Emotion Recognition of College Students' Online Learning Engagement Based on Deep Learning

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Abstract—In actual learning scenarios, learners have more and more personalized needs. The traditional measuring tools of emotional engagement can no longer meet the personalized needs of online learning. To solve the problem, this paper explores the emotion recognition of college students' online learning engagement based on deep learning. Firstly, the features were extracted from the texts related to online learning reviews and interactive behaviors of college students, and the texts were vectorized by the multi-head attention mechanism. Based on the multi-head attention mechanism, a bidirectional long short-term memory (BLSTM) emotion classification model was established, which describes the emotional attitude of learners towards learning engagement more clearly and more accurately. Through experiments, the proposed model was proved effective in emotion recognition of college students' online learning engagement.

Keywords—attention mechanism, online learning, learning engagement, emotion recognition

1 Introduction

With the rapid development of information technology and digital technology, online learning, which breaks through the limitations of time and space, has injected new vitality into the field of education [1-4]. The online learning effect is positively correlated with the learners' emotional engagement in online learning [5-8]. Therefore, online learning platforms monitor learners' emotional engagement in real time to evaluate the teaching quality throughout the learning process [9-15]. In actual learning scenarios, learners have more and more personalized needs, the learning environment becomes increasingly complex, and the learning state is more difficult to detect. The traditional measuring tools of emotional engagement can no longer meet the personalized needs of online learning [16-18]. To solve the problems with the emotion recognition of online learning engagement, it is highly necessary to examine the theories on the emotion recognition of college students' engagement in online learning.

In the wake of the coronavirus (COVID-19) pandemic, many countries resorted to distance education to ensure the continuity of teaching. To enable teachers to evaluate students' emotional states, Abdellaoui et al. [19] looked for solutions related to face detection to automatically infer emotions, and carried out experiments to qualify and quantify the students' engagement. Zatarain-Cabada et al. [20] reported a method to create a new corpus of facial expressions from electroencephalogram (EEG), which helps to identify learning-centric emotions (frustrated, bored, engaged, and excited), and explained the changes of fuzzy logic systems in intelligent learning environments.

The learners' facial emotion recognition systems can provide feedbacks, allowing teachers to understand the learning state of each student, to offer help to him/her, or to improve their teaching strategies. Hung et al. [21] improved the FaceLiveNet network to achieve high and low accuracies in basic emotion recognition, proposed a dense FaceLiveNet framework, and experimentally demonstrated that transfer learning effectively improves the accuracy of learning emotion recognition models.

Currently, context-aware learning is a hot topic in online learning. Most scholars discussed the interaction between learners and the learning environment. Kuo and Tseng [22] designed a learning system that uses physiological sensors to identify learners' emotions. According to these emotions, the system adjusts the learning level, and provide proper assistances, such that the learners can achieve better performance. Targeting the emotional illiteracy in online learning environment, Tian et al. [23] put forward an emotion-based research and application framework for text interaction recognition, defined an emotion classification model for online learners, and achieved good results through preliminary experiments.

Certain results have been achieved in the identification of emotion engagement in online learning through deep learning, laying a technical basis for real-time sensing of online learning states of learners. However, there is a severe lack of research into the effective extraction of emotional features of learning engagement. Further research is needed to simplify the structure, reduce the parameters, and improve the efficiency of emotion recognition models. Therefore, this paper explores the emotion recognition of college students' online learning engagement based on deep learning. Section 2 extracts the features from the texts related to online learning reviews and interactive behaviors of college students, and vectorizes the texts by the multi-head attention mechanism. Based on the multi-head attention mechanism, Section 3 presents a bidirectional long short-term memory (BLSTM) emotion classification model, which describes the emotional attitude of learners towards learning engagement more clearly and more accurately. The proposed model was proved effective through experiments.

2 Text feature extraction and text vectorization

2.1 Text feature extraction

This paper mainly tries to evaluate the emotional trend of learning engagement for individual college students or a group of college students, based on the information from the online learning platform. The emotions of text information were recognized by synthetizing emotional word weighting (EWW) with attention mechanism. After expounding the technical strengths and weaknesses of these algorithms, this paper introduces the word vector representation based on multi-head attention mechanism, and the EWW-based emotion analysis of learning engagement. In this way, the learning engagement emotions can be recognized more accurately from the texts related to online learning reviews and interactive behaviors of college students.

According to the type of learning engagement, the texts related to online learning reviews and interactive behaviors of college students can be divided into three classes: behavioral engagement, cognitive engagement, and emotional engagement.

Behavioral engagement texts include careful listening BI1, active thinking BI2, active participation in quality development activities BI3, active participation in social practice BI4, frequent obtainment of online learning resources BI5, and active participation in online interactions or topic discussions BI6.

Cognitive engagement texts include formulating a scientific learning plan CI1, implementing self-supervision CI2, goal completion statistics and analysis CI3, reasonably allocating learning and activity time CI4, and reasonably selecting learning resources CI5.

Emotional engagement texts include stability of learning emotions EI1, ease of coping with learning and practice EI2, strong learning resilience EI3, confidence in learning EI4, and interest in learning EI5.

Text vectorization is the prerequisite for mining the above texts. For common words, this paper adopts term frequency–inverse document frequency (TF-IDF) and EWW to characterize learning engagement emotions.

The TF-IDF is a common way to compute the weights of feature words based on document frequency statistics. Let m_{ij} be the number of occurrences of a word in text j; $\Sigma_l m_{l,j}$ be the total number of occurrences of all the words in text j. Then, the word frequency, i.e., the ability of a word to represent text contents, can be calculated by:

$$\eta_{ij} = \frac{m_{ij}}{\sum_l m_{lj}} \tag{1}$$

Let c_j be the logarithmic index representing the total number of occurrences of all words in a document; $|\{j:p_i \in c_j\}|$ be the number of documents containing the word pi; ||C| be the total number of documents in the corpus. For a specific word in the corpus, the general importance of that word can be measured by the IDF QAU:

$$SE_i = log \frac{|C|}{\left|\left\{ j : p_i \in c_j \right\}\right| + 1} \tag{2}$$

The final TF-IDF weight of a word can be calculated by:

$$TF - QAU = \eta_{i,j} * SE_i \tag{3}$$

In general, an emotional word of learning engagement is preceded by an adverb of degree, which enhances or weakens the local emotional trend of the text. Let β be the weight of an adverb of degree; qEM_SC be the emotional value of an emotional word. Then, the final emotional score QDEM of the sentence can be calculated by:

$$QD_{EM1} = \sum \beta * q_{EM\_SC} \tag{4}$$

In this paper, the representations of emotional words of learning engagement are abstracted into two types: the negative word appears before the adverb of degree and emotional word, and the negative word appears behind the adverb of degree and emotional word. The local emotions EMLO of the two types of texts can be respectively calculated by:

$$EM_{LO} = 0.5 * \beta * q_{EM\_SC} \tag{5}$$

$$EM_{LO} = 2 * \beta * q_{EM\_SC} \tag{6}$$

2.2 Text vectorization

For words that may cause semantic ambiguity or polysemy, this paper considers words as the unit of text representation, and adopts the multi-head attention mechanism to vectorize texts. Figure 1 shows the flow of the multi-head attention mechanism.

Let A=(a_0,a_1,...,a_n) be the input; B=(b_0,b_1,...,b_n) be the output; ω^{ψ}, ω^{Φ} and ω^{Ψ} be the weight matrices. For each input a, the query vector, key vector and value vector are often used to measure the degree of association between words, which can be obtained by multiplying A=(a_0,a_1,...,a_n) with ω^{ψ}, ω^{Φ} and ω^{Ψ}:

$$\psi = a \cdot \omega^{\psi} \tag{7}$$

$$\Phi = a \cdot \omega^{\Phi} \tag{8}$$

$$\Psi = a \cdot \omega^{\Psi} \tag{9}$$

Based on the semantic information of the text, the attention degree vector δ between words can be calculated by:

$$\delta = ATT\left(\psi, \Phi, \Psi\right) = softmax\left(\frac{\psi \cdot \Phi^{T}}{\sqrt{c_l}}\right) \times \Psi \tag{10}$$

Each attention head corresponds to a set of weight matrices ω^{ψ}, ω^{Φ} and ω^{Ψ}. For each attention head H, the attention level of the unit (word) can be calculated by the attention layer formula of the emotion recognition model for online learning engagement (10). The splicing operation SP( ) is performed on the calculated vector. The final attention matrix δ can be obtained by multiplying the obtained vector by the weight matrix ω^{0}:

$$\begin{aligned} &\delta = SP\left(H_0, H_1, ...H_N\right) \cdot \omega^{0} \\ &H_i = ATT\left(\psi_i, \Phi_i, \Psi_i\right) \end{aligned} \tag{11}$$

Let a be the input; ω_1,ω_2,φ_1 and φ_2 be the training parameters of the emotion recognition model for online learning engagement; SL( ) be the sub-layer; LN( ) be the layered operation. The specific operation can be expressed as:

$$\delta \leftarrow LN\left(SP\left(\delta, SL\left(A\right)\right)\right) \tag{12}$$

The output of the emotion recognition model for online learning engagement can be expressed as:

$$B\left(a\right) = max\left(0, a\omega_1 + \phi_1\right)\omega_2 + \phi_2 \tag{13}$$

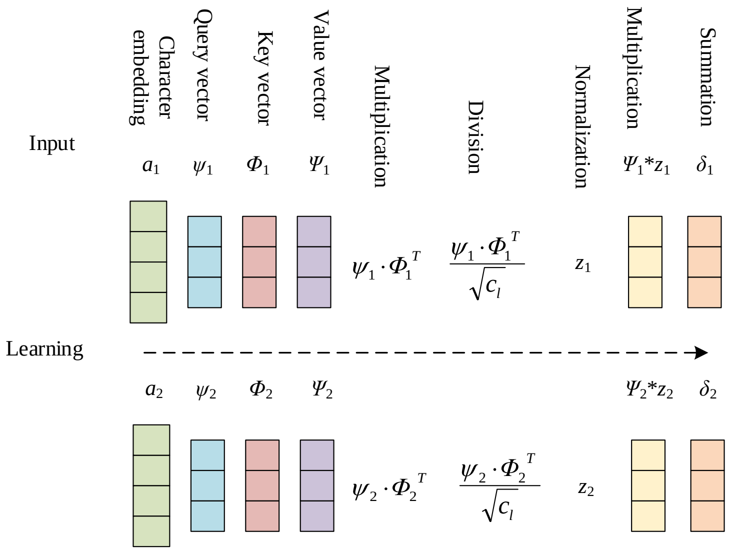

Fig. 1. Flow of the multi-head attention mechanism

3 Emotion classification model

Based on the multi-head mechanism, this paper presents the BLSTM emotion classification model, aiming to depict the emotional attitudes of learners to learning engagement, mine the emotional views of the texts related to online learning reviews and interactive behaviors of college students, and underpin the subsequent prediction of emotional trend of college students in online learning. Figure 2 shows the structure of the proposed model.

The BLSTM emotion classification model consists of two LSTMs in different directions. Each LSTM involves three gate structures: input gate i_p, forget gate E_p, and output gate g_p. Let A be the input; f be the output; D be the value of the memory unit; ε be the activation function; Q_i, Q_g and Q_e be the weights of the input, forget, and output gates, respectively; φ_i, φ_g, and φ_e be the biases of the input, forget, and output gates, respectively; $A\{a_1,a_2,...,a_p,...a_n\}$ be the input unit; $a_p(p=1,2,......,n)$ be the characters in the input text; n be the number of words in the input text. At time p, the update states of the three gate structures can be respectively calculated by:

$$g_p = \varepsilon\left(Q_g \cdot \left[f_{p-1}, a_p \right] + \phi_g\right) \tag{14}$$

$$e_p = \varepsilon\left(Q_e \cdot \left[f_{p-1}, a_p \right] + \phi_e\right) \tag{15}$$

$$f_p = e_p * tanh\left(D_p\right) \tag{15}$$

$$i_p = \varepsilon\left(Q_i \cdot \left[f_{p-1}, a_p \right] + \phi_i\right) \tag{16}$$

$$D_p = g_p * D_{p-1} + i_p * tanh\left(Q_d \cdot \left[f_{p-1}, a_p \right] + \phi_d\right) \tag{17}$$

Let Q_{i1}, Q_{i2}, Q_{g1}, Q_{g2}, Q_{e1} and Q_{e2} be the weight matrices of the three gates in the two directions, respectively; φ_f, φ_f and φ_f be the biases of the three gates, respectively. Then, the formulas of the forward and backward propagation layers can be respectively calculated by:

$$\vec{F}_p N = \varepsilon\left(Q_{i1} a_p + Q_{g1} \vec{F}_{p-1} + \phi_{f'}\right) \tag{18}$$

$$F_p = \varepsilon\left(Q_{i2} a_p + Q_{g2} \overleftarrow{F}_{p-1} + \phi_{f'}\right) \tag{19}$$

Combing formulas (18) and (19), the output $H_t F_p$ can be obtained as:

$$F_p = \varepsilon\left(Q_{e1} \vec{F}_p + Q_{e2} \overleftarrow{F}_p + \phi_f\right) \tag{20}$$

The proposed BLSTM model stitches the outputs F_p of all hidden layers in forward and backward LSTMs into $F=\{F_1,F_2,......F_n\}=\{F^{\rightarrow},F^{\leftarrow}\}$. Taking F as the input, the softmax layer of the model outputs the emotional class of the target text. This paper attempts to classify the texts related to online learning reviews and interactive behaviors into positive, negative, and neutral emotions. The regression and classification principle of the softmax layer of the model is detailed below.

The softmax layer uses l nodes to represents the l classes. Let c be the value outputted from the hidden layer to the output layer; μ_1, μ_2, …, $\mu_l \in \Omega^{m+1}$ be the model parameters; l be the number of emotional classes. Then, the normalized probability VR_j of label j belonging to emotional class l can be calculated by:

$$VR_j = \frac{1}{\sum_{j=1}^{l} o^{\mu_j^T c}} \begin{bmatrix} o^{\mu_1^T c(i)} \\ o^{\mu_2^T c(i)} \\ \cdots \\ o^{\mu_j^T c(i)} \end{bmatrix} \tag{21}$$

The final output of the model can be given by:

$$EM_{BLSTM} = \{VR_1, VR_2, ..., VR_m\} = argmax(VR_i) \tag{22}$$

The above two emotion recognition methods are based on the EWW module, and the attention-based BLSTM module, respectively. To improve the emotion recognition rate, the experimental weight coefficient representing the importance in the emotion recognition system is denoted as β. Then, the final system synthetizes the above two methods into an emotion recognition method η_{EM} for the texts related to online learning reviews and interactive behaviors:

$$\eta_{EM} = \beta EM_{LO} + (1-\beta) EM_{BLSTM} \tag{23}$$

Let $N \in R^{1\times m}$ and $F^T \in R^{\xi\times m}$ be the transpositions of the output matrix of the proposed BLSTM model; $Q_{r1} \in R^{\xi\beta\times m}$ and $Q_{r2} \in R^{1\times\xi\beta}$ be the weight matrices of our model; ξ_β be a preset hyperparameter. Then, the weights of the proposed BLSTM model can be calculated by:

$$\Omega = softmax\left(q_{s_2} tanh\left(Q_{r_1} F^T\right)\right) \tag{24}$$

Based on the obtained weight matrices, it is possible to derive the semantic vector R_i of each important word in the target sentence, such as phrases, transitional words, and negative words:

$$R_i = N \times F \tag{25}$$

The multidimensional semantic features of the sentences in the texts related to online learning reviews and interactive behaviors can be obtained by expanding the dimensionality of Q_{r2} and ξ_β. This could effectively increase the dimensionality of the context semantic embedding vector of each text.

The learning speed ϕ_i of the model is updated through exponential attenuation of the learning rate. Let [ ] be the rounding up; i be the batch size in the i-th round; γ be the learning rate updated every γ rounds; λ be the attenuation degree of learning rate; ϕ_0 be the initial learning rate of the training. Then, the learning speed can be updated by:

$$\varphi_i = \varphi_0 * \lambda^{\left[\frac{i}{\gamma}\right]} \tag{26}$$

The model is trained through the gradient descent propagation:

$$\nabla g(a,b) = grad(a,b) = \frac{\partial c}{\partial a} i + \frac{\partial c}{\partial b} j \tag{27}$$

As mentioned before, this paper intends to divide the texts related to online learning reviews and interactive behaviors into multiple emotional classes. Let b be the true number of classes; l be the number of labels; M be the number of samples;

GS_{il} be the probability of sample *i* being predicted as a member of class *l*. Then, the cross entropy can be calculated by:

$$K_{log}\left(B,GS\right)=-\log GS_s\left(B\,|\,GS\right)=-\frac{1}{M}\sum_{i=0}^{M-1}\sum_{j=0}^{l-1}b_{ij}\log GS_{ij} \tag{28}$$

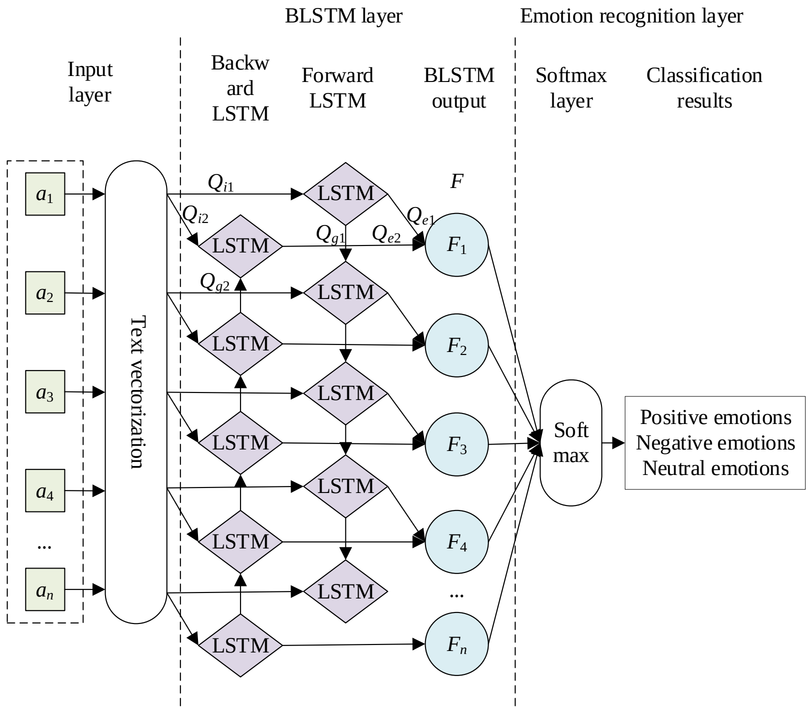

Fig. 2. Structure of the BLSTM emotion classification model

4 Experiments and results analysis

Two sets of experiments were carried out to improve the emotion recognition accuracy of our model, and to increase the precision of the hybrid model, which couples the EWW module with the attention-based BLSTM module. The first set aims to select the hyperparameter of our model, and the second aims to select the weight parameters for emotional analysis. Figures 3 and 4 show how the recognition accuracy and loss rate of our model change. After 10 iterations, the emotion recognition accuracies of our model on the training set and verification set stabilized at about 96%, while the loss rates oscillated about 0.06.

To verify the effectiveness of our model (the attention-based BLSTM plus EWW), this paper compares the performance of six different models. The results (Table 1) shows that the attention-based BLSTM achieved better results than the other five models in emotion recognition of college students' online learning engagement. The EWW ended up with the lowest emotion recognition rate, for the limited size of the emotional dictionary. Our model, which integrates the EWW, realized the lowest recall in emotion recognition of the texts containing lots of online words, and the highest overall emotion recognition rate.

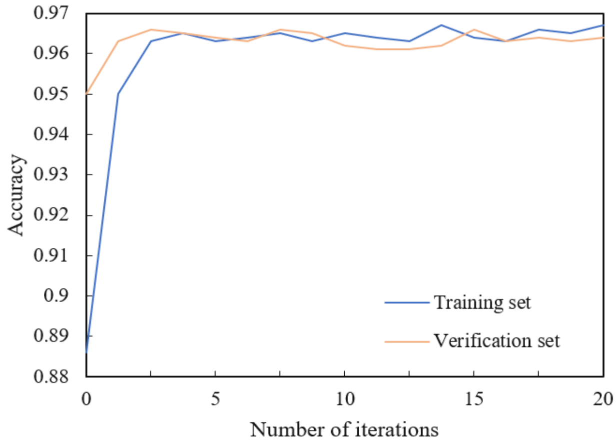

Fig. 3. Emotion recognition accuracy curves of our model

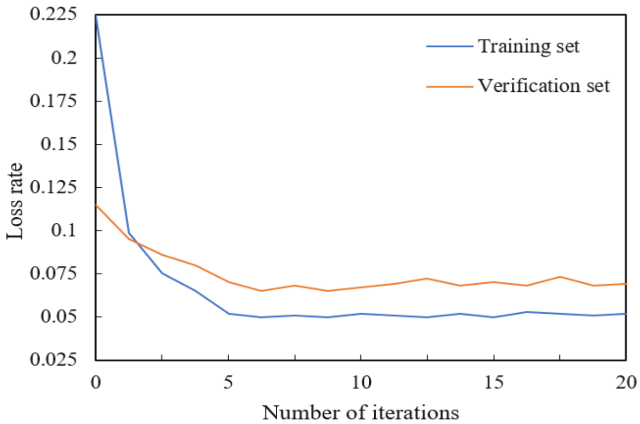

Fig. 4. Emotion recognition loss curves of our model

Table 1. Experimental results of different models

Model	EWW	CNN	LSTM	BLSTM	Attention-based BLSTM	Our model
Precision	78.15	91.35	90.82	93.27	96.13	94.61
Recall	79.57	92.08	91.74	93.19	91.46	95.73
Accuracy	78.49	94.64	90.83	83.26	88.48	93.17
F1-Score	82.16	92.75	94.52	90.84	94.16	92.63

Note: CNN is short for convolutional neural network.

Tables 2-4 report the multiple regression results on the relationship between learning emotions and the behavioral, cognitive, and emotional engagements of online learning, respectively. The behavioral engagement was adopted as the explained variable for the EWW and the attention-based BLSTM. The explanatory variable of the EWW is the control variable, and that of the attention-based BLSTM also covers the four dimensions of learning emotions: learning awareness, self-regulation, other-regulation, and emotional application.

Table 2. Regression analysis results on the relationship between learning emotions and behavioral engagement of online learning

Explanatory variable		**Constant term**	BI_1	BI_2	BI_3	BI_4	BI_5	BI_6	R^2	***Adjusted*** R^2	F
Model 1	Normalized β	0.05	-0.26	1.62^{**}	3.16^{**}	0.68	0.82	-1.48	0.85	4.35	2.158^{**}
	Sig.	0.01	7.48	0.05	0.09	0.75	0.05	6.25			
Model 2	Normalized β	0.01	-1.14	0.15^{*}	0.24	0.12	-0.035	-0.014	6.62	6.75	32.584^{***}
	Sig.	4.18	1.52	0.43	5.16	3.42	6.28	9.48			

Table 3. Regression analysis results on the relationship between learning emotions and cognitive engagement of online learning

Explanatory variable		**Constant term**	CI_1	CI_2	CI_3	CI_4	CI_5	R^2	***Adjusted*** R^2	F
Model 1	Normalized β	0.05	0.42	0.58^{**}	-0.26^{**}	0.62	-0.41^{**}	0.63	0.24	1.612^{**}
	Sig.	0.01	7.62	0.02	0.04	0.26	7.68			
Model 2	Normalized β	0.04	-0.35	0.11	0.06	0.12	-0.64	5.62	5.75	22.483^{***}
	Sig.	3.34	7.15	7.48	7.58	8.37	4.62			

Table 4. Regression analysis results on the relationship between learning emotions and emotional engagement of online learning

Explanatory variable		**Constant term**	EI_1	EI_2	EI_3	EI_4	EI_5	R^2	***Adjusted*** R^2	F
Model 1	Normalized β	0.04	0.29	3.15	-0.85	-0.42	-2.35^{**}	0.72	0.35	1.685^{**}
	Sig.	0.02	8.25	5.14	8.26	1.28	9.25			
Model 2	Normalized β	0.06	0.42	0.12	0.86	-0.04	-0.01	6.82	6.15	25.471^{**}
	Sig.	4.15	5.26	5.68	9.58	6.37	0.42			

The statistics in Tables 2-4 show that the F values were all significant, indicating that the explained variable (learning emotions) has a significant linear relationship with every explanatory variable (behavior engagement, cognitive engagement, and emotional engagement). It can be inferred from the adjusted R^2 that any dimension of the control variable and learning emotions can affect the online learning engagement of college students; learning awareness, self-regulation, and other-regulation have a significant positive correlation with the online learning engagement of college students; emotional application has an insignificant positive correlation with the online learning engagement of college students.

5 Conclusions

This paper strives the recognize the emotions of college students' online learning engagement based on deep learning. Specifically, the features were extracted from the texts related to online learning reviews and interactive behaviors of college students, and the texts were vectorized by the multi-head attention mechanism. After that, the authors created a BLSTM emotion classification model based on the multi-head attention mechanism, which describes the emotional attitude of learners towards learning engagement more clearly and more accurately. Through experiments, the variations in the recognition accuracy and loss rate of our model were observed. It was found that the model performed well in emotion recognition: the emotion recognition accuracies of our model on the training set and verification set stabilized at about 96%, while the loss rates oscillated about 0.06. Then, different models were compared experimentally, revealing that our model achieved the highest overall emotion recognition rate. Finally, the multiple regression results on the relationship between learning emotions and the behavioral, cognitive, and emotional engagements of online learning were reported, which confirms the significant linear relationship between the explained variable (learning emotions) and every explanatory variable (behavior engagement, cognitive engagement, and emotional engagement).

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