Research Article

A Hybrid Online and Offline Approach to Teaching Spoken English Based on Modern Educational Technology

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1. Introduction

From the current situation of high school English speaking instruction, the development of students’ English speaking ability has been neglected for a long time, on the one hand because exam-oriented education focuses more on the cultivation of students’ written expression ability and on the other hand due to the difficulties of implementing speaking instruction in large classrooms [1]. Inadequacies also exist in the oral language teaching evaluation system.

(1) The evaluation focus is not accurately grasped, and the results are emphasized while the language learning process is neglected. The focus is on the precision and fluency of students’ language output. For example, the focus of oral tests usually falls on the standard of speech, the naturalness of intonation, and the fluency of speech speed.

(2) The absence of standardized evaluation criteria for spoken English: Due to a lack of emphasis on the teaching of spoken English and the absence of a scientific and systematic evaluation system, students only speak “dumb English.” According to the research of several scholars, there is a great deal of enthusiasm for the study of college speaking instruction. Although English classroom exploration in elementary, middle, and high schools is also a popular research topic, the majority of studies focus on the two skills of writing and reading, whereas there is insufficient research on the two skills of listening and speaking and especially on the evaluation of English classroom speaking instruction.

(3) There is no language environment. Learning any language is inseparable from the environment in which it is used, and learners’ listening and speaking skills are formed in a certain language environment. Although, through years of language learning, students have a certain mastery of English vocabulary and grammar and have certain reading and language analysis skills, when they face a native English
speaker, they are often overwhelmed and do not know how to communicate in everyday English. The reason for this is due to the lack of a language communication environment. In addition, another obstacle is that students are afraid to speak. Although there are opportunities to train speaking during class, time is still limited due to teaching tasks, and some students are often afraid of saying the wrong thing and too shy to catch even such a small opportunity, not to mention outside of class, because there is no language environment and students can rarely be heard to communicate in English consciously.

Information technology and the Internet are currently utilized extensively in numerous fields. The education industry is well-adjusted and progressive. However, due to time and space constraints, teachers’ supervision of students’ online learning is inadequate, resulting in interruptions and abandonment of the students’ learning process, while inadequate online learning affects the development of offline activities [2]. To maximize the effectiveness of teaching and learning, online and offline instruction must be organically combined to form a scientific online and offline hybrid instruction model.

This study proposes a hybrid online and offline approach to teaching spoken English with the following innovations, based on contemporary educational technology.

The design of the teaching model includes the release of teaching tasks, the organization and uploading of teaching resources, and the design and implementation of teaching activities during the preclass online phase. In-class online and offline stage: Because a portion of the knowledge-acquisition tasks have been completed online prior to class, the classroom focuses primarily on student presentations and group activities. Postclass online phase: due to time constraints in the classroom, the teacher cannot comment on each student’s performance in order to improve the teaching effect.

In this study, we propose a novel dynamic evaluation model based on artificial intelligence that is extremely user-friendly and in its final online stage to comprehend students’ and teachers’ learning.

The experiment demonstrates that our teaching method is a revolutionary breakthrough in oral education.

2. Related Work

2.1. Blended Teaching. This study argues that online and offline hybrid teaching refers to the integration of online and offline teaching, “a teaching mode that uses computer information network technology and relies on online platforms for online learning and offline face-to-face classroom learning in a highly integrated manner using online media” [3]. In this state of instruction, the effect is not a simple addition of online learning and traditional instruction, but rather a chemical reaction of integration. Blended online and offline teaching is distinguished by the integration of two learning paths that appear to be separated in time and space.

Online teaching is not the same as traditional live web teaching, and offline teaching is not a carbon copy of traditional classroom teaching activities.

2.1.1. The Mixed Teaching Platform. Online platforms are a crucial prerequisite and an important basis for the successful deployment of blended teaching. They “studied the new hybrid teaching method by using mobile Internet + mu-class platform, pulsing the course knowledge points, and evaluating the degree of achievement” [4]. Hybrid education, as per Professor He Keban, “requires changing traditional online distant learning and traditional face-to-face teaching” [4]. In the words of Prof. He Keban, “creating smart classrooms and smart campuses is conducive to realizing the ambitious goal of education informatization, improving teaching quality of various subjects as well as improving students’ overall quality, thus cultivating a large number of innovative composite talents for the country” [5]. Zhong and Wang scholars proposed, “When carrying out online and offline hybrid teaching mode through the carrier of microcourse, it is necessary to take into account both the granularity and curriculum of microcourse, the autonomy of online mode, and the guidance of offline mode, as well as the immediacy of online assessment and the process of classroom test” [6]. This is so that the hybrid online and offline teaching with microlearning as the carrier does not lose sight of the other. Zou researched the interaction characteristics of online learning in blended based on QQ groups, and his study showed that when students learn online, there are large differences in the positive difficulties of interaction in QQ groups, and there are also differences in individual participation, and students’ participation has a direct impact on learning effectiveness, and the depth of learning participation needs to be further improved. Zou scholars have conducted practical research on online and offline hybrid teaching using the self-developed ‘Educational Technology Class’ mobile APP and WeChat public platform. He used the WeChat public platform to push course content and expand the breadth and depth of course content accordingly, while using the student performance management. “He also used the “Class Dojo” mobile APP, questionnaire star, and examination bank to evaluate and guide students dynamically and in the process, improve students’ learning autonomy and motivation, and further enhance teaching effectiveness [7]. Scholars applied the cloud classroom to the course of University Physics and carried out research on online and offline hybrid teaching. The empirical research shows that cloud classroom is a new intelligent teaching tool which is beneficial to enhance teaching effect [8].

It can be seen that the work of the predecessors is mainly based on the online platform, without considering the source and outcome of English instruction, but also considering the comprehensive training of English listening and speaking ability.

2.1.2. Effectiveness of Blended Teaching. Blended teaching combines online network instruction with traditional classroom teaching. It has advantages that cannot be compared with any single online network teaching or single
face-to-face classroom teaching, and it has vigorous vitality and great potential for cultivating high-quality talents in the 21st century [9]. Liu and Zhang, and other scholars showed that “online-offline hybrid teaching not only allows students to maximize studying time anywhere and anytime, but also allows students to independently choose what they want to learn according to their own interests and learning progress. It promotes students’ motivation in learning, independent learning habits, and the concept of lifelong learning. Combining online teaching with offline teaching, through face-to-face communication between teachers and students, and students and students, further increases the emotional communication between students and teachers and enhances students’ sense of efficacy, achievement, and acquisition, thus further stimulating their enthusiasm and enthusiasm for independent learning” [10]. Gong and Lu proposed “an investigation of online and offline mixed English teaching in higher education; it was verified that the implementation of online and offline blended teaching mode is beneficial to improve students’ learning ability” [11]. Liu conducted an investigation and online-offline hybrid teaching model research, and the study showed that “online-offline blended teaching is conducive; the overall teaching effect is good, but there are still some problems with this new teaching model” [12]. Liu conducted a study on the practical application of the hybrid teaching model, and the practical results showed the following.

The blended teaching mode is conducive to improving students’ learning autonomy, their interest in learning, and the effective transfer of learned knowledge and skills, and the teaching effect is relatively obvious. [13]

2.1.3. Factors Influencing the Effectiveness of Blended Teaching. Blended teaching is an organic whole composed of many interrelated elements and multidimensional vertical and horizontal factors, and whether it can “output” good teaching effects and achieve teaching goals is influenced by many factors in different degrees. According to Zhu et al., teachers’ teaching ability, teaching methods, academic level, and teaching attitudes play a crucial role in the effect of online and offline blended teaching; students’ learning is an issue that cannot be ignored in the implementation of blended teaching; teaching support such as face-to-face classroom teaching, course design, and online teaching also have an impact on the outcome of blended teaching [14]. Guojun and Duan, and other scholars found that “electronic monitoring has a more restraining effect on student behavior than traditional monitoring in the process of online and offline blended teaching and learning through an empirical study of classroom teaching and learning” [15]. The satisfaction of blended teaching represents the effectiveness of blended teaching to a large extent; therefore, the factors influencing the satisfaction of blended teaching are also the factors influencing the effectiveness of blended teaching. Cheng proposed a hypothetical model of the factors influencing the satisfaction of blended instruction from the perspective of learners and verified that the degree of interaction and learning achievement can directly and positively influence satisfaction; individual characteristics and learning environment can indirectly and positively influence satisfaction through the mediation of the degree of interaction and learning achievement; and the degree of interaction, individual characteristics, learning environment, and learning achievement factors influence the degree of satisfaction with teaching in descending order of strength [16].

2.2. Current Status of Research on Classroom Teaching Evaluation. Even though the Internet is becoming increasingly popular and online education is developing at a rapid rate, the primary mode of higher education is still classroom instruction. It is essential to conduct a thorough evaluation of classroom instruction, as classroom teaching is the link that directly affects the quality of talent cultivation. Due to differences in cultural background and higher education system, the index system, ideology, and evaluation methods of teaching evaluation in the United States and abroad vary.

2.2.1. The Construction and Optimization of the Teaching Evaluation System. In some Western countries, research on teaching evaluation began relatively early, and in the early 1930s, Taylor coined the term “educational evaluation” in response to the numerous problems that appeared in the tests of students’ performance in schools at the time, and a number of evaluation approaches were developed [17]. Current research on the evolution of teaching evaluation demonstrates that Western evaluation places a premium on learner self-assessment, focuses on the learner as the primary subject, and employs more diverse, relatively scientific, and reasonable evaluation methods [18]. The University of Washington’s Instructional Assessment System (IAS), the University of Arizona’s Teacher–Course Evaluation (TCE), Kansas State University’s Teaching and Learning Evaluation (TCE), and the University of Kansas State University’s Teaching and Learning Evaluation (TCE) are all employed. Kansas State University’s Individual Development and Educational Assessment (IDEA) is a representative evaluation index system [19]. National Survey of Student Engagement (NSSE), Australian Course Experience Questionnaire (CEQ), National Student Survey (NSSE), and National Student Survey (NSSE) are well-known course evaluation questionnaires in foreign countries. Among them, NSSE is the most influential teaching evaluation questionnaire in the United States’ higher education sector, with students serving as the primary evaluation subjects. In contrast, the NSSE in the United States is more comprehensive, and its questionnaire includes not only course learning experiences but also other experiences outside the classroom, which play a significant role in student learning and development [20]. Western countries such as Europe and the United States have developed more mature teaching evaluation systems, such as Cisco’s development of an advanced evaluation system to evaluate the performance of its students during the learning and training process, and the company’s implementation of continuous program and
curriculum enhancements are based on these evaluation data [21]. Zhu et al. [14] and others derived a learning performance evaluation system by integrating the K-means clustering algorithm, gray association theory, fuzzy inference, and fuzzy association rules, four computational intelligence theories. In addition, instructional evaluation research has included the emotional mining of students [22] and the extraction and analysis of instructional evaluation indicator scores [23].

2.2.2. Research in Teaching Evaluation. With the constant development of new technologies, teaching evaluation methods gradually become a mix of qualitative and quantitative ones, and quantitative assessment of varied data information often necessitates great data models. To set the weights of the evaluation indices, scholars currently use fuzzy comprehensive evaluation and hierarchical analysis [24]. For example, Liu et al. and others developed a scientific quantification methodology by combining fuzzy comprehensive evaluation of teaching quality with hierarchical analytic approach [25]. Rough set theory is used to overcome the problem of unjustified index weights [25], decision trees are used to analyze teaching evaluation data [26], and association rule algorithms are used to examine aspects impacting teaching quality [27]. Some scholars used artificial neural networks to model teaching evaluation, established relevant mathematical models, quantified the indexes synthetically, constructed BP neural network models, and obtained more reasonable evaluation results [28]. A mathematical model of teaching quality evaluation based on wavelet neural networks has been suggested. However, the neural network has its own drawbacks, such as local extreme value points and severe sample reliance [29–31].

3. Method

The concept of teaching model, also known as teaching structure, was first proposed by American scholars in the previous century and was gradually formed over a lengthy period of teaching practice by continuously summarizing and enhancing teaching. The definition of a teaching model with typical significance is a relatively stable and simplified combination of the elements of teaching and its activity procedures designed under the direction of specific teaching concepts to achieve the specified teaching objectives and contents. The teaching model consists primarily of the following components: teaching ideology, teaching objectives, teaching procedures, teacher-student pairing, and teaching evaluation. To improve the quality of instruction in various disciplines, it is essential to comprehend the evolution of the teaching model and its rules.

The so-called “blended” oral teaching mode, as its name implies, is a combination of online and offline teaching and consists of the three components shown in Figure 1.

Preclass online phase is releasing teaching assignments, arranging and uploading teaching materials, and designing instructional activities. The specific operation involves teachers releasing moderately challenging learning tasks in advance into the Blue Ink Cloud Classroom curriculum. The preclass assignments can be microlessons that require students to watch relevant content, learn words and sentences, or read chapter materials on their cell phones, in order to facilitate independent learning. Students who complete independent learning will receive the corresponding experience value, and their experience value will be considered in the final course evaluation. Teachers can also launch surveys on the platform to assess students’ mastery of learning tasks or breakthrough points, enabling them to conduct more targeted offline teaching activities.

Online and offline classroom phase: Since some knowledge-acquisition tasks have been completed online prior to class, the majority of classroom time is devoted to student presentations and group activities. Teachers request that students complete signing in and saving class time on their mobile devices in class. The platform will initially record students’ attendance, and both teachers and students will be able to view it at any time so that students can improve their attendance performance over time. Before class, teachers upload images, videos, documents, and web links to the platform using their computers to provide students with rich and engaging learning materials. According to the progression of course lectures and the needs of classroom activities, assignments are made available at any time. Content-appropriate instructional activities, such as brainstorming and group discussions, are conducted on the platform. There are a variety of classroom activities, including either topic-based discussions to practice students’ language skills or brief English letter writing. Teachers may elect to have some students present their writing in class, with both teacher and peer feedback, and require that all student work be uploaded to the platform.

Postclass online portion: Due to time constraints, the teacher cannot comment on the classroom performance of every student. To enhance teaching efficacy, the instructor must extend a portion of the classroom design to the postclass and complete it on the course platform. The teacher can comment on each student’s uploaded work, either in audio or in written form, allowing him or her to pay more attention to each student and provide a more targeted evaluation in the context of their oral or written performance, as opposed to the traditional classroom’s general evaluation.

The online and offline “hybrid” teaching model also influences the assessment method, which is a combination of process and outcome evaluation. Students must complete independent knowledge learning on the platform prior to class, and the system will keep track of those who have done so. Use the cell phone terminal in class to complete the sign-in. Participate actively in group activities, voice their opinions, and complete the assigned test tasks in class. Students can only fulfill course requirements and complete the process evaluation if they actively participate in classroom activities and do not remain outside of the classroom. The accumulation of processes lays the groundwork for the ultimate outcome evaluation. The process evaluation is
unique to each lesson and task, and obtaining the experience value requires the students’ active participation.

3.1. Evaluation Mechanism. The teaching model of this is based on the online platform of modern education to do teaching, focusing on the SVM-based teaching evaluation mechanism proposed in this study.

SVM seeks the best compromise between the complexity of the model and the learning ability based on the limited sample information to obtain the best generalization ability. The SVM method can overcome the inherent shortcomings of multilayer forward neural networks, which are specifically designed for the case of finite samples. The algorithm turns the problem into a quadratic optimization problem by obtaining optimal solution with the information provided rather than the optimal solution with an infinite number of samples, which can theoretically obtain the global optimum. The SVM also transforms the actual problem into a high-dimensional feature space through a nonlinear transformation and constructs a linear classification function in the high-dimensional space to achieve the nonlinear classification in the original space, which ensures a good generalization ability of the classification method and solves the “dimensional disaster” very cleverly. For classification problems, multilayer forward neural networks can solve nonlinear classification problems, but such networks cannot guarantee that the classifier is optimal, while SVM methods based on statistical learning theory theoretically guarantee the optimality of classification and have good generalization ability.

3.1.1. Linear Support Vector Machine (SVM). With the linear support vector machine (SVM), Vapnik proposed the principle of maximal-margin, which is also known as interval [5]. This means that the system randomly generates a hyperplane and moves it so that the sample points of different categories are on both sides of the hyperplane, and the interval between the two dashed lines is maximized, so that the resulting L-plane is the optimal hyperplane, which theoretically realizes the optimal classification problem for linearly divisible data. The specific algorithm of two-class linear separable is as follows.

Let the training sample input be $x_i (i = 1, 2, \ldots, n)$, and the desired output $y_i \in \{+1, -1\}$, assuming that the hyperplane $wx + b = 0$. In order for the hyperplane to classify the samples correctly and with classification interval, the constraints need to be satisfied:

$$y_i (w \cdot x_i + b) - 1 \geq 0.$$  \hspace{1cm} (1)

This can be achieved by minimizing $||w||^2$, and the problem of constructing an optimal hyperplane is
transformed into a minimization function 
\[ \phi(w) = \frac{1}{2}||w||^2, \] 
which is a quadratic programming problem, the solution of which can be introduced into the Lagrange function:
\[ L = \frac{1}{2}||w||^2 - \sum_{i=1}^{n} \alpha_i [y_i(x_i \cdot w + b) - 1], \] (2)
where \( \alpha_i > 0 \) is the Lagrange coefficient, i.e., solving for the \( L \)-optimal solutions for \( w, b \).

The partial differentiation of equation (1) is with respect to \( w \) and \( b \), respectively, and equal to zero; since the gradient of \( L \) in both \( w \) and \( b \) is equal to zero, we have
\[ \sum_{i=1}^{n} \alpha_i y_i = 0, \quad \alpha_i > 0, \quad i = 1, 2, \ldots, n, \] (3)
\[ \sum_{i=1}^{n} \alpha_i y_i x_i = 0. \] (4)

To find the optimal value of \( L \), substitute (2) and (3) into (1) to obtain
\[ L(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j). \] (5)

This is a QP problem, and according to the optimality condition KKT, this optimization problem needs to be satisfied:
\[ \alpha_i [y_i (x_i \cdot w + b) - 1] = 0, \quad i = 1, 2, \ldots, n. \] (6)

The support vector of the sample is the \( x_i \) for which \( \alpha_i \) is not zero and equation (5) holds.

The optimal classification function is obtained by solving the above problem:
\[ f(x) = \frac{sign (w \cdot x + b)}{\sum_{i=1}^{n} a_i y_i x_i \cdot x + b}. \] (7)

When this idea is applied to linear indivisibility, some of the samples cannot satisfy the condition of equation (1), and it is necessary to introduce the relaxation variable \( \xi_i \geq 0 \) to achieve this, which is the constraint:
\[ y_i [w \cdot x_i + b] \geq 1 - \xi_i, \quad i = 1, 2, \ldots, n. \] (8)

The objective function becomes
\[ \phi(w, \xi) = \frac{1}{2} (w \cdot w) + C \sum_{i=1}^{n} \xi_i, \] (9)
where \( C > 0 \) is a specified constant, which controls the penalty for misclassifying samples; the larger the \( C \), the heavier the penalty.

The generalized optimal classification surface is obtained by compromising the minimum misclassified samples and the maximum classification interval.
\[ f(x) = \frac{sign (w \cdot x + b)}{\sum_{i=1}^{n} a_i y_i x_i \cdot x + b}. \] (10)

### 4. Experimental Results and Analysis

#### 4.1. Data Source

The text data used in this study were obtained from the university’s online teaching system, which contains the teaching quality evaluation data for four semesters. A total of 444910 evaluations for the four semesters were used as the initial data for the experimental part. The dataset is given in Table 1.

#### 4.2. Data Preprocessing

The data collected are uneven or not evaluated according to the corresponding weights which may have an impact on the accuracy and precision of the prediction results. Therefore, the sample dataset needs to be preprocessed before using the data.

Preprocessing includes converting the data of instructional evaluation into vector form and normalizing the data. Normalization is the process of restricting the desired data to a certain range of statistical distributions of the sample after certain algorithms have been processed. On the one hand, the normalized data has the same zero mean and mean squared deviation, which is good for calculation. On the other hand, the normalized sample can avoid some small number of samples in one range being dominated by a large number of samples in other ranges, which can affect training and prediction. The convergence of training is improved after normalization of the data. There are three
normalization methods that are used to classify and simulate the data by dividing the distance linearly after dimensionality reduction.

In the process of noise reduction and dimensionality reduction of the word document matrix by LSA, some information is inevitably lost, and we expect that the more noise is lost in this process, the better, and the less useful information is better. Based on this purpose, we designed the following controlled experiments, in which 10, 15, 20, 30, 50, and 60 dimensions are reduced during the LSA operation as a comparison. The results of the experiments are given in Table 2.

As shown in Figure 2, the highest accuracy of 87.96% is achieved when compressing to 30 dimensions; the accuracy increases as the number of dimensions increases prior to compressing to 30 dimensions but decreases as the number of dimensions increases after compressing to 30 dimensions.

4.3. Dividing the Training Set and Test Set. Experiments revealed that normalizing the sample data to [0, 1] for the teaching evaluation resulted in relatively improved predictions. Classification using the method requires training of the model and, thus, requires the data required for model training. Initially, the sample dataset is split into two sections. To train the test, cross-validation of the two sample data is then performed. Table 3 and Figure 3 show the experimental graph of the effect of training test ratio on classification results.

As shown in Figure 3, the accuracy rate increases as the training-testing ratio increases, reaching a maximum of 89.29% when all data are used for training. This suggests that the size of the training set has a significant impact on the classification accuracy, and the larger the training set, the higher the classification accuracy.

Cross-validation is a technique that maximizes the use of available sample data to train the learning model while ensuring its generalizability. This is due to the fact that it is a waste of training data if the sample size is small and only a portion of the data is used for validation. Cross-validation enables the use of all data by ensuring that all data is utilized. Simply put, cross-validation begins by dividing the original data into two random parts, using one part as the training set and the other as the test set to calculate the error rate, and then exchanging the two parts and recalculating the error rate. Finally, a model is constructed with all the data, and the error rate of the model constructed with all the data is the mean of the two error rates calculated previously. A more general algorithm is dimensional cross-validation. This is the process of randomly dividing all sample data into distinct subsets.

### Table 1: Dataset.

<table>
<thead>
<tr>
<th>Semester</th>
<th>Number of courses</th>
<th>Number of students</th>
<th>Teaching evaluations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3557</td>
<td>22767</td>
<td>113225</td>
</tr>
<tr>
<td>2</td>
<td>3338</td>
<td>19367</td>
<td>103123</td>
</tr>
<tr>
<td>3</td>
<td>3631</td>
<td>22564</td>
<td>118275</td>
</tr>
<tr>
<td>4</td>
<td>3394</td>
<td>19181</td>
<td>110287</td>
</tr>
</tbody>
</table>

### Table 2: Results of dimensionality reduction control experiments.

<table>
<thead>
<tr>
<th>Dimensionality</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>30</th>
<th>50</th>
<th>60</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>86.14</td>
<td>87.49</td>
<td>87.56</td>
<td>87.96</td>
<td>87.22</td>
<td>86.20</td>
</tr>
</tbody>
</table>

### Table 3: Training test ratio classification result accuracy.

<table>
<thead>
<tr>
<th>1:1 (%)</th>
<th>2:1 (%)</th>
<th>3:1 (%)</th>
<th>4:1 (%)</th>
<th>5:1 (%)</th>
<th>All (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>56.2</td>
<td>73.55</td>
<td>78.12</td>
<td>82.40</td>
<td>85.33</td>
<td>87.10</td>
</tr>
</tbody>
</table>

One of the subsets serves as the training set, while the remaining subset is repeatedly used for testing, so that all subsets participate in the test to obtain a unique error rate. The final estimated error rate is the arithmetic mean of the error rates determined in the preceding steps. Cross-validation is currently the most popular estimation method because it is more computationally intensive and trustworthy than the leave-one-out method and the tie-breaker method. In addition to validating the performance of the classifier, cross-validation can also identify the optimal parameters and kernel function parameters. This technique is employed to examine model parameters and kernel functions.

4.4. Effect of SVM Kernel Function and Different Parameter Selection on the Correct Rate. In this experiment, we tried different kernel functions and related parameters mentioned in the method to find the best classification accuracy for a given sample.
The methods proposed in this study are better, and it is found that it is not sensitive to parameters, which further emphasizes. We can optimize the teaching effect and cultivate more high-quality talent only by organically combining online and offline instruction. We designed a machine learning-based SVM teaching evaluation mechanism, and the experimental results demonstrated that our evaluation results are useful for providing feedback on the quality of teaching and promoting learning outcomes.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References


TABLE 4: SVM kernel function and different parameter selection for different samples.

<table>
<thead>
<tr>
<th>Kernel functions</th>
<th>Parameters</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBF</td>
<td>C = 10</td>
<td>87.23</td>
</tr>
<tr>
<td>RBF</td>
<td>Default</td>
<td>83.38</td>
</tr>
<tr>
<td>Linear</td>
<td>C = 10</td>
<td>80.11</td>
</tr>
<tr>
<td>Linear</td>
<td>Default</td>
<td>79.94</td>
</tr>
<tr>
<td>Polynomial</td>
<td>D = 5</td>
<td>60.19</td>
</tr>
</tbody>
</table>

TABLE 5: Comparison test results of the feature selection algorithm.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Train time (s)</th>
<th>Test time (s)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binary tree</td>
<td>23.9</td>
<td>7.1</td>
<td>85.33</td>
</tr>
<tr>
<td>Ours</td>
<td>24.3</td>
<td>6.7</td>
<td>87.43</td>
</tr>
</tbody>
</table>

As can be seen from Table 4, the classification accuracy of the RBF kernel function is still better than that of the linear kernel function on average, indicating that, in the selection of the SVM classification parameters, specific problems need to be analyzed, and the effects caused by the kernel function and parameter selection may have completely different results on different samples.

4.5. Comparison and Validation of Results. In order to verify the superiority of the intelligent evaluation method proposed in this study, other methods are compared as given in Table 5.

As given in the table, the classification time consumed by these two algorithms is nearly identical, primarily because the categories and numbers of experimental data are relatively small and the computation is less, making the difference in classification time between the two algorithms negligible; however, as the categories of experimental data increase and the depth of the biased algorithm tree increases at a faster rate, the classification time gap between the two algorithms increases. In addition, its classification accuracy is relatively high because the improved algorithm in this study uses the relative distance between categories as the criterion for determining which categories should be segmented out first, thereby reducing the accumulation of errors caused by the binary tree structure. Therefore, applying the SVM algorithm described in this study to the evaluation system is beneficial.

In terms of parameter sensitivity analysis, after our test, it is found that it is not sensitive to parameters, which further shows that the method proposed in this study is better.

5. Conclusion

This study investigates the online and offline hybrid teaching model, applies it to English speaking classes, applies and studies online and offline hybrid teaching, and discusses the influencing factors and solutions for each variable under this teaching model. The experiment demonstrates that online and offline instruction must be tightly integrated and cannot be separated. Instead of relying too heavily on online teaching, online tasks and designs must be applied reasonably to education, and offline teaching results should be emphasized. We can optimize the teaching effect and cultivate more high-quality talent only by organically combining online and offline instruction. We designed a machine learning-based SVM teaching evaluation mechanism, and the experimental results demonstrated that our evaluation results are useful for providing feedback on the quality of teaching and promoting learning outcomes.


