Text Analysis via Learning Model in Teaching Ability Evaluation System for College Physical Education Teachers

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Abstract
With the overall increase in the state's attention to quality of higher education teaching, overall teaching level for college physical education teachers has been greatly improved. However, it is influenced by traditional academic and teaching concepts, as well as school administrators do not pay attention to physical education teaching. The development for the teaching ability of college physical education teachers is still not optimistic. Therefore, paying attention to the teaching ability of physical education teachers has gradually become a practical problem that society and schools cannot ignore and must pay attention to. Among them, the evaluation for teaching ability of physical education teachers is the most important. With the reform of the Internet, there is much textual information on teaching of physical education teachers in colleges. By analyzing these texts, an evaluation of teachers' teaching ability can be obtained. This work combines this topic with a deep learning model, and proposes a text analysis model (PEAENet) for teaching ability evaluation of physical education teachers. The model first proposes an interactive multi-head attention to enhance interaction between aspect words as well as context. The attention of two aspects is calculated at the same time, including the attention of the context to the aspect word as well as aspect word attention to context. Second, this work combines Transformer's encoder structure with LSTM to obtain a more capable feature extraction module. In the label mapping stage, the label smoothing coefficient is introduced, which makes the model have stronger generalization ability.
Keywords: Text analysis; Deep learning; Teaching ability evaluation; Physical education

1 Introduction

A new age of international rivalry will be ushered in by this century's information economy. There is a lot of competition in education and science and technology, which is the competition for talent quality. The traditional educational model is no longer adequate to meet the challenges of modern society. In this context, quality education has taken center stage in school reform efforts. College students' physical and mental well-being relies heavily on the inclusion of physical education as an essential component of a well-rounded education at their institutions of higher learning. Physical education can help college students become more physically conscious and mindful of their own health and well-being. Student athletes can benefit from learning scientific methods of physical training, as well as developing lifetime sports ideals as a result. Teaching competence is the most important component in determining the quality of physical education lessons. When teachers are good at what they do, they have a direct impact on pupils' abilities to learn, think creatively and be innovative (Adetunji & Kayode, 2016; Azimovna, 2020; Bailey, 2006).

To evaluate the quality of teaching, teachers' competence to teach is an important factor. This directly influences the quality of staff training. College and university physical education teachers have an important role in promoting the health of high-level talents picked by the state. However, looking at the physical condition of young people, it is worrying. The physical quality of college students continues to decline. Although there are many reasons for the current poor physical health of college students. There are subjective reasons such as college students' attitude towards life and health habits (Bailey et al., 2009; Darling-Hammond, 2000). There are also objective reasons such as sports venue equipment, sports awareness of school leaders and other conditions and environmental impact. College physical education and teachers, on the other hand, are responsible for ensuring that college students' exercise has a positive impact on their health. Educators and front-line instructors are more concerned about the growth of teachers' teaching abilities as the times change and quality education continues to improve. The quality of physical education and the promotion of quality education are directly influenced by the teaching abilities of college physical education teachers (Bakhmat et al., 2019; Balashov et al., 2019; Barney, Pleban, & Muday, 2019).

The cornerstone and core of college and university physical education quality is the quality of its instruction, and this

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serves as a guarantee that college and university physical education will be of high quality. Physical education professors are undervalued in all academic fields, and it is difficult to juggle research and teaching responsibilities. But despite this recognition, the quality of physical education courses in regular colleges and universities has not been addressed. As a result of the deterioration in quality of physical education instruction at ordinary colleges and universities, college students' fitness has deteriorated, failing to meet the aims of college physical education teaching. The teaching zeal of physical education teachers in ordinary colleges and universities is also dwindling as a result of this. This is why colleges and universities need to balance teaching and scientific research, improve the quality of college physical education courses, and take on the heavy load of physical education instruction. Physical education teachers at colleges and universities need to recognize and place a high value on their competence to teach physical education (Ding, Li, & Cheng, 2020). A college or university's efforts to improve the teaching abilities of its physical education instructors will not only benefit the institution's talent development efforts but also the discipline itself. It can also have a positive impact on college sports as a whole. Physical education courses in regular colleges and universities will receive better teaching quality once the standing of school physical education is elevated, creating a positive feedback loop. In other words, enhancing the ability of college and university teachers of physical education to deliver high-quality instruction is a goal that needs be attained (Casey & MacPhail, 2018; Cucui, 2019).

It is clear that how to objectively and scientifically evaluate the teaching abilities of college and university physical education teachers is of enormous practical importance. Physical education instructors' professional level and teaching quality can be improved by implementing a scientific teacher assessment system. Sports work in colleges and universities can be encouraged, and this is a crucial step toward ensuring the long-term viability of colleges and universities. It is important for college physical education teachers to have a robust evaluation system in place to help them continually improve their teaching abilities (Dwyer & Davis, 2008; Guo, 2020). Thus, college physical education can gradually achieve its objective and meet the new standards for college physical education in the new environment. There is need for improvement in terms of logic and scientific degree in the current assessment index system for college and university physical education teachers. Teachers of physical education aren't being given the attention or training they need to improve their teaching abilities, according to the assessment index system that is currently in place. This has a direct impact on the standard of college physical education. In light of this, it is imperative that college and university physical education teachers be evaluated using a set of standardized evaluation indexes that are perfect, disciplined, and judicious (Hardman, 2008; Harris & Sass, 2011; Juraevich, 2020).

2 Related Work

Literature (Kelly, 2019; Kerner, Haerens, & Kirk, 2018) suggests that physical education teachers' teaching abilities are defined in terms of their aptitude to accomplish their teaching objectives and to produce educational outcomes. It is composed of many specific factors and reflects the direct and effective psychological characteristics of the individual to successfully complete the teaching task. Literature (Lau et al., 2018; Lee et al., 2007; Lee, 2019) suggests that teaching ability is a comprehensive competence that teachers demonstrate throughout the teaching process in order to achieve the intended teaching goals. Ability to plan and develop, to organize and manage, evaluate and provide feedback, as well as to adjust and control Classroom teaching is at the heart of a teacher's capacity to instruct. From the point of view of teaching effectiveness, literature (Mihajlovic, 2019; Norris et al., 2020) argues that physical education instructors' ability to teach is the comprehensive skill they demonstrate throughout the entire teaching process in order to ensure the efficacy of instruction. Teachers of physical education are expected to have a variety of skills, including the capacity to communicate effectively, to manage an organization effectively, to conduct educational research effectively, and to organize and change information, according to literature (Place & Hodge, 2001). According to literature (Rasberry et al., 2011), cognitive psychology provides a comprehensive and in-depth examination of teaching capacity. Physical education exercises can be broken down into three categories: teaching monitoring ability, teaching cognitive capacity, and learning how to operate a device. Literature (Renshaw & Chow, 2019) has different understandings of physical education teaching ability. It believes that teachers should have good teaching skills when teaching, so that they can maximize their teaching academic ability. It is necessary to master the characteristics of students and teaching, and to know ourselves and others, so that we can truly reflect the spirit of teaching and academic research. Literature (Rink, 1993) proposed that physical education teaching practice and teaching theory are interactive, and both can better improve teaching academic ability. It also believes that physical education teaching ability is composed of teaching process and professional knowledge of education and teaching. Literature (Shimon, 2019) believes that we should focus on cultivating the professional spirit for physical education teachers, learn to change roles, notice the selection and training of talents. This promotes innovation of university teaching, understands teaching and academics from a new perspective, and guides the development of university teaching and academics.

There is a distinct view on physical education teachers' abilities to teach in the literature (Singh et al., 2012). It is of the opinion that physical education instructors must create a comprehensive assessment index. This index may simply measure the level of teaching competence of physical education teachers in order to improve and explain the real teaching scenario. Physical education faculty, according to literature (Standage, Duda, & Ntoumanis, 2005), must first get together to build an academic community dedicated to the advancement of physical education instruction. The general strength of a university's sports instruction is just as important as the university's ability to do sports research. Keeping up with the trends and implementing research in physical education are some of the ways to progress in physical education, according to a reference cited in literature (Trudeau & Shephard, 2008). Physical education teachers must also work to enhance their own teaching skills in order to maximize the impact of research. Physical education concepts need to be developed in order to increase the quality of physical education, according to the literature (Wang, Sun, & Guo, 2021). Teachers of physical education can benefit from the supervision of this notion. Literature (Yang, 2021) has advocated the priority levels, genres, and material to be used in the teaching ability structure for physical education teachers at different phases of growth. Physical education teachers' teaching abilities are not defined by this measure. According to literature (Zeng, 2020), the structure of college physical education teachers' teaching abilities consists of seven elements, which confirmatory factor analysis has verified. College physical education teachers, however, haven't been studied for important aspects that affect their capacity to teach. To put it another way, this needs to be investigated (Duan, 2023).

3 Method

This work proposes a text analysis model (PEAENet) for teaching ability evaluation of physical education teachers. The model first proposes an interactive multi-head attention to enhance interaction between aspect words as well as context. The attention of two aspects is calculated at the same time, including the attention of the context to the aspect word as well as aspect word attention to context. Second, this work combines Transformer's encoder structure with LSTM to obtain a more capable feature extraction module. In the label mapping stage, the label smoothing coefficient is introduced, which makes the model have stronger generalization ability. Finally, this work carried out multi-directional experiments to verify the feasibility and correctness for designed strategy.

3.1 LSTM Algorithm

LSTM is a model developed from RNN, which is heavily optimized for RNN. It introduces a gating mechanism and a memory unit, which enhances the memory ability of the network and alleviates the problem of gradient disappearance. Its specific structure is demonstrated in Figure 1.

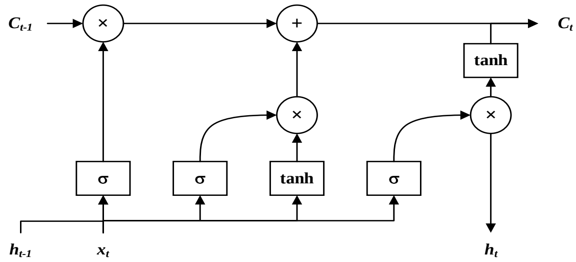

***Figure 1*: LSTM unit**

The gating unit of LSTM consists of three gate structures, including input, output, and forget gate. The cell states in LSTM are controlled by these special gate structures. The LSTM model has two different transport states: the hidden state and the cell state. A horizontal line at the top of the structure diagram represents the state of the cell. The direction the arrow points is the direction in which the information propagates through the LSTM structure. In the information flow process of each cell, not only the hidden layer state is constantly updated with time, but also the cell state is also changing with time. LSTM first decides how much cell information from past moments to keep through a forget gate.

$$f_t = \sigma(W_f[h_{t-1}; x_t] + b_f) \quad (1)$$

The output value for this formula will be controlled in the range [0, 1]. If the result is 0, it means that the information from the cell state is not selected at all at this moment. If it is 1, it means that the information from the cell state is completely preserved. Sigmoid function and input gate are used to determine which information will be updated for input. Then use the tanh function to create a new candidate cell state for subsequent operations. Finally, by adding the calculation results of the previous two steps, the cell state at the current moment can be obtained.

$$i_t = \sigma(W_i[h_{t-1}; x_t] + b_i) \quad (2)$$

$$\tilde{c}_t = tanh(W_c[h_{t-1}; x_t] + b_c) \quad (3)$$

$$c_t = f_t c_{t-1} + i_{t-1}\tilde{c}_t \quad (4)$$

The output gate structure of each cell node can output the hidden layer output at the current moment. The sigmoid function is used to initially select how much information to keep from the current state of the cell as the initial output. The current hidden layer output is obtained by multiplying the initial output by the value of tanh and the current cell state one by one.

$$o_t = \sigma(W_o[h_{t-1}; x_t] + b_o) \quad (5)$$

$$h_i = o_t * \tanh(C_t) \quad (6)$$

The LSTM network enhances the memory capacity of the network based on its predecessor. Excellent results are obtained when processing input data with time series.

3.2 Attention Mechanism

When a neural network has an attention mechanism, it is able to pay more attention to relevant input. This considerably enhances the model's performance and accuracy by reducing the interference of extraneous input. The Attention structure contains a Q and several K-V pairings, which can be thought of as an addressing method for the attention mechanism. In a specific task, given a query vector Q, calculate the similarity score of Q with each K. And combine the score information with value to get the attention value, whose structure is demonstrated in Figure 2.

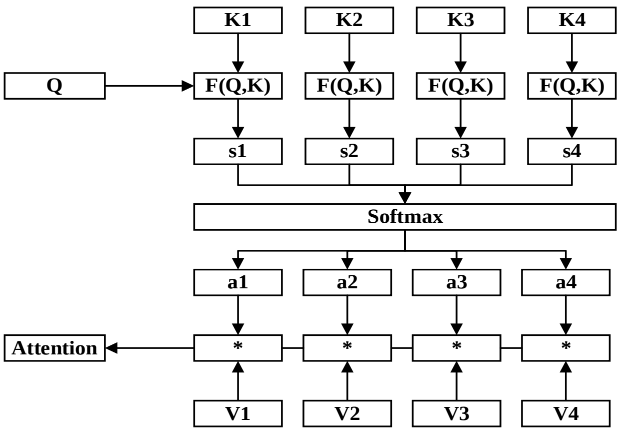

Figure 2: Attention mechanism

3.3 PEAENet Algorithm

At present, aspect-level text analysis solutions mainly combine attention mechanism and recurrent neural network model. Recurrent neural networks can better handle long-distance sequence information such as text. However, there is a problem of gradient explosion and disappearance, which makes it impossible to obtain and model long-distance information. In response to this problem, this work combines the LSTM network with the encoder part of the Transformer structure for feature extraction and encoding of word vectors. The Transformer structure has a very strong ability to obtain long-distance feature information, which can make up for the shortcomings of the LSTM network. This work combines Transformer-encoder with LSTM as a feature extraction layer. In most models, the self-attention is utilized to extract important information in text. However, in aspect-level sentiment analysis, there are two parts of information, contextual text and aspect words, which are not independent of each other. Therefore, if the self-attention operation is only performed on the text context and the aspect word itself, the relationship between the two cannot be extracted. Therefore, this work proposes an interactive multi-head attention, which calculates attention weight of context to aspect word and attention weight of aspect word to context respectively. This allows sufficient interaction and attention of the contextual text and aspect words. The proposed PEAENet is demonstrated in Figure 3.

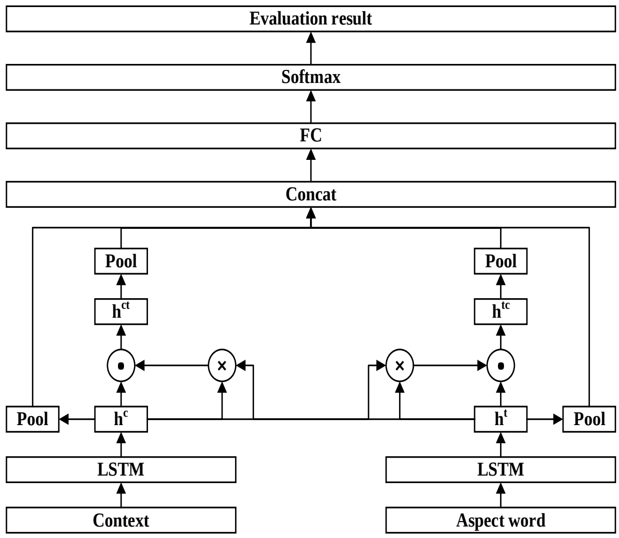

Figure 3: PEAENet pipeline

The model is divided into four modules. The word embedding uses a pre-trained model to vectorize contextual text and aspect words. The feature extraction module fuses the encoder part of the Transformer structure with the LSTM network. It performs feature extraction and encoding on contextual text and aspect words respectively. Finally, the hidden layer output of LSTM network is utilized as result, and the hidden layer vector with contextual features and semantic information is obtained. The interactive multi-head attention module obtains two different vector matrices weighted by the attention value through multi-head attention for the context and target words.

3.3.1 Word Embedding Module

During training and testing, the input to the model is natural language, and the computer can only process the digital vector form. This work employs a pretrained model to obtain word vector representations of text. The natural language is segmented, and the word vector is obtained by mapping it to the model. For words without corresponding word vectors, use random generation to obtain their word vectors. This method can represent a text word vector obtained after a certain comment text data is encoded by the model.

3.3.2 Feature Extraction Module

This is composed of Transformer's encoder layer and LSTM network. Generally speaking, both Transformer structure and LSTM structure can be used to extract features from sequence information. By introducing three gate structures, LSTM gains the ability to capture long-range feature information. And because it is input in a certain order, it is naturally suitable for processing ordered sequences. However, it still has the disadvantages of being slow, unable to perform parallel computing, and not completely solving the problem of gradient disappearance. The Transformer structure can obtain powerful learning ability by stacking attention, inputting all words and sentences at one time, allowing it to obtain the ability of parallel computing. But at the same time, because it uses the functional absolute position encoding method, a position vector is calculated for each word by means of trigonometric functions. This way causes it to lose the relative positional relationship between words. This work combines the encoder structure of Transformer with an LSTM network. It uses the powerful feature learning ability of Transformer to learn the feature relationship between words in the context and the feature relationship between words in the target word. It uses LSTM to learn the relative position features of the sequences of the two, so that the feature extraction module in the model not only has powerful feature extraction capabilities, but also cannot lose relative position information. The feature extraction module structure of the LSTM fusion Transformer-encoder is demonstrated in Figure 4.

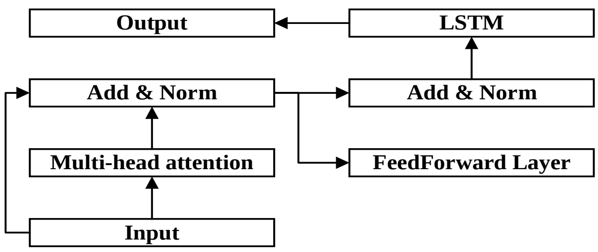

***Figure 4*:** Feature extraction module

3.3.3 Interactive Multi-Head Attention Module

Previous aspect-level text analysis models often do not model the interaction between aspect words and context. Instead, it only focuses on the separate modeling of aspect words and context. As can be seen from the overall structure diagram of the model, the interactive multi-head attention module consists of two parts. The first part is the context text matrix as Q in the attention and the target aspect word matrix as the multi-head attention part of K. The second part is the multi-head attention part with the context text matrix as K and the target aspect word as Q. These two parts respectively represent information about which content of the target aspect word is more important to the text for the context text, and which aspects of the context text are more important to the text for the target aspect word.

Through such interactive attention, the feature relationship between text and target words can be fully obtained. At the same time, the multi-head attention can greatly increase parallel computing power. Thereby improving the performance and extracting more diverse feature information in different feature spaces. For the two multi-head attention modules existing in the model, it is calculated by the following formula.

$$h^{ct} = Multi\_Head\_Attention(h^t, h^c) \quad (7)$$

$$h^{tc} = Multi\_Head\_Attention(h^c, h^t) \quad (8)$$

Finally, two vector matrices are obtained, which respectively reflect the mutual attention feature relationship between the text context and target words.

3.3.4 Vector Representation Fusion and Text Polarity Classification Module

Two vector matrices are obtained between the context text and the target aspect word after the feature extraction module, and the two vector matrices are obtained by interacting with multi-head attention. These four vector matrices are subjected to the mean pooling operation, and the obtained four vectors are concatenated.

$$y = Concat(y_1, y_2, y_3, y_4) \quad (9)$$

Then, through a fully connected layer, the high-dimensional fusion vector is mapped to the vector of the dimension of the number of labels. Finally, the probability distribution on each classification label is calculated separately by Softmax. The polarity with the highest probability is used as final evaluation prediction result.

3.3.5 Label Smoothing and Model Training

During model training, the cross-entropy loss function is usually used.

$$L = -\sum_{k=1}^{K} q_k \, log p_k \quad (10)$$

The true labels are often represented by one-hot encoding, and their values only contain 0 and 1. In the loss calculation, the information with the label 1 is completely preserved, and the information with the label 0 is completely discarded. This results in the model rewarding the most correct predictions and penalizing misclassifications the most. However, in real situations, it is often impossible to guarantee that all labels are correctly labeled. Overconfidence in the accuracy of labels can lead to model overfitting, which can have a dramatic impact on training. Label smoothing introduces a parameter, usually this value is small, from which a label vector can be obtained.

$$y_i = \begin{cases} 1 - \varepsilon, & i = target \\ \frac{\varepsilon}{K-1}, & others \end{cases} \quad (11)$$

L2 regularization term is also introduced in loss. At the same time, we also introduced a dropout mechanism during training, which is used to improve network performance. Using dropout can effectively avoid overfitting due to too many parameters. Dropout is to make each neuron have a certain probability of failure in the process of forward propagation of the network. This probability is called dropout rate. In this way, our model is not limited to the dependence on certain features, has stronger generalization ability, and reduces the probability of overfitting.

4 Experiment and Discussions

4.1 Dataset and Experimental Environment

This work collects the corresponding teaching evaluation texts for college physical education teachers as training data and test data. The training set consists of 50,397 text samples, and the test set consists of 23,107 samples. This experiment uses the popular PyTorch tool in academia to build the model. It is concise and efficient and can be developed using the Python language. The specific experimental environment and configuration are demonstrated in Table 1.

Table 1

The specific experimental environment and configuration.

Item	Configuration
Operation system	Ubuntu 16.04
Memory	64GB
CPU	Intel Xeon Gold 6330
GPU	RTX3090

4.2 Analysis on Training Loss

Training a deep learning model is an indispensable step, and the quality of the training directly affects the subsequent network testing. This work analyzes the training loss of PEAENet to judge its training process. The experimental data is demonstrated in Figure 5.

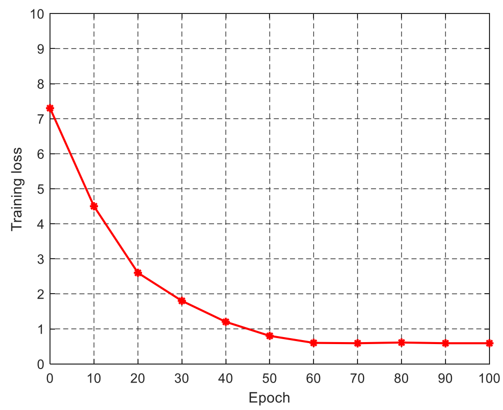

Figure 5: Analysis on training loss.

At the beginning of training, the network loss is large. As the training epoch increases, the network loss gradually decreases. When the training reaches about 60 epochs, the network loss reaches convergence and finally stabilizes around 0.6.

4.3 Analysis on Method Comparison

To further verify the superiority of PEAENet, it needs to be compared with other deep learning methods. This work selects CNN, LSTM and Transformer as the comparison methods, and the comparison data is demonstrated in Table 2.

Table 2

Analysis on method comparison.

Method	Acc	Rec
CNN	87.3%	85.7%
LSTM	89.2%	86.8%
Transformer	91.7%	89.6%
PEAENet	94.9%	92.5%

It is obvious that compared with other deep learning methods, the PEAENet proposed in this work can achieve the highest performance. Compared with any of the other listed methods, PEAENet can achieve different degrees of accuracy and recall improvement.

4.4 Analysis on LSTM

This work uses LSTM to replace the decoder in Transformer. To verify the superiority of this measure, this work compares the precision and recall when using traditional Transformer-decoder and using LSTM, as demonstrated in Figure 6.

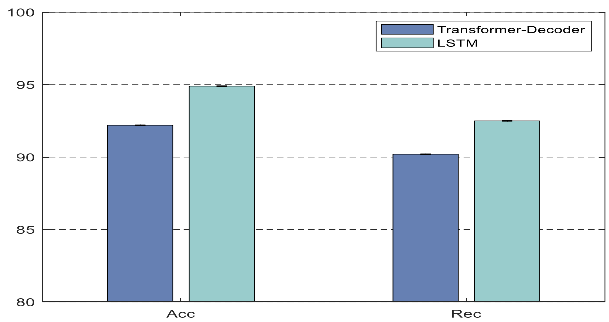

Figure 6: Analysis on LSTM

4.5 Analysis on Interactive Multi-Head Attention

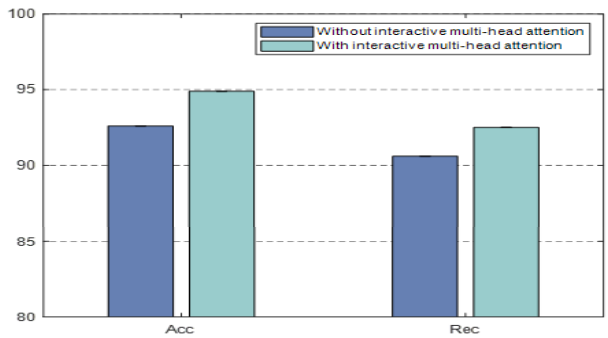

Figure 7: Comparison of using and not using interactive multi-head attention

The interactive multi-head attention module used in this work is used to improve the robustness and discrimination of features. To verify effectiveness, this work compares the network performance without using this module and using this module, as demonstrated in Figure 7.

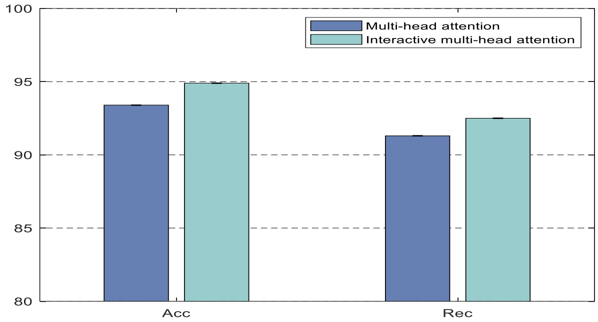

***Figure 8*:** Comparison of multi-head attention and interactive multi-head attention

To further verify the superiority of this attention mechanism, this work compares it with the traditional multi-head attention mechanism, and the comparison results are demonstrated in Figure 8.

Compared with the traditional multi-head attention strategy, after using interactive multi-head attention, PEAENet can achieve 1.5% improvement in accuracy and 1.2% improvement in recall. These data validate the superiority of interactive multi-head attention.

4.6 Analysis on Label Smoothing

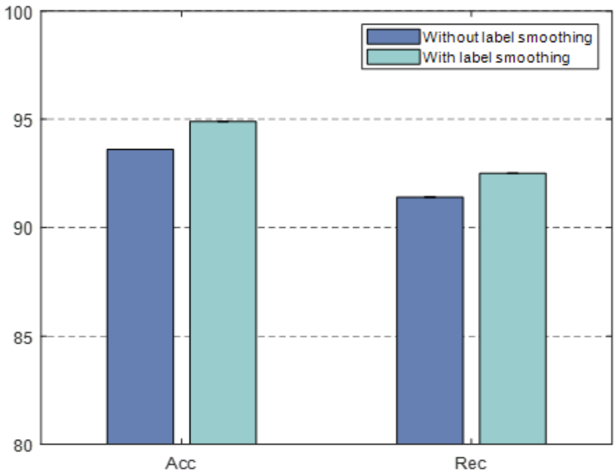

***Figure 9*:** Analysis on label smoothing

This work uses a label smoothing strategy in loss function. To verify feasibility of measure, this paper compares the performance without label smoothing and with label smoothing, as demonstrated in Figure 9.

Obviously, after using this strategy, the network can achieve a 1.3% improvement in accuracy and a 1.1% improvement in recall compared to not using label smoothing. This corroborates the correctness of the label smoothing strategy.

4.7 Analysis on L2 Regularization

This work uses a L2 regularization strategy in loss. To verify feasibility of measure, this paper compares the performance without L2 regularization and with lL2 regularization, as demonstrated in Table 3.

Table 3

Analysis on L2 regularization

Method	Acc	Rec
Without L2 regularization	93.1%	91.2%
With L2 regularization	94.9%	92.5%

Compared with not using L2 regularization, after using it, accuracy and recall rate are improved by 1.8% and 1.3%. This confirms feasibility of L2 regularization for network performance improvement.

5 Conclusion

To evaluate the quality of teaching, teachers' competence to teach is an important factor. This directly influences the quality of staff training. College and university physical education teachers have an important role in promoting the health of high-level talents picked by the state. Educators and front-line instructors are more concerned about the growth of teachers' teaching abilities as the times change and quality education continues to improve. The quality of physical education and the promotion of quality education are directly influenced by the teaching abilities of college physical education teachers. This means that how to scientifically evaluate physical education teachers in colleges and universities is of enormous practical importance. With the reform of the Internet, there is much textual information on teaching of physical education teachers in colleges. By analyzing these texts, an evaluation of teachers' teaching ability can be obtained. This work combines this topic with a deep learning model, and proposes a text analysis model (PEAENet) for teaching ability evaluation of physical education teachers. The model first proposes an interactive multi-head attention to enhance interaction between aspect words as well as context. The attention of two aspects is calculated at the same time, including the attention of the context to the aspect word as well as aspect word attention to context. Second, this work combines Transformer's encoder structure with LSTM to obtain a more capable feature extraction module.

Funding Statement

The author(s) received no specific funding for this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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