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[1]Xiaotong Shen

An Optimization Study of Artificial Intelligence in Teaching Chinese as a Foreign Language for Present and Contemporary Literature Lecture

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Abstract: - This paper takes artificial intelligence as the starting point of teaching optimization, firstly converts the present and contemporary literature into feature vectors that can be used for classification, and extracts word frequency spatial features according to the keywords. Then the lexical annotation is carried out to complete the participle extraction, and the word frequency weights are counted in order to explain the present and contemporary literature in a targeted way. Next, a convolutional neural network classification model is constructed to enhance the representation of current and contemporary literature by adding input information so that the model learns richer features. Integrate the historical learning data with the learner's forgetting mechanism to solve the problem of learning learner's knowledge forgetting. Finally, the corresponding weights of the historical data are calculated by utilizing the self-attention mechanism and the forgetting mechanism, according to which the optimal form of explanation is generated. Finally, empirical validation shows that the feature word visualization similarities are all higher than 0.6, and the classification error rate of the convolutional neural network is only 1.16% compared with other algorithms. In the teaching effect, the highest average score of the oral class grade after optimization is 93.65, and the highest student participation in the explanation of modern and contemporary literature is 99.92%. Artificial intelligence enriches and changes the traditional means of teaching Chinese as a foreign language, improves the teaching quality and optimizes the teaching effect.

Keywords: artificial intelligence; current and contemporary literature; word frequency weighting; convolutional neural network; forgetting mechanism

1. Introduction

The rapid development of artificial intelligence (AI) technology has strongly promoted the integration of various fields with AI, and the field of teaching Chinese as a foreign language is no exception [1]. In recent years, with the rise of Chinese language fever, the demand for the profession of Chinese language teachers abroad has begun to exceed the supply [2]. The application space and development potential of artificial intelligence technology in Chinese international education are great, which can innovate the teaching system and form of Chinese international education. In response to this situation, a part of colleges and universities have opened Chinese as a foreign language majors, using artificial intelligence technology to reconstruct the international Chinese language education system [3]. While China publicizes Chinese culture to the world, it also exports professional Chinese language teachers to countries that are interested in Chinese language learning for cultural explanations [4]. Compared with traditional Chinese majors, students majoring in Chinese as a foreign language will face a group of international students in the future, so in addition to teaching Chinese language, they should not neglect the introduction of Chinese cultural background [5].

At this stage, expanding the scope of organic integration of AI technology and Chinese language teaching to

[1]School of Humanities and Education,Liaodong University,Dandong, 118001 Liaoning,China. Email: shchenggong2024@163.com

foreigners, using AI to change the existing teaching system and teaching methods of Chinese language teaching to foreigners, and subsuming AI technology into Chinese language teaching to foreigners are the current research focuses in the field of Chinese language teaching to foreigners [6]. Kang, B et al. constructed an intelligent network education system by using a deep learning network. According to the influencing factors of the learning process, students with different learning methods and learning habits are taught according to their abilities, providing a broader learning space for Chinese language students [7]. Zhang, L and Michalak, W constructed an intelligent Chinese language teaching system using the histogram matching algorithm, the multidirectional cutting algorithm, and the local linear embedding algorithm to improve the quality of language teaching by using machine learning[8]. Kang, B and Chen, M et al. take the current situation of multimedia teaching resources as an entry point, combine Chinese ontology features with word segmentation features, and parse Chinese character ambiguities through the degree of semantic association. It is proved that applying multimedia information technology to the Chinese character learning platform helps Chinese pronunciation learning [9-10]. In the study of Jing, Y, a teaching system for Chinese language and literature majors was designed and implemented by combining artificial intelligence with performance under the premise of existing coordination algorithms. And in a simulated teaching environment, the limitations of the teaching system were optimized to improve students' learning potential [11]. Shen, Y and Sun, S used AI and facial recognition technology to observe students' facial expressions, analyze the contradictions that arose during the learning process, and assess the teaching effectiveness in Chinese language teaching in international Chinese language education [12]. Chai, C. S et al. investigated Chinese teachers' attitudes towards attitudes toward teaching with artificial intelligence, and the results of ANOVA showed that applying artificial intelligence in teaching practice is willing by teachers and is an important initiative to promote the development of teaching and learning [13].

For the relevance of explaining modern and contemporary literature in Chinese as a foreign language, this paper first calculates the weights of all literary feature items and categories, and constructs the word frequency space feature extraction process. Atomic slicing is performed on the current and contemporary literature, and then N-shortest path coarse slicing is performed to generate a binary lexical list. According to the results of generating participle words, complete the lexical annotation. And statistical word frequency word weight, complete the feature extraction process, and realize targeted explanation in foreign Chinese teaching. Finally, the knowledge tracking model is constructed to grasp the degree of knowledge mastered by learners of Chinese as a foreign language, recommend appropriate learning resources for them, and avoid early exposure to overly simple or complex teaching content. The temporal convolutional network is used to provide the knowledge tracking model with high-bandwidth access to historical data, and the self-attention mechanism and forgetting mechanism are used to calculate the corresponding weights of the historical data, so as to obtain the knowledge status of the learners and complete the optimization of the present and contemporary literature lectures.

2. Classification of Literary Works in Teaching Chinese as a Foreign Language with Artificial Intelligence

2.1 Text Feature Extraction

2.1.1 Word frequency space feature extraction

In the classification of modern and contemporary literature in teaching Chinese as a foreign language, text feature extraction is a very crucial step [14]. Its purpose is to convert the text into feature vectors that can be used for classification, and Figure 1 shows the flow of the word frequency space feature extraction algorithm. Through the frequency of occurrence of each item in the word frequency matrix of contemporary literature, word frequency statistics, and then according to the size of the word frequency to select a predetermined number of feature items constitute a subset of features, that is, the keywords, so as to design the word frequency space feature extraction method.

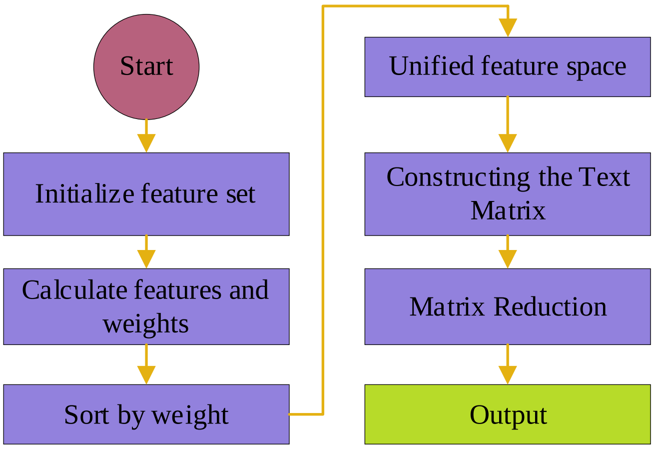

Figure 1 Feature extraction process

In the initial case, the set of feature terms contains all the original feature terms. For each category, the weights of all feature terms and that category are calculated. The weighting formula adopts the scheme of taking local weights by word frequency method and global weights by information entropy method. This ensures that the original non-zero terms remain zero, and also ensures that the feature terms that are more evenly distributed in a particular category of literature achieve higher weights [15]. The calculation formula is as follows:

$$a_{ij} = tf_{ij} \times \left(1 - \sum_{j} \frac{\left(tf_{ij} / gf_i\right)\log\left(tf_{ij} / gf_i\right)}{\log\left(N\right)}\right) \tag{1}$$

Where tf_{ij} and gf_i denote the frequency of occurrence of word i in literary works j and the whole set of literary works respectively, and N is the total number of literary works in the set of literary works.

In order to eliminate the inconsistency in the number of occurrences of words due to the inconsistency in the length of literary works, which brings inconsistency in the differentiation of weight evaluation, it is necessary to normalize the weights a_{ij}, which is calculated by the formula:

$$a_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{M} a_{ij}^2}} \tag{2}$$

Where a_{ij} denotes the weight of the i nd word in the j rd piece of literature and M is the number of words.

For each category, the top K feature terms are taken in descending order of the mutual information of the feature terms calculated above.

Input work $d \in G$, the set of keywords of collection D is T, and the output feature vector is $V(d)=(tfidf\,(d,t_1),\cdots,tfidf\,(d,t_n),w(d,a_1),\cdots,w(d,a_m)),a_i \in A$. Construct the word-text matrix, each different word corresponds to a row in the matrix, and each text corresponds to a column in the matrix, and the text features of modern and contemporary literature are extracted.

2.1.2 Segmentation Feature Extraction

In addition to the accuracy of the word frequency spatial feature results, the performance of participle feature extraction is also crucial. Since the process of teaching and explaining Chinese as a foreign language requires the retrieval of a large amount of data, the finding efficiency becomes a decisive factor in optimizing the results. The process of participle feature extraction is shown in Fig. 2, where the atomic cut is performed first, based on which the N-shortest path coarse cut is performed to find out the first N most compliant cut results, and the binary participle table is generated. Next, the participle results are generated, lexical annotation is performed and the main participle steps are completed. Finally, the word frequency statistics are used to calculate the word weights and carry out feature extraction, so as to realize the targeted explanation in the teaching of foreign Chinese [16].

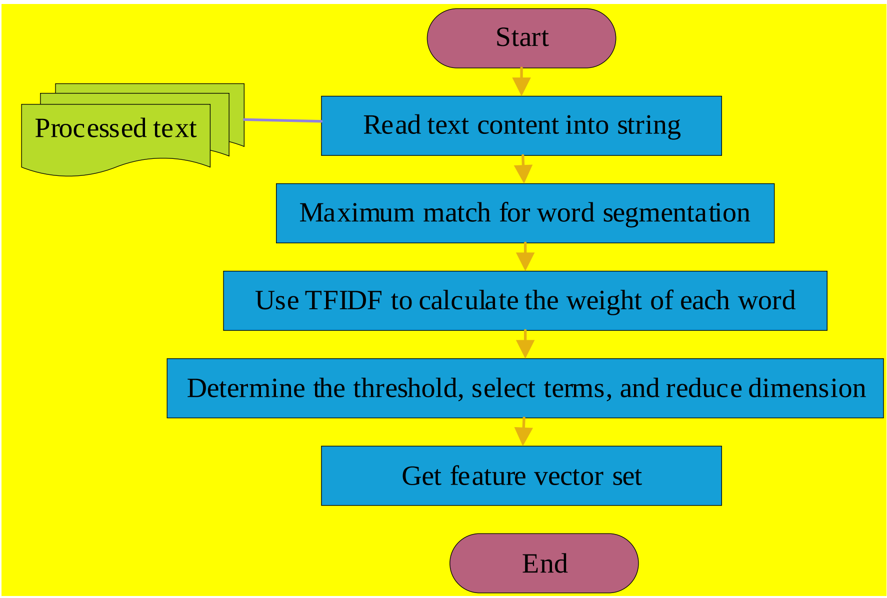

Figure 2 Word segmentation feature extraction process

2.2 Classification of literary works

Convolutional neural network is a multi-layer artificial neural network, which was initially used to solve the image recognition problem. With the continuous improvement of the model structure, it has now become one of the most effective tools for solving text classification problems. Convolutional neural network-based classification method for literary works adopts the representation of word frequency space and participle features in the text representation stage, and the performance depends largely on the representation level of word vectors to the text. Figure 3 shows the structure of the convolutional neural network classification model, by increasing the input information, the model learns richer features and improves the classification effect of modern and contemporary literature. In this paper, the multi-channel mechanism of convolutional neural network is invoked to extend the features by increasing the input channels, which seeks to make the network have a stronger ability to characterize the current and contemporary literature in foreign language teaching [17-18].

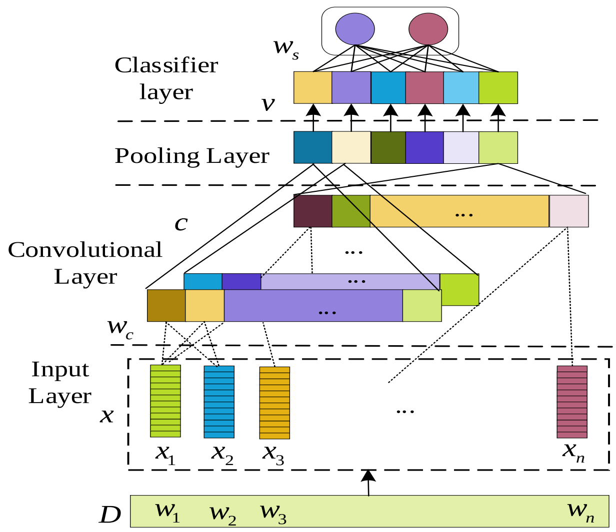

Figure 3 Convolutional neural network classification model structure

The corresponding word vectors $x_i \in R^d$ are obtained at the input layer by querying the list of word vectors w_i for each vocabulary word in the literature D, which is D transformed into a matrix form $[x_1, x_2, \cdots, x_n]$ for input.

The convolutional layer contains multiple convolutional kernels, each of which performs the convolutional computation by sliding a window capable of holding h vocabulary words to obtain the local literature feature values:

$$c_i = f\left(w_c x_{i:i+h-1} + b_c\right), w_c \in R^{hd} \tag{3}$$

where $x_{i:i+h-1}$ denotes a vector consisting of h adjacent word vectors starting at position i of the literature,

w_c denotes the convolution kernel, b_c denotes the teaching bias, f denotes the ReLU nonlinear activation function, and c_i denotes the convolution eigenvalue of the convolution kernel at position i.

The convolution kernel w_c is applied to each possible convolution window $\{x_{1:h}, x_{2:h+1}, \cdots, x_{n-h+1:n}\}$ of the input matrix to obtain the feature map:

$$c = [c_1, c_2, \cdots, c_{n-h+1}] \in R^{n-h+1} \tag{4}$$

The main role of the pooling layer is to sample features from the loser feature map, and the pooling strategy used in the study of teaching Chinese as a foreign language is maximum pooling:

$$\hat{c} = \max\{c\} \tag{5}$$

After that, all the maximum feature values computed by the pooling layer are spliced to generate a high-level feature vector of the literature, denoted using v.

The classifier layer takes the feature vectors as input and uses a fully connected Softmax classifier for classification finally outputs the probability of the current sample on both categories:

$$p(y|v, w_s, b_s) = soft\max(w_s v + b_s) \tag{6}$$

Where $y \in \{+, -\}$ denotes the classification label, w_s denotes the literature weights, and b denotes the teaching bias.

The convolutional neural network uses the back propagation algorithm to update the weights after each forward propagation is completed, and the algorithm ends after many iterations, taking the optimal model as the final text classification model.

3. Optimizing the Lecture of Modern and Contemporary Literature in Teaching Chinese as a Foreign Language

3.1 Knowledge Trace Modeling

In order to be able to achieve the optimization of contemporary literature explanations, the representation of the learner's learning state is a particularly important aspect, so it is necessary to track the learner's learning state, which leads to knowledge tracking as an important means of recommending adaptive learning resources. Knowledge tracking can model the learner's mastery of knowledge concepts to the extent that appropriate learning resources can be recommended, playing the role of skipping over overly simple learning resources and avoiding early exposure to overly complex resources [19].

The knowledge tracking task is a supervised sequence learning task, where a sequence of historical learning interactions of a learning participant is given $X=\{x_1,x_2,\cdots,x_t\}$, and the learning participant is predicted to be able to comprehend the next interaction of contemporary literature x_{t+1}. This interaction can be denoted as $x_{t+1}=(e_{t+1},r_{t+1})$, e_{t+1} denotes the literature that the student attempts at the timestamp of $t+1$, and r_{t+1} denotes the probability that the student understands the work. In teaching Chinese as a foreign language, the ability of students to understand the next exercise to explain the material and track the state of learners' knowledge are the goals of instructional optimization, which are abstracted into the mathematical formula that is i.e., prediction $p\left(r_{t+1}=1\middle|e_{t+1},X\right)$.

The model predicts whether a student can understand the next lecture e_{t+1} based on analyzing his or her previous interaction sequences $X=\{x_1,x_2,\cdots,x_t\}$. In this paper, we convert the knowledge tracking problem into a sequence modeling problem. It is reasonable to consider the input to the model as an interaction sequence $x_1,x_2,\cdots,x_t$, and an explanation sequence $e_2,e_3\cdots,e_t$ that is input one place later than the interaction sequence, and the output as the corresponding probability of understanding the sequence of works $r_2\cdots,e_t$. Define N as the set of students and K as the set of knowledge points. $k_i\in K$ for the content of contemporary literature e_i involved in the knowledge points, knowledge tracking content defined as shown in Table 1. Define the literature explanation optimization problem as when the learner's historical interaction data is given and the following two objectives need to be achieved:

(1) Tracking changes in the student's knowledge state.

(2) Predict student performance on the next lecture content e_{t+1}.

Table 1 Knowledge tracking content definition

Symbol	Describe
N	Student collection
E	Modern and contemporary literary works collection
$\hat{E}$	Modern and contemporary literature embedding matrix
K	Knowledge point collection
X	Student Interaction Sequence $\{x_1,x_2,\cdots,x_t\}$
$\hat{X}$	Start interactive embedding matrix

x_i	i -th pair of interaction tuples
n	Maximum length of interaction sequence

3.2 Introducing the forgetting mechanism to optimize the content of the lecture

In knowledge tracking modeling, the impact of learner knowledge forgetting on knowledge tracking is not considered, so in order to solve the problem of data sparse model can not be generalized, prediction location sensitive, and learner knowledge forgetting, this paper proposes a learner knowledge tracking model integrating temporal convolution, attention mechanism, and forgetting mechanism, and uses temporal convolution network, attention, and forgetting mechanism about the learner for the explanation of content optimization. .

In the literature classification model, the causal convolution of time convolution shows that the knowledge point at t moment is only related to the input and historical interaction data at the current moment, and the future data has no effect on the teaching content at the current moment. Therefore, based on the use of convolutional networks to classify literature, the information is aggregated from the historical data center in a high-bandwidth form for subsequent processing. In order for each convolution to cover the input sequence and to avoid a dramatic increase in the number of hidden layers, the expansion convolution with a null coefficient of $d = 1, 2, 4$ and a convolution kernel size of $k = 2$ is used to cover all the values in the input sequence, and the expansion convolution is accomplished through Equation (7). It is as follows:

$$F(s) = (X * f_d) = \sum_{i=0}^{k-1} f(i) \cdot X_{s-d \cdot i} \tag{7}$$

s is the sequence length, X is the input interaction sequence, f_d is the convolutional kernel, and d is the expansion factor. By adding the residual structure and dense connections to make the shallow network can be expanded into a deep network, in order to maintain the output and input dimensions of the same use of convolutional layers instead of fully connected layers, to facilitate the subsequent explanation of the content can be achieved end-to-end optimization.

The attention layer is designed to allow the explanatory content to be reasonably weighted for the literature based on the current inputs, by first obtaining the vectors of query, key, and value, $Q = \hat{E}W^Q, K = \hat{X}W^K, V = \hat{X}W^V, W^Q, W^K W^V \in R^{d*d}$ is the mapping matrix of query vectors, key vectors, and value vectors, and the respective vectors are linearly projected to different current literature, the self-attention weights of the historical interaction sequence and the current exercise are determined, and the solution uses the scaled dot product, defined as Equation (8) :

$$Attention(Q, K) = soft\max\left(\frac{QK^T}{\sqrt{d}}\right) \tag{8}$$

On the basis of self-attention, the model by incorporating a temporal forgetting mechanism in order to be able to better portray and track the learner's knowledge state. When the content explained is not understood by the learner in a timely manner, the learner develops a forgetting behavior of the knowledge point, however the resulting learning forgetting behavior does not change linearly over time. This change first shows a rapid decline, using the law of forgetting as a reference, then the time function is used to show the change in forgetting of the student's knowledge state. In this paper, Equation (9) is used to fit the forgetting curve:

$$Y = e^{-\alpha x}\left(x > 0\right) \tag{9}$$

x is the time decay parameter and α is the scale factor, which corresponds to a larger value of x when the level of forgetting is larger. x is calculated by equation (10):

$$x = {}^{d_{si}}\!\big/_{L_s} \tag{10}$$

d_{si} denotes the time difference between the first time a Chinese as a foreign language learner s learns the content i of the lecture and the last time he/she learns the work i of the lecture, and L_s denotes the time difference between the student's s first exposure to the exercise and the most recent exposure to the exercise. Combining the self-attention mechanism and the time forgetting mechanism, the forgetting layer weights can be obtained as calculated in Equation (11):

$$TIW\left(s,i\right) = e^{-\alpha \frac{d_{si}}{L_s}} \tag{11}$$

Then the output of the final composite attention layer is shown in equation (12):

$$Time\_Att\left(Q,K,V\right) = \left(1TIW\left(s,i\right) * soft\max\left(\frac{QK^T}{\sqrt{d}}\right)\right)V \tag{12}$$

The model takes the cross function that minimizes the cross function between the predicted value and the true value $\hat{r}_t$ to train the model, and the cross entropy function is shown in Equation (13):

$$L = -\sum_t \left(r_t \log\left(\hat{r}_t\right) + \left(1 - r_t\right)\log\left(1 - \hat{r}\right)\right) \tag{13}$$

According to formula (13) to get the result of forgetting of Chinese as a foreign language learners, the classroom carries out personalized effect on the forgotten part in teaching [20]. In teaching Chinese as a foreign language, the teacher's explanation skills occupy a very important position, the teacher for different types of modern and contemporary literature, with flexible methods of explanation to complete the teaching objectives, with this explanation skills, the teacher can grasp the teaching process in a holistic manner, the successful completion of the teaching objectives. Considering the mechanism of forgetting, teachers can guide students correctly, fully mobilize students' enthusiasm for learning, and teachers can integrate the connotations conveyed by the works of modern and contemporary literature to form the best teaching mode.

4. The Optimization of Artificial Intelligence in Literature Explanation in Teaching Chinese as a Foreign Language

4.1 Work feature extraction and classification effects

4.1.1 Visual analysis of literary features

The textbooks selected for this paper are those used by international students at intermediate and advanced levels. In terms of curriculum, most of the modern and contemporary literary works are compiled in the textbooks for intermediate and advanced comprehensive courses, and some literary works are selected and compiled in the reading materials for international students at intermediate and advanced levels. The selected textbooks have been published over a period of 21 years, during which the textbooks have been constantly changing, with more and more works of modern and contemporary literature being compiled into the textbooks and more and more works being selected.

Combining word frequency spatial features and analytical features extraction outputs the top 20 feature words in terms of probability value, and similarly outputs the top 20 feature words in terms of probability value in terms of the topics of present and contemporary literature lectures. Each literary theme and the textbook demand theme form a 20x20 word similarity matrix, combined with the word information, to solve the similarity between any two feature words. The word similarity matrix is averaged, and the average value is used to represent the similarity between themes, and any two themes are associated to get the similarity between different themes. Literary features visualization results are shown in Figure 4, the text theme word similarity calculation process, feature word similarity results are higher than 0.6. It shows that the proposed method can extract the teaching focus of modern and contemporary literature. In teaching Chinese as a foreign language, it is the main goal to cultivate students' language skills, focusing on words, phrases, grammar and language use, and the teacher will pay more attention to the expression of emotions and profound connotations in the literary works in the explanation.

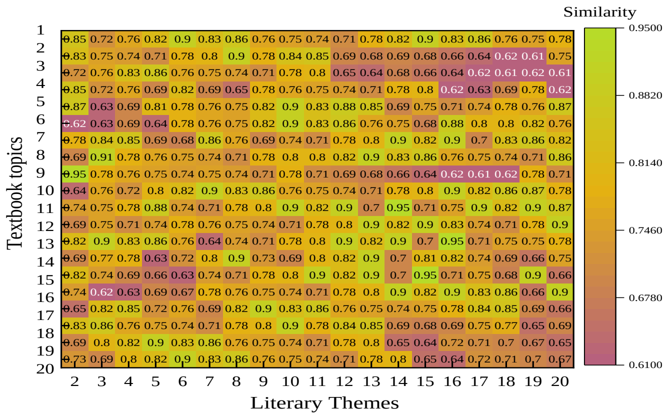

Figure 4 Literature feature visualization results

4.1.2 Convolutional Neural Network Classification Validation

In this paper, the gradient descent algorithm and the weight decay algorithm are compared with a defined convolutional neural network to test the performance of categorizing current and contemporary literature. The tests were performed on the same dataset and the results of the classification error rate comparison are shown in Figure 5. In the same number of iterations, the weight decay algorithm has the lowest classification error of 4.17%, which is significantly higher than the lowest error rate of 0.02% of the convolutional neural network. And when the number of iterations is 50 times, the error rates of convolutional neural network, gradient descent and weight decay are 1.16%, 4.66% and 4.53% in that order. The results show that the convolutional neural network achieves a low classification error rate for current and contemporary literature. When reading articles in the study of foreign Chinese, teachers are able to explain the vocabulary and analyze the articles in a targeted way to enliven the classroom atmosphere, and students are able to better understand the ingenious language in the dialogues of the characters and deepen the memory of the words and the cultivation of the sense of language.

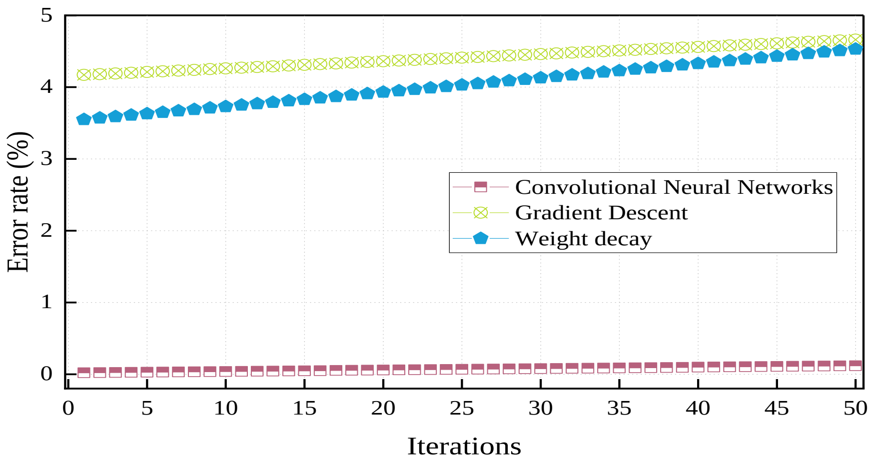

Figure 5 Comparison of classification error rates

4.2 Optimization Analysis of Teaching Effectiveness

4.2.1 Assessment of learning outcomes

To further the optimization effect of AI, the data came from the test scores of a total of 2650 international students in 12 semesters of a Chinese accelerated program in a university in Beijing, comparing the pre-optimization and post-optimization learning achievements, and analyzed by SPSS22.0 software. Table 2 shows the average scores of the test scores of each course type, which can indicate the standard deviation of the dispersion of students' internal performance. Among all the class types, the mean score of speaking class after optimization is high, 93.65, with the smallest standard deviation of 0.92. The integrated class, i.e., the grammar-based course that provides comprehensive training in listening, speaking, reading, and writing, is not very different from the reading class, with both scoring 85 or more points. In the established knowledge tracking model, a forgetting mechanism was introduced to optimize the content of the lectures, and the teaching effect was reflected here. However, before optimization, the average score of the reading course is only 55.95, which is a big drop compared with the other three types of courses. It should be attributed to the fact that most of the international students have difficulties in recognizing Chinese characters and that many domestic colleges and universities offer Chinese characters and reading courses late, which hinders international students from improving their reading ability and leads to the unsatisfactory performance of this course type. It is further verified that AI has good performance and improves the performance of Chinese as a foreign language students.

Table 2 Average scores of course test results

Course type	Mean before optimization	Standard deviation before optimization	Optimized mean	Optimized standard deviation
Comprehensive course/score	62.01	28.36	85.98	1.25
Oral course/score	63.04	21.65	90.25	1.01
Listening course/ score	70.67	23.22	93.65	0.92
Reading course/ score	55.95	36.98	89.74	1.44

Taking international students from major source countries as an example, we analyze the distribution of international students from each country on the overall assessment scores of contemporary literature. Figure 6 shows the comparison of reading scores before and after optimization. Among the international students from 10 countries, Japanese students made the highest progress in reading class, reaching 95.5 points after optimization. In the second and third places are Italian and Korean students, with pre-optimization scores of 50.89 and 55.85 respectively, and post-optimization scores of 89.5 and 90.6 respectively. For the Korean international students from the Chinese character culture circle, the average reading score of modern and contemporary literature was able to be in the second place. For international students with low progress in reading scores, teachers can summarize their forgotten learning content after class and lead students to watch excellent images adapted from modern and contemporary literature together, and students' interest in this course will naturally be raised, thus improving their reading ability in modern and contemporary literature.

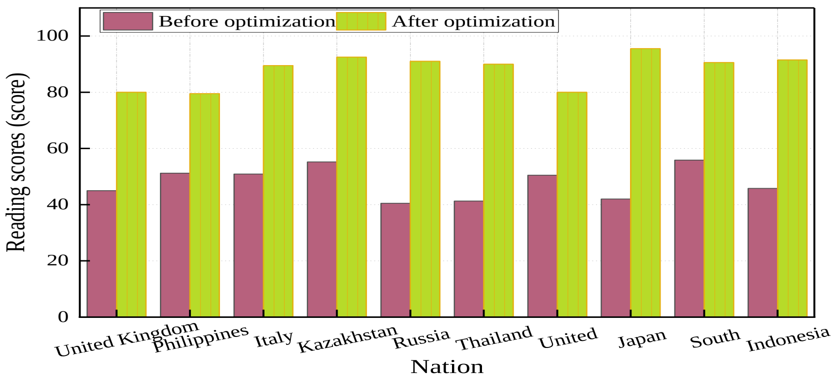

Figure 6 Comparison of reading scores before and after optimization

4.2.2 Analysis of student feedback

At the same time, in the study, statistics were compiled on the scheduling of the lectures on modern and contemporary literature in the optimized post-school Chinese language teaching classes, and Table 3 shows the classroom teaching of 7 class periods. As can be seen from the table, in terms of classroom attendance, the attendance rate of students in each lesson was kept at a high level of 88%-97.09%. However, the attendance rate of the first class was lower than that of the rest of the classes due to the fact that some students failed to submit their attendance data correctly when the first lecture on modern and contemporary literature was optimized. From the second class onwards, the attendance rate of students remained at a stable high level of 97%, which indicates that students are highly adaptable to this new way of teaching interaction. Comparison reveals that the application of AI to modern literature lectures in teaching Chinese as a foreign language significantly improves students' attendance. In terms of teaching assessment, the teacher conducted teaching assessment in every classroom teaching, and the number of assessment questions ranged from 5-10, and students showed high participation in modern and contemporary literature explanation, with the highest level of 99.92%.

Table 3 Classroom teaching situation of 7 classes

Class Order	Number of students	Attendance	Number of teaching assessment questions	Number of participants in teaching assessment	Teaching assessment participation rate
1	2332	88%	5	2281	97.81%
2	2571	97.01%	7	2569	99.92%
3	2572	97%	8	2570	99.92%
4	2573	97.05%	5	2564	99.65%
5	2571	97.09%	10	2498	97.16%
6	2575	97.01%	9	2563	99.53%
7	2571	97.09%	7	2562	99.64%

The introduction of the forgetting mechanism makes it possible to explain modern and contemporary literature in Chinese as a foreign language in a more detailed way, comparing the students' after-class review in the course before and after the AI optimization within 12 semesters. Figure 7 shows the students' revision ratio before and after the application, which shows that students in each semester after AI optimization have a high revision rate of 96.2%, and are able to actively participate in the interaction of classroom teaching in the explanation of current and contemporary literature. However, there are minor differences between semesters, for example, the post-class review rate of 90.2% in the first semester is relatively low compared to other semesters. By extracting the features of literary works and applying convolutional network classification and knowledge tracking modeling, it plays a positive role in promoting the teaching of Chinese as a foreign language. Artificial intelligence identifies literature suitable for international students at the intermediate and advanced levels, and plays an important role in teaching international students with current contemporary literature.

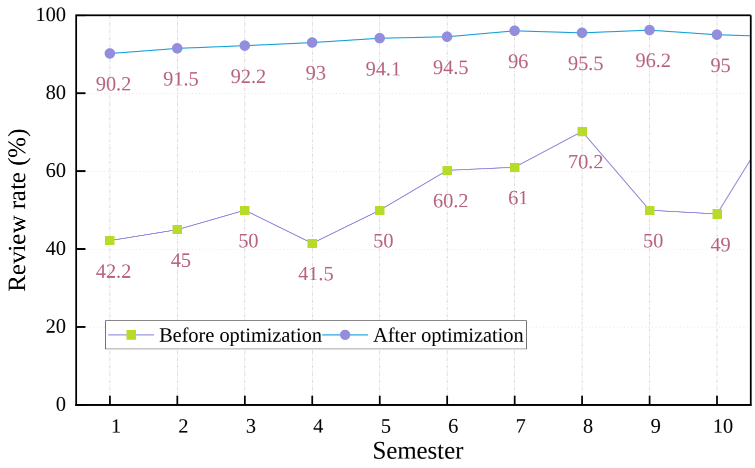

Figure 7 Student review ratio before and after application

5. Conclusion

In this paper, in the optimization of modern and contemporary literature lectures in teaching Chinese as a foreign language, artificial intelligence technology is applied to extract text features and classify literary works, and relevant mechanisms are introduced to achieve teaching optimization, and the research conclusions are as follows:

(1) In the 20x20 word similarity matrix, the results of feature word similarity are all higher than 0.6, and the convolutional neural network classification error rate is between 0.02% and 1.16%. It is verified that AI can extract the key points of the present contemporary literature explanation, and can penetrate the cultural background knowledge and emotional attitudes reflected in the works to the students and deepen the understanding of Chinese words.

(2) The average score of the speaking class after AI optimization is 93.65, with the smallest standard deviation of 0.92. The highest score of the reading class for Japanese students reaches 95.5, while the scores of Italian and Korean students after optimization are 89.5 and 90.6. It shows that AI can target the selection of teaching materials in teaching Chinese as a foreign language and improve the mastery of Chinese.

(3) In the comparison of classroom attendance, the optimized students' attendance rate stays around 97%, which is relatively stable, and the students' review rate is as high as 96.2% in the 12 semesters of the study. It further proves that students' interest in learning contemporary literature in teaching Chinese as a foreign language has been improved, which is more helpful to the development of teaching Chinese as a foreign language.

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About the Author

Xiaotong Shenwas born inDandong，Liaoning. China, in 1985. At present,she works in Liaodong University, and her main research direction is teaching Chinese as a foreign language and modern and contemporary literature.

E-mail: shchenggong2024@163.com