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Research on the Optimization of Cultivation Mode Based on Extreme Learning Machine Algorithm in College Students' Innovation and Entrepreneurship Education under the Framework of Deep Collaboration between Industry and Education

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Abstract The increasing depth of the industry-education synergy model in college education provides diverse development possibilities for college students' innovation and entrepreneurship education work. This paper combines the work of innovation and entrepreneurship education in colleges and universities, and briefly analyzes its realization methods in the framework of industry-teaching integration. At the same time, from the perspective of the recipients, it initially constructs the evaluation index system of innovation and entrepreneurship education. In order to more accurately assess the results of innovation and entrepreneurship education in colleges and universities, this paper chooses the Extreme Learning Machine (ELM) algorithm as the identification algorithm. Because the prediction accuracy of ELM algorithm is low, the cuckoo search (CS) algorithm is used to improve it, so as to form CS-ELM algorithm. On this basis, the number of neurons in each layer, the learning rate and the training function are determined separately to design a set of innovative entrepreneurship education evaluation model. In the simulation experiment of this model, the comprehensive output value of University V is 0.7281. It shows that the current innovation and entrepreneurship education of University V is better as a whole, and further improvement can still be made.

Index Terms extreme learning machine algorithm, CS-ELM algorithm, innovation and entrepreneurship education, evaluation model

I. Introduction

With the rapid development of society and changes in the employment situation, more and more college students begin to pay attention to innovation and entrepreneurship education. As a unique form of education, innovation and entrepreneurship education for college students is increasingly being widely noticed and emphasized by students and society, especially in the context of the national policy of integration of industry and education [1]-[4]. The goal of innovation and entrepreneurship education for college students is to cultivate students' innovative thinking and entrepreneurial ability, so that they can have the ability to innovate independently and implement entrepreneurship in their future work and life [5]-[7]. Through innovation and entrepreneurship education, college students can better adapt to the needs of social development and become talents with innovative spirit and entrepreneurial consciousness. At the same time, innovation and entrepreneurship education can also stimulate students' interest in learning, cultivate their comprehensive ability and improve their employment competitiveness [8]-[11].

Extreme Learning Machine is a machine learning algorithm based on a single hidden layer feedforward neural network, and its core idea is to randomly generate the connection weights between the input layer and the hidden layer, and fix these weights unchanged, and obtain the best model performance only by optimally calculating the connection weights between the hidden layer and the output layer [12]-[15]. Compared with the traditional neural network algorithm, the extreme learning machine has the advantages of fast training speed and strong generalization ability. It has a wide range of applications and research value in innovation and entrepreneurship education. By applying it in tasks such as resource classification and target detection, the extreme learning machine can help teachers and students to process and analyze innovation and entrepreneurship resources more efficiently and accurately, so as to promote the development of the integration of industry and education [16]-[19].

Aiming at the optimization of the cultivation of innovation and entrepreneurship education for college students, this paper first discusses the practical path of this educational work under the framework of industry-teaching synergy. Then from the perspective of students, the dimensions and subordinate indicators of innovation and entrepreneurship education evaluation are initially selected. Subsequently, the basic principles of CS algorithm and ELM algorithm are elaborated in detail, and the CS algorithm is used to make up for the shortcomings of ELM algorithm, and the CS-ELM algorithm is constructed. Finally, the number of neurons, learning rate and training function are determined, and the innovation and entrepreneurship education evaluation model is constructed. Taking V University as the research object, simulation experiments of innovation and entrepreneurship education work are carried out to verify the effectiveness of the model.

II. Practical paths for innovation and entrepreneurship education in an industry-education framework

II. A. Constructing a more perfect school-enterprise synergistic mechanism

Under the background of the new period, schools and enterprises need to combine the development needs of collaborative education, scientifically designed to help stimulate the two sides of the innovative vitality and innovative power of the guarantee mechanism, to ensure that the school-enterprise cooperation from the most basic shallow cooperation into a deep level of cooperation, from disordered cooperation into orderly cooperation.

II. B. Building a system of microprofessionalism

Micro-professionalism is to take students' employment as the guide, formulate the system of personnel training programs in line with students' career development needs, and ensure that personnel training can show the development trend of specialization. The scientific construction of micro-professional education system in senior technical school means that in the link of school-enterprise collaborative education, combining with the actual employment demand of enterprises, combining with the cooperative enterprises and a series of teaching accumulation in the school as well as the teachers' strength, to increase the efforts of professional construction, to build the talent cultivation program to meet the demand of the students' career development as well as the actual demand of the enterprises for talents, to improve the effect of talent cultivation and to meet the demand of the enterprises for employing people.

II. C. Scientific construction of dual-creation education system

Dual-creation education work relies on the development of the industry, therefore, in the all-round docking link between the advanced technical school and the enterprise's new development process, new development field, new skills, new marketing work and new design work, the common problems encountered by the enterprise in each key link of the industrial chain can be effectively solved, and the dual-creation program which is oriented on the core of the problem, and with teachers as the main body of the scientific research, and with dual-creation education as the hand can make a series of innovations at the technical level, service level, brand level and channel level. The dual-creation program can make a series of innovations at the technical level, service level, brand level and channel level. When the dual-creation projects are mature, they can enter the incubation platform through evaluation, thus realizing the scientific construction and fission of dual-creation projects.

III. Selection of evaluation indicators for innovation and entrepreneurship education

As can be seen from the three practical paths proposed in the previous section, the development of students in innovation and entrepreneurship education is an important subject of evaluation. However, the evaluation of innovation and entrepreneurship education based on students in existing research is still imperfect, so this chapter discusses the three selection principles of evaluation indexes of innovation and entrepreneurship education from the perspective of student identity. Four dimensions of the index system structure are selected to initially construct the evaluation index system of innovation and entrepreneurship education in colleges and universities from the perspective of students.

III. A. Principles for selecting evaluation indicators

Based on the research purpose of this paper, on the basis of the general principles of education evaluation, combined with the individual principles characterizing the evaluation of innovation and entrepreneurship education in colleges and universities, this paper establishes the following three principles of indicator selection:

First, the principle of comprehensiveness and synthesis. The purpose of this paper is to study the construction of evaluation system of innovation and entrepreneurship education in colleges and universities under the perspective of students. Previously, the literature in this field has rarely had research perspectives from the perspective of students, so the selection of indicators should be comprehensively considered in all dimensions, and should try to cover the indicators from all perspectives related to students, so as to ensure the completeness of the evaluation indicator selection.

Second, the principle of scientificity and hierarchy. Students' evaluation of education is closely related to the school, teaching process, curriculum, teacher strength, hard and software environment construction and other aspects. And the sub-indicators of teaching, teachers and courses are interpenetrating, so attention should be paid to the hierarchical nature of the selection of indicators in the design of indicators to avoid the overlapping and repetition of secondary indicators under the first-level indicators, which will lead to the loss of scientific nature of the indicator design.

Third, the principle of development and dynamics. Innovation and entrepreneurship education in colleges and universities is a dynamic and developing process, and students and education implementers interact with each other and influence each other in the environment of education implementation, therefore, the selection of student evaluation indicators should not be fixed, rigid and unidirectional, but should be a two-way flow with cyclic effect, based on the development and dynamics of innovation and entrepreneurship education in colleges and universities, and the design of the indicators should follow the principle of development and dynamics. Based on the development and dynamics of university innovation and entrepreneurship education, the design of indicators should also follow the principles of development and dynamics.

III. B. Four dimensions of evaluation

Combining the characteristics of innovation and entrepreneurship education in colleges and universities above and the research theme of this paper, we choose to sort out the indicators of students' evaluation of innovation and entrepreneurship education in colleges and universities from four dimensions: the place where innovation and entrepreneurship education is implemented (schools), the process of teaching innovation and entrepreneurship education (teachers' teaching), the environment of innovation and entrepreneurship education (hard and software facilities and activities), and the recipients of innovation and entrepreneurship education (students). The preliminary design of the specific dimension division and its subordinate primary and secondary indicators are shown in Table 1.

Table 1: Evaluation index of innovation and entrepreneurship education

Index dimension	Primary index	Secondary index
(A) Implementation of innovation and entrepreneurship education (school)	(A1) School level	(A11) theory on school management
		(A12) management system
		(A13) Policy implementation
		(A14) financial support
		(A15) research status
(B) Innovation and entrepreneurship Education Teacher Process (teacher teaching)	(B1) Innovation and entrepreneurship education teachers	(B11) Teacher qualification
		(B12) Team structure
		(B13) teaching ability
		(B14) the capacity for scientific research
		(B15) the capacity for scientific research
		(B16) Teaching enthusiasm
		(B17) training situation
	(B2) Innovation and entrepreneurship course teaching	(B21) Curriculum Provision
		(B22) content of courses
		(B23) textbook content
		(B24) teaching method
		(B25) transformation of education
		(B26) evaluation mode
(C) Innovation and Entrepreneurship Education Environment (hardware and Software Facilities activities)	(C1) Innovation and entrepreneurship practice teaching	(C11) Innovation and Entrepreneurship Competition
		(C12) Lecture on innovation and Entrepreneurship
		(C13) Innovation and entrepreneurship practice

	(C2) Education environment for innovation and entrepreneurship	(C21) Innovation and entrepreneurship incubation base
		(C22) Innovation and entrepreneurship information platform
		(C23) Innovation and entrepreneurship service facilities
		(C24) Culture of innovation and entrepreneurship
(D) Innovation and Entrepreneurship Education recipients (students)	(D1) Credit setting	(D11) incentive mechanism
		(D12) Innovation and entrepreneurship awards
		(D13) School-enterprise cooperation job opportunities
	(D2) feedback mechanism	(D21) Teaching status tracking
		(D22) feedback mechanism
		(D23) evaluation mechanism

IV. CS-ELM algorithm

IV. A. CS algorithm principle and process

Past scholars have proposed the CS algorithm by simulating the parasitic breeding behavior of cuckoos, which can quickly obtain the optimal solution based on the Lévy flight mechanism. The following three idealized rules can describe the CS algorithm in a simplified way:

(1) Each cuckoo randomly chooses a nest and lays one egg at a time.

(2) The best quality nest is reserved for the next generation.

(3) Fix the number of nests available for parasitization with a certain probability Pa Cuckoo bird eggs will be discovered by the host, which will either throw away the eggs or abandon the nest.

The bird eggs in the nest correspond to the candidate solutions in the algorithm, and the cuckoo bird eggs correspond to a new solution, which aims to realize the replacement of inferior solutions by preferred solutions during each iteration. Based on the above rules, the CS algorithm flow is shown in Figure 1.

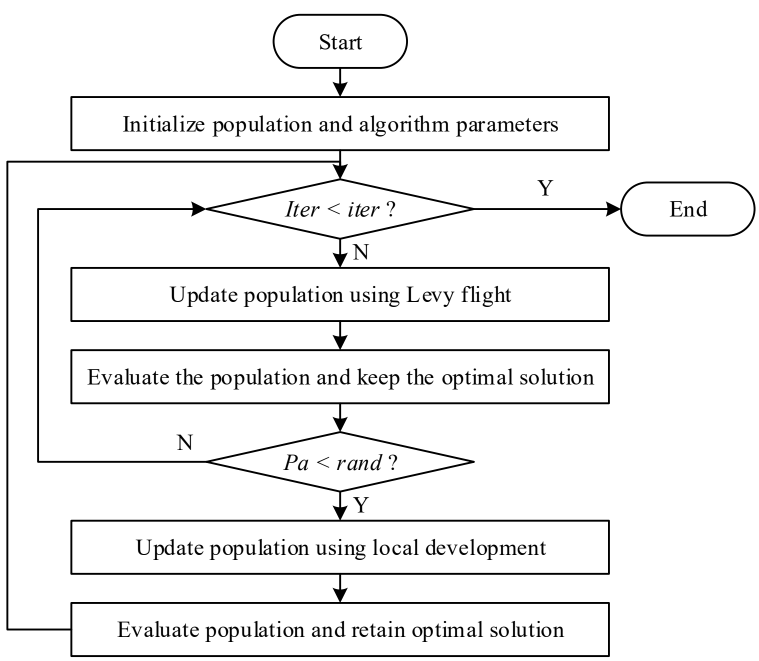


Figure 1: CS algorithm flow

The CS algorithm consists of two phases: global exploration and local exploitation, the former of which is realized by Levy flights for population updating, as in equation (1):

$$x_i^{t+1} = x_i^2 + \alpha\left(x^2 - x_i^t\right) \oplus Levy\left(\lambda\right) \tag{1}$$

where x^t and x_i^t denote the optimal solution of the t rd generation and the i th candidate solution, respectively, α denotes the step factor, and $\alpha = 0.01$. $Levy\left(\lambda\right) = \mu / \left|v\right|^{1/\beta}$, $\mu : N\left(0, \sigma_\mu^2\right)$, $v : N\left(0,1\right)$, σ_μ as in Eq. (2):

$$\sigma_\mu = \left[\frac{\Gamma(1+\beta)\times\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\times\beta\times 2^{(\beta-1)/2}}\right] \tag{2}$$

The latter realizes the substitution of superior and inferior solutions by preferring random wandering, as in Eq. (3):

$$x_i^{t+1} = x_i^t + r\left(x_j^t - x_k^t\right) \tag{3}$$

where x_i^t and x_k^t denote two random individuals different from x_i^t, $r \in rand\left(0,1\right)$.

IV. B. Extreme Learning Machines

Extreme Learning Machine is a feed-forward neural network algorithm with a single hidden layer. Extreme Learning Machine was first proposed to optimize the back-propagation algorithm to improve the learning efficiency. In traditional neural network training, the bias and weight matrices are usually adjusted using gradient descent, while the input layer weight matrix and hidden layer bias of the Extreme Learning Machine are randomly generated, and the output layer matrix is solved by the generalized inverse matrix without repeated adjustments.The network structure of ELM is shown in Figure 2.

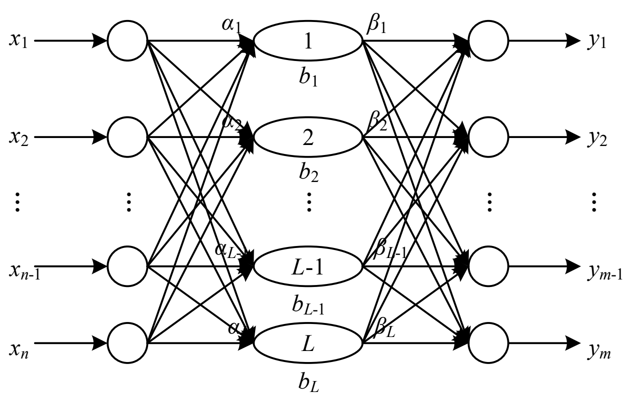


Figure 2: ELM network architecture

The network structure of the Extreme Learning Machine algorithm contains three parts: input layer, implicit layer and output layer. Assuming that there are N different sample data, the sample data can be represented as $\{X,Y\} = \left\{\left(x_i, t_i\right)\right\}_{i=1}^N$, $x_i \in R^n$, $t_i \in R^m$, the number of nodes in the implicit layer is L, and the activation function of the implicit layer is $g(x)$, the expression of ELM is as in equation (4):

$$\sum_{i=1}^{L} \beta_i g\left(a_i \cdot x_j + b_i\right) = y_j \tag{4}$$

where $j = 1,2,3\cdots\cdots,N$, β_i are output weight vectors, a_i is the input weight vector, b_i is the bias value of the i th hidden layer node, $a_i \cdot x_j$ denotes the inner product of a_i and x_j, and y_j is the network predicted output value. When the value error of the output is decreasing to no error, at this point it can be expressed as equation (5):

$$\sum_{j=1}^{N} \left\|y_j - t_j\right\| = 0. \tag{5}$$

At this point there exist β_i, a_i, b_i such that Eq. (6):

$$\sum_{i=1}^{L} \beta_i g\left(a_i \cdot x_j + b_i\right) = t_j \tag{6}$$

Simplifying the above equation (4), the matrix is represented as equations (7)-(9):

$$H\beta = T \tag{7}$$

$$H = \begin{pmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{pmatrix} = \begin{pmatrix} g(a_1 \cdot x_1 + b_1) & \dots & g(a_L \cdot x_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(a_1 \cdot x_N + b_1) & \dots & g(a_L \cdot x_N + b_L) \end{pmatrix} \tag{8}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m}, T = \begin{bmatrix} t_1^T \\ \vdots \\ t_L^T \end{bmatrix}_{L\times m} \tag{9}$$

where H in Eqs. (7) and (8) is the hidden layer node output matrix, β is the output weight matrix, and T is the desired output matrix.

When the number of nodes in the hidden layer is the same as the number of training samples, the inverse matrix of the hidden layer node output matrix H can be solved directly by Eq. (7) and the optimal output weight matrix β can be obtained, but in most cases the number of nodes in the hidden layer will be much smaller than the number of training samples, in which case the least-squares solution can be utilized to solve for the output weights, which can be obtained by Eq. (10):

$$\hat{\beta} = H^{+}T \tag{10}$$

where H^{+} is the Moore-Penrose generalized inverse matrix of the implicit layer output matrix H .

IV. C. CS-ELM algorithm

In order to improve the accuracy of early failure prediction, the cuckoo search algorithm is applied for the determination of the number of hidden layer nodes. The following are the detailed steps of the CS-ELM algorithm:

(1) Set the parameters of CS algorithm, P_a is the probability that the host bird finds the young chick, then there is an initial nest location as in equation (11):

$$x_{mest,0} = \left[x_1^0, x_2^0, \cdots, x_N^0\right] \tag{11}$$

$n_{\max}$ is the maximum number of iterations. The value in $x_{mest,0}$ is rounded and input into the extreme learning machine model as an array of the number of hidden layers $M_0 = \left[m_1^0, m_2^0, \cdots, m_N^0\right]$.

(2) Input the training samples and calculate the root mean square error of the training samples after being trained by the extreme learning machine, denoted as $f_{best,0}$, then we have equation (12):

$$f_{best,0} = \left[y_1^0, y_2^0, \cdots, y_N^0\right] \tag{12}$$

Use it as the fitness of each nest.

(3) The nest with minimum $y_i^o\left(1 \le i \le N\right)$ is selected as the optimal nest by step (1) (2) and the position is equation (13):

$$x_h^i\left(1 \le i \le n_{\max}, h \in [1, N]\right) \tag{13}$$

(4) Search for bird nest location s according to the Lévy flight mechanism, input it into the ELM model as the number of hidden layers after rounding, compute s the new fitness value f_{new}, compare it with the smallest $y_i^0\left(1 \le i \le N\right)$ obtained in step (3), and update this location if the new value is smaller.

(5) ε is the probability of generating a bird nest obeying a uniform distribution in each bird nest, and if $\varepsilon_i > P_a$, the location of the bird nest is updated.

(6) If $n_{\max}$ is reached, stop the optimization search and get x_{next} and the corresponding f_{best}, otherwise skip to step (4).

(7) Select the smallest value of f_{best} and obtain its corresponding bird's nest location, input it into the Extreme Learning Machine model as the number of hidden layers after rounding, and output the corresponding W, b, β after training, and build the CS-ELM early failure prediction model accordingly.

IV. D. Objective function

Aiming at the ELM model performance affected by the initial selection of input weights Wi and implied layer bias bi, the CS algorithm is applied to the initial selection of input weights Wi and implied layer bi of the ELM model, and an evaluation method of innovative entrepreneurship teaching effect in colleges and universities based on CS-ELM is proposed, with the objective function as in Eq. (14):

$$\min F = \sqrt{\frac{\sum_{i=1}^{n}(y_i - o_i)^2}{n}} \tag{14}$$

IV. E. Algorithmic flow

Firstly, the evaluation indexes of innovation and entrepreneurship teaching effect in colleges and universities are constructed from four aspects, namely, the place of innovation and entrepreneurship education implementation (school), the process of innovation and entrepreneurship education giver (teacher teaching), the environment of innovation and entrepreneurship education (hard and software facilities and activities), and the recipients of innovation and entrepreneurship education (students), and then the scores and the final scores of each evaluation indexes are obtained through the way of scoring by the experts, and after that, the scores of the evaluation indexes are used as the After that, the score of each evaluation index is used as the input of CS-ELM, and the final score is used as the output of CS-ELM to establish the evaluation algorithm of innovation and entrepreneurship teaching effect in colleges and universities by CS-ELM. The scores of each evaluation index and the comprehensive score of evaluation of innovative and entrepreneurial teaching effect in colleges and universities are obtained by the expert evaluation method. The scores of each evaluation index are categorized as 1, 0.7, 0.5, 0.3 and 0.1, and the corresponding grades are excellent, good, moderate, poor and poor, respectively. The process of CS-ELM-based algorithm for evaluating the teaching effect of innovation and entrepreneurship in colleges and universities can be described in detail as follows.

Step 1 Read the innovative entrepreneurship teaching effect evaluation data, divide the data into training set and test set, and normalize them.

Step 2 Set the parameters of CS algorithm: the number of bird nests is N, the maximum number of iterations is M, the probability of alien bird eggs being found by the nest host is pa, and calculate the objective function values of all bird nests according to equation (14).

Step 3 Update the bird nest location, calculate the objective function value of the updated bird nest and compare it with the objective function value before updating, and take the bird nest with better objective function value as the current location.

Step 4 Generate uniformly analyzed random number r, r∈(0,1), if r>pa, update the bird's nest position, calculate the objective function values of all bird's nests, and keep the bird's nest position with the best objective function value.

Step 5 Judge whether the algorithm is terminated or not. If the termination condition is satisfied, record the historical optimal solution. Otherwise, return to Step 3.

Step 6 The best bird's nest location corresponds to the best initial input weight Wi and the best hidden layer bias bi of ELM model, and the best initial input weight Wi and the best hidden layer bias bi are substituted into ELM model for evaluation of innovation and entrepreneurship education effect in colleges and universities.

V. Innovation and entrepreneurship education evaluation model

In this chapter, based on the evaluation index system and CS-ELM algorithm proposed in the previous section, the evaluation index data are taken as the input vector, and the rating value is taken as the output vector data. The number of neurons in the input layer, the model learning rate and the training function are determined respectively to complete the design and establishment of the evaluation model of innovation and entrepreneurship education, and to unfold the validity test of the model.

V. A. Design of the model

V. A. 1) Determining the number of neurons in each layer

Determine the number of neurons in the input layer. The number of evaluation indicators is the data already mentioned in the previous section, and the number of neurons in the input layer is an important characteristic within the neural network, based on which the two are equal and unified. From the previous section, there are 31 evaluation metrics, so the number of input layer neurons is n=31.

The relationship between the number of neurons in the hidden layer and the error is shown in Table 2. The number of neurons in the hidden layer is analyzed in Table 2 for the values of 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15.At this time, the training error decreases continuously, and there is a linkage. The test error has the ups and downs fluctuation when the value of 10, 11 and 12 is taken, and the overall analysis of the number of neurons in the hidden layer is 11 is the best choice.

Table 2: Relationship between the number of hidden layer neurons and error

Number of hidden layer neurons	Training error	Test error
3	1.2567	1.1276
4	0.7978	0.8233
5	0.6319	0.7279
6	0.5703	0.6708
7	0.5529	0.6896
8	0.4452	0.6576
9	0.3856	0.6498
10	0.2597	0.4556
11	0.1858	0.6644
12	0.1856	0.5988
13	0.1802	0.6892
14	0.1799	0.6888
15	0.1784	0.6871

V. A. 2) Determining the learning rate

The learning rate directly affects the efficiency of training and testing of neural networks. Equating the learning rate to η, there are advantages and disadvantages to the size of the η value; when the learning rate is large, the weights are large and converge quickly, causing the network to fluctuate. Smaller learning rates cause the network efficiency to be variable and converge slowly. Introducing the momentum term α can solve such problems. There is equation (15):

$$\Delta w_{ij}(n)=\alpha\Delta w_{ij}(n-1)+\eta\delta_j(n)v_i(n) \tag{15}$$

The error and number of training sessions for different learning rates are shown in Table 3. According to the evaluation index system of this paper, the error and number of training sessions in Table 3 are analyzed for a learning rate of 0.01.

Table 3: Comparison of different learning rates

Learning rate	Training times	Error(e-001)
0.005	18	6.9003
0.01	10	3.1258
0.02	20	5.8894
0.03	23	9.8908
0.04	30	3.5673
0.05	35	9.9888
0.06	45	8.7692
0.07	50	10.003

V. A. 3) Determining the training function

This subsection unfolds the comparison of the training results of four representative training functions Rprop algorithm, Gradient Descent, One Step Secant Algorithm, and Levenberg-Marquardt algorithm in terms of the number of training steps, and the performance, respectively, so as to highlight the performance advantages of the different training functions. Figure 3-Figure 6 show the grid training results of Rprop algorithm, Levenberg-Marquardt algorithm, Gradient descent method, One Step Secant Algorithm respectively.

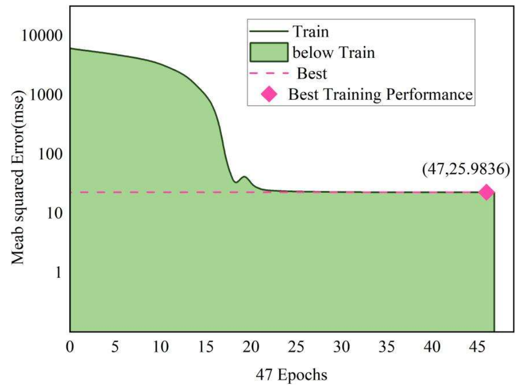


Figure 3: Grid training of Rprop algorithm

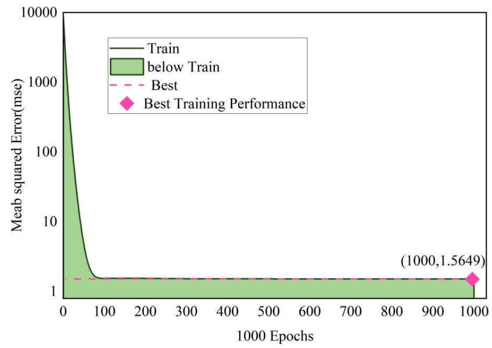


Figure 4: Grid training of Levenberg-Marquardt algorithm

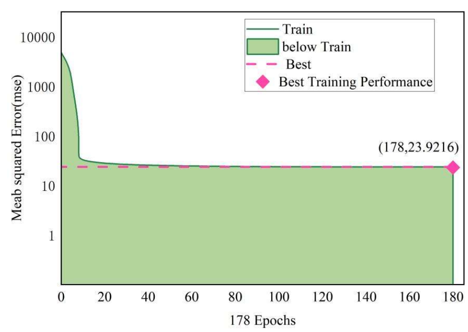


Figure 5: Grid training of gradient descent method

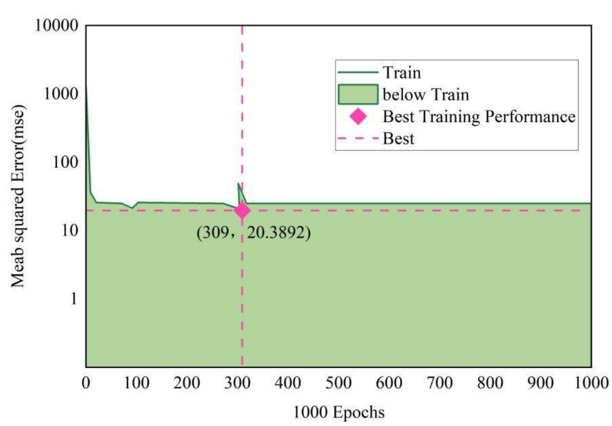


Figure 6: Grid training of One Step Secant Algorithm

Combining Figure 3, Figure 4, Figure 5, and Figure 6, it is concluded that the Levenberg-Marquardt algorithm has the best performance, which has converged at 100 training steps and has the smallest mean-square error of only 1.5649. Therefore, it is the optimal choice to select the Levenberg-Marquardt algorithm as the training function of the model.

V. B. Testing of the model

In order to verify the evaluation index system and evaluation model method of this paper, V University is selected as a research case, and four other universities are selected as sample objects (V1, V2, V3, V4). In the form of questionnaires, use the evaluation index system of this paper to evaluate their innovation and entrepreneurship education work. The empirical analysis of the model is carried out to evaluate for the implementation effect and quality.

V. B. 1) Data initialization process

The evaluation results of innovation and entrepreneurship education are divided into five grades: excellent, good, medium, passing and failing, and their output values through the model are: excellent (1.00-0.90), good (0.89-0.80), medium (0.79-0.70), passing (0.69-0.60) and failing (0.59- below). Therefore, the model has 6 points in the input layer and only 1 output node in the output layer with a value range of [0,1].

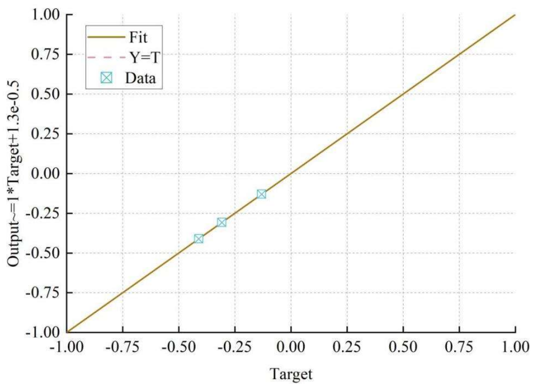
The maximum-minimum value method was applied for normalization, and the results of sample data processing are shown in Table 4.

Table 4: Processing data value

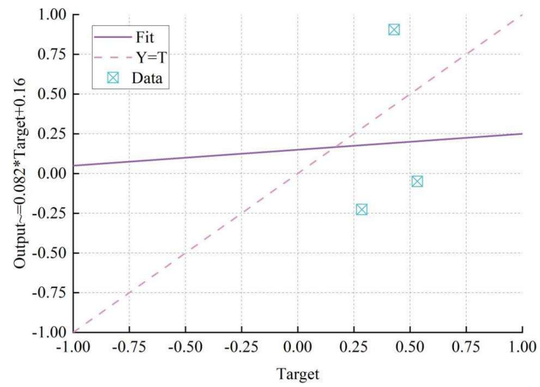
Index	V	V1	V2	V3	V4
A11	0.2949	0.1538	0.0819	0.1103	0.165
A12	0.1842	0.0418	0.2071	0.1103	0.1835
A13	0.2568	0.2492	0.0615	0.0685	0.2462
A14	0.1388	0.259	0.1428	0.2764	0.198
A14	0.1523	0.0632	0.0175	0.1672	0.258
B11	0.1484	0.0033	0.0277	0.2082	0.2939
B12	0.1043	0.1963	0.0067	0.0593	0.0296
B13	0.2023	0.1648	0.1243	0.0203	0.2505
B14	0.041	0.1458	0.2623	0.1004	0.1728
B15	0.0336	0.1987	0.2625	0.0107	0.188
B16	0.0621	0.2367	0.0579	0.1341	0.2949
B17	0.013	0.0301	0.0727	0.0019	0.0318
B21	0.0761	0.2646	0.0341	0.1244	0.0926
B22	0.1583	0.2667	0.0045	0.0957	0.0775
B23	0.0751	0.018	0.2297	0.1096	0.1278
B24	0.264	0.1996	0.005	0.0699	0.2087
B25	0.2061	0.1495	0.0295	0.2494	0.023
B26	0.0803	0.0539	0.2794	0.0491	0.1919
C11	0.2026	0.252	0.2474	0.147	0.1859
C12	0.1169	0.0457	0.1456	0.101	0.2722
C13	0.0465	0.0523	0.044	0.1106	0.0141
C21	0.0012	0.1174	0.2761	0.2044	0.1226
C22	0.2275	0.1866	0.0923	0.047	0.2784
C23	0.2477	0.0893	0.0718	0.1555	0.2614
C24	0.1695	0.2261	0.0614	0.23	0.2499
D11	0.1485	0.1741	0.17	0.2819	0.2608
D12	0.1204	0.016	0.1557	0.0059	0.299
D13	0.2002	0.1308	0.0265	0.1438	0.171
D21	0.0976	0.1946	0.0134	0.032	0.0236
D22	0.2833	0.2661	0.0373	0.2624	0.1906
D23	0.1441	0.1281	0.0854	0.2685	0.0899

V. B. 2) Simulation experiments

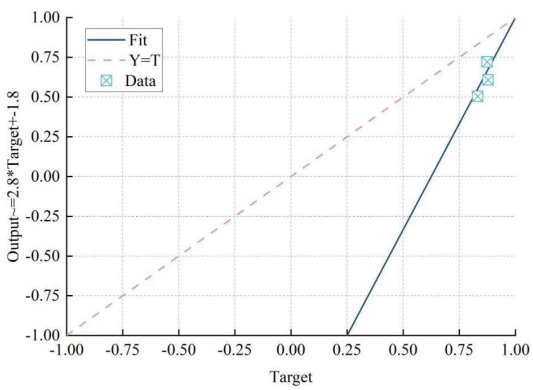
On the basis of the data completed above, the simulation training of the innovation and entrepreneurship evaluation model is launched, and the results of the training error are shown in Figure 7.



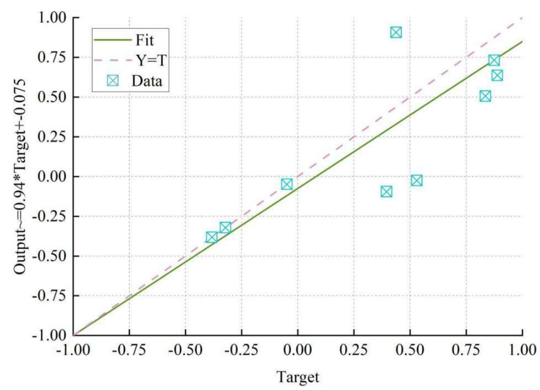
(a) Training: R=1



(b) Validation: R=0.013889



(c) Test: R=0.63322



(d) ALL: R=0.94459

Figure 7: The training error of the model

The specific output value of each indicator is shown in Table 5. Using the data collected from the questionnaire to evaluate the performance of innovation and entrepreneurship education in University V, applying the above trained innovation and entrepreneurship model, the comprehensive network output value is 0.7281.It proves that the innovation and entrepreneurship education in University V is at a medium level, and there is still a lot of room for improvement.

Table 5: Output results of each indicator

Index	Result	Index	Result
A11	0.77	B25	0.73
A12	0.89	B26	0.66
A13	0.78	C11	0.63
A14	0.66	C12	0.64
A14	0.87	C13	0.63
B11	0.88	C21	0.69
B12	0.87	C22	0.78
B13	0.85	C23	0.51
B14	0.94	C24	0.55
B15	0.81	D11	0.87

B16	0.62	D12	0.58
B17	0.88	D13	0.73
B21	0.85	D21	0.62
B22	0.74	D22	0.75
B23	0.89	D23	0.79
B24	0.71		

VI. Conclusion

Based on the improved Extreme Learning Machine (CS-ELM) algorithm, this paper proposes an evaluation model of innovation and entrepreneurship education in colleges and universities to realize the accurate assessment of innovation and entrepreneurship education in colleges and universities. It not only provides reference for the improvement and optimization of innovation and entrepreneurship training in colleges and universities, but also is an innovative attempt to apply the extreme learning machine algorithm in the field of innovation and entrepreneurship education in colleges and universities. The main findings of this paper are as follows:

(1) Combining the practical path of innovation and entrepreneurship education under the framework of industry and education and related research, the evaluation index system of innovation and entrepreneurship education containing 31 secondary indicators is designed from the four dimensions of implementation place, implementation process, implementation environment, and recipients.

(2) Aiming at the shortcomings of the Extreme Learning Machine (ELM), which has low classification accuracy due to random generation, the CS algorithm, which has strong search ability and few parameters, is utilized to make up for it and construct the CS-ELM algorithm. At the same time, in the form of data analysis and comparison experiments, the optimal number of neurons of the model is determined to be 11, the learning rate is 0.01, and the training function is the Levenberg-Marquardt algorithm, thus constructing the evaluation model of innovation and entrepreneurship education based on the CS-ELM algorithm. The model is applied to evaluate the results of innovative and entrepreneurial education work at V University, and the output value of the comprehensive grid is 0.7281.

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