Research Article

Evaluation of Women’s Entrepreneurship Education Based on BP Neural Network

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Entrepreneurship education is the key to cultivating the entrepreneurial spirit of national talents. The goal of entrepreneurship education is to cultivate a large number of pioneering talents, and women’s entrepreneurship education is particularly important. The government, enterprises, schools, and all sectors of society start from multiple channels to let students strengthen their entrepreneurial awareness and improve their entrepreneurial ability. This paper uses the most advanced BP neural network algorithm to study and evaluate women’s entrepreneurship education. This paper briefly introduces the concept and model of the artificial neural network and establishes a BP neural network model while improving the classical BP neural network. Then, we list the application process of the BP neural network model in evaluating women’s entrepreneurship education. We select college students for empirical analysis, determine the number of neurons, and select 9 items as the evaluation index of women’s entrepreneurship education. Using valid assumptions, we further determine the model learning rate and momentum factor. Finally, the results show that the actual evaluation results based on the BP neural network are basically the same as the expected results, and the maximum relative error between the actual value and the expected value is approximately 1.64%, and the comprehensive evaluation value is 92 points. The proposed algorithm can effectively avoid the problems of instability and slow convergence of the traditional model and can comprehensively improve the accuracy of the evaluation results of women’s entrepreneurship education.

1. Introduction

The quality of entrepreneurship education is directly related to the effect of national basic education, and women’s entrepreneurship education is directly related to the future development of the country. Recently, entrepreneurship education has attracted extensive attention from all walks of life in academia and industries [1]. In the context of artificial intelligence, the BP neural network is a multilayer feed-forward neural network in artificial neural network. Based on the gradient descent method, using the network output error, it can adjust and modify the network connection weight and reduce the error modulation. The research on the evaluation of women’s entrepreneurship education is mainly subjective and theoretical, therefore lacking a certain programmatic evaluation design. Furthermore, most of them adopt a centralized mode, guarantee system, and evaluation system and have not studied a complete evaluation system for the women’s entrepreneurship education. The goal of entrepreneurship education is to cultivate a large number of pioneering talents, and women’s entrepreneurship education is particularly important.

In this paper, the BP neural network algorithm is used to solve this problem. The establishment of a BP neural network model can improve the accuracy of the evaluation results of women’s entrepreneurship education. The results
obtained have certain advantages for colleges and universities in formulating teaching strategies and adjusting teaching directions. It can also help colleges and universities focus on students’ entrepreneurship education and strengthen women’s entrepreneurship education in China, comprehensively improving the ability and level of women’s entrepreneurship education. In this paper, we briefly introduce the concept and model of the artificial neural network and establish a BP neural network model while improving the traditional BP neural network. We then describe the application process of the BP neural network model in evaluating women’s entrepreneurship education. This paper uses the improved BP neural network model to evaluate women’s entrepreneurship education, which can effectively avoid the problems of instability and slow convergence of the traditional model and can comprehensively improve the accuracy of the evaluation results of women’s entrepreneurship education. The major innovations of the research conducted in this paper, in terms of women’s entrepreneurship education, can be summarized as follows:

(i) We describe the concept, topology, and network structure of the BP neural network in detail, so that we can accurately grasp the structure of the BP neural network.

(ii) We build a BP neural network model, evaluate women’s entrepreneurship education based on the model, and select 9 items as the evaluation indicators of women’s entrepreneurship education.

(iii) The indicators involve colleges and universities, society, the government, and women entrepreneurs themselves, covering all aspects, which can more accurately grasp the role of all aspects in women’s entrepreneurship education and help to accurately analyze the evaluation results of women’s entrepreneurship education.

The rest of the paper is organized as follows: in Section 2, we offer an overview of the related work. Section 3 is about the BP neural network based model. Section 4 illustrates the valuation of women’s entrepreneurship education based on the BP neural network. Section 5 describes the empirical analysis of women’s entrepreneurship education evaluations based on the BP neural network. Moreover, experimental details are also presented. In Section 4, results are discussed. Finally, Section 6 concludes this paper and offers several directions for further research and investigation.

2. Related Work

The evaluation of innovation education has become an important index for cultivating college talents in various countries, and the accuracy of the evaluation results has attracted attention in various fields. With the rapid development of the BP neural network algorithm, more and more people have begun to use the BP neural network in the evaluation of entrepreneurship education. Mars and Hoskinson pointed out that the evaluation of entrepreneurship education should abandon the traditional “rote learning” content, judge students’ thinking ability and reaction ability at a deeper level, and analyze and judge students’ entrepreneurship ability through case analysis and formulating business plans [2]. Maritz et al. proposed that the evaluation of entrepreneurship education is the core of education evaluation, and the level of graduate entrepreneurship education can be evaluated according to the GIM plan. The evaluation indicators mainly include innovation intention, personal behavior, skill return, and knowledgeability [3]. Ota et al. described in detail the education evaluation system adopted by Indian entrepreneurship, and proposed that Indian business schools take entrepreneurship as a basic course in business education, which involves joint entrepreneurship, self-entrepreneurship, and internal entrepreneurship. The knowledge of the system is conducive to knowledge creation [4].

Matlay et al. established a complete evaluation system of entrepreneurship education practice, and proposed that the United States and the United Kingdom have a small distance in entrepreneurship education. Compared with postgraduates and undergraduates, they focus on the cultivation and practice of entrepreneurship education ability in the postgraduate learning stage [5]. Papadopoulos et al. formulated ten teaching cases according to the database syllabus of seven universities established in Denmark and constructed the evaluation model of entrepreneurship education by analyzing the cases. The main forms are formative evaluation, summative evaluation, and learner-centered evaluation [6]. Fan et al. and others designed the evaluation indicators of entrepreneurship education at the undergraduate stage of colleges and universities, and the selected indicators mainly include ability level, incentive support, ability level, allocation of teachers, and resource allocation [7]. Tang and Liu and others pointed out that through background evaluation to judge entrepreneurial resources, the environment, needs, and opportunities, input evaluation as the basic demand condition, and the evaluation process is the implementation process of supervision, inspection, and feedback. Achievement evaluation is used to evaluate the results achieved, in particular, including acceptance, subject satisfaction, and so on [8]. Wang and Tian classified entrepreneurship evaluation into two dimensions: (i) subjective evaluation and (ii) objective evaluation. The subjective evaluation indicators include the innovation ability and innovation demand. The objective indicators include education process, education input, and education output. Based on these two indicators, the evaluation validity and reliability are guaranteed to be in balance [9]. Based on the CIPP model, Guan and Sun formulated 11 primary indicators and 22 secondary indicators based on input resources, entrepreneurial environment, and achievement performance, and the primary indicators and secondary indicators are input into the model to judge the achievement of entrepreneurship education [10].

3. BP Neural Network-Based Model

3.1. Artificial Neuron Model. The concept of an artificial neural network (ANN) is to regard the biological simulation process as the basic feature, and the computing structure
reflecting the local characteristics of the human brain is an artificial neural network. $u_i$ represents the output result of a combined input signal, $v_i$ represents the local sensing area of a neuron, $x_i$ represents the input signal of neuron $i$, and $W_{ij}$ represents the synaptic strength [11, 12].

$$u_i = \sum_j w_{ij} x_j. \quad (1)$$

In the above formula, $y_i$ represents the output value of neuron $i$ and $f(.)$ represents the excitation function. Because there are many types of functions, the following are common functions:

$$y_i = \left( \sum_i w_{ij} x_i + b_j \right). \quad (2)$$

3.1.1. Threshold Function. The threshold function judges the neuron state according to the neuron output result. If the neuron output result is 1, it indicates that the neuron is excited, and if it is 0, it indicates that the neuron is inhibited.

$$f(v) = \begin{cases} 1, & \text{if } v \geq 0, \\ 0, & \text{if } v < 0. \end{cases}$$

3.1.2. Piecewise Linear Function. The piecewise linear function is defined as follows:

$$f(v) = \begin{cases} 1, & \text{if } v \geq 0, \\ v, & \text{if } v + 1 > -1, \\ -1, & \text{if } v \leq -1. \end{cases} \quad (4)$$

3.1.3. Sigmoid Function. There are many differences between the sigmoid function and other functions. The sigmoid function [13] can also be called an S-type function, which is a widely used excitation function. The following is the basic formula:

$$f(v) = \frac{1}{1 + \exp(-av)} \quad (5)$$

3.2. Introduction to Artificial Neural Network. An Artificial neural network belongs to a modular adaptive nonlinear dynamic system, and its components include multiple neurons [14]. The system has strong adaptability and autonomous learning ability and shows the characteristics of nonlimitation and nonlinearity. Based on the achievements of the modern neural field, an artificial neural network is proposed. The principle is to simulate the processing mode of a brain neural network. Based on different information memory modes, a new machine is designed, which is similar to the human brain and can automatically process all kinds of information. The basic processing unit of an artificial neural network is the neuron, and the neuron structure is shown in Figure 1 below [15].

Figure 1 shows that $x_i$ represents the input signal, $W_{ij}$ is the weight of the connecting neuron between the $i$ and the $j$, $\theta_j$ represents the threshold value of the $j$ neuron, $s$ represents the set external input signal, and $y_j$ represents the output signal. Based on this model, the following represents the transformation of the $j$ neuron:

$$y_j = f\left( \sum_i w_{ij} x_i - \theta_j + S_j \right). \quad (6)$$

As a multilayer feedforward neural network, the BP neural network has a strong nonlinear mapping ability. Each layer of the neural network model is only connected to adjacent neurons and has no relationship with internal neurons. The components of neurons include the hidden layer, input layer, and output layer. In a typical BP neural network learning algorithm, the objective function is the sum of squares of network errors, and the minimum value of the objective function is calculated through the gradient algorithm. The principle is error correction. The gradient descent method is used to output the error from the network, realize backpropagation, modify and adjust the network connection weight, and reduce the error modulation to the minimum, and the neural network learning process is listed in Figure 2.

3.3. Artificial Neural Network Model. Artificial neural network model has a remarkable feature of diversity. Based on the principle of model classification, it adopts a variety of ways to summarize the types of models. Firstly, it is the network topology type [16], connecting various neurons to generate different network topologies, and then further divided into hierarchical structures. The structure is adjusted according to the hierarchy. The interconnection structure is characterized by connecting each layer. The second is the network information flow type, while the feedforward network transmits information in the order from front to back, while the feedback network transmits information in the direction from back to front, which is shown in Figure 3.

3.4. BP Neural Network Model. In 1986, Rumelhart and McClelland used the multilayer network learning algorithm in a neural network in 1986 [17]. The algorithm is the error backpropagation algorithm, that is, the BP algorithm. The algorithm belongs to a special program, and neural networks are one of the most cutting-edge disciplines at present. Combining the two becomes BP neural network. Based on the law and characteristics of function, a neural network can automatically learn more complex data experience and information. For complex functions, especially nonlinear functions, the characteristics of neural networks can be more prominent. The basic characteristics of neural networks are self-organization, self-adaptive, and self-study habits. Based
\[ \sum w_{ij}x_j + \theta_j \]

**Figure 1:** Neuron structure.

- Network parameter initialization
- Input training sample
- Calculate hidden layer, output layer
- Calculated network error
- Whether learning
  - Yes
  - No: Calculate reverse velocity
  - Adjust connection weights
- End of learning

**Figure 2:** Neural network learning flow chart.
on the functional characteristics and basic laws, the neural network deeply analyzes some complex problems and seeks the best way and strategy to deal with the problems. Figure 4 shows the topology of the BP neural network.

4. Evaluation of Women's Entrepreneurship Education Based on BP Neural Network

4.1. BP Neural Network Structure. A BP neural network is composed of three parts: the front end, the middle, and the end, which correspond to the input layer, the hidden layer, and the output layer. The beginning of the imported input is the input vector, whose formula is $x = (x_1, x_2, \ldots, x_p, \ldots, x_n)^T$, and it is assumed that $x_0 = -1$; The middle part of the neural network is the hidden layer, which will interfere with the training speed. The result of the derived data is the output vector, and its formula is $y = (y_1, y_2, \ldots, y_p, \ldots, y_n)^T$. The assumption of $y_0 = -1$ can be added. The introduction of the threshold by the output layer will directly affect the end neural network. $O = (O_1, O_2, \ldots, O_p, \ldots, O_n)^T$ represents the output vector of the output layer. The weight matrix between the input layer and the hidden layer is mainly used to receive data, while the function of the hidden layer is the adjustment and change process. The weight matrix generated by the two processes directly affects the BP neural network. $v = (v_1, v_2, \ldots, v_k, \ldots, v_p)^T$ represents the output matrix. Since the output layer is the data export port, its output result directly affects the BP neural network, $w = (w_1, w_2, \ldots, w_k, \ldots, w_n)^T$ is the matrix expression of the BP neural network.

The mathematical relationship between various parts of the network has significant advantages. The front end is the input layer, and $net_k$ and $O_k$ are the front ends. The following are the input layer formulas for the front ends:

$$O_k = f(net_k), \ k = 1, 2, \ldots, n,$$

$$net_k = \sum_{j=0}^{m} w_{jk} y_j \ k = 1, 2, \ldots, n.$$  \hspace{1cm} (7)

The middle part of the network is the hidden layer, and $net_j$ and $y_j$ have an impact on the middle part [18]. The formula is as follows:

$$y_j = f(net_j), \ j = 1, 2, \ldots, m,$$

$$net_j = \sum_{i=0}^{m} v_{ij} x_i, \ j = 1, 2, \ldots, m.$$ \hspace{1cm} (8)

A common category of functions is the unipolar sigmoid function. The transfer function $f(x)$ can be used in the neural network. At the same time, $f(x)$ can also select the corresponding unipolar sigmoid function according to the demand:

$$f(x) = \frac{1}{1 + e^{-x}}.$$ \hspace{1cm} (9)

The BP training algorithm is based on the BP neural network. The algorithm is introduced and trained. The basic process of the algorithm is to set parameters and variables first, where $n$ represents the number of samples, and the input vector is $x_k = [x_{k1}, x_{k2}, \ldots, x_{km}], (k = 1, 2, 3, \ldots, n)$. The formula is as follows:

$$w_{MI}(n) = \begin{bmatrix} w_{11}(n) & w_{12}(n) & \cdots & w_{1I}(n) \\ w_{21}(n) & w_{22}(n) & \cdots & w_{2I}(n) \\ \cdots & \cdots & \cdots & \cdots \\ w_{M1}(n) & w_{M2}(n) & \cdots & w_{MI}(n) \end{bmatrix}.$$ \hspace{1cm} (10)
The formula is the weight vector between the middle part \( I \) and the beginning of the \( n \)th iteration.

\[
w_{J}^{I} (n) = \begin{bmatrix} w_{11} (n) & w_{12} (n) & \ldots & w_{1j} (n) \\ w_{21} (n) & w_{22} (n) & \ldots & w_{2j} (n) \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1} (n) & w_{i2} (n) & \ldots & w_{ij} (n) \end{bmatrix}
\] (11)

The above formula is the weight vector between the two intermediate parts \( I \) and \( J \) in the \( n \)th iteration.

\[
w_{IJ} (n) = \begin{bmatrix} w_{11} (n) & w_{12} (n) & \ldots & w_{1j} (n) \\ w_{21} (n) & w_{22} (n) & \ldots & w_{2j} (n) \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1} (n) & w_{i2} (n) & \ldots & w_{ij} (n) \end{bmatrix}
\] (12)

The above is the weight vector between the middle part \( J \) and the end in the \( n \)th iteration. After \( n \) cyclic iterations, the output result is generated, and the actual output value is \( y_{k}(n) = [y_{k1}(n), y_{k2}(n), \ldots, y_{kn}(n)], (k = 1, 2, 3, \ldots, n) \), and the expected output result is \( d_{k} = [d_{k1}, d_{k2}, \ldots, d_{kn}], (k = 1, 2, 3, \ldots, n) \).

Secondly, during the initialization of the network, the nonzero random number is assigned to \( w_{1}(n) \), \( w_{2}(n) \), \( w_{3}(n) \), and the value of \( n \) is assumed to be 0 [18].

Thirdly, the data of sample \( x_{k} \) is input, and the basic data of the neural network is sample data, which directly affects the network effect. It is necessary to assume that the value of \( n \) is 0.

Fourth, the middle and end weights and output vectors are interrelated.

\[
v_{p} (np) = y_{kp} (n), \quad p = 1, 2, \ldots, p.
\] (13)

Fifth, \( E(n) \) is calculated based on the error between \( y_{k}(n) \) and \( d_{k} \). If it is consistent with the set error, you need to jump to the eighth step. If it is inconsistent with the required error, you can directly jump to the next step.

Sixth, the number of iterations of BP neural network parameters is calculated, and then the number of \( n + 1 \) iterations is compared. If the latter is less than the former, it needs to be readjusted to enter the eighth. If the former is less than the latter, it needs to adjust the local gradient of neurons \( \delta \).

\[
\delta_{j}^{p} (n) = y_{p} (n) (1 - y_{p} (n)) (d_{p} (n) - y_{p} (n)).
\] (14)

Seventh, the weight interference between the front end, middle, and end of the BP neural network is serious, so we should first calculate the specific weight and then readjust the weight according to the training error.

Eighth, take some time to train the neural network. If it is finished, you need to quit the training. If it is not finished, you need to readjust until the third step above.

4.2. Improved BP Neural Network. The BP neural network has significant advantages, but it also has inevitable problems, which are described in detail below:

(1) There is a great contradiction between the global optimal value and the local minimum value, so the ideal global optimal value cannot be obtained.

(2) It needs more neural network training time, but the disadvantage is that the convergence speed is slow and the efficiency is difficult to improve.

(3) Based on the theoretical guidance, the prediction results obtained by the neural network can be ensured to be very accurate, especially the number of hidden layer nodes should be determined according to the theoretical guidance.

(4) The contradiction between forgetting old samples and learning new samples: the disadvantage of a neural network is that the previous samples will be forgotten while learning new samples. In order to deal with the above problems, the algorithm should be modified and adjusted again. The measures taken are as follows:

(i) Add a new momentum term: there is a direct correlation between the BP neural network inversion and learning rate \( \eta \). High \( \eta \) value indicates that the convergence speed of the network is fast, but it will lead to the decline of stability; smaller \( \eta \) value will solve the problem of poor stability, but the corresponding convergence speed will also decrease. Therefore, the momentum term is introduced, \( \alpha \) is the momentum term, and it is added to the BP neural network to form a new BP algorithm.

\[
\Delta w_{ij} (n) = a \Delta w_{ij} (n - 1) + n \delta_{j} (n) v_{i} (n).
\] (15)

In the above formula, \( T \) represents the variable time series, and the value of \( t \) is \( 0 \) \( n \), which can be obtained:

\[
\Delta w_{ij} (n) = \eta \sum_{t=0}^{n} a^{n-t} \delta_{j} (t) v_{i} (t).
\] (16)

(ii) Adjusting the learning rate: assume \( \eta \) represents the learning rate. After reducing the weight, the overall error decreases, \( \eta = \theta \eta \) \( \theta \) \( <0 \). According to the change degree of learning efficiency, the weight will also be changed to reduce the overall
error and fully reflect the effect of the adjusting learning rate.

(iii) The odd function is used as the excitation function: the most common type of function is the odd function. Selecting an odd function as an excitation function can speed up the operation speed of the BP neural network algorithm. The following are hyperbolic tangent functions in odd functions:

\[
f(u) = a \tanh(bu) = \frac{1 - \exp(-bu)}{1 + \exp(-bu)} = \frac{2a}{1 + \exp(-bu)} - a.
\]

(17)

This paper uses the improved BP neural network model to evaluate women’s entrepreneurship education, which can effectively avoid the problems of instability and slow convergence of the traditional model and can comprehensively improve the accuracy of the evaluation results of women’s entrepreneurship education. The BP neural network simulates the thinking mode of the human brain, and its adaptability, learning ability, and memory are strong. There is no need to build a model in advance for evaluation through this mode. As long as the expert evaluation sample data is input, a large amount of relevant data can be accumulated after learning and training. This method can accurately explain the relationship between various parameters and finally get the ideal evaluation result.

5. Empirical Analysis of Women’s Entrepreneurship Education Evaluation Based on BP Neural Network

5.1. Number of Neurons in Each Layer of the BP Neural Network

5.1.1. Number of Neurons in the Input Layer. When studying the evaluation of women’s entrepreneurship education based on the BP neural network, this paper sets multiple evaluation indicators, mainly including nine indicators: family entrepreneurship background, whether there is entrepreneurship experience, social practice time, women’s entrepreneurship ability, university entrepreneurship environment, teacher team construction, women’s entrepreneurship investment, government support policies, and social assistance. Therefore, the number of neurons \( n \) is 9.

After determining the number of neurons in the output layer and hidden layer, the actual output result of the network is unique, so the number of neurons in the output layer is also unique, so the value of \( M \) is 1 [20]. By comparing the numbers of hidden layer neurons and input and output layer neurons, it can be determined that the external environment will cause direct interference to them. If the quantity decreases, the corresponding amount of information also decreases. If the quantity increases, the fault tolerance will be reduced, the training cycle will be prolonged, and the optimal value will appear. The following is the empirical formula:

\[
l = \sqrt{n + m + a}.
\]

(18)

The numbers of neurons listed in Table 1 are 3, 4, 5, 6, 7, 8, and 9, respectively. At this time, the training error continues to decrease and there is a certain correlation between them. After analysis, the number of neurons 9 is the most ideal.

5.1.2. Model Learning Rate. Learning efficiency has a decisive impact on the efficiency [21] of training and testing neural networks, and the equivalent learning efficiency is \( \eta \). If the \( \eta \) value is too high, the weight is large and the convergence speed is fast, which makes the network fluctuate greatly. Low \( \eta \) value will reduce the network efficiency and the convergence speed. For this problem, we can introduce motion vector \( a \). Based on the evaluation results of this paper, the training times and errors in Table 2 are analyzed, and the learning rate is 0.01.

5.1.3. Momentum Factor \( a \). The momentum factor plays a major role in the neural network, especially during the training period. Furthermore, the momentum factor can reduce the local maximum and local minimum problems of the network [22]. Through the experiments, it is concluded that the best value of the momentum factor is 0.85. When the neural network is used to evaluate the effect of women’s entrepreneurship, the most ideal value is 9.0.

5.2. Implementation of Women’s Entrepreneurship Education Evaluation Based on BP Neural Network. When implementing the evaluation of women’s entrepreneurship education based on the BP neural network, this paper selects a university student majoring in statistics to carry out empirical analysis and uses expert scoring and a questionnaire to evaluate the quality of women’s entrepreneurship education in colleges and universities. By collecting the entrepreneurship teaching quality of statistics majors in the same type of colleges and universities as the evaluation data, represented by \( U_i \), it is assumed that \( U_1, U_2, U_3 \), and \( U_4 \) are the training samples of the model, and the detection samples are \( U_5, U_6, U_7 \), and \( U_8 \), and then the neural network simulation is realized through MATLAB software \( \varepsilon \). The learning accuracy is \( 10^{-4} \), and the learning factor is \( \eta \). The value of \( \eta \) is 0.3. Based on this value, the weight matrix between the following hidden layer and the input layer is obtained:
The following is the weight matrix between the output layer and the hidden layer:

\[
\begin{bmatrix}
0.1045 & -0.1796 & 4.5012 & 0.5016 & -0.8106 & 4.4927 & 2.1609 & -1.3017 \\
-2.8342 & 8.9274 & -5.2207 & 0.9016 & -0.8106 & 4.4927 & 2.1609 & -1.3017 \\
\end{bmatrix}
\] (20)

Based on the parameters of the BP neural network model and the actual training results, the results show that the overall verification process and effect of the BP neural network are ideal. The analysis of Figure 5 shows that the value of \( R \) during the fitting regression of the training process is 0.9602, and the value of \( R \) on the fitting regression of the verification process is 0.9207. The closer the value of \( R \) is to 1, the better the fitting effect is. Therefore, the rationality and scientificity of the model and data are also tested.

5.3. Test BP Neural Network. According to the analysis of the data in Figure 6, after the BP neural network is improved and the training is completed, the data in the BP neural network need to be randomly selected to test the BP neural network model to obtain the evaluation results of women’s entrepreneurship education. The overall analysis of the evaluation of women’s entrepreneurship education based on the network’s expected value and actual output results shows that the expected value is generally consistent with the actual value. There is no large fluctuation, which fully reflects the high reliability of the BP neural network, and the data collected and analyzed are very reasonable. Through the test of the BP neural network, according to the actual output results, we can get the expected effect, and the maximum relative error between the actual value and the expected value is 1.64%.

5.4. Analysis of Evaluation Results of Women’s Entrepreneurship Education Based on BP Neural Network. By analyzing the evaluation results of women’s entrepreneurship education based on the BP neural network, the actual value obtained is similar to the expected results, and each score result corresponds to the nine index data of students’ evaluation of women’s entrepreneurship education. According to each score, a woman’s entrepreneurship ability can be reflected. The comprehensive evaluation result of women’s entrepreneurship education is 92 points. The evaluation results are analyzed in detail below.

(1) A high evaluation score indicates that the student has a high degree of education in female entrepreneurship education. Colleges and universities provide him with an ideal entrepreneurial environment. The school has a strong faculty. The government supports female entrepreneurship in terms of policies. It also has a large number of autonomy from...
society, a rich entrepreneurial experience, and practical experience. Families also support women’s entrepreneurship and provide them with some capital and experience. According to the data collected by the BP neural network, the university has achieved ideal results in women’s entrepreneurship education, which can cultivate a large number of female entrepreneurs with entrepreneurial experience and provide more female talents to society.

(2) Some students score less than 90 points, indicating that they have the experience of participating in women’s entrepreneurship education. Colleges and universities also provide them with a certain entrepreneurial environment, but their entrepreneurial ability is relatively insufficient. According to the data stimulated by the BP neural network model and simulation experiments, the university should continue to improve women’s entrepreneurial ability and create a good entrepreneurial environment in women’s entrepreneurship education.

(3) The evaluation results of some students are less than 80 points, indicating that they lack sufficient entrepreneurial ability and relevant entrepreneurial experience, and the school teaching staff and entrepreneurial environment are insufficient. Therefore, colleges and universities should strengthen the construction of teaching staff from this aspect and invest more funds to support women’s entrepreneurship.

6. Conclusions and Future Work
This paper uses the BP neural network model to train and test it, selects the students of a certain university in China to study the quality of women’s entrepreneurship education based on the BP neural network, and evaluates it. The final comprehensive evaluation result is 92, which shows that the university has a high level of women’s entrepreneurship education, but there are still some deficiencies. This paper focuses on analyzing the structure of the BP neural network, establishing the BP neural network model and improving the BP neural network model. Based on the BP neural network model, we comprehensively evaluate women’s innovation education, select 9 indicators as important indicators to
evaluate women’s entrepreneurship education, and determine the learning speed and momentum factor of the model. Through empirical analysis, the comprehensive evaluation results of women’s entrepreneurship education based on the BP neural network model are obtained. The results obtained in this way are more accurate, and it has become a more widely used way to evaluate women’s entrepreneurship education. However, there is little research on education quality in China. The BP neural network model established in this paper is only a theoretical model and has not been widely used in practice. It needs to be practiced and applied in the later stages. We will consider these limitations as the focus of our future research. We will also consider more advanced algorithms such as CNN and attention networks [23].

Data Availability
The data used to support the findings of this study can be requested from the corresponding author.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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References