

By comparing the implemented models, it is identified that the accuracy of hybrid method is higher than other methods. In Table 5 the accuracy of each model is indicated.

Table 5- Comparing the results of implemented models

Models	Accuracy of the test group model	Accuracy of training group model
Logit with feature selection criteria	60%	71.7%
Neural network (with two hidden layers) with feature selection indicators	66.67%	60.38%
Hybrid neural network with feature selection	64.44%	77.36%
Hybrid method (fuzzy expert, logit, neural network(	79.3%	82.4%

Thus, the major and identifying criterion for evaluating customer credit risk in these models is the hybrid method.

2-4- Credit risk software program design

To design credit risk software for medium and small enterprises, chosen indicators are divided into three groups: behavioral, financial and banking, and based on customer risk feature selection indicators based on logit regression methods, artificial neural network with two hidden layers and neural network. Combined and hybrid method is computed, if the result of computations of all methods is close to each other, operation criterion of all methods will be, if the result of customer risk computations in the implemented methods is different, the criterion of operation of hybrid method will be because it has higher accuracy in computations than other methods. Based on the risk of each customer which is computed in the designed model, the customer's credit rating and the kind and percentage of documents which should be received from the customer are identified. Due to changes in economic situations and banking policies, feature selection indicators should be constantly updated at certain times and the number of indicators may increase or decrease or change at any stage. To this objective, all indicators were regarded in the design of model. Figure 4 shows the output of the software program.

Figure 4- Software program output

5- Discussion and Conclusion

This research aimed to design a model and its software program for evaluating and forecasting the credit risk of medium and small enterprises in commercial banks. In this regard, by determining efficient indicators in evaluating the credit risk of credit customers, credit risk models of logit regression, artificial neural network and hybrid method were implemented with the relevant software. To plan a software program, indicators are grouped into three groups: behavioral, financial and banking, and with the entry of information of each customer, credit risk is computed with each of the models, but given that the hybrid method has higher accuracy and power in evaluation. Furthermore, predicting the credit risk of credit customers is the criterion for assessing customers. Moreover, based on the amount of risk of each customer, credit rating and type and percentage of documents are calculated by the system. Applying this model and software program in banks can obtain the possibility of observing the basic credit health by credit decision makers and preventing taste decisions, making a type of comparative advantage in the present competitive conditions, optimizing the credit portfolio composition and meeting the needs of central bank.

It is recommended to decrease the credit risk of banks and financial founders, software designed by experts and managers to be applied in credit decisions. For future study, it is proposed that macroeconomic indicators be utilized in evaluating the credit risk of credit customers. In this research, retrospective indicators were applied to evaluate credit risk, and it is proposed that prospective indicators be applied in evaluating and credit risk of credit customers. It is also suggested that credit risk assessments be done for corporate banking and retail banking customers.

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