DEEP LEARNING NETWORK-BASED EVALUATION METHOD OF ONLINE TEACHING QUALITY OF INTERNATIONAL CHINESE EDUCATION

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ABSTRACT

The development of vocational education in the information age requires us to think about the path and strategy of active change. Course teaching quality evaluation should also shift from passive evaluation of online teaching development to active construction of a mixed teaching quality evaluation system. In the information age, the development of teaching resources is dizzying. From paper to digital, from single to diverse, from offline to online, from scarcity to mass—various changes impact the traditional teaching model. Aiming at the online teaching quality evaluation of international Chinese education on the Internet, this paper proposes a method based on deep learning. Firstly, this paper proposes an index system construction and evaluation index weighting for online teaching of international Chinese education, and collects online data as a corpus at the same time. Then construct the CNN_BiLSTM_Att model, which is composed of the CNN module, the BiLSTM module and the Att module. Finally, compare with other model experiments. The experimental results show that CNN_BiLSTM_Att has achieved the best results in the evaluation index results, with P and F1 reaching 97.89% and 97.85%. Compared with other models, the overall effect is improved by 2%~5%. From this, the superiority of the model in the online teaching quality evaluation standard task of this paper can be obtained.

KEYWORDS

Deep learning technology; teaching evaluation; international Chinese education; online teaching

PAPER INDEX

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1. INTRODUCTION

Data in the teaching and learning process, deep learning technology has an impact on various elements of the education system in the analysis stage, strategy selection stage and evaluation stage of instructional design. Meet the teaching needs of teachers who need a lot of investigation and not enough experience guidance, and provide guidance for "learner-centered" instructional design [1-3].

(1) The analysis phase of instructional design: Conduct a learning needs analysis. Through the deep learning technology to analyze the student's online learning behavior, it is possible to accurately grasp the students' mastery of knowledge. Learner characteristic analysis, the application of deep learning can help teachers determine the cognitive development level of learners and analyze the starting ability of learners[4].

(2) Strategy selection phase: Deep learning technology has changed the traditional teaching environment of teachers and courseware, and formed an intelligent teaching and learning environment that can analyze intelligently and assist students' personalized learning [5-7].

(3) Teaching evaluation stage: Teacher and student evaluation, based on deep learning data analysis technology, makes the evaluation of students' learning results more scientific and accurate, reduces the difficulty of analysis, shortens the feedback cycle, and enables teachers to have a more accurate grasp of students' learning status. The artificial intelligence technology based on deep learning assists teachers in supervising and evaluating students' learning behavior, reducing the burden of teachers' teaching management, and the intelligent marking system helps teachers reduce repetitive work [8].

International Chinese education is not only a discipline, but also a "national and national cause", with the dual attributes of discipline and career. As a discipline, since its inception, international Chinese education has been "growing up with the progress of the Republic" [9]. Encourage teaching institutions, teachers, students and resource builders to adjust, change and innovate accordingly. Especially the sudden epidemic has exacerbated this change. How to effectively construct resources to deal with the new online teaching quality evaluation method is a problem we need to solve.

Online Chinese teaching for international students provides conditions for liberating teachers, innovating the research of international Chinese education, solving old problems, discovering new problems, exploring new laws, and enriching the content of subject research. It is necessary to make full use of the opportunity of international Chinese online teaching, data, and teachers' division of labor and cooperation models brought by online teaching. On the other hand, it is necessary to start from promoting the upgrading of international Chinese education and international Chinese education, improve online Chinese teaching from the aspects of system, model, platform construction, etc., and lead the development of online Chinese teaching [10-11].

Under traditional conditions [12], the evaluation data is obtained by means of a questionnaire survey, and then the results are finally obtained through tedious sorting

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work. This method requires a lot of time and material resources, and there are problems such as inaccurate data collected in special questionnaires. Using intelligent technical means to obtain real-time online course evaluation data and analyze it, the results obtained by using deep neural network learning technology have high accuracy, and the feedback results are used as the basis for teachers to change their learning methods.

Therefore, this paper proposes a method based on deep learning. The main work is highlighted as follows:

(1) The evaluation standard system is constructed for the online teaching quality evaluation method of international Chinese education on the Internet.

(2) Design a set of analytical methods to weight the evaluation indicators.

(3) The CNN_BiLSTM_Att network framework is built to realize the online teaching quality evaluation of international Chinese education [13-14].

2. METHODOLOGY

2.1. CONSTRUCTION OF ONLINE TEACHING QUALITY EVALUATION INDEX SYSTEM

Online teaching quality evaluation system is an important foundation and guarantee for online teaching quality, is shown in Fig 1. In order to ensure that the online teaching quality evaluation index system plays the functions of supervision and incentives, it is required to follow the objectivity, purpose, consistency, comprehensiveness and operability of the indicators [15].

(1) The principle of objectivity is important guarantee for the effectiveness and credibility of online teaching quality evaluation results, and requires scientific formulation. The process of evaluation criteria should be open and transparent, and the evaluation results should be collected to ensure the reliability of online teaching quality evaluation data.

(2) This paper is to improve the level of teaching evaluation quality, stimulate teachers' enthusiasm for teaching.

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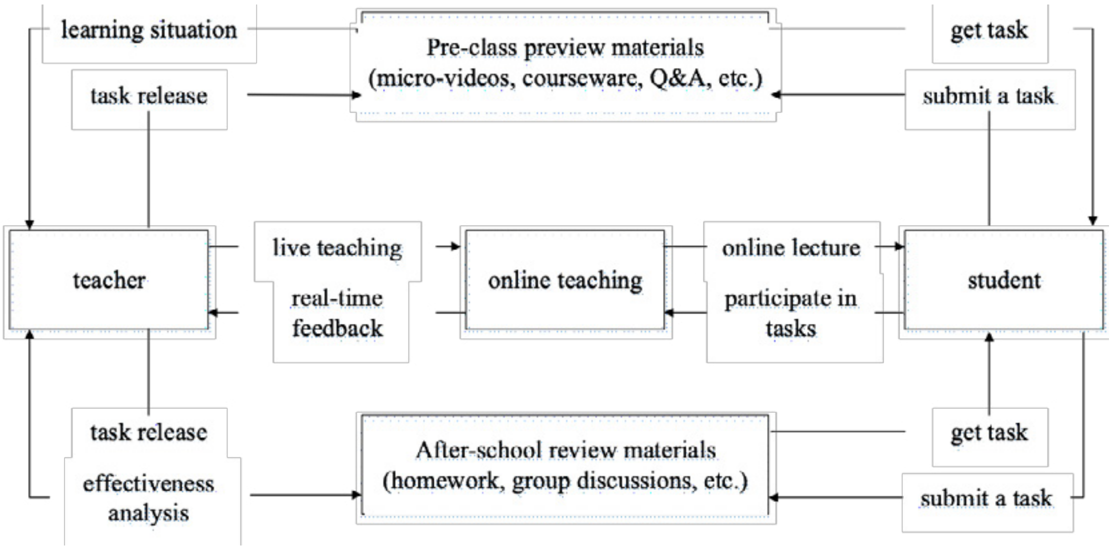

Figure 1. Online teaching quality evaluation index system

(3) The principle of consistency refers to scientific, standardized and systematic selection of online quality evaluation indicators, requires evaluation indicators to be based on the laws of online teaching at different ages.

(4) The principle of comprehensiveness requires that online teaching quality evaluation indicators should cover various cannot be limited to certain aspects and certain indicators.

(5) The principle of operability requires system is practical and feasible, and can be carried out continuously and effectively on a large scale.

2.2. WEIGHTING OF EVALUATION INDICATORS BASED ON ANALYTIC HIERARCHY PROCESS

Online teaching quality evaluation index system based on the questionnaire survey method and the expert online consultation method based on the analytic hierarchy process. Colleges and universities at different levels need to consider many factors such as online course settings, teaching methods, and student source quality when building an online teaching quality evaluation system [16-18].

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Table 1. Weights of online teaching quality evaluation indicators

Evaluation subject	Weights	Evaluation indicators	Weights	Weights ratio
Teaching management department	21. 61%	teacher behavior	50%	10. 805%
		student behavior	50%	10. 805%
Teaching supervision	18. 31%	teaching process	48. 5%	8. 88%
		teaching effect	26. 67%	4. 88%
		instructional Design	15. 27%	2. 8%
		education resources	9. 56%	1. 75%
Student	34.82%	teaching method	45. 35%	15. 79%
		teaching content	24. 2%	8. 43%
		teaching effect	19. 72%	6. 87%
		teaching attitude	10. 72%	3. 73%
Ministry of international Chinese education	14. 32%	teaching materials	61. 44%	8. 88%
		assessment link	26. 84%	3. 84%
		teaching routine	11. 72%	1. 68%
Chinese teacher	10. 95%	teaching readiness	60%	6. 57%
		teaching implementation	20%	2. 19%
		teaching feedback	20%	2. 19%

(1) According to the index system of online quality evaluation, target evaluation layer online teaching quality evaluation, and the criterion evaluation layer includes the teaching management department, the evaluation of teaching supervision, and students, the evaluation of the ministry of international Chinese education and the self-evaluation of Chinese teachers. The scheme evaluation layer is the evaluation index of each evaluation subject, and a hierarchical structure evaluation model is constructed.

(2) Constructing a comparative judgment matrix by conducting online special consultation and analysis on the relative importance of the pairwise comparison between the evaluation subjects and the evaluation indicators to 10 experts;

(3) Carry out the consistency test, the results show that each judgment matrix CR < 0.1, all passed the test;

(4) The weight of the quality evaluation index, calculation results is shown in Table 1.

2.3. CNN_BILSTM MODEL

Online teaching quality evaluation model for international Chinese education is constructed convolutional neural network (CNN) and bidirectional long short-term memory network (BiLSTM)-based. The attention mechanism is introduced on the basis of BiLSTM and CNN, and structure is shown in Fig 2.

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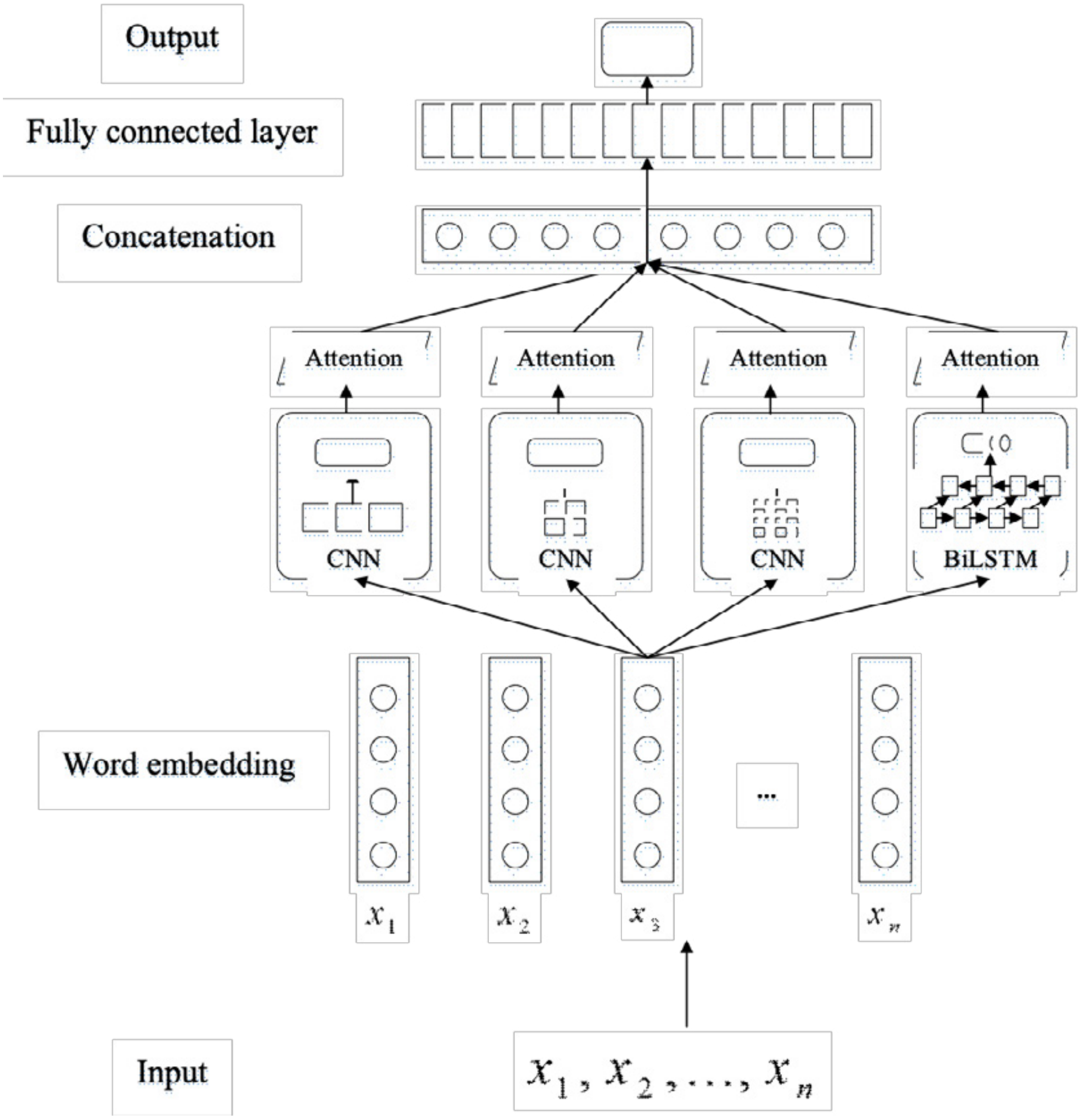

Figure 2. CNN_BiLSTM model

2.4. WORD VECTOR REPRESENTATION LAYER

After the text data is preprocessed, it is vectorized and then input into the online teaching quality evaluation model for the next step [19]. The corpus data size is about 6.3GB, and the Word2Vec tool is used for large-scale text training to convert the text into a low-density vector space. This paper selects the Word2Vec tool skip-gram model to training word-vectors. The skip-gram model takes all the words in the corpus as the central word, and predicts the lexical information of its context through the conditional probability distribution of the correspondence between the central word and the context. The expression formula is as follows:

$$P(W_i | W_t) = \frac{P(W_i | W_t)}{P(W_t)} P(W_i) \qquad (1)$$

where $i = t-1, t-2, t+1, t+2$, W_i is the context, that is, the representation vector of the surrounding words; W_t is the center word; word-vectors obtained by

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training as $[W_1, W_2, ..., W_n]$, where n is the total number of text words. The word embedding layer converts words into$[x_1, x_2, ..., x_n]$. The training parameters of the Word2Vec is shown in Table 2.

Table 2. Word2Vec model parameters

parameter	value	Parameter meaning
sg	1	training model selection Skip-gram
window	5	window size
min_count	3	Minimum number of occurrences of a word
vector_size	350	vector dimension
epoch	8	number of iterations
hs	0	negative sampling
negative	6	number of negative samples

2.5. CNN NETWORK

As a special type of forward neural network, CNN is used in the field of natural language processing (NLP) in recent years [20]. The basic structure is divided into three parts, input layer, convolutional layer and pooling layer, and fully connected layer, as shown in Fig 3. The features extracted by the convolution layer first represent the text in the form of word vector matrix, and then scan the matrix through convolution kernels of different sizes. During the scanning process, the parameter values of the filters composed of the convolution kernels are fixed. After filtering new feature map is mapped, and all elements on the feature map come from filters with consistent parameters.

(1) Enter the evaluation index text input sequence $S = \{x_1, x_2, ..., x_n\}$, the pre-trained word vector is R^d. The convolution formula for the number of words h in each window is:

$$c_i = ReLU\left(\omega w_{i:i+h-1}\right) + b \qquad (2)$$

where, c_i is the convolution result; ReLU is the nonlinear activation function; i is the number of words taken per convolution.

(2) The text sequence is n, and the window length is n-h+1. Result formula is:

$$\mathrm{C} = [C_1, C_2, \ldots, C_{n-h+1}] \qquad (3)$$

(3) Then, the pooling operation is performed on the result of the convolutional layer according to the pooling layer, and the output sequence features the parameters and calculation next layer to prevent over-fitting.

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(4) Finally, the CNN model convolves the contextual semantic content of the word window to better represent the local features of the text sequence.

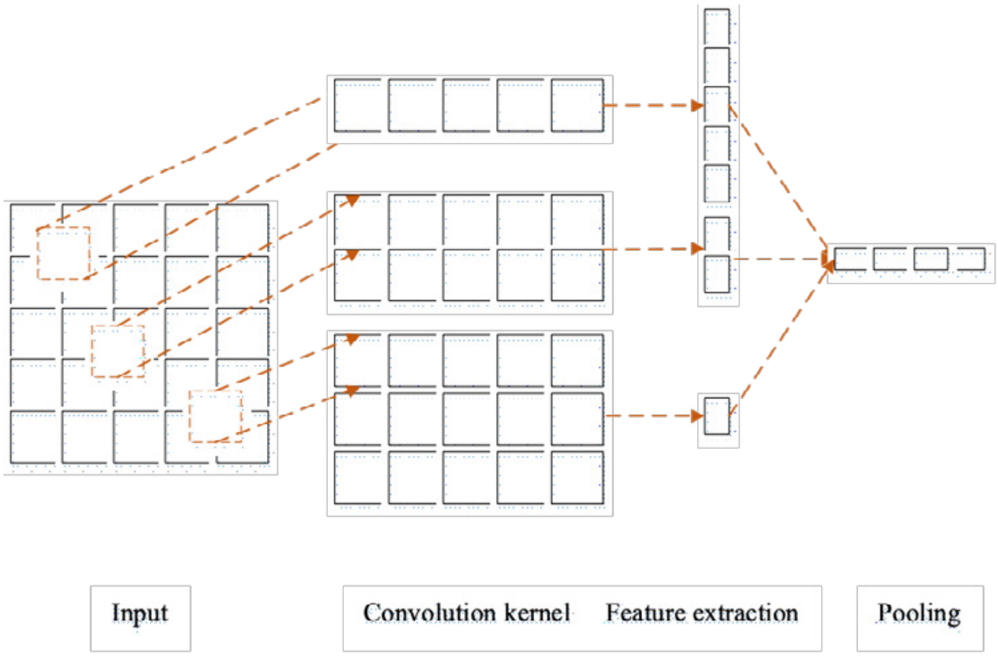

Figure 3. CNN network structure example

2.6. BILSTM NEURAL NETWORK LAYERS

LSTM is a special recurrent neural network (RNN) composed of one cell unit and three gates, is shown in Fig 4. The cell unit is the core computing power and records the current computing state. Forget gates, input gates, and output gates regulate the flow of information to and from memory cells. The forget gate clears the memory cells of useless information. The input gate selects the input information of the current memory cell. The output gate determines the final output of the information, so that the storage unit can effectively store the semantic information of a longer sequence.

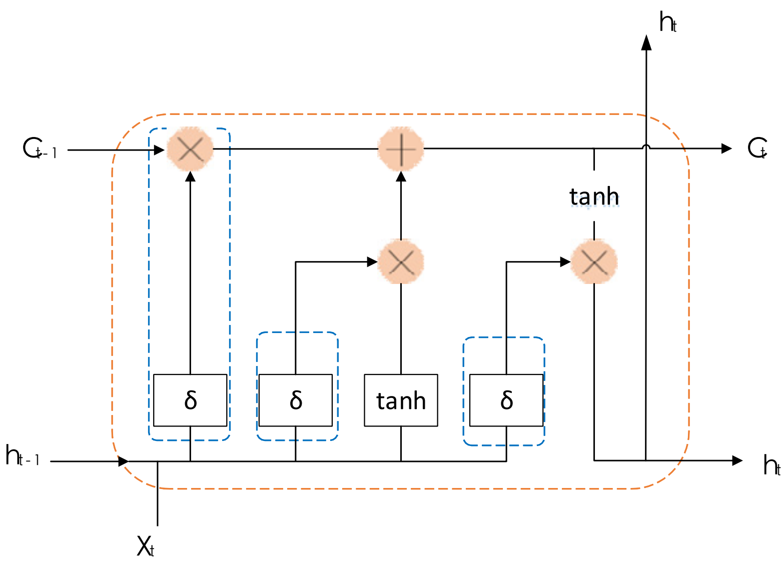

Figure 4. LSTM network structure example

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(1) The LSTM unit calculation process is as follows:

$$i_t = \delta(W_i x_t + U_i h_{t-1} + b_i) \tag{4}$$

$$o_t = \delta(W_o x_t + U_o h_{t-1} + b_o) \tag{5}$$

$$f_t = \delta(W_f x_t + U_f h_{t-1} + b_f) \tag{6}$$

where x_t is the input text vector; δ is the sigmoid function and tanh is the activation function; i_t, o_t, f_t are the input gate, output gate and forget gate, respectively.

(2) The information unit stored at time t is c_t, where the input gate and forget gate are not used to adjust the information unit.

$$c_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{7}$$

where, $W_i, W_o, W_f\, and\, W_c$ are the weights of different gate control mechanisms on the input text vector x_t; U_i, U_o, $U_f\, and\, U_c$ are the weights of different gate control mechanisms on the hidden layer vector h_{t-1}; b_i, b_o, $b_f\, and b_c$ are bias vectors.

(3) Then, the unit information input gate at the previous moment is stored in c_t.

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t \tag{8}$$

$$h_t = o_t \tanh(c_t) \tag{9}$$

where, the hidden-layer h_t is the output gate and the storage gate c_t.

(4) Finally, the forward and backward outputs of the LSTM unit at time t are concatenated by using and building the BiLSTM network layer is shown in Fig 5.

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \in R^n \tag{10}$$

where n represents the vector set.

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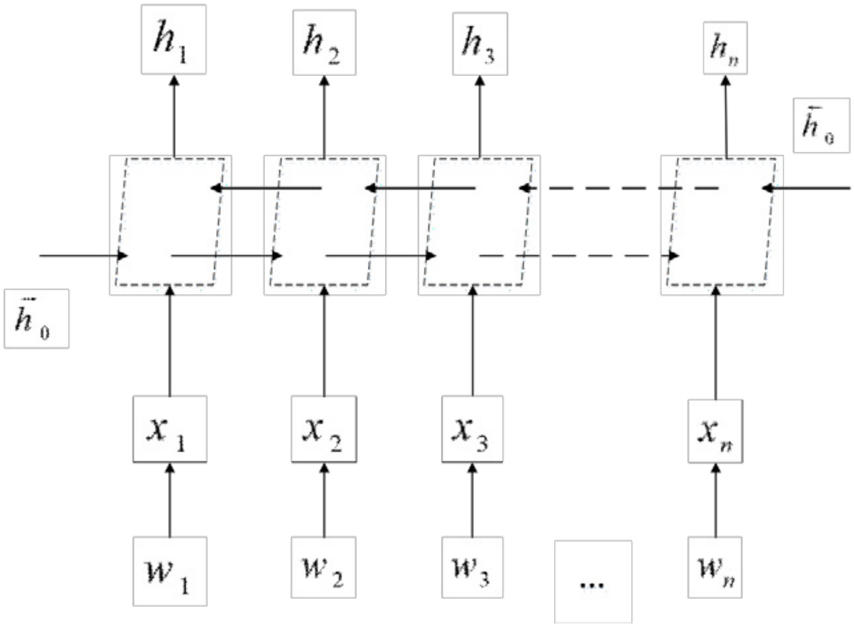

Figure 5. BiLSTM network structure example

2.7. ATTENTION MECHANISM

Although BiLSTM neural network can establish context-related semantic vector information, it does not highlight the relevance of current semantic information and context [21-22]. Introducing the attention mechanism at the output of the BiLSTM layer can effectively emphasize the importance in the contextual information, and enhance the feature expression of semantic information. The attention mechanism is shown in Fig 6.

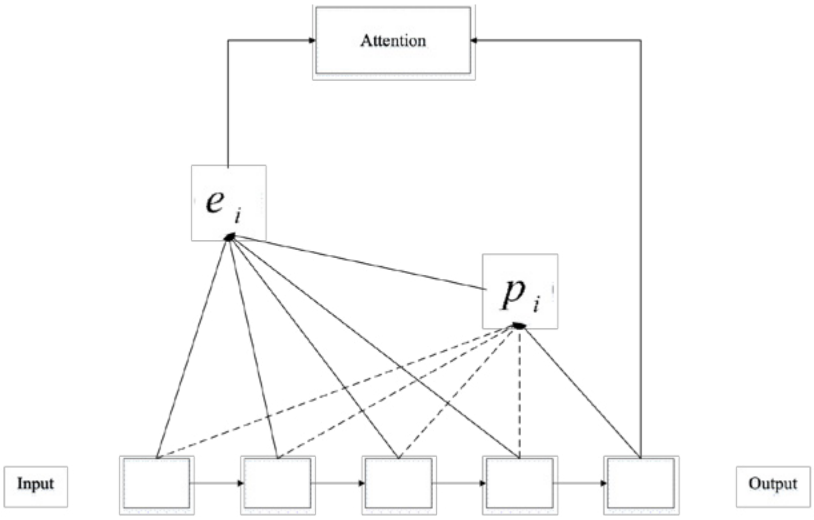

Figure 6. attention mechanism structure

(1) First, calculate the weight score e_i as shown in the formula:

$$e_i = \tanh(W_i h_t + b_i) \tag{11}$$

where, W_i is the weight matrix; h_t is the BiLSTM output vector; b_i is the bias vector.

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(2) Then, adopt the softmax function to calculate the attention mechanism weight score.

$$P_i = \frac{\exp(e_i)}{\sum_{i=1}^{n} \exp(e_i)} \tag{12}$$

(3) Finally, the point multiplication and accumulation operations are performed on the output vector h_t of the BiLSTM layer and the weight vector P_i to obtain the output Attention of the attention layer.

$$\text{Attention} = \sum_{i=1}^{n} P_i h_t \tag{13}$$

2.8. OUTPUT LAYER AND LOSS FUNCTION

A fully connected layer is introduced after the attention layer [23]. First, the weighted vector of text features is mapped into the label space of evaluation categories. Then the Dropout mechanism is introduced after the fully connected layer to avoid the weight update only relying on some features and model overfitting. Finally, the softmax classifier is evaluation category to which the text belongs, and the model prediction result is directly output.

Among them, set the softmax classifier loss function as the overall training of the model:

$$\text{Loss}\left(y, \hat{y}\right) = -\sum_{i=1}^{k} y_i \ln \hat{y}_i \tag{12}$$

where, $\hat{y}$ is the label normalization probability; y is the true label probability; the Adam optimizer is set to continuously update the model parameters and continuously reduce the loss function value of the model.

3. ACTUAL CASE ANALYSIS AND VERIFICATION

3.1. DATA DESCRIPTION

In the 2019-2021 online storage data of International Chinese Education Online Teaching Quality Evaluation, text is randomly selected as the corpus. The experiment is carried out by means of cross-validation, and the training set 80%, validation set 10% and test set 10%.

The development environment is Linux system, GPU uses NVIDIA GeForce RTX 2080Ti (11GB), Python version 3.6.5, framework uses pytorch1.7 and tensorflow1.15 version, CUDA uses version 10.1.

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The experiment adopts a 3-layer CNN model architecture[24-25]. The word vector convolution windows are set to 3, 4, and 5 respectively. After the pooling operation, the outputs of each layer are fused to enrich the local features of the context. Set the number of LSTM units to 128 and the dropout ratio to 0.5. A multi-class cross-entropy loss function is used. Set the batch sample size to 32, the number of training rounds to 20, optimizer Adam, and cross-validation to evaluate the prediction performance, where models hyperparameter settings are shown in Table 3.

Table 3. Setting of experimental parameters

parameter	value	parameter	value
vee_win	100	activation	relu
vec_dim	4	lstm_untis	128
lr	0.001	dropout	0.5
max_len	100	optimizer	Adam
mum_filters	128	batch_size	32
kernel_size	3、4、5	epochs	20

3.2. MODEL PREDICTION AND EVALUATION INDEX

The experimental evaluation system includes recall rate (R), precision rate (P) and F_1 (F-measure) as indicators for evaluating model performance. The specific formulas of each standard are as follows:

$$R = \frac{TP}{TP + FN} \tag{14}$$

$$P = \frac{TP}{TP + FP} \tag{15}$$

$$F_1 = \frac{2PR}{P + R} \tag{16}$$

where, TP is the correct number of correct text predictions; FP is the correct number of incorrect text predictions; FN is the correct number of correct text predictions; F_1 is the harmonic mean of precision and recall.

3.3. COMPARISON OF PREDICTION RESULTS BETWEEN DIFFERENT MODELS

Mechanism of CNN neural network, LSTM and Attention mechanism in model fusion is also discussed. Ten groups of comparative experiments are set up, and the input is word2vec pre-trained word vector. To verify the influence of various models on the expression and extraction of text features when processing text sequences. The comparative experiment is constructed as follows.

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(1) CNN model: CNN performs convolution, pooling, and Flatten operations on word vectors. The input extracts the local features, and uses the fully connected layer to reduce the dimension. Finally, the softmax classifier is used to output the prediction result.

(2) TextCNN model: Set 3 convolution kernel windows of different sizes. Convolutional layer and pooling layer with the same parameters, splicing the output vector of the pooling layer by line, enriching the semantic expression of local features of the text.

(3) LSTM model: The input sequence is used for backward semantic modeling, the high-level features of the text are extracted, the two fully connected layers are connected to reduce the dimension, and the prediction result is directly output.

(4) CNN_LSTM model: First use CNN to extract the local features, and then use LSTM to extract the backward semantic information output by CNN.

(5) LSTM_CNN model: first use LSTM for backward semantic modeling, and then use CNN to extract local features from the output of LSTM.

(6) CNN-BiLSTM model: First use CNN to extract the local features and then use BiLSTM to extract the forward and backward semantic information output by CNN, and further construct the feature expression of the text.

(7) BiLSTM model: Forward and backward semantic modeling is performed on the input sequence, high-level features of the text are extracted, two fully connected layers are connected to reduce the dimension, and the prediction result is directly output.

(8) CNN_Att model: CNN extracts the local features of the input sequence, and the Attention mechanism weights the text features to reduce the impact of noise features on the classification effect.

(9) BiLSTM_Att model: BiLSTM constructs the contextual semantic information of the input sequence, extracts the high-level features of the text, and the Attention mechanism weights the text features to reduce the impact of noise features on the classification effect.

(10) CNN_BiLSTM_Att model: CNN extracts the local features of the input sequence, and then uses BiLSTM to extract the forward and backward semantic information output by the CNN, and further constructs the feature expression of the text. The Attention mechanism weights the text features to reduce the influence of noise features on the classification effect.

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Table 4. Results of different models.

Model	P/%	R/%	F_1/%
CNN	86.93	87.23	86.31
TextCNN	88.31	87.62	89.64
LSTM	89.20	90.31	91.24
CNN_LSTM	90.98	91.98	90.31
LSTM_CNN	92.35	93.09	93.02
CNN-BiLSTM	94.13	93.92	93.97
BiLSTM	93.16	94.36	92.49
CNN_Att	96.20	96.08	93.52
BiLSTM_Att	94.12	93.92	93.49
CNN_BiLSTM_Att	97.89	97.76	97.85

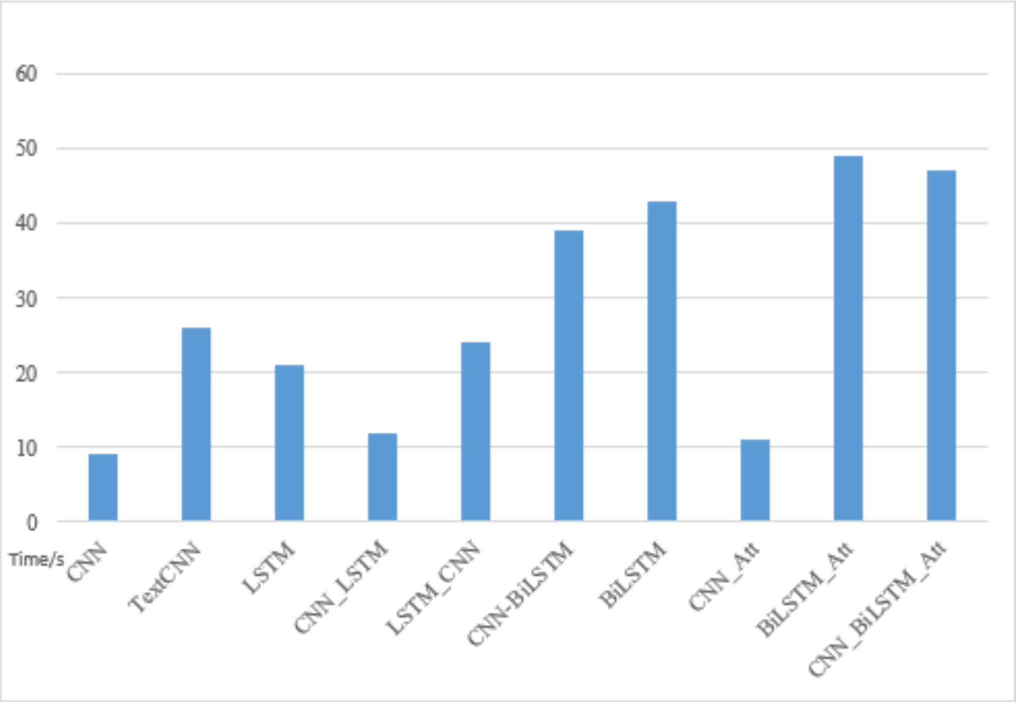

Figure 7. Execution time of models

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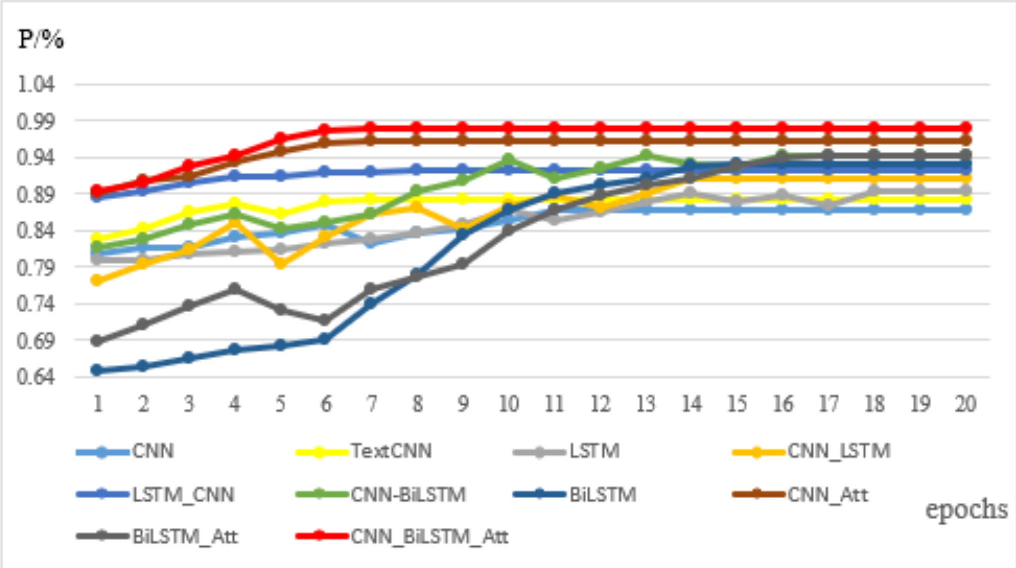

Figure 8. Precision trend of validation set of models

After multiple rounds of experiments and cross-validation of the experimental results, the evaluation results of various baseline models and fusion models are shown in Table 4, and the model execution time is shown in Fig 7. Visually demonstrate the superiority of the CNN_BiLSTM_Att model, the training process of each model is analyzed, and the accuracy change process of the validation set for each model training process is shown in Fig 8.

From the experimental results in Table 4, CNN_BiLSTM_Att model proposed in this paper has achieved the results in the evaluation index results, with F1 reaching 97.85%. Compared with other models, the overall effect is improved by 2%~5%. The superiority of this model can be obtained. According to the change trend of the accuracy rate of the validation set of various algorithm models during the training process, due to the characteristics of the corpus, the various models with CNN as the baseline basically reach the convergence state after 10 epochs, and the accuracy rate is high. The model with LSTM as the baseline has a turbulent trend as a whole, and it basically reaches convergence after 18 epochs. The variation trend of the accuracy rate of the validation set of the model in this paper is the best, reaching a state of convergence after 7 epochs, and the accuracy rate converges at 97.89%, which is significantly higher than other models in the comparison experiments, which further verifies the effectiveness and robustness of the model in this paper.

4. CONCLUSION

Aiming at the characteristics of online teaching quality evaluation of international Chinese education on the Internet, this paper first proposes the online teaching quality evaluation method of international Chinese education on the Internet to construct the evaluation standard system and to give weights to the evaluation indicators. Then, combined with the characteristics of CNN, LSTM and Attention mechanism, CNN_BiLSTM_Att-based Chinese education online teaching quality evaluation.

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(1) The model extracts text local features within word windows through a multi-layer CNN structure. At the same time, the local feature representation of the concatenated text is used as the input of BiLSTM.

(2) BiLSTM performs forward and backward text semantic modeling to obtain high-level feature representations of text sequences.

(3) The Attention mechanism performs feature weighting to reduce the influence of noise features.

The experimental results show that the execution efficiency and accuracy of the CNN_BiLSTM_Att model have achieved excellent results in various model comparison experiments, which are suitable for online teaching quality evaluation of international Chinese education. In the following research, we will focus on further analysis from the aspects of word vector encoding, attention mechanism algorithm, overall model structure and model hyperparameter settings to improve the overall efficiency of the model.

CONFLICT OF INTEREST

The authors declared that there is no conflict of interest

REFERENCES

(1) Wu, Y., & Wang, J. (2022). **Three-stage blended Chinese teaching online and offline for international students: a case study on Chinese teaching for international students in s university**. *Journal of Higher Education Research*, 3(2), 207-211.

(2) Yang, H., Chen, J., & Zhan, X. (2022). **"Integrated" Ideological and Political Education System for TCSOL Major**. *The International Conference on Artificial Intelligence and Logistics Engineering. Springer, Cham.*

(3) Kong, L., Woods, O., & Zhu, H. (2022). **The (de) territorialized appeal of international schools in china: forging brands, boundaries and inter-belonging in segregated urban space**. *Urban Studies*, 59.

(4) Owens, L. M. D., & Kadakia, C. (2022). **Instructional Design in a Digital Age: A New Model Is Taking Hold**. *The Learning Ideas Conference. Springer, Cham.*

(5) Yan, Y. (2021). **Analysis on the strategies of information technology to improve autonomous learning in higher vocational english teaching.**

(6) Liu, L., & Tsai, S. B. (2021). **Intelligent recognition and teaching of english fuzzy texts based on fuzzy computing and big data.** *Wireless Communications and Mobile Computing*, 2021(1), 1-10.

(7) Kaire, U., Mari, K., & Liisa, P. (2018). **Relations between students' perceptions of the teaching-learning environment and teachers' approaches to teaching: a qualitative study**. *Journal of Further & Higher Education*, 1-20.

(8) Mishra, A. R., Chandel, A., & Saeidi, P. (2022). **Low-carbon tourism strategy evaluation and selection using interval-valued intuitionistic fuzzy additive**

https://doi.org/10.17993/3ctecno.2023.v12n1e43.87-106

ratio assessment approach based on similarity measures. *Environment, Development and Sustainability: A Multidisciplinary Approach to the Theory and Practice of Sustainable Development*, 24.

(9) Sang, G., Valcke, M., Braak, J. V., Tondeur, J., & Chang, Z. (2011). **Predicting ict integration into classroom teaching in chinese primary schools: exploring the complex interplay of teacher-related variables**. *Journal of Computer Assisted Learning*, 27(2), 160-172.

(10) Chen, Z. F., Zhi-Gang, Y. U., Liu, S., & Li-ping. (2010). **Research on software engineering one frame with four aspects in practical teaching system**. *Computer Education* (9), 136-139.

(11) Hong, TAN, College, of, International, & Studies, et al. (2014). **The problems in rural english teaching and the optimization path: a study based on the chinese general social survey data**. *Asian Agricultural Research* (8), 4.

(12) Vandebroek, I., Thomas, E., Sanca, S., Damme, P. V., & Kimpe, N. D. (2008). **Comparison of health conditions treated with traditional and biomedical health care in a quechua community in rural bolivia**. *Journal of Ethnobiology and Ethnomedicine*, 4(1), 1.

(13) Chen, W., Ye, S., Xu, G., & Yang, L. (2022). **Futures Trend Forecasting Based onAttention Hybrid Neural Network**. *The International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery. Springer, Cham.*

(14) Ying L, Qian Nan Z, Fu Ping W, et al. (2021). **Adaptive weights learning in CNN feature fusion for crime scene investigation image classification[J]**. Connection Science, 33(3), 719-734.

(15) Zhao, P., & Peng, J. (2001). **High efficient and intensified use of urban land and its evaluation index system**. *Resources Science.*

(16) Liu, F., & Hai, H. L. (2005). T**he voting analytic hierarchy process method for selecting supplier**. *International Journal of Production Economics*, 97(3), 308-317.

(17) Nydick, R. L., & Hill, R. P. (1992). **Using the analytic hierarchy process to structure the supplier selection procedure**. *International Journal of Purchasing & Materials Management*, 28(2), 31-36.

(18) Mei, & Liang. (2011). **Research of index weighting on evaluation index system of partner selection in technical standard alliance by using fuzzy analytic hierarchy process**. *Energy Procedia*, 13, 9922-9929.

(19) Sadr, H., & Soleimandarabi, M. N. (2022). **Acnn-tl: attention-based convolutional neural network coupling with transfer learning and contextualized word representation for enhancing the performance of sentiment classification**. *The Journal of Supercomputing*, 78(7), 10149-10175.

(20) Shan W. (2022). **Digital streaming media distribution and transmission process optimisation based on adaptive recurrent neural network[J]**. *Connection Science*, 34(1), 1169-1180.

(21) Wang, Xuan, Xu, Ruifeng, He, & Yulan, et al. (2017). **Improving sentiment analysis via sentence type classification using bilstm-crf and cnn**. *Expert Systems with Application.*

(22) X. Ning, K. Gong, W. Li, and L. Zhang. (2021). **JWSAA: Joint Weak Saliency and Attention Aware for person re-identification**, *Neurocomputing*, 453, 801-811. https://doi.org/10.1016/j.neucom.2020.05.106.

(23) W Cai, B Zhai, Y Liu. (2021). **Quadratic polynomial guided fuzzy C-means and dual attention mechanism for medical image segmentation**. *Displays*, 70, 102106. https://doi.org/10.1016/j.displa.2021.102106.

(24) Kaseng, F., Lezama, P., Inquilla, R., y Rodriguez, C. (2020). **Evolution and advance usage of Internet in Peru**. *3C TIC. Cuadernos de desarrollo aplicados a las TIC*, 9(4), 113-127. https://doi.org/10.17993/3ctic.2020.94.113-127

(25) Yan Kang,Jinling Song,Mingming Bian,Haipeng Feng & Salama Mohamed. (2022). **Red tide monitoring method in coastal waters of Hebei Province based on decision tree classification**. *Applied Mathematics and Nonlinear Sciences, 7(1), 43-60.* https://doi.org/10.2478/AMNS.2022.1.00051.