Int. J. Nonlinear Anal. Appl. 15 (2024) 4, 23–42
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.28382.3874

Machine learning support to provide an intelligent credit risk model for banks' real customers

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(Communicated by Seyed Hossein Siadati)

Abstract

Artificial intelligence plays an important role in the field of personal computers. Right now personal computers are part of our lives, so AI should be used in all everyday tasks. Humans are great thinkers, but machines can be more effective at counting than humans. The machine cannot fully explain different conditions, but it can create a different type of connection between different salient points and features. Either way, there can be many benefits to establishing machine learning computing in our daily lives. Machine learning or machine learning is one of the subsets of artificial intelligence that enables systems to learn and improve automatically without explicit programming, and controlling the credit risk of real bank customers is one of these benefits that can help the monetary and banking system to improve conditions and reduce risk. Therefore, the use of machine learning to create an algorithm to manage credit risks is a topic addressed in this research.

Keywords: intelligent model, credit risk, real customers, banks, machine learning algorithm
2020 MSC: 91B05, 68T07

1 Introduction

Since the global financial crisis, risk management in banks has become more important and there has been a continued focus on how to identify, measure, report and manage risks. Significant research [11, 17, 27, 28], both academic and industry, has focused on developments and current challenges in banking and risk management. At the same time, there has been a growing impact of machine learning, with many solutions already implemented in business applications.

Chamberlain et al. in [6] emphasized that by 2025, risk functions in banks will need to be fundamentally different than they are today. Widening and deepening regulation, changing customer expectations and evolving risk types are expected to bring changes in risk management. New products, services and risk management techniques are enabled using emerging technologies and advanced analytics.

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Received: June 2022 *Accepted:* September 2022

Machine learning, considered as one of the technologies with significant implications for risk management, can enable the creation of more accurate risk models by identifying complex and non-linear patterns in large datasets. The predictive power of these models increases with each bit of information added, so the predictive power increases over time. Machine learning is expected to be applied in various areas of the bank's risk organization. Moreover, machine learning has been proposed as an initiative that can help change the performance of risk management in banks. Machine learning algorithms have been used in many areas of business, business management, human resource management and medical purposes and have shown good success in data mining and decision support systems [1, 7].

2 Literature

2.1 The importance of risk

The phenomenon of risk is one of the main features of decision-making in the field of investment, financial markets and various economic activities. In most economics books, three factors are mentioned as the main inputs of production: labor, land and capital. However, a little reflection reveals that three factors are a necessary condition for production, but a sufficient condition in the production process is nothing more than a risk factor. That is, if there are three factors but the producer does not accept the possible losses of this process, production will never take place. Therefore, in some studies, the risk factor is mentioned as the fourth factor in the production process [16].

2.2 Risk calculation methods

There are different methods for calculating risk and the most important ones are as follows:

1. **Value at Risk (Var) method:** This method was first proposed by Wetherstone in 1994 [2, 3]. In 1995, the Bal Committee (an organization that supervises the activities of international banks) required banks to use this model to determine their capital adequacy. This method means estimating the maximum loss at a given confidence level (e.g. 95%) and over a given time period. Current risk can be measured using this method [25].
2. **Acute conditions test:** This method is used as a tool to estimate the maximum amount of possible economic losses in abnormal market conditions. The purpose of this tool is to try to increase the transparency of risks by marketing potential events that have a very low probability of occurring; in such a way that these harmful events fall outside the statistical range used by the previous method.
3. **Risk coverage:** Most companies involved in manufacturing and production, retail, wholesale or service delivery do not have sufficient expertise and skills in forecasting variables such as interest rates, exchange rates and commodity prices. Therefore, it makes sense to cover the risk caused by these variables so that companies can focus on their core business [25].

Hedging strategy on buy positions (LoHs): Investors who take a trading position in a futures contract in order to hedge risk are said to use the strategy of hedging call positions. This strategy is suitable for a company that plans to buy a product in the future and stabilize its future price now [25].

selling positions (SHs): This strategy is to adopt a trading position in future contracts and would be appropriate when it already owns the hedged asset and expects to sell it at some point in the future. For example, a farmer who has a crop and knows that his crop will be ready for sale in the market in the next two months can use this strategy [10].

2.2.1 Risk management

In general, until the 1950s, the view of risk was one-dimensional and qualitative. Markowitz, an American scientist, was the first to quantify the category of risk. Later, more complete views were presented, risk was recognized as a measurable phenomenon and risk measurement became the focus of attention of companies, institutions and financial institutions. Addressing the phenomenon of risk in financial and economic activities requires the design and implementation of a more comprehensive risk management framework than that recommended at the level of micro-units, which is recommended in the comprehensive risk management framework for institutions, companies and banks in general. it can be done a little differently, for micro-units, issues such as identification, prevention of risk phenomenon, corrective action, collateral acquisition, definition of thresholds and ceilings are important, and for the macro sector, it is more a matter of drafting regulations and supervisory rules. it is important to find solutions and expand markets. In general, risk management is the process of measuring or assessing risk and then planning strategies for risk management. Strategies generally used in banks and financial institutions include risk transfer, risk avoidance, mitigating the adverse effects of risk, and accepting some or all of the consequences of a particular risk. It is clear that risk management helps institutions and organizations to find an efficient and cost-effective way to manage risks by using the attitude of the board of directors and managers, using a comprehensive strategy instead of single and unilateral methods.

2.2.2 Classification of risks

Banks and financial institutions face many risks from the very beginning due to the nature of their activities, but due to the breadth and diversity of banking activities, researchers do not agree on the types of risks of banking operations, so some credit risks, interest rates and liquidity are included as risks. In this sense, the risks affecting the financial institution can be divided into three levels, as explained below (fig. 1):

Level one: risks over which the financial institution has no control and over which it has no influence.

Second level: There are risks where the financial institution has an impact, but this impact is smaller and more impactful accepts.

Third level: There are risks that affect the financial institution, but the financial institution can control and manage them by applying methods and tools [18].

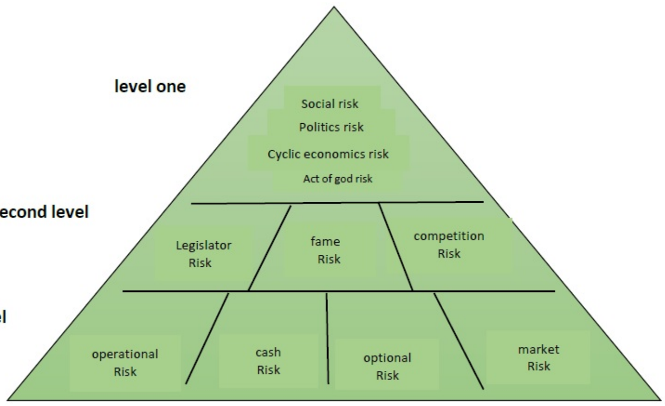

Figure 1: Classification of risk levels [18].

Among the risks that threaten banks and financial institutions, credit risk is considered to be the most important risk due to its centrality, transaction volume and especially its sensitivity. Therefore, it is the only third level risks that the financial institution can overcome and control through risk management methods and tools, so the focus of the discussion is on the third level risks shown in Fig. 2.

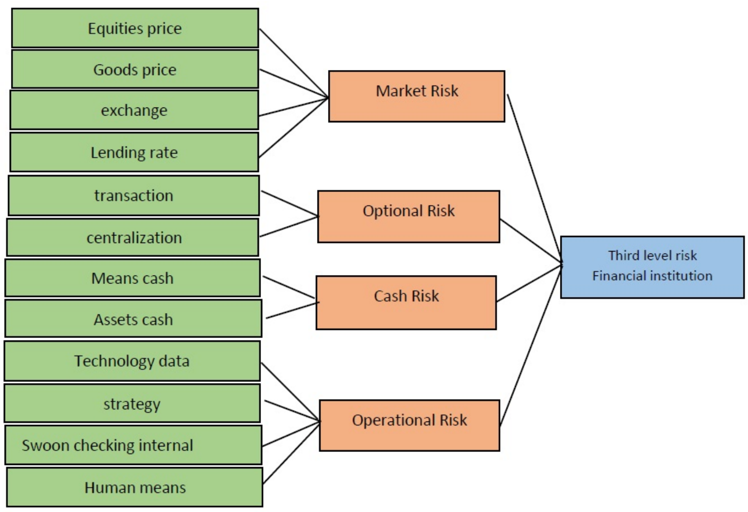

Figure 2: Risks of financial institutions [18].

The financial institution should also consider the actions and reactions of these risks on each other because one risk may have a negative correlation with another risk. And these two can cover each other or, on the contrary, the two risks together have a double or negative impact on the entire portfolio of a financial institution, so the role of integrated risk management of financial institutions becomes clear [18].

3 The concept of credit risk

Credit risk is the possibility that the value of some of the bank's assets, particularly loans granted, may decrease or depreciate, and arises from the inability or failure of the contracting party to fulfill its obligations. Therefore, credit risk can be defined as a possible loss that may occur as a result of a credit event. More precisely, banks' credit risk is defined as the probability that the borrower or the bank's counterparty will be unable to fulfill its obligations according to the agreed terms. Although there are other definitions of credit risk referred to in a bank's operations, bank office and trading office, for the majority of banks, loans are the largest and most obvious source of credit risk creation [9]. According to standard banking theory, bank profits are maximized at an optimal level of credit risk. This optimal level is procyclic for the bank and is higher than the realized credit risk during relatively stable economic periods of high profitability opportunities for banks, but declines rapidly during periods of financial turmoil. Bank managers make risky decisions about converting debt into assets to generate profits.

However, if they take on too much risk or if structural or macroeconomic conditions change unexpectedly, they may suffer significant losses. Therefore, the relationship between risk and return is non-linear and there must be an optimal level of credit risk available [9].

Credit risk is one of the most important factors affecting the health of the banking system. The level of credit risk depends on the quality of the bank's assets, and the quality of the bank's assets depends on the trend in the level of demand receivables and the health and profitability of the bank's borrowers [21]. According to research, the impact of exchange rate changes on financial institutions shows that many institutions are at risk due to the impact of these changes [6, 14].

Ryan and Worthigton [22] used a generalized M-GARCH model to investigate the time-series sensitivity of Australian bank stock returns to interest rate risk, market risk and exchange rate risk. Australia paid the index of short-term, medium-term and long-term interest rates and exchange rate changes during the period 1996-2011. According to the research results, market risk is an important factor in determining bank stock returns, and there is a relationship between interest rates and their volatility in the short and medium term. In the long run, interest rate and exchange rate have no significant impact on the returns of Australian bank stocks.

Flamini, Macdonald and Schumacher [8] investigated the factors affecting the profitability of banks in 41 different countries. The sample of his research included 389 banks. The results of the research show that the most important factors affecting the profitability of banks are credit risk and bank size. Aydemir and Demirhan [4] tested the relationship between the exchange rate risk variable and stock price using daily data from February 23, 2001 to June 11, 2008 on 100 service, financial, industrial and technology institutions. The results of their study showed that exchange rate risk has a positive relationship with the stock index.

Allen and Saunders [2] showed that macroeconomic factors are effective on the profitability of the banking system by affecting the credit risk of banks. Hoffmann [12] by simultaneously examining the impact of three variables: changes in the stock market index, interest rate fluctuations and exchange rates on commercial banks admitted to the Istanbul Stock Exchange, found that all three factors had a significant impact on banks' returns, but the effect of fluctuations The total market index has been more than two factors.

The set function (result): It is calculated by the weighted average of all the data in each of the processing elements (neurons). A sum function multiplies the values of the data (X_j) in its zones (W_{ij}) and then calculates their sum (Y). For example, for n data that are entered into processing element k, we have:

$$Y_k = \sum_{i=1}^{n} X_j W_{jk} \tag{3.1}$$

Assuming that the determined network has two layers, in this case the sum function of the Hahn layer is the sum of the product of the weights matrix and the data matrix plus the bias weights matrix. Therefore, we will have:

$$Y^H = \left(\sum_{j}^{n} \sum_{k} W_{jk}^{1} \right) + W_{jb} \tag{3.2}$$

Having the sum function of the hidden layer, the sum function of the output layer will also be defined as follows:

$$Y^{\cdot} = \sum_j W_{kj}^2 \left(g \left(\sum_j \sum_k W_{jk}^1 X_j \right) + W_{jb}^1 \right) + W_{jb}^2 \tag{3.3}$$

in the above relations, W_{jk}^i the data weight matrix of J-th calculated in the K neuron and the i-th layer and the variable bias weights matrix of J-th in the i-th layer show.

Changing function(Transfer): The summation function calculates the internal excitation or internal activation level of a neuron. For this reason, the summation function is also called the activation function. Depending on this activation level, the neuron may or may not produce a spike. The relationship between the internal activation level and the output may or may not be linear. Such a relationship is described by the transformation function. There are different types of this function. Choosing a particular type of this function determines the operation of the network. One of these very famous nonlinear functions that is often used in perceptron neural networks is called the sigmoid function:

$$F_x = \frac{1}{1+e^{-y}} \tag{3.4}$$

in the above relationship, y represents the result of the sum function in the layers. The purpose of this adjustment is to change the data level to a reasonable value (e.g. between zero and one).

What is important in a neural network model is to optimally estimate the weights in the neural network. It is clear that the cost vector can be easily estimated after optimally determining the weights given the vector of input variables.

One of the major disadvantages of artificial neural networks is the lack of transparency. Although the neural network is a viable market for forecasting, the process of operation and the relative importance of the variables are not obvious; that is, the neural network does not reveal anything about the intermediate steps that lead to the final result [23].

Learning in neural networks is based on error testing. This means that a neural network learns based on its errors how the relationship between data and data would be in the given problem. Usually the learning process in neural networks involves the following three activities:

- Calculation of takes
- Comparison of takes with desired (Expected) responses.
- Adjusting the weights and repeating the process

The learning process starts with random selection of weights. The difference between the actual and the target is called the delta. In neural networks, the goal is to minimize the delta (or better to reduce it to zero). Delta reduction is done by gradual changes in the weights. One of the common features of neural networks is that they can classify input data despite not having a clear knowledge of the rules and can use an arbitrary weight model to memorize the categories. During the learning process, the associative weights change according to the training data given to the system. Neural networks calculate the error and adjust the weights in different ways. There are more than a hundred learning algorithms for various conditions and situations. One of the most important learning algorithms used in neural networks is the gradient descent algorithm and error back propagation. In this method, small random values are first assigned to the weights so that the search starts from a relatively stable position, and at each step the minimum amount of error is passed back to the network and the values are passed back to the network and the weights are adjusted [23].

4 Research background

In their research, Yu et al. [29] proposed a VSG method based on extreme learning machine (ELM) with feature engineering for credit risk assessment with data scarcity. In this method, the VSG method based on ELM is first used to generate virtual samples and solve the problem of lack of data samples (i.e., small sample). Secondly, a special engineering method is used to solve the problem of lack of signs (i.e. low dimensions). Finally, various classifiers are used to predict the performance of the generated virtual instances. For validation purposes, two public loan datasets are used to perform data-deficient loan classification. The experimental results show that the proposed method can effectively improve the classification performance for data scarce credit risk assessment.

In their paper, Shi et al. [24] systematically reviewed a number of original research contributions (76 papers) over the past eight years using statistical, machine learning, and deep learning techniques to address credit risk problems. In particular, they proposed a new classification method for ML-based credit risk algorithms and performance rankings using publicly available datasets. We further discussed challenges such as data imbalance, dataset inconsistency, model transparency, and underutilization of deep learning models. The results of their review show that:

1. most deep learning models outperform classical machine learning and statistical algorithms in credit risk prediction, and
2. ensemble methods provide higher accuracy compared to single models.

In their research, Bussmann et al. [5] propose an explainable AI model that can be used for credit risk management, and in particular for measuring the risks that arise when taking out loans using peer-to-peer lending platforms. The model applies correlation networks to Shapley values to group AI predictions based on similarity in underlying explanations. Empirical analysis of 15,000 loan-seeking SMEs shows that risky and non-risk borrowers can be grouped on the basis of a set of similar financial characteristics that can be used to explain their credit scores and hence can be used for preliminary exploitation to predict their future behavior.

Qin et al. [20] proposed a hybrid strategy to integrate unsupervised learning and supervised learning for credit risk assessment. The difference between their work on unsupervised fusion and other previous work is that this group applied unsupervised learning techniques in two different phases: the consensus phase and the dataset clustering phase. The comparison of model performance is based on three validation datasets in four groups: individual models, individual models+consensus model, clustering + individual models, clustering+individual models+consensus model. As a result, integration at the consensus stage or clustering stage of the dataset is effective in improving the performance of credit scoring models. Moreover, the combination of these two steps achieves the best performance, thus confirming the superiority of the proposed integration of unsupervised and supervised machine learning algorithms, which strengthens their confidence that this strategy can be applied to many other credit datasets from Financial institutions.

Based on the results of Addo et al. [1], they investigated binary classifiers based on deep and machine learning models on real data in predicting default probability. The 10 most important features of these models were selected and then used in the modeling process to test the stability of the binary classifiers by comparing their performance on separate data, and it was observed that tree-based models were more stable than models based on multilayer neural networks. This opens several questions regarding the intensive use of deep learning systems in companies.

In their research, Zhu et al. [30] proposed an advanced hybrid ML approach called RS-MultiBoosting by combining two classical ML approaches, random subspace (RS) and MultiBoosting, to improve the accuracy of credit risk prediction of SMEs. The prediction result shows that RS-MultiBoosting has a good performance in dealing with small sample size. From the SCF perspective, the results show that ”traditional” factors such as the current and quick ratio of SMEs remain critical to improve the financing ability of SMEs. Other SCF-specific factors, such as commodity characteristics and CE profit margins, play an important role.

Based on the findings of Tripathi et al. [26], an extreme learning machine (ELM) is used as a classification tool for a credit risk assessment model. The performance of the ELM depends on the activation function, weights and biases assigned to the hidden neurons. A suitable approach to select the activation function, weights and biases can improve the performance of the ELM. Therefore, they proposed a new activation function and an evolutionary approach to obtain the optimal weights and biases using the bat optimization algorithm. Furthermore, simulations were performed on four credit scoring datasets with different activation functions. Simulation results show that the proposed evolutionary ELM (EELM) is more suitable for credit risk assessment.

Ma and colleagues [15], based on the machine learning algorithm, developed the machine learning algorithm and named it MLIA algorithm. Meanwhile, this study decomposed the objective function into a weighted sum of several basis functions. In this study, three common test functions are used to compare the performance of MLIA prediction algorithm and logistic prediction algorithm. Simultaneously, this study analyzed the performance of the MLIA financial credit risk prediction model by taking the data of an internet financial company as an example. In addition, this study used the AUC (area under the curve) value as a specific index to validate the performance of the model. The research shows that machine learning has a good predictive effect in predicting the financial credit risk of MLIA and can provide a theoretical reference for further related research.

In a benchmarking study of some of the most widely used scoring models, Moscato et al. [19] proposed credit risk to predict loan repayment on a P2P platform. They addressed a problem of imbalance in classifications and used classifications commonly used in papers based on different sampling techniques. In fact, the risk prediction score is one of the main challenges in the financial sector to support people in making investments. However, due to the high dimensions and imbalanced data, the P2P lending platform faces different challenges than the traditional ones. The proposed approach aims to design a benchmark for machine learning approaches to predict credit risk for social lending platforms that can also handle imbalanced datasets. The evaluation performed on real-world social lending platforms provides an explanation of w.r.t. analytics approaches.

In their research, Alonso and Carbo [3] propose a new framework for auditors to quantify the costs and benefits of evaluating ML models in order to clarify the alignment of this technology with regulations. They followed three steps. First, they identified the benefits by reviewing the literature and observed that ML provides prediction gains of up to 20% in default classification compared to traditional statistical models. Second, they used the internal rating system (IRB) validation process for regulatory capital to identify the limitations of ML in credit risk management. They identified up to 13 factors that could increase regulatory costs. Finally, they proposed a method to assess these costs. For illustrative purposes, they calculated the benefits by estimating the predictive benefits of six ML models using a publicly available database of credit defaults. They then calculated a supervisory cost function through a scorecard based on how the model is used by the financial institution and the risk tolerance of the supervisory authority, where they weighted each of the factors for each ML model. From a regulatory perspective, having a structured method for evaluating ML models can increase transparency and remove barriers to innovation in the financial sector. In summary, based on the findings of this research, the evolution of ML in the credit sector should take into account the evaluation process of the supervisory internal model. It should also meet the explanatory needs of the results supported by academic papers with significant advances in the field of interpretable machine learning. In this context, financial authorities such as the Basel Committee are trying to understand these issues in order to establish a framework for the appropriate use of this technology in the provision of financial services.

5 Statistical Society

Given that the purpose of the research is customers' credit rating, the statistical population in this research includes 450 customers of Madaraba credit studies of Mellat Bank of Tehran province in 1400. These total 450 customers in Tehran province were used as a benchmark to investigate the trend and study customer behavior.

The statistical population consists of customers of Mellat Bank of Tehran province with good account (less credit risk), overdue (medium credit risk) and bad account (high credit risk).

5.1 Statistical sample

Considering the use of statistical texts and neural networks to design the model, in this research, a number of past customers of the bank with special characteristics should be considered. Based on the number of statistical population and using the following statistical formula, 350 customers were selected as a statistical sample.

confidence level 95% error percentage 1%

Based on the pre-sample that was taken, the standard deviation is 9%.

$$n = \left(\frac{Z_{\frac{\alpha}{2}}\delta_x}{d}\right)^2 = \left(\frac{1.96 \times 0.09}{0.01}\right)^2 = 311$$

6 Research assumptions

In applied research, it is of special importance to examine the research assumptions. In this research, the main purpose of the research is to determine the credit rating of bank customers who want to get a loan. For this purpose, the hypotheses of the research were considered and investigated.

First hypothesis: It is possible to rank the bank's credit customers using the coordinates of the credit customers (job, income,...).

Sub-hypotheses:

1. There is a significant relationship between the amount of collateral of the facility applicant and his/her credit rating (customers with good, overdue and bad credit).

2. There is a significant relationship between the education of the applicant and the credit rating (customers with good, overdue and bad credit).
3. There is a significant relationship between the income of the facility applicant and his/her credit rating (customers with good, overdue and bad credit).
4. There is a significant relationship between the credit history of the facility applicant and his/her credit rating (customers with good, past due and bad credit).
5. There is a significant relationship between the applicant's job and his/her rating (customers with good, past due and bad credit).

Second hypothesis: It is possible to rank the bank's loan customers using a multilayer perceptron neural network.

First hypothesis: It is possible to rank the bank's loan customers using the characteristics of loan customers.

This hypothesis is of particular importance in achieving the objectives of the research, as it is clear that a number of key factors should be used in achieving the objectives of the research and in determining the credit rating of the customers who use the bank's credit facilities. Factors that can be used to rank the credit customers using the bank's credit facilities.

What is important in analyzing customers' invoices is to pay attention to the credit aspect of these invoices, so factors are taken into account as characteristics of the customers, and when indicating the status of the dependent variables related to each customer, the necessary credit and reputation. These factors are expressed in most of the predictor variables in this research.

Second hypothesis: It is possible to rank the bank's credit customers using artificial neural networks.

After identifying the important characteristics that affect the credit rating of the bank's customers, it is necessary to design the output. This model is actually a function with several input variables and three output variables. In this function, customers' characteristics are considered as input variables of the function. The intended function must take the input variables and transform them into output variables. One of the strengths of this model is that it predicts simultaneously. Therefore, the neural network model is accepted as one of the hypotheses of the research. Considering the ability of the neural network model to predict multiple variables simultaneously, this research attempts to use this model simultaneously in the credit ratings of bank customers.

6.1 Research scope (spatial, timic, thematic)

From this point of view, the present research was conducted on the loan files of real customers of credit facilities in the Mudaraba sector. In terms of time, the Mudaraba facility files of the year 1400 were taken into consideration, and Mellat Bank loan files of Tehran province were used as the location.

7 Data collection

Considering that a lot of research has been done in this bank and according to the opinions of experts, no research has been done on providing facilities with the help of neural networks, it was deemed necessary. This research was conducted for easier and faster access to the results in the awarding of facilities and evaluation of customers. There is no specific order in the selection of training and test data and three important recommendations for data selection should be considered in this research.

A. Various characteristics of the network inputs should be considered.

B. Considering the issues of generalizability and convergence in neural networks, 234 of the 350 samples selected were used as training samples and the remaining 116 were tested.

C. One of the most important things in network training is to realize when to stop network training. In fact, Lack of training in a network is one of the main problems in the network. This happens more and more as the number of hidden layers and the number of nodes increases, but the number of training 30,000 times provides an almost appropriate and acceptable response in this network. With continuous repetition, the average error decreases and the learning capacity and ability increases. Of course, there is disagreement about the repetition, but the results of the research show that at 30,000 and above, the error increases again. 30,000 times the same number of iterations was found to be appropriate. 30,000 iterations seems to be a good compromise between the time required and the accuracy of the model. The necessary information had to be obtained from the clients and this information was extracted from their files and used.

7.1 Determination of sample and sample size

To conduct the research, Mudaraba facility files were used at Bank Mellat in Tehran province in 2015. The analysis of the cases showed that 50% of the cases were related to low credit risk, 33.43% of the cases were related to medium credit risk loans and 16.57% of the cases were related to high risk credit loans.

Krejcie and Morgan in [13] presented a good decision-making model with scientific and generalized guidelines for sample size. Since the number of files in the branches is 450, 350 files are needed for sampling according to this table. According to the percentage mentioned above, 175 creditworthy customers (117 for training and 58 for testing), 117 medium credit risk customers (78 for training and 39 for testing) and 58 NPL or high credit risk customers (39 for training and 19 for testing) are required. The indicated numbers are randomly selected from the two groups. Stratified random sampling was then used.

7.2 Data Collection tools

For data collection, firstly, documents and consultant experts were utilized, and then the data needed for training and testing the model were used from files containing data on the inputs and outputs of the model.

7.3 Information analysis method

The information collected is reviewed and analyzed in several stages.

First stage: In this stage, the data collected from the branches is manually reviewed and necessary measures are taken to correct it.

Second stage: At this stage, the research data is classified and coded using EXCEL software and becomes an information worksheet.

Third step: Data is analyzed using Neurosolution software and data collection is performed.

Step four: Research variables are classified using Neurosolution software and then, using advanced calculations performed by this software, variables that have a significant relationship with the dependent variable are identified among the independent variables and the relevant variables of the model are used. The neural network is designed using neurosolution software.

Its mathematical applications are summarized in the following section.

The input vector with 5 input values is propagated to the activation vector with one layer towards the upper layer, which is the product of the coefficients in the activation values. A sigmoid function is used as below to determine the activation value of a unit, Aj, in the upper layer.

$$Aj^{(l)} = \frac{1}{1 + \exp\left[\sum_{i=0}^{n} WxAi^{(L-1)(L)} - Oj\right]} \tag{7.1}$$

If the upper layer is not an output layer, this vector is re-propagated to the front. The symbols $L-1$ and L indicate the upper and lower layers. If the upper layer is an output layer, the activation value of each output unit is compared with its desired value and the error is measured based on the following relationship.

$$E = \frac{1}{2}\sum_{j=0}^{n}(Di - Aj)^2 \tag{7.2}$$

7.4 Error function

The normal learning algorithm modifies the coefficients in order to reduce the error. Therefore, BPLA is a reduction algorithm in which the network coefficients are adjusted sequentially to minimize the overall mean squared errors between the desired (DJ) and actual (AJ) values of all output units on the input pattern.

The value of the coefficients for each input pattern is determined based on the derivative of the error function in terms of coefficients as follows.

$$\Delta Wji = -\alpha \frac{\partial E}{\partial Wji} \tag{7.3}$$

This derivative gives the error signal (error signal) for one unit, that is:

$$\delta j = (Dj - Aj)Aj(l - Aj) \tag{7.4}$$

and for hidden layers

$$\delta j = Aj(l - Aj)\sum_{K=0}^{n} \partial_R W_{Ri} \tag{7.5}$$

Finally, the connection coefficients between the j-th unit in the L-th layer and the j-th unit in the L-1th layer are adjusted according to the following relationship:

$$\delta j = Aj(l - Aj)\sum_{K=0}^{n} \partial_R W_{Rj} \tag{7.6}$$

$$1A\varepsilon_t = BU_t \tag{7.7}$$

$$\begin{bmatrix} \varepsilon_{Size} \\ \varepsilon_{Ex} \\ \varepsilon_{open} \\ \varepsilon_{GDP} \\ \varepsilon_{M} \\ \varepsilon_{inf} \end{bmatrix} = A(L) \times \begin{bmatrix} U_{Size} \\ U_{Ex} \\ U_{open} \\ U_{GDP} \\ U_{M} \\ U_{inf} \end{bmatrix} \tag{7.8}$$

$$\begin{bmatrix} \varepsilon_{Size} \\ \varepsilon_{Ex} \\ \varepsilon_{open} \\ \varepsilon_{GDP} \\ \varepsilon_{M} \\ \varepsilon_{inf} \end{bmatrix} = \begin{bmatrix} a_{11}(1) & 0 & 0 & 0 & 0 & 0 \\ a_{21}(1) & a_{22}(1) & 0 & 0 & 0 & 0 \\ a_{31}(1) & a_{32}(1) & a_{33}(1) & 0 & 0 & 0 \\ a_{41}(1) & a_{42}(1) & a_{43}(1) & a_{44}(1) & 0 & 0 \\ a_{51}(1) & a_{52}(1) & a_{53}(1) & a_{54}(1) & a_{55}(1) & 0 \\ a_{61}(1) & a_{62}(1) & a_{63}(1) & a_{64}(1) & a_{65}(1) & a_{66}(1) \end{bmatrix} \times \begin{bmatrix} U_{Size} \\ U_{Ex} \\ U_{open} \\ U_{GDP} \\ U_{M} \\ U_{inf} \end{bmatrix} \tag{7.9}$$

$$\begin{cases} \beta_{t+1} = \beta_t + u_{\beta t}, \\ a_{t+1} = a_t + u_{at}, \\ h_{t+1} = h_t + u_{ht}, \end{cases} \begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \sum_\beta & 0 & 0 \\ 0 & 0 & \sum_\alpha & 0 \\ 0 & 0 & 0 & \sum_h \end{pmatrix}\right) \tag{7.10}$$

$$Inflation_{i,t} = Inflation_{i,t-1}\beta_{i,t} + \varepsilon_{i,t},\ \varepsilon_{i,t} \sim N(0, Q_{i,t}) \tag{7.11}$$

$$\beta_{i,t} = \beta_{i,t-1} + \gamma_{i,t},\ \gamma_{i,t} \sim N(0, R_t) \tag{7.12}$$

where Ai is the activation value of the i-th unit and alpha the learning rate used to determine the speed of the training process of the network.

7.5 Research process

Several ways for data preparation and network modeling have been presented by different authors. By selecting and combining several views and taking into account the characteristics of the statistical population and the availability of information, the following steps were considered for the development of the neural network prediction model.

The main stages of the research are as follows:

A. Initial review phase

B. Theoretical studies and literature on the subject

C. Model design

D. Model testing and analysis of results

A. Initial review phase

In the first phase, general studies on credit rating systems and artificial neural networks were conducted. In addition, in this stage, the research on the research topic was briefly reviewed, and as a result, the research topic became more specific and an initial model was created with research questions and hypotheses.

B. Theoretical studies

At this stage, due to the interdisciplinary nature of the research topic and the link between the two different areas of finance and artificial intelligence, care has been taken to conduct a broad study in the two areas and use different branches related to the research area.

C. Model design

The following steps are followed to design and implement neural network models.

1. Data preparation
   (a) Definition and collection of data
   (b) Review and preliminary data processing
   (c) Dividing the data into two training and test groups
2. Network design
   (a) Selecting the model type
   (b) Determine the number of processor elements in each layer
   (c) Hidden layers
   (d) Conversion function
   (e) Learning rules
3. Finalizing and training the model
   (a) Final decision model
   (b) Model training

7.6 Definition and collection of data

As mentioned earlier, it tries to rank the customers of the facilities with the help of neural networks. With this ranking, customers are sorted into different categories on the basis of credit and it is determined which customers are eligible for credit and which customers are not eligible for credit. For this, you need a system that can incorporate a range of data and process it according to the program and give the right result. If we want to rely on the power of mathematics for this, we will not be successful because the power of mathematics to solve a large number of problems is largely limited to linear relationships, and this power diminishes when faced with complex non-linear conditions. Computers, designed as the main computational tools, suffer from the same limitations because they have a similar approach to mathematics. Brain networks are built in parallel, which is not comparable to the way computers build sequences. This is so powerful that many believe that if the process of brain function can be simulated to some extent, it will solve problems that cannot be solved by traditional math methods. Artificial neural networks are the answer to this problem as they have parallel structures that can learn and process large amounts of data. Using the neural network's capabilities, neurosolution software analyzes this data and variables into a table by conducting interviews and examining documents from clients' files.

The variables related to Mudaraba loans were identified as follows.

A- From the facility request form

1- Applicant's job 2- Applicant's education 3- Monthly income 4- Desired amenities 5- Gender

B- From credit files

1- Credit record (returned check or promissory note and overdue installments) 2- History of purchasing facilities

C- From the contract arrangement form

1- Principal amount of the facility 2- Interest amount of the facility 3- Monthly installment amount 4- Collateral value 5- Collateral type 6- Fee type 7- Penalty rate

Some variables were omitted due to the limitations of the files, and then the following variables were selected using theoretical foundations and expert opinions.

1- Occupation of the applicant 2- Education 3- Income 4- Collateral value 5- Credit history

It is necessary to explain that the customer's behavior of using mudaraba loans is defined by the components a-stability b-repayment ability c-efficiency. The first and second variables represent stability, the third variable represents repayment ability, and the fourth and fifth variables represent competence. In this research, a sample of 350 customers, of which 175 are good customers (low credit risk), 117 are overdue customers (medium credit risk) and 58 are bad customers (high credit risk), is the right opportunity to identify the characteristics of high credit risk accounts, net of the percentage given by other accounts. The same problem applies to overdue accounts compared to good accounts.

7.7 Data analysis and pre-processing

The necessary checks were made to ensure the usefulness of the data, as well as the scaling of the data, i.e. the scale with which we should measure each variable, and finally the format of the data accepted by the network software. Therefore, the variables of the model are as follows.

Table 1: Variables of Mudarabah loan facility

array	variables	values
1	income	Real income
2	Education	1. Sub-diploma 2. Diploma to Bachelor 3. Masters degree to PHD
3	Collateral	Actual amount
4	Credit history	Yes – No
5	Job	Service- Production - etc

7.8 Divide the data into two sets

The data of the model set should be divided into two subsets, one for training the network and one for validating the model. Each set should contain various results. Normally, more numbers should be assigned to the training part to increase the probability of the network learning with more samples and there should be a balance between convergence and generalizability of the network. In choosing the training set, the following should be considered:

First: The training set should contain the full range of values for all features.

Second: You should pay attention to the time needed to train the network. The more features of the variables, the slower the network convergence, so more samples are needed. A large number of examples leads to strong convergence and low generalizability.

The last important point is the provision of input data. Due to the network's dependence on historical data, it is important to ensure the availability of this data to the network.

The training part of the collection includes 117 low-risk account instances, 78 medium-risk instances and 39 high-risk instances. In the test section, there are 58 low-risk, 39 medium-risk and 19 high-risk instances.

8 Network design

8.1 Select the type of model

The chosen model is a multilayer perceptron, which has been successfully used to solve a number of problems, especially ranking problems.

This model is part of multilayer feed-forward networks, where a number of receiver units form an input layer, and there are one or more hidden layers of computational nodes, and there is also a computational node output layer at the end.

8.2 Number of processor elements

There are several proposals for determining the number of processor elements in the hidden layer, the number of variables in the first layer is equal to the number of input variables, i.e. five, the number of elements in the last layer is equal to the output, i.e. three, and the number of elements in the middle layers is based on trial and error from the number that has less error.

8.3 Number of hidden layers

In this research, it is addressed due to the lack of proposals and the existence of a general theory based on trial and error at the layer.

8.4 Transformation function

The transformation function is related to the mathematical model of data transformation. In this research, tangent functions, which are often used in sorting problems, are used.

8.5 Learning rules

In this research, the learning rule paradigm of tutoring and error correction was used.

9 Finalizing and training the model

9.1 Final decision model

Based on the materials described and the results of the previous steps in the neural network credit rating model for this type of facility, we will train and test as follows.

Table 2: Finalizing the final decision model

Model	Transform function	layers	Number of elements in a hidden layer	Repeat values
A	Hyperbolic tangent	4	10	25000
B	Hyperbolic tangent	4	15	30000

That each of the above models are multi-layered perceptron type with specified processing elements in each hidden layer and with the trial and error learning rule of the supervised training paradigm.

9.2 Model training

Each of the models includes 350 examples, including 175 loans with low credit risk, 117 examples with medium credit risk, and 58 examples with high credit risk. Each training course for model A included 25,000 repetitions and for model B included 30,000 repetitions. Of course, there are differences of opinion about the number of repetitions, but 30,000 repetitions stated according to the theoretical foundations is a good agreement between the opinions and the balance between the required time and accuracy. It looks like a model. The results of model training are given in the attachment.

9.3 Outputs, good, average, bad loans

To determine the outputs ,which include good, average and bad loans, codes are defined in the table, identified by codes 1, 2, 3 according to the capabilities of the software in question. A good loan refers to a loan where a person is not in default and pays the installments on time. An average loan or an overdue loan is considered to be a loan where the person is slightly late in paying the installments but repays them, for example with a reminder and a warning from the bank. A bad or overdue loan refers to a loan where a person may be more than six installments late. Code 1 for good credit corresponds to people who are eligible for a loan. Code 2 corresponds to an average loan, i.e. people who pay average installments, and code 3 is defined for bad loan , i.e. people who are not eligible for a loan.

Neurosolution V5 software is used for network prediction modeling. Then, according to the variety of available models and the experimental nature of the network design, different types of networks with different numbers of inputs, different network architectures, different numbers of elements in the hidden layers of different networks are defined and compared according to the 2-R and RMSE coefficient of determination. Neurosolution software has the ability to start solving the model based on the input data and starts working by training the model first.

9.4 Model testing and analysis of results

The network was trained after 30,000 iterations of training. In this section, the results obtained from the model, indicating the type of good or bad, are compared with each other according to the criteria of the coefficient of determination, which are 2R and MSE, and according to the criteria of acceptance or non-acceptance according to this criterion. in the testing section, the network tests the data and shows its accuracy. Testing and data maintenance was performed using EXCLE 2003 software. Neurosolution V5 software is used to simulate the network models.

9.5 Preparation of input data for rating customers using neural networks

A- Data preparation

In order to prepare the data, first of all, the necessary data were prepared from the files of the facility customers and the desired variables were prepared. It should be noted that the selection of variables was based on the literature on this subject. discussed in detail in chapter 3. To select customers and extract data from their files, it was done randomly, which resulted in the amount of errors in each layer being equal, and an attempt was made to select files with more complete documentation.In this research R^2, MSE Calculated for ranking using neural network. Data for the year 85 were placed in an EXCEL table. The variables used according to expert opinions and researches are as follows:

1. Collateral value (colla-val)
2. Education (Educate)
3. Income (income)
4. Credit record (bank-ref)
5. Work (job)

B- Network architecture

A four-layer generalized feed-forward neural network with 5 elements in the first layer and 3 elements in the last layer and different elements in the two middle hidden layers (in models A and B) was used to train the network using the theoretical foundations of Section 2. According to the research, 4 layers were considered for the network. The number of neurons in the last layer is equal to the number of outputs of the network, which in this research includes 3 outputs. The number of neurons in the first layer includes the number of inputs, i.e. 5, and the number of neurons in the middle layer is determined by the efficiency of the network.

The number of trainings is another important factor in the network architecture. The software used supported up to 50,000 trainings, but the software was recommended for 1000 trainings and in this research the network training was done 25,000 and 30,000 times.

The results obtained from 30,000 trainings were with less error. Then, from the generalized feedback multilayer perceptron network with 2 hidden layer numbers of 3-10-10-5 model A and 3-15-15-5 model B hidden layer elements, the training was used 25000 times for model A and 30,000 times for model B.

The neural network was trained with training data containing 234 samples, 117 low-risk samples, 78 medium-risk samples and 39 high-risk samples.

In the final model, the following variables are used as inputs.

1. Value of collateral
2. Education
3. Income
4. Credit history
5. Job

Table 3: model A

Performance	**Out put (1)**	**Out put (2)**	**Out put (3)**
MSE	0.05964872	0.062085918	0.037877917
NMSE	0.23859488	0.279386633	0.272720961
MAE	0.140680756	0.154224109	0.105212329
Min Abs Error	0.000608107	0.001592124	0.000177976
Max Abs Error	0.910641516	0.755785332	0.948448497
r	0.87285756	0.851551454	0.852973159
Percent correct	94.01709402	92.30769231	74.35897436

As can be seen, the network in model A was able to be trained with an error rate (MSE) of 0.085. And then, with a standard deviation of 0.85, bad credit customers, 0.85 overdue customers, and 0.87 credit customers were ranked (Table 3).

Table 4: model A

Best Network	Traning
Epoch #	25000
Minimum MSE	0.085888677
Final MSE	0.131171759

Table 5: model B

Performance	Out put (1)	Out put (2)	Out put (3)
MSE	0.050905325	0.054243446	0.0326584
NMSE	0.203621298	0.244095508	0.235140478
MAE	0.120618186	0.133064573	0.095359186
Min Abs Error	0.00080379	1.17722E-O5	0.000134769
Max Abs Error	0.882390503	0.667410742	0.753558877
r	0.892427956	0.86973055	0.875873612
Percent correct	94.87179487	93.58974359	74.35897436

Table 6: model B

Best Network	Traning
Epoch #	30000
Minimum MSE	0.072960933
Final MSE	0.075751159

Table 7: Comparision table of results

Model	Accounts with high credit risks	Accounts with average credit risks	Accounts with low credit risks
A	74.35	92.30	94.01
B	74.35	93.58	94.87

In model B, the network was able to be trained with an error rate of 0.072. (Table 4) and then with a standard deviation of 0.87 bad account customers, 0.86 overdue customers and with a rate of 0.89 good account customers (Table 3).

The table and curve related to network training and testing are given in the attachment. The results of the implementation of model A show that the model has been able to predict bad credit customers with 74.35% accuracy, overdue customers with 92.30% accuracy, and good credit customers with 94.01% accuracy.

You can see costumers who false predicts in every raw

Table 8: Results of model A process

Desired \ Out Put	Out Put (1)	Out Put (2)	Out Put (3)
Out Put (1)	110	5	3
Out Put (2)	6	72	7
Out Put (3)	1	1	29

The results of the implementation of model B show that the model has been able to predict bad credit customers with 74.35% accuracy, overdue customers with 93.58% accuracy, and good credit customers with 94.87% accuracy. The number of customers who were wrongly predicted in each category is shown in table 9.

As seen in Table 9, Model B has the highest resolution. This is because it was able to evaluate the facility customers with a higher percentage. Here we reach the answers to the research questions because the credit rating of the facility customers was made using the characteristics of the loan customers, the number of overdue or overdue loans was also determined and with the help of this system, managers can avoid or prevent paying overdue or overdue loans and if they have to pay this loan, they can get more agents or guarantors from loan applicants.

Table 9: Results of model B implementation

Desired \ Out Put	**Out Put (1)**	**Out Put (2)**	**Out Put (3)**
Out Put (1)	111	5	3
Out Put (2)	5	73	7
Out Put (3)	1	0	29

10 Resulting

Providing banking facilities to qualified customers is one of the most important and complex tasks of banks. Banks collect their financial resources domestically and allocate them to their real and legal customers in different ways. The way these resources are allocated to these customers in the form of facilities will guarantee greater profitability and employment in the country only if these facilities are optimally allocated to qualified and valued customers. The correct allocation of financial resources, apart from the economic consequences and benefits it can have for the country, also provides the necessary background for the continued existence of banks. Therefore, banks should include indicators and criteria on the effectiveness of their risk and credit assessment before providing facilities to their customers.

10.1 Hypothesis test results

This section describes the results of the hypothesis testing. As stated in the first chapter, this study has put forward two main hypotheses and several sub-hypotheses, each of which is stated here.

1. First main hypothesis
   The bank's loan customers can be sorted using the coordinates of the loan customers.
   This hypothesis, whose purpose is to determine and evaluate the basic coordinates of the bank's loan customers, is of special importance in this research. Because if it is possible to evaluate the customers by using the coordinates of the customers before granting loans, loans can be granted to qualified customers. To test this hypothesis, customers' coordinates were first divided into five categories using the 5C model. After the division using Neurosolution software, the relationship between the set of customers' coordinates and their ranking was checked. The survey results showed a statistically significant relationship in all three data sets examined. Therefore, this hypothesis was confirmed. This means that customers can be ranked using their coordinates.
2. Testing the secondary hypotheses
   (a) There is a significant relationship between the amount of collateral and the rating of the facility applicant (customers with good, overdue and bad credit).
   This variable was investigated using neurosolution software and the results of the research showed a statistically significant relationship in all three data groups studied (it is worth noting that the closer the corresponding numbers are to zero, the more accurate the corresponding variable will be). And since in the case of good credit clients it is 0.48, overdue clients 0.16 and bad credit clients 0.47, the hypothesis is confirmed. This means that the amount of collateral has an impact on the clients' rating.
   (b) There is a significant relationship between the applicant's education towards the facilities and their ranking (customers with good credit, customers with overdue credit and customers with bad credit).
   This variable was investigated using neurosolution software, and the results of the research in all three groups of data showed that there is a statistically significant relationship between them, in the case of customers with good accounts, 0.12, overdue customers, 0.32, and bad customers, there. Therefore, this hypothesis is confirmed. This means that the level of education is effective in rating customers.
   (c) There is a significant relationship between the income of the facility applicant and its rating (clients with good, overdue and bad credit).
   After analyzing the relevant variable using Neurosolution software, it was concluded that there is a statistically significant relationship between the relevant variable and the output variables, namely 0.14 good customers, 0.29 overdue customers and 0.36 bad customers. Therefore, the hypothesis is confirmed. This means that the income of the applicant has an impact on their ranking.
   (d) There is a significant relationship between the applicant's credit history and their rating (customers with good credit, overdue customers and customers with bad credit).
   This variable was analyzed using neurosolution software and the results showed that this variable had a statistically significant relationship with the output variables, namely 0.33 good account customers, 0.11 overdue customers and 0.28 bad account customers. Therefore, this hypothesis was confirmed. This means that credit history is effective in rating customers.

(e) There is a significant relationship between the applicant's job and the facilities they have and their rating (customers with good credit, overdue and bad credit).
The relevant variable was analyzed using neurosolution software. And the results showed that there is a statistically significant relationship between this variable and the output variables, namely 0.004 good customers, 0.095 overdue customers and 0.093 bad customers. Therefore, this hypothesis is confirmed. This means that the applicant's job has an impact on customers' rating.

3. Second main hypothesis
It is possible to rank the bank's loan customers using a multilayer perceptron neural network.
This hypothesis, considered as part of the research innovations, sought to evaluate the effectiveness of neural network models in fitting the appropriate model to predict the three variables. The research results showed that the multilayer perceptron neural network model has the necessary effectiveness in achieving this goal. For this purpose, after observing the significant relationship between customers' coordinate sets and their ranking as the main elements of effective credit allocation, the effective base coordinates of the neural network model were designed using neurosolution software. In this model, the base coordinates identified using the neuro-solution software were introduced as an input layer (input vector) to the multilayer perceptron neural network model and then the corresponding neural network model was embedded. The results of fitting and checking the test data showed that this model can act as one of the useful models in determining the degree of credit customers.

Therefore, since loans are given for the purpose of helping people and except in special cases, the bank cannot refuse to give loans. If the branch management finds with the help of the rating that the loan will be delayed or burned, they can refuse to grant the loan to the applicant or ask for more guarantors from the loan applicant.

10.2 Research recommendations

According to the practical and theoretical aspects of the research, the recommendations are presented in two sections: practical recommendations in the banking system and theoretical recommendations for future research.

10.3 Practical recommendations in the banking system

1. Designing a software system for an intelligent system to be used in the management of total loans
2. Software design of intelligent system for the use of bank branches
3. Training of business personnel in the credit facilities department to use the system
4. Preparing and setting up an efficient system for obtaining credit information from customers of credit facilities

10.4 Suggestions for future research

Designing an intelligent system to assess the riskiness of investment projects by the bank

1. Designing an evaluation model for economic projects in the country
2. Designing an intelligent system for ranking universities in the country
3. Using other network models

Table 10: Results of education model B

Best Network	**Training**
Epoch #	30000
Minimum MSE	0.072960933
Final MSE	0.075751159

Table 11: Persons who rate false in every group in model B

Desired \ Out Put	**result (1)**	**result (2)**	**result (3)**
result (1)	111	5	3
result (2)	5	73	7
result (3)	1	0	29

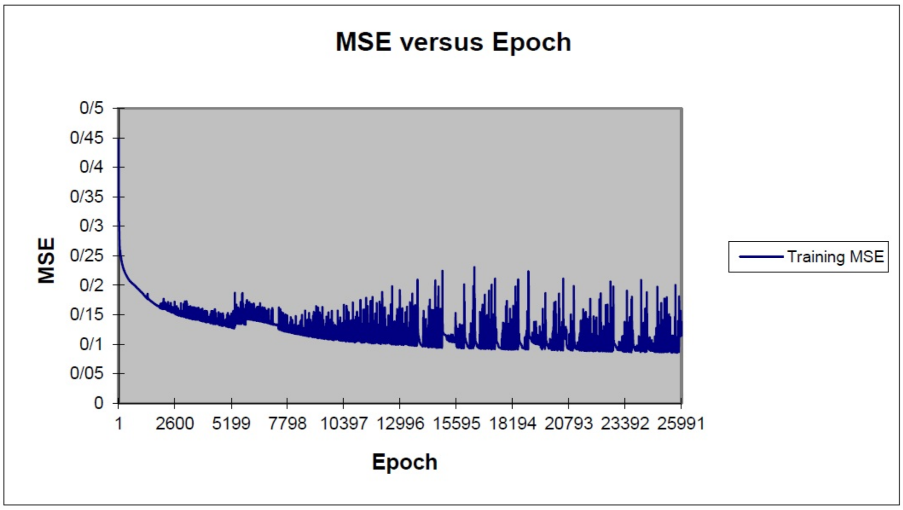

Figure 3: Average percent of error in B model

Table 12: Comparison results of average error in model B

Performance	result (1)	result (2)	result (3)
MSE	0.050905325	0.054243446	0.0326584
NMSE	0.203621298	0.244095508	0.235140478
MAE	0.120618186	0.133064573	0.095359186
Min Abs Error	0.00080379	1.17722E-05	0.000134769
Max Abs Error	0.882390503	0.667410742	0.753558877
r	0.892427956	0.86973055	0.875873612
Percent correct	94.87179487	93.58974359	74.35897436

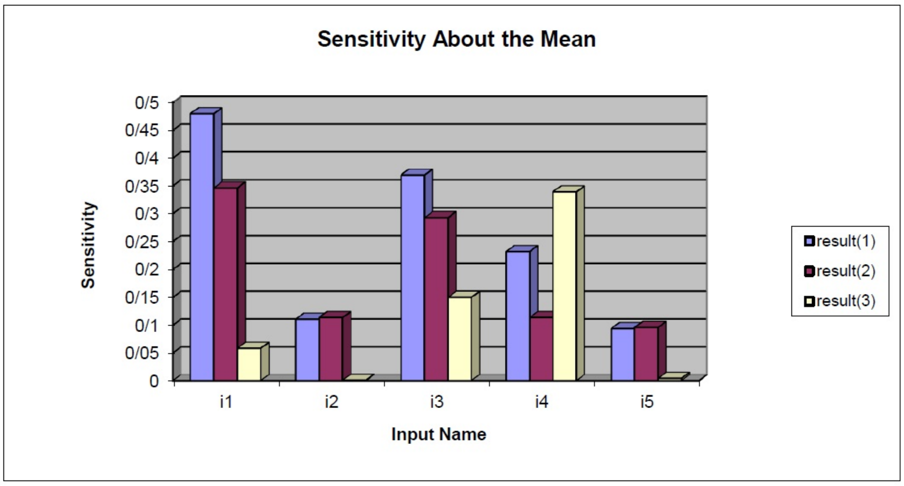

Figure 4: The sensitivity of inputs in model B

Table 13: Percentage of inputs sensitivity in model B

Sensitivity	result (1)	result (2)	result (3)
i1	0.47919212	0.346076945	0.058166087
i2	0.110315423	0.113437608	0.000886072
i3	0.369143955	0.292813365	0.149469065
i4	0.231799106	0.113424718	0.33888386
i5	0.093587924	0.095758002	0.004181319

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