

## *Retraction*

# **Retracted: Synthetic Network and Search Filter Algorithm in English Oral Duplicate Correction Map**

### **Complexity**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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. Chen, "Synthetic Network and Search Filter Algorithm in English Oral Duplicate Correction Map," *Complexity*, vol. 2021, Article ID 9960101, 12 pages, 2021.

## Research Article

# Synthetic Network and Search Filter Algorithm in English Oral Duplicate Correction Map

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Combining the communicative language competence model and the perspective of multimodal research, this research proposes a research framework for oral communicative competence under the multimodal perspective. This not only truly reflects the language communicative competence but also fully embodies the various contents required for assessment in the basic attributes of spoken language. Aiming at the feature sparseness of the user evaluation matrix, this paper proposes a feature weight assignment algorithm based on the English spoken category keyword dictionary and user search records. The algorithm is mainly based on the self-built English oral category classification dictionary and converts the user's query vector into a user-English-speaking type vector. Through the calculation rules proposed in this paper, the target user's preference score for a specific type of spoken English is obtained, and this score is assigned to the unrated item of the original user's feature matrix as the initial starting score. At the same time, in order to solve the problem of insufficient user similarity calculation accuracy, a user similarity calculation algorithm based on "Synonyms Cilin Extended Edition" and search records is proposed. The algorithm introduces "Synonyms Cilin" to calculate the correlation between the semantic items, vocabulary, and query vector in the user query record to obtain the similarity between users and finally gives a user similarity calculation that integrates user ratings and query vectors method. For the task of Chinese grammar error correction, this article uses two methods of predicting the relationship between words in the corpus, Word2Vec and GloVe, to train the word vectors of different dimensions and use the word vectors to represent the text features of the experimental samples, avoiding sentences brought by word segmentation. On the basis of word vectors, the advantages and disadvantages of CNN, LSTM, and SVM models in this shared task are analyzed through experimental data. The comparative experiment shows that the method in this paper has achieved relatively good results.

## 1. Introduction

In higher education, the examination and evaluation of spoken English have long been mentioned as an extremely important position [1]. There is an independent oral test whether it is in the college English Test Band 4 or Band 6, or in the English Majors Band 4 and Band 8. In addition, many college students have participated in the English proficiency test held by various foreign examination institutions, including oral English tests. Regardless of the classification of paper textbooks or online textbooks, most of the current textbooks have one thing in common, that is, they mostly rely on flat text media to deliver information. It is true that the spoken language teaching materials will also have some media other than text such as illustrations and CDs to add

color, but their number is relatively small and the usage rate is not high. Such spoken language textbooks cannot make students have a strong interest in the learning of spoken English, let alone the methods and strategies used by native English speakers to help produce meaning in actual spoken communication through media other than language [2, 3]. When students use English to communicate, because there is no such reinforcement in the input link, their oral English expression often lacks elements other than speech that assist their meaning generation, and there are no other strategic elements required in oral English expression [4].

Since the concept of "communicative competence" was put forward, many domestic and foreign researchers have launched a round of thinking and discussion on "what is

communicative competence” and “what constitutes communicative competence.” As scholars have different perspectives on the construction of communicative competence, they have their own way of understanding it. From a multimodal perspective, to construct the connotation of communicative competence, especially oral communicative competence, and to fully develop and enrich previous theoretical research on communicative competence is one of the main purposes of this research [5]. In order to help college students to continuously and steadily improve their oral English, this research transcribes students’ oral output into multimodal texts and builds a corpus. While constructing a multimodal perspective on the research model of oral communicative competence, it also analyzes students’ oral characteristics. It fundamentally promotes the solution of current college students’ lack of motivation in oral English learning, poor autonomous learning ability, and time-consuming and low-efficiency learning. Therefore, in terms of practical significance, this research comprehensively analyzes the characteristics of college students’ spoken English under this model so that it can play an important role in realizing the content of “curriculum requirements” in the true sense [6].

This article embeds the research theory of multimodal perspective into the study of oral communication ability, which can be mainly reflected through the two main modules of “oral language” and “nonverbal characteristics.” Among them, the “spoken language” module can be divided into two indicators: “spoken and written language characteristics” and “tone.” This paper proposes a search filtering algorithm based on the user’s search keyword content. First, in view of the common problems of feature sparseness and insufficient accuracy of search filtering algorithms, the implicit input information of user search records is analyzed to find the possibility of improving traditional search filtering algorithms. A feature weight assignment algorithm based on English spoken category keyword dictionary and user search records is proposed to improve the feature sparse problem of user evaluation matrix. At the same time, a user similarity based on “Synonyms Cilin Extended Edition” and search records is proposed. The calculation algorithm is used to improve the accuracy of the traditional user similarity calculation method. We give the overall design framework and search filtering process of the search filtering algorithm. This paper proposes classifiers based on CNN, LSTM, and SVM and replaces the word text with word vector as the initial feature text. It can be seen from the comparison between the experimental process and the experimental results that the word vector is very adaptable in this task, and it can be seen that using the SVM classifier and the n-gram model to fit the peculiar laws of natural language is not appropriate, not only because the text collection is too small but also because it introduces many related features with unclear meaning.

## 2. Related Work

Researchers have found that there seems to be a competing relationship. Research has shown that accuracy and

grammatical complexity can improve together. Although the above studies are based on horizontal comparison, they have laid a solid foundation for the longitudinal study of the internal relationships of complexity, accuracy, and fluency (CAF) [7]. Related scholars analyzed 54 writing samples of a Finnish language learner in three years and found that vocabulary complexity and syntactic complexity can grow together, noun phrase complexity and syntactic complexity compete with each other, and the relationship between complexity indicators is over time; the study did not find any obvious relationship between accuracy and complexity [8]. For second language researchers and educators, it is very important to find out the factors that affect CAF. Some factors affect the performance of CAF at a certain point in time, and some factors play an important role in the diachronic development of CAF. There are many factors that affect CAF, including internal linguistic factors and external factors. Task-based research is also affected by task types. Internal linguistic factors refer to a language phenomenon or feature that may have an impact on the performance and development of CAF due to its special attributes (such as attributive clauses), and external factors include individual learner differences (such as anxiety, devotion, and academic ability) [9].

Related scholars believe that users’ comments after purchasing products can best reflect the user’s satisfaction with the products and proposed a model that uses the text of the comments to extract features for learning and combines it with the prediction score [10]. But these also did not solve the problem of data sparsity. The problem of data sparseness is that users have low data density on some new items, which makes the information incomplete, and it is impossible to accurately obtain the user’s interest level. In response to this problem, the researchers remove other information and only retain the features that reflect the user’s main interests and preferences and use singular value decomposition technology to reduce the dimensionality of the rating matrix, which increases the data density [11]. In order to overcome the problems caused by data sparseness, relevant scholars modeled based on user data with sufficient data and then calculated the similarity between users based on the Pearson correlation coefficient. They use the similarity between users to find the set of nearest neighbors, calculate user preferences based on the weighted average of the neighbor sets, and filter product searches to users according to their scores. Later, with the development of deep learning, in addition to its power in mining hidden features, more features that express user preferences can be discovered through deep mining, making the user preference model more accurate in describing user preferences [12–14].

Researchers have proposed that collaborative tagging is used to obtain and filter user preferences for items. Therefore, they proposed a coordinated filtering method derived from user-created tags to improve the quality of search filtering [15]. They also explored that coordinated tagging is useful for solving data sparseness, and the advantages of the cold start problem. Related scholars believe that the latest advances in location technology have fundamentally enhanced social network services, and location

search filtering plays an important role in helping people find places they might like [16]. Through a systematic review of previous research, they proposed a search filtering framework based on content-aware implicit feedback search filtering. Studies have confirmed that the framework effectively improves the efficiency of search filtering and further strengthens the service functions of social networks. Relevant scholars study the relationship between the user's browsing record and the final product purchased by the user, establish an interest preference model based on the user's browsing record, and mine the user's preference to filter the user's interest in the product search. Research has confirmed that the proposed model solves the cold start problem to a certain extent and optimizes the search filtering effect. Relevant scholars first calculate a part of the data that can be easier and more accurate through the project-based CF algorithm and then calculate the degree of similarity between users according to the user-based CF algorithm based on the data obtained in this part [17]. The obtained data fill the entire scoring matrix, which is a perfect combination of project-based CF and user-based CF algorithms.

Researchers use the BP neural network to obtain the scoring matrix and then predict the locations that are not scored to make the scoring matrix complete [18]. Due to the sparse data, after calculating the user similarity, the nearest neighbors of the user will be relatively sparse, and the user preferences obtained in this way will also be biased. In order to obtain more datasets under such data, relevant scholars expand the user's nearest neighbor set first on the original basis. Of course, it is not an infinite expansion. This threshold allows the transfer of a similarity greater than the threshold on a limited path length, which solves the inaccurate calculation of neighboring values due to data sparseness, and even the nearest neighbors have no data [19]. For the same problem of cold start and data sparseness, researchers use kernel functions. In view of the shortcomings of traditional Euclidean distance, researchers optimized the method based on Euclidean distance and introduced normalization processing on this basis and finally made evaluation prediction and search filtering [20].

For English error correction tasks, although English auxiliary learning tools have achieved good development under the machine learning method, due to some shortcomings of the machine learning itself, these auxiliary learning systems still do not achieve the expected results [21]. It is manifested in that the amount of data is too small, and it is very easy to overfit [22, 23]. In order to avoid overfitting, pruning processing will be used, but the pruning processing will lose some subtle features. There are a lot of very important information in these features, for example, the disadvantage of the model generated by Naive Bayes is that it requires independent assumptions, which will sacrifice certain accuracy and make the classification performance not high [24, 25]. In addition, the number of texts processed by machine learning is small and does not have strong adaptability. It will play a very good effect in a specific environment [26, 27]. However, due to the huge English vocabulary and the many commonly used words, it can only do some calibrations. Good specific English information

makes it unable to fully cover all English features, and the classification model is not conducive to preservation, which makes computer-assisted English learning strategies made with machine learning models not fully applicable to the English texts of various foreign learners, so its accuracy will be reduced, and the desired effect will not be obtained. This makes more and more scholars pay more attention to deep learning models [28, 29].

### 3. An Initial Model for the Study of Oral Communicative Competence from a Multimodal Perspective

*3.1. The Initial Model of Oral Communicative Competence.* Figure 1 shows the initial model of oral communicative competence research proposed in this study from the multimodal perspective. From an internal point of view, the core of this initial model is the two aspects of oral communicative competence specifically reflected by the communicative language ability (CLA) model from a multimodal perspective, namely, oral and nonverbal features. The former is based on the linguistic analysis of pure language and companion language based on traditional text and multimodal text. In essence, this analysis takes the form and semantics of the language as the consideration object; the latter is completely based on multimodal text. The analysis of nonverbal factors is essentially independent of language form and semantics.

From the perspective of expression, the initial model follows the body-based and environment-based aspects of the general model of multimodal perspective research. Since the two aspects of nonverbal features interact with each other, the interactive arrow is used in the initial model. In addition, the verbal and nonverbal features are inherently interactive, and arrows are also used in the model to indicate the relationship between the two.

From a multimodal perspective, this study can observe the specific performance of these three components through the focus of the learner's spoken English output. In particular, it is worth pointing out that the CLA model has extremely detailed discussions on the language ability and strategic ability of it, and it has also been found in empirical research that a large number of previous studies have focused on these two aspects. However, the CLA model does not have a systematic description of the psychological and physiological mechanism, and related research is extremely rare in empirical research. However, the multimodal perspective can not only use the theoretical basis of this aspect as the guidance of this research but also enrich and explain the long-standing gap of the CLA model in this aspect. Therefore, investigating learners' oral English from a multimodal perspective is still investigating their communicative language ability. They still cannot do without language ability, strategic ability, and psycho-physiological mechanisms. It is still necessary to deal with certain people under this very inclusive model. An analysis is carried out on one side, but the difference is that behind

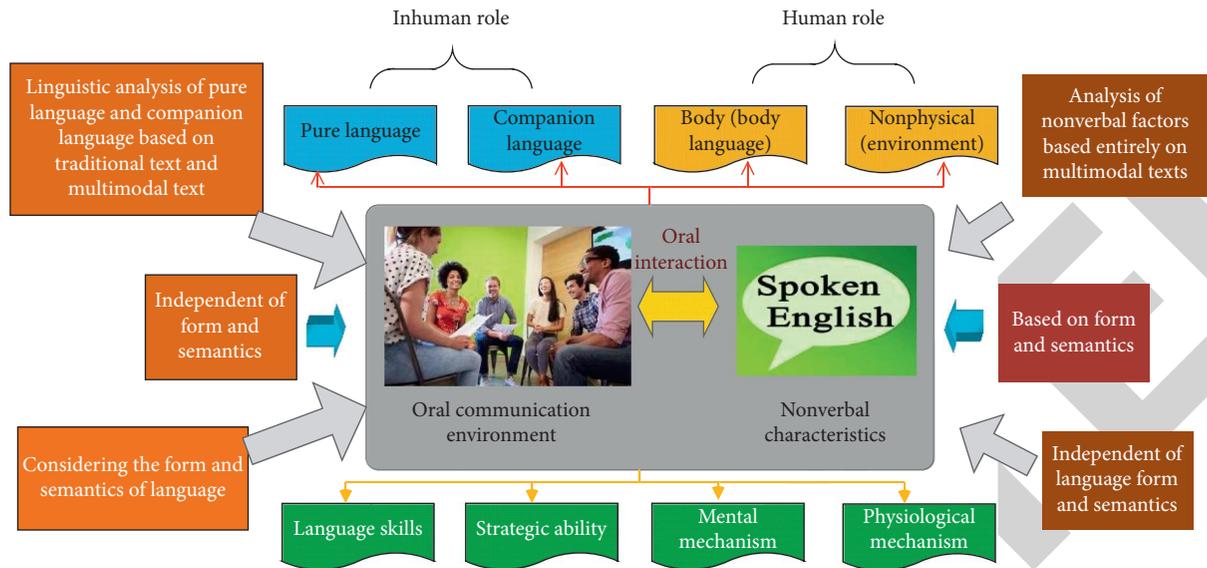


FIGURE 1: The initial model of the study of oral communicative competence from a multimodal perspective.

this theoretical foundation, this research will further consolidate the theory itself.

Multimodal research focuses more on the content that generates meaning outside of discourse as its research object. Based on this consideration, the part of “tonality” in “oral” visually examines the consistency of students’ use of tones, fluctuations, and ideograms in the process of spoken English output, and the extent to which they can help them generate meaning. The “nonverbal characteristics” are even more obvious. This research needs to observe whether students use certain nonverbal strategies to help them realize meaning generation through a multimodal perspective, whether they have a series of interactions with the surrounding environment, and whether they are involved in the process of expressing meaning. Therefore, combining “oral language” and “nonverbal features,” this research can find breakthroughs in learners’ other features of spoken English from the multimodal theoretical guidance framework, and these two modules also cover to a large extent.

### 3.2. The Operability and Explanatory Power of the Model.

After clarifying the various components of this initial model, it is necessary to explain the operability and explanatory power of the model. Operability determines whether each indicator in the model is feasible in measurement and judgment, and whether there will be indicators overlap. The explanatory power shows how much the model can reflect the learner’s oral communication ability under the multimodal perspective.

**3.2.1. The Operability of the Model.** The measurement of the “spoken language” module in this model is a combination of monomodal text and multimodal text. In the measurement of “spoken and written language features,” this research will use corpus automatic tagging and retrieval technology to

extract all language features. In the measurement of “tone,” this research mainly used human judgment (two annotators) to classify all sentences according to five different tones. Because the researcher’s perception of tones can often be judged by combining the semantic features of students’ speech output and their own experience, this classification is relatively simple, and its consistency is also guaranteed. In the event that certain sentences cannot be classified, this study will adopt a joint discussion among multiple researchers and finally reach a consensus.

This study finds the characteristics of learners on this indicator by calculating the abovementioned statistics and then analyzes the effect of the indicator itself on the realization of communication. Although many things need to be measured and the accuracy requirements are high, due to the advancement of modern software technology, the calculation of these statistics in this study, especially the measurement of time statistics, can be accurate to 0.1 second. Furthermore, for a large number of nonverbal features, this research only reflects their manifestations descriptively when labeling them and does not make functional judgments on these manifestations in the labeling. Therefore, in the later data analysis, this research can extract a large number of keywords describing these manifestations from different angles and then functionally merges the nonverbal features among them. In this way, in terms of the reliability of the measurement and judgment of the “spoken language” module and the “nonverbal characteristics” module, the measurement goals are very clear, the judgment basis is more reliable, and the overall operability is also ideal.

**3.2.2. The Explanatory Power of the Model.** In addition to the operability of the model, another notable feature of this model is its explanatory power for the entire process of spoken language production based on a multimodal perspective. Since this initial model is the product of the CLA model and the multimodal research theoretical guidance

model, its explanatory power is reflected in the ability to observe oral communication from multiple modalities, and the greatest value of this explanatory power lies in reflecting the interaction between different modes. The output has a certain impact; is it positive? Will learners of different levels make differences in the course of these behaviors? How are these differences distributed? These questions have not yet been answered, and this research can give answers to the abovementioned questions under the framework of this initial model. Therefore, “oral language” and “nonverbal characteristics” are optimized indicators to interpret learners’ oral communicative competence from a multimodal perspective.

#### 4. Design of Search Filter Algorithm

*4.1. The Design of Word Similarity Algorithm Based on Synonym Word Forest.* Word similarity is usually represented by a value of [0, 1]. If two words are not semantically replaceable, the similarity is 0, and the similarity between the word and itself is 1. Word similarity is a very subjective concept. The meaning of word similarity refers to the probability that two words can replace each other without affecting the original context and semantic environment. The greater the possibility, the greater the likelihood of the two words will be. In fact, word similarity is usually described by the concept of word distance, and word distance and word similarity are actually two different manifestations of semantic relevance. For words  $W_1$  and  $W_2$ , assuming that the similarity between the two is  $SIM(W_1, W_2)$  and the word distance is  $DIS(W_1, W_2)$ , there is a simple conversion relationship:

$$SIM(W_1, W_2) = \frac{\alpha + 1}{DIS(W_1, W_2) - \alpha}. \quad (1)$$

Among them,  $\alpha$  is the adjustment parameter. According to experience, the range of  $\alpha$  is (0.01, 0.3). Of course, the above formula is only one of the conversion relationships between the two, and the form is not unique. In addition, word relevance represents the possibility of cooccurrence of two words in the same context. It and word similarity are two different concepts, and the two are not directly related.

Since the organization of words in the synonym word forest is a hierarchical tree structure, the similarity of two words can be expressed by the distance between two word nodes, and the distance between word nodes can be described by the 8-bit code of the word. We determine whether two words are in the same level of branch by judging the 8-bit word code and determine the hierarchical relationship of the two words from the word code from the first level.

In addition, the word density of the paragraph line where the word is located is also an important factor that affects the vocabulary similarity. The more words in the paragraph line, the more scattered the semantics of the line, and the smaller the similarity. For example, there are 4 words in the paragraph line of “Ga01A04 = joyous joy, dancing, and dancing, cheering, and jumping,” while there are only 2 words in the paragraph line of “Ga01A08# Tianlunzhiyue Housewarming.” Obviously, the similarity of words in the latter

paragraph line is higher than that of the former. Finally, the node density of the hierarchical tree where the word is located also affects the word similarity, which is similar to the word density of paragraph lines. The smaller the tree node density, the more precise the semantics of the word and the higher the similarity between the two words will be.

In the synonym word forest, since a word often has multiple meanings, a word may have multiple coding items, that is, meaning items. Obviously, the similarity of words can be obtained through the similarity of meanings. Assuming that the two meanings are  $X$  and  $Y$ , the similarity calculation method based on the synonyms of Cilin is as follows:

If the two meanings are not on the same tree, then

$$SIM(X, Y) = f. \quad (2)$$

If the two meanings are in the same branch at the first level, then

$$SIM(X, Y) = \frac{a}{n_1} \cdot \sin \frac{\pi}{180} n_1. \quad (3)$$

If the two meanings are in the same branch at the second level, then

$$SIM(X, Y) = \frac{b}{n_2} \cdot \sin \frac{\pi}{180} (n_1 + n_2). \quad (4)$$

If the two meanings are in the third level branch, then

$$SIM(X, Y) = \frac{c}{n_3} \cdot \sin \frac{\pi}{180} (n_1 + n_2 + n_3). \quad (5)$$

If the two meanings are in the fourth level branch, then

$$SIM(X, Y) = \frac{d}{n_4} \cdot \sin \frac{\pi}{180} (n_1 + n_2 + n_3 + n_4). \quad (6)$$

If two meanings are in the same fifth level branch, there are two situations. If the eighth bit is “=,” it means that the ambiguous terms are similar, then there are

$$SIM(X, Y) = \frac{d}{n_5} \cdot m \cdot \sin \frac{\pi \cdot e}{180} (n_1 + n_2 + n_3 + n_4 + n_5). \quad (7)$$

If the eighth bit is “#,” it means that the ambiguous terms are related, and there are

$$SIM(X, Y) = \frac{e}{n_5} \cdot m \cdot \sin \frac{0.5 \cdot \pi}{180} (n_1 + n_2 + n_3 + n_4 - n_5). \quad (8)$$

Among them,  $a, b, c, d, e,$  and  $f$  are the similarity adjustment coefficients,  $n_1 \sim n_5$  are the total number of nodes in each branch layer, and  $m$  is the number of synonyms in the paragraph line.

*4.2. The Design of Query Vector Similarity Calculation Method Based on Synonym Word Forest.* This section will give a quantitative calculation method for the similarity of the user query keyword vector and use the similarity value as the

supplement and improvement of the user similarity value in the search filtering algorithm to improve the search filtering effect and accuracy of the search filtering algorithm. The dimensions of the query vectors of different users are not consistent, so the linear algebra theory's vector angle cosine method cannot be used to calculate the similarity of the query vector, and the similarity between the vocabulary elements in different vectors can only be calculated in the form of traversing vector elements, so as to get the similarity between the whole vectors.

The overall structure of the search filtering algorithm based on user search content proposed in this paper is divided into three parts: input module, search filtering module, and output module. The data information of the input module is mainly composed of the user's evaluation scores on the spoken English project and the keyword records searched by the user; the output module feeds back the spoken English works that the user may be interested into the target user through page display or e-mail. Specific processing is performed on the input data to obtain the content of the item that the target user is interested in, and the output module feeds back to the target user. Figure 2 is the overall design framework of the algorithm.

The system output module selects 50 neighboring users of the target user. In other words, the system considers the 50 users with the greatest similarity to the target user as the target user's neighbor set. After the target user's neighbor set is converted into a neighbor user evaluation matrix, the score of the neighbor set user for the target user's unrated item is calculated as the target user's predicted score for the spoken English item. In this paper, the 10 spoken English items with the highest predicted scores are used as the user's customized search filtering content and feedback to the user via e-mail and web page display.

The search filtering algorithm based on the key of user search records proposed in this paper is mainly divided into three main modules, namely, the user evaluation matrix improvement module, the user similarity calculation improvement module, and the search filter module. The user evaluation matrix improvement module uses a feature weight assignment algorithm based on the English spoken category keyword dictionary and user search records; the user similarity calculation improvement module uses a user similarity calculation algorithm based on "Synonyms Cilin Extended Edition" and search records. The search filter module uses the traditional calculation method of predicting scores. Looking at the entire search filtering system, it follows the traditional search filtering algorithm "user evaluation matrix-similarity calculation-predictive score" search filtering mode and, at the same time, integrates synonym word forest and user search records to achieve sparse user evaluation matrix and user similarity calculation insufficient precision improvements, improve the search filtering precision of traditional search filtering algorithms and improve user experience.

**4.3. CNN Syntax Network Classifier.** Convolutional neural network is a feedforward neural network, which includes a convolutional layer and a pooling layer. For a sentence, each

word in the sentence can get the corresponding word vector through the word embedding method. The pooling layer acts on the calculated feature vector  $f$ , where the pooling layer is divided into the maximum pooling layer and the average pooling layer. The maximum pooling layer selects the maximum value in the feature vector  $f$ , and the average pooling layer selects the average value of all the values in the feature vector  $f$ .

The basic frame diagram of the CNN classifier is shown in Figure 3. Suppose the size of the convolution kernel is  $n$  words, and the sentence matrix  $S$  is extracted from the local pattern features between  $n$  words through the convolution operation of the convolution kernel. Each convolution kernel will output an eigenvector, and the eigenvector will go through. The max-pooling layer will extract the most important information in the sentence text features. After that, the fully connected layer will further process the features output by the max-pooling layer. The number of neurons in the classification output layer is determined by the classification label. However, due to the imbalance of the training samples, the effect of such multilabel classification is extremely poor. Therefore, this article adopts a two-class classification method. In fact, each time training is performed using only positive samples and negative samples of a wrong sample, respectively. It is enough to train a classifier that can classify four types of errors.

## 5. Experimental Evaluation

**5.1. Experimental Process and Experimental Environment.** The gated recursive unit (GRU) model is a variant of LSTM. It has two-door controls, an "update door," and a "reset door." GRU maintains the effect of LSTM while the structure becomes simpler. It combines "forgotten gate" and "input gate" into a single "update gate." The "update gate" is used to control the extent to which the state information from the previous moment is brought into the current state. The larger the "update gate," the more state information from the previous moment is brought in. The "reset gate" determines how to combine the new input and the previous memory.

For a support vector machine classifier, a word and its context can be considered as a training sample. In the experiment, this article sets the window in a sentence to 7 in order to judge whether there is an error in the middle word. It brings the corresponding word vector into the training sample, gets the characteristics of the sample, and uses the SVM classifier to classify and judge the position of the error in a sentence. This article uses the  $n$ -gram model to find the inner connection in a sentence, which is a concept in the category of computer linguistics and probability theory, and refers to a sequence of  $N$  items in a given piece of text or speech. The meaning of the item is a syllable, letter, word, or base pair.

In this experiment, we use  $K$ -fold cross-validation to debug the parameters of the classifier, where  $k = 4$ . First, we divide the sample data into 4 groups and make a validation set for each subset of data. That is, we use 3 sets of data as the test set and 1 set of data as the verification set and loop 5 times. This method can avoid the occurrence of overfitting and underfitting.

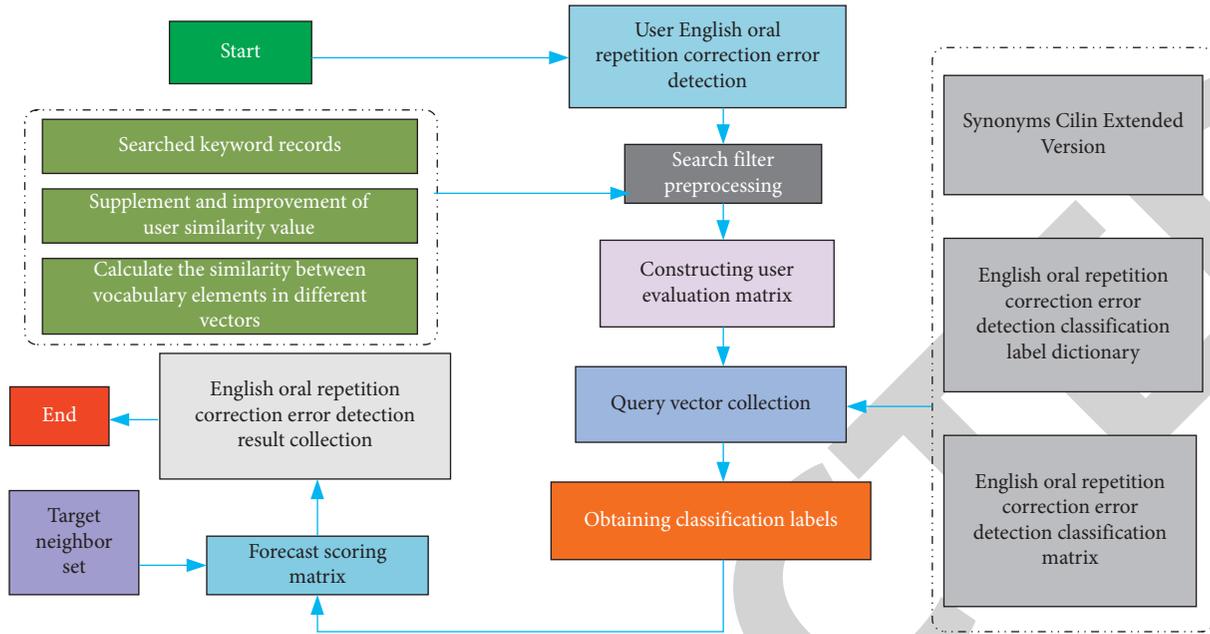


FIGURE 2: The overall design framework of search filtering algorithm based on user search content.

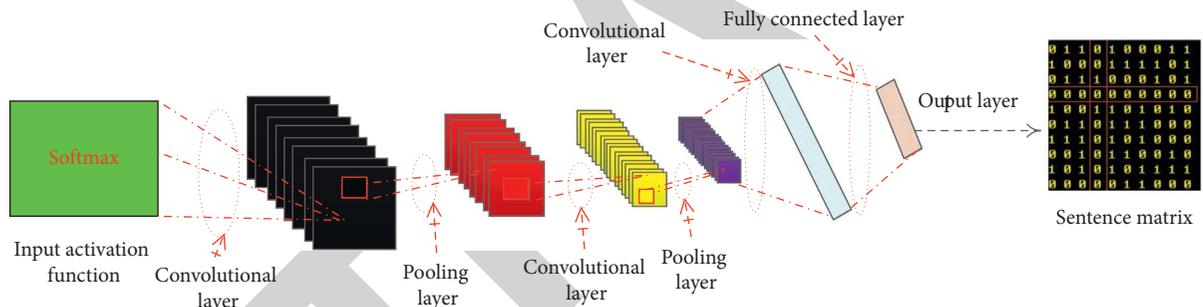


FIGURE 3: CNN syntax network model.

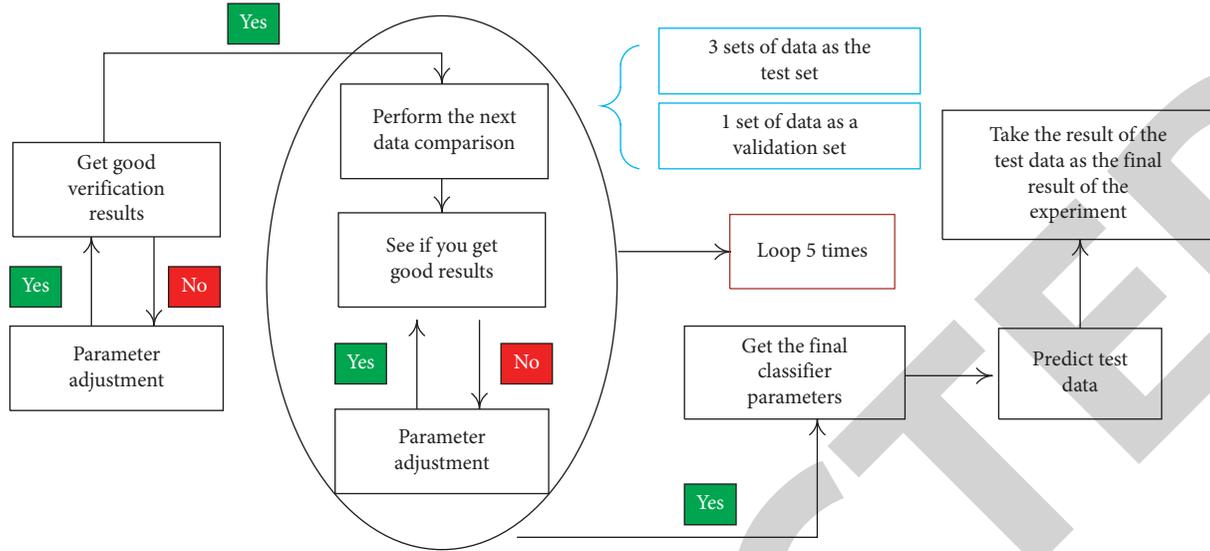
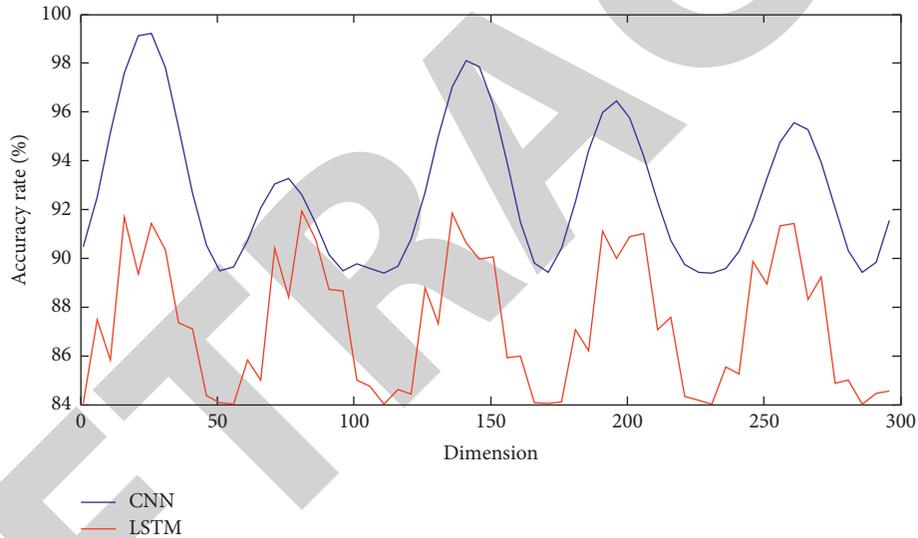
When the classifier parameters obtained after one set of data training are applied to the next set of data, each set of data can achieve better results. If good results are obtained in one set of data, but not good results in other sets of data, then the classifier has overfitting. At this time, some methods to prevent overfitting are needed to prevent overfitting. Finally, the trained classifier is saved as the final version for predicting the test data, and the result of the test data is used as the final result of the experiment. The  $K$ -fold cross-validation process is shown in Figure 4.

The experimental environment uses Python 3.5 as the compiler and uses Gensim Suite 7 to train Word2Vec word vectors. The training of GloVe word vectors uses open source tools provided by Stanford Labs. For the structure of the grammatical error correction neural network classifier, the Keras suite is used as the front-end development, and the back-end uses the TensorFlow-gpu10 suite. Unless otherwise specified, all the experimental environments in this article use this set of experimental environments.

All classifiers fix the sentence length to 100, delete the part of the sentence longer than 100, and fill in the word with the word vector of all 0 after the sentence length is less than

80. The stochastic gradient descent algorithm is used for training, the batch size of each epoch is 32, and 10 groups are trained. The number of convolution kernels set by the CNN classifier is 400, and the width of the convolution kernel is 3, after the maximum pooling layer. The number of hidden layers of LSTM is 128, and the activation functions all use softmax function.

When using  $K$ -fold crossvalidation, this article uses the trained 300-dimensional Word2Vec and GloVe word vectors to train CNN and LSTM, respectively. Because the detection level results are very important in the Chinese error correction task, the results of the identification level and the positioning level need to be classified and predicted in the results of the detection level, so the more grammatical sentences detected, the more prompt the identification level and the positioning level. Therefore, the  $F1$ -score indicator at the detection level is counted in crossvalidation. Figure 5 shows the performance of using Word2Vec word vectors, and Figure 6 shows the performance of using GloVe word vectors. It can be found that the result of using GloVe word vector is not as good as that of Word2Vec word vector, because both of them encode the semantics and other

FIGURE 4:  $K$ -fold crossvalidation process.FIGURE 5: Word2Vec word vector detection level  $F1$  results in crossvalidation.

characteristics of words in different ways. But GloVe trains word vectors based on the word frequency in the co-occurrence matrix in the text. Therefore, in the case of expressing the direct relationship between two words, the training method of GloVe is not as good as Word2Vec. For example, the meaning of “trade” is close to “transaction,” but under the training method of GloVe, the meaning of “trade” will be closer to “trade law.” This is not right. This makes the word vector trained based on the word frequency in the co-occurrence matrix not as good as the word vector trained by Word2Vec. Therefore, in the formal comparison of predictions, this article uses the word vectors obtained by Word2Vec training.

At the same time, in order to compare the impact of word vectors of different dimensions on the performance of the classifier in different classifiers, a test was also made in crossvalidation. More word vector dimensions should

have been used, but due to the limitations of GPU device performance, the continuous improvement of the dimensions will double the calculation time, so only these 300 dimensions are used for comparison. The  $F1$  under the detection level is also used for comparison, and the result is shown in Figure 7.

*5.2. Comparison of Experimental Results and Analysis.* The models used in this paper are CNN and LSTM models and word vectors are used as text features. The comparison results of the methods are shown in Figures 8–10.

It can be seen from Figures 8 and 9 that the evaluation result of LSTM is lower than the result of CNN classifier. This is because LSTM only considers local features, which makes sentences that may not have similar meanings appear to have a high degree of similarity. The CNN classifier takes

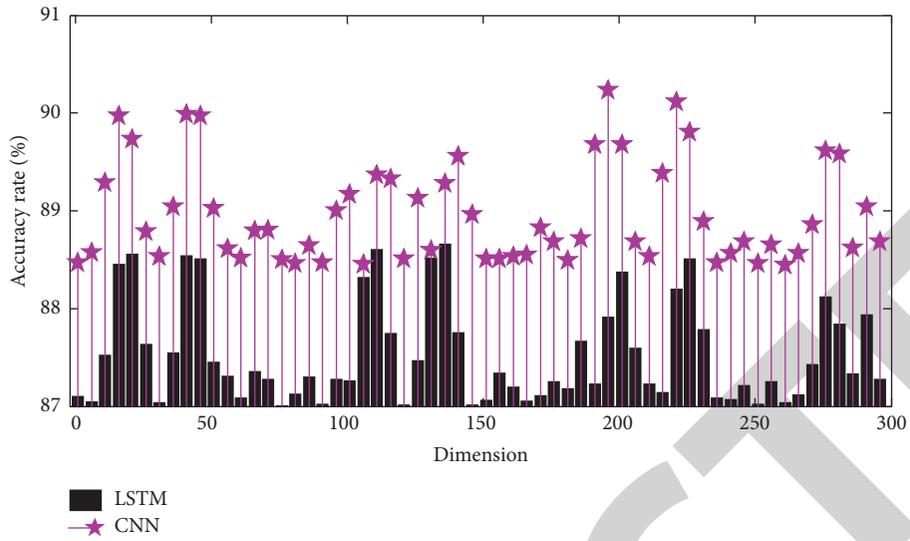


FIGURE 6: GloVe word vector detection level F1 result in crossvalidation.

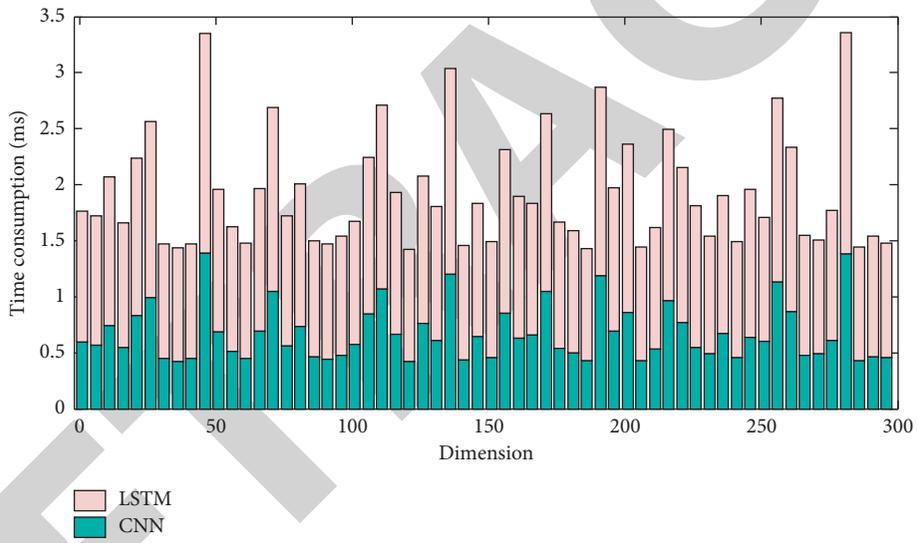


FIGURE 7: The time consumption of F1 in the detection stage of the CNN classifier and LSTM classifier in different dimensions.

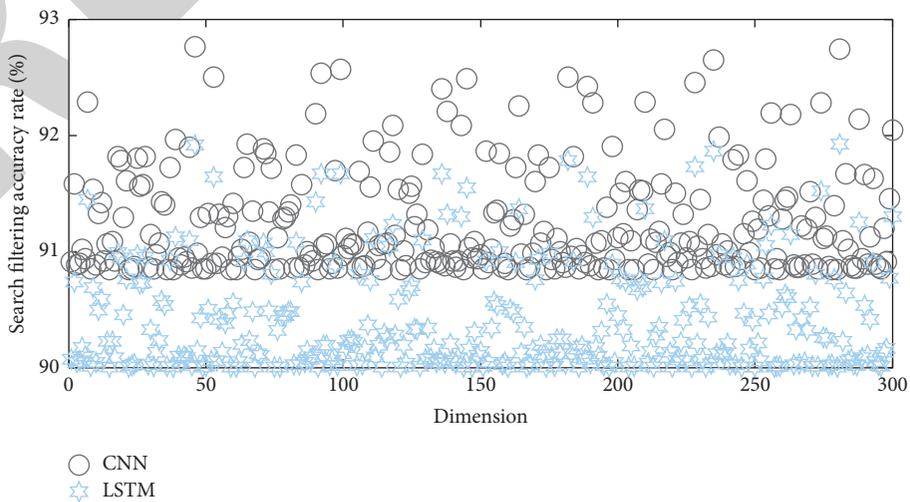


FIGURE 8: The accuracy of search filtering at the detection level.

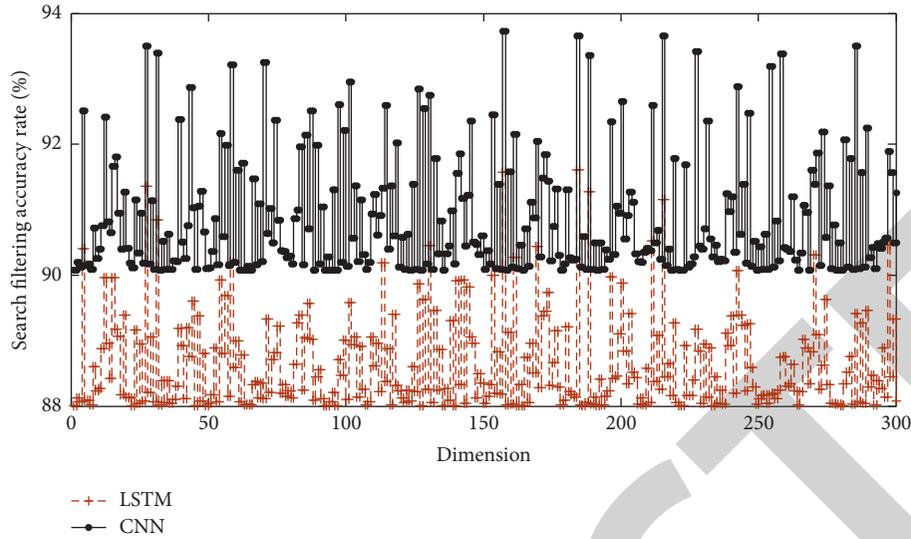


FIGURE 9: The accuracy of search filtering at the appraisal level.

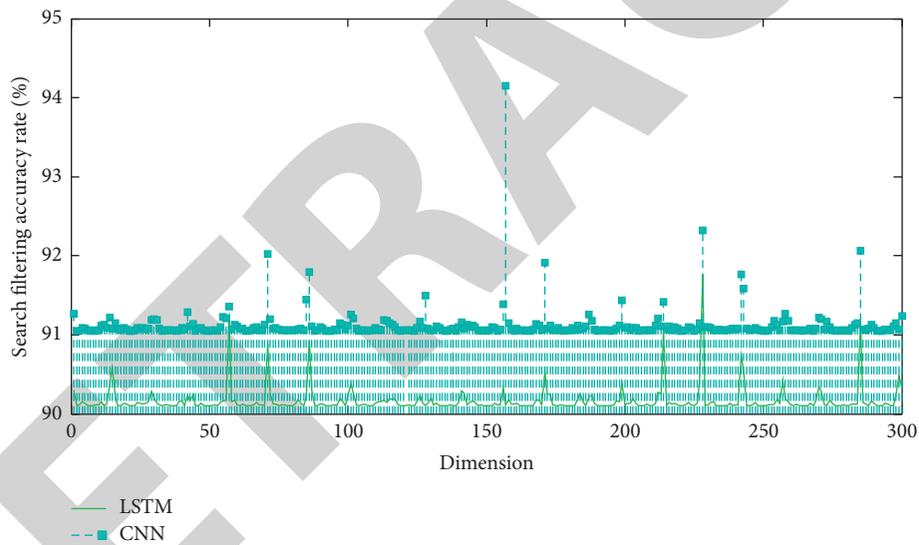


FIGURE 10: The accuracy of search filtering at the positioning level.

into account the logical features between sentences, which is particularly important for every language. This is only because the LSTM classifier only considers the local features of the sentence “to see the spoken English tomorrow,” which is obviously wrong.

Analyzing Figure 10, we can know that the LSTM classifier has almost no effective results on the task of finding the location of grammatical errors. This is caused by two reasons. On the one hand, because it is necessary to check whether each word is wrong in a sentence, the features of the LSTM classifier need to add “0” as the complement of each feature. These introduced features will make the feature matrix sparse, which is not conducive to feature learning. On the other hand, it also makes the features of the sentence cut into fragments, and it is difficult to use them as the true features of the text.

## 6. Conclusion

This article constructs an initial model for studying the learners’ oral English from a multimodal perspective and introduces the characteristics of the model and the definition and composition of the oral communicative competence from the multimodal perspective in detail. From the perspective of the characteristics of the model, the model is mainly supported by the CLA model and the multimodal research theoretical guidance model and consists of two modules: “oral language” and “nonverbal characteristics.” These two modules not only organically integrate the connotation and extension of the CLA model but also fully reflect the content that needs to be investigated in the basic attributes of spoken language. This paper makes a detailed analysis of the feature sparseness problem and search

filtering accuracy of search filtering algorithms, focusing on the objective analysis of the possibility of the invisible input information of user search content being applied to search filtering algorithms. We propose a feature weight assignment algorithm based on the keyword dictionary of spoken English categories and user search records. Combined with the self-built spoken English classification label catalog, the data density of the user feature matrix is realized, and the problem of the user evaluation matrix data of the traditional search filtering algorithm is too sparse. Aiming at the problem of insufficient accuracy of similar calculation methods in traditional search and filtering algorithms, a user similarity calculation algorithm based on “Synonyms Cilin Extended Edition” and search records is proposed, and the similarity reflected in the user query vector is similar to the user evaluation matrix. This article mainly introduces the classification model used in the task of using word vectors to integrate text features to correct grammatical errors in Chinese writing by foreign learners and compares them with models that do not use word vectors as text features. Error correction tasks are divided into detection level, identification level, and positioning level. The detection level is used to determine whether there are grammatical errors in a sentence; the identification level is used to determine the types of grammatical errors in a sentence with grammatical errors; the positioning level is to find the position of the corresponding grammatical error in the sentence.

### Data Availability

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

### Conflicts of Interest

The author declares no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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