The Impact of Particle Swarm Optimization Method on the Improvement of Bankruptcy Predictability Using Neural Networks

Amirhadi Manavi Moghadam and Maryam Hossein Zadeh
Master of Accounting, Maryam_h641@yahoo.com

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Abstract
One of the common approaches to predicting the bankruptcy is to use neural network models. Among neural network methods, multi-layer perceptron method is a supervised learning algorithm which is highly capable of predicting and classifying the problems. The above-mentioned model is not free of defects. It fails to find global optimums when it stops at local optimums. To overcome this flaw, particle swarm optimization method has been used in this paper in order to optimize the multi-layer perceptron neural network. The statistical population of this research falls into two groups which are healthy and bankrupt companies. The sample includes 60 bankrupt companies and 60 healthy ones between 2005 and 2013. The companies which were covered by Article 141 of the Commercial Code were selected as bankrupt companies, and simple Tobin's Qwas chosen as ameasureto select the healthy company. The results indicate that the model constructed by the multi-layerperceptron neural network is capable of predicting bankruptcy in the companies listed in Tehran Stock Exchange. Also, the multi-layer perceptron neural network which has been enhanced by particle swarm optimization method can predict bankruptcy in the above-mentioned companies. Its predictability indicates a considerable increase in comparison with simple perceptron neural network.

Keywords: Bankruptcy, Bankruptcy-Predicting Models, Multi-Layer Perceptron Neural Network, Particle Swarm Optimization

1. Introduction

Bankruptcy is a publicly-known word. Bankruptcy may occur in a small retail shop which is not able to pay the rent and is, therefore, closed or in a large manufacturing company due to inadequate liquidity and ongoing annual loss. Investors and creditors are so willing to predict bankruptcy in companies because a great deal of expenses will be imposed on them in case of bankruptcy. Predicting the continuous activity of economic sectors in future periods is one of the important elements in deciding for investment.Several patterns wereproposed to predict bankruptcy over the last years. This research aims to investigate the efficiency of multi-layer perceptron (MLP) neural network and to improve its predictability using particle swarm optimization (PSO) method.

2. Problem Statement

Many researchers such as Tam & Kiang, Alfaro, and Chen have used neural networks to predict bankruptcy and studied its strengths and weaknesses. Stopping at local optimums and high variance are among the weaknesses of this method [1, 2]. On the other hand, PSO is not able to classify data on its own, so it is not efficient alone [3]. The combination of neural network and PSO can be used to resolve these problems. If the problem of stopping at local optimums is resolved, the objective function will be stopped at global minimum and the variance obtained by prediction results will decrease.

The Importance and Necessity of Research

Predicting the bankruptcy is important in two aspects: first, the company can be warned of bankruptcy occurrence by providing them with necessary warnings; second, investors and creditors can invest their resources in more promising opportunities by using these predictive models. It appears essential to generate and present new modeling methods which are more cognitive, reliable and generalizable than the previous ones. Given

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some obvious weaknesses in common bankruptcy-predicting models based on neural networks, it would be very helpful to improve this modeling method and to generate more reliable bankruptcy-predicting methods in an effort to achieve the best result.

The Main Purpose of Research

In this research, the main objective is to study the impact of PSO in improving the predictability of bankruptcy models generated by multi-layer perceptron neural networks.

The Research Questions

- Are the models which have been generated by multi-layer perceptron neural networks capable of predicting bankruptcy in the companies listed in Tehran Stock Exchange?
- Are multi-layer perceptron neural network models which have been improved by PSO capable of predicting bankruptcy in the companies listed in Tehran Stock Exchange?
- Are multi-layer perceptron neural network models which have been improved by PSO more capable of predicting the bankruptcy in comparison with the commonmulti-layer perceptron neural network models?

The Research Hypotheses

- Models generated by multi-layer perceptron neural network method are capable of predicting bankruptcy in the companies listed in Tehran Stock Exchange.
- Multi-layer perceptron neural network models which have been improved by PSO are capable of predicting bankruptcy in the companies listed in Tehran Stock Exchange.
- Multi-layer perceptron neural network models which have been improved by PSO are more capable of predicting the bankruptcy in comparison with the common multi-layer perceptron neural network models.

3. Theoretical Basics

Neural Networks: One of the common methods of predicting financial distress is to use neural network models.Artificial neural networks, especially multi-layer perceptron model, have been used to design models for predicting financial distress since the early 90s. Perceptron neural networks, especially multi-layer perceptron neural networks which are more capable than single-layer neural networks, are among the most applicable neural networks [4].

Particle Swarm Optimization: This is an efficient method for optimization problems. It operates on the basis of probability regulations and population. In PSO algorithm, some agents named particles search the space to find the optimum. The particles change their positing in space in each step in order to reach the target. The new position of each particle is determined according to the previous position, the best optimumwhich the particle has found so far, and the best optimum to which the swarm has reached so far [5].

Multi-Layer Perceptron Neural Networks: They are one of the most applicable models of artificial neural networks.In multi-layer perceptron networks, each neuron on each layer is connected to all neurons on the previous layer. Such networks are named fully-connected networks. With its weighted coefficients, each perceptron aggregates the outputs resulting from every perceptron on the previous layer and transfer them to the next layer through the benchmark function [6].

The following items should be specified in designing the neural network models: the number of hidden layers in the network, the number of neurons on each layer, learning algorithms, benchmark function, learning rate, frequencies, data normalization, the size of learning set, and the size of test set. There are no systematic methods to determine these items; therefore, the best network design is achievedthrough experiment, trial and error [7].

Training the Neural Network through PSO: In PSO algorithm, each solution is named a particle. The closer the particle is to the target in the search space, the fitter it is [8]. However, this algorithm is not able to classify data alone,

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and it merely searches for the optimum in the model. Multi-layer perceptron model has weaknesses which are high variance and stopping at local minimums. To resolve these problems, the combination of multi-layer perceptron neural network with PSO algorithm can be used so that the objective function would be stopped at global minimum and the variance of prediction results would decrease.

Some Definitions

Cessation of Activities: In this research, this word applies to the companies which have been covered by Article 141 of Iran's Reform CommercialCode.

Bankruptcy: It results from cessation which has occurred according to the verdict issued by court, and the bankruptcy affairs are referred to the head of settlements.

Financial Ratios: The mathematical expression of the relationship between one value and another one. The financial ration is also the mathematical expression of the relationships among the items of financial statements [9].

4. The Research Background

Domestic Researches:

Using artificial neural networks with nervous design (5-7-1), Falahpour predicted financial distress in manufacturing companies and compared it with multiple discriminant analysis. He concluded that neural networks model was significantly more precise in prediction rather than multiple discriminant analysis [8].

Foreign Researches:

Tam and Kiang compared the predictability of neural networks with linear discriminant analysis, logistic regression, decision trees, and k-nearest neighbor algorithm. The research findings indicate that the results of neural networks model were more precise [10].

Alfaro *et al.* studied two models including AdaBoost algorithm and artificial neural networks to predict financial distress in the companies. The results of this research indicated that AdaBoost algorithm had a better performance than artificial neural networks did[11].

Using 37 financial rations and 68 companies in generating a model to predict financial distress, Chen *et al.* concluded that neural networks model had a higher predictability precision than data-mining classification methods [12].

5. Research Methodology

Inductive inference and retrospective study were used in this research which of applied type. Regression analysis, stepwise diagnostic analysis, SPSS, and Matlab were used to test the hypotheses.

Statistical Population and Sample:

The statistical population consisted of all companies listed in Tehran Stock Exchange between 2005 and 2013. It falls into two groups which are healthy companies and bankrupt ones. The companies which were included in Article 141 of the Commercial Code for three consecutive years were selected as bankrupt companies. According to Article 141, if the amount of accumulated losses exceeds the half of a company's capital, the company is supposed to increase its capital or stop its activities. Selection of healthy companies was done according to simple measure of Tobin's Q:

Simple Tobin's Q = (Liabilities Book Value + Value of Stock Market)/Book Value of Total Assets

When the calculated Tobin's Q exceeds one, it indicates that there is an incentive to invest in the company. Using the random sampling method and in the same number of bankrupt companies which were 60, healthy companies were selected out of the companies whose Tobin's Qs were more than one in three consecutive years.

Data Collection Methods:

All the data required in this research were collected from library references, financial statements audited in the sample companies, information published by Tehran Stock Exchange, the comprehensive companies' databank on the official website of Tehran Stock Exchange, Tadbir Pardaz Information Application (Stock Report), and Central Bank of the Islamic Republic of Iran's Website.

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Data Collection Tools:

The necessary data were collected through document mining, observation, studying the audited financial statements, checking the documents, published reports, and information banks.

6. Interpreting and Processing the Model

After providing the financial ratios for sample companies, the information was normalized in [0, 1]. Data normalization is necessary because if data pertaining to two neurons are in different ranges, then the neuron which includes greater absolute values is preferred during learning. Also, if the information used in the learning system is not scaled to an appropriate extent, the network will not converge on one point while learning, so it will not produce significant results.

Variable Selection:

A comprehensive study was conducted on the research literature in order to determine appropriate ratios and indicators for predicting the bankruptcy. The results include 52 financial ratios and indicators which were used to predict the bankruptcy in the previous researches:

The first step of modeling is to delete variables which are less capable of diagnosing the bankruptcy; therefore, *t*-test is used. As a result, the group of financial ratios which are potentially appropriate for predicting the bankruptcy can be selected. The test's hypotheses are as follows:

H_0: The mean of the financial ratio X in two groups of bankrupt and non-bankrupt companies are equal.

H_1: The mean of the financial ratio X in two groups of bankrupt and non-bankrupt companies are not equal.

If the hypothesis zero is refuted, we conclude that the values of test financial ratio in bankrupt companies are different from those of non-bankrupt companies. Thus, this financial ratio can be used to predict bankruptcy. The significance level is considered to be 5% in every test.

According to the results of *t*-test, 37 ratios out of 52 ones are capable of participating in the model. However, modeling with all of these ratios would make the model complicated and decrease the efficiency.The diagnostic analysis is capable of selecting a set of predicting variables among an extensive set of variables in a way that the selected variables can effectively represent the members of the initial group. Table 1 indicates the equality test forgroup means of financial ratios which have been used. The probability values which are smaller than 5% indicate a significant difference between the mean of bankrupt groups and healthy ones.

Table 1:Equality Test for Group Means

Financial Ratios	Wilks' lambda	F	df1	df2	Sig.
Net Profit to Total Assets	**0.549	96.818	1	118	*0.00
Total Liabilities to Total Assets	0.723	45.242	1	118	*0.00
Current Liabilities to Total Liabilities	0.757	37.928	1	118	*0.00
Long-Term Liabilities to Total Assets	0.914	11.043	1	118	*0.001
Shareholders Equity to Total Assets	0.684	54.584	1	118	*0.00
Profit before Taxation and Unexpected Items and Interest to Total Assets	*0.549	97.010	1	118	*0.00
Last Year's Total Assets to Total Assets	0.891	14.390	1	118	*0.00
Working Capital toTotal Assets	0.808	27.981	1	118	*0.00
Operating Cash toTotal Assets	0.722	34.943	1	118	*0.00
Sales to Total Assets	0.881	15.955	1	118	*0.00
Profit before Taxation and Unexpected	*0.481	127.331	1	118	*0.00

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Items and Interest to Total Liabilities					
Sales to Total Liabilities	0.724	45.084	1	118	*0.00
Shareholders Equity to Current Liabilities	**0.481	127.371	1	118	*0.00
Current Assets to Total Liabilities	0.724	44.975	1	118	*0.00
Net Profit to Current Liabilities	**0.499	118.508	1	118	*0.00
Shareholders Equity to Total Liabilities	**0.496	119.778	1	118	*0.00
Shareholders Equity to Long-Term Liabilities	0.720	45.919	1	118	*0.00
Working Capital to Shareholders Equity	0.939	7.616	1	118	*0.007
Profit before Taxation and Unexpected Items and Interest to Shareholders Equity	0.966	4.158	1	118	*0.044
Change in Net Profit to Sum of Absolute Values of Every Two Year	0.849	21.062	1	118	*0.00
Profit before Taxation to Current Liabilities	**0.507	114.543	1	118	*0.00
Profit before Taxation and Unexpected Items and Interest to Sales	0.800	29.469	1	118	*0.00
Net Profit before Taxation to Sales	0.758	37.664	1	118	*0.00
Net Profit to Sales	0.774	34.496	1	118	*0.00
Sales to Current Assets	0.894	14.040	1	118	*0.00
Cost of Interest to Profit before Taxation and Unexpected Items and Interest	0.952	5.937	1	118	*0.016
Sales to Last Year's Sales	0.883	15.693	1	118	*0.00
Gross Profit to Sales	0.837	23.013	1	118	*0.00
Profit before Taxation to Current Assets	0.643	65.421	1	118	*0.00
Retained Earnings to Capital	**0.557	93.855	1	118	*0.00
Operating Cash to Current Liabilities	0.675	56.818	1	118	*0.00
Shareholders Equity to Capital	**0.550	96.650	1	118	*0.00
Retained Earnings to Total Assets	0.747	40.014	1	118	*0.00
Operating Cash to Total Liabilities	0.674	56.975	1	118	*0.00
Cash Flow minus Net Profit to Total Assets	0.901	13.006	1	118	*0.00
Sales minus Last Year's Sales to Sales	0.871	17.553	1	118	*0.00
Interests to Total Assets	0.791	31.169	1	118	*0.00

Direct discriminant analysis was used to determine the effective variables. In this regard, 9 variables whose Wilks' lambda statistics are smaller than 0.6 were selected as effective variables. Table 2 indicates the financial ratios selected through direct discriminant analysis.

Table 2: Financial Ratios Selected through Direct Discriminant Analysis

Number	Ratio	Number	Ratio
1	Net Profit to Total Assets	6	Shareholders' Equity to Total Liabilities
2	Profit before Taxation and Unexpected Items and Interest to Total Assets	7	Profit before Taxation to Current Liabilities
3	Profit before Taxation and Unexpected Items and Interest to Total Liabilities	8	Retained Earnings to Capital

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4	Shareholders' Equity to Current Liabilities	9	Shareholders' Equity to Capital
5	Net Profit to Current Liabilities	-	-

Data Partitioning through Five-Step Cross-Validation Method:

One of the measures used to evaluate a predictive model is the prediction rate. The prediction rate on learning data is usually higher than the prediction rate on data which have not been considered in the learning process. With this reasoning, the prediction rate cannot be used to compare the two algorithms. Therefore, in addition to learning dataset, another dataset is required for evaluation [9].Since the learning process occurs in neural networks too many times, another dataset named validation data set, which is selected out of the learning dataset, is required as well as two above-mentioned sets. Therefore, each dataset falls into three independent subsets which are learning data, validation data, and evaluation data. One of the usual methods of doing so is to divide data into K sets [13]. In Figure 1, the first four repetitions are indicated for the selection of learning datasets, validation datasets, and evaluation datasets.

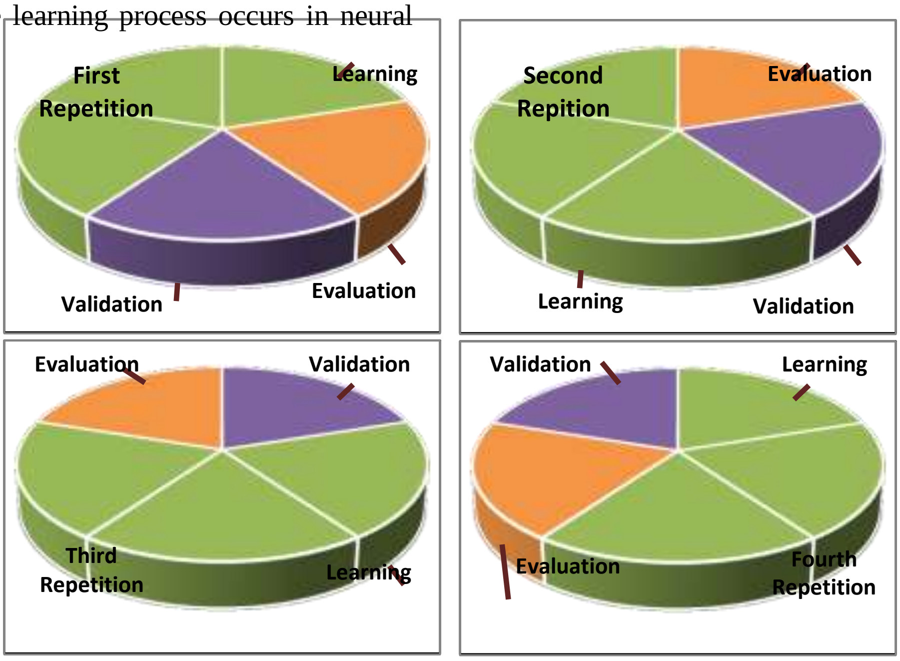

Figure 1: The First Four Stages of Selecting Three Datasets of Learning, Validation, and Evaluation with K=5

Multi-Layer Perceptron Neural Networks:

The appropriate structure of designing the optimal system for neural networks was obtained by changing the number of layers and the number of neurons on the hidden layer continuously. The four-layer structure of neural network used in this research (Figure 2) includes the input layer, two hidden layers, and the output layer. Considering the optimal variables selected through statistical methods, the numbers of neurons pertaining to these layers are 9, 18, 11, and 1, respectively.

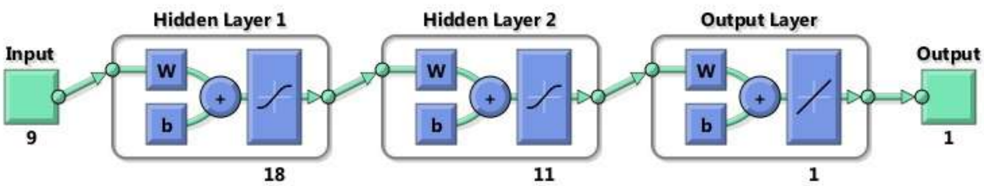

Figure 2: The Proposed Multi-Layer Perceptron Neural Network

The predicted results by multi-layer perceptron neural networks are indicated in Table 3 for steps 1 to 5.

Table 3: The Results of Multi-Layer Perceptron Neural Network

Sets		The Results of Multi-Layer Perceptron Model in the First Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	46	1	47	13	0	13	59	1	60
	Bankrupt	6	43	49	2	9	11	8	52	60
	Healthy (%)	98	2	100	100	0	100	98	2	100
	Bankrupt (%)	12	88	100	18	82	100	13	87	100
Total Precision	Total (%)	98	88	93	100	82	91	98	87	92.5
Sets		The Results of Multi-Layer Perceptron Model in the Second Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	48	2	50	9	1	10	57	3	60
	Bankrupt	4	42	46	0	14	14	4	56	60
	Healthy (%)	94	6	100	90	10	100	95	5	100
	Bankrupt (%)	9	91	100	0	100	100	7	93	100
Total Precision	Total (%)	94	91	92.5	90	100	95	95	93	94
Sets		The Results of Multi-Layer Perceptron Model in the Third Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	43	6	49	9	2	11	52	8	60
	Bankrupt	3	44	47	1	12	13	4	56	60
	Healthy (%)	88	12	100	82	18	100	87	13	100
	Bankrupt (%)	6	94	100	8	92	100	7	93	100
Total Precision	Total (%)	88	94	91	82	92	87	87	93	90
Sets		The Results of Multi-Layer Perceptron Model in the Fourth Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	44	3	47	12	1	13	56	4	60
	Bankrupt	1	48	49	2	9	11	3	57	60
	Healthy (%)	94	6	100	92	8	100	93	7	100
	Bankrupt	2	98	100	18	82	100	5	95	100

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	(%)									
Total Precision	Total (%)	94	98	96	92	82	87	93	95	94
Sets		The Results of Multi-Layer Perceptron Model in the Fifth Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	44	3	47	13	0	13	57	3	60
	Bankrupt	3	46	49	1	10	11	4	56	60
	Healthy (%)	94	6	100	100	0	100	95	5	100
	Bankrupt (%)	6	94	100	9	91	100	7	93	100
Total Precision	Total (%)	94	94	94	100	91	95.5	95	93	94

The results obtained from the mean of five steps are indicated in Table 4 as general results of neural network model. Given the results of test sample which is the main measure, investigating the results of this pattern indicates that multi-layer perceptron model is 89% precise for the correct classification of bankrupt companies, while it is 93% precise for the correct classification of healthy companies.

Table 4: The Mean Results of Five Steps in Multi-Layer Perceptron Neural Network

Sets		The Results of Multi-Layer Perceptron Model in the First Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Total Precision	Total (%)	93.5	93.5	93.5	93	89	91.5	94	92	93

In order to train the neural network by using PSO in the current research, a population including 100 particles was used, and PSO algorithm was executed on them for 10 times. The results of predictions by multi-layer perceptron neural network model optimized through PSO are indicated in Table 5.

Table 5: The Results of Neural Network Model Optimized throughPSO

Sets		The Results of Neural Network Model Optimized through PSO in the First Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	47	2	49	11	0	11	58	2	60
	Bankrupt	2	45	47	1	12	13	3	57	60
	Healthy (%)	96	4	100	100	0	100	97	3	100
	Bankrupt (%)	4	96	100	8	92	100	5	95	100
Total Precision	Total (%)	96	96	96	100	92	96	97	95	96
Sets		The Results of Neural Network Model Optimized through PSO in the Second Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrup	Total	Health	Bankrup	Total	Health	Bankrup	Tota

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			t		y	t		y	t	l
Group Companies	Healthy	45	1	46	12	2	14	57	3	60
	Bankrupt	2	48	50	1	9	10	3	57	60
	Healthy (%)	98	2	100	86	14	100	95	5	100
	Bankrupt (%)	4	96	100	10	90	100	5	95	100
Total Precision	Total (%)	98	96	97	86	90	88	95	95	95
Sets		The Results of Neural Network Model Optimized through PSO in the Third Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	47	2	49	11	0	11	58	2	60
	Bankrupt	1	46	47	1	12	13	2	58	60
	Healthy (%)	96	4	100	100	0	100	97	3	100
	Bankrupt (%)	2	98	100	8	92	100	3	97	100
Total Precision	Total (%)	96	98	97	100	92	96	97	97	97
Sets		The Results of Neural Network Model Optimized through PSO in the Fourth Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	45	2	47	12	1	13	57	3	60
	Bankrupt	2	47	49	0	11	11	2	58	60
	Healthy (%)	96	4	100	92	8	100	95	5	100
	Bankrupt (%)	4	96	100	0	100	100	3	97	100
Total Precision	Total (%)	96	96	96	92	100	96	95	97	96
Sets		The Results of Neural Network Model Optimized through PSO in the Fifth Step								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Group Companies	Healthy	47	2	49	10	1	11	57	3	60
	Bankrupt	2	45	47	0	13	13	2	58	60
	Healthy (%)	96	4	100	90	10	100	95	5	100
	Bankrupt (%)	4	96	100	0	100	100	3	97	100
Total Precision	Total (%)	96	96	96	90	100	96	95	97	96

The results obtained from the mean of five steps are indicated in Table 6 general results of neural network model optimized through PSO. Given the results of test sample which is the main measure, investigating this model indicates that the neural network model optimized through PSO is 94.5%

precise in the correct classification of bankrupt companies, while it is 93.5% precise in the correct classification of healthy companies.

Table 6: The Mean Result of Five Steps in Neural Network Model Optimized through PSO

Sets		The Mean Results of Neural Network Model Optimized through PSO in Five Steps								
		Training Sample			Test Sample			Total Samples		
		Healthy	Bankrupt	Total	Healthy	Bankrupt	Total	Healthy	Bankrupt	Total
Total Precision	Total (%)	96.5	96.5	96.5	93.5	94.5	94	95	96	95.5

7. Conclusion

As it is indicated in Table 7, the multi-layer perceptron neural network model predicted 89% of bankrupt companies correctly; however, the capability of this model increased to 94.5% as it was improved through PSO. Regarding the correct classification of healthy companies after improving the model, its capability also increased from 93% to 93.5%. The variance of results obtained from prediction after using PSO to improve multi-layer perceptron neural network decrease as much as a considerable extent. The variance of results obtained from prediction in multi-layer perceptron neural network is 15.87, while it is 2.23 in multi-layer perceptron neural network improved through PSO.

Table 7: Results of Hypotheses

Model	Modeling Method	Enhanced / Original	Prediction Capability		
			Bankrupt	Non-Bankrupt	Total
Multi-Layer Perceptron Neural Network	Artificial Intelligence	Original	89%	93%	91.5%
Multi-Layer Perceptron Neural Network Enhanced through PSO	Artificial Intelligence	Enhanced	94.5%	93.5%	94%

It is important to note that introducing a healthy company as bankrupt through a model results in the lack of appropriate investment by the user of the model. However, introducing a bankrupt company as healthy through a model results in the investment by the individual depending on the model in a bankrupt company; therefore, the capital is lost and irreversible damages are caused. Thus, it is considered to be highly commendable to increase the predicting capability of multi-layer perceptron neural network model through PSO from 89% to 94.5% in order to identify bankrupt companies correctly. The total capability of model increased from 91.5% in multi-layer perceptron neural network to 94% in multi-layer perceptron neural network enhanced by PSO.

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