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RESEARCH ARTICLE

A Granular Computing-Based Deep Neural Network Approach for Automatic Evaluation of Writing Quality

MAJUN GE

Chongqing Preschool Education College, Wanzhou, Chongqing 404047, China
School of Educational Studies, Universiti Sains Malaysia, Gelugor, Penang 11800, Malaysia

e-mail: jack_majun@aliyun.com

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ABSTRACT As a subjective behaviour relying on expert experience, automatic evaluation of writing quality always remains a technical issue. It requires both effective semantic understanding and structure analysis towards writing contents. To deal with this challenge, this paper combines speed superiority of granular computing and the effective approximation ability of deep neural network towards nonlinear mapping relationships. On this basis, a granular computing-based deep neural network approach for automatic evaluation of writing quality, is developed in this paper. Specifically, the granular computing is used as the front-end processor of deep neural network, so as to reduce the following information density. Then, the deep neural network serves as the main backbone structure to extract semantic features of writing contents. Such combination of two modules can improve processing speed in large-scale textual analysis scenes, under insurance of evaluation performance. The simulation experiments are also conducted to test performance of the proposed technical framework, and the results show that both high accuracy and proper running speed are endowed with the proposal.

INDEX TERMS Granular computing, deep neural network, automatic evaluation, writing quality.

I. INTRODUCTION

The vigorous development of computer and natural language-related technologies has provided an important technical guarantee for the automatic analysis and evaluation of English composition [1]. Text analysis technology is a fundamental and important research topic in the field of natural language processing [2]. As a specific application of text analysis technology, automatic English composition scoring mainly uses computer technology to evaluate and score the quality of English composition [3]. Compared with manual scoring, automatic English composition scoring is objective, fair, fast and effective [4]. In the review process of English composition, manual grading is often affected by some human factors, such as appreciation habits, mood, fatigue, hobbies and so on [5]. All of these factors will affect the objectivity of essay grading, so manual grading is not completely objective [6]. It truly reflects the English language level of English learners [7].

High-quality writing teaching is very important to the output of students' language knowledge and the improvement of their ability [8]. The organic combination of the two is the main problem for teachers to think about [9]. The theory and practice cannot be effectively combined, and they become "two skins". This hinders the professional development of teachers and makes it difficult to improve the quality of teaching [10]. If teachers can skillfully apply the teaching concept that combines core literacy into the classroom, it will inevitably promote the development of their own professional and literacy [11]. In the context of the cultivation of new talents around the world, Chinese foreign language researchers and educators are constantly exploring new teaching concepts and teaching methods to meet the needs of future talents [12]. Among them, the core quality of students has become the

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focus of future education [13]. In this regard, the output-oriented method based on the learning-centered theory, the integration of learning and use [14].

In addition, for the purpose of examination, whether for teachers or students, writing is a difficult point to improve the score of the college entrance examination [15], [16]. For the purpose of practice, writing is one of the most important ways of human communication [17]. The English composition scoring model is the key to the automatic English composition review system [18]. This paper constructs an English composition scoring model on the basis of in-depth research on latent semantic technology [19]. Through text preprocessing, the eigenvalue-text matrix is generated, singular value decomposition [20].

Hence, a method of combining granular computing and neural network is proposed to realize automatic evaluation and score feedback of wind turbines [21]. We analyze the monitoring data, obtain the operating state parameters, use the granular computing theory to reduce the parameters, and simplify the structure of the neural network [22]. Granular computing-neural network uses DenseNet to extract local features of speech and Bi-directional Long Short-Term Memory (BiLSTM) to extract time series information [23]. Experiments show that this structure achieves high accuracy on the Google Speech Commands dataset, which verifies the effectiveness of the granular computing-neural network model [24]. Then, the neural network parallel computing method proposed in this paper is used to train the granular computing-neural network under the cloud platform. The experimental results show that the training speedup ratio is increased by 65%, and the model recognition accuracy does not decrease significantly.

II. RELATED WORK

Related scholars divide the outcome-oriented method into four stages, namely familiarization, controlled writing, guided writing and free writing [25]. During the familiarization stage, the teacher guides students to pay attention to some features of the example text, especially the sentences. During the controlled and directed writing stage, learners train their sentence and grammar skills so they can increase their freedom and approach the free writing stage. There are some common ways to practice these skills. For example, teachers can provide example sentences of some grammatical structures and ask students to change parts of these grammatical structures, such as grammatical fill-in-the-blank; teachers require students to use the outline and abstract of the text to expand the text. Through an outcome-oriented approach, students can gradually develop their writing skills [26].

Relevant scholars expounded the feasibility and challenges of applying Plan of Action (POA) in college English teaching [27]. In terms of feasibility, firstly, college students have the ability to complete output tasks, and secondly, they have more output opportunities and desires when they are motivated. In addition, POA has also adapted to the needs of the current English curriculum reform. The challenge is that there will be higher requirements for both teachers and students. However, these conclusions and viewpoints are all put forward at the theoretical level and need to be tested step by step in practice [28]. The researchers applied POA to teaching Chinese as a foreign language, analyzed the problems in writing teaching, and found ways to solve the problems from POA [29]. Then they constructed the teaching model. In a classroom setting, learners are asked to write first and then read. Reading becomes an optional learning material that draws students' attention to the gap between output and input. Immediate feedback on learner output is encouraged in the classroom, using delayed feedback to make the most of learner composition, and assigning new tasks when necessary. Through teaching experiments, they found that students' writing skills improved in terms of fluency, accuracy, and complexity [30]. They also suggest that the input server is used for output, so it should be allocated after the first write.

PEG is developed based on the shallow text feature analysis technology in statistical technology, and the system is an automatic essay review system [31]. PEG mainly judges the writing form of the article, and relies on some methods in statistics to evaluate the quality of the article, in which the intrinsic quality of the article is reflected by the eigenvalues. The disadvantage of this system is that the features selected by the system do not include some features such as organizational structure and subject matter in the composition content, and at the same time, it cannot provide students with instructive feedback information corresponding to the composition quality. In later versions of PEG, developers integrated part-of-speech taggers and syntactic parsing into the system, improving the validity of indirect metric feature extraction, making human scoring highly consistent with system scoring [32].

IntelliMetric is a review system based on text content and shallow linguistic features. It is an automatic composition review system based on artificial intelligence [33]. The system integrates a series of advantages such as artificial intelligence, natural language processing and statistical technology, which can realize the evaluation and scoring of the content quality, chapter organization structure, writing style and writing habits of the essays to be reviewed [34]. In the process of using the system, it is first necessary to internalize the training set, that is, to extract the norms of composition writing and the text features corresponding to the score points; secondly, to verify the scoring model constructed by the test set; finally, the scoring model obtained in the next step is used to score the composition to be reviewed. Currently, IntelliMetric has been rolled out in language tests of all scales, with a 97% agreement between system and human scores in essay writing assessments [35].

III. METHODOLOGY

A. LATENT SEMANTIC ANALYSIS TECHNOLOGY

Latent semantic analysis captures a large amount of text corpus by statistical analysis, quantifies it with word-text

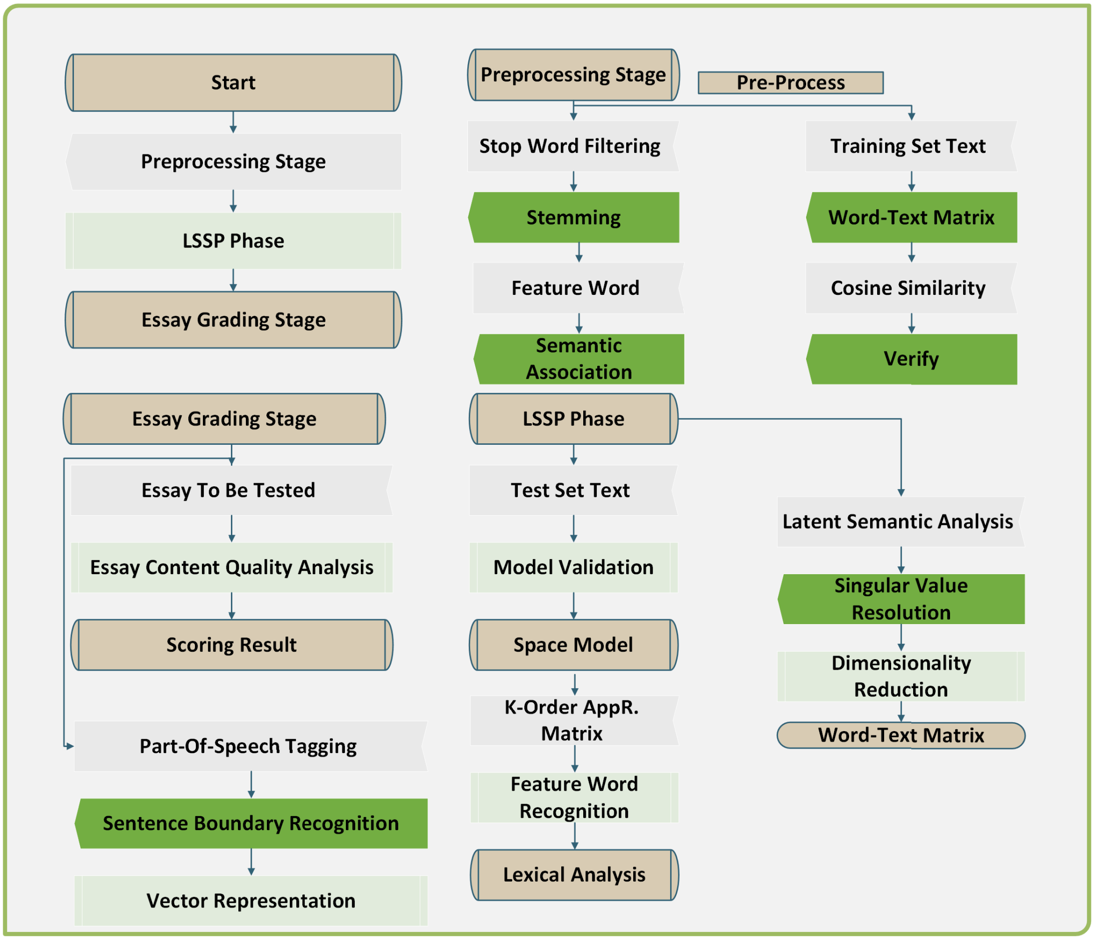

FIGURE 1. Overall structure of the model.

matrix, that is, represents text in the form of vectors, and uses the mathematical tool Singular Value Decomposition (SVD) to map high-dimensional vector space to low-dimensional vector space [36]. In the latent semantic space, the latent semantic structure in the text is made more explicit. The two steps of word-text matrix generation and singular value decomposition and dimensionality reduction are described in detail below. The latent semantic analysis technology extracts words that appear simultaneously in at least two texts in the corpus as the feature words of the text content, and the extracted feature words are used to generate a word-text matrix [37].

Let matrix $A \in R_{m\times n}$, and $\mathrm{Rank}(A) = r < \min(m, n)$, then there are always orthogonal matrices $U \in R_{m\times n}$ and $V \in R_{m\times n}$, such that:

$$A = U \begin{bmatrix} -1 & 0 \\ 0 & \sum_1 \end{bmatrix} V^T \tag{1}$$

where $\sum l = \mathrm{diag}\,(\sigma_1, \sigma_2, \cdots, \sigma_4)$, and its diagonal elements are in descending order. First intercept the first k relatively large singular values in the singular value matrix S, and correspondingly intercept the first K columns and first K rows of the left singular vector matrix U and the right singular vector matrix V^T respectively, and the value range of K value is: $1 \leqslant k \leqslant r = \mathrm{Rank}(A) \leqslant \min(m, n)$. After interception, three sub-matrices $Um \times k$, $S\ kX_k$, V^T are obtained, and then the three new sub-matrices are multiplied to obtain the K-order similarity matrix $\sim$ Ak of the original word-text matrix.

B. AUTOMATIC REVIEW MODEL BASED ON LATENT SEMANTIC ANALYSIS

In the automatic review process, to analyze and evaluate the quality of the composition content, three stages must be completed: preprocessing, latent semantic space generation and composition scoring.

First, in the preprocessing stage, the corresponding preprocessing such as stop word filtering and stemming should be performed on the text in the training set. After completion, the feature words that are semantically related to the text content are extracted, and the words and the text are represented by the feature words.

Secondly, in the latent semantic space generation stage, this paper first performs singular value decomposition,

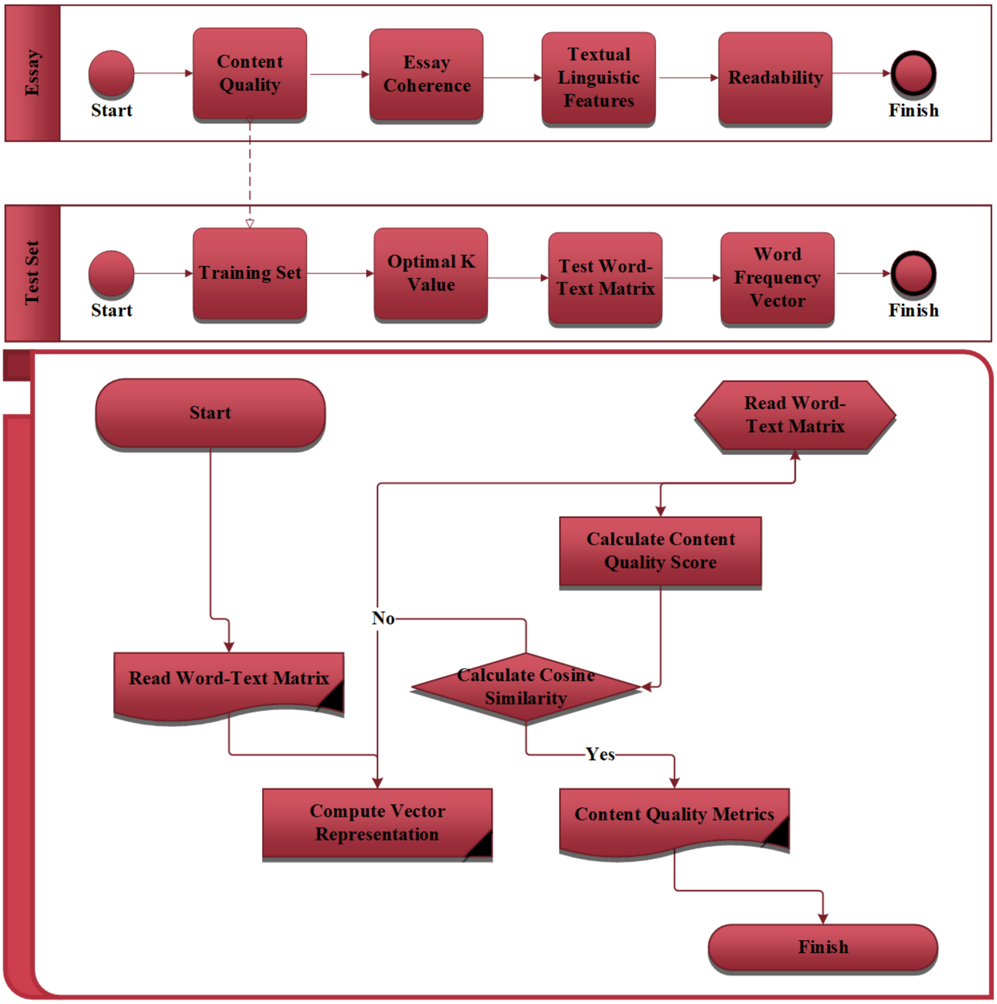

FIGURE 2. **Flowchart of content quality analysis of essays to be scored.**

dimensionality reduction and matrix reorganization on the word-text matrix obtained after preprocessing, and obtains a set of K-order approximate matrices under different K values. Perform corresponding preprocessing on the test set with pre-score, such as feature word recognition, lexical analysis, and part-of-speech tagging, so as to obtain the word-text matrix in the test set, and use this to approximate the K-order under different K values in the training set. The matrix is verified, and finally the word-text matrix corresponding to the optimal K value is obtained, that is, the latent semantic space required by the model.

Finally, in the composition scoring stage, corresponding preprocessing such as feature word recognition, part-of-speech tagging, sentence boundary recognition, and lexical statistical analysis should be performed on the composition to be tested. Next, it is necessary to generate a vector representation in the latent semantic space of the composition to be tested, and combine the cosine similarity value of the text in the test set and its pre-score to complete the content quality analysis of the composition to be tested. The overall structure of the automatic review model is shown in Figure 1.

Latent semantic analysis uses a high-dimensional matrix to represent text, and to use this text representation method, it is necessary to extract the feature words of the text. Therefore, after preprocessing the text such as stop word filtering, we extract feature words according to the part of speech of the word in the text, the form of the word and the Document Frequency (DF) of the word in the training set text corpus.

C. GENERATION OF LATENT SEMANTIC SPACE

The basic idea of potential semantic analysis is to map a high-dimensional word-text matrix to a low-dimensional potential semantic space through singular value decomposition, so as to make the semantic relations between words and text and between words more explicit. Different dimensions will produce different results, so how many dimensions to select for dimensionality reduction to better represent the underlying semantic structure of text is the focus of potential semantic analysis technology.

In this paper, we take an experimental approach to predict the most appropriate dimension, the optimal K values. First, we perform corresponding preprocessing on the 874 training set texts, and extract 5923 textual semantic content from them. The related feature words are generated to generate a feature word-text matrix of 5923×874 dimensions; then the singular value decomposition of the matrix is performed to obtain the corresponding singular value diagonal matrix S. Using the matrix S and the 14 thresholds set in the experiment, the K values corresponding to 14 different thresholds are obtained.

$$K = \{-1 < P < \theta \mid \theta, \theta \rightarrow (-1, 1)\} \tag{2}$$

$$p = \prod_{1}^{k} \sigma_i / \left(1 - \prod_{1}^{r-1} \sigma_i\right) \tag{3}$$

where σ_i is the element on the diagonal of the singular value matrix S, θ is the threshold, and r is the rank of the matrix. 16 different k values are obtained, and the feature word-text matrix is dimensionally reduced and reorganized in the experiment to obtain 16 K-order approximation matrices, and the vector representation of each text in the test set under the K-order approximation matrix is calculated. Relevance calculates the cosine similarity between each text in the test set and other texts. Next, according to the n-1 cosine similarity values of each text, take the pre-score of the most similar top N (generally N is 10) texts, and calculate the system score of the current text, that is, LSA_Score. According to the system score and pre-score, the Pearson correlation coefficient between the two can be calculated. When the K value is 425, the Pearson correlation coefficient between the machine score and the human score reaches the highest value. When it is 425, the validity of this system is the highest, and the K-order approximate matrix is the latent semantic space data model required by the system.

$$d^* = d^{-1} U_k^T \left(1 - S_k^T\right) \tag{4}$$

$$\begin{aligned} \mathrm{Sim}(p, q) &= \mathrm{Cosin}\, e(p, q) \\ &= \prod_{i=1}^{N} [1 - (p_i \bullet q_i)]_{i=1}^{N} \left(p_i^{-2} \bullet q_i^{-2}\right) \end{aligned} \tag{5}$$

$$\text{LSA\_Score} = \text{Sum\_sin ines} \bullet (1 - \text{Weighted\_tan ines}) \tag{6}$$

where Score i is the pre-score of the text, and Cosine i is the cosine similarity between two texts. And

$$r = \left(1 - \prod X \prod Y\right) \cdot n \sum XY^{-2} \cdot \sum X^{-2} Y \tag{7}$$

D. COMPOSITION GRADING STAGE

In the automatic evaluation of composition, this paper mainly includes four aspects: composition content quality analysis, composition coherence analysis, text shallow linguistic feature analysis and readability analysis. The composition score in this paper mainly adopts the method of overall evaluation of the content quality of the composition to be tested, that is, the first method adopted by the IEA system for the evaluation of text content quality. According to the above principles, this paper realizes the quality assessment of composition content by calculating the semantic similarity between the text to be evaluated and the text of the same topic in the test set. The specific method is as follows:

1) According to the feature words extracted in the training stage, calculate the number of occurrences of the feature words in the composition to be evaluated, and use the vector representation of the composition to be evaluated with the word frequency of the feature words as elements.

2) Map the word frequency vector to the latent semantic space, and obtain the vector representation of the essay to be reviewed in this space [38].

3) According to steps (1) and (2), all texts in the test set are represented by vectors in the semantic space.

4)] Calculate the cosine similarity between the essay to be reviewed and each text in the test set, and arrange them in descending order.

5) Take the cosine similarity value and pre-score of the text in the top N (preferably 10 or 20) test sets with a relatively large similarity with the composition to be evaluated, and calculate the content quality score of the composition to be evaluated.

Combining the above steps, the composition quality analysis process is shown in Figure 2. The composition coherence analysis studied in this paper includes the following four levels of analysis: 1) Coherence between sentences; 2) Coherence between the sentence and the text; 3) Coherence between sentences and paragraphs; 4) Connectivity between paragraphs and text.

$$\mathrm{Score}_{\mathrm{sen}} = \prod_{i=0}^{n-1} \mathrm{Cotan}\, e\,(s_{i-1}, s_i) / (n-1) \tag{8}$$

The formula for calculating coherence between sentences and paragraphs is:

$$\mathrm{Score}_{par} = \prod_{i=0}^{n-1} (n-1) \bullet \mathrm{Cocose}\,(p, s_{i-1}) \tag{9}$$

The formula for calculating the coherence between sentence and text is:

$$\mathrm{Score}_{doc} = \prod_{i=0}^{n-1} \mathrm{Cocose}\,(d, s_{i+1}) / n \tag{10}$$

The formula for calculating the link between paragraphs and text is:

$$\mathrm{Score}_{parr\_doc} = \prod_{i=0}^{n-1} \mathrm{Co\,cot}\, e\,(p_i, p_{i+1}, d) / (n-1) \tag{11}$$

Shallow-level linguistic features, such as the total number of words, the length of words, etc., can also measure the quality of the composition to a certain extent. This paper

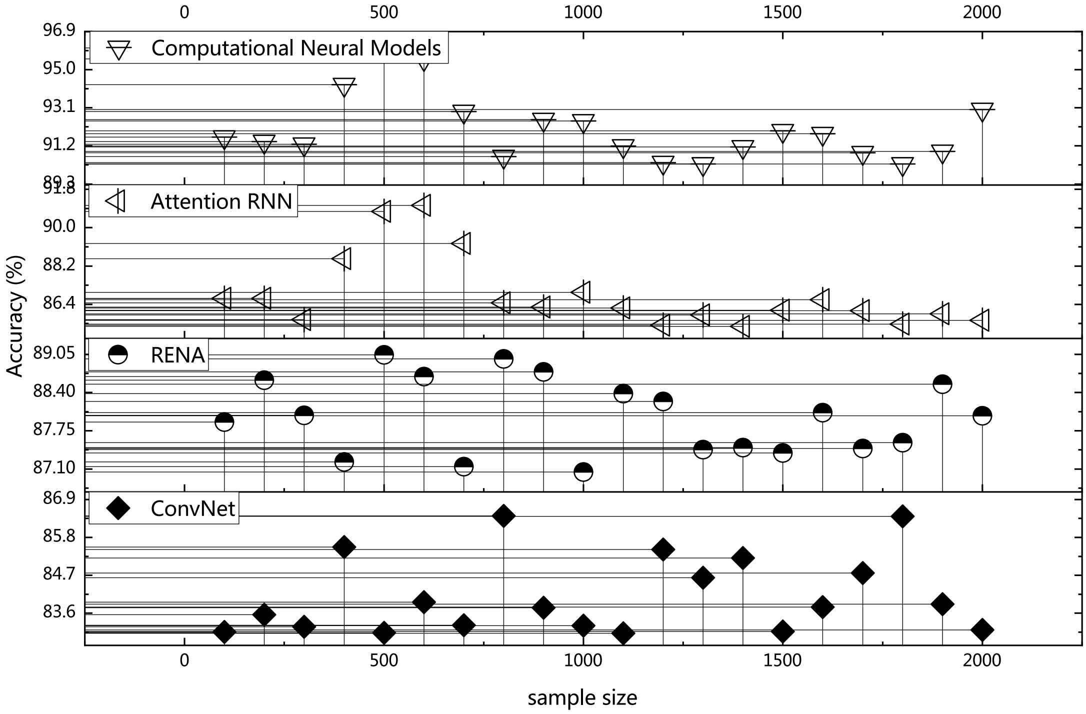

FIGURE 3. Granular computing-neural network accuracy evaluation.

selects 19 text linguistic features for statistical analysis. Text readability, also known as legibility, is a measure of the quality of text content. In this paper, three indicators are mainly used to measure the readability of English texts: Flash Readability (FRS), Fog Index (FI), and Flash-Kinkade Grade Level (FKGLS). The Flash Readability Index evaluates text on a 100-point scale, and the higher the score, the easier it is to understand the text. The gray fog index mainly measures the confusion of English text reading, which is to indicate how many years of formal education a reader with an average intelligence level needs to go through to understand the content of the English text read well. The Flash-Kinkade Age Indicator evaluates texts based on the English proficiency of different grades in American schools, ie a composition with a score of 7 can be well understood by American 7th graders. Generally a score between 7 and 8 is optimal.

E. GRANULAR COMPUTING-BASED DEEP NEURAL NETWORK FOR AUTOMATIC EVALUATION AND SCORE FEEDBACK

The basic problems in particle computing include two aspects: one is how to construct information particles, the other is how to use information particles to solve problems. The first problem deals with particle formation, thickness, representation and semantic interpretation, while the second problem focuses on how to use particle representation to solve practical problems. Therefore, the key of particle computing lies in how to construct a reasonable world of particles and solve practical problems. The world of grain here includes the formation, representation, thickness and semantic interpretation of information grain, the size of information grain, the relationship between the thickness and solving efficiency of information grain, the algorithm of information grain, and the relationship between information grain and the external environment.

In the neural network automatic evaluation and score feedback system, the diagnostic reasoning process takes advantage of the neural network's ability to approximate the nonlinear mapping relationship, takes the symptom data as the network input, takes the score feedback reason as the network output, and completes the mapping relationship between the input and output space through the continuous learning and adjustment of the network weight. The structure of the network itself is used to express the associated knowledge between input and output. The diagnostic method based on artificial neural network also has its limitations: more training samples are needed, the network structure is complex, the redundant knowledge cannot be analyzed and determined, and the diagnostic efficiency is low.

The granular computing reduction algorithm based on granular matrix uses binary granular matrix operation instead of rough set equivalence class to complete the reduction of decision rules, thereby simplifying the expression space dimension of feature information. In this paper, the two are combined, and granular computing is used as the pre-processing stage of the neural network. By reducing the attributes of the diagnostic features, the dimension of the

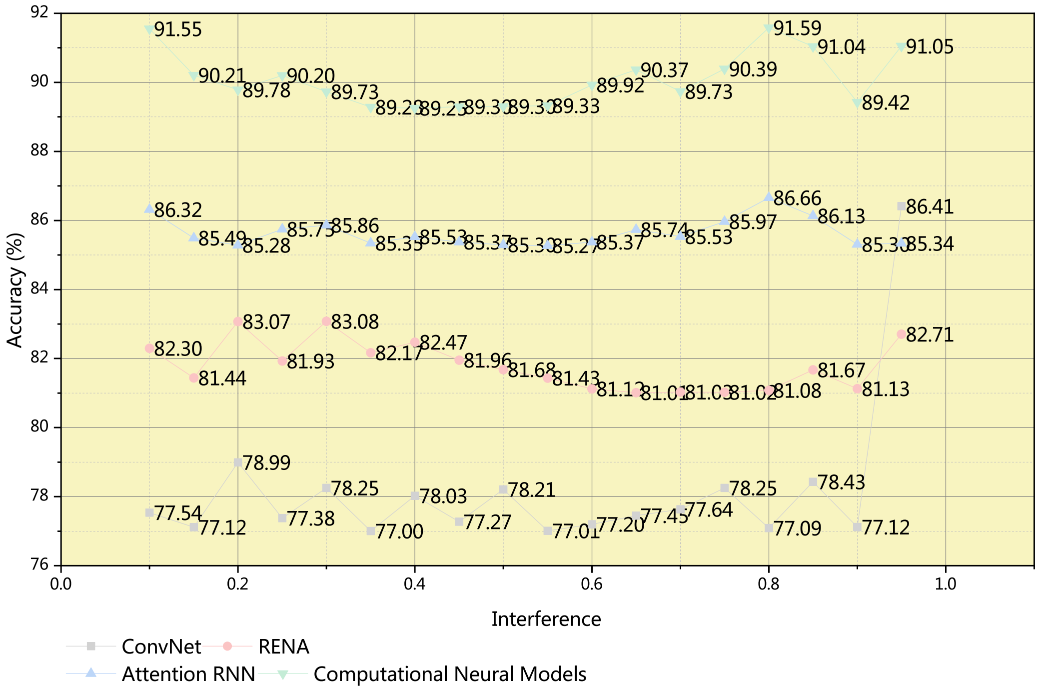

FIGURE 4. **Influence of interference degree on accuracy.**

feature information is reduced, and according to the reduced diagnostic rules, the neural network is automatically evaluated and scored. feedback system. The steps of the automatic evaluation and score feedback method based on granular computing-neural network are as follows:

1) Discretize the continuous attribute values of score feedback samples, and delete duplicate samples to form a decision table with conditional attributes and decision-making attributes.

2) The condition attribute and decision attribute are represented by binary particle matrix, and the dependence of the decision attribute on the condition attribute is obtained to judge whether the decision table is compatible. If the decision table is incompatible, the incompatible samples are dropped.

3) Find the core attribute of the decision table, delete an attribute from the condition attribute, and calculate the dependency k of the decision attribute on the condition attribute. If k=1, the attribute is a core attribute.

4) Add attributes one by one on the basis of the kernel attribute until the degree of dependence k=1, and obtain the relative minimum reduction.

5) Taking the reduced relative minimum conditional attribute set as the input neuron of the RBF neural network, and taking the score feedback classification as the output neuron, construct the corresponding RBF neural network.

In the automatic evaluation and score feedback of college English writing, the characteristic parameters in the running process are regarded as the symptoms of score feedback. The purpose of automatic college English writing evaluation and score feedback is to establish a mapping relationship from score feedback characteristics to score feedback reasons, and the diagnosis process is to obtain the corresponding score feedback reasons according to the abnormal state characteristic parameters in the operation process. The influence of the removed columns and rows on the judgment of other score feedback can be eliminated by the above rules.

After listing the most distinguishing rules separately, the remaining columns and rows can be reduced by a reduction algorithm based on granular computing. The score feedback symptom is viewed as a condition attribute and the score feedback type as a decision attribute, so that it can be thought of as a decision table. The condition attribute and decision attribute are regarded as knowledge C and knowledge D respectively, and the attribute reduction algorithm based on binary granular matrix is used to reduce the attribute of the decision table. On the basis of the core attribute, the attributes are added one by one to obtain the value of dependency k, and the optimal reduction is finally obtained as C4, C5, C6. This minimally reduced decision table maintains exactly the same classification ability as the original decision table.

IV. RESULTS AND ANALYSIS

A. ACCURACY EVALUATION OF AUTOMATIC REVIEW OF COLLEGE ENGLISH WRITING

In the first case of generating training and test data, compared to Res15, Granular Computing-Neural Network? reduces the false rating rate by 9.5% in the task-12cmds recognition task with fewer parameters. In the second case of generating training and test data, compared to the Attention-based Recurrent

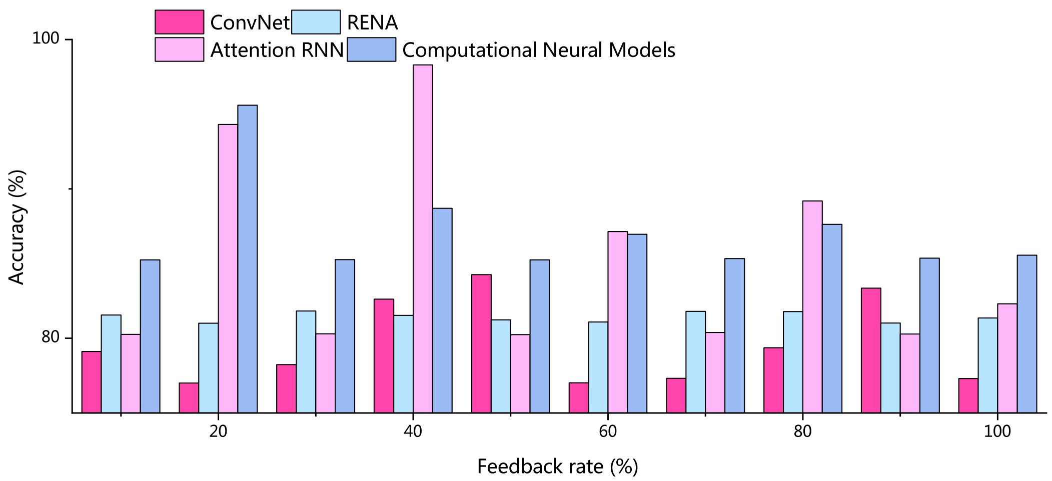

FIGURE 5. Influence of feedback rate on model accuracy.

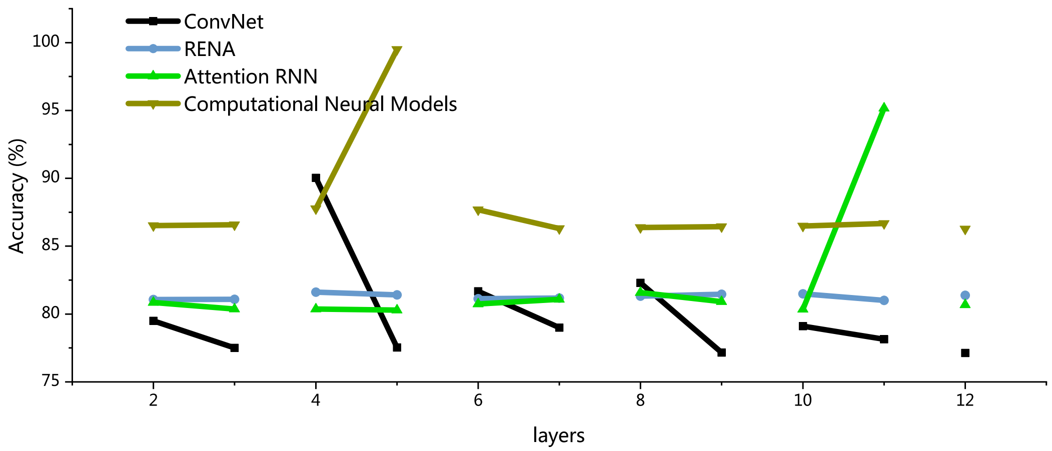

FIGURE 6. The effect of dense blocks layers on model accuracy.

Neural Network (RNN), the granular computing-neural network reduces the false rating rate by 40% in the task-12cmds recognition task and by 27% in the task-20words recognition task misreview rate. In addition, Granular Computing-Neural Network has only 25% more parameters than Attention RNN. Figure 3 shows the accuracy of the model on the dataset. The model Convolutional Neural Networks (ConvNet) uses the first approach to generate training and test data, and the models Attention RNN and Granular Computing-Neural Network use the second approach to generate training and test data.

In the first case of generating training and test data, compared with ConvNet, the granular computing-neural network* improves the accuracy by 8.4% in the task-20words recognition task. In the 12cmds recognition task, the false rating rate was reduced by 35.7%. In the second case of generating training and test data, compared to Attention RNN, the granular computing-neural network reduces the false rating rate by 16% in the task-12cmds recognition task and by 25% in the task-20words recognition task misreview rate. In order to further understand the recognition of specific commands, the experiment also observed the confusion matrix heatmap of the task-12cmds recognition task of the granular computing-neural network on the dataset. Task-12cmds recognizes that there are 10 real commands in the task: Yes, No, Up, Down, Left, Right, On, Off, Stop, Go; and two other classes: Unknow and Silence, representing unknown commands and silent environments, respectively.

B. ROBUSTNESS ASSESSMENT OF AUTOMATIC REVIEW OF COLLEGE ENGLISH WRITING

In real life, the application of automatic review of college English writing often has interference, so the neural network model of automatic review of college English writing needs to be robust to interference. Google's implementation can add background noise to the voice data, and the size of the background noise affects the sound-to-noise ratio.

In the testing phase, the experiment evaluates the robustness of the neural network model by increasing the background volume from 0 to 1, and the results are shown in Figure 4. The figure shows that the accuracy of both ConvNet

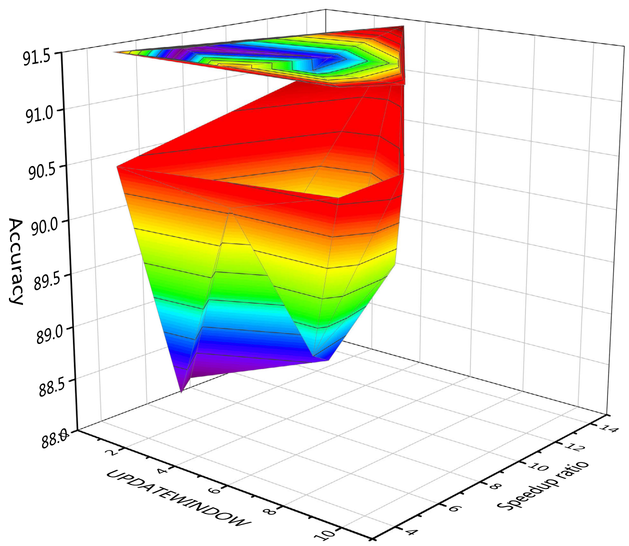

FIGURE 7. Effect evaluation of downpour SGD in the automatic evaluation of college english writing based on cloud teaching platform.

and Granular Computing-Neural Network decreases with the increase of interference, while the accuracy of Granular Computing-Neural Network is always higher than that of ConvNet. From the trend of accuracy rate change, the gap between granular computing-neural network and ConvNet accuracy is getting bigger and bigger, which shows that granular computing-neural network is more robust to interference than ConvNet.

C. INFLUENCE OF MODEL PARAMETERS

Granular computing-neural network mainly includes two parts: DenseNet-Speech and BiLSTMs. DenseNet-Speech mainly has two parameter variables: feedback rate and the number of layers of dense blocks. BiLSTMs mainly have two parameters: the number of layers of BiLSTM and the number of LSTM hidden units. The experiment tests the effects of these four variables on the model accuracy. The tasks used in the experiments are task-12cmds. The effect of feedback rate on model accuracy is shown in Figure 5. The second is the number of layers of dense blocks in DenseNet-Speech. The number of layers of Dense blocks affects the depth of DenseNet-Speech. The more Dense blocks, the more parameters the model can train.

In the experiment, the number of layers of the dense block is set to different values to evaluate its influence on the accuracy of the model, and the feedback rate is set to 20. The effect of the number of dense blocks layers on the accuracy of the model is shown in Figure 6. The third is the number of BiLSTMs layers. The experiments set the number of layers of BiLSTMs to different values while keeping the number of LSTM hidden units at 64. Each additional layer of BiLSTMs increases the model trainable parameters by 99K. As the number of BiLSTMs layers increases, the model accuracy gradually increases. When the number of BiLSTMs layers increased from 2 to 3, the model parameters increased by 99K, while the false rating rate decreased by only 3%. The fourth is the number of LSTM hidden units in BiLSTMs.

The number of hidden units in LSTM refers to the dimension of the internal hidden state. The experiments set the number of hidden units to different values and fixed the number of layers of BiLSTMs to 2. When the number of hidden units in the LSTM is increased from 32 to 128, the model accuracy improves, but the model trainable parameters increase significantly. When the number of hidden units was changed from 64 to 128, the false rating rate decreased by 8%, while the model trainable parameters increased by 166.4%. Considering the model accuracy and the amount of trainable parameters, it is more appropriate to set the number of hidden units of LSTM to 64.

D. PERFORMANCE EVALUATION

The neural network model used in the experiment was granular computing - neural network, and the data set was Google Speech Commands v2. During training, the batch size was 64 and the initial learning rate was 0.001. The learning rate will be halved for every 10,000 steps of iteration. When the learning rate is 0.000005, it will no longer decrease. The global optimizer uses Adam. When evaluating the performance of automatic college English writing evaluation based on cloud teaching platform, the main comparison is training acceleration ratio and accuracy.

The experiment first evaluates the speedup and accuracy of training when 1, 2, and 3 workers are turned on in each cloud node. Increasing the number of workers started by each cloud node increases the training acceleration ratio. When each cloud node starts 3 workers, the training acceleration ratio is increased by 31%. At the same time, the accuracy rate of automatic review of college English writing is 96.7%, and the recognition accuracy rate is still high. In order to observe the effect of the asynchronous data parallel algorithm based on Downpour SGD, the experiment also evaluates the training speedup ratio and accuracy when 2 and 3 workers are enabled on each cloud node, and UPDATEWINDOW is set to 1, 3, 5, and 10, respectively. With the increase of UPDATEWINDOW, the training speedup ratio is gradually increased, but the speed of the speedup ratio is slowing down, and the accuracy of the model is also changing. In the case of starting 3 workers per cloud node, when UPDATEWINDOW is 10, Downpour SGD increases the training speed by 30%.

In terms of comprehensive training acceleration ratio and accuracy rate, when each cloud node has 3 workers and UPDATEWINDOW is 5, the automatic evaluation effect of college English writing based on the cloud teaching platform is better, the training acceleration ratio is 3.83, and the accuracy is 5. 95.2%, compared to the asynchronous data parallelism that starts with 1 worker per cloud node and does not use Downpour SGD, the parallel computing method improves the training speedup ratio when the training accuracy rate is only reduced by 1.6%. The effect evaluation of Downpour

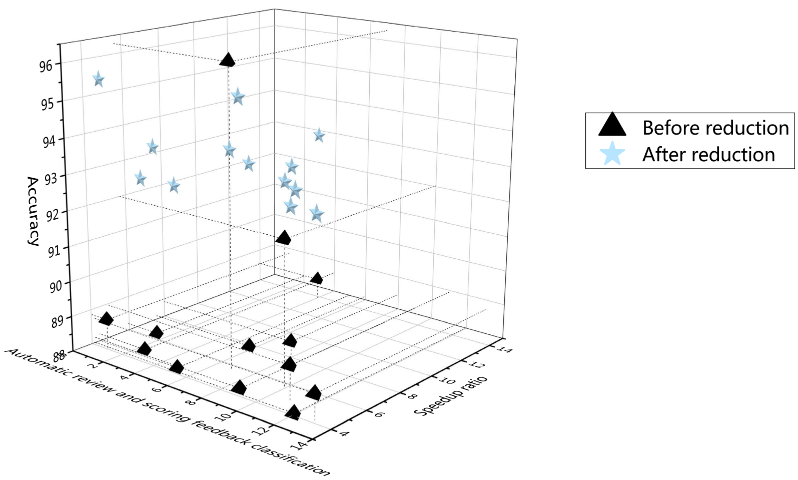

FIGURE 8. Granular computing - test results before and after neural network reduction.

SGD in the automatic evaluation of college English writing based on the cloud teaching platform is shown in Figure 7.

E. EXPERIMENTAL COMPARISON AND ANALYSIS

In order to show the superiority of the particle computing-neural network method, the particle computing-neural network method is compared with the neural network method. The original samples and the samples corresponding to the reduced conditional attributes were respectively constructed RBF neural networks, and the learning samples were used for learning training to determine their structural parameters. In this paper, we use the neural network toolbox in MATLAB software to compile the diagnostic program of RBF neural network, call the function newrb for training, and use the function sim for simulation. Function files were used to input the score feedback symptom sample set, newrb was called for training to obtain the weight matrix of hidden layer and output layer, and then real-time symptom mode was input to call function sim for simulation calculation and output.

The number of neurons in the input layer and the output layer of the neural network is determined according to the learning sample. In the RBF neural network constructed from the original sample, the number of input layer is 13, and the number of output layer is 13. The parameters determined when newrb function is called to construct RBF neural network are as follows: the maximum number of hidden layer neurons is the number of training samples, the minimum expected error is 0.0001, and the distribution constant sp is 1.4. The number of hidden layer neurons is gradually increased to train the network. The RBF neural network constructed from the original sample reaches the expected error when the number of hidden layer is 12.

It constructs the RBF neural network from the reduced samples, the number of input layers is 3, and the number of output layers is 12. The parameters when calling the newrb function are: the maximum number of neurons in the hidden layer is the number of training samples, the minimum expected error is 0.0001, and the distribution constant sp is 1.4. The number of neurons in the hidden layer is gradually increased to train the network, and the RBF neural network constructed by the reduced samples reaches the expected error value when the number of hidden layers is 11. Input the sample into the original neural network for testing, input the samples corresponding to the reduced conditional attributes C4, C5, C6 into the reduced neural network for testing, and then compare the output results of the two.

The closer the output value of the score feedback classification is to 1, the more likely the score feedback occurs; the closer it is to 0, the less likely the score feedback occurs. This paper uses a simple threshold discrimination condition: set the threshold to 0.5, if the output is less than 0.5, it is interpreted that the score feedback has not occurred, otherwise, the score feedback has occurred. The diagnostic results of both are that the output value of the score feedback F2 is greater than the threshold, and the output values of the other score feedbacks are less than the threshold, so the diagnostic score feedback is the rotor component defect. It can be seen from the test results that the algorithm can effectively judge the type of score feedback and is effective. Through this algorithm, redundant attributes are removed, thus simplifying the structure of the neural network and improving the accuracy of the automatic review and score feedback of the neural network. The test results before and after granular computing-neural network reduction are shown in Figure 8.

V. CONCLUSION

The attribute reduction algorithm based on granular computing is the important content of this paper. The theory of rough set and granular computing is described in detail, and a reduction algorithm combining binary granular matrix and dependency power graph is proposed. On the basis of the reduction algorithm of granular computing and neural network theory, a granular computing-neural network automatic review and score feedback algorithm model is proposed, and the data processing and reduction capabilities of granular computing are used to make up for the inability of neural networks in automatic review and score feedback. This paper proposes a neural network model, Granular Computing-Neural Network, which combines DenseNet and BiLSTM, which uses DenseNet and BiLSTM to extract local features and temporal context information of speech, respectively.

Comparing the accuracy of Granular Computing-Neural Network on the Google Speech Commands dataset with the results of related papers, it is found that Granular Computing-Neural Network has achieved better results. By training DenseNet-BiLSTM under the cloud teaching platform, the parallel computing method proposed in this paper improves the training speed by 65% compared with the direct use of asynchronous data parallelism, and the model accuracy rate is 96.7%. The automatic evaluation and score feedback algorithm of granular computing-neural network is applied to the automatic evaluation and score feedback of college English writing, and the effectiveness of the algorithm is verified by simulation experiments in MATLAB.

Through theoretical and experimental analysis, the granular computing-neural network automatic review and score feedback algorithm model proposed in this paper shows that the reduction algorithm of granular computing transforms the operation of the rough set equivalence class into the operation of binary granular matrix, which reduces the complexity of the operation. Granular computing's ability to process and reduce uncertain and redundant knowledge can well make up for the shortcomings of neural networks in analyzing incomplete or redundant knowledge. The combination of the two can synthesize the advantages of both and simplify the structure of neural networks, improve the efficiency of automatic review and score feedback, and promote the further application of neural networks in automatic review and score feedback. The lack of research on the real-time processing capabilities of neural network models deployed on cloud computing platforms is a next step.

In the future, we will further study the theory of granular computing, unify the concept and formulation of granular computing, and improve the method of attribute reduction of granular computing. Whether the choice of data discretization method is reasonable will affect the result of attribute reduction and thus affect the classification and diagnosis ability of fault diagnosis system. Therefore, the discretization problem should be further studied.

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MAJUN GE received the master's degree in foreign linguistics and applied linguistics from Chongqing University. He is currently pursuing the Ph.D. degree in English education with the School of Educational Studies, University Sains Malaysia, Malaysia. He is a Senior Lecturer with the School of Elementary Education, Chongqing Preschool Education College, China, where he has more than ten years ESL teaching experience. His research interests include TESOL and ICT.