

Research Article

Formal Credit-Assisted New Agricultural Business: A Multifactor Analysis Based on BP Neural Network

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In recent years, the new agricultural business entities have grown rapidly in all parts of the country and have become an effective carrier to achieve the basic stability of China's rural family operation system and moderate-scale agricultural operation. However, the systemic defects of rural financial market and the credit rationing of formal financial institutions make the capital needs of rural areas unsatisfied for a long time. Financial demand determines the direction of supply reform. Therefore, in order to improve rural financial supply and promote the transformation and development of agricultural economy under the current situation, it is necessary to effectively understand the formal credit demand and the impact factors of accessibility of the new agricultural business entities, which represents the direction of China's agricultural development in the future. Based on back propagation (BP) neural network, this paper constructs the farmers' formal credit availability prediction model and studies the formal credit demand and the impact factors of the availability of new agricultural business entities. The experimental results show that the farmers' formal credit availability prediction model has good performance in prediction accuracy, prediction time, and mean squared error.

1. Introduction

With the gradual improvement and development of rural credit infrastructure, credit products, and credit services that meet the needs of agriculture, "rural areas and farmers" are emerging [1]. From the perspective of credit suppliers, credit supply can be mainly divided into formal credit and informal credit [2]. Formal credit generally refers to a type of credit provided by the government and other institutions and subject to legal constraints and unified supervision by monetary authorities, mainly provided by banks and other formal financial institutions. Informal credit refers to the private lending permitted by the government but not limited by banks and some financial regulatory agencies, mainly loans between relatives and friends [3–5]. At present, the development of rural economy in China depends on the loan of farmers besides the financial support of the state, and with the continuous improvement of the whole credit system, formal credit is more and more popular. In the process of social

transformation and economic development in China's rural areas, the scale and role of informal credit are constantly weakening. Existing studies show that formal credit accounts for nearly two-thirds of the total, and the long-term trend of the development of China's rural financial market is dominated by formal finance and supplemented by informal finance [6]. To better grasp farmers' credit behavior, it is necessary to understand its determinants.

Compared with traditional agriculture, the subject of new agricultural business is to adhere to the basic agricultural management system based on household contract management. It is a modern agricultural management organization that realizes large-scale, professional, intensive, and market-oriented management through land transfer, mainly including professional large households, family farms, farmers' cooperatives, and agricultural leading enterprises [7, 8]. In recent years, with the acceleration of China's urbanization and industrialization, the large-scale transfer of rural labor force, and the growth and differentiation of

agricultural production and management organizations, the new agricultural business entity has continuously developed and become the backbone of China's agricultural modernization and an important subject of rural economy and rural financial demand [9, 10].

Whether the rural financial system, financial products, and financial services accord with the reality of rural areas depends on whether they can meet the financial needs of rural areas. Therefore, the study of the characteristics of rural financial demand and its satisfaction is the basic premise of the rational arrangement of rural financial system [11]. Due to its characteristics of scale, specialization, marketization, and intensification, the new agricultural business entities have much greater demand and dependence on capital than the traditional household leavers and present significantly different financial demand characteristics from the traditional household leavers. However, due to the adverse impact of China's dual economic structure, China's rural financial market has always been underdeveloped. At present, China's rural financial services are still difficult to adapt to the development of rural economic entities. The financing difficulty of new agricultural business entities is becoming increasingly prominent and has become the core element restricting their development [12]. Therefore, it is very important to study the ability of farmers to get loans in the new agricultural business assisted by formal credit.

Due to farmers' limited risk control ability, weak rural credit foundation, and high nonperforming loan rate, farmers' formal credit has a certain difficulty. At the same time, for financial institutions, how to correctly assess farmers' repayment ability plays an important role in reducing their risk. In the farmer household credit rating, generally through the loan officer, the village committee's subjective opinion or the use of scoring scale to determine the score, although these methods are simple and feasible, they are highly subjective and their execution process is not standardized. Without the help of quantitative mathematical models, it is easy to lead to inaccurate evaluation of farmers' credit status, which cannot fully meet the needs of formal credit risk management. This study attempts to use back propagation (BP) neural network to establish the ability of farmers to get formal credit, so as to identify the credit risk of farmers in formal credit, improve the quality of formal credit, and help the development of new agricultural business.

The contributions of this study are as follows.

- (i) After the same characteristic parameters are normalized in data normalization, the normalization among different characteristic parameters is added
- (ii) Genetic algorithm is introduced to avoid BP neural network falling into local minimum and can accelerate the convergence speed of the network
- (iii) Momentum term is added into weights that can effectively prevent BP neural network from falling into local minimum and shorten learning time

The remainder of the paper is structured as follows: Section 2 reviews the related context. In Section 3, BP neural

network is optimized. In Section 4, a multifactor farmers' formal credit availability prediction model based on BP neural network is established and experiments are conducted. Section 5 gives the conclusion of this paper.

2. Literature Review

Relevant scholars have carried out abundant studies on the factors affecting farmers' access to loans, and scholars have done a lot of empirical studies on farmers' loan difficulties and put forward many new ideas to solve the problems. Machine learning has been proved to be able to use a large number of financial data to improve prediction; in [13], the authors used agricultural loan arrears to approximate financial pressure and used logistic regression and several machine learning methods to predict financial pressure. In [14], the authors evaluated whether social capital affected farmers' ability to obtain formal and informal loans. In [15], the authors combined the fuzzy comprehensive model and fuzzy control method to establish the model and indicator system of farmers' credit risk characteristics. Using the data of new agricultural management entities, in [16], the authors investigated the impact of agricultural land management scale on loan availability. In [17], the farmers' credit optimization decision-making model based on common risk guarantee fund and its application were proposed, which had scientific guiding significance and practical application value for farmers' credit decision-making. Starting from the traditional analysis model based on loan approval rejection or default rate, in [18], the authors reexamined the discrimination of a few borrowers in agricultural loans, focusing on the decision-making of loan packaging.

Now, many scholars apply neural network to the study of credit. In [19], peer-to-peer (P2P) lending provided convenient and efficient financing channels for enterprises and individuals, but P2P lending faced credit risk crisis of borrowers in the process of transaction, and the default rate of borrowers was relatively high. The authors used P2P-BP-LM algorithm to build the credit risk assessment model of P2P loan borrowers, so as to establish and improve an accurate and effective credit risk management system of borrowers. In [20], the authors proposed a Deep Genetic Hierarchical Network of Learners (DGHNL) for credit scoring. In [21], the authors proposed a Cost-sensitive Neural Network Ensemble (CS-NNE) model for default prediction. In [22], the authors proposed a deep neural network model for behavioral credit rating. In [23], the authors constructed a personal credit evaluation model and compared the weight adjustment method with BP neural network. In [24], the authors studied the application of radial basis function neural network model combined with optimal segmentation algorithm in personal loan credit rating model of banks or other financial institutions. In [25], the authors used genetic algorithm to adjust and determine the initial weight and threshold of BP neural network to evaluate credit risk. Throughout the literature, there are few neural networks to study formal credit-assisted new agricultural business. Therefore, in this paper, the optimized BP neural network

is used for the prediction of farmers' formal credit availability under new agricultural business.

3. Methods

3.1. Data Normalization. In this study, the actual credit status of farmers is taken as the output neuron of BP neural network, and some indicators of farmers are taken as the input neuron. Because the data types of each information indicator are not unified, there are characters and numbers, and the magnitude of data varies greatly, such data source is easy to cause deviation to the prediction results and affect the accuracy of prediction. Therefore, data normalization is necessary before the prediction of farmers' formal credit availability, which is to convert all data into numbers between [0,1] [26]. Its purpose is to cancel the magnitude difference between data of various dimensions and avoid large network prediction error due to large difference in the number and level of input and output data.

In order to solve the problem of less connection between different feature parameters in common normalization methods, this paper proposes that the row vector is normalized after the column vector of sample space $\Omega_{M \times N}$ is normalized; that is, after the same feature parameter is normalized, the normalization between different feature parameters is added, which is called joint normalization method.

Let the number of BP neural network input nodes be N , select N different characteristic parameters (X^0, X^1, \dots, X^{N-1}) under the same conditions as the input of the network, and select M eigenvalues ($X_0^i, X_1^i, \dots, X_{M-1}^i$, where $i = 0, 1, \dots, N-1$) for each characteristic parameter, which constitutes the sample space $\Omega_{M \times N}$. The joint normalization method is divided into two steps.

3.1.1. Column Vector Normalization. A common normalization method is selected, and the maximum value method is taken as an example for column vector normalization, which is similar to other methods. After normalization,

$$\widehat{X}_j^i = \frac{X_j^i - X_{\min}^i}{X_{\max}^i - X_{\min}^i}, \quad (1)$$

where $i = 0, 1, \dots, N-1$ and $j = 0, 1, \dots, M-1$.

3.1.2. Row Vector Normalization. A common normalization method is selected, and the maximum value method is taken as an example for row vector normalization, which is similar to other methods. After normalization,

$$\bar{X} = \frac{\widehat{X}^i - \widehat{X}_{\min}^i}{\widehat{X}_{\max}^i - \widehat{X}_{\min}^i}, \quad (2)$$

where $i = 0, 1, \dots, N-1$.

To sum up, the data after joint normalization can be used as the input of the network.

3.2. Genetic Algorithm Optimized BP Neural Network. Given the limitations of BP neural network, genetic algorithm has a

strong adaptability to the environment and self-learning ability; its highly parallel global search algorithm can overcome its own shortcomings [27]. The combination of these not only help to avoid the BP neural network into a local minimum value but also can accelerate the convergence speed of the network. Meanwhile, it can also improve their ability of learning and dissemination of model generalization ability. We mainly use genetic algorithm in the training process of neural network to adjust the initial connection weight and threshold value of the farmers' formal credit availability, so that the model can have better performance. The optimized model mainly includes the following steps.

Step 1. Train individuals in the population, calculate errors and fitness, and determine fitness values for each individual in the population. Here, individual refers to the factors affecting the availability of farmers' formal credit. The error can be calculated as follows.

$$\text{Err} = \sum_{j=1}^Q \sum_{i=1}^P (a_{ji} - b_{ji})^2, \quad (3)$$

where a_{ji} represents the actual output, b_{ji} represents the ideal output, P represents the number of nodes in the output layer, and Q represents the number of samples. Here, the fitness function is defined as follows.

$$\text{Fit} = \frac{1}{\text{Err}}. \quad (4)$$

Step 2. Population initialization. Parameters such as population size are initialized by binary coding.

Step 3. Evaluate each individual in the population, calculate the individual fitness value according to the global error of the neural network corresponding to each group of weights and thresholds, and output the individual meeting the fitness requirements. For those individuals with low fitness, crossover and mutation are then performed, new chromosomes are generated, and fitness is calculated again and sorted according to fitness value. The higher the sequence, the better the chromosome.

Step 4. According to the sorting results of the previous step to calculate the selection probability corresponding to each chromosome.

According to the sorting results, the selection probability corresponding to each chromosome is calculated according to equation (5). The partial derivative of the error function with respect to the j th element of the n th layer of the neural network is defined as follows.

$$\frac{\partial \text{Err}}{2 \partial b_j^n} = b_j - a_j. \quad (5)$$

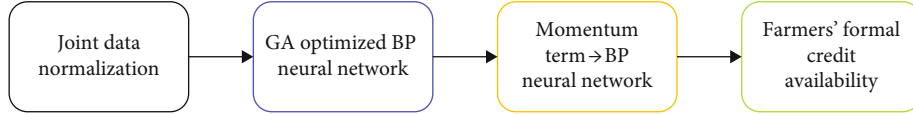


FIGURE 1: Flowchart of farmers' formal credit availability prediction model.

TABLE 1: Basic information of farmers.

Age of householder					Average age	Gender	
20-30	31-40	41-50	51-60	>60		Male	Female
15	44	82	69	55	48.6	242	23

TABLE 2: Relationship between age and formal credit availability.

Formal credit availability	Age ≤ 30	31-40	41-50	51-60	Age > 60
0	7	24	48	39	37
1	8	20	34	30	18
Total	15	44	82	69	55
Formal credit probability	53.30%	45.50%	41.50%	43.50%	32.70%

TABLE 3: Relationship between education level and formal credit availability.

Formal credit availability	Education level of farmer			
	Elementary school	Middle school	High school	College
0	90	72	9	4
1	18	51	14	7
Total	108	123	23	11
Formal credit probability	16.70%	41.50%	60.90%	63.60%

Step 5. The selection process is performed by using the roulette wheel method. Let c_i represent chromosome number and cp_i represent cumulative probability; that is,

$$\begin{cases} cp_0 = 0, \\ cp_i = \sum_{j=1}^i eval(c_j), \end{cases} i = 1, 2, \dots, 50 \quad (6)$$

where $eval()$ function evaluates the string as a valid expression and returns the result and then the random number R is taken from 0 to 1. If $cp_{i-1} \leq R \leq cp_i$ is satisfied, chromosome i is selected.

Step 6. >In farmers' formal credit availability prediction, the evolutionary process includes two stages: gradual stage and mutation stage. The former has strong intersection, and the latter has strong variation. If the fitness value is large, a smaller value is given to the crossover probability and mutation probability to increase the opportunity left by the individual. On the contrary, a larger value is given to the crossover probability and mutation probability.

Step 7. Go to Step 3, output the corresponding weights and thresholds if the requirements are met, and proceed to the next step. If the requirements are not met, continue the cycle process.

Step 8. The optimal weights and thresholds obtained by the above operations are given to the neural network to start the neural network training process.

Compared with the standard BP neural network, the improved BP neural network by genetic algorithm mainly includes three parts, which are determining the structure of BP neural network, determining the optimal initial weight and bias value by genetic algorithm, and predicting by BP neural network. In the part of the main basis for determining the model structure to solve the problem of input and output of the model parameters, the genetic algorithm is used to determine the initial weights and bias value and to calculate the individual fitness value, through the selection, crossover, and mutation operation to determine the optimal weights and bias of individual corresponding values. Since each individual contains the ownership of the neural network value and threshold value, we only need to assign the corresponding value of the individual to the neural network, and the farmers' formal credit availability prediction of BP

TABLE 4: Relationship between business type and formal credit availability.

Formal credit availability	Business type				
	Mainly agricultural	Mainly agricultural and engaged in other	Unclear	Mainly nonagricultural	Totally nonagricultural
0	79	50	16	6	5
1	28	38	25	10	6
Total	107	88	41	16	11
Formal credit probability	26.2%	43.2%	61.0%	62.5%	54.6%

TABLE 5: Relationship between annual household income and formal credit availability.

Formal credit availability	Annual household income					
	<10,000	10000-30,000	30000-50,000	50000-70,000	70000-90,000	>90,000
0	23	63	53	19	10	6
1	2	10	13	22	21	23
Total	25	73	66	41	31	29
Formal credit probability	8.0%	13.7%	20.0%	53.7%	67.7%	79.3%

TABLE 6: Variables selection.

Type	Variable	Mean	Standard deviation	Minimum	Maximum
Family characteristic	Age of household head	48.6	10.27	25	65
	Education level ^a	1.79	0.78	1	4
	Burden of family ^b	0.46	0.27	0	1
	Business type	2.02	1.11	1	5
	Land area	6.48	12.56	1	200
Agricultural production characteristic	Agricultural insurance ^c	1.96	0.88	1	2
	Agricultural subsidy ^d	1	0.47	1	2
	Fixed assets	2.25	1.12	1	5
Physical capital characteristic	Annual household income	7.81	0.92	3.41	15.16
	Annual household expenditure	5.46	1.02	2.46	9.73
	Expected loan amount	2.75	1.14	1	5
Social capital	Degree of intimacy with relatives and friends ^e	3.74	0.82	1.25	5
	Degree of trust with relatives and friends	3.12	0.81	1	5

^aEducation level: 1 = elementary school; 2 = middle school; 3 = high school; 4 = college. ^bBurden of family: (Number of old men + Number of children)/Total number of households. ^cAgricultural insurance: 1 = buy agricultural insurance; 2 = do not buy agricultural insurance. ^dAgricultural subsidy: 1 = receive subsidy; 2 = without subsidy. ^eDegree of intimacy with relatives and friends: 1, 2, 3, 4, and 5 indicate that the degree increases in turn.

neural network is mainly based on the final structure of the network determined in the previous two steps to predict the new data.

3.3. Improvement of Standard BP Neural Network. Adding momentum term into weights can effectively prevent BP neural network from falling into local minimum and shorten learning time. Since the gradient of the error surface of the standard BP neural network is not uniform, the step size of the standard algorithm is unchanged; if the small step size is adopted, the convergence speed of the error surface in the flat region is slow [28]. Nevertheless, when the step size is large, it is easy to produce oscillation in farmers' formal credit availability prediction. While the BP neural network algorithm with momentum term is improved to solve this

problem, consider the weight modification of standard BP neural network, which is summarized as follows.

$$\begin{cases} w'_{kl}(t_0 + 1) = w'_{kl}(t_0) + \eta \sum_{p=1}^p \mu_{kl}^{p1} x' k^{p1}, \\ w'_{jk}(t_0 + 1) = w'_{jk}(t_0) + \eta \sum_{p=1}^p \mu_{jk}^{p1} x' k^{p1}, \\ w'_{ij}(t_0 + 1) = w'_{ij}(t_0) + \eta \sum_{p=1}^p \mu_{ij}^{p1} x' k^{p1}, \end{cases} \quad (7)$$

where x is input signal of the BP neural network, η is

TABLE 7: Farmers' formal credit availability prediction indicators.

Target layer	Primary indicator	Secondary indicator
Farmers' formal credit availability	Family characteristic	Education level
		Burden of family
		Business type
	Agricultural production characteristic	Agricultural insurance
		Agricultural subsidy
		Fixed assets
	Physical capital characteristic	Annual household income
		Annual household expenditure
		Degree of intimacy with relatives and friends
	Social capital	Degree of trust with relatives and friends

TABLE 8: Weight of indicators.

Primary indicator	Weights	Secondary indicator	Weights
Family characteristic	0.197	Education level	0.451
		Burden of family	0.556
		Business type	0.368
Agricultural production characteristic	0.256	Agricultural insurance	0.108
		Agricultural subsidy	0.099
		Fixed assets	0.292
Physical capital characteristic	0.314	Annual household income	0.404
		Annual household expenditure	0.387
		Degree of intimacy with relatives and friends	0.392
Social capital	0.231	Degree of trust with relatives and friends	0.366

learning rate (step size), μ_{gh}^{p1} ($gh = ij, jk, kl$) is the error of each layer, $p1$ is the $p1$ th sample, and t_0 is the t_0 th training. The damping term δ is added into the equation (7), and $\Delta w_{sq}(t_0)$ is the modification direction of the weight at the previous moment.

$$\begin{cases}
 w'_{ki}(t_0 + 1) = w'_{ki}(t_0) + \eta \sum_{p1=1}^p \delta_{ki}^{p1} x'_{i'} k^{p1} + \delta \Delta w'_{ki}(t_0), \\
 w'_{jk}(t_0 + 1) = w'_{jk}(t_0) + \eta \sum_{p1=1}^p \delta_{jk}^{p1} x'_{j'} k^{p1} + \delta \Delta w'_{jk}(t_0), \\
 w_{ij}(t_0 + 1) = w_{ij}(t_0) + \eta \sum_{p1=1}^p \delta_{ij}^{p1} x'_{i'} k^{p1} + \delta \Delta w_{ij}(t_0).
 \end{cases}
 \quad (8)$$

Consider the change of two adjacent training errors, which is summarized as follows.

$$\begin{aligned}
 \Delta E &= E_{\text{tot}}(t_0) - E_{\text{tot}}(t_0 - 1), \\
 FCA &= \frac{1}{2} \sum_{p1=1}^p \sum_{l=1}^m \left(e_i^{p1} - y_l^{p1} \right)^2,
 \end{aligned}
 \quad (9)$$

TABLE 9: Parameter settings.

Parameter	Setting
Number of neurons in input layer	14
Number of neurons in output layer	3
Number of hidden layer	1
Number of hidden layer neurons	12
Transfer function between input layer and hidden layer	logsig
Transfer function between hidden layer and output layer	logsig
Training function	traingdx
Error training target	0.0001
Training times	5000
Learning rate	0.2
Damping term	0.6

where E_{tot} is the error of the sample population and FCA is the farmers' formal credit availability.

In equation (9), p is the total number of sample signals, m is the number of output signals, e_i^{p1} is the expected value of input, and y is the calculated value of input.

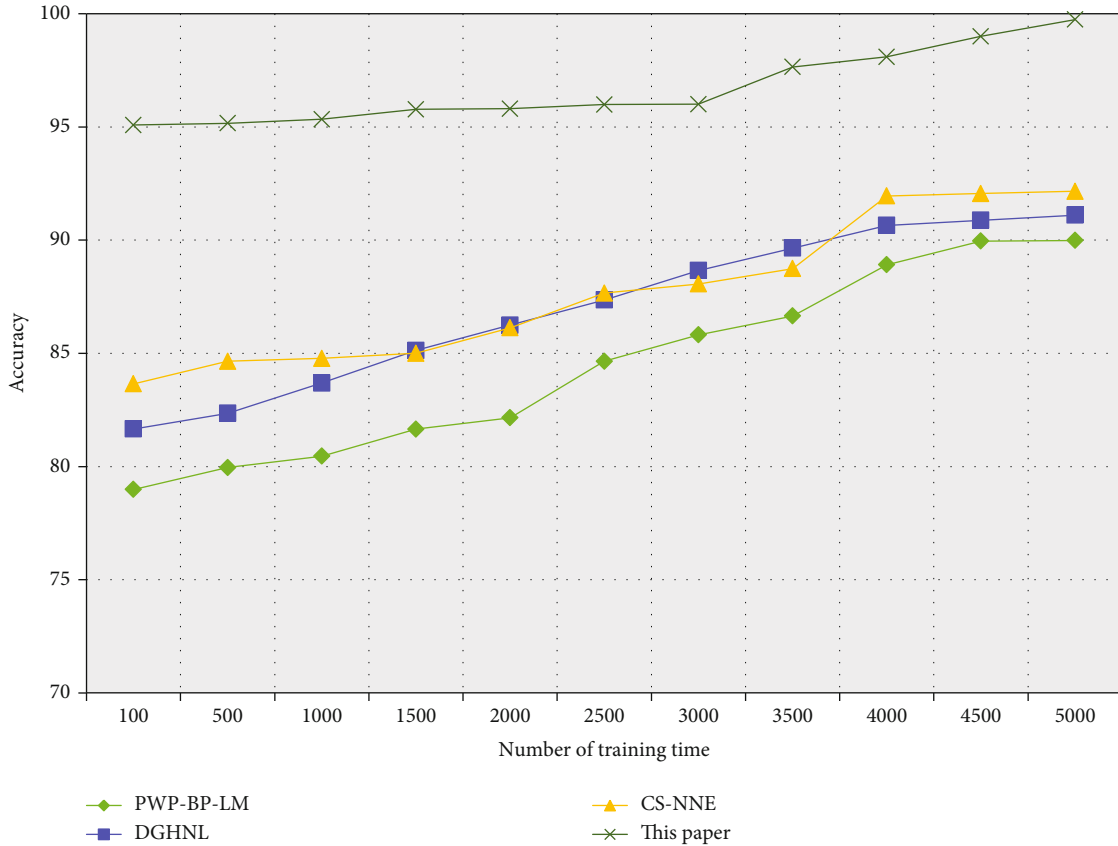


FIGURE 2: Performance comparison of accuracy.

Given this, the flowchart of farmers’ formal credit availability prediction model is shown in Figure 1.

4. Experiments

4.1. Data Source. The analysis of farmers’ formal credit availability factors is to establish the indicator system of formal credit availability. The indicator factors obtained based on objective data are scientific. The sample data of this study came from the questionnaire survey of A town and B town, Jiutai District, Changchun City, Jilin Province, in November 2021. Household interviews and questionnaires were conducted in selected villages. A total of 392 questionnaires were issued and 348 were recovered. 265 samples from 25 to 65 years old were selected according to their age. The basic information of farmers is shown in Table 1.

According to the survey data, the surveyed farmers ranged in age from 41 to 60 years old, with an average age of 48.6 years old. There were 242 male householders and 23 female householders. When surveyed whether they had a loan in the past two years, 106 people chose “yes” and 159 people chose “no.” Among the most important reasons for not applying, 46 people chose “high interest rate, not cost-effective,” 120 people chose “no collateral, no guarantee,” and 15 people chose “troublesome procedures, attached many conditions.” The other 85 people did not make a choice.

From the overall questionnaire, most of the farmers have loan needs, and the actual people cannot meet all their

needs. In the evaluation of financial institutions, most of the farmers are not satisfied with the loan policies of banks. However, to the extent of understanding the loan policies, the farmers are basically half-aware. It can be seen that the farmers have no initiative in financial loans and their own level of knowledge needs to be strengthened.

4.2. Sample Characteristics and Loan Availability Descriptive Analysis. According to the analysis of sample data obtained from the survey, age is negatively correlated with the availability and age of farmers’ loans, and the availability exceeds 44% between 30 and 40 years old. Under 30 years old, due to the educational level and the nature of work, the availability is relatively high, while over 60 years old has a strong risk aversion and low availability of loans. For farmers over 70 years old, the bank generally does not accept loan applications. Under 25 years old and over 70 years old are not considered in this sample.

There is no gender difference between farmers in terms of family. At the same time, according to the actual survey data of Jiutai District, there is not much difference between male and female farmers. From the perspective of culture and education, people with a high degree of education will generally have a greater social contact, have advantages in new agricultural business awareness and ability, are more likely to understand and grasp better financial policies, and have better planning for loan investment. This paper makes a statistical analysis of the relationship between age, education level, business type, and annual household income, as shown in Tables 2–5.

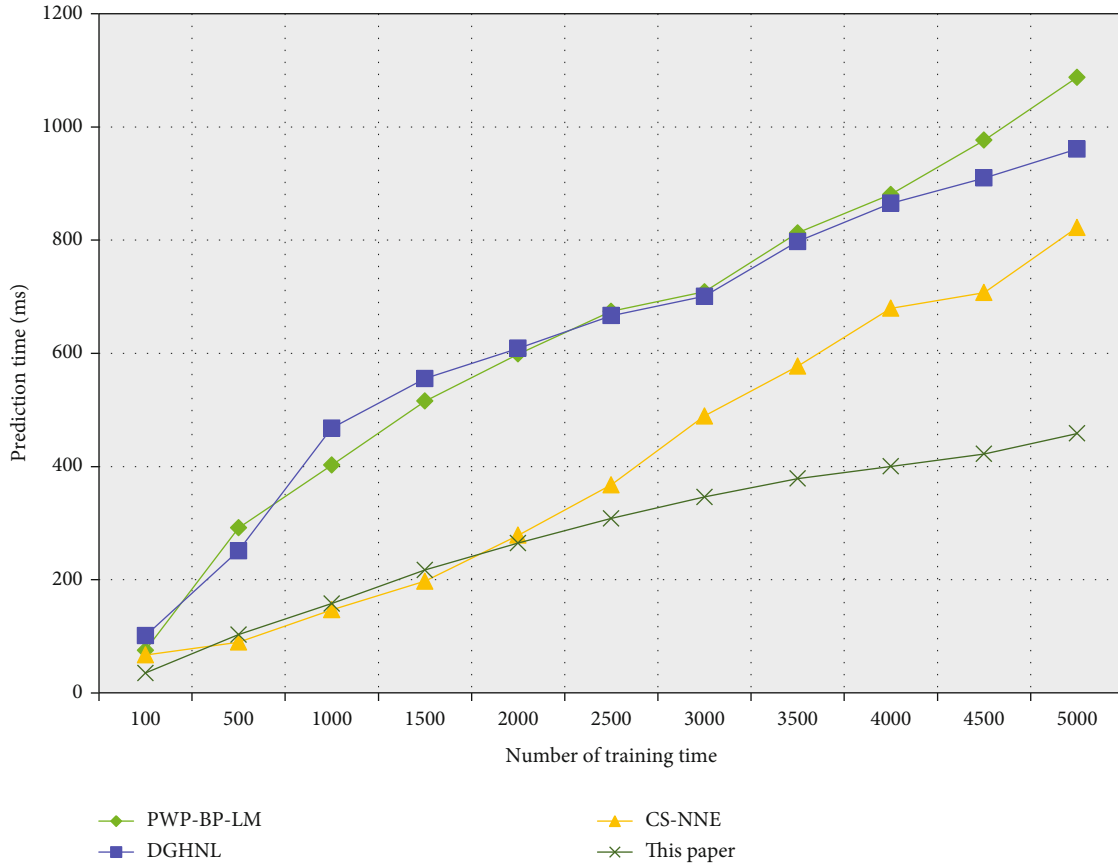


FIGURE 3: Performance comparison of prediction time.

4.3. Variables Selection. This paper measures farmers' ability to get formal credit from four aspects: family characteristics, agricultural production characteristics, physical capital characteristics, and social capital, as shown in Table 6.

4.4. Impact Indicators of Farmers' Formal Credit Availability. Through the collation and analysis of data, the significant factors affecting the availability of farmers' formal credit in Jiutai District are obtained, which are used as evaluation indicators for the ability of obtaining formal credit. The following formal credit availability prediction indicator system is established, as shown in Table 7.

Equation (7) is used to calculate the weight of each indicator, as shown in Table 8.

On the basis of analyzing the impact factors of farmers' obtaining formal credit, a comprehensive evaluation system is established by selecting several indicators to classify the availability of formal credit and obtain the ability of obtaining formal credit. Ultimately, farmers' formal credit availability can be predicted through equation (8).

4.5. BP Neural Network Training Parameters Setting. Before BP neural network training, the setting of parameters has a great influence on the accuracy and stability of neural network.

4.5.1. Training Times. The training times have direct influence on the accuracy and generalization ability of BP neural

network. If the training times are too large or too small, there will be problems. If the training times are too large, it will easily cause overlearning, and if the training times are too small, it will not reach the target error set. To find the best training times, it can be achieved by the change of error. In this paper, the maximum training time is set as 5000 times; when the training time is exceeded, the learning will be terminated even if the network is not within the expected error.

4.5.2. Training Target Error. In the process of BP neural network training, the expected error is obtained by comparing the final network output value with the expected output value. Any prediction model wants the prediction accuracy to get 100%, but it cannot be satisfied under realistic conditions. When the error is reduced to a minimum, it costs longer network training time at least, but the prediction accuracy and prediction time must be weighed in the construction and application of the model. Therefore, from the practical point of view, it is feasible to allow the existence of certain error. According to the actual needs, the expected error determined in this paper is 0.0001.

4.5.3. Transfer Function. The transfer functions of BP neural network mainly include purelin function, tansig function, and logsig function. S-type function converges faster than linear function, and the nonlinear mapping capability of BP neural network is reflected by S-type function. As the

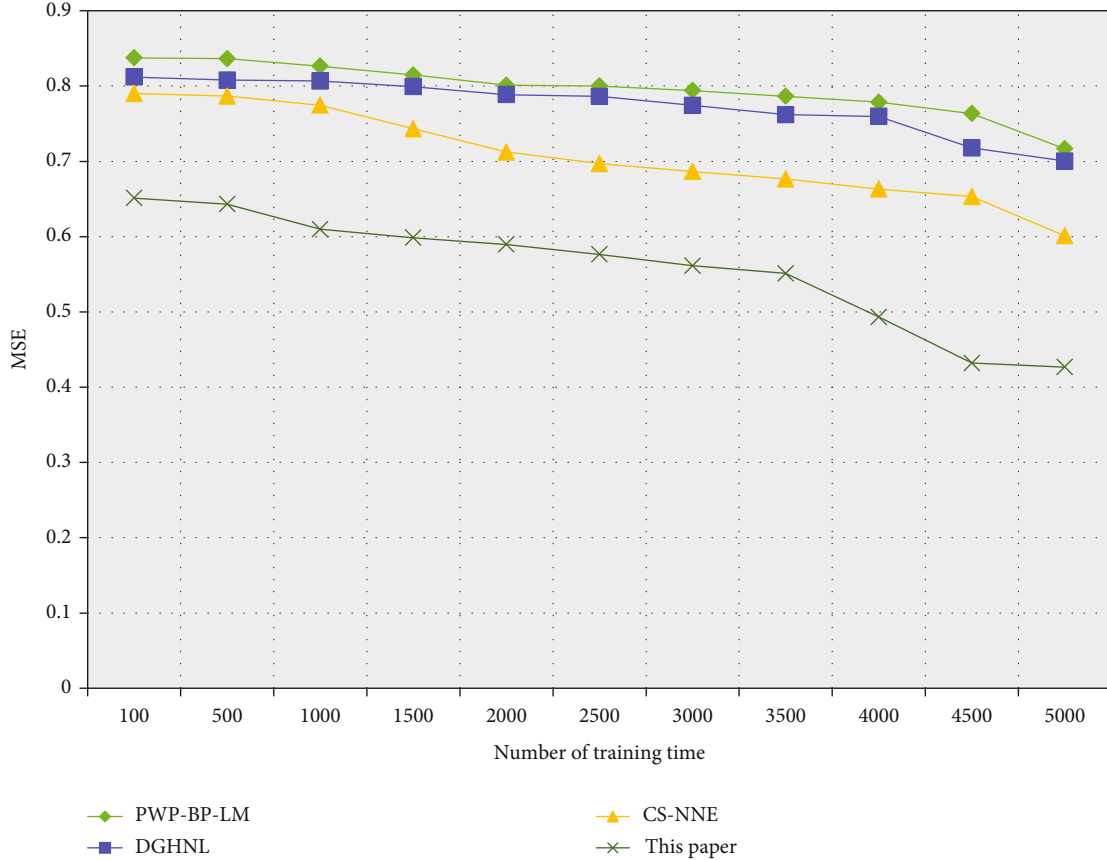


FIGURE 4: Performance comparison of MSE.

input data is normalized within the range of (0,1), logsig is selected as the transfer function of the hidden layer and output layer in this paper.

4.5.4. Training Function. The commonly used training functions of BP neural network include gradient descent method, L-M momentum method, fast BP algorithm, and traingdx optimization method. The main difference of these algorithms is the difference in learning efficiency. Traingdx optimization method is an optimization method that combines gradient descent optimization with adaptive learning rate method. This method has fast convergence speed, good learning effect, and high precision, so this paper selects the traingdx optimization method as the training function.

4.5.5. Learning Rate. Learning rate refers to the weight adjustment range of each training network layer, which affects the convergence speed of the network. Since the adaptive learning rate adjustment strategy is adopted in this paper, the learning rate can be adjusted according to the variation range of the error curve. After repeated tests, the learning rate is finally selected as 0.2.

Therefore, parameter settings of the BP neural network model are shown in Table 9.

4.6. Comparison Analysis. To verify the effectiveness of the proposed farmers’ formal credit availability prediction

model, P2P-BP-LM [19], DGHNL [20], and CS-NNE [21] were used for comparison in terms of accuracy, prediction time, and mean squared error (MSE). MSE is the average sum of squares of deviations from the true value.

As can be seen from Figure 2, the farmers’ formal credit availability prediction model proposed in this paper is of high accuracy. Compared with other three baselines, the predicted accuracy has been more than 90%. This is because through descriptive analysis and variable selection of research data, the algorithm proposed in this paper makes a significant analysis by empirical method and obtains the main factors affecting the formal credit of farmers. By analyzing the factors of farmers themselves, financial institutions, and external factors, this paper classifies the indicators of farmers into four aspects: family characteristics, agricultural production characteristics, physical capital characteristics, and social capital to measure the ability of farmers to obtain formal credit. As indicated in Figure 3, with the increasing of training times, the prediction time of the model in this paper increases, but the range is small and tends to be stable. In contrast, the prediction time of PWP-BP-LM and DGHNL algorithms show an obvious upward trend. The prediction time of CS-NNE algorithm has a good performance in the first 2000 training sessions, but after 2500 training sessions, the prediction time increases exponentially. This also confirms the validity of the proposed algorithm in prediction time. As shown in Figure 4, with the

increasing number of training times, the MSE of the proposed model has always been decreasing, indicating the good performance of the farmers' formal credit availability model.

5. Conclusion

This paper studies the multifactor analysis based on BP neural network to analyze the formal credit to assist the new agricultural business. At first, since the data types of farmers' relevant information indicators are not unified, there are characters and numbers, and the amount of data changes greatly, and this data source is easy to bias the prediction results and affect the accuracy of prediction, so a joint normalization method is proposed in this paper. Then, genetic algorithm is introduced to avoid BP neural network falling into local minimum and can speed up the convergence speed of the network. Meanwhile, momentum term is added into weights that can effectively prevent BP neural network from falling into local minimum and shorten learning time. Finally, a multifactor farmers' formal credit availability prediction model based on BP neural network is established. The experiments results reveal that the proposed model outperforms baselines with respect to accuracy, prediction time, and MSE.

Nevertheless, this paper only puts forward relevant suggestions to assess farmers' ability to get formal credit from the perspective of meeting farmers' demand for loans but does not analyze how to effectively solve the difficulty of farmers in China to get formal credit from the perspective of fund supply. In addition, this paper is limited by the regional limitations of the sample, and its representativeness is limited. If we can have larger data resources, it will certainly improve the accuracy. Meanwhile, the situation of farmers is a dynamic process, so the application of static method in this paper to predict and study is slightly inadequate. These will be studied in the next step.

Data Availability

All data used to support the findings of the study is included within this paper.

Conflicts of Interest

The authors declare no conflicts of interest in this paper.

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