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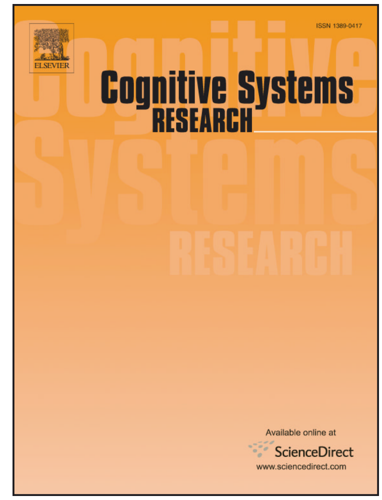

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Enterprise Credit Risk Evaluation Based on Neural Network Algorithm

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Abstract: To explore the enterprise credit risk evaluation, the application effect of several common neural network models in Chinese small and medium-sized enterprise data sets was compared and the optimal parameters for each model were determined. In addition, the classification accuracy and the applicability of the model were compared, and finally the common problem of optimization neural network algorithm based on population was solved: need to determine the dimensions in advance. The experimental results showed that the probabilistic neural network (PNN) had the minimum error rate and second types of errors, while the PNN model had the highest AUC value and was robust. To sum up, the algorithm makes some contributions to solve the financing problem of small and medium-sized enterprises in China.

Keywords: credit risk assessment; artificial intelligence; neural network

1. Introduction

Credit risk is an important issue in the decision-making and profit of the banking industry. Credit risk is still a single biggest risk that is difficult to offset for banks and it expresses the concept of future loss. Because the customer does not fulfil the repayment obligation, the credit risk also embodies the loss of the bank's profit.

Usually, the general approach of credit risk assessment is to apply the classification model to past customer data, including default and non-default customers, so as to find the relationship between user characteristics and potential default. The credit risk assessment model based on statistical data has become the main analysis tool for the financial institutions to assess the credit risk. By analysing the multiple risk factors of the evaluation object, the credit risk assessment is an independent process of assessing the borrower's willingness and ability to repay. The credit risk assessment model has been widely used to assess corporate risk by bond investors, debt issuers, and government officials. They provide a means to determine the risk premium and bond market, so that companies can assess the possible return on investment to issue bonds. The advantages of building a credible credit risk assessment system are: reducing the cost of credit analysis, ensuring fast decision-making, guaranteeing credit collection and reducing possible risks.

The credit risk assessment was initially judged by the personal experience manager, and then based on the 5C factor. However, with the rapid increase of applicants, it is almost impossible to do the work manually. Many institutions in the credit industry are proposing new models to support credit decisions. Recent studies have shown that the existing artificial intelligence (AI) technology, such as decision tree (DT), support vector machine (SVM) and so on, in the problem of credit risk assessment, shows a better performance than the statistical model and optimization method. Different from statistical models, AI model does not require the assumption of variable distribution, and can acquire knowledge directly from training data sets. In the field of credit risk assessment, especially when the credit risk assessment problem is nonlinear mode classification, the performance of AI model is better than that of the statistical model.

2. State of the art

Chang et al. [1] proposed a short-term credit risk assessment model based on decision tree, which is used to evaluate credit risk. The goal is to use a decision tree to filter short term breaches to produce a highly accurate model that can distinguish between default loans. In this paper, a credit risk model is established by combining Bootstrap aggregation with the minority of sampling techniques to improve the stability of decision tree and the performance of unbalanced data. Zhang et al. [2], based on the neural network of particle swarm optimization genetic algorithm, studied the cross border e-commerce credit risk assessment model, and put forward the construction process of credit risk assessment model based on PSO-GA in BP neural network. The results showed that the above model could effectively meet the requirements of the cross-border e-commerce credit risk assessment. Bao [3] used BP neural network simulation to obtain the credit rating of individual borrowers from P2P network. And the simulation was carried out in the absence of data. Compared with the website rating, the simulation results were more accurate, and the credit risk of individual borrowers could be effectively evaluated. On the basis of the analysis, some suggestions and countermeasures of the network platform were given. Bekhet and Eletter [4] proposed two credit scoring models using data mining technology to support the loan decision of commercial banks in Jordan. The loan application assessment will improve the effectiveness of the loan decision, control the task of the loan office, and save the analysis time and cost. Loan applications that are accepted and rejected from different commercial banks in Jordan are used to establish a credit scoring model. The results showed that the logistic regression model was superior to the radial basis function (RBF) model in terms of the overall accuracy rate. However, the radial basis function is better than the identification of those who may default.

Yang [5] firstly proposed an improved quantization method, that is, IDM, based on statistical independence. Then, data mining technology, namely, decision tree C4.5, naive Bias and SVM classifier, were used to classify and predict the quantified credit data. The impact of quantitative methods on the classification of credit approval data was studied. The experimental results showed that this method significantly improved the average accuracy of the classification than other known quantized methods. This showed that the proposed method could effectively explain and illustrate the design ability of a new type of intelligent aid credit approval data system. Zhang and others [6] established a credit risk assessment index system, and adopted the supply chain view that considered the credit status of the enterprise and the relationship between the supply chains. In addition, the credit risk assessment model based on support vector machine (SVM) and the implementation technology of BP neural network were also carried out. The credit risk assessment index system, including the credit status of the leading enterprises in the supply chain and the cooperative relationship between the small and medium-sized enterprises (SMEs) and the leading enterprises, could help banks to predict the accuracy of the default of SMEs. As a result, more SMEs can get loans from the banks through SCF. Fatemi and Fooladi [7] believed that the SCF credit risk assessment model based on support vector machine (SVM) had good generalization ability and robustness, which was more effective than BP neural network evaluation model. Therefore, the application of support vector machine model can improve the accuracy of credit risk assessment for small and medium-sized enterprises, thus alleviating the problem of credit rationing in small and medium-sized enterprises.

We use the financial data of 46 unlisted SMEs in the triangle area to formulate indexes, and make a deep comparative study of 4 kinds of neural network models and decision tree methods used for risk assessment. The credit risk assessment model in this study can provide powerful tools and technical support for effective early warning of bank credit risk, and it can provide a scientific and reasonable quantitative basis for loan approval. Therefore, the risk management level and the comprehensive competitiveness of the bank can be improved. At the same time, it can also play a certain role in promoting the development of the enterprise.

3. Methodology

Backward propagation (BP) is the most popular application of neural network structure. The main reason for the popularity of backward propagation is that backward propagation can learn and obtain very complex mapping. The BP neural network uses a supervised learning model and a backward propagating network structure, as shown in Figure 1.

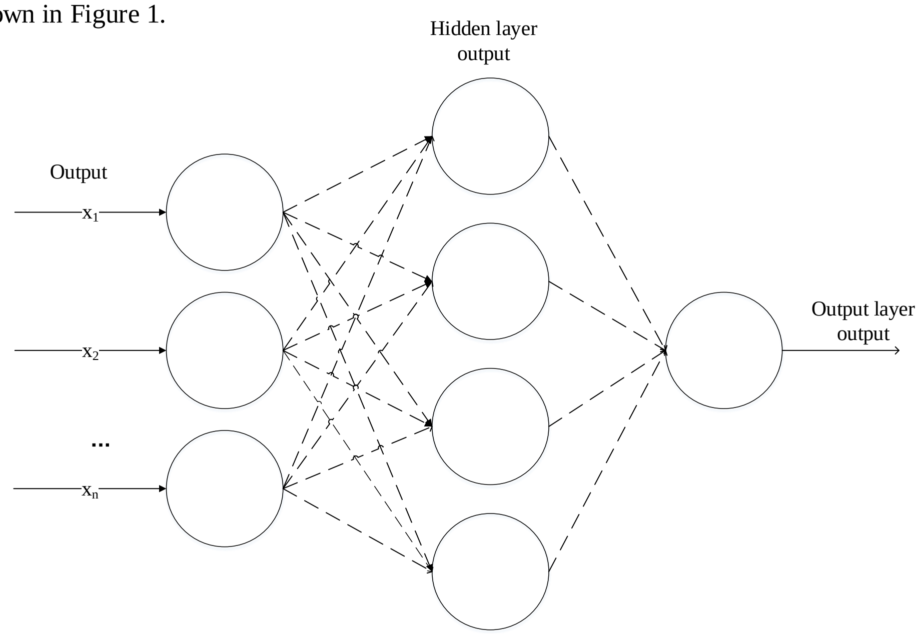

Figure. 1 BP neural network topology

Topology is shown above: the input layer, the hidden layer, and the output layer. BP describes the relationship between the layer's input and the output by using the activation function that can be guided, and the S type function is commonly used. The input unit receives a foreign input sample x, which is adjusted by the weight coefficient w of the network by the training unit, and then outputs the result by the output unit. In this process, the desired output signal can be used as a teacher's signal to input, and the error generated by the comparison between the teacher's signal and the actual output can control the modification weight coefficient w.

The input sample signal acts through the weight coefficient and produces the output results in X. The desired output signal y and net are compared, and the error signal e is produced. The weight adjustment mechanism modifies the weight coefficient of the learning system according to the error e. The direction of modification should make the error e smaller and continue to go down, so that the error e is zero. When the actual output value net is exactly the same as the expected output value y, the learning process is finished. A particular sample produces the expected value of d.

The specific formulas are as follows:

Input:

$$X = x_1 w_1 + x_2 w_2 + \ldots + x_n w_n \tag{1}$$

Output:

$$y = f(X) = \frac{1}{1+e^{-net}} \tag{2}$$

Derive:

$$y' = f(net)' = f(net)[1 - f(net)] \tag{3}$$

The RBF neural network is a three layer feed-forward network, which is the input layer, the hidden layer and the output layer. From the input layer to the hidden layer, it is a nonlinear to linear transformation process, and from the hidden layer to the output layer, it is a linear processing process. RBF neural network in dealing with nonlinear problems, introduces RBF kernel function to map nonlinear space into linear space. It greatly improves the nonlinear processing ability, and RBF neural network applies the self-organizing supervised learning algorithm for training and the training convergence speed has significant advantages.

The data used in the experiment come from the financial and default situations of 46 SMEs in the Yangtze River Delta Region, of which 21 businesses default, and the other 25 do not default. The evaluation index will be formulated from three aspects to determine the input variables of the model. These three indicators are the operation capacity of enterprises, debt paying ability and profitability, respectively (Table 1). The measurement of enterprises' operating capacity chooses current assets / net sales this index; the measurement of the solvency of enterprises selects current assets / current liabilities and cash flow / total debt two indicators; the measurement of the profitability of the enterprise uses the net income / total assets.

Table 1 Data selection indexes and measurement

Index	Measurement
Current assets / net sales	Operational capacity
Current assets / liquidity negative cash flow / total debt	Solvency
Net income / total assets	Profitability

The training set has plenty of samples to have better representativeness, thus ensuring the good generalization ability of the established model. It is generally believed that 2/3 to 3/4 of the total number of samples are the most representative training set samples, and the remaining 1/4 ~ 1/3 is the test set sample. At the same time, the distribution of the training set and the test set sample is almost the same as much as possible. Therefore, in this experiment, we chose the 30+16 combination to provide training and testing datasets. That is, 30 companies were randomly selected as the training data set, and the remaining 16 companies as test data sets. In the neural network model, the output of default enterprise and non-default enterprise is represented by (0,1) and (1,0), respectively.

In this experiment, three common metrics in the field of credit risk assessment are selected as the criteria to measure the quality of the models. The three indicators include the average accuracy (Average), the first type error (Type I error) and the second type error (Type II error). Among them, the first and second types of errors are the two common types of classification errors in the credit risk assessment system. For banks, the first type of error classifies good customers into bad customers and rejects the customer's loan application, which would reduce the bank's profits. In contrast, the second type of error indicates that the bad customer is classified as the good customer and the loan is provided, which makes it easier to cause loss. Researchers tend to pay more attention to the second type of errors, because the second types of errors are generally considered to have a more serious impact on financial institutions. In the previous study of the credit risk assessment model, SVM is generally considered better than ANN because its objective function can control the second type of errors. However, the role of the first type of errors cannot be ignored in improving the bank's income.

According to the obfuscation matrix (Table 2), the calculation method of the three indexes is as follows:

$$\text{Average} = (\text{TP}+\text{TN})/(\text{TP}+\text{FP}+\text{FN}+\text{TN}) \tag{4}$$

$$\text{Type I error} = \text{FN}/(\text{TP}+\text{FN}) \tag{5}$$

$$\text{Type I error} = \text{FP}/(\text{TN}+\text{FP}) \tag{6}$$

Table 2 Credit risk assessment obfuscation matrix

		Physical truth	
		The result of the test is positive (non - default)	Negative value (breach of contract)
Test result	Positive value (non default)	True value (TP)	False positive value (FP)
	Negative value (breach of contract)	False negative value (FN)	True negative (TN)

In this paper, the AUC value in the RoC curve is used as a tool to verify the predictive power of the credit risk assessment model. For example, the RoC curve is a two-dimensional graph, which represents the ratio of classifying the bad applicants as bad applicants (known as "sensitivity" ordinates) to wrongly judging good applicants as bad applicants (abscissas called "1- specific"). The R0C curve is a measure of the overall performance of the model under different boundary values. In fact, sensitivity is equal to 1 minus second kinds of errors, and specificity is equivalent to 1 minus the first kind of errors. AUC (Area Under Curve) value is an important index of RoC curve, that is, the area between RoC curve and abscissa. The bigger the AUC value is, the better the credit risk assessment model is. The maximum value is 1. When the RoC curve coincides with the 45 degree line, the value of AUC equals to 0.5, and the corresponding credit risk assessment model has no identification. It is more comprehensive and objective to evaluate the predictive ability of the model by using the AUC value. The conclusion is more reliable when comparing the prediction ability of various models.

4. Results and discussion

4.1 Credit risk evaluation

The bank is described by microeconomics language, that is, banks are the most suitable (Pareto optimal) organization to collect individual participants. It can play three main intermediary functions: liquidity intermediary, risk intermediary and information intermediary. The meaning of a bank is that it can complete intermediary services well and fill the gap in the financial market. Nowadays, bank risk has become one of the most important research topics in the financial field, especially in the banking industry. Among them, credit risk is the risk that threatens the survival of the bank. It is the main cause of the bankruptcy and the most obvious risk in the management of the banking industry.

It is necessary to reduce the credit risk faced by the bank. In order to reduce the adverse effects of credit risk, banks must evaluate the ability of customers to perform repayment obligations according to the agreements signed by both sides, so as to evaluate the possibility of user default. It is necessary to use qualitative tools and quantitative methods in assessing the risk of breach of contract. Credit rating is one of the most familiar forms in qualitative measurement. The credit rating is carried out by the rating agency, which guarantees the benefits of investors active in the bond market and supervises the debt sector. The goal of the rating agency is to issue an independent credit opinion based on a series of accurate standards.

At present, banks are making more and more efforts to replicate the rating process of the rating agencies in order to rating their large customers. However, it is impossible for banks to appoint an analyst to analyse the large number of small - scale risk loans on their balance sheets. For retail and small and medium-sized loans, banks need to identify borrowers' credit based on statistical methods, so as to automatically distinguish "good borrowers" and "bad borrowers". This statistical method is called credit risk evaluation.

4.2 Credit rating

Credit ratings can be divided into two types, one for debt or financial problems, and the other for bond issuers. The first one is the most common, often called "bond rating" or "credit rating". It is very useful to get the possibility that an investor can gain the desired benefits in an issued bond. The latter is an assessment of the financial obligations of the bond issuer, which conveys information about the basic credibility of the issuer. The assessment focuses on the ability and willingness of the issuer to fulfil the burden of political participation in time. The results can be called "the credit rating of the counterparty", the "default rating" or "the issuer's credit rating". The two types of rating are very important in the investment world.

The way that companies get credit rating information is to get a credit rating for a particular bond or debt problem by contact with a professional rating agency. Usually, the document information that enterprises need to submit include: annual reports in recent years, recent quarterly reports, income statements, balance sheets, recent debt problems, and other specific information and statistical reports. The rating agencies will then allow analysts to do some basic analysis of the information submitted by the enterprise. After the analysis is completed, the analyst will submit an analysis report to the rating committee and give its own rating recommendations. The rating committee will discuss with analysts after browsing the analysis report. The final rating agency will give the final results and be responsible for the results.

It is generally believed that credit ratings include the distribution of highly subjective qualitative and quantitative factors, and the identification of variables in the industrial level and the market level. The rating agencies and some researchers have stressed the importance of subjective judgment in bond ratings and some statistical and artificial intelligence models. However, in the following part, we will explain that some credit rating prediction models based on statistics and artificial intelligence can achieve very good prediction results and capture important characteristics in the process of bond rating.

4.3 Determination of the parameters of BP neural network

Figure 2 describes the influence of the number of hidden layer neurons on the BP neural network performance. In order to reduce the impact of the selection, weight and threshold of initialized training set and test set on the results, here the selected evaluation index is the mean value of the error rate for the algorithm operating 50 times (30 training sets and 16 different test sets are randomly selected each time). The error loss estimate divides the two different losses in the case of accepting bad loan applicants and rejecting good loan applicants. The standard index of the evaluation is also based on the obfuscation matrix. For banks, the bad applicants are misjudged to be good applicants, which will lead to greater losses. The loss of the first kind of errors (the good applicants are wrongly judged as the bad applicants) and the second kind of errors (the bad applicants are misjudged as the bad applicants) is significantly different, and the loss brought by the second kind of errors is much greater than that brought by the first kind of errors.

It can be seen from the figure that when the number of neurons in the hidden layer is 7, the total error rate of the test set and the second types of errors are the smallest, which are 0.248 and 0.128, respectively. Therefore, in the subsequent experiments, the value of the number of neurons in the hidden layer of the BP neural network is 7.

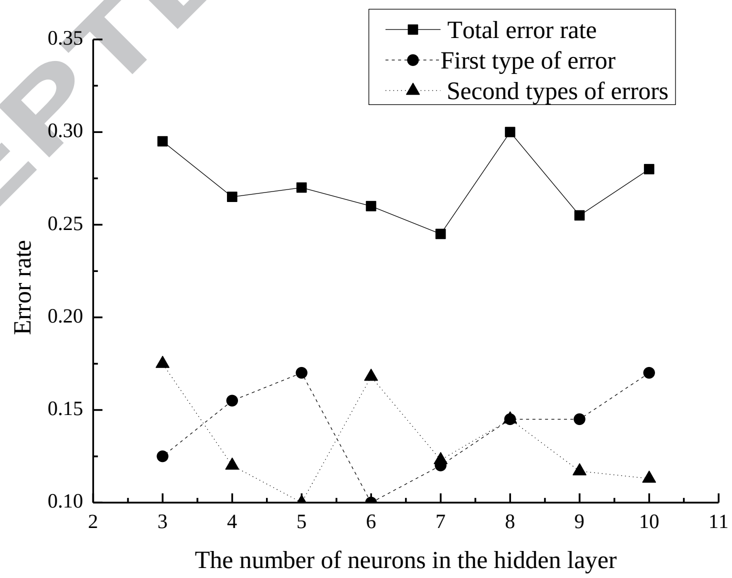

Figure. 2 Influence of the number of hidden layer neurons on the BP neural network

4.4 Determination of the parameters of RBF neural network

In the RBF neural network, the number of neurons in the hidden layer is the same as the number of that of the training set, and the weights and thresholds are directly given by the linear equations. Generally speaking, the performance of RBF neural network is greatly influenced by the expansion velocity of radial basis function.

Figure 3 shows the effects of different spread values on the performance of the RBF neural network. Similarly, in order to reduce the influence of initial training set and test set's selection, weight and threshold on the result, the evaluation index selected here is the mean value of the corresponding 10 erroneous fraction of the program running. It is found that the spread value has little effect on the performance of the RBF neural network. When the value of spread is 0.5, the network performance is slightly better. Therefore, in the subsequent experiments, the spread value of the RBF neural network is taken 0.5.

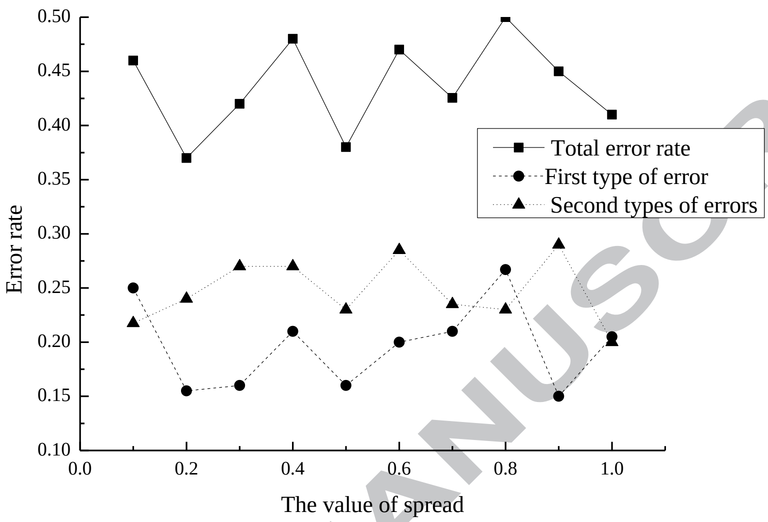

Figure. 3 Effect of SPREAD value on the performance of RBF neural network

4.5 Determination of GRNN and PNN parameters

GRNN is the input layer, the pattern layer, the summation layer and the output layer. Compared with the BP neural network, GRNN has the following advantages: the training of the network is one-way training that it does not need iteration; the number of hidden neurons is determined by adaptive training samples; the weights between each layer of the network is only determined by the training samples, to avoid the weight modification of BP neural network in the iteration revision; the activation function of hidden layer node uses the Gauss function with local activation on the characteristics of the input information, so the input close to the local neurons characteristics has strong appeal.

Probabilistic neural network (PNN) is a kind of feed-forward neural network, proposed by Specht in 1989. He adopted the Gauss function proposed by Parzeri to form the estimation method and Bayesian optimization rules of joint probability distribution. As a result, it constructs the probability density estimation and neural networks with parallel processing. Therefore, PNN not only has the characteristics of the general neural network, but also has good generalization ability and fast learning ability.

The structure of PNN is similar to that of GRNN, which consists of the input layer, the hidden layer and the output layer. Unlike GRNN, the output layer of PNN uses competitive output to replace linear output. Each neuron solves and estimates different kinds of probabilities only on the basis of Parzen method, and the competition layer inputs the response opportunities of patterns. Finally, only one neuron wins the competition, and such winning neuron represents the classification of the input mode. The learning algorithm of PNN is close to the learning algorithm of GRNN, and there is only a slight difference in the output layer.

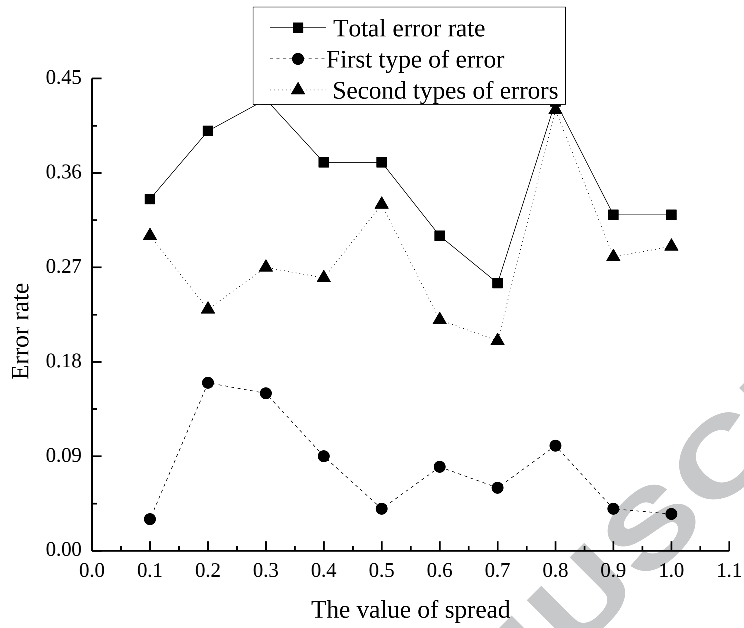

Figure. 4 Effect of SPREAD value on the performance of GRNN neural network

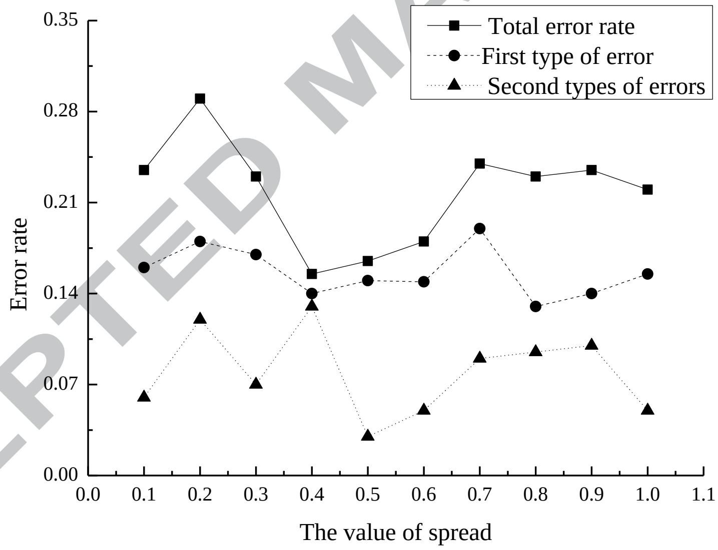

Figure. 5 Impact of SPREAD value on the performance of PNN neural network

Similarly, as shown in Figure 4 and Figure 5, in order to determine the optimal spread value in GRNN and PNN, the experiment compares the average value of the error rate for the program running 10 times. The optimal spread value of GRNN is 0.7, and the spread value of PNN is 0.5.

4.6 Comparison of the error rate of different models

In order to compare the effectiveness of different neural networks in the small and medium-sized enterprise credit risk evaluation problem, the experiment uses the financial and default data of 46 small and medium-sized enterprises in the Yangtze River Delta Region. In the MATLAB platform, programming of BP neural network is realized. We apply neural network toolbox to achieve RB> neural network and PNN, and realize ID3 decision tree algorithm. Assuming that there is a set of loan applicants in the database, each applicant can be divided into two groups of "good credit" and "bad credit". The credit risk assessment model is to find a classification model that can distinguish between good credit and bad credit samples. A decision tree contains a group of Boolean divisions of the data. The algorithm begins with a group of root nodes that contain good credit samples and bad credit samples. Next, the algorithm loops down to find the best split position, and then begins to split into the leaf node and the internal node. The attributes in the ID3 algorithm are discrete values, and the attributes of the continuous values must be discretized. The experiment compares the error rate of each algorithm in the data set (to solve the mean value by operating each algorithm for 10 times), and the specific results are shown in Table 3.

Table 3 Error rate of different models

Model	Total error rate	First type of errors	Second type of errors
BP	0.29	0.13	0.16
RBF	0.47	0.26	0.21
PNN	0.17	0.07	0.10
GRNN	0.25	0.07	0.18
ID3	0.31	0.15	0.16

Table 3 shows the misclassification rate of different model predictions. The observation shows that the credit risk assessment model based on probabilistic neural network (PNN) has the lowest misclassification rate, followed by GRNN, and RBF neural network has the worst prediction effect. The experimental results demonstrate the effectiveness of the model based on PNN neural network in credit risk assessment.

For banks, the bad applicants are misjudged to be good applicants, which will lead to greater losses. The losses brought by first type of errors (good applicants are misjudged to be bad applicants) and second type of errors (bad applicants are misjudged to be good applicants) are significantly different. And compared to the first type of errors, the possible loss caused by second type of errors may be much larger. The analysis of the German credit data set by a scholar West shows that the proportion of losses brought by the second type of errors and the first type of errors is 5:1. A scholar Abdou used this analytical method to further analyse this proportion, and Abdou pointed out that, through sensitivity analysis, this proportion was extended to 7:1 and 10:1.

As shown in Figure 6, it is observed that the credit risk assessment model based on the probabilistic neural network (PNN) has the lowest second type of error rates.

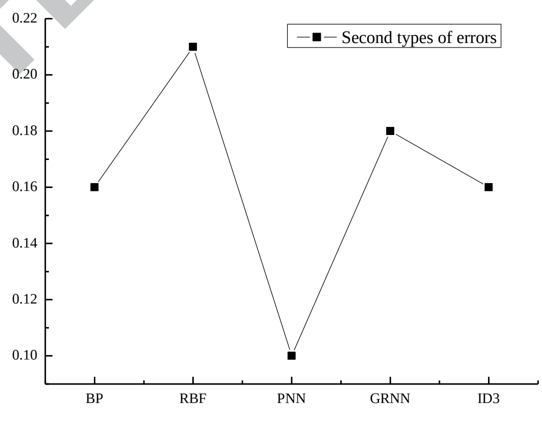

Figure. 6 Second type of errors in different models

Through running each model for 10 times, we solve the mean value. In the experiment, we calculate the prediction result misclassification rate in 46 small and medium-sized enterprises data set in the Yangtze River Delta Region of five kinds of benchmark models. We first of all compare the total misclassification rate of several models. Then, we compare the second type of errors of different prediction models. The experimental results showed that the credit risk assessment model based on the probabilistic neural network (PNN) was the most effective in credit risk assessment.

4.7 Comparison of AUC values of different models

In order to further prove the validity of the model proposed in this paper, the AUC value of the model running results is also selected to compare the prediction ability of different models. Similarly, in order to reduce the effect of selection, initial weights and threshold of the training set and test set on the results, the selected evaluation indexes are the 10 results obtained after running the program for 10 times, and the results are imported into SPSS software, to make their RoC curves. The AUC value of results in each group is recorded and the average value is taken.

Table 4 AUC value and mean value of the running results of different models

Test	1	2	3	4	5	6	7	8	9	10	AVG
BP	0.75	0.82	0.79	0.67	0.55	0.81	0.75	0.61	0.81	0.71	0.73
RBF	0.72	0.71	0.69	0.33	0.51	0.33	0.68	0.54	0.76	0.64	0.59
GRNN	0.61	0.69	0.73	0.69	0.73	0.55	0.61	0.73	0.64	0.90	0.69
PNN	0.66	0.87	0.88	0.82	1.00	0.82	0.94	0.88	0.68	0.72	0.83
ID3	0.90	0.75	0.70	0.75	0.75	0.93	0.87	0.88	0.87	0.80	0.82

Table 4 shows the AUC value and its average value (AVG) of the results of the 10 corresponding results of the different credit risk assessment models. The observation showed that: in the 4 kinds of neural network models, PNN has achieved the best classification results, and obtained the highest AUC value and the highest mean AUC in the 5 set of experiments; ID3 classification results are just followed PNN; the classification results of RBF neural network are the worst, and the value of AUC of a few groups is even less than 0.5.

Figure 7 and Figure 8 show the broken line graphs of AUC values and mean values of different models running results. We can see that the probabilistic neural network (PNN) model has the highest average AUC value and is robust.

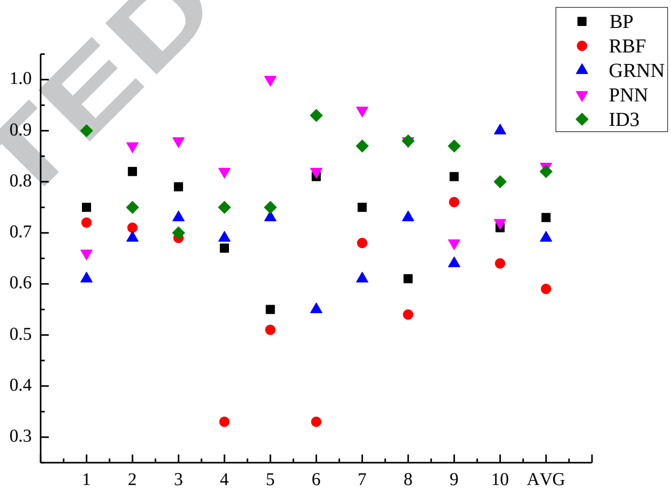

Figure. 7 AUC value and mean value of the running results of different models

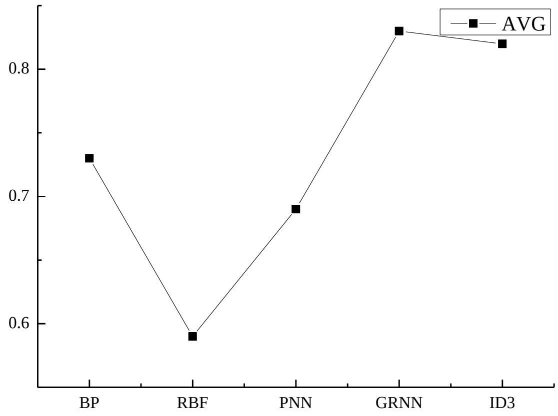

Figure. 8 The AUC mean value of the running results of different models

Table 5 compares the times that different models achieve the maximum AUC value in the 10 times tests. It is observed that the probabilistic neural network (PNN) model achieves the best results (5 times).

Table 5 Comparison of the number of maximum AUC values obtained by different models

Model	BP	RBF	GRNN	PNN	ID3
Optimal number of times	0	0	1	5	4

5. Conclusion

On the basis of the Chinese private SMEs based on data set, we compare the classification accuracy and applicability of several common neural network models and thus propose some corresponding suggestions for the specific application of the credit risk assessment model. In addition, we prove the error rate of several common credit risk assessment models. The experimental results showed that the probabilistic neural network (PNN) had the minimum error rate and second type of errors, and the PNN model had the highest AUC value and was robust.

The purpose is to make some contribution to solve the problem of financing for small and medium-sized enterprises in China. However, because of a variety of factors involved in credit risk assessment, we need further exploration and research in this field. The complexity of credit risk assessment is also in urgent need of interdisciplinary practice of multidisciplinary technology and theory.

Acknowledgements

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