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Deep Neural Network Adaptive Learning Model Design for English Literacy Instruction

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ABSTRACT
Writing skills not only promote the learning of other English skills such as listening, speaking and reading, but also effectively promote the internalization of language knowledge, laying the foundation for further improving the development of students' comprehensive language skills. In this paper, with reference to the application path of information technology in English literacy teaching, we design a SCN-LSTM-based language model, and on this basis, we adopt a bidirectional recurrent network as the language model, and propose an improved SCN-BiLSTM network, which can effectively obtain the contextual relationship of the input sequence. Through the linear interpolation of the language model, the cached language model adaptation is obtained, and the teaching scene corpus is utilized to train the model, and the teaching context-oriented language model adaptation is obtained. Construct ANFIS model to improve the evaluation of English literacy teaching. After the empirical research experiment, the average English reading score of the students in the experimental class after the experiment is 53.631, which is 11.942 points higher than that before the experiment. The writing score is 8.45, which is 0.97 points higher than before the experiment. The application of the adaptive model of English reading and writing based on SCN-LSTM network is very effective.

Keywords: SCN-LSTM language model, bidirectional recurrent network, linear interpolation, corpus training, English literacy adaptive

1. Introduction

Combining reading and writing is a common and effective teaching method in English writing teaching, which helps to improve students' thinking ability and writing ability. In reading and writing teaching, reading is input and writing is output, and input and output are two inseparable and important links in language acquisition. Therefore, closely linking language input and language output can provide students with the opportunity to imitate and utilize the language they have learned [1]. At present, the teaching concept of combining reading and writing is increasingly

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recognized by high school English teachers. However, there are some problems in the actual reading and writing teaching. For example, although there are reading and writing activities in classroom teaching, the logical relationship between the activities is weak, and teachers usually do not provide enough support for students' writing, which makes it difficult for students to complete writing tasks [2]. The application of deep learning has become a key force in driving innovation in English literacy teaching methods and enhancing students' learning experience. Deep learning is a new research direction in the field of machine learning, which combines shallow features to form more abstract high-level features by building multi-layer neural networks, with the aim of being able to mimic the mechanisms of the human brain to analyze and interpret raw data and discover deeper distributed feature representations of the data. Deep learning, with its powerful learning classification ability, has achieved better-than-ever results in many popular fields, such as recognition and detection of images, speech recognition, etc [3-4].

Education informatization is an inevitable choice to adapt to the development of education in the intelligent environment of the new era, and adaptive learning is one of the key technologies to promote education informatization, and accurate analysis of learners' personalized characteristics is a prerequisite for the construction of adaptive learning systems [5]. The learner knowledge level model is an important content for describing learners' personalized characteristics, which is a formal representation of learners' knowledge state. The dynamic modeling of learners' knowledge level mostly adopts traditional deep learning techniques, so a deep neural network adaptive learning model for English literacy teaching can be designed [6]. According to different students' learning situations, different teaching modes are carried out to provide students with adaptive learning, and for those who have already learned the knowledge points and those who do not know the knowledge points can be adjusted in a focused way, so as to improve the learning efficiency of the students in the teaching of English reading and writing. Recommend different levels of homework course practice, so as to achieve personalized teaching [7].

In this paper, the application of information technology in English literacy teaching is elaborated from three aspects: constructing literacy teaching context, strengthening the penetration of writing ideas, and perfecting the evaluation of literacy teaching. Firstly, the SCN-RNN network model is constructed to reduce the related computation with the help of factor decomposition and derive the set of learnable RNN weight matrices. Then, the LSTM network is used to replace the RNN network, and the CNN features are fused into the LSTM in a new way to complete the construction of the SCN-LSTM model. Using the bidirectional recurrent neural network, an improvement scheme is proposed for the SCN-LSTM model. Finally, the adaptive algorithm of language model is fused to design the adaptive model of language teaching for teaching context. Construct ANFIS performance evaluation model to evaluate students' English literacy learning performance.

2. Overview

1) Teaching English reading and writing. In order to improve students' comprehensive English application skills, especially reading and writing skills, the teaching mode of English in colleges and universities needs to be innovated. Literature [8] implemented activities based on Genially games in English online teaching and explored the effect of the method on students' reading and writing skills through a pre- and post-test experiment, and the results showed that the use of Genially games can effectively improve learners' English reading and writing skills. Literature [9] highlights the special position of English in the modern system of higher education, considers the basis of English language teaching as a clearly organized system of educational speech actions, and introduces this system of exercises aimed at developing students' communicative competence in the form of reading instruction in English texts. Literature [10] used a private language institute in Athens, Greece, to teach young English language learners reading and writing skills with the help of blogs, and the results of the experiment showed that blogs can enhance collaborative foreign language learning and

social interaction. Literature [11] used a descriptive nature of research method to find out what methods are used by tenth grade English teachers in teaching reading to first grade students at Toulon Gargons Secondary School and the results pointed out that English teachers use guided reading to deliver material in order to facilitate the provision of guidance, direction, and information to their students in the teaching of reading. Literature [12] verified through a randomized controlled trial that an instructional program called SRSD Plus improves students' writing, discourse knowledge, planning, speaking, and spelling skills, and the study has important implications for the theory, practice, and direction of reading instruction in the future. Literature [13] focused on English adolescent learners (ELs) in English classes in Danglang Gading Erbang and examined how to improve the writing skills of ELs through the use of abstract recognition cards. Literature [14] states that language change affects reading, spelling, and writing in predictable ways, using African American English as an example to assess the development and learning of literacy skills in African American children when the language of the home and the language of the school are different.

2) Deep Neural Network Adaptive Learning Models. Adaptive learning model is a learning model that provides learners with different learning paths and dynamically presents learning content and resources according to learners' characteristics to meet learners' personalized learning needs. Literature [15] combines SAM with adaptive learning rate and momentum acceleration to obtain an AdaSAM algorithm, and surprises a large number of experiments in random non-convex environments, and the results show that the AdaSAM algorithm has a superior convergence rate and can better improve the sharpness-aware minimization. Literature [16] tries to solve the time covariate shift problem by using adaptive rnn, which mainly establishes an adaptive model with good generalization ability to unknown test data, and the feasibility of the proposed method is verified by algorithmic analysis. Literature [17] attempted to establish a prediction model in the field of educational data mining through a transfer learning approach, aiming at effectively accomplishing the task of predicting students' performance in higher education, and the scientific and practicality of the proposed method was verified by empirical analysis. Literature [18] took 3,552 students in a university in Taiwan as the experimental subjects, and tested the accuracy of statistical learning methods and deep neural network-based machine learning methods in predicting their dropout probability through experiments, and the results showed that the deep neural network-based machine learning methods had higher accuracy rates, and could intervene with students in time to reduce the dropout rate, which in turn could promote adaptive learning and achieve a win-win situation for both the university and the students. Literature [19] proposes a design and development method for adaptive learning based on personalized access conditions, who can provide models for each learner and store a variety of objects for repetitive learning, meet tailored individual needs and respond to search queries. Literature [20] designed a personalized e-learning system based on artificial intelligence in order to facilitate the provision of specific learning content and assessment for learners, which is proposed to provide personalized education acting on the importance of the system. Literature [21] develops a method to predict e-learner's attention based on recurrent neural network model. And experimentally verified the effectiveness and feasibility of the method to improve the interaction between teachers and students to maintain attention. Literature [22] proposed an adaptive web-based learning environment modeling method based on facial expressions and fuzzy logic using loose coupling integration between convolutional neural networks (CNN) and fuzzy systems, and verified the practicality of the method through an example analysis, which not only provides an adaptive learning process that matches the learning abilities of all the learners, but also allows the decision maker to monitor each learner's learning performance.

3. Application of information technology in the teaching of English reading and writing

3.1. *Constructing a reading-for-writing teaching context*

In traditional English teaching, there are problems such as single form, boring content, and insufficient integration between reading and writing, resulting in students not being able to put what they have learned into practice, and often frowning at the thought of putting pen to paper and not being able to get started. In order to better stimulate students' interest in reading and writing, teachers should make full use of the characteristics of information technology, intuitive, image, and actively create a relevant teaching situation, create the best time to read and write, and deepen students' understanding of the reading text at the same time, guide students to learn how to use English for the expression of thoughts and feelings, and contribute to the effective combination of reading and writing.

3.2. *Enhancement of writing ideas guidance penetration*

In English writing, clear writing ideas can improve writing efficiency and effectiveness. When students have a clear writing plan and writing structure, they will be able to organize their ideas in a more structured way, thus reducing hesitation and confusion in the writing process. Teachers should make good use of reading teaching to strengthen the guidance and penetration of students' writing ideas, so that on the basis of understanding the reading text, students can also have a fruitful harvest in terms of writing life, improve students' thinking ability and expression ability, so as to write distinctive compositions.

3.3. *Improve the evaluation of reading for writing instruction*

In traditional English teaching, teachers mainly evaluate students according to the completion of their homework and test scores, and even if some teachers pay attention to the learning process of students, they simply evaluate students according to classroom questions and classroom interactions, which lacks objectivity and scientificity and fails to pay attention to the learning process of each student. The integrated application of big data has improved and innovated the traditional teaching evaluation, improved the pertinence and effectiveness of teaching evaluation, and can make English evaluation more humanized and comprehensive.

4. SCN-LSTM-based language model design and implementation

4.1. *SCN-LSTM networks*

SCN network is an English description model based on the semantic Attention mechanism, the core technology is to fuse the text probability vector derived from the English semantic detector with the weight matrix of the LSTM network, so that the network's understanding of the input English is not only limited to the CNN features of the English language, but also determined by the text probability vectors that are fused with the weight of the LSTM, which largely enhances the English extracted information (CNN features and text probability vectors) on the language model [23].

Firstly, the probability vector of dictionary semantic tags related to English is detected by the semantic tags of English, and then this vector is fused with the CNN features of English and fed into the LSTM network, and finally the natural language sequence describing the English is output using the LSTM network. Next, the specific principles of SCN network will be described in combination with RNN network and LSTM network.

4.1.1. SCN-RNN. SCN-RNN converts the weight matrix in an RNN network into a series of matrices based on text label vectors, and the resulting matrix represents the probability that a text label is related to the input English language. The structure of SCN-RNN network is shown in Fig. 1.

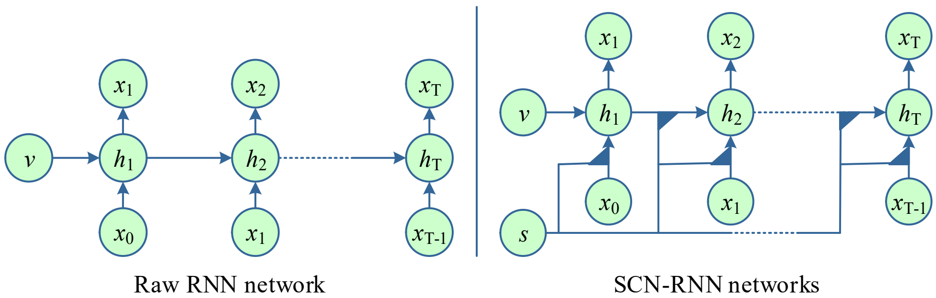

Fig. 1. SCN-RNN network

The RNN hidden layer is computed by fusing the weight matrix with the English related label probability vector:

$$h_t = \sigma\left(W(s)x_{t-1} + U(s)h_{t-1} + z\right) \tag{1}$$

where $z = 1(t=1)\cdot Cv$, s are vectors of text labels, and $W(s)$ and $U(s)$ are weight matrices based on text labels indicating the probability that each label will be used as an English labeled output result at the t moment.

To concretely represent the weight matrices $W(s)$ and $U(s)$ of the network, define $s \in \mathbb{R}^K$, two weight matrices $W_T \in \mathbb{R}^{n_h \times n_x \times K}$ and $U_T \in \mathbb{R}^{n_h \times n_h \times K}$, n_h is the dimension of the hidden layer and n_x is the dimension of each word vector, then the weight matrices $W(s) \in \mathbb{R}^{n_h \times n_x}$ and $U(s) \in \mathbb{R}^{n_h \times n_h}$ can be represented as:

$$W(s) = \sum_{k=1}^{K} s_k W_T[k] \tag{2}$$

$$U(s) = \sum_{k=1}^{K} s_k U_T[k] \tag{3}$$

where s_k is the k rd element of s, and $W_T[k]$ and $U_T[k]$ denote the k th two-dimensional matrices of the 1st dimension of the weights matrices W_T and U_T, respectively. It follows that the probability s_k of the k th word as an output result is related to $W_T[k]$ and $U_T[k]$. However, the parameters of weight matrices W_T and U_T are closely related to k, and the solution process is equivalent to training k RNN networks, which is too much computational effort. In order to reduce the computational amount, $W(s)$ and $U(s)$ are defined with the help of factorization method:

$$W(s) = W_a \cdot diag(W_b s) \cdot W_c \tag{4}$$

$$U(s) = U_a \cdot diag(U_b s) \cdot U_c \tag{5}$$

where n_f is the dimension of the factor, $W_a \in \mathbb{R}^{n_h \times n_f}$, $W_b \in \mathbb{R}^{n_f \times K}$, $W_c \in \mathbb{R}^{n_f \times n_x}$, and identically $U_a \in \mathbb{R}^{n_h \times n_f}$, $U_b \in \mathbb{R}^{n_f \times K}$, $U_c \in \mathbb{R}^{n_f \times n_h}$.

The above equation is obtained by bringing the above equation into the RNN network:

$$\tilde{x}_{t-1} = W_b s \odot W_c x_{t-1} \tag{6}$$

$$\tilde{h}_{t-1} = U_b s \odot U_c h_{t-1} \tag{7}$$

$$z = 1(t=1)\cdot cv \tag{8}$$

$$h_t = \sigma\left(W_a \tilde{x}_{t-1} + U_a \tilde{h}_{t-1} + z\right) \tag{9}$$

where $\odot$ denotes the multiplication of elements at the corresponding position.

In order to express more intuitively the fusion of the RNN weight matrix with the text label vector, $W(s)$ and $U(s)$ can be rewritten as:

$$W(s) = \sum_{k=1}^{K} s_k \left[W_a \cdot diag\left(w_{bk}\right) \cdot W_c\right] \tag{10}$$

$$U(s) = \sum_{k=1}^{K} s_k \left[U_a \cdot diag\left(w_{bk}\right) \cdot U_c\right] \tag{11}$$

The $W_a \cdot diag\left(w_{bk}\right) \cdot W_c$ in Eq. (11) denotes the k nd weight matrix of the network, which corresponds to the probability of the k rd text word, whereby the probability of each word is fused with the corresponding dimension matrix of the network, and the network eventually learns a set of K RNN weight matrices.

4.1.2. SCN-LSTM. Using LSTM network to replace the RNN network in the above network, the SCN-LSTM network is calculated as follows:

$$t_t = \delta\left(W_{ia} \tilde{x}_{i,t-1} + U_{ia} \tilde{h}_{i,t-1} + z\right) \tag{12}$$

$$f_t = \delta\left(W_{fa} \tilde{x}_{f,t-1} + U_{fa} \tilde{h}_{f,t-1} + z\right) \tag{13}$$

$$o_t = \delta\left(W_{oa} \tilde{x}_{o,t-1} + U_{oa} \tilde{h}_{o,t-1} + z\right) \tag{14}$$

$$\tilde{c}_t = \delta\left(W_{ca} \tilde{x}_{c,t-1} + U_{ca} \tilde{h}_{c,t-1} + z\right) \tag{15}$$

$$c_t = i_t \odot \tilde{c}_t + f_t \odot c_{t-1} \tag{16}$$

$$h_t = o_t \odot \tanh\left(c_t\right) \tag{17}$$

where $z = 1\left(t=1\right) \cdot C_v$, and also define that for $* = i, f, o, c$ there is:

$$\tilde{x}_{*,\ t-1} = W_{tb} s \odot W_t x_{t-1} \tag{18}$$

$$\tilde{h}_{*,t-1} = U_{*b} s \odot U_{*c} h_{t-1} \tag{19}$$

The SCN-LSTM network is characterized by fusing the CNN features of English and the label vectors related to English into the LSTM in a new way. From the Encoder-decoder framework aspect, the CNN network acts as an Encoder to get the features of the input English, and then inputs the features into the LSTM at the initial moment to make the LSTM read the overall content of the English language, and at the same time, the LSTM adopts the fusion of the state values of the input layer and the hidden layer with the text label vectors, which exacerbates the influence of the text labels on the generated language sequence, and thus achieves experimental results that are superior to other methods.

4.1.3. Improvements to the SCN-LSTM. For the traditional recurrent neural network, the network reads the input from the first moment, and then reads the data of the corresponding moments of the input sequence until the end of the sequence, and the network always processes the sequence along the direction from one end of the sequence to the other end, so the numerical state of any moment in the network is only related to the input information of the past moments and the current moment, however, the words at the current position of a natural language sequence are not only related to the words located in front of them, but also have a negligible semantic association with the words located behind them in the sequence [24]. In order to address the above shortcomings of the traditional RNN network, bidirectional recurrent neural network (BRNN) is proposed [25].

1) Bidirectional recurrent neural network. The forward propagation process of BRNN is as follows:

$$\vec{s}_t = \sigma\left(\vec{U}x_t + \vec{W}\vec{s}_{t-1} + \vec{b}_s\right) \tag{20}$$

$$\overleftarrow{s}_t = \sigma\left(\overleftarrow{U}x_t + \overleftarrow{W}\overleftarrow{s}_{t-1} + \overleftarrow{b}_s\right) \tag{21}$$

$$y_t = g\left(\vec{V}\vec{s}_t + \vec{V}\overleftarrow{s}_t + b\right) \tag{22}$$

In Eqs. (20)~(22), the parameter with stored positive question arrows indicates that the forward RNN network has $\upharpoonleft$ number in, the parameter with reverse arrows indicates the correlation value of the backward RNN network, and 1 indicates the softmax function. From Eq. 1, the hidden layer of the posterior homogeneous RNN network at the moment of $g(\cdot)$ is computed from the inputs at the moment of f and the hidden layer at the moment of $t+1$, which is opposite to the computation of the positive-question RNN network.

2) SCN-BiLSTM. In order to obtain the contextual relationships of the input sequences more effectively and improve the sequence prediction quality of the language description model, this paper proposes an improved SCN-BiLSTM network based on the SCN-LSTM model, which uses the bidirectional recurrent network as the language model, and its structure is shown in Fig. 2.

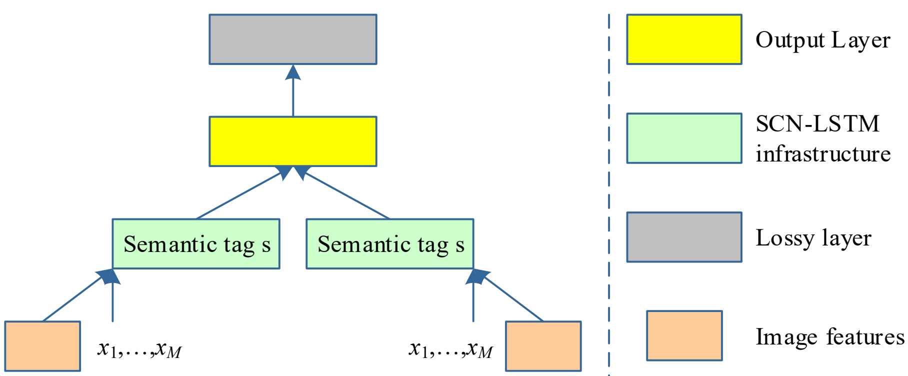

Fig. 2. SCN-BiLSTM network

The SCN-BiLSMT network is composed of the infrastructure of two SCN-LSTM networks. For the two SCN-LSTM parallel elements in the forward and backward directions, the output layer outputs of the SCN-BiLSTM network are assumed to be $\vec{h}_t$ and $\overleftarrow{h}_t$ for the hidden layer outputs of the two units, respectively:

$$\vec{p}_t = g\left(\vec{W}_1\vec{h}_t + \vec{b}\right) \tag{23}$$

$$\overleftarrow{p}_t = g\left(\overleftarrow{W}_2\overleftarrow{h}_t + \overleftarrow{b}\right) \tag{24}$$

$$y_t = \max\left(\sum_{t=1}^{T}\vec{p}_t\left(\omega_t|l\right), \sum_{t=1}^{T}\overleftarrow{p}_t\left(\omega_t|l\right)\right) \tag{25}$$

Among them:

$$\vec{p}_t\left(\omega_t|l\right) = \prod_{t=1}^{T} p\left(\omega_t|\omega_1,\omega_2,\dots,\omega_{t-1},l\right) \tag{26}$$

$$\overline{p_t}\left(\omega_t \middle| l\right)=\prod_{t=1}^{T} p\left(\omega_t \middle| \omega_{t+1}, \omega_{t+2}, \ldots, \omega_T, l\right) \tag{27}$$

For Eq. (23) and Eq. (24), where $\overrightarrow{W}_1$ and $\overleftarrow{W}_2$ are learnable weight matrices, the loss function is the same as in the SCN-LSTM network.

4.2. *Adaptation of Language Models*

4.2.1. Cache-Based Language Model Adaptation. The adaptive algorithm addresses the problem that the probability that a sequence of words appearing in the previous text in a passage is more likely to appear in the subsequent text than the probability calculated using a N-tuple [26]. The basic idea of cache-based language model adaptation is derived by linear interpolation of the language model:

$$\hat{P}\left(w_i \middle| w_1^{i-1}\right)=\lambda \hat{P}_{Cache}\left(w_i \middle| w_1^{i-1}\right)+(1-\lambda)\hat{P}_{n-gram}\left(w_i \middle| w_{i-n+1}^{i-1}\right) \tag{28}$$

Where the interpolation coefficient λ can be obtained by the Expectation Maximization (EM) algorithm for the first M words saved in the cache model, the cache probability for each word is calculated using the relative frequency value of occurrence in its cache:

$$\hat{P}_{Cache}\left(w_i \middle| w_1^{i-1}\right)=\frac{1}{K}\sum_{j=i-K}^{i-1} I_{\{w_i-w_i\}} \tag{29}$$

where I_c is an indicator function that takes the value of 1 if the event denoted by ε occurs, and 0 otherwise.

In cache-based language models, the importance of a word is independent of the distance between the word in the cache and the current word. This approach is more used in systems with N-tuple language models, but the adaptive technique is not used by industry in neural network based language models. However, in the field of English language teaching in neural network-based language modeling, cached language modeling adaption can be used to build a reading-for-writing teaching context and create an immersive English learning environment for students.

4.2.2. Hybrid-based Language Model Adaptation. The core idea of hybrid-based language model adaptation is to fuse language models trained on datasets from different contexts, regardless of the algorithms according to which the individual language models were trained. A language model that can be successfully applied for teaching scenarios requires not only a training corpus for teaching scenarios but also a corpus for the general domain. This results in different training corpora being heterogeneous, with corpora from different domains differing greatly in their topics, styles, and contexts.

The basic approach is:

1) The training corpus is categorized into generic domain and scene-specific corpus.

2) Determine the vertical domain training corpus, and utilize these corpora to train a good scene-oriented language model.

3) Set the model scaling parameters according to the background of the test corpus when using the model.

4) Linearly interpolate the language models trained using different background corpora to obtain the whole language model. The specific formulas are as follows:

$$\hat{P}\left(w_i \middle| w_1^{i-1}\right)=\sum_{j=1}^{N}\lambda_j \hat{P}_{Mj}\left(w_i \middle| w_1^{i-1}\right) \tag{30}$$

The maximum expectation algorithm calculates the interpolation factor λ:

1) Randomly initialize the interpolation scale factor λ for the training corpus of N backgrounds.

2) Calculate the new expectation and probability values according to the previously described formulas.
3) For the r th iteration, the coefficients of the j th language model on the training corpus of class $i\left(i <= N\right)$:

$$\lambda_{ij}^{r} = \frac{\lambda_{ij}^{r-1} P_{ij}\left(w|h\right)}{\sum_{i=1}^{n} \lambda_{ij}^{r-1} P_{ij}\left(w|h\right)} \tag{31}$$

4) Keep iterating the maximum expectation algorithm until the model converges.

4.3. Adaptive Language Modeling for Teaching Contexts

In the following description of the formulas, $P(x)$ denotes the probability of occurrence of word x, and subscript c denotes a generalized domain language model, corresponding to a model trained from a large-scale generalized domain corpus. Subscript a denotes an adaptive language model, which corresponds to a language model trained from a corpus of teaching scenarios. No subscript indicates the final language model after adaptation. w denotes current words and h denotes historical words. The generalized language model used in this paper is the ternary language model $P\left(W_n|W_{n-1}, W_{n-2}\right)$ and the adaptive language model is the SCN-LSTM language model. In general the interpolation algorithm is interpolation in the probabilistic sense, i.e.:

$$P\left(w|h\right) = \lambda P_c\left(w|h\right) + \left(1-\lambda\right) P_a\left(w|h\right) \tag{32}$$

Using the English language adaptive model trained in the English literacy teaching scene corpus, it assists teachers in guiding students' reading and writing thoughts and helps in the learning of English literacy aspects.

5. Evaluation Model Construction of English Literacy Learning Achievement Based on ANFIS

5.1. ANFIS modeling

The establishment process of the English literacy learning evaluation model based on ANFIS is shown in Figure 3 below, which is mainly divided into seven steps, namely, the determination of the evaluation indexes of the model, the collection of the model samples, the preprocessing of the sample data, the determination of the affiliation function and fuzzy rules, the establishment of the evaluation model, the training of the evaluation model, and the examination of the evaluation model in seven stages.

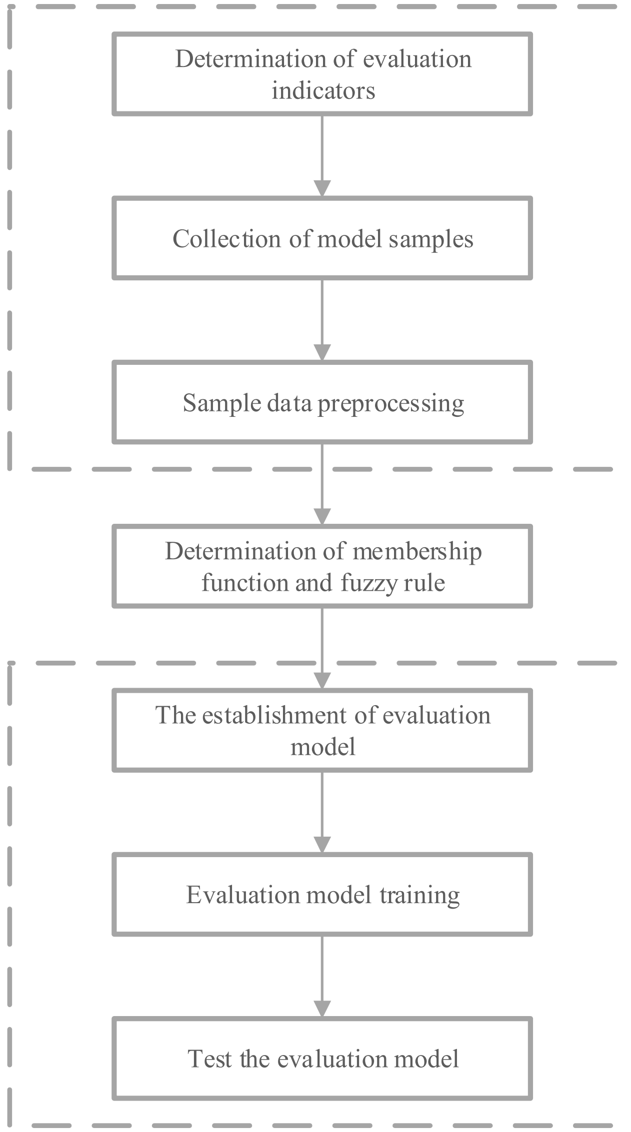

Fig. 3. English vocabulary learning evaluation model based on ANFIS

The first step is to first determine the evaluation indexes of the whole model, based on literature research, platform analysis and teachers' experience to summarize the main factors affecting students' English literacy learning performance and determine the evaluation indexes. The second step is to collect data on the identified indicators, and to determine the initial sample data of the evaluation model by collecting data from the background of the English literacy learning platform used in this study. In the third step, data preprocessing is carried out to eliminate invalid and discrete data and categorize the data into training sample data, validation sample data and test sample data. The fourth step is to divide the fuzzy sets of the identified indicators, determine the type of affiliation function and establish fuzzy rules. The fifth step is to establish the corresponding evaluation model based on ANFIS in MATLAB software through the determined affiliation function and fuzzy rule base, and the sixth step is to use training samples to train the model and determine the optimal parameter values of the front and rear parts and affiliation function through several training iterations, and carry out the refinement of the accuracy of the affiliation function. Finally, the trained ANFIS-based evaluation model is tested using test samples to prove the accuracy of the model, which is sufficient preparation for the subsequent formal teaching experiments.

The first step in evaluating the model is to load the sample data into the MATLAB workspace, name the sample data excel sheet as normalized table, and use the data loading command in the

MATLAB editor. Subsequently the overall sample data, training training sample data and testing test sample data named as total, respectively, are obtained in the workspace.

Figure 4 shows the MATLAB presentation of training samples and testing samples, the horizontal axis represents the number of samples and the vertical axis represents the value of the normalized data with a range interval of [0,1], and in the left editing area of the figure, it can be seen that there are a total of 714 training samples, 129 testing samples, 4 input variables and one output variable, and by default the number of fuzzy sets for each variable is 3 when the affiliation function is not determined. Then the data in the training and testing matrices in the workspace are saved as ASCII code to the current directory file for subsequent calls. As can be seen from the figure, the index range of the dataset for the training samples is much larger, between [0,250], while the range for the testing samples is between [0,60], and the output ranges of the two sample sets are similar.

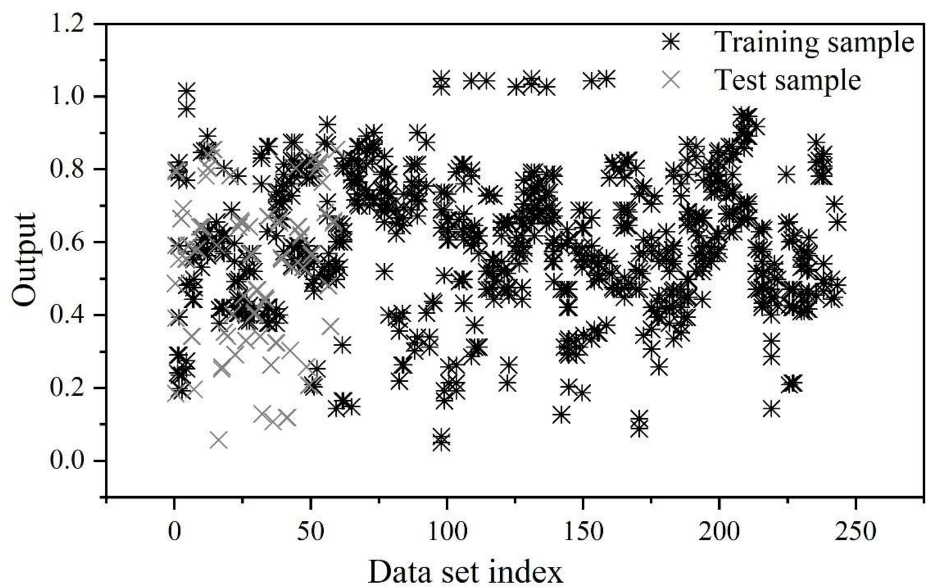

Fig. 4. MATLAB demonstration of training samples and test samples

5.2. Study design

5.2.1. Objects of study. In this study, a total of 50 students were recruited through the summer public welfare training, these students came from the University of T. With the student samples who built the ANFIS-based evaluation model from the region and did not accept duplicate enrollment, the student samples who participated in the construction of the model will not be able to participate in the teaching experiment and the students are required to have no intelligent learning experience. 50 students reported the final number of 40 students, and the 40 students were ranked through the pre-test scores to be These 40 students were cross-assigned to the experimental and control groups by ranking their pre-test scores, ensuring that both groups had the same level of English literacy. Twenty students in the experimental group learned English using the adaptive language model of the ANFIS evaluation model, while 20 students in the control group learned English reading and writing using the traditional learning system, and the two groups were assessed for their adaptive performance in English reading and writing.

5.2.2. Analysis of research data. The independent samples t-test showed that there was no significant difference between the control group and the experimental group's pretest English literacy learning achievement, t(38)=0.126, p=0.918, d=-0.056, and that there was no significant difference between the students' learning achievement under the traditional learning system (M=54.699, SD=5.766) and that of the students who used the adaptive learning system for English literacy (M=54.593, SD = 6.196) were not significantly different, and Table 1 shows the t-test analysis of the pre-test and post-test scores of students with different learning systems. At the end of the experiment, independent samples t-test was used to analyze the posttest scores between the control and experimental groups. The study shows that there is a significant difference between the posttest English literacy learning achievement between the control group and the experimental group under different learning systems, t(38)=-2.264, p=0.038, d=0.685, and the learning achievement of the students under the traditional learning system (M=57.963, SD=5.363) is lower than that of the students who use the adaptive learning system (M=61.269, SD = 5.896) and there is a significant difference. Therefore, the study proved that students using adaptive learning system for English literacy get better academic performance than students using traditional learning system.

Meanwhile, the study shows that there is a significant difference in the post-test foreign language learning anxiety between the control group and the experimental group under different learning systems, and the post-test foreign language learning anxiety score of the control group (M=13.763, SD=6.389) is higher than that of the experimental group (M=10.639, SD=3.169) and there is a significant difference, which shows that students who use the English literacy adaptive learning system are better than those who use the traditional learning system. The results indicate that students using the English literacy adaptive system showed lower foreign language learning anxiety than students using the traditional learning system.

Table 1. Test analysis of the test results of different learning systems

Pre-test						
/	Mean (SD)		df	t	p	d
	Traditional learning system	Adaptive learning system				
Academic performance	54.699 (5.766)	54.593 (6.196)	38	0.126	0.918	-0.056
After-test						
/	Mean (SD)		df	t	p	d
	Traditional learning system	Adaptive learning system				
Academic performance	57.963(5.363)	61.269(5.896)	38	-2.264	0.038*	0.685
Pre-test						
/	Mean (SD)		df	t	p	d
	Traditional learning system	Adaptive learning system				
Learning anxiety	11.715 (6.495)	11.593 (5.929)	38	0.169	0.993	-0.048
After-test						
/	Mean (SD)		df	t	p	d
	Traditional learning system	Adaptive learning system				
Learning anxiety	13.763(6.389)	10.639(3.169)	38	2.266	0.027*	-0.639

6. Analysis of the effectiveness of English literacy teaching

6.1. Analysis of students' reading skills

6.1.1. Impact on Students' English Reading Skills. Table 2 shows the data analysis of the English reading survey, showing the changes in the pre-test scores of the two classes, from the pre-test questionnaire scores of the experimental class and the control class, the two were 41.689 and 41.293 respectively, although the experimental class was slightly higher but the difference was not significant, and there was no statistical significance in the comparison between the two classes. The test for the pre-test questionnaire scores and the difference shows t=0.193,P=0.863 (>0.05). This shows that the English reading of the students in both classes is comparable. The students' post-test English reading scores were analyzed. The experimental class scored 53.631, which is 12.999 points higher compared to the control class's 40.632, a large difference in this result. A paired t-test was conducted which showed t=6.539,P=0.000 (<0.05), suggesting that there is a significant difference in the change of English reading interest between the two classes after the experiment. It is inferred that the application of SCN-LSTM based English literacy adaptive modeling helps to increase English reading interest and the students in the experimental class benefited from it and they were more influenced by this pedagogy. A paired-sample t-test was conducted on the questionnaires before and after the experiment to understand the overall change in reading interest of the students in the two classes before and after the experiment, and the specific results are shown in the table below:

As can be seen from the table, the average score of the students in the experimental class after the experiment was 53.631, which was 11.942 points higher compared to 41.689 before the experiment, and there was a large difference between the scores of the two groups in comparison. The paired-sample t-test for the two groups of data, the result is t=-8.636,P=0.000 (<0.05), that is, after the experiment the reading interest of the students in the class has changed greatly, before and after the comparison of the significant difference, based on the SCN-LSTM adaptive model of English literacy can be effective in affecting the students' interest in reading in English, and the inference may be able to obtain the overall level of improvement.

Table 2. English reading survey data analysis

/	Class	N	Mean	SD	T	Sig.(2 tailed)
Pretest	Experimental class	20	41.689	9.986	0.193	0.863
	Comparison class	20	41.293	11.669		
Aftertest	Experimental class	20	53.631	10.648	6.539	0.000
	Comparison class	20	40.632	10.263		
Comparison class	Pretest	20	41.293	11.669	1.896	0.063
	Aftertest	20	40.632	10.263		
Experimental class	Pretest	20	41.689	9.986	-8.636	0.000
	Aftertest	20	53.631	10.648		

6.1.2. Interest in reading. Figure 5 shows the dimensions of students' interest in English reading. Question 2 is that the teacher's teaching content is colorful, question 3 is that the reading class is interesting, and question 5 is that the teacher's teaching style is preferred. The scores obtained about the above questions before the experiment and lower, question 2 scored 3.015, question 3 scored 3, and question 5 scored 2.852, which shows that the teacher's teaching content is not colorful, and the lack of teaching style that attracts the students, which leads to the latter unable to arouse interest. Question 4, which was about the comprehensibility of the framework structure covered by the teacher, scored 2.963. The scores for all questions after the experiment exceeded those before the experiment, showing that the students' interest had increased, suggesting that the project-based learning approach could yield better results. Among them, question 4 and question 5, the scores of these two questions are close to 4, indicating that the use of SCN-LSTM's adaptive model of English literacy for instruction was recognized by most students and improved their interest in reading.

For the analysis of students' interest in teaching activities in class, the score of question 2 in terms of cooperating with teaching activities again is 2.963, which is close to the medium critical value, and the scores of the rest of the questions are all lower than this criterion, indicating that before the experiment, students were not interested in teaching activities in the classroom, that is, it did not enable them to actively think about the problem or attract their attention, resulting in the opportunity for cooperation and communication and exploration and the motivation decreased significantly.

Comparison of the mean values of the questions before and after the experiment showed that the mean values were significantly higher and reached more than 3 after the experiment. It is inferred that they all have higher interest in English reading after applying the SCN-LSTM adaptive language teaching model. This is especially true for Question 1, Question 4 and Question 5, where the change in scores was more pronounced compared to the preexperiment scores. It can be inferred that applying the SCN-LSTM adaptive language teaching model to English teaching can effectively improve students' motivation and interest in reading, and students' English literacy adaptive status is good.

The scores of each question before the experiment were below the critical value of 3. Question 4, which was about multiple ways to actively complete the pre-reading task, had a score of 2.915, which was the highest compared to the other questions. It can be seen that the students' interest in this area before the experiment was low, and it was inferred that they might have been involved in the task for the sake of completing the task, and they usually had fewer opportunities for exposure to the lack of rich reading materials, and there was a significant lack of related activities. After the experiment compared to the pre-experiment scores significantly improved, all over the critical value of 3. It can be seen that after the application of the SCN-LSTM adaptive language teaching model the experimental class students are more interested in extracurricular English reading activities, they can read outside the classroom through more channels, and motivation will be increased.

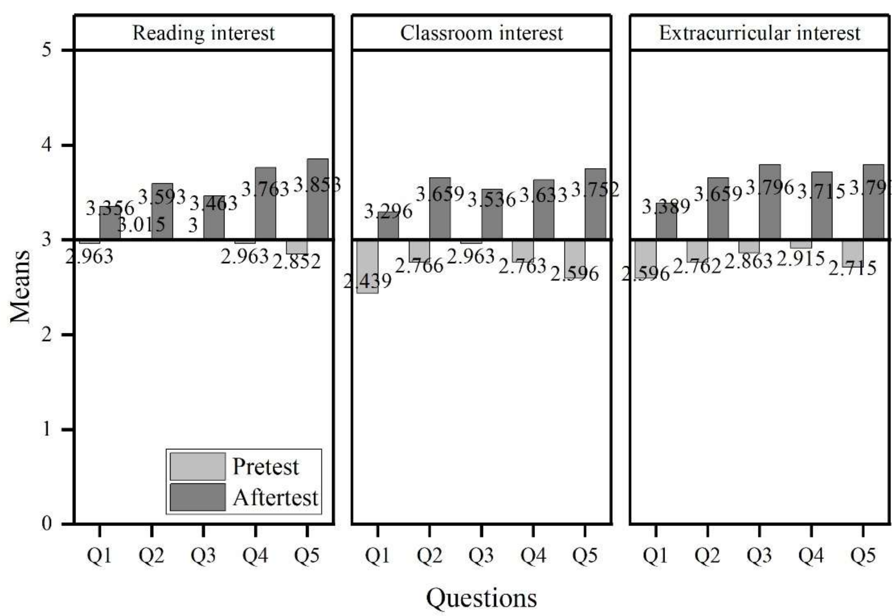

Fig. 5. Students' English reading interest dimension

6.2. Analysis of writing performance

6.2.1. Changes in Cognitive, Emotional and Behavioral Tendencies in Writing. Figure 6 shows the changes in students' cognitive, affective, and behavioral tendencies in English writing, in which the questions in the writing cognitive items are: I think English writing is very important, I think English writing is difficult and I don't know how to write good English compositions, I think that learning English writing can also improve the general English skills, such as listening, speaking, and reading, I think I am very good at writing in English, and I think that before writing teacher can provide writing samples and useful expressions is necessary. The questions in writing emotions are: I am interested in English writing and pay attention in writing class, I believe I can finish a composition in the time limit, I am confident in English writing and I don't give up even if I have difficulties sometimes, I believe I can solve the difficulties through hard work, I feel anxious about English writing and worry that I won't be able to write or I can't write well. The problems in the tendency of writing behavior are: I do English writing only when the teacher asks me to and I don't practice English writing on my own during the day, I think positively and concentrate on my writing in English writing class, I discuss with others positively and like to listen to and think about other people's opinions and comments in English writing, I will insist on finishing an English composition as required in a writing class or in an exam, and after the teacher has corrected it. After the teacher's correction, I will read back and think about the English composition I have finished.

In writing cognition, compared with the data in the questionnaire before the experiment, the mean values of questions 1, 2, 4 and 5 in the questionnaire after the experiment increased by 0.489, 0.06, 0.01, 0.219, respectively, indicating that compared with the preexperiment, there are many changes in students' cognition of English writing after the experiment of teaching English writing, i.e., more students realize the importance of English writing, and become more confident in their own English writing ability. English writing ability more confidently.

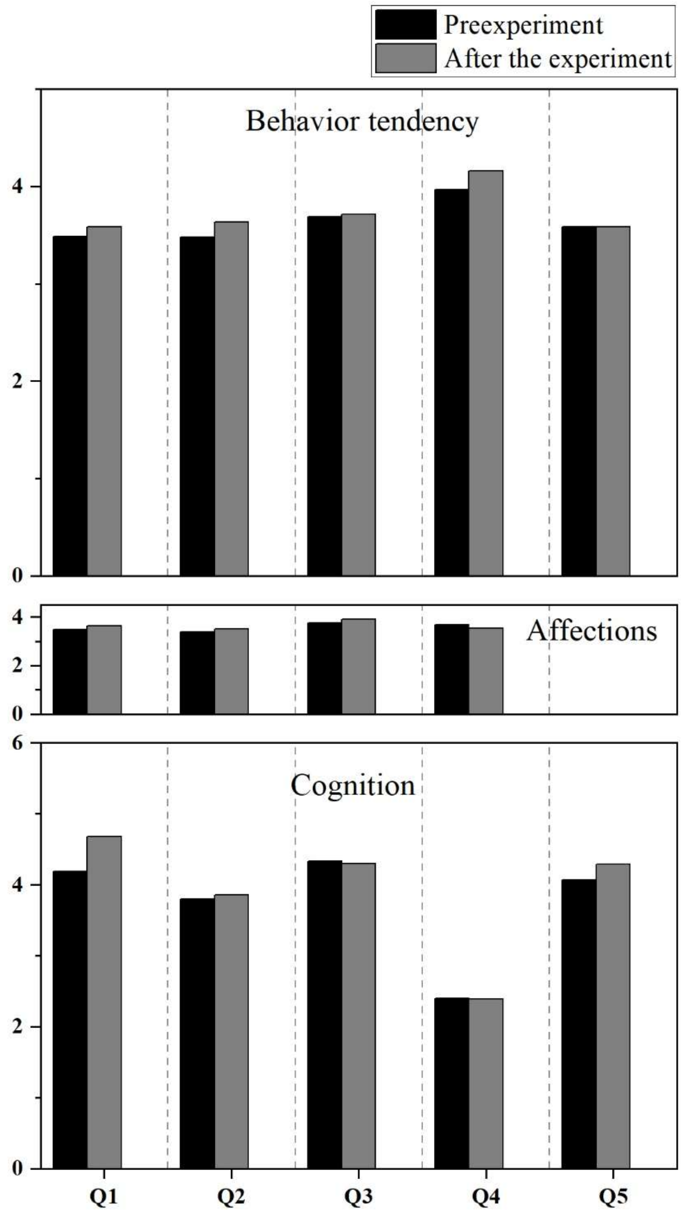

Fig. 6. Writing cognition, emotion and behavioral tendencies

6.2.2. Writing achievements. Figure 7 shows the pre- and post-tests of the writing scores of the experimental and control classes. The mean values of the writing pre and post test scores of the students in the experimental class are 7.48 and 8.45, and each student has improved. On the other hand, the mean values of students' writing pre- and post-test scores in the control class are 7.615 and 7.515, which have decreased, while the progress of each student's score is not obvious, and some students even have regression.

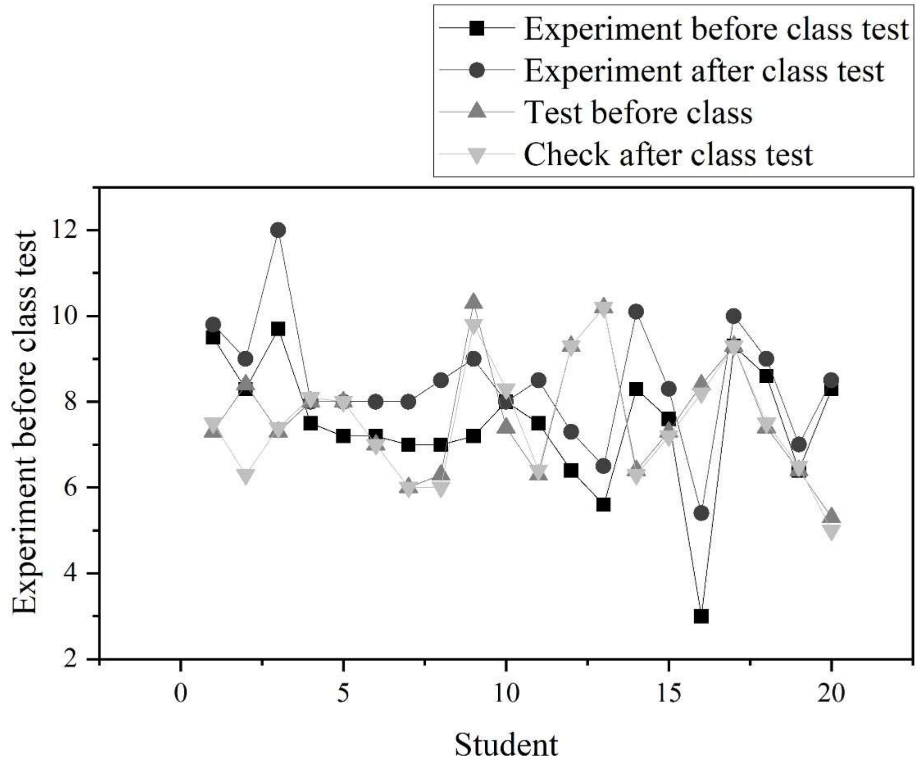

Fig. 7. Test of the test of the experiment class and the comparison class

7. Conclusion

This paper explores the application of information technology in English literacy teaching, constructs a language adaptive model based on SCN-LSTM network to make the application to the teaching context, and, at the same time, combines with the ANFIS model to improve the evaluation of English literacy performance. Research experiments were designed to analyze the effect of the model's English literacy teaching application. From the analysis of English reading and writing posttest scores, it can be seen that the students' scores under the traditional learning system are M=57.963, SD=5.363, and the students' scores under the adaptive learning are M=61.269, SD=5.896, which the study proves that the students who use the adaptive learning system get better academic performance than the students who use the traditional learning system. The two aspects of English reading and writing were further analyzed respectively, from the point of view of English reading ability, the average score of the students in the experimental class after the experiment was 53.631, which was 11.942 points higher compared with 41.689 before the experiment, and the paired samples t-test was conducted on the two groups of data, and the result was t=-8.636,P=0.000 (<0.05), and the students' performance based on the SCN-LSTM language adaptive Adaptive Modeling can effectively influence students' interest in English reading, and the inference may be gained that the overall level increases. In the writing achievement, the mean values of the pre and post writing test scores of the students in the experimental class are 7.48 and 8.45 respectively, while the mean values of the pre and post writing test scores of the students in the control class are 7.615 and 7.515, which shows that the writing achievement of the students in the experimental class is more obvious to be improved.

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