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Research Article

Research on Enterprise Financial Customer Classification Method and Preference Based on Intelligent Algorithm

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Compared with the past questionnaire survey, this paper applies the intelligent algorithm developed rapidly in recent years to identify the tendency of customers to buy financial products in the market. In addition, for the single state customer classification indicators based on the previous demographic information and action information, it is proposed to combine the action of market activities with demographic information; that is, the static integrated customer classification index is further combined with the improved neural network model to study the classification and preference of enterprise financial customers. Firstly, the enterprise financial customer classification model based on neural network algorithm is studied. Aiming at the shortcomings of easy falling into the local optimal solution of neural network algorithm, slow convergence speed of algorithm, and difficult setting of network structure, combined with the characteristics of genetic algorithm, the concept of adaptive genetic neural network algorithm is proposed. Then, the design of adaptive genetic neural network model is studied. Secondly, combined with the customer data of a financial enterprise and the characteristics of enterprise finance, this paper analyzes the risk influencing factors of enterprise financial customers, analyzes the customer data, evaluates the enterprise financial customers through the adaptive genetic neural network model, and realizes the classification of enterprise financial customers. Through an example, it is proved that the enterprise financial customer classification and preference model based on the adaptive genetic neural network algorithm discussed in this paper has better customer classification accuracy and can provide better method support for enterprise financial customer management.

1. Introduction

Customers in modern society have more choices. Customers' needs have been personalized. The competition among enterprises will also become fierce [1]. At the same time, with the progress of production technology, the differences between commodities become smaller, and the focus of competition changes from "product-centered" to "customer-centered" [2]. Only the enterprises that meet the needs of customers as quickly as possible can realize the sales of products. Only financial enterprises that can quickly respond to the individuation and change of customers can survive and develop in the fierce market competition. The most important index of enterprise management has changed from profit and cost to customer satisfaction. Customer relationship management is an important means for financial enterprises to gain competitive advantage. Therefore, this paper uses the improved self-adaptive genetic neural network customer classification model, which can distinguish the customers with different purchasing tendencies of financial enterprises and provide financial enterprises with different customers as the target, differentiated, and effective marketing services, which not only reduces the cost but also improves the operating profit and facilitates the financial customer relationship management of enterprises [3].

The effective classification of customers is the key to maintain and manage customer relationships in various fields, so it has attracted much attention. This paper puts forward a new method of customer value classification based on BP-AdaBoost, which is based on BP and AdaBoost algorithm, and analyzes the characteristics of different customers according to the designed evaluation system. AdaBoost algorithm is used to form a strong classifier, so as to improve the accuracy of traditional BP network [4]. Experiments show that this method is also effective for the application of financial customer classification, and the accuracy is satisfactory.

By collecting 2000 social media reviews of financial banks on the Internet, we studied the research framework for establishing financial bank data sets. In today's intelligent network, the role of social media in various fields cannot be ignored, including financial institutions. It can provide ways and channels to analyze needs and understand how to improve product quality and service, so that financial institutions can tailor personalized needs for customers. This framework uses various machine learning methods and technologies to classify emotions [5]. With fierce market competition, many financial institutions have to take sales as the first premise and use the quickest way to focus on "possible" customers. At the same time of competition, although financial institutions have a series of documents and methods to control risks, the borrower's intention is not obvious, which leads to a great reduction in the controllability of risks. In view of this serious phenomenon, we study the method of machine learning to promote handwriting analysis, which reflects a certain degree of intention from the unique properties of handwriting, and the recognized handwriting association is helpful to map individuals to corresponding personality types. When using machine learning technology to collect the samples of personal management questionnaire, it shows that extroversion is related to financial behavior as a "risk seeker" [6]. The early warning model of Internet finance is of great significance for enterprises in the financial field to prevent and control risks. We propose an improved K-means algorithm based on quantum evolution, which combines initial value and risk value to determine the risk early warning interval, and introduce quantitative algorithm into this algorithm to improve the search efficiency, so as to get the accurate early warning interval. Finally, we calculate the risk value with GMDH prediction mining method. Comparing nearly 10,000 data of Internet financial companies with real financial institutions, it shows that its model is available and effective [7].

2. Adaptive Genetic Neural Network Algorithm

2.1. Theory of Artificial Neural Networks. Artificial neural network is a complex system composed of many processing units similar to biological neurons [8].

2.1.1. Neuron Model. Artificial neural network is composed of artificial neurons as many basic processing units [9]. To establish an artificial neural network, we must first decide the artificial neuron model. Figure 1 is a general model structure diagram of artificial neurons.

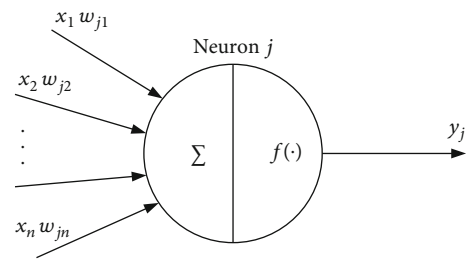

Figure 1: Neuron model.

2.1.2. BP Algorithm. BP algorithm is the most commonly used algorithm in neural network model learning. BP algorithm is a supervised learning algorithm. The idea of BP algorithm is that initial weights and thresholds are first provided to the network; an actual output value of the network is calculated from the input value [10, 11]; then, the desired output value is compared with the actual output value; such learning is repeated on the training samples based on the obtained weights and thresholds of the error correction network, and finally, the error between the actual output and the desired output is minimized.

The specific process is as follows:

It is assumed that the neural network is an I input unit and a K output unit, the implicit layer is a layer, and the J unit is shared. The BP algorithm is executed primarily to minimize the square error between the actual output, and the expected output obtained after the data is input into the network. The formula for the sum of squared errors is as follows.

$$E = \frac{1}{2}\sum_{k=1}^{k}(d_k - o_k)^2. \tag{1}$$

Among them, $o_k = f(\text{net}_k)$ is the actual output value of neuron k in the output layer, d_k is the expected output value of neuron k in the output layer, and y_j is the output value of hidden layer neuron j.

For the E value, in order to achieve the goal of the ideal value, it is necessary to change the weight value of the network. First, adjust the connection weights between the implicit layer and the output layer.

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj}. \tag{2}$$

In the above formula, the value obtained by the gradient method is the adjusted value of the connection weight between the implicit layer and the output layer.

$$\Delta w_{kj} = -\eta\frac{\partial E}{\partial w_{kj}} = \eta(d_k - o_k)f'(\text{net}_k)y_j. \tag{3}$$

In the above formula, η is the normal value, which is expressed as the iteration step.

In a similar manner, you can adjust the join weights between the input layer and the implicit layer. Formula

adjustment is as follows:

$$v_{ji}(t+1) = v_{ji}(t) + \Delta v_{ji}. \quad (4)$$

In the above formula, Δv_{ji} is the adjustment amount for determining the connection weight between the input layer and the implicit layer by the gradient method. It can be obtained from the following formula:

$$\Delta v_{ji} = -\eta \frac{\partial E}{\partial v_{ji}} = \eta \sum_{k=1}^{k} (d_k - o_k) f'(\text{net}_k) w_{kj} f'(\text{net}_j) x_i. \quad (5)$$

When there are samples, if there are P training samples, the total error sum form of the above calculation method is as follows:

$$E_p = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{K} (d_k - o_k)^2. \quad (6)$$

As long as the operation is repeated for P samples as described above, E_p reaches the minimum requested value, and the algorithm ends.

2.2. Adaptive Genetic Algorithm. Adaptive genetic algorithm is evolved from basic genetic algorithm [12, 13]. It has strong global search performance and strong local search ability and accelerates the convergence speed to a certain extent. But it also has inherent defects.

2.2.1. Improvement of Adaptive Genetic Algorithm. The adaptive change formulas of crossover probability P_c and mutation probability P_m used in traditional adaptive genetic algorithm are as follows:

$$p_c = \begin{cases} \dfrac{k_1 \left(f_{\max} - f'\right)}{f_{\max} - f_{\text{avg}}}, & f' \geq f_{\text{avg}} \\ k_2, & f' < f_{\text{avg}} \end{cases}, \quad (7)$$

$$p_m = \begin{cases} \dfrac{k_3 (f_{\max} - f)}{f_{\max} - f_{\text{avg}}}, & f \geq f_{\text{avg}} \\ k_4, & f < f_{\text{avg}} \end{cases}. \quad (8)$$

Among them, f_{avg} is the average fitness value of all individuals in the population, $f_{\max}$ is the maximum individual fitness value in the population, f' is the fitness value of the individual with the larger fitness value among the two individuals to be crossed, and f is the fitness value of the individual to be mutated, any number comes from $k1$, $k2$, $k3$, $k4$, 0 and 1.

Srinivas et al., by proposing $K1 = K2 = K$, $K3 = K4 = K'$, represent adaptive adjustment curves for crossover probabilities and change probabilities in Figures 2 and 3.

As shown in the figure, in the early stage of evolution, individuals with higher fitness values may not be the global optimal solution.

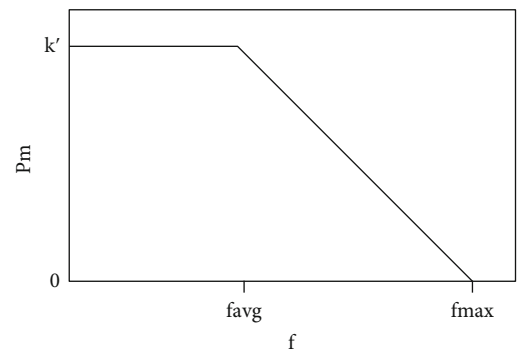

Figure 2: Variation curve of mutation probability.

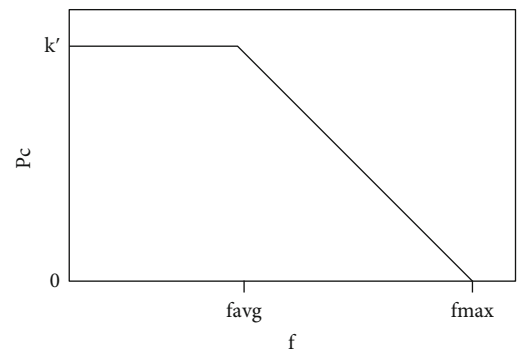

Figure 3: Cross probability change curve.

To solve this problem, this paper proposes an adaptive genetic algorithm. In addition, in order to maintain a better individual pattern after the evolution of the algorithm, the adaptive adjustment curve in $f_{\max}$ should be smoothed as much as possible. The formulas of crossover probability and mutation probability are as follows.

$$p_c = \begin{cases} p_{c1} * \dfrac{1}{\exp\left(\left(f' - f_{\text{avg}}\right) / \left(f_{\max} - f_{\text{avg}}\right)\right)}, & f' \geq f_{\text{avg}} \\ p_{c1}, & f' < f_{\text{avg}} \end{cases}, \quad (9)$$

$$p_m = \begin{cases} p_{m1} * \dfrac{1}{\exp\left(\left(f - f_{\text{avg}}\right) / \left(f_{\max} - f_{\text{avg}}\right)\right)}, & f \geq f_{\text{avg}} \\ p_{m1}, & f < f_{\text{avg}} \end{cases}, \quad (10)$$

where f' is the fitness value of the larger of the two individuals to be crossed, f_{avg} is the average fitness value of all individuals in the population, $f_{\max}$ is the largest individual fitness value in the population, f is the fitness value of the variant individual, and P_{c1} and P_{m1} are the largest crossover probability and mutation probability, respectively.

The adaptive adjustment curves of crossover probability and mutation probability are shown in Figures 4 and 5.

2.3. Adaptive Genetic Algorithm Evolutionary Neural Network

2.3.1. Defects of Neural Networks. BP neural network is the most widely used model of neural network in classification [14, 15], and this algorithm is simply analyzed here. BP algorithm is an effective algorithm, but it also has some defects in practical application:

(1) Once a complex problem is solved, the result will fall into a local minimum, which will lead to the failure of learning

(2) If the learning speed decreases, the convergence speed will definitely slow down, but if it increases, the correction will not only be excessive but also cause vibration and divergence

(3) The number of input and output nodes of the network can be known according to the problem, and the selection of the number of hidden nodes is based on experience and lacks theoretical guidance

(4) The robustness is poor, and the initial setting value of the network has great influence on the overall performance of the network

Because BP neural network still has a series of defects [16, 17], we need to make some improvements to optimize its performance in order to get more satisfactory results. In this paper, the improved adaptive genetic algorithm is combined with neural network to make up for the abovementioned one or two shortcomings of neural network and the shortcomings of genetic algorithm itself, such as the reduction of convergence efficiency in the early stage and the middle and late stage.

2.3.2. Adaptive Genetic Neural Network. Up to now, the combination direction of genetic algorithm and neural network can be roughly divided into the following three types [18, 19].

(1) Optimizing network connection weights and thresholds

(2) Optimizing the topological structure of the network

(3) Optimize the learning rules of the network

The first optimization method is used most for BP neural network. This process corresponds to dividing the whole network into two steps. In the first step, genetic algorithm is used to derive the initial weights and thresholds of the network. In the second step, BP algorithm is applied to finally complete the training of the network. There are three key aspects in the optimization process: the expression of chromosome, the definition of fitness function, and the construction of genetic operator.

(1) Chromosome expression (i.e., coding mode)

Real numbers are used here. Because the scope of network rights is unclear, using real numbers can avoid coding becoming difficult. In addition, the efficiency of the learning algorithm can be improved without coding and coding. Real numbers are easy to retrieve in a large space, which can meet the accuracy requirements of genetic algorithm [20].

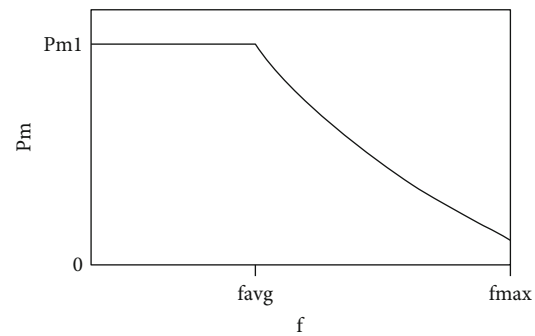

Figure 4: Variation curve of mutation probability after improvement.

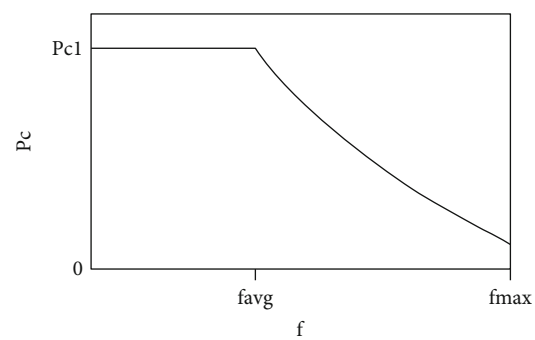

Figure 5: Modified curve of crossover probability.

Taking a three-layer neural network as an example, chromosome length is as follows:

$$l = W_1 + b_1 + W_2 + b_2. \tag{11}$$

Chromosomes are composed of l random numbers between 0 and 1.

(2) Definition of fitness function

After determining the initial weights and thresholds of the BP neural network, an estimate of the number of inputs for training can be used as an evaluation function of the chromosomes. The evaluation function may be expressed as the reciprocal of the absolute value of the error between the actual output value and the expected output value obtained by the adaptation function, namely,

$$f = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{k}\left|y_{ij} - o_{ij}\right|}. \tag{12}$$

(3) Construction of selection operator

By using the best individual preservation strategy, the individual with the highest adaptability in the current group

is prevented from participating in the subsequent cross-meaning and mutation operations. By replacing the individual with the lowest adaptability in the generation group, the best individual obtained so far will not be destroyed, and the convergence of the algorithm can be guaranteed.

(4) Construction of crossover operator and mutation operator

Adaptive crossover operators and mutation operators change adaptively according to the evolution of groups [21, 22].

For BP neural network which determines the overall structure, the algorithm flow is as follows.

(1) *Group Initialization*. N groups of initial network weights are randomly generated, and each group is used as a chromosome

(2) *Select the Operation*. Calculate the proportion corresponding to the fitness value of each chromosome, and select N individuals to the next generation by roulette and the best individual preservation strategy

(3) Cross operation

(4) *Mutation Operation*. The number of iteration steps reached is (5), otherwise (2)

(5) Substituting the best chromosome into the initial value and threshold value of BP neural network and continuing in the training group until the error accuracy, or the set maximum algebra is reached

The algorithm flow chart is shown in Figure 6:

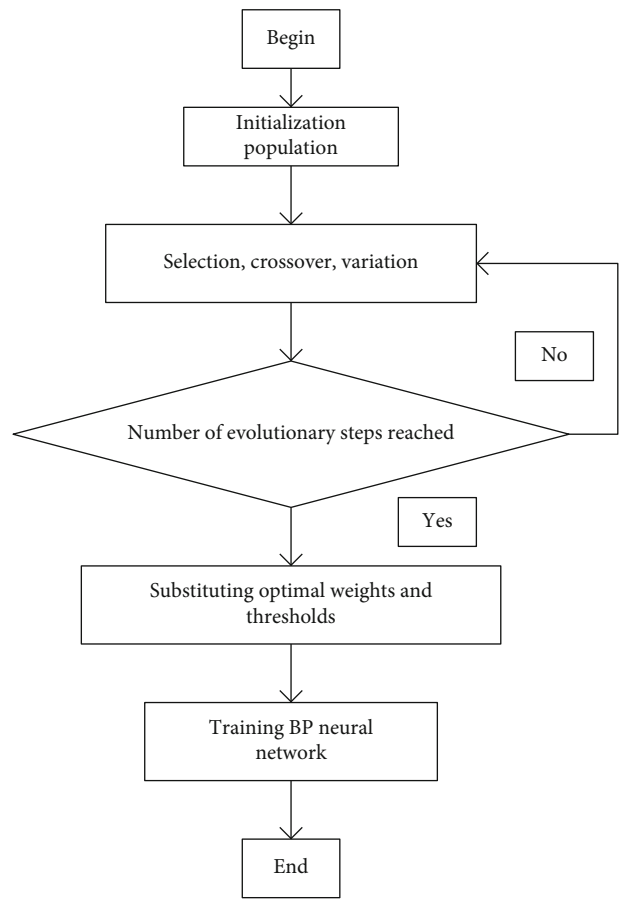

Figure 6: Flow chart of adaptive genetic neural network algorithm.

3. Research on Classification and Preference of Enterprise Financial Customers Based on Adaptive Genetic Neural Network Algorithm

3.1. Parameter Modification of BP Neural Network. In this paper, the gradient descent method is mainly used to study the classification and preference of enterprise financial customers by using BP neural network, and the weight of each BP neuron in the network is adjusted [23]. The specific operation process is as follows.

Analyze the output of hidden nodes in the network

$$y_i = f\left(\sum_j \omega_{ij} x_j - \theta_i\right) = f(\text{net}_i). \tag{13}$$

Among them:

$$\text{net}_i = \sum_j \omega_{ij} x_j - \theta_i. \tag{14}$$

In the three-layer BP neural network structure, the input of output nodes is the output of hidden nodes.

Table 1: Sample index numeralization.

Indicators	Default	Housing	Loan	Marital	Contact	Day
0	No	No	No	—	—	—
1	Yes	Yes	Yes	Married	Unknown	0-9
2	—	—	—	Divorced	Telephone	10-19
3	—	—	—	Single	Cellular	20-31

$$s_k = f\left(\sum_i u_{ij} y_i - \theta_k\right) = f(\text{net}_k), \tag{15}$$

$$\text{net}_k = \sum_i u_{ij} y_i - \theta_k. \tag{16}$$

The error between the output node of BP neural network and the actual value of training samples is calculated as follows.

$$E = \frac{1}{2}\sum_k (z_k - s_k)^2 = \frac{1}{2}\sum_k \left(z_k - f\left(\sum_i u_{ij} f\left(\sum_j \omega_{ij} x_j - \theta_i\right) - \theta_k\right)\right)^2. \tag{17}$$

Table 2: Sample index digitization (continued).

Indicators	Education	Balance	Month	Poutcome	Plays
1	Unknown	0以下	1-3	Unknown	-1
2	Secondary	0-999	4-6	Other	0-99
3	Primary	1000-4999	7-9	Failure	100-199
4	Tertiary	More than 5000	10-12	Success	200-299
5	—	—	—	—	More than 300

Table 3: Sample index digitization (continued).

Indicators	Age	Duration	Job
1	0-19	0-99	Admin
2	20-29	100-299	Unknown
3	30-39	300-499	Unemployed
4	40-49	500-599	Management
5	50-59	600-899	Housemaid
6	60以上	900-999	Entrepreneur
7	—	1000-1699	Student
8	—	More than 1700	Self-employed
9	—	—	Blue-collar
10	—	—	Retired
11	—	—	Technician
12	—	—	Services

The weights between output nodes, hidden nodes, and errors are analyzed. If the output nodes in BP neural network are independent of each other, the following relations exist.

$$\frac{\partial E}{\partial U_{ij}} = -\delta_t y_i. \tag{18}$$

3.2. Sample Data Acquisition. The experimental data comes from the enterprise financial customer data set in UCI machine learning database. This data is about whether the marketing products of financial enterprises can finally be purchased by customers. A total of 2000 sets of data samples were taken. Each sample consists of 16 attributes and 1 category. The 16 attributes can be divided into three categories.

Demographic variables: describe some basic information of customers.

Demographic variables: describe some basic information of customers, including age (age), work (job), marital status (marriage), education, default, annual average balance, housing, and personal loan (loan).

Some variables of communication between financial enterprises and customers about current marketing activities include communication mode (contact), the date of the last communication in a month, month of the last communication in a certain year, the last communication time (duration), and the number of communications with this customer during this activity.

Some variables that a financial enterprise communicates with a customer about the last event include the last event and the last communication from the customer (pdays), the number of communications with the customer prior to the event (previous), and the result of the last marketing event (poutcome).

This category indicates whether the customer purchased the marketing products of the financial enterprise this time.

3.3. Sample Data Preprocessing. The steps of data preprocessing are as follows. Firstly, the nonnumerical attributes in the sample are numerized to discretize the continuous attributes. Then, the description and statistics of sample indicators are carried out to analyze the rationality of the application model. After that, principal component analysis is used to extract the hidden main features as input variables of neural network.

3.3.1. Numerical Properties. The nonnumerical attributes in the index are numerized, and the continuous attributes are discrete. The specific process is shown in Tables 1, 2, and 3, and the attributes are listed as the actual attribute values.

3.3.2. Descriptive Statistics of Sample Indicators. In order to explain whether the model is feasible, first of all, the sample indicators are explained and counted, and the statistical results are expressed in Table 4.

From the various values shown by the deviation and peak coefficients in Table 4, these coefficients of age, balance, and month are close to zero, that is, close to normal distribution, but other indicators hardly follow. Therefore, the traditional statistical model, which is constrained by many indexes, cannot be used to analyze and solve this problem. However, because these constraints cannot limit the model based on neural network technology, the classification and preference model based on genetic neural network can be applied here.

3.3.3. Sample Impact Factor Analysis. Factor analysis is a statistical technique, which can summarize a large number of indicators into a few factors and explain a large number of observed facts. When the main features are fuzzy and covered by redundant data, it is difficult for general neural networks to identify them [24, 25]. However, if the main features are clear and the same accuracy is obtained, the operation efficiency of the network model is greatly improved.

Principal component analysis is carried out on the numerical attribute data, and the eigenvalues and contribution rates of the correlation coefficient arrangement of variables are shown in Table 5.

Table 4: Sample index description statistics.

Variable	N	Minimum value	Maximum value	Mean value	Standard deviation	Skewness	Kurtosis
Age	2000	1	6	3.65	1.021	334	-0.540
Job	2000	1	12	7.06	3.493	-0.24	-1.181
Marital	2000	1	3	1.67	0.879	0.695	-1.346
Education	2000	1	4	2.70	0.947	0.301	-1.319
Default	2000	0	1	0.02	0.133	0.256	50.704
Balance	2000	1	4	2.32	0.725	0.534	0.174
Housing	2000	0	1	0.57	0.495	-0.275	-1.926
Loan	2000	0	1	0.16	0.365	1.877	1.524
Contact	2000	1	3	2.38	0.892	-0.823	-1.235
Day	2000	1	3	2.06	0.789	-0.115	-1.384
Month	2000	1	4	2.42	0.809	0.290	-0.395
Duration	2000	1	8	2.34	1.380	1.758	3.244
Campaign	2000	1	32	2.72	2.840	4.069	24.843
Pdays	2000	1	5	1.47	1.096	2.267	3.874
Previous	2000	0	20	0.54	1.607	5.191	38.656
Poutcome	2000	1	4	1.36	0.797	2.038	2.757

Table 5: Sample variance contribution rate table.

Composition	Initial eigenvalue			Extract sum of squares and load			Rotation sum of square loading
	Total	Variance%	Cumulative%	Total	Variance%	Cumulative%	Total
1	2.544	15.898	15.898	2.544	15.898	15.898	2.506
2	1.569	9.808	25.706	1.569	9.808	25.706	1.475
3	1.414	8.835	34.541	1.414	8.835	34.541	1.408
4	1.242	7.761	42.302	1.242	7.761	42.302	1.251
5	1.159	7.246	49.548	1.159	7.246	49.548	1.256
6	1.100	6.877	56.425	1.100	6.877	56.425	1.254
7	1.023	6.396	62.820	1.023	6.396	62.820	1.063
8	0.937	5.858	68.678				
9	0.880	5.499	74.176				
10	0.837	5.232	79.409				
11	0.803	5.018	84.427				
12	0.753	4.706	89.133				
13	0.620	3.877	93.010				
14	0.555	3.471	96.482				
15	0.397	2.483	98.965				
16	0.166	1.035	100.000				

It can be seen from Table 5 that the correlation coefficient matrix of variables has seven largest characteristic roots, which are 2.554, 1.599, 1.414, 1.242, 1.159, 1.100, and 1.023, respectively. The cumulative contribution rate of eigenvalue reaches 62.80%; that is to say, it contains most of the information of the original index. Based on the principle that the eigenvalue is greater than 1, seven main components can be extracted. In order to show the influence degree of principal components on the original index, it is necessary to establish their original factor load matrix. In order to facilitate the extraction of information and maximize the dispersion of principal components, the orthogonal rotation method is used to further process the structurally simplified rotated factor load matrix, and the results are shown in Table 6. Finally, using these seven main component factors, instead of the original indicators, we can study the classification and preference of customers.

Table 6 only shows the load above 0.4, which clearly indicates the economic significance of each major component.

After determining the economic significance of the main component factors and calculating the score coefficient of the sample factors, the linear combination equation of 7 main component indexes and the original 16 indexes can

Table 6: Factor load matrix after sample rotation.

Attribute	Composition						
	1	2	3	4	5	6	7
Pdays	0.923						
Poutcome	0.913						
Previous	0.813						
Housing		-0.727					
Contact		0.687					
Month		0.584					
Marital			0.836				
Age			-0.800				
Balance				-0.656			
Default				0.635			
Loan				0.591			
Job					-0.806		
Education					0.742		
Day						0.744	
Campaign						0.693	
Duration							0.914

Table 7: Prediction errors corresponding to different hidden layer node numbers.

Number of hidden layer nodes	Prediction error	Number of hidden layer nodes	Prediction error
4	0.1176	9	0.0186
5	0.0933	10	0.0267
6	0.0658	11	0.1064
7	0.0872	12	0.0561
8	0.0143	13	0.0751

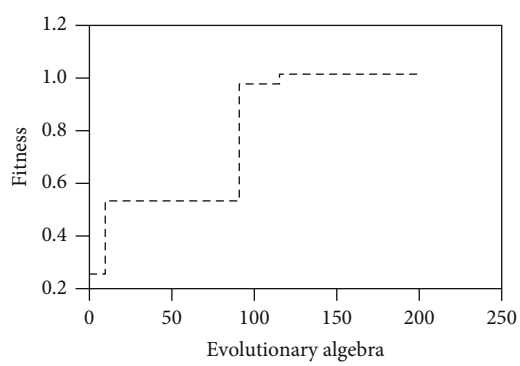

Figure 7: Variation diagram of fitness curve of traditional AGABP.

be obtained. These seven main component indicators can be replaced by the original 16 indicators as a new index system, which can be used as the input data of the follow-up model.

4. Experiment

4.1. Definition of Model Structure and Selection of Parameters. The sample data obtained from the principal component analysis of the original index of the sample is composed of 7 variables, so the number of input rows of the network is 7.

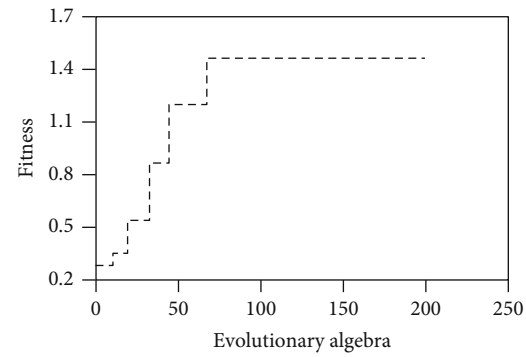

Figure 8: Change diagram of fitness curve of improved AGABP.

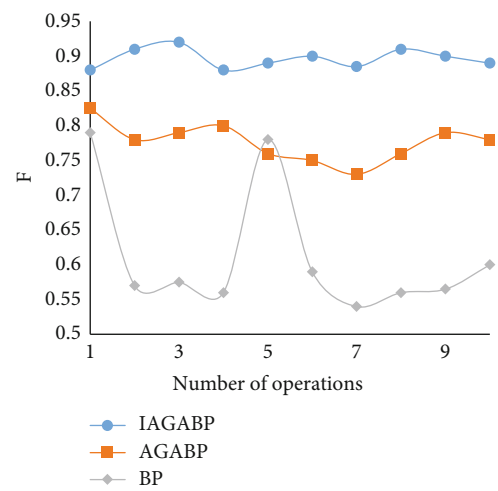

Figure 9: Comparison results of different algorithms.

Determine the number of output layer nodes. The number of output layer nodes is determined by the number of desired output results of the network. This model divides the customer's output into two types, 1 for the customer's purchase and 0 for the customer's nonpurchase. Therefore, the number of output nodes of BP network model should be 1.

Determine the number of hidden layer nodes. Although there is no accepted standard so far, too much or too little is not appropriate. If the number is too large, the learning time will become longer, and the popularity of the network will decline. If the number is too small, the network may not be able to train or recognize new samples. Fault-tolerant performance is also greatly reduced. Here, the calculation is based on the following empirical equation (21).

$$n = \sqrt{a + b} + c. \tag{19}$$

Use estimates and show the results in Table 7.

The data in the table shows that when the number of implicit layer nodes is 8, the prediction error corresponding

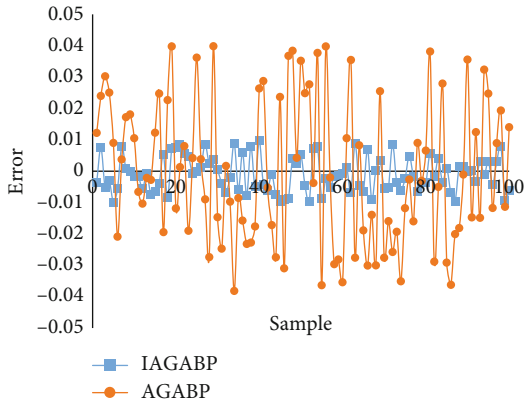

Figure 10: IAGABP and AGABP classification error result diagram of test set.

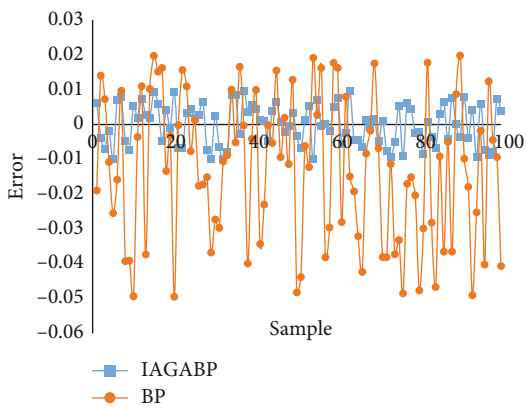

Figure 11: IAGABP and AGABP classification error result diagram of test set.

to BP neural network is the smallest, and 8 is selected as the number of implicit layer nodes. Make up a 7-8-1 network.

4.2. Network Training and Result Verification. In this paper, 2000 corporate financial customer data samples are randomly divided into two groups, and 1900 groups of data are used as training group training network. Another data set 100 examples detect the generalized performance of the network as a test set and predict customer categories and preferences.

4.2.1. Algorithm Performance Analysis

(1) Comparison of Convergence Rate of Genetic Algorithm. Set the end algebra to 200, and Figure 7 converges faster than Figure 8. This shows that the algebra of the latter should be much smaller than that of the former after setting a fixed convergence value, so the latter is much more efficient than the former.

People expect the same from all algorithms. I hope to converge early and realize overall optimization, but they are just a pair of contradictory requirements. As far as genetic algorithm is concerned, if it converges quickly, the speed close to the best state will become faster, which cannot guarantee the diversity of combinations and makes it difficult to realize the overall optimization. In order to obtain the global optimum value, we must try our best to avoid falling into local extremum. This is because the population must keep the diversity of individuals as much as possible, so it cannot converge quickly. Therefore, if you want to combine the two, you should consider them comprehensively and choose from them. The method proposed in this paper not only pursues global optimization but also considers the operation speed of genetic algorithm, so as not to affect the global convergence speed as much as possible, thus finding a good balance between them.

Table 8: Summary of prediction effect of each model.

Neural network type	BP neural network (BP)	Traditional adaptive genetic neural network (AGABP)	Improved adaptive genetic neural network (IAGABP)
Classification accuracy	73%	82%	97%

(2) Stability Analysis. In order to verify the performance of the adaptive genetic neural network algorithm proposed in this paper, BP neural network algorithm, traditional adaptive genetic neural network algorithm, and improved adaptive genetic neural network algorithm are executed several times, respectively, and the correctness of the calculation method is evaluated according to F evaluation index. Here, the higher the F value, the higher the correctness of the result. The stability of the algorithm can be judged by whether the data has great changes. The experimental results are shown in Figure 9.

Through the above experimental results, it can be seen that the F value of the improved adaptive genetic neural network algorithm proposed in this paper is obviously higher than the other two algorithms in the global range, and the fluctuation in the global range is small, reflecting better stability. Among them, BP neural network algorithm has the smallest F value, which fluctuates greatly, and the lowest accuracy rate drops to less than 60%. As far as the traditional adaptive genetic neural network algorithm is concerned, its stability and accuracy have been improved to some extent, but compared with the improved adaptive genetic neural network algorithm, there are still some shortcomings, and the latter maintains better stability and higher accuracy.

From the above experimental results, it can be seen that the F value of the adaptive genetic neural network algorithm proposed in this paper is significantly higher than the other two algorithms in the global situation, and it fluctuates less in the global situation and shows better stability. The F number of BP neural network algorithm is the smallest, and it is easy to change greatly, and the lowest accuracy will reach below 60%. In the traditional adaptive genetic neural network algorithm, its stability and accuracy have been improved to some extent, but compared with the improved

adaptive genetic neural network algorithm, it is not sufficient, and the latter maintains better stability and high accuracy.

4.2.2. Comparison of Classification Accuracy. Figures 10 and 11 show the error results of classification test for 100 sets of data. It can be seen intuitively that the error of IAGABP is closer to 0 than that of AGABP and BP. To sum up, it can be concluded that IAGABP is more accurate than BP and AGABP in the application of corporate financial customer classification and preference.

According to the prediction results, if the indication with error within 0.01 is classified accurately, the prediction effects of each model on samples are summarized as shown in Table 8.

According to the data, the classification accuracy of adaptive genetic neural network is the highest, which is 24% and 15% higher than BP neural network and traditional adaptive genetic neural network, respectively.

5. Conclusion

Through the above research, we should provide targeted services to different types of customers.

(1) Buy customers

Maintaining such customers plays a stable and important role in the income of financial enterprises. Therefore, financial enterprises must take measures to maintain long-term contact with them. For example, keep the communication channel smooth at all times. When issuing products or services, financial enterprises should let customers know in time, actively attract their opinions and actively improve to meet their needs. For example, the fee and annual fee of various cards are reduced, the agency business fees are eliminated, and the remittance fee rate and personal insurance rate are reduced.

(2) Unpurchased customers

For such low-value customers, there is almost no contribution rate to financial products, but there are small deposits. For their needs, financial enterprises can reduce their counters and use the electronic equipment of financial enterprises. Such customers basically have no development value. The development cost is much higher than the income they create for the enterprise. Therefore, there is no need to carry out any marketing of products and services for such customers.

After analyzing the classification and preference of existing customers, financial enterprises should strive to provide corresponding services for different types of customers, maintain existing high-value customers to the maximum extent without wasting resources, and obtain more benefits for corporate finance. The future work needs to be carried out from the following points: (1) The data dimension of financial customers is insufficient, so we hope to analyze and predict the data under a large amount of data and adopt a deep multilayer learning complex model for learning and analysis; (2) intelligent algorithms can be applied to financial credit classification to dig deep into risky customers.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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