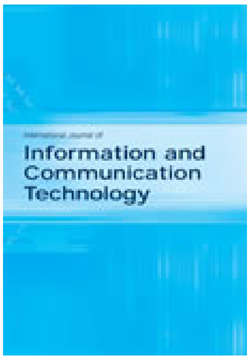

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

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Article History:

Received:	16 October 2024
Last revised:	04 November 2024
Accepted:	04 November 2024
Published online:	13 December 2024

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Deep learning semantic understanding and classification of student online public opinion for new media

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Abstract: In the era of thriving new media, analysing student online sentiment is crucial for understanding student group dynamics and ensuring campus stability. This paper introduces a deep learning-based method for semantic understanding and categorisation of student online sentiment in new media. We collected extensive student speech data from social media, forums, and comments, creating a high-quality dataset through text pre-processing. A combined model that leverages both convolutional neural networks and long short-term memory networks efficiently captures textual characteristics and performs sentiment analysis. By incorporating an attention mechanism, the model focuses on key sentiment expressions. Experiments show our method's superiority in semantic understanding and categorisation tasks, with accuracy and F1 score improvements of approximately 15% and 18% over existing techniques, offering valuable insights for educational administrators and robust technical support for new media public opinion monitoring and analysis.

Keywords: resource student online opinion; deep learning; semantic understanding; sentiment analysis; attention mechanism.

Reference to this paper should be made as follows: Wang, D. and Wang, L. (2024) 'Deep learning semantic understanding and classification of student online public opinion for new media', *Int. J. Information and Communication Technology*, Vol. 25, No. 10, pp.62–76.

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1 Introduction

In the context of the new media era, the analysis of student online public opinion is of great significance in grasping the ideological dynamics of the student population and maintaining campus stability and harmony (Kastrati et al., 2020). With the rise of social media and online platforms, students' activity on the internet has been increasing, generating a large amount of text data. These data not only contain students' emotional attitudes, but also reflect their views on education, social events and other issues. Therefore, how to effectively monitor and analyse these data is crucial for educational administrators and policy makers (Prinsloo et al., 2019). Recently, advancements in deep learning have greatly impacted natural language processing, offering innovative approaches to comprehend and classify student online sentiments. Deep learning's proficiency in unveiling intricate data relationships is attributed to its layered structure, which enables the extraction of higher-level features and patterns from raw data. This capability is pivotal for our approach, as it allows for the nuanced interpretation and categorisation of student online sentiment within the complex new media landscape. Investigations into student online opinions have transitioned from initial rule-based methods to employing machine learning and deep learning strategies for sentiment analysis and opinion extraction. The application of deep learning in sentiment analysis is expanding, with notable advancements in leveraging convolutional neural networks (CNN) and long short-term memory networks (LSTM) for sentiment detection in texts, as highlighted by Ray and Chakrabarti (2020). Studies such as Birjali et al. (2021) have demonstrated the efficacy of deep CNNs in sentiment classification through feature extraction. Meanwhile, Basiri et al. (2021) have showcased the capability of recurrent neural networks (RNNs) with character and word-level attention to identify sarcasm in tweets, underscoring the robustness of deep learning in addressing intricate sentiment analysis challenges. Additionally, Tao et al. (2017) conducted a comparative analysis on aspect-based sentiment categorisation using deep learning, reinforcing its viability in the field of sentiment analysis. Rida-E-Fatima et al. (2019) explores the deep learning opportunities and challenges of pulsed neurons, which provides new insights into understanding the role of deep learning in sentiment analysis by providing new perspectives on its application. As multimedia content proliferates, there's a shift in research towards integrating various data types – including text, images, and videos – for sentiment analysis. In a notable contribution, Dang et al. (2020) explored how to use deep learning techniques for cross-lingual sentiment analysis in their 2018 study, proposing an adversarial training-based model for improving the model's ability to generalise across different languages. On social media platforms, it is becoming increasingly important to monitor and analyse users' emotional tendencies in real time. Zhang et al. (2018) discuss the challenges and opportunities of sentiment analysis and propose some possible solutions in their study. Rim et al. (2022) have advanced targeted sentiment analysis through the introduction of a sparse-attention-guided separable expansive CNN, underscoring the value of attention mechanisms in this field. In a related vein, Wen et al. (2021) have delved into the realm of impulse neural networks powered by deep learning, offering a novel computational framework for sentiment analysis. This provides a new approach to corpus construction for sentiment analysis.

Previous studies have primarily aimed to boost the precision of sentiment analysis, yet have frequently neglected the practical implementation and adaptation of these methods within the realm of new media. To bridge this void, our research presents a pioneering deep learning strategy aimed at grasping and categorising the semantics within student-generated online content. By harnessing the combined strengths of CNN and LSTM, our technique significantly amplifies the accuracy of detecting sentiment trends and thematic classifications. This innovation stands as a milestone, delivering groundbreaking methods and substantial contributions to the domain of new media analytics.

The main innovations and contributions of this work include:

1. This paper introduces a pioneering model that integrates CNN and LSTM, capitalising on CNN's proficiency in feature extraction and LSTM's adeptness at handling sequential data and long-range dependencies. The synergistic integration markedly enhances the precision of sentiment analysis within student online discourse, particularly in scenarios involving intricate contexts and rich semantic content.
2. This paper enhances the model's sentiment analysis capabilities by incorporating a sophisticated attention mechanism. This mechanism enables the model to automatically focus on the key words and phrases of sentiment expression in the text, thus achieving more accurate semantic understanding in sentiment analysis. In particular, the application of the attention mechanism greatly improves the model's recognition accuracy and the depth of sentiment analysis when recognising student speech that contains complex emotional expressions such as irony and metaphor.
3. In this study, three large-scale, high-quality datasets of students' online speech were constructed, which widely covered a variety of new media platforms such as microblogs, forums, and comment sections, and the accuracy and diversity of the data, were ensured through a meticulous manual labelling process. Creating this dataset lays a robust groundwork for both the training and validation phases of our study, and it also offers a treasure trove of data for subsequent investigations into student online sentiment analysis.

2 Relevant technologies

In our methodology, we strategically employ CNN to extract local textual features and LSTM to handle the sequential aspects of the data, thereby capitalising on their complementary capabilities for comprehensive feature extraction. Furthermore, the integration of an attention mechanism is pivotal, as it enables the model to allocate varying levels of importance to different segments of the input, which significantly bolsters the model's ability to comprehend semantics and classify student sentiments with precision.

2.1 Convolutional neural networks

Deep learning, particularly through CNN, has seen substantial success across a range of applications, from recognising images and videos to processing natural language. The essence of CNN is their capacity to autonomously extract and recognise input features that remain consistent despite transformations in the data, such as rotations or distortions

(Liao et al., 2017). This capability is pivotal for managing and interpreting the voluminous textual content produced by students on various new media platforms.

A CNN comprises fundamental elements such as convolutional and activation layers for feature processing, a pooling layer for data reduction, and fully-connected layers that facilitate comprehensive data analysis. The theoretical basis of CNN is to build a hierarchical feature extraction process in which each convolutional kernel is responsible for identifying specific patterns in the input data, which, in the case of text analytics, can be individual words, phrases, or more complex semantic structures. The CNN generates a feature map by sliding these convolutional kernels over the input data, and calculating the relationship between them and the dot product of localised inputs to generate a feature map, a process shown in equation (1):

$$F(x, y) = \sum_i \sum_j I(i, j) \cdot K(x - i, y - j) + b \tag{1}$$

where $F(x, y)$ is the value of the feature map at position(x, y), $I(i, j)$ is the value of the input data at position(i, j), $K(x - i, y - j)$ is the weight of the convolution kernel at the corresponding position, and b is the bias term.

Commonly following the convolutional stage, the activation layer introduces nonlinearity to the model, which is crucial for detecting complex patterns. The rectified linear unit (ReLU) is widely used for activation, as described by equation (2):

$$f(x) = \max(0, x) \tag{2}$$

Subsequently, a pooling layer is employed to condense the feature map's dimensions, thereby minimising the computational load and parameter count, and enhancing the robustness of feature detection. Maximum pooling is the predominant method utilised in this process:

$$P(x, y) = \max_{i,j} F(i + x, j + y) \tag{3}$$

where $P(x, y)$ is the value of the pooled feature map at position(x, y).

The network concludes with fully connected layers that transform the features extracted from the convolutional and pooling stages into the final output of the model. This layer involves extensive connectivity, with each neuron receiving inputs from all activations of the preceding layer. The computation within these layers can be articulated as follows:

$$O(k) = \sum_i W_{ik} A(i) + b_k \tag{4}$$

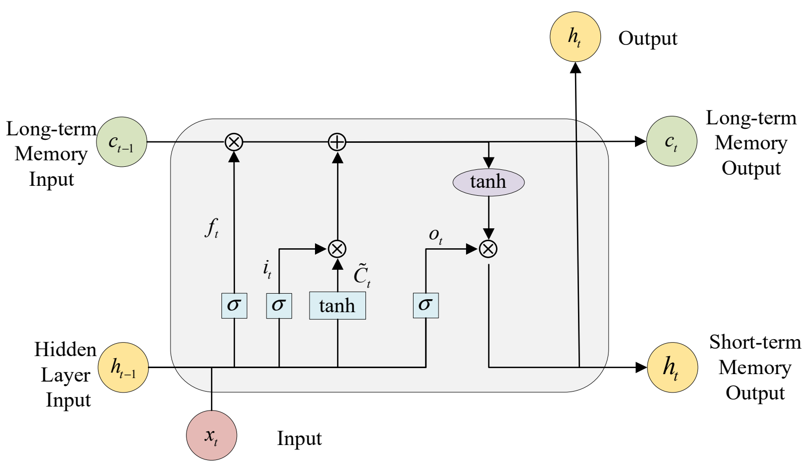
where $O(k)$ is the value of the k^{th} output neuron, $A(i)$ is the i^{th} activation value of the previous layer, W_{ik} is the weight, and b_k is the bias term.

CNN training often employs backpropagation and gradient descent to refine the model by minimising a loss function, such as cross-entropy loss, which quantifies the discrepancy between predictions and actual outcomes. Through their distinctive architecture and training processes, CNN autonomously absorb essential feature representations from data, which are vital for addressing diverse and intricate pattern recognition challenges.

2.2 Long and short-term memory networks

As a sophisticated variant of RNNs, LSTM excel at managing sequential data and capturing long-term dependencies. They boost predictive accuracy by using gates to control information flow within memory cells. Employed extensively in NLP applications like sentiment analysis and speech recognition, LSTMs incorporate three principal gates: input, output, and forget (Xu et al., 2019). The LSTM's operation involves Sigmoid-regulated gates that oversee the cell's memory, with the input gate deciding on new data inclusion, the forget gate determining past state retention, and the output gate dictating the output based on current and previous states. These gates dynamically adjust the cell's state, with the output gate governing the information flow to subsequent layers. LSTM model is adapted to account for the sequential nature of textual data, which is crucial for capturing the evolving sentiments over time. The model is further customised by integrating syntactic and semantic insights through dependency parsing and graph convolutional networks, enhancing its ability to analyse complex social media texts and accurately classify student opinions. Figure 1 illustrates the LSTM neuron structure.

Figure 1 LSTM neuron structure framework diagram (see online version for colours)



The diagram highlights the critical functions of the forget, input, and output gates in LSTMs, noting their use of the sigmoid activation function. The LSTM's workings can be summarised through the subsequent steps:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{6}$$

$$\tilde{c}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_c\right) \tag{7}$$

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

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{9}$$

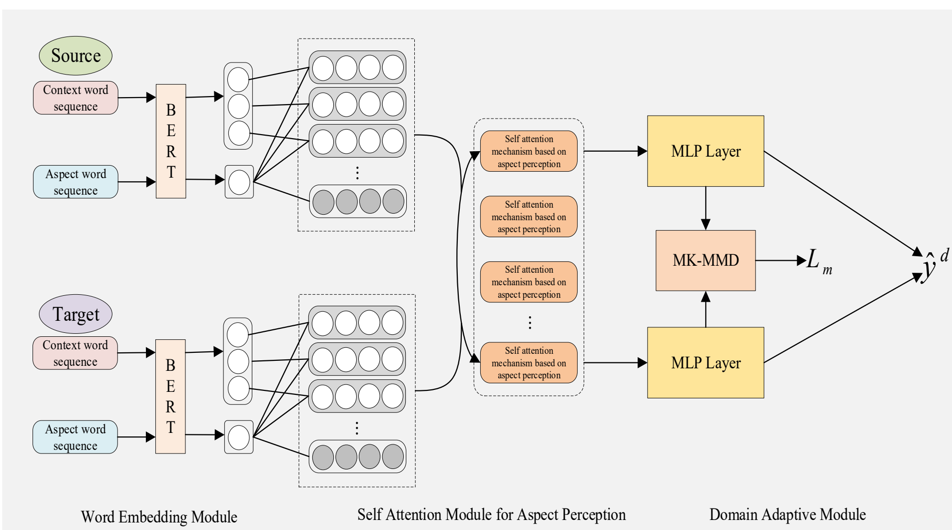
$$h_t = o_t \odot \tanh(c_t) \tag{10}$$

where W_f, W_i, W_C and W_o denote the weight matrices for the forget gate, input gate, cell state, and output gate of the LSTM, respectively. b_f, b_i, b_c and b_o correspond to the bias terms for these gates. σ signifies the Sigmoid function, while h_t is the hidden state at time t, c_t is the cell state at time t, x_t is the input to the input gate at time t, and $\tilde{c}_t$ is the cell's candidate state. f_t, i_t and o_t denote the outputs of the forget gate, input gate, and output gate, respectively. Lastly, the symbol $\odot$ represents the element-wise multiplication, also known as the Hadamard product.

3 Semantic understanding and classification modelling framework construction

In this section, for the static semantic complexity of fine-grained semantics that is difficult to extract, a semantic understanding and classification model framework based on aspect-aware mechanism is proposed to improve the effect of fine-grained text sentiment analysis, as shown in Figure 2, which contains three main parts: word embedding module, aspect-aware self-attention module, and domain adaptive module.

Figure 2 A semantic understanding and classification model framework based on aspect perception mechanism (see online version for colours)



Suppose there are two domains, one is the source domain $D^s = \{x_i^s, a_i^s, y_i^s\}_{i=1}^{n_s}$ where x_i^s is a text corpus, (e.g., user comments) and y_i^s is the sentiment semantic label corresponding to its aspect a_i^s. The other domain is the target domain without labelling information, which is defined as $D^t = \{x_j^t, a_j^t\}_{j=1}^{n_t}$, and is just missing the sentiment semantic labels compared to the source domain (Prottasha et al., 2022). The objective is to develop a resilient aspect-level sentiment analysis model that leverages both labelled and unlabeled data from domain D^t, with the aim of accurately predicting nuanced sentiment labels for aspects in an unlabeled target domain (Li et al., 2020a). To enhance the representation of both aspect semantics and contextual word meanings, it is essential to embed each word into a compact, real-numbered vector space. Specifically, the inputs of the proposed model in this paper are the sequence of aspect words $a = \{w_1^a, w_2^a, \cdots, w_m^a\}$ and the corresponding sequence of context words $c = \{w_1^c, w_2^c, \cdots, w_n^c\}$ to which it corresponds (Li et al., 2020b). In this paper, we input each word as tokens into the BERT model and obtain the initial embedding vectors of context words $e_c = \{e_1^c, e_2^c, \cdots, e_n^c\} = BERT(\{w_1^c, w_2^c, \cdots, w_n^c\})$ and aspect word embedding vectors $\{e_1^a, e_2^a, \cdots, e_m^a\} = BERT(\{w_1^a, w_2^a, \cdots, w_m^a\})$. It should be highlighted that the representation of an aspect is straightforward when it's a single word, like 'food'; in this case, it corresponds to the word's initial embedding vector. For multi-word aspects like 'customer service', the representation is generated by computing the mean of the initial embedding vectors for each individual word. The word embedding process of aspect can be expressed as follows:

$$e_a = \begin{cases} e_1^a, & m = 1 \\ \sum_{\ell=1}^{m} e_\ell^a / m, & m > 1 \end{cases} \tag{11}$$

where m is the number of words contained in a given aspect and e_ℓ^a is the initial embedding representation of the first aspect word.

To enhance the capture of semantic interactions between aspects and the surrounding text, this paper utilises the heuristic matching between the initial embeddings of aspects e_a and the initial embeddings of context words $\{e_1^c, e_2^c, \cdots, e_n^c\}$. Meanwhile, in this paper, the vectors of aspects are stacked together h_a, and then the output result H is used as the input of the aspect-aware self-attention mechanism based on aspects, and the semantic alignment can be formulated thus:

$$h_i = \left(e_i^c, e_a, e_i^c \odot e_a, e_i^c - e_a\right) \tag{12}$$

$$h_a = \left(e_a, e_a, e_a, e_a\right) \tag{13}$$

$$H = \left[h_1, h_2, \cdots, h_n, h_a\right] \tag{14}$$

Once we have the integrated representation H of aspects and their surrounding context, the next step is to delve into extracting the profound semantic connections between them. The essence of the self-attention mechanism lies in generating a representation for each sequence element by taking a weighted sum of all elements in the sequence (Rezaeinia et al., 2019). This mechanism calculates the input sequence's positional similarities, where the weight magnitudes are based on the elements' correlations. These correlations are ascertained by evaluating the attention scores between element pairs. The process can be encapsulated as follow:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{15}$$

where Q represents the query matrix, K denotes the key matrix, and V signifies the value matrix. Meanwhile, d_k refers to the dimensionality of the key vectors.

The system gradually acquires the ability to generalise across domains through a domain adaptation module, which is composed of three principal components: an MLP layer, a sentiment classifier, and a domain classifier. This component is designed to reduce the gap between source and target domains, as measured by equation (16).

$$L_m = \sum_{\ell=1}^{h} d_k^2\left(D_\ell^s, D_\ell^t\right) \tag{16}$$

where $D_\ell^* = \{R_{\ell_i}^*\}$ represents the vectorised representation of the ℓ^{th} layer for both the source and target domains, while $d_k^2\left(D_\ell^s, D_\ell^t\right)$ signifies the magnitude of the multicore maximum mean discrepancy assessed on the ℓ^{th} hidden layer's output from the MLP. The final MLP layer's output is utilised as the feature vector for the source data, which is subsequently fed into the softmax layer for the classification of sentiment at the aspect level. Within this layer, the probabilities for the sentiment labels pertaining to aspects are calculated as detailed below:

$$p_i^s = softmax\left(W^s R_h^s + b^s\right) \tag{17}$$

where $i \in [1, C]$, C is the number of sentiment categories, p_i^s is the estimated probability of each sentiment category. The goal of the sentiment classifier is to reduce the cross-entropy loss for the labelled data within the source domain. Concurrently, the domain classifier aims to enhance domain invariance by learning shared features across domains, which aids in transferring knowledge between them and boosts the model's generalisation and transferability. In this research, all feature representations R_h are funnelled through the softmax layer to classify the domain, with the goal of determining the origin of each training sample, whether it is from the source or target domain, as detailed subsequently:

$$\hat{y}^d = softmax\left(W^d R_h + b^d\right) \tag{18}$$

Through the synergy of these three modules, the proposed modelling framework is able to comprehensively understand and analyse text data, thus achieving superior performance in fine-grained text sentiment analysis tasks. This holistic method not only boosts the precision of sentiment analysis but also strengthens the model's capacity to generalise across a variety of textual data.

4 A deep learning semantic understanding and classification method for student online opinion for new media

4.1 Student online public opinion targeting new media

In the current new media era, students increasingly rely on instant messaging tools such as WeChat, QQ groups, campus BBS, and RenRen for daily information exchange and expression of opinions. Information is rapidly disseminated through diversified channels in the form of text, sound, pictures, videos, etc. which makes the amount of information college students are exposed to greatly increase (Shivaji and Manit, 2021). They have shown unprecedented concern and interest in social events, news hotspots, policies and regulations, and other different views of public opinion. However, the explosive growth of information also brings challenges: how to efficiently extract valuable information from massive data and accurately grasp students' real emotions and opinions has become an urgent problem. Traditional text processing techniques are often overstretched when facing such complex and high-dimensional data (Stieglitz and Dang-Xuan, 2013). Addressing this challenge, our study presents a deep learning model geared towards understanding and categorising student sentiments expressed online within the new media landscape. We utilise BERT, a pre-trained language model known for its superior performance in NLP, to leverage its advanced capabilities in language representation for our task. BERT's architecture allows for the capture of intricate patterns and correlations, offering a level of precision that surpasses traditional methods, making it well-suited for analysing the complex sentiments expressed by students in new media environments. By making innovative improvements to the BERT model, our method aims to enhance the accuracy of fine-grained text sentiment analysis and better adapt to the specific needs of student online public opinion analysis, which can not only provide educational administrators with more accurate insights into the dynamics of students' thoughts, but also provide policy makers with strong technical support for monitoring and analysing public opinion in the new media environment.

4.2 Improvement of BERT model

For the sentiment analysis task, the model is designed to forecast the sentiment polarity associated with a given sentence and its specified aspect, while the dataset under the task is pre-given a 'sentence-aspect' representation pair(S, A), where S denotes the sentence to be analysed, and A denotes the aspect that needs to be analysed for sentiment analysis. The sentence is denoted as $S=\left\{w_1^s, w_2^s, \ldots, w_{ls}^s\right\}$, which consists of a series of words. The specific aspect is denoted as $A=\left\{w_1^a, w_2^a, \ldots, w_{la}^a\right\}$. It should be noted that A is a segment of S, representing the length of the aspect term. The objective of aspect-based sentiment analysis (ABSA) is to develop a sentiment classifier that can precisely determine whether a sentence X exhibits positive, negative, or neutral sentiment towards specific aspects. As previously highlighted, the semantic information related to aspects is crucial for detailed sentiment analysis. This paper, therefore, proposes an enhancement to BERT by introducing a dynamic re-weighting adapter (DRA) that dynamically identifies and updates the significance of words for the ABSA task. Through the DRA-BERT model, we selectively encode aspect-aware semantic information dynamically. The model's architecture, depicted in Figure 3, primarily includes two foundational elements: the BERT encoder and the DRA, along with two operational modules: the embedding module and the sentiment prediction module.

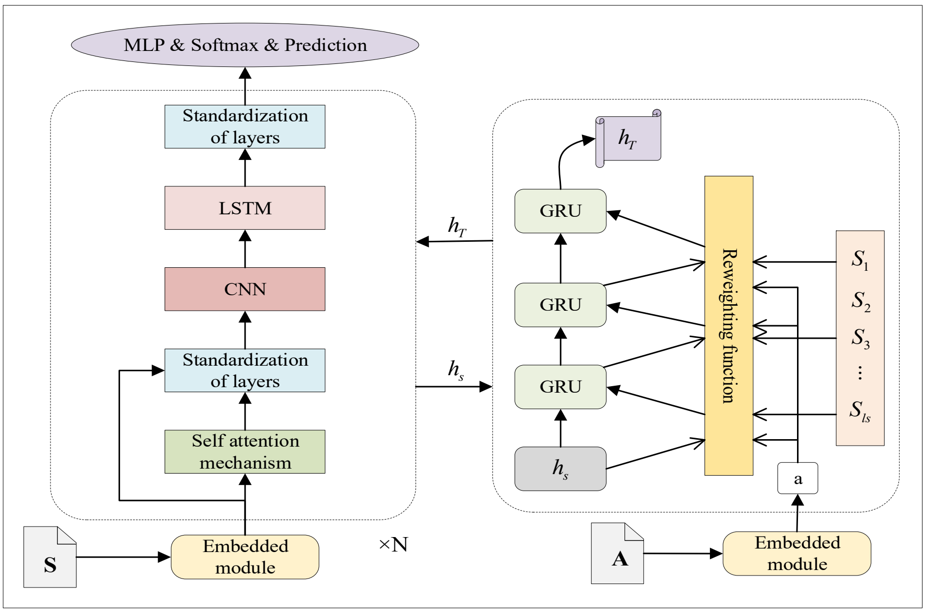
The DRA refines the overall sentence semantics by identifying the most pertinent words in relation to the specific aspect representation at each step. The DRA takes as input the BERT encoder's final output and the initial embeddings of the aspect word sequences. In each iteration, the paper employs a reweighted attention mechanism to pinpoint the most significant word for the given aspect from the input sequence. Subsequently, a gated recurrent unit is applied to iteratively encode the chosen word and refine the aspect-related semantic representation. The entire computational process can be encapsulated as follows:

$$a_t = F\left(\left[s_1, s_2, \cdots, s_{ls}\right], h_{t-1}, a\right) \tag{19}$$

$$h_t = GRU\left(a_t, h_{t-1}\right), t \in [1, T] \tag{20}$$

where a signifies the original embedding vector of the aspect term, a_t represents the output from the reweighting function F and T indicates the adaptive reweighting span across the sentence.

Figure 3 DRA-BERT model framework diagram (see online version for colours)



The DRA-BERT model employs an attention mechanism for the re-weighting function F, designed to dynamically pinpoint the most crucial aspect-related words during each semantic update iteration, with the calculation detailed as follows:

$$M = W_s S + \left(W_d h_{t-1} + W_a a\right) \otimes w \tag{21}$$

$$m = \omega^T \tanh(M) \tag{22}$$

where S denotes the original sentence embedding and M is the fused representation of aspects and sentences. W_s, W_d, W_a and ω is the trainable parameter matrix.

Following the application of the BERT layer and the DRA to the input sentence, the initial feature representation is converted into a sentiment-laden semantic representation denoted as e.

$$e = \left\{e_i \middle| i = 1, 2, \cdots, l_s\right\} = \left(W_e f + U_e h_T + b_e\right) \tag{23}$$

Post the N^{th} iteration of the stacked BERT layer, the model derives the conclusive representation of sentence e_N. This representation is subsequently input into a multilayer perceptron, where it progresses through several layers to ultimately yield the likelihoods of various sentiment polarities, as delineated subsequently:

$$R_l = Relu\left(W_l R_{l-1} + bl\right) \tag{24}$$

$$\hat{y} = softmax\left(W_o R_h + b_o\right) \tag{25}$$

where R_l is the hidden state representation of the l^{th} MLP layer, R_h is the feature representation of the last layer, and $\hat{y}$ is the sentiment label predicted by the final model.

5 Experimental results and analyses

Under the new media environment, the analysis of students' online public opinion is of great significance in grasping the ideological dynamics of the student body and maintaining campus stability and harmony. In order to gain a deeper understanding of students' online behaviours and emotional tendencies on platforms such as instant messaging, e-mail, and microblogging, this study plans to collect and construct these three datasets to comprehensively reflect the content of students' communications and emotional expressions. The collected data will undergo rigorous pre-processing, including data cleaning, denoising, formatting and anonymisation to ensure data quality and user privacy. We will develop an extensive, meticulously labelled dataset categorised into positive, negative, and neutral sentiments, with dataset specifics outlined in Table 1. Following established research practices, our experiments reserve a 10% sample of the training data for validation.

Figure 4 Comparison results of different baselines on the instant messaging dataset (see online version for colours)

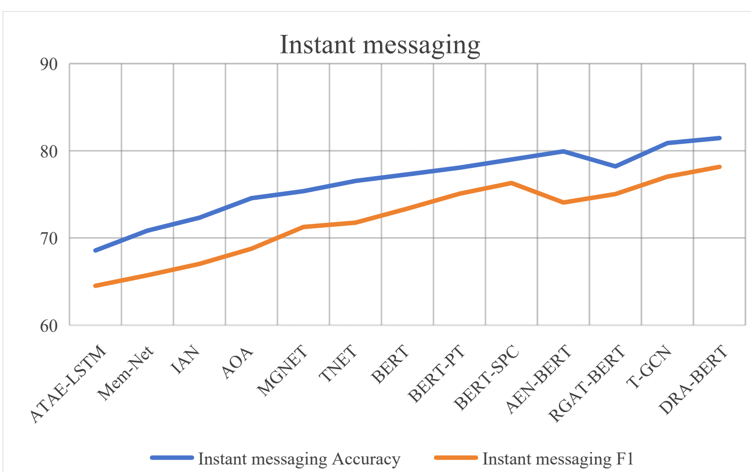


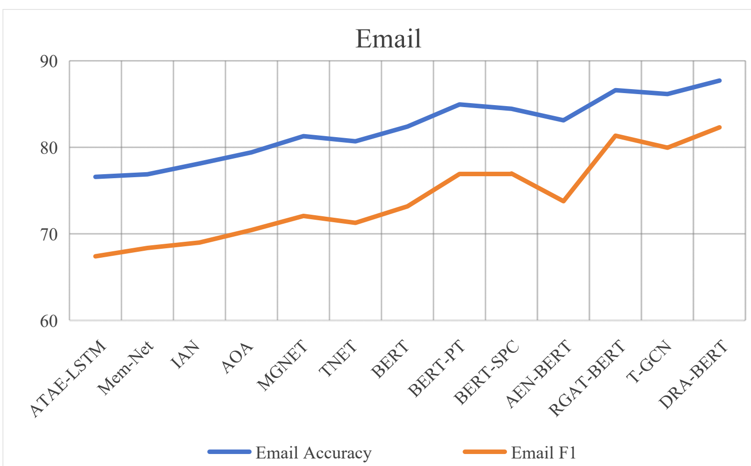
Table 1 Dataset description

Dataset	*Positive*	*Negative*	*Neutral*
Instant messaging	2,164	807	637
E-mail	994	570	464
Weibo	1,561	1,560	3,127

Table 2 Comparative experimental results of various models on three datasets

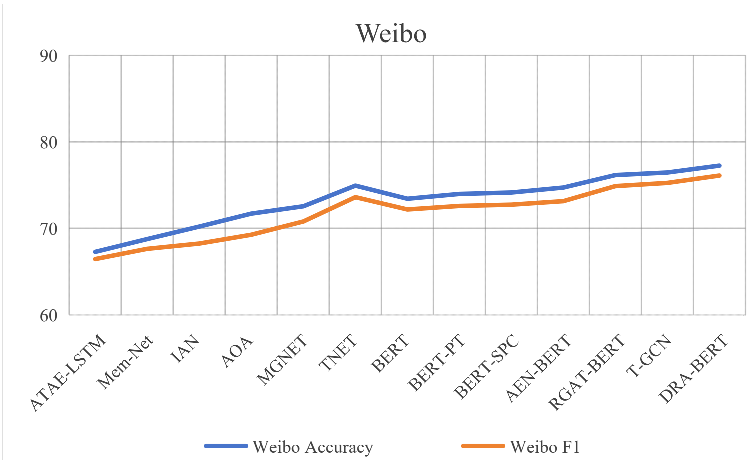
Experimental methods	*Instant messaging*		*E-mail*		*Weibo*	
	Accuracy	*F1*	*Accuracy*	*F1*	*Accuracy*	*F1*
ATAE-LSTM	68.57	64.52	76.58	67.39	67.27	66.43
Mem-Net	70.84	65.73	76.88	68.36	68.74	67.61
IAN	72.32	67.03	78.12	68.99	70.19	68.22
AOA	74.56	68.77	79.42	70.43	71.68	69.25
MGNET	75.37	71.26	81.28	72.07	72.54	70.78
TNET	76.54	71.75	80.69	71.27	74.93	73.60
BERT	77.29	73.36	82.40	73.17	73.42	72.17
BERT-PT	78.07	75.08	84.95	76.92	73.96	72.58
BERT-SPC	78.99	76.31	84.46	76.98	74.13	72.73
AEN-BERT	79.93	74.07	83.12	73.76	74.71	73.13
RGAT-BERT	78.21	75.03	86.60	81.35	76.15	74.88
T-GCN	80.88	77.03	86.16	79.95	76.45	75.25
DRA-BERT	81.45	78.16	87.72	82.31	77.24	76.10

Figure 5 Comparison results of different baselines on the e-mail dataset (see online version for colours)



In developing our model, we established its core architecture with 12 layers, 12 attention heads, and a hidden size of 768 units. The GRU's hidden dimension and the DRA mechanism's reweighted sequence length were both configured to 256 and 7, respectively. We fine-tuned the learning rate across a range of values from 2e-5 to 1e-3, experimented with batch sizes of 16, 32, 64, and 128, and applied a dropout rate of 0.2. Meticulous adjustments to the hyperparameters ι, β, and λ resulted in optimal values of 3, 0.8, and 100. Utilising the Adam optimiser for training, we assessed the model's performance using standard metrics, ensuring reliability by running each experiment with varied random seeds and averaging the outcomes. For comparative analysis, we benchmarked our model against several cutting-edge models prevalent in the field. These models can be categorised into models based on attentional mechanisms (ATAE-LSTM, Mem-Net, IAN, AOA, MGNet, and TNet) and pre-training-based language models (BERT, BERT-PT, BERT-SPC, AEN-BERT, RGAT-BERT and T-GCN).

Figure 6 Comparison results of different baselines on the Weibo dataset (see online version for colours)



To establish the efficacy of the DRA-BERT approach, this study conducts comparisons against established baselines using three well-known public datasets and assesses the model's performance utilising accuracy and F1-score as the metrics of evaluation. According to the results in Table 2 and Figures 4–6, it can be found that the BERT-based method beats most of the attention-based methods in both metrics, a phenomenon that suggests the limitations of attention-based networks in learning deep semantic representations compared to pre-trained methods. Another possible reason for this is that pre-trained language models have strong semantic representation capabilities. To address the limitations of existing models, this paper employs BERT as the foundational encoder to capture comprehensive sentence semantics. Our modification leads to a tailored BERT variant that significantly outperforms the general-purpose version on the task of student online opinion analysis. Moreover, our proposed DRA-BERT model surpasses current benchmarks in terms of accuracy and F1-score, thereby validating the effectiveness of our targeted approach. It also shows that DRA is able to better characterise the aspectual-level affective semantics of sentences compared to the BERT component in previous approaches.

6 Conclusions

This research introduces a deep learning framework that combines CNN and LSTM, along with an attention mechanism, to enhance the precision of sentiment analysis for student online discourse within the realm of new media. In addition, by constructing a large-scale student speech dataset covering a wide range of new media platforms, this study provides rich and accurate data resources for model training. Although this study achieved significant results in improving the accuracy of sentiment analysis, future research still needs to explore in-depth in multimodal data analysis, cross-cultural communication, real-time sentiment prediction, model interpretability, algorithm efficiency, and data ethics and privacy protection. These explorations will promote the development of public opinion analysis technology to a deeper level, contributing to the creation of a more harmonious cyberspace and the enhancement of social governance effectiveness.

Acknowledgements

This work is supported by the Sichuan Center for Rural Development Research (No. CR2018), the Sichuan University Ideological and Political Education Research Center (No. CSZ21096), the Center for Research on Rural Community Governance (No. SQZL2022D02).

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