An Evaluation Model of Online Autonomous English Learning Efficiency Using an Artificial Neural Network

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Abstract—Traditional classroom teaching model is constantly impacted by online education model. To enhance the online English learning efficiency of college students, one of the primary paths is to cultivate their autonomous learning ability. However, the existing research is limited to quantitative research. Therefore, this paper devises an evaluation model of online autonomous English learning efficiency based on artificial neural network. Firstly, the students participating in online English learning were classified, the evaluation indices of online autonomous English learning efficiency were determined and weighed, and the classification method was introduced for the evaluation results. Next, the improved particle swarm optimization (PSO) was adopted to optimize the traditional backpropagation neural network (BPNN). The improved BPNN was employed to evaluate the online autonomous English learning efficiency. The superiority of the improved model was demonstrated through experiments.

Keywords—neural network, online English learning, autonomous learning, learning efficiency evaluation

1 Introduction

With the continuous development of Internet communication technology and computer technology, traditional classroom teaching model is constantly impacted by online education model [1-5]. Currently, the best education and teaching resources can be shared across the globe, and the number of online learning courses is on the rise [6-10]. Autonomous learning refers to an inner mechanism of online learning, which integrates learning attitude, learning ability, with learning strategy. It reflects how well a student can control his/her goals, contents, methods, and materials of online learning [11, 12]. Listening, speaking, reading, writing, and viewing are the basic abilities of college English learners. To enhance the online English learning efficiency of college students, one of the primary paths is to cultivate their autonomous learning ability.

Wu [13] analyzed some problems in the autonomous English learning process of college students, improved the Iterative Dichotomiser 3 (ID3) algorithm in the field of data mining, and applied the original and improved ID3 separately to study college students' autonomous English learning. The multimedia sets the stage for students to learn English phonetics, for the multimedia application in autonomous learning of English phonetics, and for teachers to train students' autonomous learning ability of English phonetics in the multimedia environment. Guo [14] believed that college students cannot effectively learn college English online, without a certain autonomous learning ability, and held that the students' self-supervision Is crucial to improving their autonomous learning ability. Zhang et al. [15] discussed two environmental factors (social support, and learning pressure) and one individual factor (social support, learning pressure), and an individual factor (autonomous learning ability) that may affect college students' learning burnout in the online environment. The results show that social support only suppresses learning efficacy of college students, while learning pressure and autonomous learning ability produce significant positive or negative effects on the three kinds of learning burnout. The autonomous learning of students not only improves their course scores, but also promotes their lifelong learning and sustainable development. Massive open online courses (MOOCs) have an immense impact on the traditional English courses and teaching models. Xiao [16] aimed to reveal the motivation of students' autonomous learning in English MOOC teaching based on big data analysis. Drawing on theories of educational psychology, they expounded the intrinsic correlations between English MOOC teaching model and learning motivation theory in the big data environment. In terms of knowledge update, teachers need to train the students' ability to learn independently, apart from teaching the students English knowledge. Peng [17] designed a research-oriented learning model based on autonomous learning. The model advocates the combination between autonomous learning and research-oriented learning.

To date, researchers have completed experiments on the training of autonomous learning ability for language learners in higher education, and examined the influence of college students' autonomous learning ability over language learning efficiency. But the relevant research is largely qualitative. Machine learning gradually becomes the new research direction of online learning management, and boasts the ability to mine information value from the massive data. To solve the strong subjectivity, randomness, and delay in the evaluation of students' autonomous learning efficiency, this paper applies the improved backpropagation neural network (BPNN) to the evaluation of online autonomous English learning efficiency. The research results are of certain theoretical significance to the management of online English learning platform, and the scientific innovation of online English learning model. The main contents cover the following aspects: Firstly, Section 2 classifies the students participating in online English learning, determines and weighs the evaluation indices of online autonomous English learning efficiency, and introduces the classification method for the evaluation results. Section 3 adopts the improved particle swarm optimization (PSO) to optimize the traditional backpropagation neural network (BPNN). The improved BPNN was employed to evaluate the online autonomous English learning efficiency. The superiority of the improved model was demonstrated through experiments.

2 Construction of evaluation index system (EIS)

The students participating in online English learning have different autonomous learning efficiencies, depending on their willingness and ability of autonomous learning. According to the efficiency of autonomous learning, this paper divides the students participating in online English learning into three categories: the problematic students, who cannot timely solve learning problems, or learn persistently; the efficient students, who can independently look for solutions, learn quite persistently, and achieve a relatively high efficiency of autonomous learning; the strategic students, who feature mature learning methods/models, learn highly persistently, and achieve a very high efficiency of autonomous learning. In addition, the student' autonomous learning efficiency was evaluated from the two dimensions, namely, autonomous learning willingness, and autonomous learning ability. The specific evaluation indices are shown in Table 1.

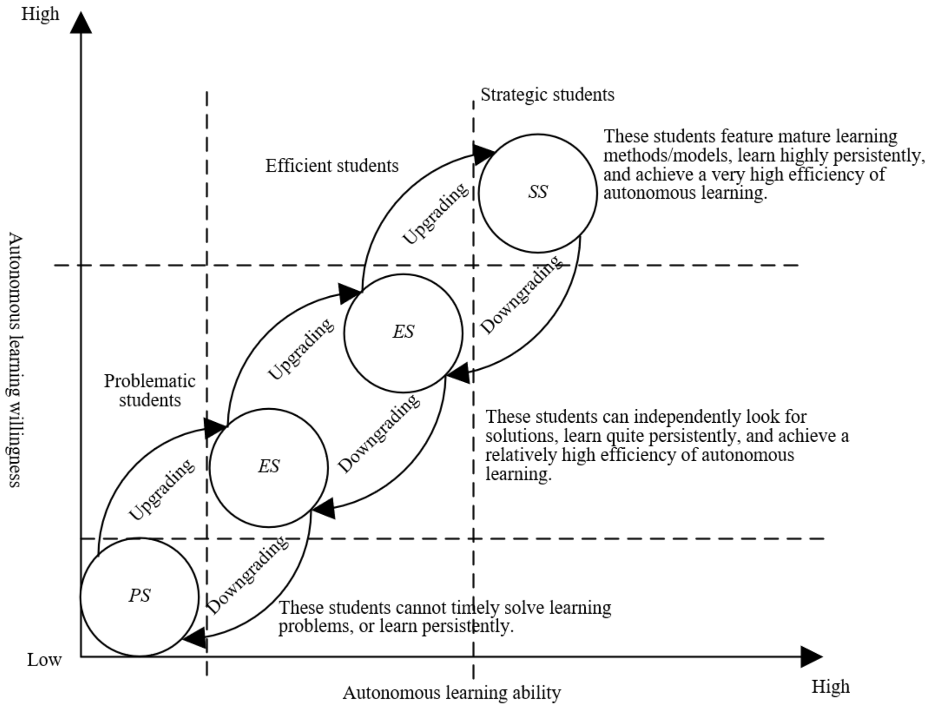


Fig. 1. Classification of students participating in online learning

Table 1. Evaluation indices of autonomous learning efficiency

Primary index	Secondary index	Index type	Quantification formula
Autonomous learning willingness	Subjective consciousness	Quantitative	Formula calculation
	Independence	Qualitative	Expert scoring
	Learning interest	Quantitative	Formula calculation
	Self-discipline	Qualitative	Expert scoring
Autonomous learning ability	Self-exploration	Quantitative	Formula calculation
	Self-selection	Qualitative	Expert scoring
	Self-construction	Qualitative	Expert scoring
	Self-creativity	Qualitative	Expert scoring

2.1 Index weighting

The above indices were weighed by analytic hierarchy process (AHP) and entropy method. In the AHP, the consistency index is denoted as *CI*, and the consistency ratio is denoted as *CR*. Let χ_{max} be the maximum eigenvalue of the judgement matrix; q be the dimensionality of the judgement matrix; *RI* be the mean randomness index of the judgement matrix. Then, *CI* and *CR* can be respectively calculated by:

$$CI = \frac{\chi_{\max} - q}{q - 1} \tag{1}$$

$$CR = \frac{CI}{RI} \tag{2}$$

The element values of the judgment matrix are determined by proportional scaling. Let ϖ_p be the final weight of learning efficiency indices; d_{ab} be the solution to the judgment matrix. Then, the index weight can be calculated by:

$$\varpi_p = \sum \left(d_{ab} \cdot j_b \right), b = 1, 2, 3 \tag{3}$$

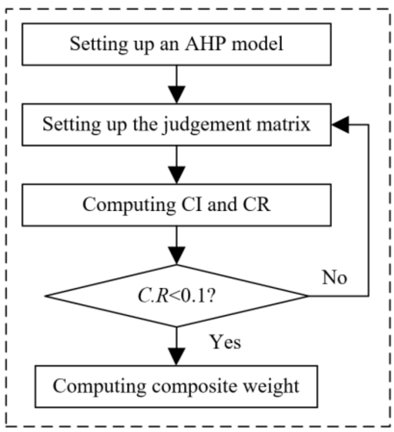


Fig. 2. Flow of index weighting

The AHP is a subjective method, while the entropy method is an objective approach. Figure 2 provides the index weighting process of the hybrid strategy coupling the AHP with the entropy method. The two methods are combined to set a composite weight coefficient $\gamma \in [0, 1]$ in the actual evaluation scenario of online autonomous English learning efficiency. By the entropy method, the original evaluation data on online autonomous English learning efficiency are assumed as a dataset of p rows and q columns. The value of the index in row a and column b is denoted as $U_{ab}=V_{ab}/\Sigma^{p}_{a=1}U_{ab}$, with $f_b=-\Sigma^{p}_{a=1}(V_{ab}\times lnV_{ab})$, $t_b=1-f_b$, and $\varpi_a=t_b/\Sigma^{q}_{a=1}t_b$. Let ϖ be the final weight; δ_a and ε_a be the weights obtained by the AHP and the entropy method, respectively. Then, we have:

$$\varpi = \gamma\delta_a + (1-\gamma)\varepsilon_a, a = 1,2,...,q \tag{4}$$

2.2 Classification algorithm

In the proposed EIS for online autonomous English learning efficiency, some indices are nonlinearly correlated, and fuzzy. The evaluation results can be classified effectively with the aid of artificial learning (AI).

Relying on probability statistics, the Bayesian classifier is a simple method with high classification accuracy and fast speed. This paper introduces this classifier to divide the evaluation results on online autonomous English learning efficiency into different classes. The evaluation results were allocated to the most probable class.

For a q-dimensional sample of online autonomous English learning efficiency $U=\{u_1, u_2, u_3, \ldots, u_q\}$, the q attributes can be denoted as $\{I_1, I_2, I_3, \ldots, I_q\}$. The total number of classes is set to p, and denoted as D_1, D_2, D_3, ..., D_p. The naïve Bayesian classifier divides the sample into D_A ($1 \leq a \leq p$) classes. If and only if $M(D_a|U) > M(D_a|U)$, then $1 \leq b \leq p$, and $b \neq a$. Based on Bayesian theorem, the probability can be defined as:

$$M(D_a \mid U) = \frac{M(U \mid D_a)M(D_a)}{M(U)} \tag{5}$$

where, probability $M(U)$ is a constant. Let O_a be the number of training samples in D_a; O be the total number of training samples. Then, we have $M(D_a)=O_a/O$. Assuming that the attributes are independent of each other, formula (5) can be adjusted as:

$$M(D_a \mid U) = \frac{M(D_a)}{M(U)}\prod_{w=1}^{q} M(u_w \mid D_a) \tag{6}$$

where, $\prod^{q}_{w=1}M(u_w|D_a)$ can be used in sample training, laying the basis for estimation. Then, the naïve Bayesian classifier can be expressed as:

$$X_{qj} = \arg\max M(D)\prod_{w=1}^{q} M(u_w \mid D) \tag{7}$$

3 Efficiency evaluation model

This paper optimizes the traditional BPNN with improved PSO, and adopts the improved BPNN to evaluate the online autonomous English learning efficiency. Figure 3 shows the structure of the proposed BPNN, which updates the weights and thresholds on each layer of the model. The model update process is detailed as follows:

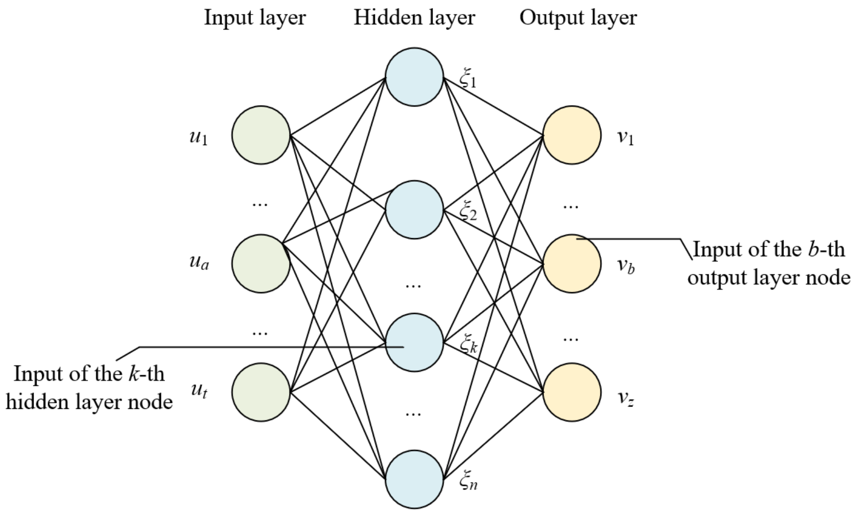


Fig. 3. Structure of the proposed BPNN

Let $C=\{(u_1, v_1), (u_2, v_2), ..., (u_q, v_q)\}$ be the dataset on the evaluation indices of online autonomous English learning efficiency for network model training, where $u_a \in G^t$, and $v_a \in G^z$; ρ_k be the threshold of the k-th hidden layer node; ε_b be the threshold of the b-th output layer node; i_k be the input of the k-th hidden layer node; δ_b be the input of the b-th output layer node. Each layer is activated by sigmoid function.

The output vector $v^*_w=(v^*_1, v^*_2, ..., v^*_z)$ of the neural network can be expressed as:

$$v^*_b = h\left(\delta_b - \varepsilon_b\right) \tag{8}$$

The mean squared error (MSE) can be calculated by:

$$ERROR = \frac{1}{2}\sum_{b=1}^{z}\left(v^*_b - v_b\right)^2 \tag{9}$$

Any parameter can be updated by:

$$y = y + \Delta y \tag{10}$$

By the gradient descent strategy, the BPNN model adjusts the weights and thresholds of each layer in the negative gradient direction of the target error. Let υ be the network learning rate. For the MSE $ERROR_w$, we have:

$$\Delta s_{kb} = -\upsilon \frac{\partial F_w}{\partial s_{kb}} \tag{11}$$

According to the chain rule, the following equation can be obtained:

$$\frac{\partial ERROR_w}{\partial s_{kb}} = \frac{\partial ERROR_w}{\partial v^*{}_b} \cdot \frac{\partial v^*{}_b}{\partial \delta_b} \cdot \frac{\partial \delta_b}{\partial s_{kb}} \tag{12}$$

Following the definition of the input δ_b of the input layer nodes, and drawing on the above two formulas and the properties of Sigmoid function, we have:

$$\Delta s_{kb} = \upsilon r_a \xi_k \tag{13}$$

where,

$$r_a = -\frac{\partial ERROR_w}{\partial v^*{}_b} \cdot \frac{\partial v^*{}_b}{\partial \delta_b} = v^*{}_b \left(1 - v^*{}_b\right)\left(v_b - v^*{}_b\right) \tag{14}$$

Similarly,

$$\Delta \varepsilon_b = \text{-}\upsilon r_a \tag{15}$$

When the weights and thresholds of each layer are optimized by PSO, each particle position represents a potential solution. Suppose there are p particles in the swarm. In the l-th iteration, the position and velocity of particle i are denoted as $U_a=(u_{a1}, u_{a2}, \ldots, u_{aq})$, and $Y_a=(y_{a1}, y_{a2}, \ldots, y_{aq})$, respectively, with $q=1,2,...,p$. Let $G^l{}_a$ and $G^l{}_r$ be the individual optimal solution and global optimal solution, respectively; $\phi \in [0, h]$ be the inertia weight; d_1, d_2, κ_1, and κ_2 be learning factors, which are random numbers in $[0, h]$. The velocity and position of the swarm can be updated by:

$$Y_a^{l+1} = \varphi Y_a^l + d_1 \kappa_1 \left(G_a^l - U_a^l\right) + d_2 \kappa_2 \left(G_r^l - U_a^l\right) \tag{16}$$

$$U_a^{l+1} = U_a^l + Y_a^{l+1} \tag{17}$$

The above PSO was improved to divide the swarm, preparing for mutation. The swarm division was carried out according to the calculated fitness of particles. Let $fitness^l{}_{AV}$ be the mean fitness of particles in the l-th generation. A sufficiently small integer is defined as the threshold σ. If inequality (18) holds, then $U^l{}_a$ is an elite particle; otherwise, $U^l{}_a$ is an inferior particle.

$$\frac{fitness\left(U_a^l\right)}{fitness_{AV}^l} \le \sigma \tag{18}$$

where, $fitness^l_{AV}$ satisfies:

$$fitness^l_{AV} = \frac{1}{p}\sum_{a=1}^{p} fitness\left(U^l_a\right) \tag{19}$$

All elite particles form a child swarm $PO^l_{EX\_i}$, $i \in (1,2,..,\delta)$; all inferior particles form another child swarm $PO^l_{IN\_j}$, $j \in (1,2,..,\eta)$. Note that $\delta+\eta=p$. The child swarms are divided through dynamic setting of threshold σ. Let σ_S and σ_E be the initial and final values of the threshold, respectively ($\sigma_1>\sigma_2$); MP be the maximum allowable number of iterations; l be the number of current iteration. Then, we have:

$$\sigma = \sigma_E - \frac{MP-l}{MP}\left(\sigma_E - \sigma_S\right) \tag{20}$$

In the early phase of iteration, the improved PSO mutates many particles, making the swarm much more diverse; in the late phase of iteration, there are very few mutable particles, i.e., the individuals cluster toward the optimal solution.

The traditional adaptive mutation does not reasonably define the mutation probability of particles, which hinders the convergence to the optimal solution. Since the position of the mutated particles would change, it is assumed that the new position of the mutated particles is $PO^l_{NL\_\delta}$, and the mutation probability of particles is Ω_y. The direction coefficient φ is regarded as a $1\times D$-dimensional matrix, where the elements are random numbers in [-1, 1]. Let ○ be the Hadamard product. Then, the mutation operator of the particles can be expressed as:

$$PO^l_{NL\_j} = PO^l_{IN\_j} + \Omega_b \sqrt{\sum_{t=1}^{T}\left(PO^l_{j,t} - PO^l_{\Omega_b,t}\right)^2}\,\phi \circ Y^l_{IN\_j} \tag{21}$$

Ω_y can be calculated by:

$$\Omega_b = fitness\left(PO^l_{IN\_j}\right) / \sum_{j=1}^{\Gamma} fitness\left(PO^l_{IN\_j}\right) \tag{22}$$

The Euclidean distance of the j-th inferior particle deviating from the global optimal position in the current iteration can be calculated by:

$$DIS = \sqrt{\sum_{t=1}^{T}\left(U^l_{j,t} - U^l_{\Omega_b,t}\right)^2} \tag{23}$$

In the early phase of the improved PSO, the Euclidean distance of the inferior particles deviating from the global optimal position is relatively large. In this phase, the ability of particles searching for the global optimal value is improved. In the middle phase of iterations, the Euclidean distance of particles from the global optimal solution gradually shortens, i.e., the particles approach the global optimal solution. In this phase, the exploratory ability is relatively strong. In the late phase of iterations, the particles converge to the global optimal solution.

Figure 4 explains the flow of the improved BPNN under Bayesian classifier. The specific process is as follows:

Firstly, the network structure is determined, and network parameters are initialized, including the number of input layer nodes N_1, number of hidden layer nodes N_2, number of output layer nodes N_3, activation function, maximum number of iterations, target error, and network learning rate.

Then, the swarm information, particle positions, and particle velocities are initialized. The algorithm parameters include swarm size, particle dimensionality, maximum number of iterations, initial and final inertia weights, learning factors, as well as the maximum and minimum velocities of particles. The particle dimensionality is derived from BPNN structure by $T=N_1 \times N_2+N_2 \times N_3+N_2+N_3$.

Furthermore, the target error function of the BPNN is adopted as the fitness function of the swarm:

$$FIT = \frac{1}{M}\sum_{m=1}^{M}\sum_{b=1}^{z}\left(v_{b}^{*m} - v_{b}^{m}\right)^2 \tag{24}$$

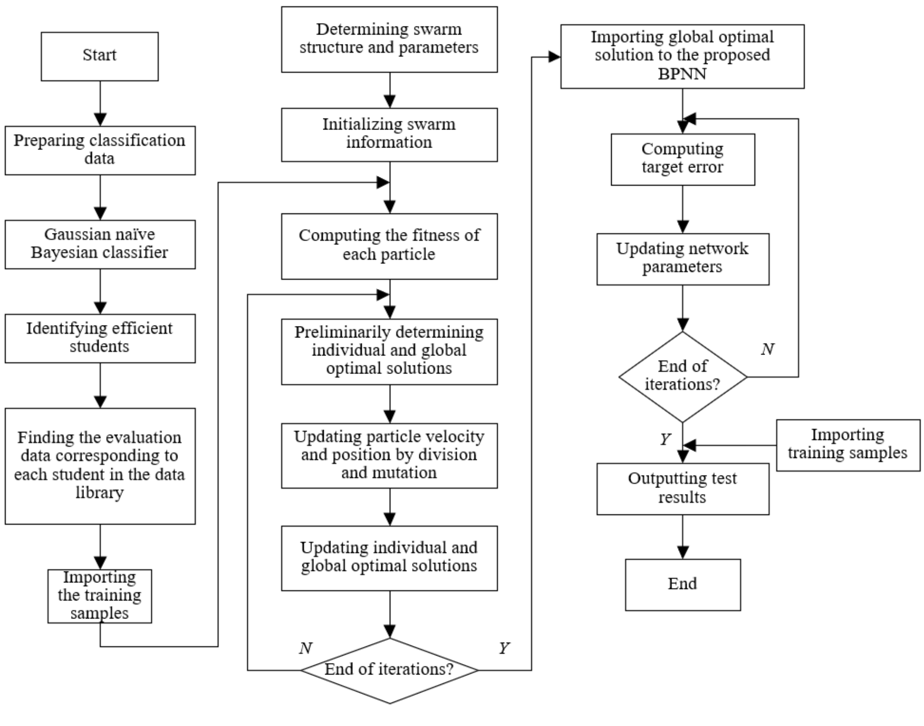
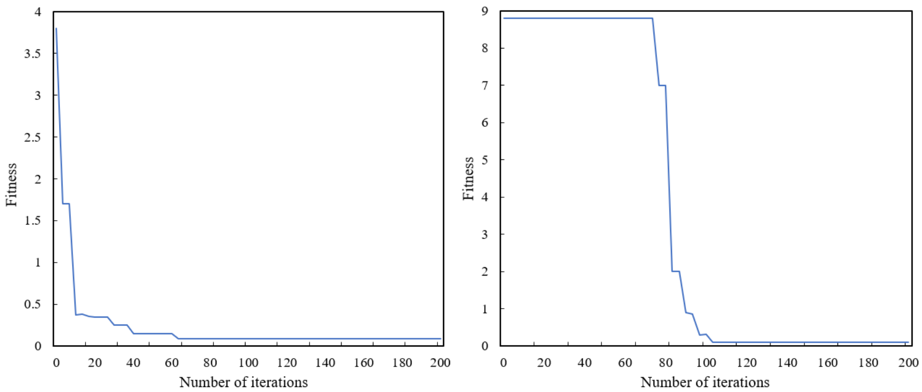


Fig. 4. Flow of improved BPNN under Bayesian classifier

After the swarm is divided by the classifier into a child swarm of elite individuals and a child swarm of inferior individuals, the individual and global extreme values are searched for based on fitness, and the particle velocity and position are updated. Then, whether the algorithm meets the termination condition is checked, and the global optimal solution of the swarm is outputted. Moreover, the solution is imported to the BPNN to update the initial weights and thresholds. After that, the proposed BPNN is trained, and the training error is adopted to update the weights and thresholds in the network.

4 Experiments and results analysis

To verify its effectiveness of the improved PSO, this paper compares the fitness of the original algorithm with that of the improved algorithm. As shown in Figure 5, the fitness of the traditional PSO tended to be stable after 55 iterations, producing the optimal individual fitness. Meanwhile, the improved PSO tended to be stable after 102 iterations, and the obtained optimal individual fitness was consistent with the global optimal fitness. This means the improved PSO effectively prevents the premature convergence of the traditional algorithm, and jumps out of the local optimum trap.



(1) Original algorithm (2) Improved algorithm

Fig. 5. Fitness curves of original and improved algorithms

This paper applies support vector machine, decision tree, and our algorithm separately on the evaluation results on online autonomous English learning efficiency. Before the experiments, all evaluation data samples were divided into a training set and a test set at the split ratio of 2:1. The resulting training set and test set contain 1,000 and 500 random samples, respectively. Table 2 compares the accuracies of different classifiers. It can be seen that our algorithm achieved relatively stable training and test results, and lived up to the expected goal of online autonomous English learning. On the contrary, the other two classifiers were not so stable.

Table 2. Accuracies of different classifiers

Classifiers	Support vector machine	Decision tree	Our algorithm
Training set size	1520	1548	1592
Classification accuracy of training set	95.26%	93.37%	98.15%
Test set size	602	614	625
Classification accuracy of test set	82.31%	92.1%	93.06%

Next, the traditional BPNN, the BPNN optimized by traditional PSO, and our model were trained and tested separately. The outputs of these evaluation models are displayed in Figure 6. It can be observed that the predicted value of our model was the closest to the true value, among the three contrastive models. Table 3 compares the prediction accuracies of the three models. Our model outshined the other two models in mean relative error (MRE), MSE, and coefficient of determination (R^2). To sum up, our model achieves better prediction accuracy of online autonomous English learning efficiency than the traditional BPNN, and the BPNN optimized by traditional PSO. The predicted results of our model have a relatively high reference value.

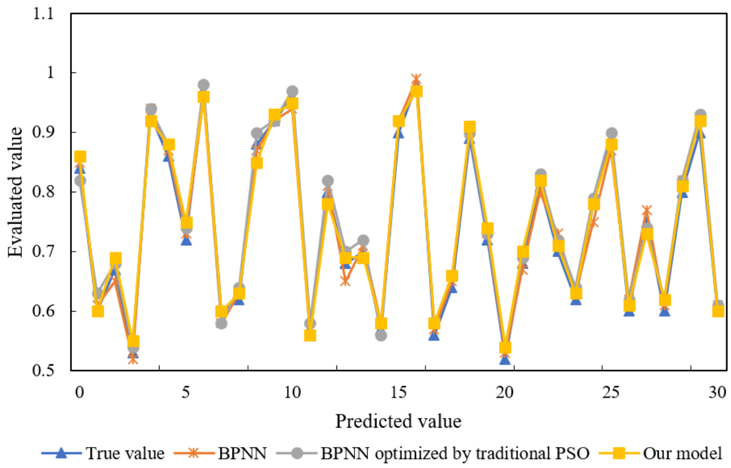


Fig. 6. Outputs of different evaluation models

Table 3. The prediction accuracies of the three models

Model	Traditional BPNN	BPNN optimized by traditional PSO	Our model
MRE	1.02%	0.45%	0.08%
MSE	1.12%	0.57%	0.05%
R^2	0.9284	0.9625	0.99

In addition, comparative experiments were carried out to analyze the difference of students with different learning behavior preferences in terms of autonomous online English learning efficiency. Figure 7 presents the time efficiency functions of English learning progress in different online learning periods. For the students used to learning

English online in the morning and at night, the time efficiency curves have only one peak; for the other students, the curves have two or more peaks. The former group of students had a much higher learning efficiency than the other students. The learning efficiency of the former group was sometimes multiple times that of the other students. Table 4 ranks the autonomous online English learning efficiencies of a student in different periods in descending order. The learning efficiencies on different learning contents at different time points were manifested very clearly.

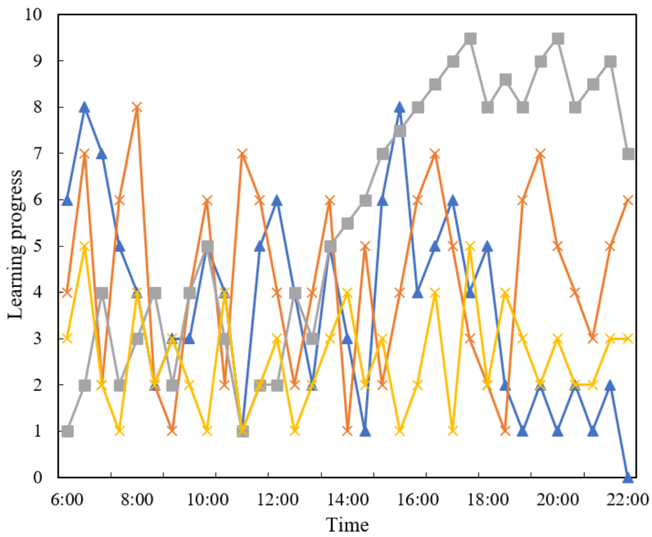


Fig. 7. Time efficiency functions of English learning progress in different online learning periods

Table 4. Ranking of learning efficiencies

	Memory-oriented		Practice-oriented	
Serial number	***Time***	***Learning efficiency***	***Time***	***Learning efficiency***
1	6: 05	2.61	9: 35	7.25
2	21: 05	2.53	11: 20	7.13
3	20: 05	2.46	8: 40	7.08
4	7: 50	1.25	20: 05	7.29
5	11: 20	1.14	14: 15	6.85
6	17: 00	1.08	7: 50	6.31
7	8: 40	1.01	10: 20	6.18
8	9: 35	0.95	21: 05	5.86
9	14: 00	0.99	12: 25	5.47
10	17: 50	1.02	17: 50	5.26
11	19: 05	1.04	19: 05	4.72
12	14: 15	1.01	6: 05	4.19
13	10: 20	1.03	16: 00	4.24
14	12: 25	1.01	17: 00	3.82

5 Conclusions

Based on artificial neural network, this paper explores an evaluation model of online autonomous English learning efficiency. Firstly, the authors classified the students participating in online English learning, determined and weighed the evaluation indices of online autonomous English learning efficiency, and detailed the classification method of the evaluation results. Secondly, the traditional BPNN was optimized by the improved PSO, and applied to evaluate online autonomous English learning efficiency. The effectiveness of the improved PSO was demonstrated by comparing the fitness of the original and improved algorithms. Next, the evaluation results on online autonomous English learning efficiency were classified separately by support vector machine, decision tree, and our classifier. The comparison shows that our algorithm achieved relatively high training and test results, and lived up better to the expected goal of online autonomous English learning. After that, the outputs of the different models were contrasted, revealing that our model was relatively accurate in predicting online autonomous English learning efficiency, and our predicted results were of relatively high reference value. Finally, the authors plotted the time efficiency functions of English learning progress in different online learning periods, and analyzed the difference of students with different learning behavior preferences in terms of autonomous online English learning efficiency.

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