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Retraction

Retracted: An Intelligent Assessment Method of English Teaching Ability Based on Improved Machine Learning Algorithm

Security and Communication Networks

Security and Communication Networks has retracted the article titled "An Intelligent Assessment Method of English Teaching Ability Based on Improved Machine Learning Algorithm" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

References

[1] N. Liu and D. Li, "An Intelligent Assessment Method of English Teaching Ability Based on Improved Machine Learning Algorithm," *Security and Communication Networks*, vol. 2022, Article ID 3025374, 10 pages, 2022.

[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2022, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

An Intelligent Assessment Method of English Teaching Ability Based on Improved Machine Learning Algorithm

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In order to fully exploit the effect of intelligent evaluation of English teaching ability and explore the quality of English teaching, an intelligent evaluation method of English teaching ability based on improved machine learning algorithm is proposed, which can ensure the rational allocation of English teaching resources, analyze the big data of constraint parameters of English teaching ability evaluation, and obtain frequent item sets of English teaching quality based on big data mining technology. The particle swarm optimization (PSO) method was used to improve the parameters of the SVM, and the optimal parameters of the support vector machines (SVM) were obtained, which were input into the sample of English teaching effect evaluation, and a method was constructed to maximize the SVM. The optimal parameters are introduced into the decision function, so as to achieve the purpose of English teaching quality assessment. The experimental results show that the proposed method has a high convergence speed and can achieve rapid convergence with only 30 network trainings. At the same time, the evaluation accuracy of English teaching quality is as high as 95%, the correlation coefficient of the results is as high as 0.95, and the evaluation time is low. It is less than 150 ms, and the keyword frequency identification is better and better, which can realize the objective evaluation of online teaching quality.

1. Introduction

With the continuous deepening of English teaching, the evaluation of English teaching ability has become particularly important [1]. The traditional English teaching ability evaluation method uses the manual evaluation method. The advantage of the manual evaluation method is that the evaluation process is very flexible, but the human evaluation has a certain degree of subjective consciousness. At the same time, accompanied by certain mixed factors, it is easy to cause great evaluation errors. Therefore, to achieve an accurate evaluation of the effect of English classroom teaching, it is necessary to establish a reliable teaching quality evaluation model [2]. However, because English teaching involves the dynamic process of teaching and learning, there are many factors that affect teaching quality, and the influence factors have different degrees of influence on

teaching quality, and there is a complex nonlinear relationship between evaluation indicators and teaching effects, so it is difficult to construct accurate and reliable teaching quality evaluation model [3]. Therefore, the intelligent evaluation method of English teaching quality has become a hot research issue at present.

Reference [4] proposes a teaching quality assessment method based on interval-valued double hesitant fuzzy sets and introduces a weighted interval-valued double hesitant fuzzy set (WIVDHFS), which describes membership and nonmembership values and their weights in the form of intervals. These assigned weights provide more detail about the level of agreement and disagreement, which can help decision makers (DMs) achieve precise, reasonable, and consistent decision outcomes. A new weighted interval-valued dual hesitant fuzzy environment is constructed for multicriteria group decision making. Finally, an application

case of teaching quality assessment is presented. However, the teaching quality evaluation of this method takes a long time and needs to be further improved. Reference [5] proposed an English teaching ability evaluation algorithm based on big data fuzzy K-means clustering and information fusion. Using the idea of K-means clustering, analyze the collected original error data, such as teacher level, teaching facility investment, and policy relevance, eliminate the data that the algorithm considers unreliable, and use the remaining valid data to calculate and correct fuzzy logic. The weighting factor of the algorithm is weighted and averaged with the node measurement data to obtain the final fusion value. Combining big data information fusion with K-means clustering algorithm, the clustering and integration of English teaching ability index parameters are realized, the corresponding English teaching resource allocation plan is compiled, and the evaluation of English teaching ability is realized. However, the intelligent evaluation accuracy of this method needs to be further improved.

In view of the problems existing in the above methods, this paper proposes an intelligent assessment method of English teaching ability based on improved machine learning algorithm. The frequent item set of English teaching quality is obtained by analyzing the big data of constraint parameters, the SVM parameters are improved by particle swarm optimization algorithm, and the optimal parameters are introduced into the decision function, so as to realize the evaluation of English teaching quality.

2. The Big Data Analysis Model of English Teaching Ability Evaluation

2.1. Big Data Analysis of Constraint Parameters of English Teaching Ability Evaluation. In order to achieve an accurate assessment of English teaching ability, it is first necessary to construct an information sampling model for the constraint parameters of English teaching ability. The nonlinear information fusion method is an optimal control algorithm based on the information fusion estimation theory, which can convert all the requirements and various constraints of the control system into "measurement information" about the control quantity and estimated amount of control. The time series analysis method can use random models to fit time series and improve the data observation effect, and can fit simple time series, stationary time series, and their special cases. Therefore, the combination of nonlinear information fusion method and time series analysis method can effectively improve the statistical analysis ability of English teaching. The English teaching ability constraint index parameter is a set of nonlinear time series [6]. A high-dimensional feature distribution space is constructed to represent the parameter index distribution model of English ability evaluation. The main index parameters that constrain English teaching ability include teacher level, investment in teaching facilities, and policy relevance level. The information flow model of constructing a differential equation to express the constraint parameters of English teaching ability is as follows:

$$x_n = x(t_0 + n\Delta t) = h[z(t_0 + n\Delta t)] + \omega. \tag{1}$$

In the formula, $h[z(t_0 + n\Delta t)]$ is the multivariate value function of English teaching ability evaluation, and ω is the evaluation error measurement function. In the high-dimensional feature distribution space, the solution vector of the English teaching ability assessment is calculated by the correlation fusion method, and the characteristic training subset $S_i (i = 1, 2, \ldots, n)$ of the teaching ability assessment is obtained, which meets the following conditions:

$$\bigcup_{i=1}^{L} V - v_s. \tag{2}$$

Let x_{n+1} be the conjugate solution of a statistical information model for English teaching ability evaluation, which satisfies the initial value eigendecomposition condition $U = \{u(t)|u(t) \in X\}$. For the statistical feature distribution sequence $x(n)$ of a group of multivariate English teaching ability assessment, the data information flow model for English teaching ability assessment is constructed based on the previous statistical measurement values as follows:

$$c_{1x}(A) = E\{x(n)\} = 0. \tag{3}$$

According to the constructed data information flow model of English teaching ability assessment, a set of scalar sampling sequence components is constructed into a big data distribution model, which provides an accurate data input basis for English teaching ability assessment.

2.2. Frequent Item Set of English Teaching Quality Based on Big Data Mining Technology. The convolutional neural network method is selected to extract the features of the English teaching quality evaluation text, and the convolutional neural network automatically learns the input data features through the convolutional layer and the pooling layer. Use the evaluation text to build a training set, and use labels to label all the samples in the training set. After inputting the test dataset, use the trained neural network to obtain the classification labels of the new samples. Use cluster analysis algorithm to improve data mining technology, mine association rules with minimum confidence and minimum support in massive data, and determine the final evaluation index of English teaching quality through cluster analysis [7].

The convolutional neural network method not only has the characteristics of analyzing the contextual semantics of the review text and feature learning, but also has the advantages of high noise resistance and high classification degree.

The feature structure diagram of extracting and evaluating text using convolutional neural network is shown in Figure 1.

It can be seen from Figure 1 that the process of extracting the features of the evaluation text by the convolutional neural network is filtering the useless comments of the English teaching quality evaluation text through data preprocessing and dividing the filtered evaluation text into short sentences. Avoid noise interference in the process of evaluating the quality of English teaching through data filtering.
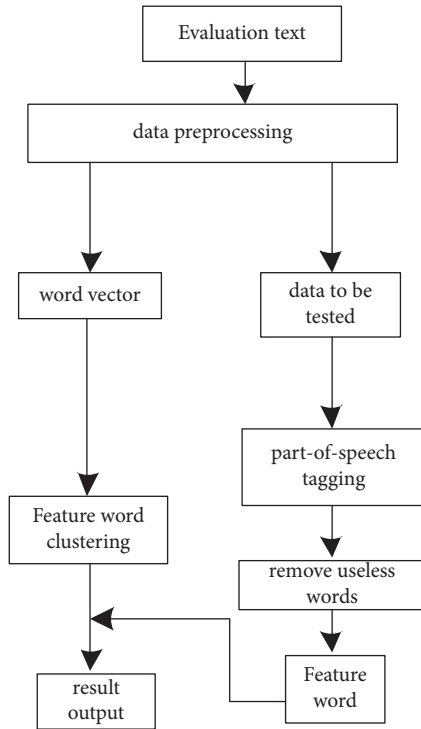
Figure 1: Structure diagram of feature extraction of evaluation text.

When using convolutional neural networks to classify text reviews, it is necessary to deal with reviews composed of many short texts in sentences. Quantitatively transform evaluation texts, use distributed word vectors to represent evaluation texts, select large-scale unsupervised methods to train distributed word vectors, so that quantitatively transformed texts can reflect more grammatical information and semantics, and use the filtered evaluation texts to achieve Word vector training [8]. Extract part of the data and set it as the training set, complete the classification training, mark the new label with the label added by the manual labeling through the model, compare the label marked by the model with the existing label, and adjust the model parameters according to the error of the comparison result. The evaluation text represented by the word vector is input into the convolutional neural network, and the corresponding label is output by the convolutional neural network. Label the evaluation text part-of-speech and extract the nouns in the evaluation text to obtain a set of characteristic words. The labels that form the feature words are the same as those in the evaluation text [9].

If the same evaluation text contains multiple feature words, it is necessary to determine the final evaluation index of English teaching quality through cluster analysis. Big data mining technology is to mine association rules with minimum confidence and minimum support in massive data. Big data mining technology mining association rules mainly includes two parts: (1) mining frequent item sets with minimum support in transaction database; (2) using the mined frequent item sets to generate association rules for English teaching quality assessment.

Apriori algorithm is an important algorithm for mining frequent item sets in data mining algorithms. This algorithm is used to obtain item sets whose support degree is higher than the minimum support degree. The Apriori algorithm uses k item sets to obtain $k + 1$ item sets through a layer-by-layer search method.

Use B to represent the transaction database, $I = \{I_1, I_2, \ldots, I_m\}$ to represent the item set in the database, and I_i to represent the element in the item set. $W = \{T_1, T_2, \ldots, T_n\}$ and T_i, respectively, represent the transaction set and the elements contained in it, and satisfy $T_i \subseteq T$. All transactions are identified with individual tags T. The length or dimension of the item set in massive data indicates the number of elements contained in the item set. When the number of elements in the item set is k, it means that the item set is a k-item set. Assuming that there is a random English teaching quality transaction database B, the process of mining its frequent item sets is as follows.

(1) Calculate all 1 item sets with C_1, search for all commonly used 1 item sets greater than or equal to the minimum support that has been set, and use L_1.

(2) Use the commonly used 1 item set to obtain the candidate 2 item set, which is represented by C_2. Search for all 2-item sets greater than or equal to the set minimum support from the acquired 2-item sets and denote by L_2.

(3) According to the above process, the candidate 3-item set is obtained by using the acquired common 2-item set, which is denoted by C_3. Search for all 3 item sets that are greater than or equal to the set minimum support degree from the obtained 3 item sets and denote by L_3.

(4) Repeat the above process of iteration until the frequent items of higher dimension cannot be obtained, and terminate the iteration.

It can be seen from the above process that the Apriori algorithm obtains the final frequent item sets through continuous iteration and forms too many candidate item sets in the search process, which has high complexity and low operating efficiency. The Boolean matrix is introduced into the Apriori algorithm, which makes it suitable for massive big data mining. Massive databases of big data are prone to excessive memory. The database needs to be divided, and the divided database will be scanned in segments. Assuming that there is a total of N transaction database that has completed the segmentation, which is represented by $\{B_1, B_2, \ldots, B_N\}$, it can be seen that the number of Boolean matrices is N, and there is a one-to-one correspondence with the transaction database that has completed the segmentation. The Apriori algorithm adopts the iterative method of layer-by-layer search, which is simple and clear, suitable for sparse data sets, without complicated theoretical derivation, and easy to implement. However, due to the excessive number of scans on the database at the same time, a large number of candidate item sets may be generated. The process of obtaining frequent item sets using the Apriori algorithm optimized by Boolean matrix is as follows.

(1) Set the number of copies of the divided massive transaction database, and determine the size of the different copies to be divided. Initialize the loop variable to 1, and set the minimum support for the Apriori algorithm.

(2) Read B_i in the transaction database, and map it to the Boolean matrix R_i.

(3) Calculate the local minimum support of R_i against B_i using the following formula:

$$\min s_i = \min s \times \frac{|B_i|}{|B|}. \tag{4}$$

In Formula (4), s is the only support, and $|B_i|$ and $|B|$ represent the number of elements in the transaction database and the number of elements in the massive transaction database, respectively.

Obtain the corresponding row vector of the frequent item sets in B_i in the Boolean matrix R_i through the above formula, save the row vector obtained by searching, release the memory space of the Boolean matrix R_i to update the data set, and obtain the updated matrix R_i.

(4) Set $i = i + 1$, when condition $i \leq N$ is satisfied, and go back to step (2) to repeat the iterative calculation. Otherwise, go to step (5).

(5) Recombine the corresponding Boolean matrix R_i of all frequent item sets in the transaction data set B_i, and establish a new Boolean matrix represented by $R = (R_1, R_2, \ldots, R_N)^T$. The minimum support degree of the established new Boolean matrix is searched again, and the corresponding row vector of the frequent item sets of the massive transaction database B is determined to obtain the frequent item sets that can finally evaluate the quality of English teaching. Obtaining frequent item sets of English teaching quality is conducive to improve the effect of teaching quality assessment, and it provides theoretical support for the innovation of English teaching content. Inputting the English teaching frequent item set into the English teaching ability intelligent evaluation model can improve the evaluation effect of English teaching quality.

3. An Intelligent Assessment Model of English Teaching Ability Based on Improved Machine Learning Algorithm

On the basis of obtaining the frequent item sets that can evaluate the quality of English teaching, the particle swarm algorithm is used to improve the parameters of the least squares support vector machine, and the optimal parameters of the support vector machine are obtained through this improved machine learning algorithm, and the evaluation data of college English teaching effect are input. The sample is constructed, the decision function is constructed, and the optimal parameters of the support vector machine are brought into the decision function to realize the evaluation of English teaching quality based on support vector regression.

3.1. Select the Evaluation Index of English Teaching Quality. There are a large number of evaluation indicators in the English teaching quality evaluation system, and each evaluation index has different degrees of importance. Among them, there are some indicators that have little impact on the evaluation results. For the entire English teaching quality evaluation model, these indicators have little significance, but these redundant indicators increase the workload of the evaluation model, thereby affecting the effect of the evaluation model [10]. Therefore, it is necessary to recombine the indicators with a higher degree of importance among the many evaluation indicators and to construct an English teaching quality evaluation index system that is easier to calculate later.

Conditional information entropy is the expected information amount of all possible events, which is beneficial to find the attribute with the largest information gain among all attributes. Conditional information entropy is used to filter the evaluation indicators. Let G and J represent two attribute sets, and the division of G and J on U is represented by P and Q, and $P = U/\text{ind}(G) = \{P_1, P_2, \cdots, P_n\}$, and $Q = U/\text{ind}(J) = \{Q_1, Q_2, \cdots, Q_m\}$. Then, the following probability distribution is formed by G and J on the subset of U:

$$\begin{cases} [P: p] = \begin{bmatrix} P_1 & P_2 & \cdots & P_n \\ p(P_1) & p(P_2) & \cdots & p(P_n) \end{bmatrix}, \\ [Q: p] = \begin{bmatrix} Q_1 & Q_2 & \cdots & Q_n \\ p(Q_1) & p(Q_2) & \cdots & p(Q_n) \end{bmatrix}. \end{cases} \tag{5}$$

In the formula, $p(\cdot)$ represents the probability of the element appearing, $p(P_i) = \text{card}(P_i)/\text{card}(U)$, $p(Q_j) = \text{card}(P_j)/\text{card}(U)$, $\text{card}(\cdot)$ is the base of the geometry, and $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m$.

Based on the above information, a selection model of English teaching quality evaluation indicators is established, with $S = (s_1, s_2, \ldots, s_n)$ representing the n English teaching quality evaluation indicators to be screened, $K = (k_1, k_2, \ldots, k_m)$ representing the m evaluation condition attribute index vectors, and $K(S) = (k_1(S), k_2(S), \ldots, k_m(S))$ representing the overall target set of English teaching quality evaluation. In function $K(S)$, each conditional attribute index has different effects on the evaluation of English teaching quality. For the attribute evaluation index of the increasing function, the higher the attribute value, the better the corresponding evaluation result. For the attribute evaluation index of the decreasing function, the higher the attribute value, the worse the corresponding evaluation result. Therefore, the conditional attribute indicators are divided into l increasing functions K_+ and $m - l$ decreasing functions K_- for calculation:

$$\begin{cases} K_+ = k_1(s), k_2(s), \ldots, k_l(s), \\ K_- = k_{l+1}(s), k_{l+2}(s), \ldots, k_{m-l}(s). \end{cases} \tag{6}$$

Since different conditional attributes will have different effects on the evaluation results of English teaching quality, it is necessary to assign different weights W, $W = W_1$, $W_2, \ldots, W_m$ to the conditional attributes, use W_i to represent the weight of i attribute and w_i to represent the weight of i attribute condition, $W_i > 0$, $\sum_{i=1}^{m} W_i = 1$, $i = 1, 2, \ldots, m$, and W_i and w_i are related as follows:

$$W_i = \frac{w_i}{\sum_{i=1}^{m} w_i}. \tag{7}$$

The relative superiority degree is a dominance degree that emphasizes the relative superiority and inferiority relationship between species and is expressed by the sum of the relative values of density, frequency, and coverage. Under the constraint of relative pros and cons, filter the most unsatisfactory points of each conditional attribute, and obtain the unideal set $\hat{K}$ as follows:

$$\hat{K} = \left(\hat{k}_1, \hat{k}_2, \ldots, \hat{k}_m\right) = \left(k_1^-, k_2^-, \ldots, k_{l+1}^+, k_{l+2}^+, \ldots, k_m^+\right). \tag{8}$$

Construct a new relative merit matrix V with the postscreening condition attribute, where the elements in V are represented by v_{ij}, and the definition of V is as follows:

$$V = \left(v_{ij}\right)_{m \cdot n} = \left(F_i\left(s_j\right)\right)_{m \cdot n} = \left(V_1, V_2, \ldots, V_m\right). \tag{9}$$

Use $D(s_j)$ to represent the weight set comprehensively considered for all evaluation indicators. $D(s_j) = (W_1(1 - v_{1j}), W_2(1 - v_{2j}), \ldots, W_m(1 - v_{mj}))$, and use the size of the L2 norm value $d(s_j)$ to describe the pros and cons of the English teaching quality evaluation indicators, and the calculation method of $d(s_j)$ is as follows:

$$d\left(s_j\right) = \left\|D\left(s_j\right)\right\| = \sqrt{\sum_{i=1}^{m} W_i^2 \left(1 - v_{ij}\right)^2}. \tag{10}$$

3.2. Evaluation Principle of Least Squares Support Vector Machine.

Support vector machines are based on statistical theory, and support vector machines are often used in machine learning in the case of small samples. The support vector machine uses the optimization method to obtain the global optimal solution, which can effectively avoid local optimization and overlearning [11–13], and can be applied to regression and classification problems. Least squares support vector machine evaluation principle is as follows: set a training sample set to be described by $s = \{x_i, y_i\}$, where $i = 1, 2, \ldots, l$. The input data of the least squares support vector machine is described by x_i; the number of training samples is described by l; and the output data is described by y_i. The linear regression function in d-dimensional space is

$$y = \omega x + b. \tag{11}$$

Among them, the deviation is described by b, and the weight vector is described by ω.

The regression function in the high-dimensional feature space is described by the following equation:

$$f(x) = \omega\varphi(x) + b. \tag{12}$$

Among them, $\varphi(x)$ is the nonlinear mapping from the input space to the high-dimensional feature space.

The optimization objective function of the least squares support vector machine is described by the following formula:

$$\min = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}c\sum_{i=1}^{l} e_i^2, \tag{13}$$

$$s.t. \ \omega^T\varphi(x_i) + b + e_i = y_i, i = 1, 2, \ldots, l. \tag{14}$$

Among them, c is the regularization parameter control and represents the degree of penalty for the error; e_i represents the error variable.

By introducing the Lagrange multiplier, the constrained optimization is transformed into an unconstrained optimization problem, and the solution of the optimization problem is realized. That is,

$$\min J = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}c\sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} \lambda_i\left(\omega^T\varphi(x_i) + b + e_i - y_i\right), \tag{15}$$

where Lagrange multipliers are described by λ.

The calculation of the optimal value is obtained under the Karush-Kuhn-Tucker (KKT) optimization conditions. The optimal value solution is described by the following formula:

$$\begin{cases} \dfrac{\partial J}{\partial \omega} = 0 \longrightarrow \omega = \sum_{i=1}^{l} \lambda_i\varphi(x_i) \\[2ex] \dfrac{\partial J}{\partial b} = 0 \longrightarrow \sum_{i=1}^{l} \lambda_i = 0 \\[2ex] \dfrac{\partial J}{\partial e_i} = 0 \longrightarrow \lambda_i = ce_i, i = 1, 2, \ldots, l \\[2ex] \dfrac{\partial J}{\partial \lambda_i} = 0 \longrightarrow \omega^T\varphi(x_i) + b + e_i - y_i = 0, i = 1, 2, \ldots, l \end{cases} \tag{16}$$

Eliminate ω and e in Formula (16), and replace the quadratic optimization problem with the calculation problem of solving linear equations, and the calculation result is

$$\begin{bmatrix} 0 \\ y \end{bmatrix} = \begin{bmatrix} 0 & Q^T \\ Q & \Omega + c^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \lambda \end{bmatrix}. \tag{17}$$

Among them, $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_l]^T$, $Q = [1, 1, \ldots, 1]^T$ the identity matrix is described by I, and $\Omega \in R^{l \times l}$, $\Omega_{ij} = \varphi(x_i)^T\varphi(x_i) = K(x_i, x_j)$, and $K(\ )$ is the function. Use the kernel function in the original space to obtain the

regression function of the least squares support vector machine, which is described by the following formula:

$$y = \sum_{i=1}^{l} \lambda_i K(x_i, x_j) + b. \tag{18}$$

In order to avoid the disaster of dimensionality, the radial basis kernel function commonly used in the least squares support vector machine is introduced to replace the inner product operation of the high-dimensional feature space [14]. Radial basis kernel function, specifically is as follows:

$$K(x_i, x_j) = \exp\left(-\frac{\|x - x_i\|^2}{\sigma^2}\right). \tag{19}$$

Among them, the kernel function parameter width is σ.

Optimization c and σ represent two parameters and enhance the generalization ability of the least squares support vector machine. The least squares support vector machine parameter optimization problem adopts particle swarm optimization. The process of implementing the college English teaching effect evaluation model by least squares support vector machine is as follows.

Step 1: Input a sample of college English teaching effect evaluation data.

Step 2: The optimal kernel function parameter σ and the regularization parameter c are solved, and the particle swarm algorithm is used to implement the search [15–17].

Step 3: Select the appropriate kernel function.

Step 4: Calculate and obtain the optimization problem, and calculate the optimal solution, which is described by α. The calculation formula is as follows:

$$\alpha = (\alpha_1, \alpha_1^*, \alpha_2, \alpha_2^*, \ldots, \alpha_l, \alpha_l^*)^T. \tag{20}$$

Step 5: The construction of the decision function, the construction process, is shown in the following formula:

$$y = \sum_{i=1}^{l} (\alpha_i^* - \alpha_i) K(x, x_i) + b. \tag{21}$$

Step 6: Implement model evaluation through decision function.

3.3. Particle Swarm Algorithm to Search the Parameters of the Least Squares Support Vector Machine. Set a population composed of m particles, in a d-dimensional search space, where the searched optimal position of the i-th particle in the d-dimensional space is described by pi, the velocity is described by v_i, and the i-th particle is described by pi. The position of the particle in the d-dimensional space is described by xi; the definition vector is described by $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$, $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$, $p_i = (p_{i1}, p_{i2}, \ldots, p_{id})$, of which $i = 1, 2, \ldots, m$; the optimal position searched by

the entire population is described by $i = 1, 2, \ldots, m$. Regarding the formula for updating the particle position and velocity of the particle swarm algorithm [18], respectively, use the following formula:

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}, \tag{22}$$

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 (p_{id} - x_{id}^k) + c_2 r_2 (p_{gd} - x_{id}^k). \tag{23}$$

Among them, the inertia weight coefficient is described by ω; the acceleration constant is described by c_1, c_2; the optimization algebra is described by k; the search speed and position of the particle in the d-dimensional space in algebra k are described by v_{id}^k and x_{id}^k, respectively; and r_1, r_2 is a random number.

The process of particle swarm optimization support vector machine parameters c and σ is shown in Figure 2.

Step 1: Normalize and preprocess the evaluation data of college English teaching effect [19].

Step 2: Set parameter values (maximum iteration number T max, acceleration constant c_1, c_2, inertia weight coefficient ω, search range of population particle number m, c, σ, and individual particle dimension n).

Step 3: Initialize the particle swarm.

Step 4: Set the individual extreme value $P_{i\text{best}}$ and the global extreme value g_{best}, and the calculation of the fitness value of each particle is based on the current position of the particle. The calculation process is as follows:

$$f = \sum_{i=1}^{N} |y_i - y_1'|. \tag{24}$$

Among them, the predicted value is described by y_1'; the number of training samples is described by N; and the actual value is described by y_i.

Step 5: In order to generate a new population, update Formula (22) and Formula (23) according to the particle position and velocity.

Step 6: Find the fitness value f [20] of each particle in the new population.

Step 7: Compare the optimal speed and optimal position of the previous population. If it is good and can be converted, it will not be adjusted anyway.

Step 8: If it does not meet the optimization end conditions, it is necessary to set the number of iterations to $t = t + 1$, and return to Step 4 to search for an optimization solution.

Step 9: If the optimal solution of kernel function parameter σ and regularization parameter c of the least squares support vector machine is found, the search is completed.

By substituting the coefficients obtained from the above solutions into Formula (21), the English teaching quality evaluation based on support vector regression can be realized.
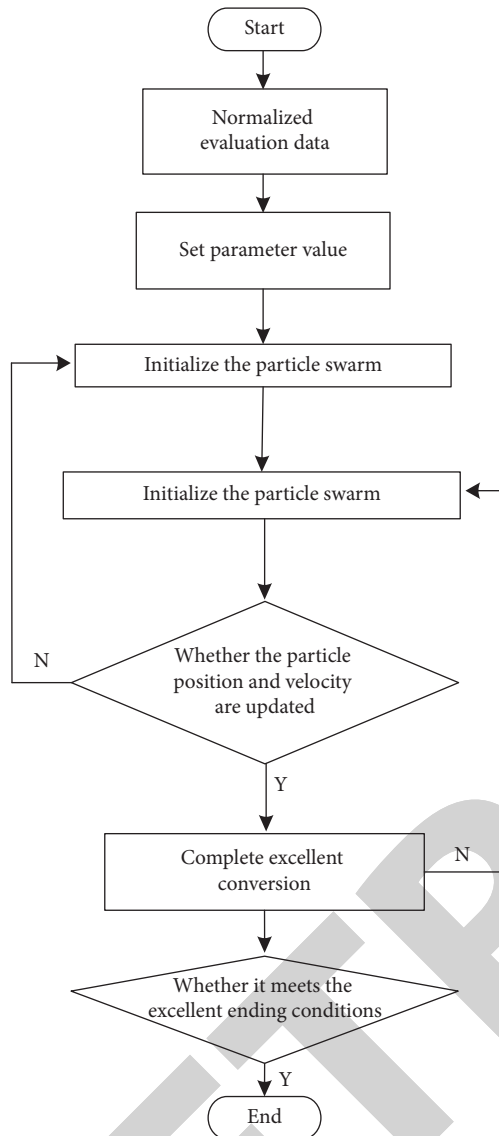
Figure 2: Particle swarm optimization support vector machine flow chart.

4. Experimental Analysis

In order to verify the effectiveness of the intelligent evaluation method of English teaching ability based on the improved machine learning algorithm, a teacher's English teaching course was selected as the test object. A total of 8,700 people attended the English teaching. After the students completed the lectures, they gave feedback on the evaluation texts, deleted useless evaluation texts and spam evaluation texts, and collected a total of 8,500 valid evaluation texts. By comparing the convergence speed of the method in this paper with the method in literature [3] (a teaching method of English emotional expression based on gamification) and the method in literature [4] (weighted interval-valued double hesitant fuzzy set and its application in teaching quality evaluation), English teaching quality evaluation accuracy, result correlation coefficient, evaluation

time, and keyword frequency recognition effect verify the superiority of this method.

The results of selecting convolutional neural network hyperparameters are shown in Table 1.

According to the determined parameters, the convolutional neural network is trained and tested by the ten-fold cross-validation method. The convergence of the convolutional neural network is shown in Figure 3.

As can be seen from the experimental results in Figure 3, the model in this paper uses a convolutional neural network to extract the features contained in the evaluation text and only needs about 30 network trainings to achieve rapid convergence. The second time mean square error is 0.1. It shows that the convolutional neural network selected in this model has a high convergence speed, which can improve the computing performance of the English teaching quality evaluation model.

In order to further verify the ability of the method in this paper, the method in Reference [4] and the method in Reference [5] to evaluate the quality of English teaching, the evaluation accuracy, and correlation are selected as the experimental test indicators for the method in this paper, the method in Reference [4], and the method in Reference [5]. For evaluation, the larger the evaluation accuracy and correlation coefficient, the more accurate the results of the corresponding model to evaluate the English teaching quality. The experimental results obtained by calculation are shown in Figures 4 and 5.

It can be seen from Figures 4 and 5 that the rating accuracy of the method in this paper is significantly higher than that of the method in Reference [4] and the method in Reference [5], reaching more than 95%, while the method in Reference [4] is about 70%, and The method in Reference [5] is higher than the method in Reference [4], about 88%, but it is still lower than the method in this paper. The correlation of the results of the method in this paper is also higher than that in the method in Reference [4] and the method in Reference [5], indicating that the method in this paper has a good evaluation. It is more suitable for practical English teaching quality evaluation.

Statistically, the method in this paper is used to evaluate the time required for each first-level index of English teaching quality, and the method in this paper is compared with the method in Reference [4] and the method in Reference [5]. The comparison results are shown in Figure 6.

From the experimental results in Figure 6, it can be seen that the evaluation time of English teaching quality evaluation using this method is lower than the other two methods, and the evaluation time of each first-level index using this method is within 200 ms. Combined with the experimental results in Figures 3 and 4, it can be seen that the method in this paper can maintain a high evaluation accuracy and at the same time have a high real-time performance, which verifies that the method in this paper has a high evaluation performance. The evaluation performance of this method is excellent, and it can be applied to the practical application of English teaching quality

TABLE 1: Hyperparameter settings.

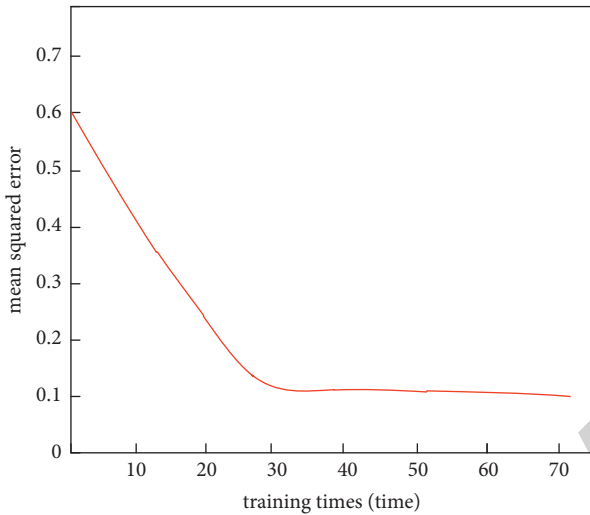| Hyperparameter metrics	Numerical results
Number of feature maps	80
L2 regularization coefficient	3
Convolution kernel size	(5, 350), (6, 350), (7, 350)
Dropout ratio	0.6
Batch value	8

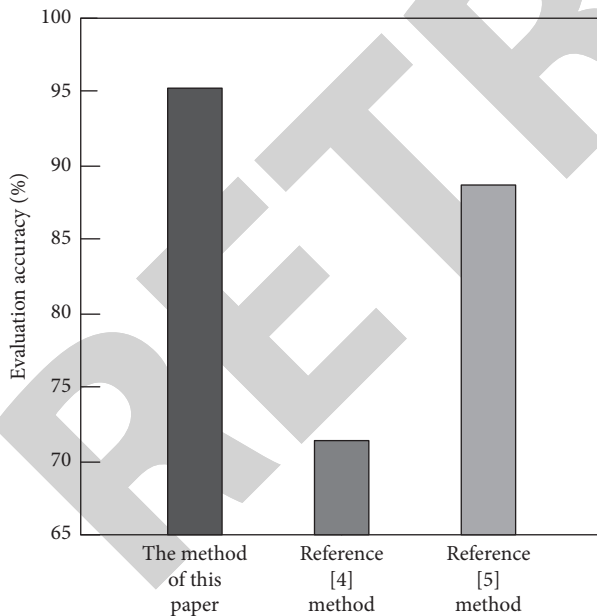FIGURE 3: Convolutional neural network convergence results.

FIGURE 4: Evaluation accuracy test results.

FIGURE 5: Results correlation test results.

The method of this paper
Reference [4] method
Reference [5] method
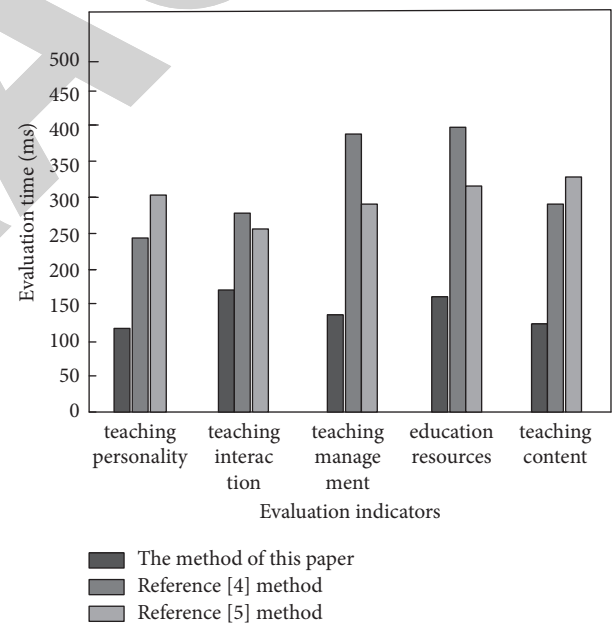
FIGURE 6: Comparison of evaluation time of different methods.

evaluation. Because the method in this paper uses the PSO method to improve the parameters of the SVM, the optimal parameters of the SVM can be quickly obtained. Privacy shortens evaluation time.

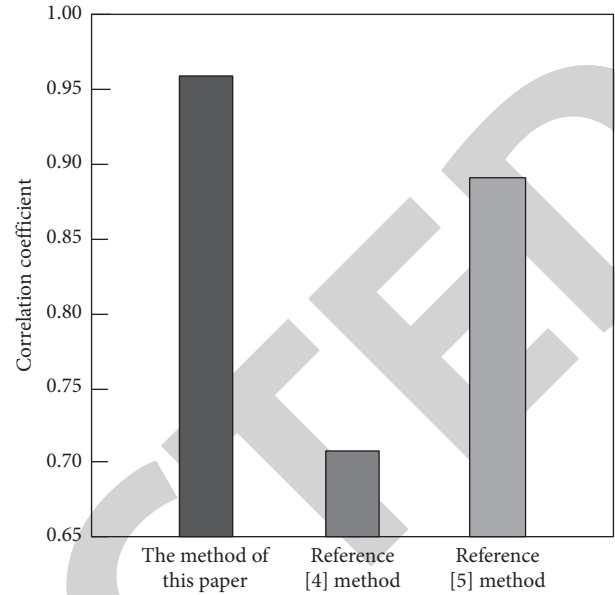An opinion answering part is set up in the questionnaire, useless information such as "no" and "no" are removed from the questionnaire, and the online word frequency analysis tool is used to obtain opinions and words with high frequency in the strategy, as shown in Figure 7.

From the experimental results in Figure 6, it can be seen that the interactive and interesting words are ranked higher and appear more frequently, indicating that college students pay more attention to the vividness and interest of English. When opening English courses in colleges and universities, they should pay attention to the improvement of liveliness and interest. It can improve the quality of English teaching in terms of teaching content
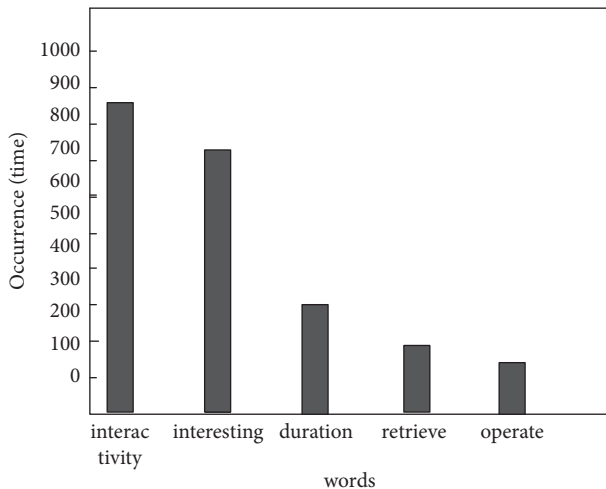
Figure 7: Keyword frequency results.

and evaluation methods, activate English teaching classrooms, and cultivate college students' self-learning awareness.

5. Conclusion

The evaluation of English teaching ability is more important in teaching. In order to improve the accuracy and efficiency of English teaching evaluation, this paper adopts an intelligent evaluation method of English teaching ability based on improved machine learning algorithm. The parameters of the support vector machine are optimized by the particle swarm algorithm, and the establishment of the English teaching quality evaluation model is completed. And through example analysis, it is verified that this method can effectively evaluate the quality of English teaching in colleges and universities, the evaluation effect is good, and it can achieve accurate evaluation of the quality of English teaching. With the increase of training times, the mean square error decreases, and the mean square error is 0.1 at 70 times. At the same time, the accuracy of English teaching quality evaluation is 95%, the correlation coefficient of the results is 0.95, and the evaluation time is less than 150 ms. In the evaluation of specific English teaching quality, the evaluation index system can be changed according to the specific situation to improve the versatility of English teaching quality evaluation. In future research, we will expand the research sample and apply it to other aspects of the English subject to expand the scope of application of this method.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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