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Risk Assessment in Banking Needs Using Neural Networks

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Abstract: *Banking system is one of the most complex and sensitive institutions of human society. Failure to pay attention to different circumstances - The management of this financial organization may result in irreparable damage. In this regard, bankruptcy of the bank and the creation of public discontent can be noted. Hence, risk assessment in banking systems, especially in transactions, is a major part of the process in the banking system. One of the strategies to prevent trading risk is the use of classification techniques to predict the current risk of a current transaction. Among the classifying methods, the neural network is very common and the results of it Is obtained. According to the above, in this thesis, we propose a method that we propose using the neural network and Cuckoo algorithm to investigate the risk of trading and then decide on it.*

Keywords: *Risk of Transactions, Banking System, Neural Network.*

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I. INTRODUCTION

In recent years, with the introduction of new technologies and the Internet, competition between banks has increased dramatically. Big and powerful banks are pursuing their anticipated goals in order to increase their competitive ability. This is a matter of practical importance. The Bank's risk prevention model, risk mitigation measures, and the prevention of the spread of banking risks are identified initially. The BP Neural Network has three important advantages in economic data analysis. Initially, neural networks have the ability to learn high. Some of the backgrounds of the neural network can be seen in the early twentieth and late nineteenth centuries. During this period, fundamental work in physics, psychology, and neurophysiology was carried out by scientists such as Hermann von Helmholtz, Ernest Mach and Ivan Pawlf These early works generally focused on general learning theories and did not refer to specific mathematical models of neuronal function. The new view of neural networks in the twenties of the twentieth century was right when Warren McCluto and Walter Pitts showed that nerve networks can basically calculate any logical and functional function. These people can be called the starting point of artificial neural networks. This issue was continued by the individual Donaldsdob who provided a beta action to learn biological neurons.

Due to the application of AI techniques and modeling tools in the banking sector is increasingly increasing. In this regard, expert systems have found a special place. In the past few decades, two types of neural networks and genetic algorithms have been the topic of interest to many academics. These two have been recognized and used as a powerful tool in solving problems that were no longer solvable by traditional methodologies and methods of the past. These days, their use of our social life has also been extended to the point where their use in decision making plays a vital role. Neural Networks is an information processing technique based on the method of biological nervous systems such as the brain and information processing. The fundamental concept of neural networks is the structure of the information processing system, which consists of a large number of processing units (neurons) associated with the networks.
A biological neural cell or neuron, the unit of the nervous system in humans. A neuron is composed of the following main parts:
1. The body of the cell where the nucleus is located and the other parts of the cell are derived from it.
2- core Axon, whose task is to transfer information from the nerve cell. Dendrites whose task is to transfer information from other cells to the neuronal cell. A neural network system uses techniques used by humans to learn by citing examples of problem solving.One of the areas of application of neural networks in financial activities is customer rating and loan appraisal assessment. By this, it is possible to decide who and what loan amount can be paid to. How to assess the risk of non-payment, ie, how much the borrower can pay. The soldier In this case, multilayer perceptrons have been successfully used. The advantage of the neural network is that it can use thousands of previous examples in the history of corporate finance, capture outstanding features, and predict outcomes through them. In most Iranian banks, the loan is granted on the basis of evaluators' opinion that this method requires a considerable amount of time and requires expert resources, and it is also cost-effective.

II. RELATED WORKS

Maletera and Maltera (2002) compared the effectiveness of compatible neuro-fuzzy argumentation systems with multiple audit analyzes. In their study, they used a 500 data set (250 well-off clients and 250 blind counters) that randomly selected learning and experimental data from these observations. The results of their studies indicated that the ANIF method was superior to MDA.
Dissa et al. (2003) examined the multilevel perceptron neural network, the neural network of experts, the linear separator analysis, and logistic regression for credit applicants in the credit union industry. Their methodology, including cross-validation, is a part of the underlying data obtained from three credit unions, assuming equal payoffs for good and bad credit risks. They concluded that neural network models had better performance than linear separation analysis, but only a few logistic regression models were better.
Maltera and Maltera (2005) used a multi-layered perceptron neural network model to classify clients of 12 financial institutions in the United States and compared their results with the audit analysis method, which showed a neural network model with higher classification accuracy.
In a comprehensive study, Henley and India (1997) compared the accuracy of four different methods in ranking using data from a large sales company. In their research, four methods of linear regression, logistic regression, closest neighbors, and decision tree of logistic regression, linear regression, and decision tree are classified in the following categories in terms of classification accuracy.
Zang and Jiang (2016) investigated in a paper entitled "The Bank BP prediction model based on accurate calculations." They analyzed the structure of bank risk forecasting using the BP

neural network and the principal components of the models. The results showed that the neural model was 88% successful.

III. THE PROPOSED METHOD

The UCI site is a very valid reference for research in the areas of AI, data mining, and so on. In many branches of science, it provides comprehensive and complete datasets. The data used in this research is downloadable and viewed at;
https://archive.ics.uci.edu/ml/datasets/statlog+(german+credit+data). Using the sequential search method, some of the data properties that are text-based are converted to a number. For this purpose, for example, first the first text is considered as the number one, and up to the last line of the data in that attribute, all the text is equal to the first cell of the same. This process continues until the last feature until numerical data is obtained.

3-1: *Multilayer Perceptron Neural Network (MLP)*

Multi-layer perceptron is a bunch of artificial neural networks. Typically, these networks contain a set of sensory modules (base neurons) that comprise an input layer, a hidden layer, and an output layer. The input signal is released in a vacuum network and in a forward direction in a layer-to-layer manner. This type of network is commonly referred to as the Layer Perceptron (MLP).

The hidden double sigmoid dual network and the softmoon outlet neuron can well categorize the arbitrary vector: if the neurons are given sufficiently in its hidden layers.

3.2 *Cuckoo Search Algorithm*

Cuckoo Search (CS), Coco Search, or Nightingale Search, is an optimization algorithm designed by Zain Xieang and Swashback in 2009. This algorithm is based on the requirement of the parasite egg of some species of nightingale to put its eggs in the nest of host birds (other species). Some host birds can fight and clash with overhead creatures. For example, if a bird hosts eggs that they do not own, they will discard these eggs or leave their nest easily and make a new nest. Some species of cucumber, such as the new breed of eggs, tapera, are shaped in the same way that female parasite cucumbers often specialize in imitation in the colors and pattern of eggs of a number of host species of choice. Cuckoo's search is based on this kind of cultivating method and can therefore be implemented for a variety of optimization issues. It seems that this method can be applied to other meta-heuristics algorithms. It is likely that the corresponding algorithm is also called the Cuckoo Recycling Executive, which was designed by Ross Moussegag and Fleming Richard Roddler in 2001, for any consideration.To define a neural network, we need two sets of data. An input dataset that contains the bank account information of individuals and another set of data that indicates the existence or absence of risk for the allocation of credit to each individual. The initial data set, which contains the account parameters and other characteristics of each individual, is an input, and refers to the status of the existence or non-existence of the risk of paying the credit to the same person, goals, or output. A part of the input dataset and the target dataset has just been written.

3-3: *Proposed schema*

To benefit from the benefits of the MLP Neural Network and the Cuckoo Search Algorithm, we combined these two and implemented them with macro codes and introduced a new model for optimizing and accelerating risk assessment in bank transactions.

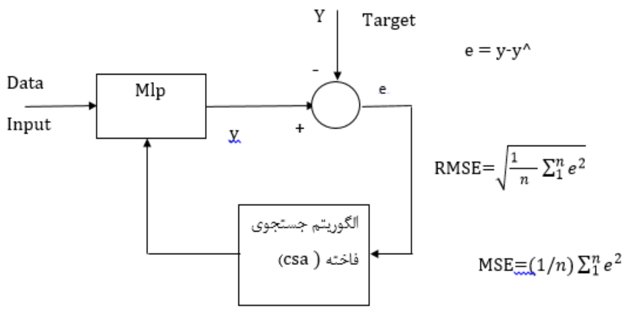

Figure 1: Proposed Model

This shape represents the generated neural network. In this figure, 20 inputs are considered as attributes of each individual, 10 hidden neurons and 2 outputs (presence or absence of bank risk).

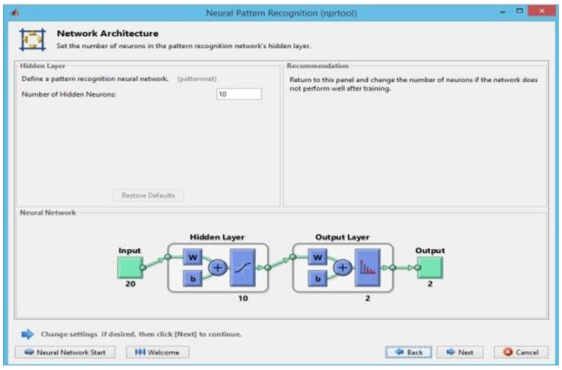

Figure 2: Neural network of the proposed layout with 10 layers

IV. EVALUATOIN

TWhat is important in this research is the efficiency of the neural network, so the main study is done on the output of a dual-layer feeder neural network. The number of inputs of a neural network depends on the set of data and the characteristics defined therein. Because of the use of the german dataset, 20 features or 20 inputs are defined for a dual-layer nerve grid. The number of latent neurons in the initial state is defined as 10, which may change for further investigation. In addition, the output of the neural network is designed in two modes of existence or non-existence of risk.

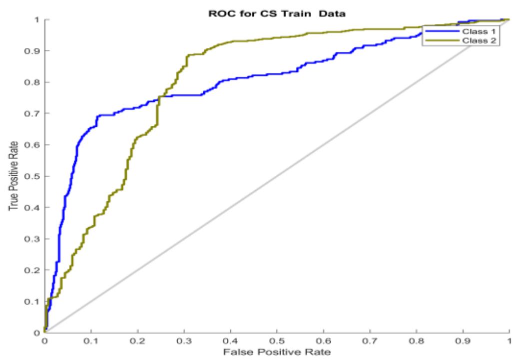

Figure 3: ROC for the Mlp Neural Network with CSA in Tarin Data

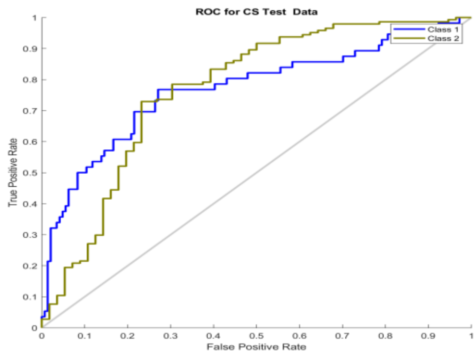

Figure 4: ROC for the Mlp Neural Network with CSA in Test Data

Fig. 3 and 4 Recipient Functional Characteristics (ROC) in the Mlp Neural Network are shown using the Cuckoo Search Algorithm. Functional characteristics of the receiver are the criteria used to check the quality of the classifier. For each classifier class, threshold values between 0 and 1 are used for outputs. For each threshold, two positive real values (TPR) and false positive rates (FPR) are calculated. There is always a positive real rate in either class of existence or absence of bank risk much more than a false positive rate. By virtue of the close and close to point 1 curves, it is possible to achieve high performance of the diagnostic system with a training and testing dataset assured Made

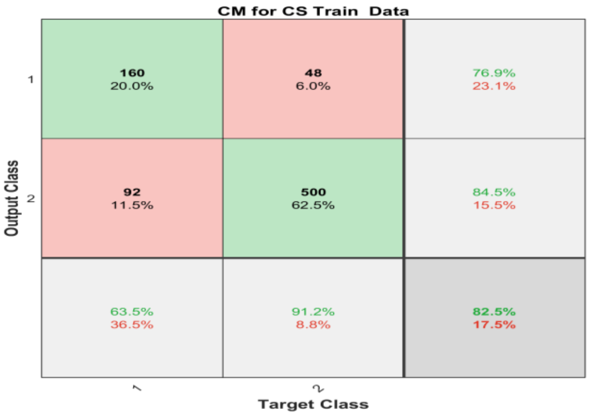

Figure 5: Disturbance matrix for the Mlp neural network with the CSA in Tarin Data

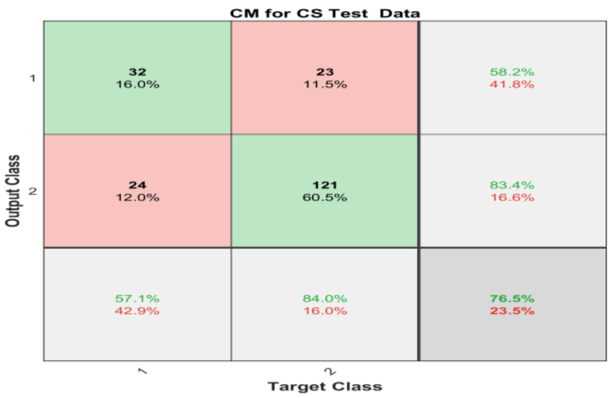

Figure 6: Turbulence Matrix for the Mlp Neural Network with CSA in Test Data

In Figure 5, two primary diagonal cells show the number and percentage of the correct categorization using the trained network, and 160 samples are correctly identified as bank risk. This is consistent with 20.0% of the total sample. Similarly, 500 individuals were placed in the category of risk aversion, which is 62.5% of the total sample. 48 samples of risk individuals are classified for non-risk monetization and are consistent with 6.0%. Similarly, 92 of the risk-free individuals are in the banking risk category, which is 11.5% of the total sample. Overall, 82.5% of the predictions are correct and 17.5% are mistaken.
In Figure 6, the samples are correctly identified as bank risk. This is consistent with 16.0% of the total sample. Similarly, 121 individuals were properly placed in the category of bank non-risk, which corresponds to 60.0% of the total sample. 23 samples of risk individuals are classified for risk-free mistakes and According to 11.5%. Similarly, 24 of the risk-free individuals are in the banking risk category, which is consistent with 12.0% of the total sample. Overall, 76.5% of the predictions are correct and 23.5% are mistaken.

Table 1: Comparison of Methods in Train Data

Negative Predictability	Positive Predictability	Being proprietary	Sensitivity	Accuracy	Method
82.1% True 17.9% False	54.5% True 45.5% True	82.6% True 17.4% False	53.6% True 46.4 False	74.5% True 25.5% False	MLp
83.4% True 16.6% False	58.2% True 41.8 False	84% True 16% False	57.1 True 42.9 False	76.5 True 23.5 False	MLP – CS
71.7% True 28.3% False	55.9% True 44.1% False	88.8% True 11.2% False	28.8% True 71.2% False	69% True 31% False	KNN
72.8% True 27.2% False	64.5% True 35.5% False	91.8% True 8.2% False	30.3% True 69.7% False	71.5% True 28.5% False	Decision Tree

Table 2: Comparison of Methods in Test Data

Negative Predictability	Positive Predictability	Being proprietary	Sensitivity	Accuracy	Method
82.1% True 17.9% False	54.5% True 45.5% True	82.6% True 17.4% False	53.6% True 46.4 False	74.5% True 25.5% False	MLp
83.4% True 16.6% False	58.2% True 41.8 False	84% True 16% False	57.1 True 42.9 False	76.5 True 23.5 False	MLP – CS
71.7% True 28.3% False	55.9% True 44.1% False	88.8% True 11.2% False	28.8% True 71.2% False	69% True 31% False	KNN
72.8% True 27.2% False	64.5% True 35.5% False	91.8% True 8.2% False	30.3% True 69.7% False	71.5% True 28.5% False	Decision Tree

V. CONCLUSION

In this paper, a method for discovering the amount of bank risk, a neural network has been selected among methods, algorithms and techniques available in computer inference, so that a model for converting collected data from a person referring to a bank to receive a loan to amounts And given the various issues, such as complex distributed data processing, the unreliability of data communications and the uncertainty in data analysis, can itself be used as a proper tool for bankers in order to provide more accurate and timely and more successful monitoring Recent Ajh be. Also, with the development of the model, other criteria could be included in the evaluation and achieved more general outcomes. The purpose of this study was to predict bank risk using the combination of MLP neural network with Cuckoo algorithm, and according to the results of simulation, high accuracy was obtained. In general, we can say that evaluation of the proposed method for identifying bank risk and optimizing the best using MLP neural network combination with Cuckoo algorithm. Based on the results, the use of 10 hidden layers can be the most suitable for designing this neural network. In the studies, the proposed method has been able to increase the accuracy of bank risk detection to an acceptable level.

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