

PAPER

Intercultural Communication Competence Improvement of Students under the International Education Management Model

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ABSTRACT

With the acceleration of globalization, international education has gradually become the core content of higher education. In this context, students have encountered lots of intercultural challenges, making the evaluation and improvement of their intercultural communication competence (ICC) a key issue. It is difficult for traditional evaluation methods, such as questionnaire surveys, interviews, and teacher evaluations, to meet the needs of current educational institutions because they are subjective, time-consuming, and inefficient. After describing the ICC evaluation process of students under the international education management model, this study proposed a new automatic evaluation method based on the dual-scale convolutional neural network (CNN) model and the bi-directional long-short-term memory (Bi-LSTM) model of characters and words. The new method evaluated students' ICC more accurately and objectively, providing a new perspective and tool for future research and educational training.

KEYWORDS

international education, intercultural communication competence (ICC), convolutional neural network (CNN) model, bi-directional long-short-term memory (Bi-LSTM) model, automatic evaluation

1 INTRODUCTION

With the development of globalization, international education has become an important component of higher education [1, 2]. Students have more opportunities to study abroad, communicate, and do internships, which provides them with a unique intercultural experience [3–6]. At the same time, intercultural communication competence (ICC) gets more and more attention and has been considered a necessary skill to help students better adapt and integrate into different cultural

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backgrounds [7, 8]. However, many students face the challenge of intercultural communication in reality, which makes their ICC evaluation and improvement particularly important.

Intercultural communication competence is related to not only language expression but also involves understanding, respect, and adaptation to cultural differences [9–11]. How to accurately and efficiently evaluate students' ICC has profound significance for educational institutions, students, and even future career development [12–16], because the evaluation helps educators understand students' strengths and weaknesses in intercultural communication, thereby providing more targeted education and training.

Traditional ICC evaluation mainly relies on subjective methods, such as questionnaire surveys, interviews, or teacher evaluations [17–19], which are not only time-consuming and inefficient but also susceptible to subjective biases from evaluators [20]. In addition, it is difficult for these traditional evaluation methods to capture the subtle changes and details of students in actual intercultural communication, thereby maybe not fully and accurately reflecting their true competence [21, 22].

This paper is divided into two parts. The first part of this paper describes the ICC evaluation process of students under the international education management model, providing a systematic and scientific evaluation framework for educational institutions. The second part introduces the dual-scale CNN model and the Bi-LSTM model based on characters and words for ICC evaluation. These models automatically extracted key word vector features and semantic features from the text, making the evaluation more accurate and objective. This study not only provides a new evaluation tool for international education but also lays a solid foundation for future research on ICC and educational training.

2 PROBLEM DESCRIPTION

In a globalized world, the ICC is the foundation of various international cooperation and exchanges. ICC improvement directly enhances the efficiency and effect of international cooperation. The research and improvement of the ICC help educational institutions attract more international students and expand their international influence. The ways to enhance students' ICC mainly include the cultivation of cultural awareness, adaptation to cultural strategies, language competence and non-verbal communication skills, intercultural team cooperation, and other aspects. That is, students are provided with various cultural background knowledge to know and understand different cultural traditions, values, and beliefs, thereby better interacting with people with different cultural backgrounds. Students are taught to identify and respond to cultural conflicts and misunderstandings, as well as how to effectively adapt and integrate into the new cultural environment. In addition, students are taught the importance of nonverbal communication, such as body language, facial expressions, etiquette, etc. In the context of internationalization, team members often come from different cultural backgrounds, and it is crucial to teach them how to promote intercultural teamwork and collaboration.

As the mobility of students increases, educational institutions need to accommodate students from different cultural, economic, and social backgrounds, which requires the education management system to have greater flexibility and scalability to meet various needs. Modern technologies, such as cloud computing and big data analysis, help organizations effectively handle this diversity. At the same time, globalization promotes the rapid development of online education and distance

learning. Educational institutions need effective technical platforms to support various aspects of online education, including content distribution, interaction, evaluation, and feedback. Modern technologies enable educational institutions to easily collect and analyze a large amount of data, ranging from students' online behaviors to their academic performance. These data provide powerful tools for managers to help them make more informed and timely decisions.

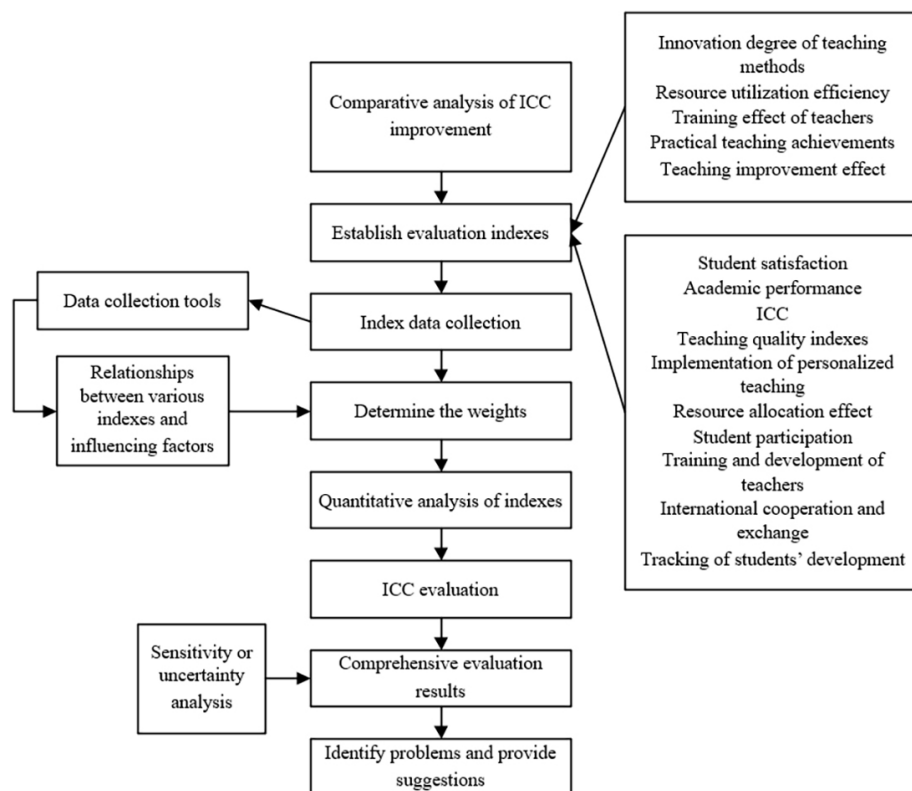


Fig. 1. Process of the ICC evaluation method

In terms of value, international education management in the big data environment helps improve the quality of education and cultivate talents with a global perspective. Big data analysis helps deeply understand the learning needs, interests, and growth trajectories of students, thereby providing a scientific basis for personalized teaching and making teaching more precise and effective. An intelligent recommendation system provides appropriate course resources and learning materials based on students' characteristics and needs, stimulating their learning interests and enthusiasm. In addition, big data technology promotes innovation in teaching methods and provides richer and more diverse intercultural teaching methods, thereby helping students comprehensively improve their intercultural communication competence.

In recent years, the development of big data technology has provided new perspectives and methods. These tools have more apparent value and significance, especially when deep learning models are used to try to evaluate the ICC of students. Under the international education management model, the social interactions, online discussions, writing samples, and video interactions of students provide rich data for ICC evaluation. Deep learning models deeply explore subtle differences in the text, thereby more accurately evaluating students' ICC. The text-based automatic scoring model provides objective, consistent, and timely evaluations for lots of students, greatly reducing the burden on educators.

In the big data environment, the content of international education management should be effective and practical, because effectiveness focuses on the degree to which teaching goals are achieved and the ICC improvement of students, while practicability focuses on the applicability and ease of use of teaching methods, technologies, and resources in practical applications. Through comparative analysis, educators are able to identify the best practices suitable for specific environments and student needs, and further improve teaching quality, thereby cultivating outstanding talents with intercultural communication competence.

The intercultural communication competence evaluation of students under the international education management model was made in several steps, namely, determining evaluation indexes, collecting and analyzing data, comparing the results, identifying problems, and providing suggestions (Figure 1). The purpose of evaluation should be clarified first, i.e., to what extent students have mastered intercultural communication skills and knowledge. Related indexes may include cultural awareness, language skills, nonverbal communication skills, cultural adaptation strategies, and the competence of resolving intercultural conflicts. A standard was set for each index to quantitatively evaluate students' performance. Based on the evaluation indexes, appropriate data collection tools were then selected, such as questionnaires, observations, interviews, or tests. Data were collected at designated times and occasions to ensure their integrity and reliability. The collected data were stored on a secure platform or database for subsequent analysis.

The data were further cleaned, transformed, and integrated to make them suitable for analysis. Suitable statistical methods or deep learning models were selected to analyze the data. Key information on the ICC of students was extracted from the analysis results. Then the actual performance of the students was compared with the pre-set standards to see if they achieved the expected level. The results were compared with previous evaluation results to see if students improved their ICC. The performance of students within the same group was compared in order to identify those whose performance was good or needed to be improved.

Finally, the specific ICC that students had gaps in was recognized. The reasons contributing to these gaps were explored, such as teaching methods, students' backgrounds, or external environments. Targeted teaching strategies or methods were proposed based on the recognized problems. Personalized learning resources or tutoring suggestions were provided based on the specific needs of students. Based on the evaluation results, whether the evaluation indexes or standards needed to be adjusted was considered in order to better reflect the ICC of students.

3 ICC EVALUATION OF STUDENTS BASED ON THE TEXT AUTOMATIC SCORING MODEL

To evaluate students' ICC under the international education management model, this study constructed an evaluation model suitable for text automatic scoring using the combined dual-scale CNN and Bi-LSTM model based on characters and words. The word vector captured the semantic meaning and contextual relationships of words, providing rich representations for the text. This study used the dual-scale CNN to simultaneously extract and evaluate text features at both character and word levels, ensuring the integrity and diversity of information. At the same time, features extracted from different scales were effectively integrated, further enhancing the model's expression ability and robustness. Bi-LSTM captured long-term dependencies and recognized complex semantic structures in the text. This model processed

text information from beginning to end, as well as from end to beginning, thereby ensuring the integrity and coherence of the text. The dual-scale CNN was combined with Bi-LSTM, which comprehensively evaluated the text from micro to macro levels, ensuring accuracy and comprehensiveness of the evaluation. Figure 2 shows the structure of the evaluation model.

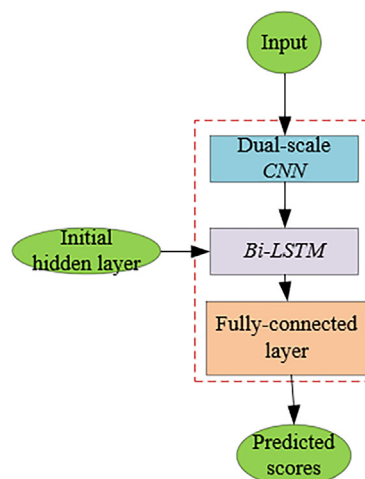


Fig. 2. Structure of the evaluation model

3.1 Extraction and fusion of evaluation text features

The input of the dual-scale CNN is the word vector representation of the ICC evaluation text of students. Therefore, it is a key step to obtain the word vector representation, which provides a foundation for subsequent feature extraction and model training. The specific steps to obtain a word vector representation were described as follows:

Step 1. Pre-processing: After removing irrelevant characters, punctuation marks, numbers, and special symbols from the text, the evaluation text was split into separate words or phrases. Specialized word segmentation tools may be required for Chinese text. For example, some common words without significant contributions to the analysis were removed, such as “of,” “is/are,” “in,” etc.

Step 2. Word vector training: For the word vector training, a large amount of unlabeled text data is usually required to train the word vector model. This study used an existing evaluation text dataset for training on the training data, which obtained the word vector.

Step 3. Obtaining the word vector representation of the evaluation text: For each word in the evaluation text, the trained word vector model was used to obtain its corresponding word vector. If certain words in the evaluation text did not appear in the training data, then specific strategies were used for processing, such as ignoring the words, using the zero vector, or adopting the word vector provided by the pre-training model.

Step 4. Text representation fusion: All text representations may need to be adjusted to a fixed length because CNN requires a fixed-size input. The adjustment was achieved by truncating the long text or adding padding to the short text. The dual-scale CNN not only required the word vector representation but may also need the character-level representation, which required further decomposition of each word into characters to obtain the character vector representation.

Step 5. Standardization: The word vector was usually standardized to ensure the stability and convergence speed of the model.

Specifically, under the assumption that the evaluation text set $F = f_1, f_2, \dots, f_b$ contains B evaluation texts, let $Q = q_1, q_2, \dots, q_l$ be the vocabulary size, q_u be the u -th word in the vocabulary, and z_{uk} be the number of times that the k -th word in the vocabulary occurs in the text f_u . For the evaluation text f_u , its vector expression was given as follows:

$$Z_u = [z_{u1}, z_{u2}, \dots, z_{ul}] \tag{1}$$

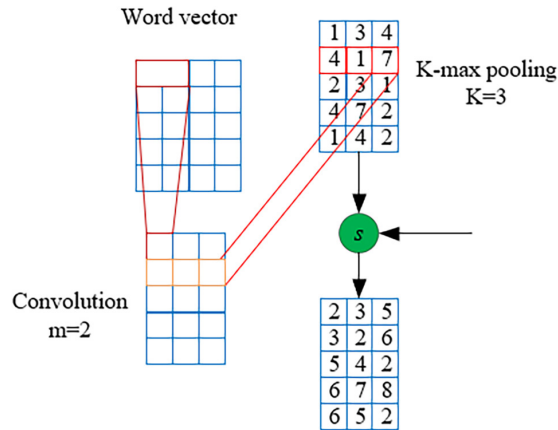


Fig. 3. Structure of dual-scale CNN processing the word vector

Figures 3 and 4 show the structures of the dual-scale CNN processing word and character vectors. To achieve the maximum efficiency of evaluation text feature representation, this study set up convolutional and feature fusion layers in the dual-scale CNN. The convolutional layer slid the input data through filters to extract local features. For text data, this meant that local patterns, such as phrases, were captured within the text. Filters of different sizes in the convolutional layer captured patterns of different lengths, providing multi-scale feature representations for text data. An appropriate number of filters were selected to compress the original data, thereby reducing the data dimension. The feature fusion layer aimed to integrate features based on both character and word scales into a unified feature representation. The fused features contained both macro and micro information about the text, representing the text more comprehensively. Figure 5 shows the overall structure of the dual-scale CNN model.

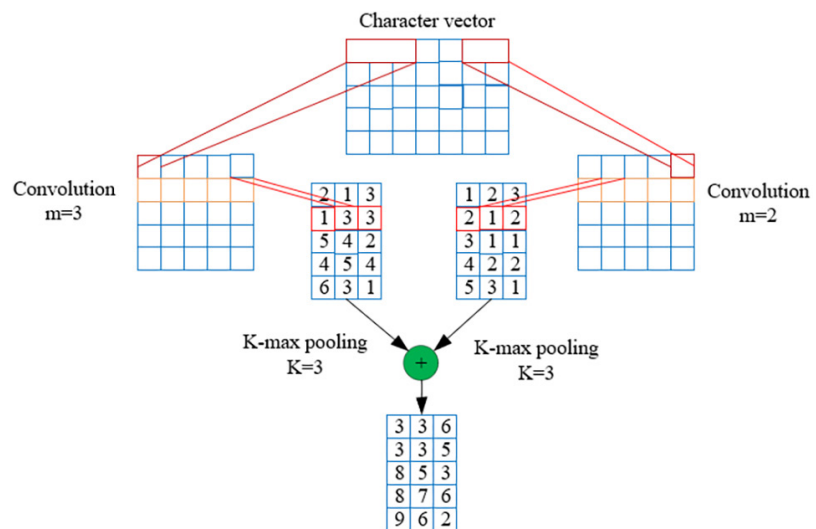


Fig. 4. Structure of dual-scale CNN processing the character vector

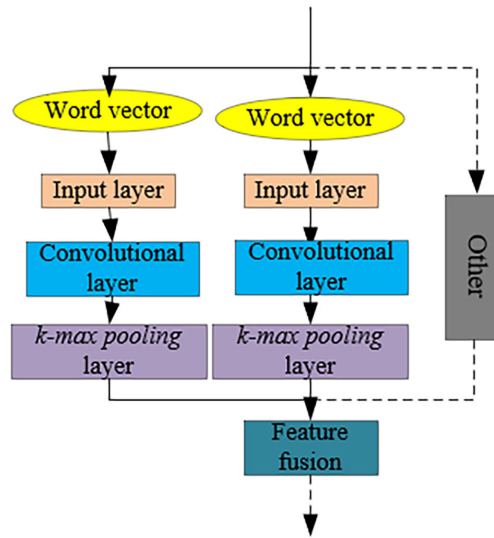


Fig. 5. Structure of the dual-scale CNN model

Specifically, the convolutional layer has two parallel convolutional sub-layers, with one processing the character vector and the other processing the word vector. Each convolutional sub-layer has multiple filters, with each filter corresponding to a specific local pattern size. The convolutional layer uses nonlinear activation functions, such as ReLU, to enhance the nonlinear expression ability of the model.

A feature matrix $a \in E^{a \times r}$ of evaluation text sequences was constructed based on the evaluation text vector:

$$a \Phi l = v \tag{2}$$

The dot product calculation operation in the above equation was performed for the feature matrix a and the convolution kernel $l \in E^{l \times f}$, which extracted feature information between words in the vector. The dimension of the matrix v was $(a - l + m) \times (r - f + m)$ after convolution. $l \in E^{2 \times f}$ was taken to extract the correlation feature information between two words. For the matrix v , a value of j , which was less than $a - l + 1$, was given. k-max pooling processed each embedded dimension $u (u = 1, 2, \dots, r)$ based on the following equation:

$$o = v_{MAX}^{j,u} = \underset{k=1}{\overset{j}{\text{MAX}}}(v^{a-l+1,u}) \tag{3}$$

Through the processing using the above equation, the sub-sequences $v_{MAX}^{j,u}$ with j maximum values of $r^{a-l+1,u}$ were obtained. The output matrix passing through the k-max pooling layer was $o \in E^{j \times (r-f+1)}$.

The feature fusion layer spliced character-based features with word-based ones, which formed a longer feature vector. According to actual tasks, different weights were assigned to the features based on characters or words to balance their contributions. Let o_{uv} be the pooling layer output of the $u \in [m, b]$ -th convolution kernel in the character channel, and o_{qk} be the pooling layer output of the $k \in [1, l]$ -th convolution kernel in the word channel, then the fusion feature matrices d_v and d_q of the character and word channels were obtained using the following equations:

$$d_v = o_{v_1} \oplus o_{v_2} \oplus \dots \oplus o_{v_b} \tag{4}$$

$$d_q = o_{q_1} \oplus o_{q_2} \oplus \dots \oplus o_{q_l} \tag{5}$$

Finally, the features of both character and word channels were fused. Let $\beta \in [0, 1]$ be the learnable parameter, then the fusion feature matrix d output by the feature fusion layer was expressed as follows:

$$d = (1 - \beta)d_v + \beta d_q \quad (6)$$

3.2 Semantic structure recognition of evaluation text

Bi-LSTM is an extension of LSTM and captures forward and backward information in text. For the ICC evaluation text of students, Bi-LSTM effectively understands its contextual relationships, thereby providing deeper semantic features for evaluation. Bi-LSTM was used in this study to extract the semantic features of evaluation text in the following steps:

Step 1: Establishing the Bi-LSTM structure. The number of units for LSTM was set, and the appropriate activation function was selected. Forward and backward propagation were added on the basis of LSTM. Forward LSTM processed the text from beginning to end, and backward LSTM processed the text from end to beginning. The LSTM model contained memory units responsible for storing information on long memory sequences, and the forget and output gates d_y and p_y controlled which information was deleted or output from the memory units, respectively. At each time step, each gate structure received the current input z_y and the hidden state v_{y-1} output from the memory units of the previous time step. Let v_y be the unit state of LSTM at time y , g_y be the output, g_{y-1} be the hidden state of the storage unit at time $y-1$, and n_d be the bias term of the forget gate. Based on the current inputs z_y , g_{y-1} , and n_d , the activation value of the forget gate for time step y was calculated. Then the sigmoid function was used to further normalize the activation value.

$$d_y = \delta(q_{dz}z_y + q_{dg}g_{y-1} + n_d) \quad (7)$$

$$u_y = \delta(q_{uz}z_y + q_{ug}g_{y-1} + n_u) \quad (8)$$

Let u_y be the activation value of the input gate, then the equation for updating the unit state was given as follows:

$$\tilde{v}_y = \tanh(q_{vz}z_y + q_{vg}g_{y-1} + n_v) \quad (9)$$

The unit state v_y of the current time step y was further updated:

$$v_y = d_y \Phi v_{y-1} + i_y \Phi \tilde{v}_y \quad (10)$$

The output information was obtained using the following equation:

$$p_y = \delta(q_{pz}z_y + q_{pg}g_{y-1} + n_p) \quad (11)$$

The bidirectional output was merged in various ways, such as splicing, averaging, or weighted averaging.

Step 2: Model training. An appropriate loss function was used to optimize the evaluation task. This study adopted the cross-entropy loss function. In addition, this study selected the Adam optimizer and set parameters such as learning rate and batch size. Multiple rounds of iterative training were conducted until the model converged or reached the established termination conditions.

Step 3: Feature extraction. The evaluation text was input into the model using the trained Bi-LSTM model, which obtained the hidden state of each time step or the last time step. These hidden states represented the semantic features of the text and were used as input for subsequent evaluation or classification.

Step 4: Combining with dual-scale CNN features. In order to fully leverage the structured and semantic information within the text, the features derived from the dual-scale CNN were integrated with those extracted from Bi-LSTM, resulting in a comprehensive feature vector. According to the specific requirements of the task, these features were directly used for scoring, classification, or other tasks.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Figure 6 shows the scoring frequency histogram of students' ICC evaluation text. As shown in the figure, the scoring range is between 0 and 130, while the main non-zero values in the density distribution are between 50 and 95, indicating that most of the scores are concentrated within this range. In this range, the scores of 50 and 75 have significant peaks, which are 100 and 750, respectively, indicating that there are more students in these two scoring ranges. Within the scoring range of 75 to 95, there is a significant concentration of data, especially between 75 and 85, which may indicate that the majority of students' ICC is within this range. The histogram data provide educational institutions and educators with a clear perspective on the ICC distribution of students. Based on these data, corresponding training strategies can be developed for students at different ability levels to improve their ICC.

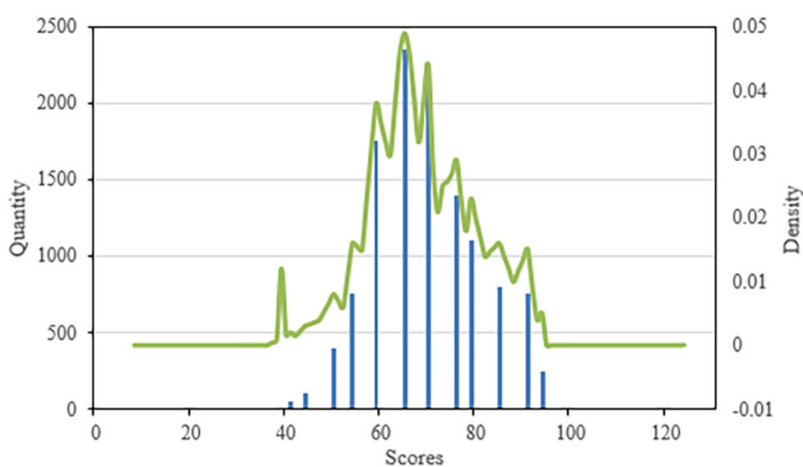


Fig. 6. Scoring frequency histogram

Table 1. Experimental results of different convolution kernel types

Word-Scale Convolution Kernel Types	Character-Scale Convolution Kernel Types	RMSE	SA (%)
(2,3,4)	(2,3,4)	4.62	76.25
	(3,4,5)	4.69	76.23
	(2,3,4,5)	4.41	76.45
(2,3,4,5)	(2,3,4)	4.69	76.39
	(3,4,5)	4.89	75.48
	(2,3,4,5)	5.12	74.26

Table 1 shows the experimental results of the dual-scale CNN under different word-scale and character-scale convolution kernel types. It can be seen from the table that the combination of the word-scale convolution kernel type (2,3,4) and the character-scale convolution kernel type (2,3,4,5) has the best performance, with the lowest root mean square error (RMSE) (4.41) and a relatively high SA value (76.45%). However, the combination of the word-scale convolution kernel type (2,3,4,5) and the character-scale convolution kernel type (2,3,4,5) performs poorly, with the highest RMSE (5.12) and the lowest SA value (74.26%), which indicates that more convolution kernels do not mean better results for the dual-scale CNN. Therefore, it is necessary to find a suitable convolution kernel combination to achieve the optimal effect.

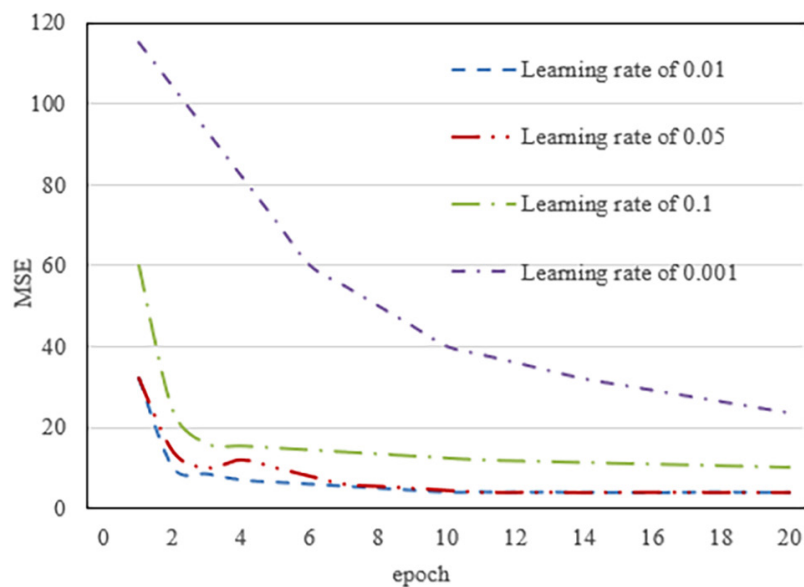


Fig. 7. Comparison of learning rate initialization

Figure 7 shows the performance of the Bi-LSTM model in 21 consecutive training epochs under different learning rates in terms of mean square error (MSE). As shown in the figure, the model with a learning rate of 0.01 performs best within 20 epochs, with an MSE of 3.96, which is the lowest of the four learning rates. The model with a learning rate of 0.001 learns at a slower speed, and more epochs are required to achieve a lower MSE. Although the initial decline rate of the model with a learning rate of 0.05 and 0.1 is relatively fast, its performance is not as good as the model with a learning rate of 0.01 in the later stage. Choosing an appropriate learning rate is the key to optimizing the model's performance. Too small a learning rate may lead to slow training speed, while too large a learning rate may lead to instability and oscillation. Based on the above analysis, a learning rate of 0.01 may be the best choice within the limited number of epochs. If there is sufficient training time and resources, a learning rate of 0.001 can also be considered, but more epochs are needed to achieve better performance.

Figure 8 shows the loss curve of the Bi-LSTM model. As shown in the figure, the Bi-LSTM model exhibits strong learning ability in the early training stage on the whole, with a rapid decrease in loss value. When the loss drops to a lower range, the learning speed of the model slows down and the loss value begins to oscillate, which is common, especially when the model begins to approach its optimal performance. To further optimize the model and avoid overfitting in subsequent training, it is possible to consider using the early stopping technique, adjusting the learning rate, or introducing the regularization strategy. Combined with the text automatic

scoring scenario, such a loss curve indicates that the model has achieved relatively good performance, but there is still room for subtle tuning.

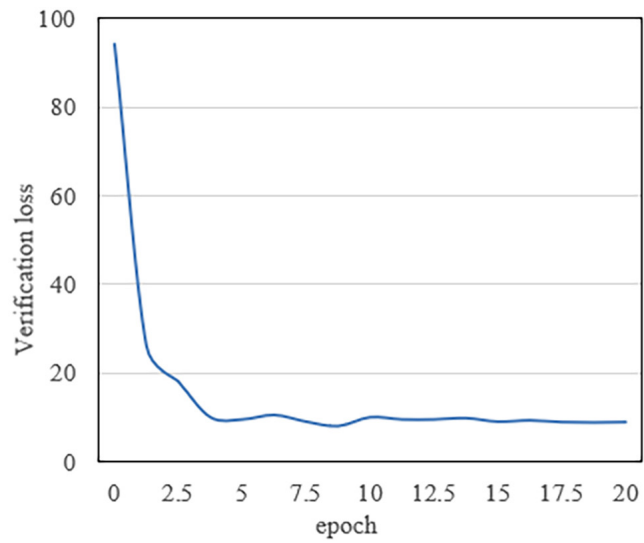


Fig. 8. Loss curve

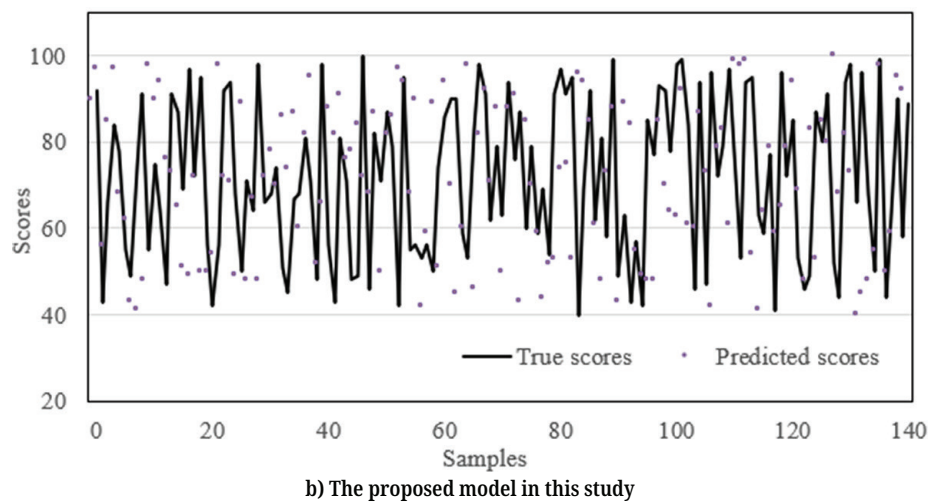
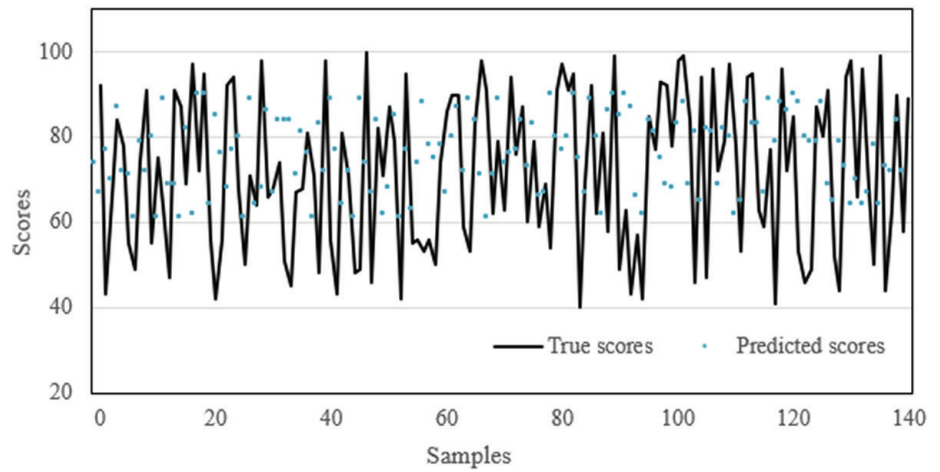


Fig. 9. Prediction results of each model

Text automatic evaluation is a challenging task, especially when evaluating the ICC of students, because it evaluates not only the language correctness of the text but also how students express, communicate, and understand information in an intercultural context. Based on the data in Figure 9, a comparative analysis can be made for the evaluation performance of the attention mechanism-LSTM model and the model proposed in this study. In terms of data, the scores predicted by the proposed model are very close to the true scores on many samples, while the differences between the predicted scores of the reference model and the true scores are relatively large. The scores predicted by the proposed model are relatively stable on most samples, and the differences between them and the true scores are not large. However, there are significant differences between the predicted scores of the reference model and the true scores on certain samples, which may indicate insufficient stability of the reference model.

Therefore, when evaluating students' ICC under the international education management model, the model combining dual-scale CNN with Bi-LSTM proposed in this study shows high accuracy and stability, which proves that the proposed model evaluates the text from micro to macro levels effectively and comprehensively. However, the traditional or reference model may only capture certain characteristics of the text, leading to deviations in its evaluation results from the actual situation. Overall, the research method used in this study has strong effectiveness and advantages in evaluating the ICC of students.

5 CONCLUSION

This research mainly studied a new evaluation model that combined dual-scale CNN with Bi-LSTM, aiming to comprehensively evaluate the text from micro to macro levels, especially the ICC of students under the international education management model. In the experiment, the MSE of the Bi-LSTM model under different learning rates was compared, and the optimal learning rate was selected to ensure the model's optimization. Then the loss curve of Bi-LSTM was analyzed to confirm the convergence and stability of the model. Finally, the real text data were predicted and evaluated using the proposed model and a reference model, and they were compared with true scores. Among multiple learning rates, the model of some learning rates achieved better performance, but problems of overfitting or slow convergence speed existed. By observing the loss curve, it was found that Bi-LSTM performed well under certain conditions with stable performance. In the actual evaluation task, the consistency between the scores predicted by the proposed model and the true scores was significantly higher than that of the reference model, demonstrating high accuracy and stability.

The evaluation model proposed in this study demonstrated superior performance in evaluating students' ICC under the international education management model. This combination model method not only comprehensively evaluated the text from micro to macro levels but also demonstrated high accuracy and stability in the experiment, making it innovative and valuable in application to some extent in related research fields.

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