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Retraction

Retracted: Study on College English Online Teaching Model in Mixed Context Based on Genetic Algorithm and Neural Network Algorithm

Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] X. Ma, "Study on College English Online Teaching Model in Mixed Context Based on Genetic Algorithm and Neural Network Algorithm," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 8901469, 10 pages, 2021.

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Research Article

Study on College English Online Teaching Model in Mixed Context Based on Genetic Algorithm and Neural Network Algorithm

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College English classroom teaching evaluation is an important basis for understanding teaching level and improving teaching quality. The traditional college English classroom teaching evaluation is mainly carried out through questionnaires and scales, but this method is time-consuming and laborious, inevitably introduces subjective errors, and reduces the accuracy and credibility of the evaluation results. In recent years, the rise and development of wisdom education not only provides a more convenient and efficient modern education form but also brings new ideas for classroom teaching evaluation. A subjective and objective fusion statistical evaluation model based on multidirectional genetic variation method and optimized neural network is proposed. The algorithm avoids subjective errors and improves the accuracy and reliability of the evaluation results, and a comprehensive evaluation model is constructed. Finally, according to different evaluation indexes, a systematic visualization scheme is designed to generate students' classroom learning evaluation report and teachers' classroom teaching evaluation report, respectively, and visualize them on the web.

1. Introduction

The integration between intelligent analysis and educational big data makes learning evaluation move from digital learning evaluation to digital intelligent evaluation. Combining and analyzing relevant platforms at home and abroad from the perspective of the development of intelligent evaluation technology, it is found that the intelligent evaluation platform has some problems, such as single evaluation data collection, lack of depth of evaluation analysis, low visualization level of evaluation results, and weak intelligence of evaluation feedback. Intelligent education promotes learners' conceptual understanding of knowledge points, which is an important purpose of learning evaluation. In terms of concept understanding, especially the concept of science knowledge, there are different concepts, myth concepts, and intuitive concepts that are easy to confuse learners. Therefore, it is necessary to find and promote learners to complete concept transformation through intelligence evaluation, including the analysis of topics and options, and analyze and change the ontological and cognitive assumptions behind the previous concepts. In addition, the evaluation of learner modeling can understand its transformation process and reorganize the knowledge structure by changing the concepts being studied.

In recent years, intelligent education has gradually sprung up and developed, especially intelligent learning and evaluation, as an important application of intelligent education, provides a new idea for college English classroom teaching evaluation. On one hand, with the support of various intelligent education policies, the deployment of intelligent campus has begun to take shape in the country, and the development of intelligent hardware technology also provides equipment foundation for the intellectualization of college English classroom teaching evaluation. On the other hand, artificial intelligence, big data, and other technologies provide an algorithm basis for the intellectualization of college English classroom teaching evaluation. Therefore, the combination of information technology, especially artificial intelligence technology, and traditional teaching quality evaluation forms a new form of modern teaching evaluation. Through sensors and other equipment,

multidimensional audio, and video data can be deployed and collected in the classroom. Big data, machine learning, and other technologies can carry out structural analysis of classroom audio and video data, obtain teaching content, teaching level, and quantitative evaluation results of teaching style, and provide strong basic data support for subsequent teaching management, decision-making, and improvement.

The traditional college English classroom teaching evaluation is mainly carried out through questionnaires and scales, but this method is time-consuming and laborious, and inevitably introduces subjective errors and abstracts a set of classroom teaching evaluation index system suitable for the combination of traditional scale and artificial intelligence analysis. It avoids introducing subjective errors and increases the accuracy and credibility of the evaluation results and builds a visual comprehensive evaluation model. According to different evaluation indexes, a systematic visualization scheme is designed to generate students' classroom learning evaluation report and teachers' College English classroom teaching evaluation report, respectively, and visualize them on the web. This paper provides a more convenient and efficient modern education form and also brings new ideas for classroom teaching evaluation.

This paper is divided into five parts. The first part is the research background, and the second part is the literature review to analyze the research results of the problem. The third part is the introduction of multidirectional mutation genetic algorithm and optimized neural network model. The fourth part is the concrete empirical analysis and completes the visualization of the college English classroom teaching evaluation system. The fifth part is the conclusion of the article.

2. Related Work

The traditional college English classroom teaching evaluation is carried out through questionnaires and scales. When evaluating teaching, it is often mixed with many subjective factors, resulting in the evaluation being not objective enough, and there is not enough objective analysis data to support. Moreover, the evaluators generally go deep into the classroom and directly listen to and evaluate the class; classroom teaching with evaluators present and students' learning are affected by the subjective enthusiasm of teachers and students, which is different from daily teaching and will affect the authenticity and reliability of traditional teaching evaluation [1–4]. At present, the domestic education system and education methods have been reformed for many times, the information education has been gradually deepened, and the smart classroom has developed for many years, especially the construction of smart campus and the application of multimedia technology have become mature. For example, the popularization and use of class to class teaching equipment has made courseware teaching a general trend, and the classroom intelligent attendance system realizes convenient attendance punch in [5–11]. For AI based college English classroom teaching evaluation, there have been many relevant studies in China. Xiaoling et al. proposed that cameras and other devices in the classroom can capture the behavior of students in the classroom, and then through big data analysis, teachers can get the report on the knowledge mastery and learning interest of each student in the class and teach different students according to their aptitude and improve the teaching effect [12]. The research shows that college English classroom teaching evaluation based on big data monitoring and AI analysis can overcome the shortcomings of subjectivity and experience dependence of traditional teaching evaluation to a certain extent, and information technology makes college English classroom teaching evaluation a tool not only for evaluating teachers' teaching quality. More importantly, it can get the personality and characteristics of teaching and learning in different classes through real-time analysis, so as to provide teachers with teaching methods more suitable for themselves and students and greatly improve the teaching level.

On the other hand, some teaching evaluation system applications based on AI technology have appeared in the domestic market. The cloud recording and broadcasting teaching evaluation system launched by Beijing Normal Liyun Education Technology Co., Ltd., transmits the teaching process to the teaching quality research group through the Internet for online evaluation and presents the feedback of class evaluation. However, the traditional evaluation scale is still used, and the evaluation scale is scored online by the research group to realize teaching evaluation [13]. The teacher can collect and reflect on the teaching effect of MAGIC MIRROR based on the real-time image recognition system in the classroom, which can help the teacher to better recognize the teaching effect of magic mirror and students after the class and then improve teaching ability [14]. Tal also launched WISROOM smart classroom products focusing on students' learning evaluation. Based on face detection, face recognition, expression recognition, posture recognition, and other technologies, combined with students' exercise process data in the classroom. Tal evaluates students' classroom learning concentration, so that teachers can get students' classroom learning evaluation report through AI analysis and pay attention to the learning situation of each student in the class [15]. The college English classroom teaching evaluation system launched by Kuangshi technology is based on face recognition, behavior recognition, expression recognition, and other technologies integrated in the attendance and behavior analysis camera and behavior analysis server to obtain students' behavior, expression, concentration, front seat attendance, and other data, conduct AI analysis on the video data of the classroom, and output AI teaching evaluation results and assisted traditional teaching evaluation [16]. The EduBrain data-driven smart classroom launched by qingfan technology is deployed by cameras, pickups, and other equipment in the classroom to noninvasively collect multidimensional data such as teachers' and students' facial expressions, voice intonation, and behavior actions in the classroom. Based on this data, it uses AI technologies such as knowledge map, emotion calculation, and posture recognition to calculate classroom concentration interactive degree and other index data and then generate visual college English classroom teaching evaluation results, which are

visually presented on PC and mobile terminals together with college English classroom teaching audio and video. At present, they have been applied in Shijiazhuang No. 1 middle school, Academy of Fine Arts of Tsinghua University, Wuhan Yucai Primary School, and other schools, and their development is relatively mature [17]. Looking abroad, since the 21st century, many foreign countries have basically realized the construction of smart campus and introduced many information technologies in the field of education, such as the introduction of robots in high school campuses in Japan to assist classroom education and Programming Education [18, 19]. In Korea, the curriculum model, evaluation model, and teaching learning model combined with informatization are added to steam education and promoted to local campuses [20–24]; Australia combines virtual reality technology with children's education to pilot virtual space classroom education [25].

For AI based college English classroom teaching evaluation, some foreign schools, such as Marist College, effectively collect students' feedback on classroom learning problems, online reading materials, and online speech with the help of big data and AI technology on the basis of the construction of smart campus, so as to provide reference for students' classroom learning and after-school learning at the same time. It is also helpful for teachers to improve teaching quality. However, the research on classroom monitoring in western countries is relatively few in China, and the focus of the existing AI based college English classroom teaching evaluation application is not on the evaluation of teaching quality. For example, the "intelligent classroom behavior system" uses technologies such as face recognition, which is mainly used to monitor students' classroom attendance. When evaluating teaching quality abroad, colleges and universities mainly organize students to evaluate teachers, and the evaluation method is still based on the subjective evaluation of scales and questionnaires.

3. Construction of Neural Network Model Based on Multidirectional Mutation Genetic Algorithm and Its Optimization

3.1. Multidirectional Mutation Genetic Algorithm and Its Calculation Principle of Optimized Neural Network Model

3.1.1. Calculation of Subjective Weight by Multidirectional Genetic Variation Method. The steps of calculating subjective weight by multidirectional genetic variation method are as follows.

Construction of analytic hierarchy process model is as follows. The analytic hierarchy process model is constructed according to the classroom teaching evaluation index system in Chapter 2. The highest level is the college English classroom teaching evaluation index, and the constituent factors are the corresponding characteristic sequence.

Construction of judgment matrix is as follows. Through the consistent matrix method, compare the different constituent factors of each layer, and calculate the relative weight of constituent factors according to the importance quantification table.

Hierarchical ranking and consistency test are as follows. Calculate the corresponding eigenvector of the maximum eigenroot $\lambda_{\max}$ of the judgment matrix, and rank the elements in the eigenvector after normalization. Check the consistency of the relative weight of each layer. If the consistency check fails, repeat steps 1–3.

Consistency test to obtain subjective weight is as follows. Conduct consistency test CR = (CI/RI) on the result feature vector of hierarchical ranking, where CI = $(\lambda - n/n - 1)$ and RI are random consistency indicators.

If CR < 0.1, it is considered to pass the consistency test, and the normalized eigenvector is the obtained subjective weight.

3.1.2. Optimizing Neural Network to Calculate Objective Weight. Optimization neural network is a method of objectively giving weight. The calculated value is the objective weight in this model. The specific steps of optimizing neural network to calculate objective weight are as follows.

For N samples and corresponding M features, for the ith sample, the jth eigenvalue is as follows:

$$x_{i,j}\,(i = 1, 2, \ldots, N;\ j = 1, 2, \ldots, M). \tag{1}$$

Data standardization processing is as follows. Firstly, all feature sequences are normalized, and then the positive influence features and negative influence features are processed, respectively, such as (2) and (3).

Positive influence characteristics are as follows:

$$x_{ij} = \frac{x_{ij} - \min\{x_{1j}, \ldots, x_{nj}\}}{\max\{x_{1j}, \ldots, x_{nj}\} - \min\{x_{1j}, \ldots, x_{nj}\}}. \tag{2}$$

Negative influence characteristics are as follows:

$$x_{ij} = \frac{\max\{x_{1j}, \ldots, x_{nj}\} - x_{ij}}{\max\{x_{1j}, \ldots, x_{nj}\} - \min\{x_{1j}, \ldots, x_{nj}\}}. \tag{3}$$

The eigenvalue after standardization is recorded as x_{ij}. For the jth feature, its eigenvalue is as follows:

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij}), \quad j = 1, 2, \ldots, m, \tag{4}$$

where $k = (1/\ln(n)) > 0$ meets $e_j \geq 0$.

For the jth feature, its information redundancy is

$$d_j = 1 - e_j, \quad j = 1, 2, \ldots, m. \tag{5}$$

Calculate objective weights. For the j-th feature, its weight is

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}. \tag{6}$$

3.2. College English Classroom Teaching Evaluation Model Based on Statistical Modeling of "Multidirectional Genetic Variation Method and Optimized Neural Network Comprehensive Evaluation".

The subjective and objective weights of the index are calculated, respectively, through the

multidirectional genetic variation method and the optimized neural network, and the comprehensive weight is obtained by combining the order information and strength information of the two, so as to obtain the membership degree of the index, that is, the multidirectional variation genetic algorithm of "analytic hierarchy process optimized neural network comprehensive evaluation" and its optimized neural network model in this subject.

In college English classroom teaching evaluation, indicators can be divided into two categories: score indicators and category indicators. Corresponding to the classroom evaluation index system proposed in Chapter 2, students' listening concentration, classroom activity, and knowledge mastery are evaluated in the form of score data, which belongs to score index. Teachers' teaching type evaluation, teaching style evaluation, and teaching media evaluation are evaluated in the form of category and belong to category indicators. For the score index, the multidirectional mutation genetic algorithm and its optimized neural network model directly take the index as the calculation goal, and the calculated membership degree is used as the evaluation result of the score index. For category indicators, multidirectional mutation genetic algorithm and its optimized neural network model take various categories of classroom evaluation indicators as the goal, calculate the membership degree of each category, and take the corresponding category with the largest membership degree as the evaluation result of category indicators.

3.2.1. Example Analysis: Evaluation Index "Students' Listening Concentration". This paper takes "students' listening concentration" in the college English classroom teaching evaluation index system as an example.

Judge the index type, find the corresponding characteristic sequence, and normalize it.

In the data preprocessing part of Chapter 3, the occurrence frequency and average duration of 8 types of classroom procedural behaviors and 2 types of classroom procedural emotions are obtained through the student data set (including student behavior data set and student emotion data set). The occurrence frequency and average duration of behaviors "listening with head up," "taking notes with head down," "lying on the table," "looking around," "reading," and the occurrence frequency of emotion, "laughing," are selected as the relevant characteristics of students' listening concentration, including 11 types of characteristics, "looking around." The occurrence frequency and average duration of "lying on the table" are negative impact indicators, and the rest are positive impact indicators.

After the feature sequence is obtained, it is normalized to the range [0,100]. Here, the normalization range determines the membership of the reference index. For example, the final evaluation result of the "listening concentration" index is the score of the percentage system, so the normalization range of its characteristic sequence is [0,100].

Calculate the subjective weight and objective weight corresponding to 12 types of features.

The subjective weights, ranking, and objective weights corresponding to 11 types of features were obtained by multidirectional genetic variation method and optimized neural network. X1-x12 are the frequency of "listening up," "taking notes down," "lying on the table," "looking around," "reading," "laughing," "average duration of listening up," average duration of "taking notes down," the average duration of "lying on the table," "looking around," and "reading."

The combination weight optimization model is used to calculate the comprehensive weight.

According to formula (7) of combined weighting optimization model,

$$\min \sum_{i=1}^{n} (\omega_i - \beta_i)^2$$
$$\text{s.t.} \begin{cases} \omega_i \geq \omega_j i < j, \\ \alpha_{i.}^{-} \leq \omega_i \leq \alpha_{i.}^{+}, \\ \sum_{i=1}^{n} \omega_i = 1, \end{cases} \tag{7}$$

where n is the number of features, ω_i is the combined weight of the i feature, β_i is the objective weight of the i feature, and the reasonable value range of the i feature is $[\alpha_i^-, \alpha_i^+]$.

The reasonable value range of the comprehensive weight is calculated according to the subjective weight and objective weight and then the comprehensive weight of the characteristics related to students' listening concentration is calculated according to formula (7).

Calculate the membership of each sample to the "listening concentration" index.

The weighted sum of the normalized feature sequence in step 1 and the comprehensive weight sequence of each feature calculated in step 3 are used to obtain the membership score of each sample for the "listening concentration" index. The formula is as follows:

$$\text{score} = \sum_{i=1}^{n} W_i a_i, \tag{8}$$

where n is the number of features, a_i is the normalized eigenvalue of i, and W is the comprehensive weight corresponding to the i feature.

3.2.2. Calculation Description of Other Evaluation Indicators. For the score index "student classroom activity," the calculation step is to make corresponding changes to the input data set and finally calculate the membership of "student classroom activity," that is, the evaluation result of the index.

For the category indicators "teacher teaching type evaluation," "teacher teaching style evaluation," and "teacher teaching media evaluation," first calculate the membership of each category of the evaluation index, and finally compare and find out the maximum membership of each category. The corresponding category is the evaluation result of the index. For example, "teacher's teaching type evaluation" is divided into "indoctrination type/natural type/interactive type." The indicators of the presentation map, such as "classroom cloud map," "S-T teaching analysis map," and

"knowledge point extraction map," are presented directly through visualization and are not calculated here.

4. Results and Analysis

4.1. Performance Analysis of Multidirectional Genetic Mutation Algorithm. After constructing the multidirectional mutation genetic algorithm and its optimized neural network model, taking the behavior and emotion occurrence frequency and average duration of 200 teacher samples and 300 student samples as the model input, the evaluation results of various college English classroom teaching evaluation indexes are calculated.

4.1.1. Performance Analysis of "Score Index" Evaluation Model Based on Multidirectional Genetic Mutation Algorithm. For the score index, that is, students' attention and classroom activity, the evaluation results are continuous scores. Draw the multidirectional mutation genetic algorithm and its optimized neural network model, and compare the prediction results with the label data. The overall prediction results of both are good, and the fitting degree between the predicted value and the label value is high. After calculation, the root mean square error RMSE between the predicted value of listening concentration and the label value is 11.167, and the root mean square error RMSE between the predicted value of classroom activity and the label value is 13.409. Compared with the two, the prediction results of multidirectional mutation genetic algorithm and its optimized neural network model in the index "listening concentration" fit better with the label value.

4.1.2. Performance Analysis of "Category Index" Evaluation Model Based on Multidirectional Genetic Mutation Algorithm. For category indicators, that is, teachers' teaching type evaluation, teaching style evaluation, and teaching media evaluation, the specific evaluation performance analysis of multidirectional mutation genetic algorithm and its optimized neural network model are as follows.

Evaluation model of "teaching type evaluation" based on statistical modeling is as follows: the evaluation results of "teaching type evaluation" are divided into "indoctrination type/natural type/interactive type," which are three classification indicators. Figure 1 shows the confusion matrix of the multidirectional mutation genetic algorithm and its optimized neural network model for the evaluation of the "teaching type evaluation" index, the corresponding calculated accuracy P, recall R, F1 values of each class, and the macro accuracy macro used to evaluate the global performance of the model_ P. Macro recall_ R. Macro F1 value, overall accuracy.

As can be seen from the above figure, the multidirectional mutation genetic algorithm and its optimized neural network model have good accuracy, recall, and F1 value in each category of "teaching type evaluation," and the performance of "natural type" and "interactive type" is general, and the overall performance of the model is good in accuracy, macro accuracy, macro recall, and macro F1 value.

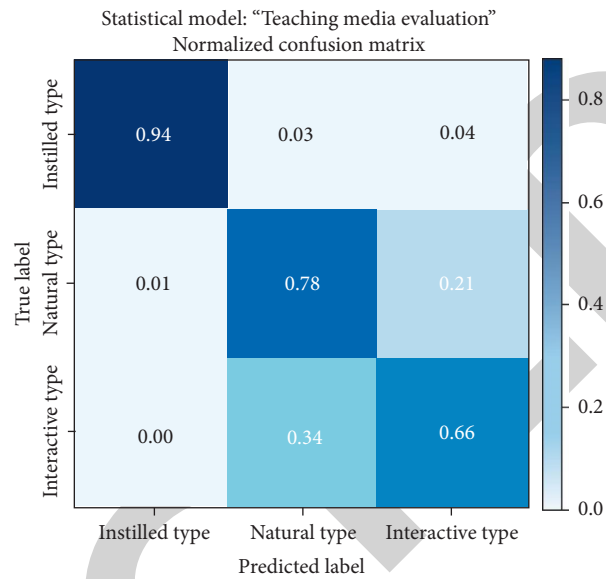

Figure 1: Statistical model: display of evaluation performance of "teaching type evaluation" indicator.

Evaluation model of "teaching style evaluation" based on statistical modeling is as follows. The evaluation results of "teaching style evaluation" are divided into "passionate type/humorous type/solemn and rigorous type," which are three classification indicators. Similar to the three classification indexes "teaching type evaluation," Figure 2 shows the confusion matrix of the multidirectional mutation genetic algorithm and its optimized neural network model for the evaluation of the "teaching style evaluation" index, the corresponding calculated accuracy P, recall R, F1 values of each class, and the macro accuracy macro used to evaluate the global performance of the model_ P. Macro recall_ R. Macro F1 value, overall accuracy.

It can be seen from the above figure that the multidirectional mutation genetic algorithm and its optimized neural network model have good accuracy, recall, and F1 value in the various categories of "teaching style evaluation," and the performance of "solemn and rigorous" is general, while the performance of "humorous and intimate" is relatively poor. For the overall performance of the index, the model performs generally in accuracy, macro accuracy, macro recall, and macro F1 value. Evaluation model of "teaching media evaluation" based on statistical modeling is as follows. The evaluation results of "teaching media evaluation" are divided into "courseware display type/blackboard writing type," which are two classification indicators. We agree that "courseware display type" is the positive example of the category. Figure 3 shows the confusion matrix of the multidirectional mutation genetic algorithm and its optimized neural network model for the evaluation of the index of "teaching media evaluation" and the accuracy P, recall R, F1, and overall accuracy of the positive example "courseware display type."

As can be seen from the above figure, the overall performance of the multidirectional mutation genetic algorithm and its optimized neural network model in the "teaching

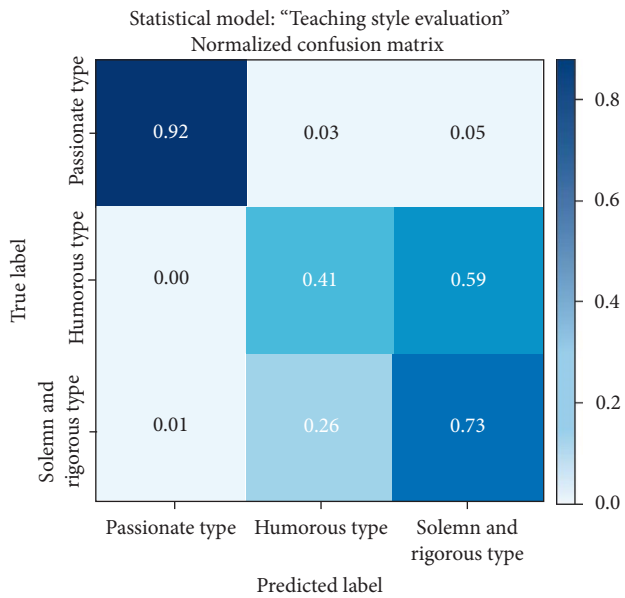

Figure 2: Statistical model: display of the evaluation performance of the "evaluation of teaching style" indicator.

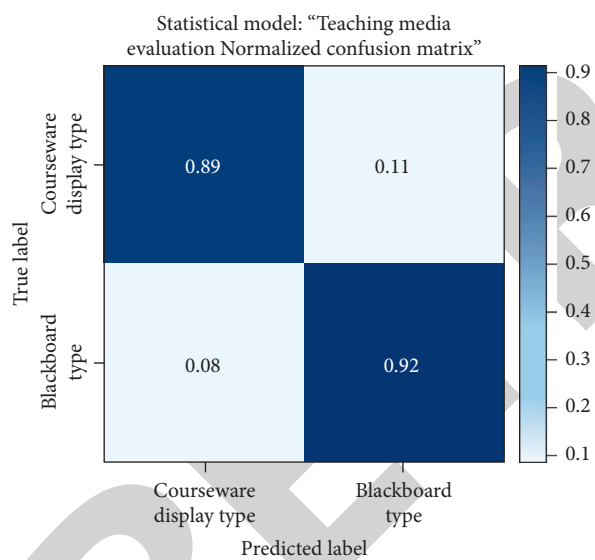

Figure 3: Statistical model: display of evaluation performance of "evaluation of teaching media."

media evaluation" index is good. Relatively speaking, the real classification of "courseware display type" is mistakenly classified as "blackboard type" more than the real classification of "blackboard type" and mistakenly classified as "courseware display type."

4.2. Performance Analysis of Optimized Neural Network Model. The average occurrence time and continuation time of 300 samples of teachers and students' teaching behavior are calculated as the evaluation indexes.

4.2.1. Performance Analysis of "Score Index" Evaluation Model Based on Optimized Neural Network Model. For the score index, that is, students' attention and classroom activity, the evaluation results are continuous scores. Draw the multidirectional mutation genetic algorithm and its optimized neural network model, and compare the prediction results with the label data. Evaluation model of "listening concentration" is based on integrated learning: prediction diagram and prediction results of training set and test set.

The integrated learning model has a good evaluation performance for the index of "listening concentration" and has a good prediction effect on the training set and the test set. Among them, the root mean square error of prediction results and label data on the training set is RMSE = 8.318, and the root mean square error of both on the test set is RMSE = 9.3749. Compared with the evaluation performance of multidirectional mutation genetic algorithm and its optimized neural network model in the index of "listening concentration" (RMSE = 11.167), the integrated learning model has better evaluation performance for this index.

The evaluation model of "classroom activity" is based on integrated learning: the prediction diagram of training set and test set and the root mean square error between prediction results and label data. The integrated learning model has a good prediction effect on the "classroom activity" index in the training set and the test set. Among them, the root mean square error of prediction results and label data on the training set is RMSE = 8.571, and the root mean square error of both on the test set is RMSE = 9.663. Compared with the evaluation performance of multidirectional mutation genetic algorithm and its optimized neural network model in the "classroom activity" index (RMSE = 13.409), the integrated learning model has better evaluation performance for this index.

4.2.2. Performance Analysis of "Category Index" Evaluation Model Based on Optimized Neural Network Model. For the category indicators, that is, teachers' teaching type evaluation, teaching style evaluation, and teaching media evaluation, the specific evaluation performance analysis of the integrated learning model is as follows: The "teaching type evaluation" evaluation model is based on integrated learning: the evaluation results of "teaching type evaluation" are divided into "indoctrination type/natural type/interactive type," which are three classification indicators. Figure 4 shows the confusion matrix of the integrated learning model for the evaluation of "teaching type evaluation" indicators, the corresponding calculated accuracy P, recall R, and F1 values of each category, and the macro accuracy macro used to evaluate the global performance of the model_ P. Macro recall_ R. Macro F1 value, overall accuracy.

As can be seen from the above figure, the accuracy rate, recall rate, and F1 value of the integrated learning model are better for the "indoctrination type" in the evaluation of various categories of "teaching type evaluation," and the performance of the "natural type" and "interactive type" is

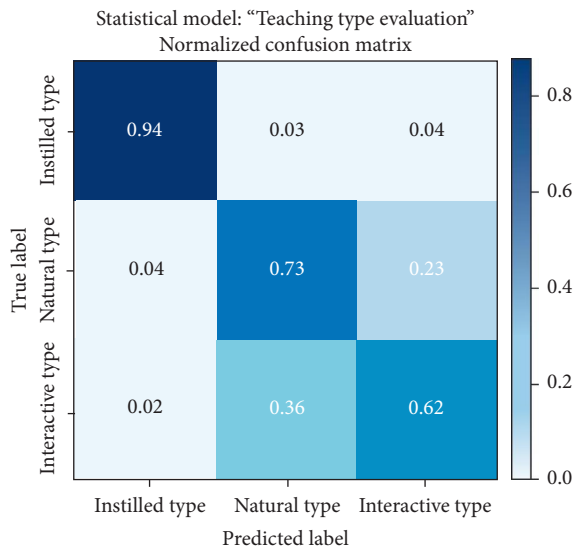

Figure 4: Integrated learning model: display of evaluation performance of "teaching type evaluation" indicators.

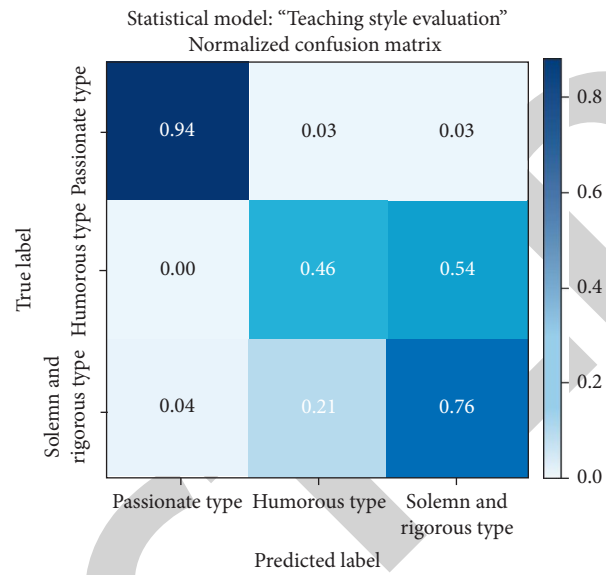

Figure 5: Integrated learning model: the evaluation performance display of the "evaluation of teaching style" indicator.

general, which is similar to the performance of the statistical model in various categories. Compared with the macro model, the accuracy of the macro integrated neural network is reflected in the macro value, the accuracy of the macro integrated neural network, and its multidirectional learning rate.

The evaluation model of "teaching style evaluation" is based on integrated learning: the evaluation results of "teaching style evaluation" are divided into "passionate type/humorous type/solemn and rigorous type," which are three classification indicators. Similar to the three classification indexes "teaching type evaluation," Figure 5 shows the confusion matrix of the integrated learning model for the evaluation of the "teaching style evaluation" index, the corresponding calculated accuracy P, recall R, F1 values of each category, and the macro accuracy macro used to evaluate the global performance of the model_ P. Macro recall_ R. Macro F1 value, overall accuracy.

As can be seen from the above figure, the accuracy rate, recall rate, and F1 value of the "passionate type" in the evaluation of "teaching style" of the integrated learning model are better, the performance of the "solemn and rigorous type" is average, while the performance of the "humorous and friendly type" is relatively poor. Compared with the multidirectional mutation genetic algorithm and its optimized neural network model, the integrated learning model performs better in the overall performance of the index in accuracy, macro accuracy, macro recall, and macro F1 value.

Evaluation model of "teaching media evaluation" is based on integrated learning: the evaluation results of "teaching media evaluation" are divided into "courseware display type/blackboard writing type," which are two classification indicators. We agree that "courseware display type" is the positive example of the category. Figure 6 shows the confusion matrix of the integrated learning model for the evaluation of "teaching media evaluation" indicators and the

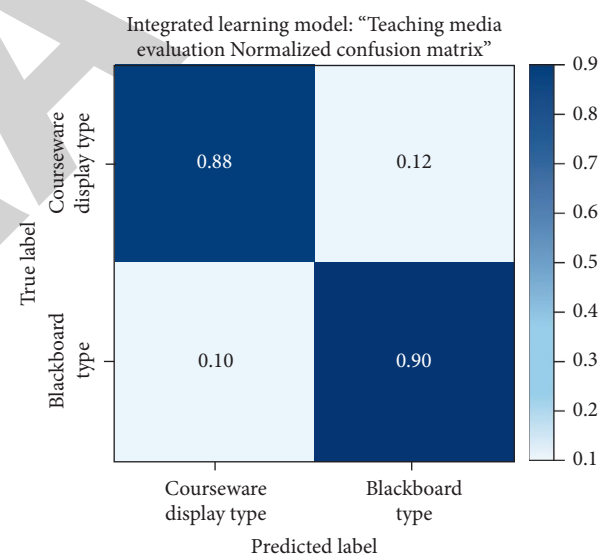

Figure 6: Integrated learning model: display of evaluation performance of "teaching media evaluation" indicator.

accuracy P, recall R, F1 values, and overall accuracy of the positive example "courseware display type."

4.3. Construction of Comprehensive College English Classroom Teaching Evaluation Model Based on Multidirectional Mutation Genetic Algorithm and Its Optimized Neural Network Model. For the three indicators of "students' concentration in class," "students' classroom activity," and "teachers' teaching style evaluation," the multidirectional mutation genetic algorithm and its optimized neural network model can better mine the index features, amplify the complementarity between different types of data features through the integration idea, and have better evaluation

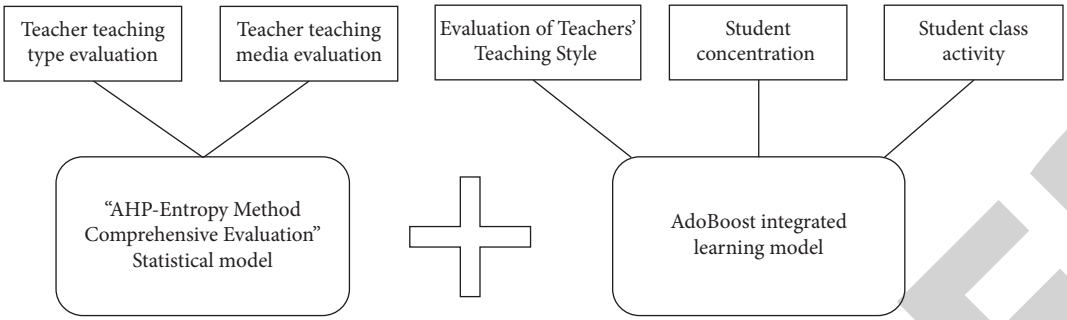

Figure 7: Comprehensive evaluation model.

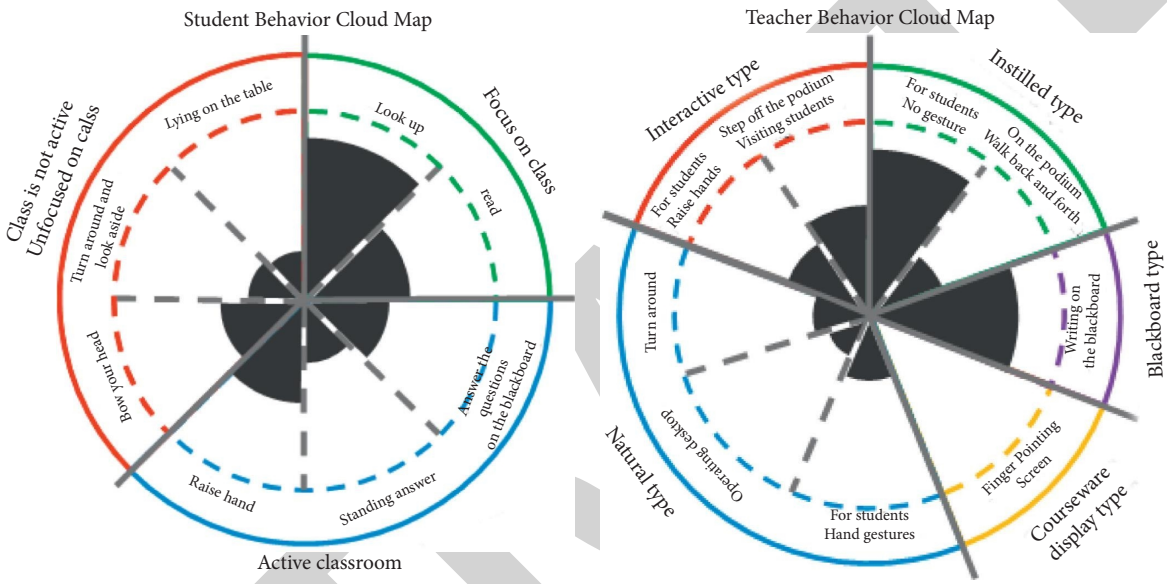

Figure 8: Visualization: classroom cloud map.

performance. For the two indicators of "teacher teaching type evaluation" and "teacher teaching media evaluation," the advantages of multidirectional mutation genetic algorithm and its optimized neural network model are not obvious, while the traditional model can better extract the correlation between features, and the evaluation performance is better. Combined with the above performance analysis, the comprehensive evaluation model under the background of this subject is obtained through optimal combination, as shown in Figure 7.

4.4. Visual Presentation of College English Classroom Teaching Evaluation System Based on Multidirectional Mutation Genetic Algorithm and Its Optimized Neural Network Model. The specific visual presentation scheme is shown in Figure 8. In the student behavior cloud diagram, the sectors near "listening attentively" and "classroom active" are filled more, and the sectors near "listening inattentively" and "classroom inactive" are filled less, indicating that the students in this classroom are more attentive and active. The sectors near "indoctrination" and "blackboard writing" in the teacher behavior cloud are filled more, indicating that the teachers in this classroom prefer indoctrination and blackboard teaching.

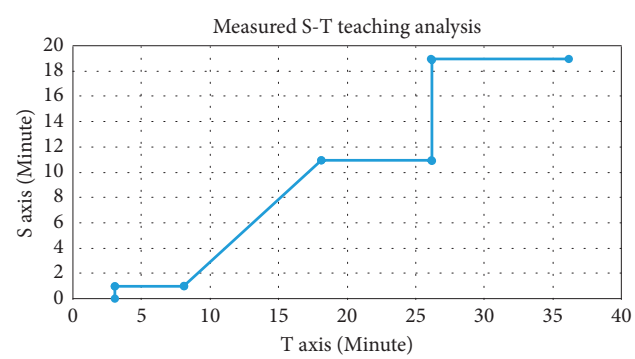

Figure 9: Visualization: S-T teaching analysis diagram.

ST teaching analysis chart is shown in Figure 9; the total time of teachers' behavior exceeds 35 minutes, and the total time of students' behavior is less than 20 minutes, of which about 10 minutes are the behavior of teachers and students at the same time (teacher-student interaction). It can be seen that the classroom is dominated by teachers' teaching, supplemented by teacher-student interaction.

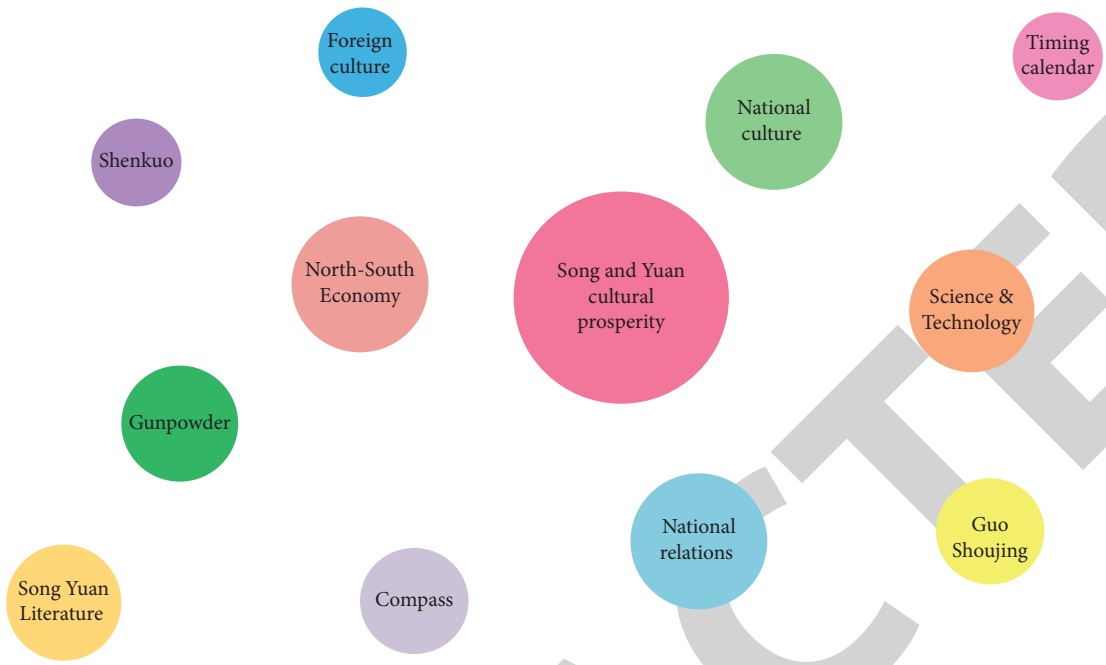

Figure 10: Visualization: knowledge point refinement diagram.

Map of knowledge points extraction is shown in Figure 10; it can be seen that the theme of the course is "cultural prosperity of song and Yuan Dynasties," and important knowledge points include "North-South economy," "national culture," and "national communication".

5. Conclusion

Aiming at accelerating the construction of educational informatization and intelligent education, this paper constructs a set of college English classroom teaching evaluation system based on multidirectional mutation genetic algorithm and its optimized neural network model. Firstly, a set of classroom teaching evaluation index system suitable for the combination of traditional scale and AI analysis is investigated and refined. Then, a subjective and objective fusion statistical evaluation model based on multidirectional genetic variation method and optimized neural network is proposed, and a comprehensive evaluation model is constructed by comparing the performance complementarity between the model and the traditional model in different college English classroom teaching evaluation indexes. Finally, according to different evaluation indexes, the visualization scheme of the system is designed, and the students' classroom learning evaluation report and teachers' college English classroom teaching evaluation report are generated, respectively, which are visualized on the web. Through experimental tests, the accuracy of the comprehensive model for classification index evaluation is generally between 80% and 90%, and the root mean square error for regression index evaluation is about 10. However, the research of this paper does not collect the data model of actual teaching in colleges and universities and lacks the data simulation of the created model. Therefore, in practical application, more data need to be collected for evaluation.

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.

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