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Constructing a big data modular evaluation system for college students' innovation and entrepreneurship education in universities: enhancing evaluation efficiency and accuracy

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ABSTRACT

In this paper, the evaluation system of college students' innovation and entrepreneurship education is constructed and the indexes are assigned by combining the hierarchical analysis method. After that, PSO algorithm is introduced in the optimization of weights and thresholds of BP neural network, the neural network model using particle swarm optimization (PSO-BP) is constructed, and the process of PSO algorithm optimization of BP neural network is described. It was found that the combined weight of five indicators, namely, "examination results of innovation and entrepreneurship courses, entrepreneurial experience, participation in centralized entrepreneurship training camps, obtaining financial support from entrepreneurship funds, and participation in innovation or entrepreneurship clubs", accounted for more than 10%, while the combined weight coefficients of the rest of the indicators were all below 0.1. Compared to the BP model, the PSO-BP model has better network performance and its training samples have higher correlation with the test samples. In addition, the PSO-BP model can be used for predicting data prediction after 9 iterations of training, and the maximum relative error between the actual value and the expected value of the model network test output is very small (<1.4272%), which makes the model ideal. After PSO optimization PSO-BP model has almost no prediction error (<0.34%), which can improve the evaluation efficiency and accuracy.

Keywords: innovation and entrepreneurship evaluation system, hierarchical analysis method, BP neural network, PSO algorithm

1. Introduction

With the continuous promotion of innovation and entrepreneurship education in colleges and universities, the form of entrepreneurship education has become increasingly rich and three-dimensional, and most colleges and universities have set up additional mandatory courses on entrepreneurship, encouraged college students to participate in innovation and entrepreneurship training camps and various entrepreneurship competitions, and increased the school-enterprise co-

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innovation and university-industry research cooperation [1-2]. Under the encouragement and support of the state for innovation and entrepreneurship, the pace of innovation and entrepreneurship education in colleges and universities is constantly following up. How to use big data information combined with the actual situation of colleges and universities to build a set of scientific, efficient and feasible comprehensive evaluation index system of entrepreneurship education quality is a problem that needs to be studied urgently.

Big data is based on information network technology and information science and technology, effectively integrating content through a wide range of data and information collection methods, thus forming a huge information data system [3-5]. Big data is characterized by large data volume, complex structure, and fast data updating speed, which provides a broader space for people to obtain information [6-8]. Comprehensively collecting data related to students, effectively mining and analyzing the huge amount of data contained therein through scientific means, and exploring new modes and methods of education in the era of big data are of great significance in promoting the development of education [9-12]. Colleges and universities should seize the opportunity of the development of the era, improve the ability of data processing and analysis, and gradually form an atmosphere of speaking with data and making decisions with data [13-14]. Under the guidance of the policy of "mass entrepreneurship and innovation", we should actively use new technologies in the Internet era such as big data, strive to promote the formation of a pattern of evaluation of college students' entrepreneurial quality of "a set of evaluation mechanisms, multi-party data collection, and comprehensive evaluation", and continuously improve the scientific level of innovation and entrepreneurship education teaching [15-18].

This paper adopts the hierarchical analysis method and PSO-BP neural network method to construct a modular evaluation system for college students' innovation and entrepreneurship education big data, and for the inherent defects of BP neural network itself, it uses particle swarm optimization algorithm (PSO) to optimize the BP network model, and puts forward the evaluation of college students' innovation and entrepreneurship big data based on particle swarm optimization neural network (PSO-BP) algorithm to improve the efficiency and accuracy of evaluation. Evaluation, to improve the evaluation efficiency and accuracy. Finally, this paper uses PSO-BP model and BP model to train the sample data respectively, and analyzes the training results of the two models.

2. Evaluation system of college students' innovation and entrepreneurship based on PSO-BP model

2.1. Construction of Evaluation System for Innovation and Entrepreneurship Education of College Students in Colleges and Universities

Combined with the content of talent cultivation work in colleges and universities and the characteristics of innovation and entrepreneurship education, the educational elements that play an effective role in innovation and entrepreneurship education in colleges and universities are selected as the evaluation indexes, and the evaluation index system of innovation and entrepreneurship education in colleges and universities is constructed as a result. The evaluation system of innovation and entrepreneurship education in colleges and universities is shown in Table 1. The evaluation index system of innovation and entrepreneurship education in colleges and universities constructed in this paper includes four first-level indexes, i.e., students' background, students' professional ability, students' practical ability, and students' expansion ability. According to the actual work of colleges and universities, the first-level indexes are decomposed and refined, resulting in "participation in innovation or entrepreneurship clubs, entrepreneurial experience, innovation and entrepreneurship course examination results, participation in school-level, provincial-level and national-level competitions ("Internet+", Youth Creation, Challenge Cup) and awards, participation in national-level innovation and entrepreneurship training programs for college students, participation in national-level training programs for college students, and participation in national-level training programs for college students in innovation and entrepreneurship. The 12 secondary indicators include "participation in innovation and entrepreneurship training programs for college students, participation in centralized entrepreneurship training camps, obtaining financial support from entrepreneurship funds, participating in scientific research projects, writing business plans and research reports, and actively taking part in innovation and entrepreneurship online courses".

Table 1. Innovation entrepreneurship education evaluation system

Primary indicator	Secondary indicator
Student background	Participate in innovation or entrepreneurship
	Entrepreneurial experience
Student expertise	The achievements of the innovation entrepreneurship course test
Student practical ability	Internet plus, youth, challenge cup and winning awards
	Provincial (Internet +, youth, challenge) and awards
	The national competition (Internet +, youth, challenge) and awards
	The students of the participating countries will develop the training plan for the innovation and entrepreneurship
	Attend a centralized training camp
	Get a start-up fund
	Secondary indicator
Student development ability	Participate in innovation or entrepreneurship
	Entrepreneurial experience

2.2. *Steps for calculating indicator weights*

2.2.1. Constructing a judgment matrix. In the hierarchical analysis method [19], it is necessary to use the pairwise comparison method to construct the indicators as a two-by-two comparison judgment matrix, using the 1-9 degree method for the evaluation scale. 1-9 degree method evaluation scale is shown in Table 2.

The specific method of two-by-two comparison: when a factor of the previous level is used as a comparison criterion, the relative importance of the ist factor and the jnd factor at the next level can be expressed by using the comparison scale, and the matrix formed by a_{ij} is called the comparison judgment matrix $A=(a_{ij})$.

Characteristics of the comparative judgment matrix:

$$A=\begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \tag{1}$$

Of these, $a_i j>0; a_{ij}=1/a_{ji}; a_{ii}=1; (i,j=1,2,\dots\dots n)$.

Table 2. 1-9 degree evaluation scale

Quantitative value	Factor i ratio j
1	Equally important
3	Slightly important
5	stronger
7	Strong importance

9	Extreme importance
2,4,6,8	The median of the two adjacent judgments
Reciprocal	If the factor i is more important than the importance of the factor j, the ratio of the element j to the element i is aji=1/aij

2.2.2. Calculation of single-ranking weights for hierarchical indicators. Normalize the judgment matrix target layer by columns:

$$a_{ij'} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} (i, j = 1, 2, n) \quad (2)$$

Column summation of the judgment matrix is performed and it is normalized:

$$w_i' = \sum_{j=1}^{n} b_{ij}' (i = 1, 2, n) \quad (3)$$

Normalize vector W:

$$w_i = \frac{w_i'}{\sum_{i=1}^{n} w_i'} (i = 1, 2, n) \quad (4)$$

The obtained $W = (w_1, w_2, ..., w_n)$ is the indicator weights of the requested evaluation system.

2.2.3. Consistency test for judgment matrices. When comparing multiple factors, it is usually difficult to ensure the consistency of the data before and after the comparison, which requires the use of consistency tests to check the coordination of the relative importance of the factors. In order to make the judgment matrix can be used normally and avoid the occurrence of contradictory situations, each judgment matrix needs to be consistent test.

The steps of consistency test are as follows:

Calculate the largest characteristic root of the judgment matrix $\lambda \max$:

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{AW}{nw_i} \quad (5)$$

Find the judgment matrix consistency index CI:

$$CI = \frac{\lambda \max - n}{n - 1} \quad (6)$$

where n is the order of the judgment matrix.

Find the consistency ratio CR:

$$CR = \frac{CI}{RI} \quad (7)$$

If $CR < 0.10$, this judgment matrix is used as an acceptable range, and if $CR > 0.10$, it needs to be adjusted. RI is the average consistency metric, and the RI values corresponding to the n th order matrix can be viewed according to the table of average consistency metric values.

2.3. BP Neural Network

2.3.1. BP network model. BP neural network consists of input layer, hidden layer and output layer, and each layer realizes complete connection between them. The input layer receives information from the outside world, and the input signal passes from the input node through each hidden layer in turn, and then passes to the output node, and the output layer transmits the information processed by the network to the outside world. The number of nodes in the input layer is equal to the number of variables in the input sample, and the number of nodes in the output layer is equal to the number of target output parameters.

2.3.2. Learning rules. The learning process of the BP algorithm is divided into two stages: forward propagation of the signal and back propagation of the error. In forward propagation, the input samples are passed in from the input layer, and after being processed by the implicit layer, they are passed to the output layer. The actual output results are compared with the target output results, and if they do not agree, the back propagation of error stage is transferred. Error back-propagation is to back-propagate the output error in some form to the input layer through the implicit layer and apportion the error to all the units in each layer. Under the guidance of this error signal, the weights and thresholds of the connection between the input layer and the implicit layer, and between the implicit layer and the output layer are constantly corrected, so that the error decreases along the direction of the gradient until the output error achieves the preset accuracy or carries on up to the set maximum number of times of learning.

2.3.3. Mathematical models. The input vector of the BP neural network is denoted by X, $X=(x_1,x_2,\ldots\ldots,x_n)^T x_i(1\le i\le n)$ the hidden layer vector is denoted by Y, $Y=(y_1,y_2,\ldots\ldots,y_m)^T y_j(1\le j\le m)$; the output vector is denoted by Z, $Z=(z_1,z_2,\ldots\ldots,z_t)^T z_k(1\le k\le t)$; the desired output vectors are D, $D=(d_1,d_2,\ldots\ldots,d_i)$; the connection right from the i th node of the input layer to the j th node of the hidden layer is denoted by v_i; the connection right from the jth node of the hidden layer to the kth node of the output layer is denoted by w_{jk} ; The threshold for the jth node of the implicit layer is denoted as γ_j and the threshold for the kth node of the output layer is denoted as θ_k.

1) Transfer function:

$$f(x)=\frac{1}{1+e^{-x}} \tag{8}$$

$$net_j=\sum_{i=1}^{n} v_{ij}x_i-\gamma_j \quad j=1,2,\ldots,m \tag{9}$$

2) The implicit layer is given by:

$$y_j=f(net_j) \tag{10}$$

3) The formula for the output layer is:

$$z_k=f(net_k) \tag{11}$$

$$net_k=\sum_{j=1}^{m} w_{jk}\, y_j-\theta_k \quad k=1,2,\ldots,t \tag{12}$$

4) The error is calculated as:

$$E=\frac{1}{2}(D-Z)^2=\frac{1}{2}\sum_{k-1}^{t}(d_k-z_k)^2 \tag{13}$$

Substituting the output layer formula into the error calculation formula, i.e:

$$\begin{aligned} E &= \frac{1}{2}\sum_{k=1}^{t}\left[d_k - f(net_k)\right]^2 \\ &= \frac{1}{2}\sum_{k=1}^{t}\left[d_k - f\left(\sum_{j=1}^{m} w_{jk} y_j - \theta_k\right)\right]^2 \\ &= \frac{1}{2}\sum_{k=1}^{t}\left\{d_k - f\left[\sum_{j=1}^{m} w_{jk} f\left(net_k\right) - \theta_k\right]\right\}^2 \\ &= \frac{1}{2}\sum_{k=1}^{t}\left\{d_k - f\left[\sum_{j=1}^{m} w_{jk} f\left(\sum_{i=1}^{n} v_{ij} - \gamma_j\right) - \theta_k\right]\right\}^2 \end{aligned} \tag{14}$$

5) Calculation formula for weights and threshold adjustment

Output layer general error signal δ_{zk}:

$$\begin{aligned} \delta_{zk} &= -\frac{\partial E}{\partial net_k} = -\frac{\partial E}{\partial z_k}\frac{\partial z_k}{\partial net_k} \\ &= -\frac{\partial E}{\partial z_k} f^{'}(net_k) \\ &= (d_k - z_k) z_k (1 - z_k) \end{aligned} \tag{15}$$

Implicit Layer General Error Signal δ_{yj}:

$$\begin{aligned} \delta_{yj} &= -\frac{\partial E}{\partial net_j} \\ &= -\frac{\partial E}{\partial y_j}\frac{\partial y_j}{\partial net_j} \\ &= -\frac{\partial E}{\partial y_j} f^{'}(net_j) \\ &= \left[\sum_{k=1}^{t}(d_k - z_k) f^{'}(net_j) w_{jk}\right] f^{'}(net_j) \end{aligned} \tag{16}$$

Output Layer Weighting Adjustment Calculation Formula:

$$\Delta w_{jk} = -\eta\frac{\partial E}{\partial w_{jk}} = -\eta\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial w_{jk}} = \eta\delta_{zk}\, y_j = \eta(d_k - z_k) z_k (1 - z_k) y_j \tag{17}$$

Implicit layer weight adjustment calculation formula:

$$\Delta v_{ij} = -\eta\frac{\partial E}{\partial v_{ij}} = -\eta\frac{\partial E}{\partial net_j}\frac{\partial net_j}{\partial v_{ij}} = \eta\delta_{yj} x_i = \eta\left(\sum_{k=1}^{t}\delta_{zk} w_{jk}\right) y_j (1 - y_j) x_i \tag{18}$$

where η reflects the learning rate. The output layer threshold adjustment is calculated by the formula:

$$\Delta\theta_k = -\eta\frac{\partial E}{\partial\theta_k} = -\eta\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial\theta_k} = -\eta\delta_{zk} \tag{19}$$

Implicit layer threshold adjustment calculation formula:

$$\Delta\gamma_j = -\eta\frac{\partial E}{\partial net_j}\frac{\partial net_j}{\partial\gamma_j} = -\eta\delta_{yj} \tag{20}$$

2.3.4. BP Algorithm Flow. The implementation process of the BP algorithm is as follows:
1) Initialization, set the network structure of the neural network and the number of nodes in each layer, assign random values to the weight matrix and threshold matrix, and assign initial values to parameters such as preset accuracy and learning rate;
2) Given input vector X and target output vector D;
3) Calculate the actual output Y of the implicit layer and the actual output Z of the output layer;
4) Find the error E between the target output and the actual output of the output layer; if the error is within the preset range, the learning ends; otherwise, continue (5);
5) Calculate the weights and threshold adjustment size of the implicit and output layers, respectively;
6) The error signal is propagated backward along the original direction, modifying the weights and thresholds of each layer; and then propagated forward from the input layer.

These two processes are repeated, and the learning ends if the preset accuracy is reached or the maximum number of learning times is reached.

2.4. PSO-BP Modular Evaluation Model Construction

2.4.1. PSO Optimization Algorithm:
1) Mathematical description of PSO optimization algorithm [20]. Set a D-dimensional search space, a group has m particle, the position of the i nd particle is a D-dimensional vector, that is, $X_i=(X_{i1},X_{i2},\cdots,X_{iD})$; the flight speed is also a D-dimensional vector, denoted as $V=\left(V_{i1},V_{i2},\cdots,V_{iD}\right)$, where $i=1,2,\cdots,m$; the particle currently searches for the optimal position is $P_i=\left(P_{i1},P_{i2},\cdots,P_{iD}\right)$; the optimal position searched for by the whole group of particles is $P_g=(P_{gl},P_{g2},\cdots P_{gD})$, and the particle position and speed equations change as follows:

$$V_{id}^{(k+1)}=wV_{id}^{(k)}+c_1r_1(P_{id}^{(k)}-X_{id}^{(k)})+c_2r_2(P_{gd}^{(k)}-X_{id}^{k}) \tag{21}$$

$$X_{id}^{(k+1)}=X_{id}^{(k)}+V_{id}^{(k+1)} \tag{22}$$

where $d=1,2,\cdots,D$, k are the current evolutionary generations; w is the inertia weight; r_1,r_2 is a random number distributed between [0, 1], randomly generated at each iteration; and c_1,c_2 is the acceleration coefficient, called the learning factor.
2) PSO optimization algorithm flow. The specific flow of PSO optimization algorithm is as follows:

(1) Initialize the particle swarm: set the initial particle swarm parameters such as random position, speed, maximum number of iterations, and learning factor.

(2) Calculate the adaptation value of each particle: the particle adaptation function is shown below.

$$f_i=\sum_{j=1}^{J}(y_{ij}-Y_{ij})^2 \tag{23}$$

$$f_m=\frac{1}{N}\sum_{i=1}^{N}f_i \tag{24}$$

Where, N is the number of samples, J is the number of output nodes, y_i is the jth actual output of the ith sample, Y_{ij} is the jth desired output of the ith sample, $m=1,2,\cdots,M$ (M is the number of particles).

(3) Compare the adaptation value of each particle with its own optimal value pbest, if it is better than pbest, set pbest to the current value, otherwise pbest value remains unchanged.

(4) Compare the fitness value of each particle and its global optimum value gbest, if better than gbest, set gbest as current value, otherwise gbest value is unchanged.

(5) Update the velocity and position of the particles according to Eqs. (23) and (24) to produce a new population.

(6) Check the end condition, if it is satisfied then the optimization search ends, otherwise, $k = k + 1$, go to step (2). The end condition is that the optimization search reaches the maximum number of evolutionary generations or the error value is less than the given accuracy.

2.4.2. PSO-BP modeling. PSO as a population theory optimization tool, combining PSO with BP neural network and using PSO algorithm to optimize the weights and thresholds of neural network can improve the performance of BP neural network.

PSO-BP model [21] is a three-layer structure, which are input layer, hidden layer and output layer. The input layer is "participation in innovation or entrepreneurship clubs, entrepreneurial experience, innovation and entrepreneurship course examination results, participation in school-level, provincial-level and national-level competitions (Internet+, ChuangYuen, Challenge Cup) and won the award, participation in the national college students' innovation and entrepreneurship training program, participation in centralized entrepreneurship training camps, obtaining entrepreneurship fund, participating in scientific research projects, writing business plans and research reports, actively participating in innovation and entrepreneurship online courses, and actively participating in innovation and entrepreneurship online courses. The output layer of the network is the comprehensive score of innovation and entrepreneurship performance of college students, therefore, the number of neurons in the output layer is set to 1. According to the empirical formula, the number of nodes in the implied layer can be initially determined to be 5-13 layers, and then finalized according to the method of trial and error. The number of neurons in the hidden layer is finally determined according to the trial-and-error method.

The specific design steps to realize the combination of particle swarm and BP neural network are as follows:

1) Determine the number of population particles. Based on the research experience of experts and scholars, when using the particle swarm optimization algorithm to solve the general function optimization problem, the number of particles in the PSO-BP neural network model in this paper is 12 because there are 12 indicators in this paper.

2) Determine the inertia particle w . The inertia factor w plays a big role in the convergence of the particle swarm algorithm, and w can be taken as a random number in the interval 0-1. In this paper, we take w the maximum value of 0.90 and the minimum value of 0.30.

3) Determine the value of the dimension of individual particles of the particle swarm. According to the experience of previous research, the dimension of the single particle of the particle swarm satisfies the following equation:

$$n = Y_1 * (A+1) + (Y_1 + Y_2) \tag{25}$$

Where Y_1 is the number of nodes in the single implicit layer, Y_2 is the number of nodes in the output, A is the number of nodes in the input layer, and according to the research-designed innovation and entrepreneurship evaluation index system for college students, there are a total of 12 indexes, and the output is a composite evaluation score, which is $A = 12, Y_1 = 5 - 13, Y_2 = 1$, which means that the dimensionality of each particle of each particle of each particle swarm is obtained as $n = 61 - 157$

4) Determine the initial position of each particle of the particle swarm. Since the dimension of each particle is 61 a 157, the position matrix of each particle has 61 a 157 elements, according to experience the value of each element can be between [-1.5, 1.5], that is, the lower limit of the position is -1.5, the upper limit is 1.5.

5) Determine the velocity of individual particles of a particle swarm. Since the dimension of the particle is 73, the velocity vector of the particle is assumed to be $V(V_1, V_2, \ldots, V_{73})$. The velocity value

of each dimension is initialized to one-tenth of the position value, and the velocity vector formula is shown below:

$$V_i = (V_1, V_2, \cdots, V_{73}), 0 < i < 73, 0 \le V_i \le V_{\max} \tag{26}$$

6) Determine the velocity threshold of individual particles of the particle swarm $V_{\max}$. Since the number of particles selected in this paper is 10, the $V_{\max}$ range is set to [-10, 10], which is $V_{\max} = 20$
7) Determine the acceleration constants c_1 and c_2. The acceleration constants are the weights that adjust the role played by their own experience and social experience in their motion. For routine problems, $c_1 = c_2 = 2.0$ is taken in general.
8) Selection of termination conditions. The maximum number of iterations in PSO optimized BP neural network is generally taken as 100-4000.In this paper, the optimal solution of the network is obtained after several experiments are carried out, and it is concluded that the network reaches a stable value during the solution process, and at this time, the maximum number of iterations is 500, so when the number of iterations reaches the maximum number of times 500, then terminate the program run.
9) Design the fitness function. The definition of mean square error is shown below:

$$\sigma^2 = E = \frac{1}{2}\sum_r \sum_j (Y_{rj} - D_{ij})^2 \tag{27}$$

where Y_{rj} is the desired output in the training dataset and D_{ij} is the actual output of the node during training.

2.4.3. PSO-BP modeling process. The PSO-BP modeling process is shown in Fig. 1 as follows:
1) Establish the number of neurons in the three-layer structure of the BP neural network
2) Initialize the particle swarm: initialize the data such as individual extreme value and global optimal value of each particle.
3) Determine the fitness function: the particle search performance index is represented by the minimum mean square error MSE of the neural network.
4) Calculate each particle adaptation degree:

(1) Input a particle first, you can calculate the output value of the network according to the pre-feedback method of BP neural network, and then calculate its error according to Eq. (23); use the same method to calculate the error of all samples, and then calculate the mean squared error of all the samples according to Eq. (24), that is, the fitness of the particle.

(2) Return to 1) and continue to input other particles, thus calculating the fitness of all particles.

5) According to the adaptation degree of each particle history of the new individual extreme value and the global optimal value

If $present < P_i, P_i = present, P_i = X_i$, otherwise P_i is unchanged; if $present < P_g, P_g = present, P_g = X_i$, otherwise P_g is unchanged. Where present is the fitness of the current particle, P_i is the individual extreme value of the particle, and P_g is the global optimum.

6) Update the velocity and position of the particle and generate a new population according to Eqs. (23) and (24):

(1) Consider the velocity. If $V_{id} > V_{\max}$, then $V_{id} = V_{\max}$; if $V_{id} < -V_{\max}$, then $V_{id} = -V_{\max}$, otherwise V_{id} remains unchanged.

(2) Consider the position. If $X_{id} > X_{\max}$, then $X_{id} = X_{\max}$; if $X_{id} < X_{\min}$, then $X_{id} = X_{\min}$, otherwise X_{id} remains unchanged. Where, $V_{\max}, X_{\max}, X_{\min}$ is the initialized value.

7) Calculate the error of the algorithm as follows:

$$E = \frac{\sum_{i=1}^{k} f(P_g^{(i)})}{k} \tag{28}$$

k in the formula is the current iteration number, and $f(P_g^{(i)})$ is the fitness of the global optimum of the i rd iteration.

8) Determine whether to meet the conditions for iteration stopping. If the error of the algorithm reaches the preset accuracy or the maximum number of iterations, the algorithm converges, and the weights and thresholds of each dimension in the global optimal value P_g of the last iteration are the optimal solution; if the number of iterations does not reach the maximum, the algorithm returns to step 4) and continues to iterate, otherwise the algorithm is terminated.

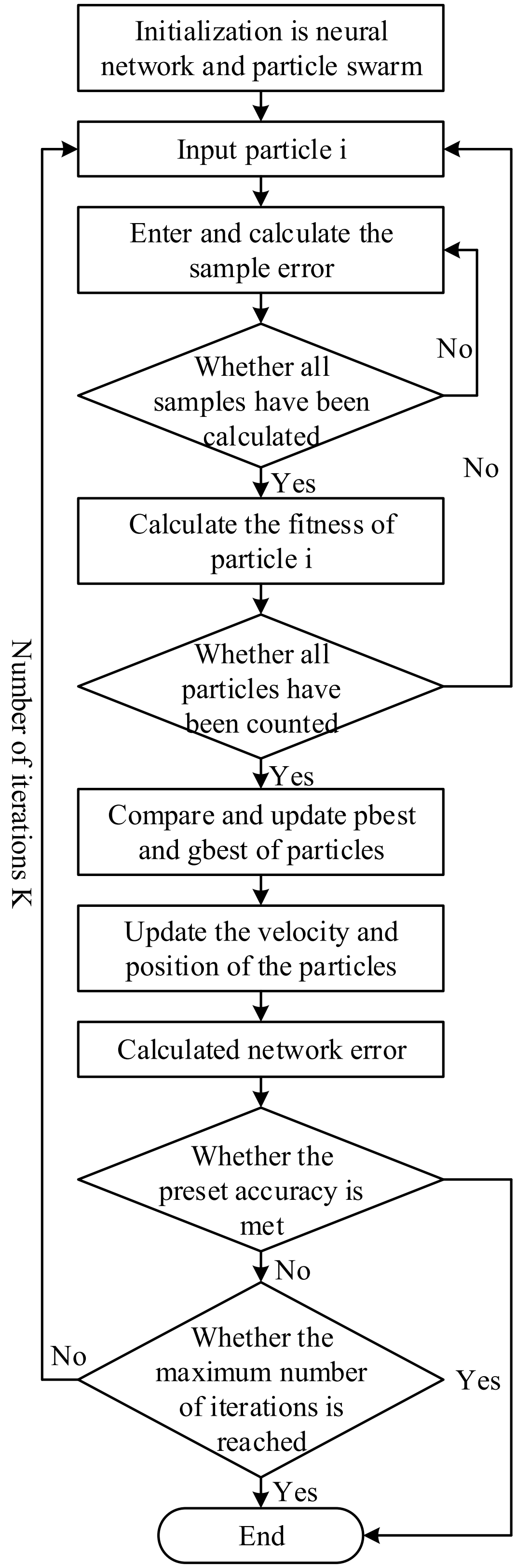

Fig. 1. Flow chart of PSO-BP model

3. Analysis of the efficiency and accuracy of innovation and entrepreneurship evaluation of college students

3.1. *Weight Synthesis Collation and Determination*

After calculating the indicators at the same level of the indicator judgment matrix, the above steps are repeated to calculate the weight coefficients of the secondary indicators corresponding to each level of indicators. The results of the weights of the evaluation indicators of innovation and entrepreneurship education in colleges and universities are shown in Table 3. The results show that among the 12 indicators, there are 5 indicators with combined weight coefficients above 0.1, which are innovation and entrepreneurship course examination results, having entrepreneurial experience, attending centralized entrepreneurship training camps, obtaining entrepreneurship fund grants, and participating in innovation or entrepreneurship clubs, and their corresponding weights account for 12.06%, 11.08%, 10.77%, 10.48%, and 10.17%, respectively. The remaining seven indicators have a combined weight of 0.1 or less, and their share ranges from 1.26% to 9.65%.

Table 3. Innovation entrepreneurship education evaluation index weight result

Primary indicator	Weight factor	Secondary indicator	Synthetic weight
Student background	0.2125	Participate in innovation or entrepreneurship	0.1017
		Entrepreneurial experience	0.1108
Student expertise	0.1206	The achievements of the innovation entrepreneurship course test	0.1206
Student practical ability	0.5836	Internet plus, youth, challenge cup and winning awards	0.0543
		Provincial (Internet +, youth, challenge) and awards	0.0647
		The national competition (Internet +, youth, challenge) and awards	0.0808
		The students of the participating countries will develop the training plan for the innovation and entrepreneurship	0.0965
		Attend a centralized training camp	0.1077
		Get a start-up fund	0.1048
		Secondary indicator	0.0748
Student development ability	0.0833	Participate in innovation or entrepreneurship	0.0707
		Entrepreneurial experience	0.0126

3.2. *Model Training*

In this paper, the model network construction function is newff function, and the collected 24 groups of data are used as the samples for training and testing of the model, the first 18 groups of data are the training samples, and the rest of the data are used as the test samples, and the order of the first 18 groups of data is disrupted and randomly sorted during the training to ensure the reliability of the training results. Among them, Fig. 2 and Fig. 3 show the comparison of the training results of PSO-BP model and BP model, respectively. As can be seen from the figures, the PSO-BP neural network model has a significantly stronger training ability than the simple BP neural network, and the network performance is better.

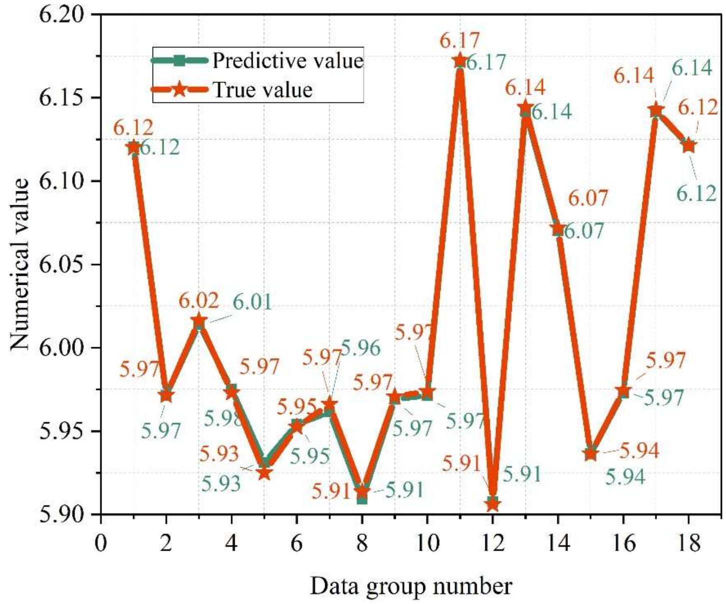

Fig. 2. Comparison of the results of the PSO-BP model training results

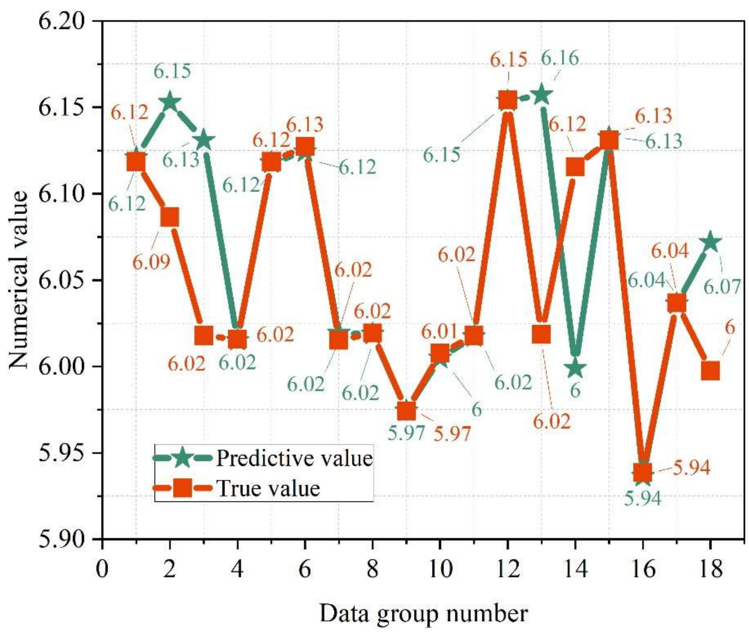

Fig. 3. Comparison chart of BP model training results

Figures 4 and 5 show the correlation curves of PSO-BP and BP model training results, respectively. As can be seen, R is the correlation of the model training results, when the output value is basically the same as the actual value, the regression image is a straight line with an inclination angle of about 45°, and the closer R is to 1, it means that the correlation is better, the R of the PSO-BP model = 0.99998, and the R of the BP model = 0.99801, comparatively speaking, the correlation of the PSO-BP neural network model is better than that of the BP neural network The correlation of PSO-BP neural network model is better than that of BP neural network.

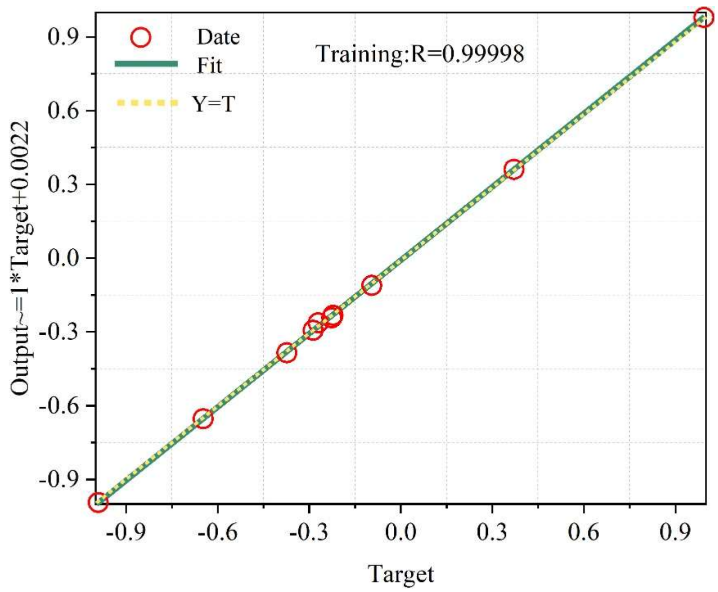

Fig. 4. Correlation between PSO-BP model training results

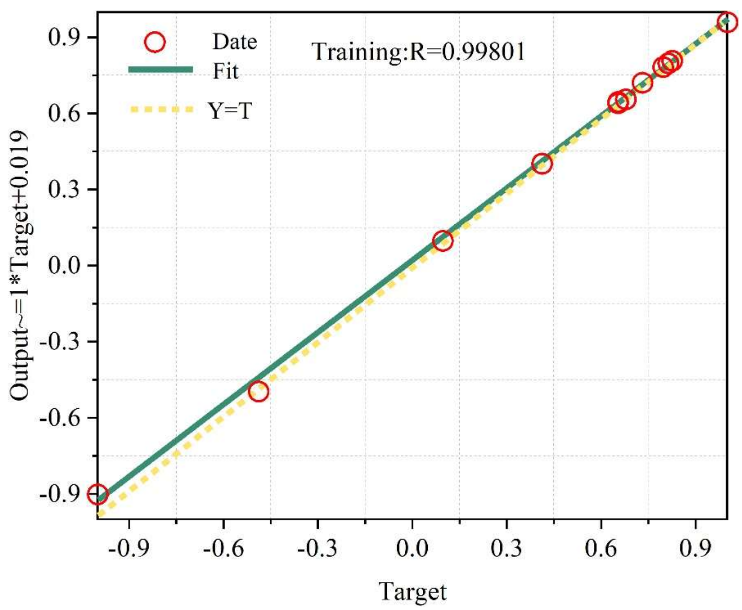

Fig. 5. The correlation curve of the BP model training results

The error change curve of PSO-BP neural network training is shown in Fig. 6. It can be seen that after 9 iterations of training, the PSO-BP neural network reaches the preset performance index, and the training completion is good enough to be used for tasks such as prediction and classification.

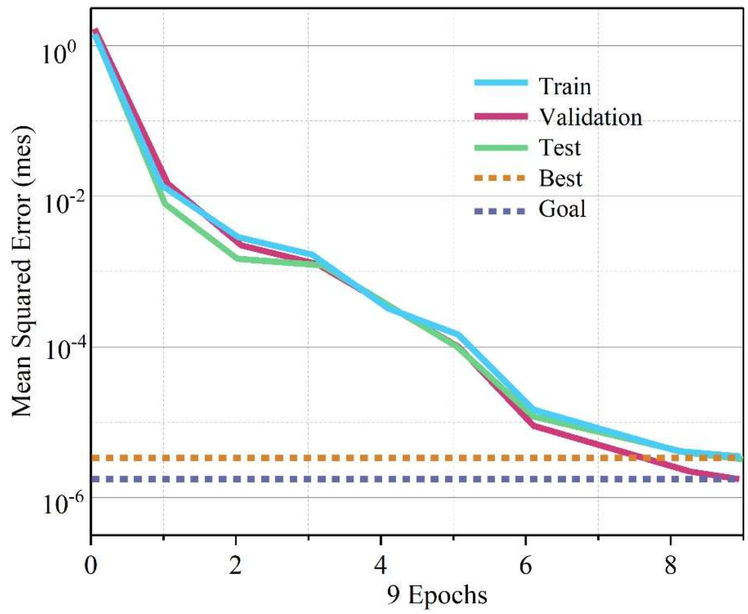

Fig. 6. Error variation curve of PSO-BP neural network training

3.3. *Testing of PSO-BP neural network models*

After the training of PSO-BP neural network was completed, some test data were randomly selected to test the PSO-BP neural network model to get the corresponding value of students' innovation and entrepreneurship education evaluation. Table 4 shows the results of the comparison between the expected value and the actual value of the PSO-BP model, and Figure 7 shows the comparison between the predicted actual value and the expected value of the PSO-BP model. Through the PSO-BP neural network testing and outputting the actual value, the actual value is valid, the expected value is reasonable, and the maximum relative error of the two is 1.4272%, which is basically convergent to the ideal state. It can be seen that the results of the comparison between the actual value and the expected value are relatively ideal, and each scoring result corresponds to the data of 12 evaluation indexes of a student, which is mapped to the level of the individual student's innovation and entrepreneurship ability through the different scores. Therefore, the evaluation results are analyzed as follows.

1) Students with higher evaluation scores have a more solid professional foundation. Professional knowledge and skills, participation in national-level competitions and participation in centralized entrepreneurship training camps have a profound impact on students' innovation and entrepreneurship ability. Students should be led by solid professional knowledge, participation in national-level competitions and college student training programs in carrying out innovation and entrepreneurship education. From the analysis of the collected data, students' professional knowledge is relatively solid.

2) Some of the students with evaluation results above 90 points have the experience of participating in national-level competitions and attending centralized entrepreneurship training camps. Participating in national-level competitions and entrepreneurship training camps plays a key role in enhancing students' innovation and entrepreneurship abilities. According to the evaluation indicators, especially students who have won awards for participating in national-level competitions, they participate in national-level competitions and attend centralized entrepreneurship training camps at the same time on the premise of mastering solid professional knowledge. Participating in national-level competitions is a comprehensive application of students' mastery of professional knowledge, while participating in centralized entrepreneurship training camps and obtaining financial support from entrepreneurship funds is a balance and integration of all aspects of professional knowledge and

innovation and entrepreneurship. Analyzing the data collected from the school and the results of simulation experiments, the practical ability of students needs to be improved.

3) Most of the students with evaluation results above 80 points have the experience of participating in social practice. Participating in social practice and having entrepreneurial experience promote students' innovation and entrepreneurial ability. The evaluation indicators of the length of participation in social practice and having entrepreneurial experience both play a positive role in personal innovation and entrepreneurial ability. Because participating in social practice allows one to recognize the pain points and deficiencies in life, and then put forward their own ideas and solutions. From the analysis of the collected data and the results of the simulation experiment, it is found that the students' social practice experience is relatively rich.

Table 4. The expected value and the actual value of the PSO-BP model

Serial number	Desired output	Actual output	Error(%)
1	96.0739	96.8404	-0.7665
2	93.8768	94.3391	-0.4623
3	81.1964	82.1449	-0.9485
4	92.0797	91.3959	0.6838
5	87.7404	86.7382	1.0022
6	84.811	84.5426	0.2684
7	88.2302	89.1472	-0.917
8	97.2111	98.6383	-1.4272
9	76.8108	77.5451	-0.7343
10	79.4865	80.7389	-1.2524
11	84.1191	83.8079	0.3112
12	97.8901	96.8172	1.0729

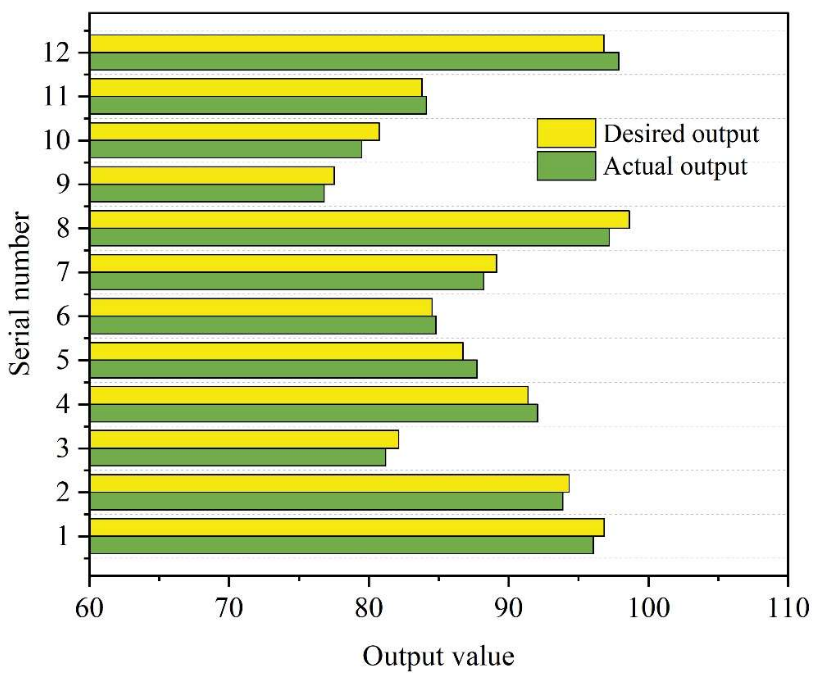

Fig. 7. Forecast actual value and expected value of the PSO-BP model

3.4. Results of PSO-BP model application

The PSO-optimized BP neural network was used to test the innovation and entrepreneurship performance samples of 300 students from six schools, namely CS, ZZ, LD, BJ, GZ and WH. Since the BP neural network is easy to fall into the local optimum, we chose to optimize the adjustment of its weights and thresholds using the PSO algorithm. The comparison of test results before and after optimization is shown in Table 5. Before optimization, it was found through extensive training that the basic BP neural network would fall into local optimum almost twice every 30 times, while the PSO-optimized model would not fall into local optimum. The test results show that the error between the actual value and the true value of the optimized PSO-BP model is between 0.02% and 0.34%, while the error between the actual value and the true value of the BP model before optimization is between 0.462% and 2.3815%. Obviously the optimized PSO-BP network model possesses a smaller error.

Table 5. Compare the results before and after optimization

Survey object	Expected value	Optimized actual value	Optimized absolute error	Optimized pre-actual value	Absolute error before optimization
CS	7.0549	7.0545	0.0004	7.6249	0.57
ZZ	4.7975	4.797	0.0005	7.179	2.3815
LD	1.9792	1.9842	0.005	2.122	0.1428
BJ	4.624	4.6166	0.0074	5.1104	0.4864
GZ	4.6085	4.5745	0.034	6.1871	1.5786
WH	1.9421	1.9423	0.0002	2.4041	0.462

4. Conclusion

In this paper, we first constructed the evaluation system of innovation and entrepreneurship education for college students, used the hierarchical analysis method to assign weights to the indicators, and then used the particle swarm optimization neural network method (PSO-BP) to assess the constructed evaluation system for innovation and entrepreneurship education, and finally tested the application effect of the PSO-BP model.

1) The combined weight coefficients of the 12 indicators are above 0.1 for 5 of them, which are innovation and entrepreneurship course examination results, having entrepreneurial experience, attending centralized entrepreneurship training camp, obtaining entrepreneurship fund grants and participating in innovation or entrepreneurship clubs, and their corresponding weight shares are between 10.17% and 12.06% respectively. The combined weights of the remaining seven indicators are less than 10%.

2) The PSO-BP neural network model has better network performance, and its predicted value is closest to the real value while the correlation between the training samples and the test samples is better (R=0.99998,). The PSO-BP model can be used for prediction and classification after 9 iterations of training. The PSO-BP neural network tests and outputs the actual value and the expected value with a maximum relative error of only 1.4272%, the model tends to be ideal. The PSO-optimized prediction model has a very small error (<0.34%).

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References

[1] Wang, F., Luo, H., Wang, F., & Wang, J. (2016, May). Analysis on the Factors Influencing the Performance of Innovation and Entrepreneurship Education in Colleges and Universities. In 2016 International Conference on Education, Management and Computer Science (pp. 172-177). Atlantis Press.

[2] Bao, Z., Teng, H., Peng, J., Jin, D., & Liu, X. (2017, December). The Influencing factors and Countermeasures of College Students' Innovation and Entrepreneurship Ability from the Perspective of College Students and Teachers. In 2017 7th International Conference on Mechatronics, Computer and Education Informationiz💞tion (MCEI 2017) (pp. 237-240). Atlantis Press.

[3] Aijun, D. (2020, February). Analysis on the evaluation model of the teaching effect of innovation and entrepreneurship course based on big data. In 2020 12th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA) (pp. 848-851). IEEE.

[4] Zhang, W. (2022). Quality improvement of college students’ innovation and entrepreneurship education based on big data analysis under the background of cloud computing. Scientific Programming, 2022(1), 8734474.

[5] Tan, L., & Du, F. (2022). Integrating entrepreneurship and innovation education into higher vocational education teaching methods based on big data analysis. Wireless Communications and Mobile Computing, 2022(1), 4616446.

[6] Yuan, F., & Hu, D. (2021, April). Research on the application of big data technology in college students’ innovation and entrepreneurship guidance service. In Journal of Physics: Conference Series (Vol. 1883, No. 1, p. 012171). IOP Publishing.

[7] Xin, H., Xu, J., & Yang, J. (2021, December). Research on The Construction of Innovation and Entrepreneurship Education Curriculum System in Local Colleges Based on Big Data. In 2021 Smart City Challenges & Outcomes for Urban Transformation (SCOUT) (pp. 141-145). IEEE.

[8] Quanli, W., & Chu-jian, G. (2019, December). Research on Evaluation of Innovation and Entrepreneurship Education in Local Universities under the Background of Big Data. In Proceedings of the 2019 Annual Meeting on Management Engineering (pp. 169-173).

[9] Jia, Y. (2023, August). Evaluation Method of Innovation and Entrepreneurship Education Teaching Effect Based on Fuzzy Clustering. In International Conference on E-Learning, E-Education, and Online Training (pp. 102-116). Cham: Springer Nature Switzerland.

[10] Wang, H., & Yu, Y. (2022, July). Research on Teaching Effect Evaluation of Innovation and Entrepreneurship Based on Collaborative Filtering Algorithm. In International Conference on E-Learning, E-Education, and Online Training (pp. 614-626). Cham: Springer Nature Switzerland.

[11] Zhou, Y., & Wu, L. (2019). Extension priority evaluation extension model for quality evaluation of innovation and entrepreneurship education. Journal of advanced computational intelligence and intelligent informatics, 23(2), 242-247.

[12] Jian, S., Lu, L., & Huang, Y. (2023, August). The Improvement Index of College Students' Innovation and Entrepreneurship Ability Based on Crawler Algorithm. In EAI International Conference, BigIoT-EDU (pp. 60-70). Cham: Springer Nature Switzerland.

[13] Wei, W. (2022, July). Research on Quality Evaluation of College Students' Innovation and Entrepreneurship Education Based on Grey Correlation Algorithm. In EAI International Conference, BigIoT-EDU (pp. 153-164). Cham: Springer Nature Switzerland.

[14] Zheng, Z. (2022, July). Research on Evaluation Method of College Students' Innovation and Entrepreneurship Training Mode Based on Deep Neural Network. In International Conference on E-Learning, E-Education, and Online Training (pp. 377-387). Cham: Springer Nature Switzerland.

[15] Mao, L., & Zhang, W. (2021). Analysis of entrepreneurship education in colleges and based on improved decision tree algorithm and fuzzy mathematics. Journal of Intelligent & Fuzzy Systems, 40(2), 2095-2107.

[16] Cheng, C., & Cao, J. (2021). Design of Undergraduate Innovation and Entrepreneurship Ability Evaluation System. International Core Journal of Engineering, 7(7), 263-267.

[17] Jing, G. (2022). Research on evaluation algorithm of innovation and entrepreneurship effect of college graduates based on DL. Mathematical Problems in Engineering, 2022(1), 1802156.

[18] Leng, M., Sui, M., & Zhang, H. (2022). Research and analysis on the evaluation system of innovation and entrepreneurship education in local universities. International Journal of Social Science and Education Research, 5(12), 25-29.

[19] Melissa De Regge,Paul Gemmel,Leen Ackaert,Let Dillen,Peter Pype,Nele Van Den Noortgate... & Kristof Eeckloo. (2024). Correction: Addressing integration in the organization of palliative care in Belgium: a multilevel ecosystems approach using the analytic hierarchy process (AHP) method.. BMC palliative care(1),266.

[20] Guanqing Kong,Shuang Ma,Wei Zhao,Haifeng Wang,Qingxi Fu & Jiuru Wang. (2024). A novel method for optimizing epilepsy detection features through multi-domain feature fusion and selection. Frontiers in Computational Neuroscience1416838-1416838.

[21] Guo Wenru. (2021). Safety Risk Assessment of Tourism Management System Based on PSO-BP Neural Network. Computational Intelligence and Neuroscience1980037-1980037.