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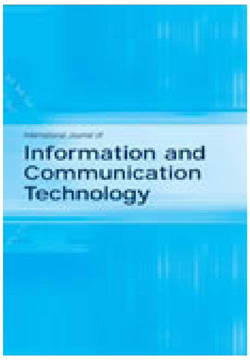

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A study into text sentiment analysis model based on deep learning

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A study into text sentiment analysis model based on deep learning

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Abstract: Deep learning models for text sentiment analysis are employed to analyse the human emotions conveyed by natural language representation in text data. The BERT-ABiLSTM model, a large-scale pre-trained model, is utilised for text data by transforming text word embeddings and extracting global features to analyse the emotions expressed in the text. However, due to the emphasis of ABiLSTM on global features, there are limitations in extracting local features from data. To address this limitation, the TextCNN model is introduced to enhance the local feature extraction capabilities of the model, optimising the process of extracting features from text data. This paper aims to study the text-sensitive analysis model based on the deep learning BERT-CNN-AbiLSTM model. This paper first introduces BERT-AbiLSTM, improves the TextCNN module to enhance local feature extraction, constructs a BERT-CNN-AbiLSTM model, and then analyses the feasibility and reliability of the optimised model through comparative experiments. In the end, this paper introduces the application scenarios of the BERT-CNN-AbiLSTM model to achieve sentiment analysis of natural text language.

Keywords: BERT; TextCNN; BiLSTM; pre-training; feature.

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1 Introduction

In the current information age, the widespread use of the internet has led to the proliferation of online platforms such as social media, e-commerce platforms, and news reporting, resulting in an exponential growth in the volume of textual data generated. These data not only contain vast amounts of explicit information but also encapsulate users' emotions, attitudes, and personal opinions. In such an era of information explosion, accurately understanding and analysing the sentiment information contained within these texts has become crucial.

In today's business environment, consumer sentiment and attitudes play a crucial role in influencing the influence and market position of brands. Therefore, businesses and organisations need effective ways to understand and analyse user sentiment to guide their business decisions and brand management strategies. Additionally, sentiment analysis and user feedback analysis on platforms such as social media and news reporting are also crucial for governments, public institutions, and enterprises. By performing sentiment analysis on textual data, they can quickly grasp public sentiment and attitudes, respond promptly, and formulate relevant strategies.

However, traditional text analysis methods face challenges in dealing with long-distance dependencies and complex contexts. These methods often require manual design of features or rules, making it difficult to cope with the high dimensionality and complexity of the data. Therefore, researchers have begun to explore text sentiment analysis methods based on deep learning technology. Deep learning techniques can learn high-level abstract features from data and handle long-distance dependency relationships and complex contexts in text, making them a powerful tool for solving text sentiment analysis problems (Xu et al., 2023).

In this context, the BERT-ABiLSTM model emerged. The BERT model, as a pre-trained language model based on the Transformer structure, has powerful representation learning capabilities and can learn rich language representations from large-scale text corpora. The ABiLSTM model, on the other hand, is a bidirectional long short-term memory (BiLSTM) network that incorporates attention mechanisms and can capture long-term dependency relationships in text sequences. By combining these two models, the BERT-ABiLSTM model can better understand the context and semantic information of text, thereby achieving more accurate sentiment analysis. Of course, the BERT-ABiLSTM model also has some limitations. For example, during the pre-training phase, the model does not consider domain-specific knowledge, resulting in poor performance in sentiment analysis tasks requiring specialised domain knowledge. To address this issue, we consider introducing a TextCNN module into the BERT-ABiLSTM model. The TextCNN module, as a convolutional neural network structure, can effectively extract local features from text, further enhancing the model's ability to capture sentiment information. In this way, we can improve the model's performance in sentiment analysis tasks in specific domains and enhance its generality and robustness.

Therefore, text sentiment analysis models based on deep learning have significant importance in today's information age, and optimised models can better improve the accuracy of text sentiment analysis. Through continuous research and exploration, we can continually improve and optimise these models to better cope with the complexity and diversity of textual data and provide users with more accurate and reliable sentiment analysis services.

2 Text sentiment analysis model based on deep learning

2.1 BERT-ABiLSTM analysis model

The BERT-ABiLSTM model combines the BERT and ABiLSTM models for text sentiment analysis. Among them, the BERT model is a pre-trained model based on Transformer, which is pre-trained on large-scale text data and has excellent contextual understanding ability due to its mastery of universal language representation; BiLSTM is a BiLSTM network that introduces attention mechanisms, which can handle important information in sequences more flexibly (Zhang and Cai, 2023); the BiLSTM layer is a BiLSTM network within the ABiLSTM model. It enhances flexibility in handling crucial information within sequences. The functionality of the self-attention layer, fully connected layer, and classification layer in the ABiLSTM model is to map the final features to the ultimate output. Through the end-to-end coordination of the above three modules, the BERT-AbiLSTM analysis model can extract global and local features in sentiment analysis of text information, thereby achieving detailed and accurate sentiment classification.

2.1.1 BERT pre-training layer

As the input to the entire model, the BERT pre-training layer consists of three crucial elements: token embeddings, segment embeddings, and positional embeddings. These elements collaborate to empower the BERT-ABiLSTM model in contextual comprehension and semantic representation (Pu et al., 2023). Specifically, token embeddings primarily represent each vocabulary item in the input text, primarily obtained through the masked language model (MLM) task within the BERT model. BERT maps each word to a high-dimensional vector and learns the semantic information of each word by predicting another word, thereby mastering its contextual representation in the text. Embedding of text segments refers to the unique vector representation of sentences or paragraphs during text processing. The BERT model divides the text into segments in the pre-training phase, creating embedding vectors. It then predicts the adjacency of two segment embedding vectors in the next sentence prediction (NSP) task. Position embedding allows BERT to compensate for the lack of processing input sequences in the Transformer architecture. It represents the order of words through position embedding and adds it with word element embedding to represent the position of each word in the text. Through word element embedding, fragment embedding, and positional embedding, the BERT model can take natural language text information as input data, convert it into contextual representation, and provide basic data information for subsequent processing.

2.1.2 BiLSTM layer

The BiLSTM layer is a type of recurrent neural network (Yang et al., 2023). BiLSTM incorporates both forward and backward modules as a component of the BERT model, enabling it to gather information from the past and future of input sequences. This facilitates feature extraction of textual context, enhancing the BERT model's ability to capture sentiment information in the text. Among them, the key to effectively handling long-distance sequences is the implementation of bidirectional encoding in the BiLSTM layer. BiLSTM facilitates the simultaneous processing of information in both forward and backward directions by utilising bidirectional encoding. When combined with the BERT model, it ensures the synchronised handling of current, past, and future information, capturing dependencies in the text's contextual relationships. Furthermore, the BiLSTM layer incorporates specialised memory units that selectively store and discard crucial information within lengthy text sequences, such as input and output details.

In the BERT-ABiLSTM model, the BiLSTM layer takes the output from the BERT model. Leveraging BERT's global contextual understanding, BiLSTM performs local sequence modeling on the text information. This allows the BERT-ABiLSTM model to comprehensively capture the text's global and local features, enabling a more nuanced consideration of contextual information for sentiment analysis.

2.1.3 Self-attention layer and fully connected and classification layer

The BERT-AbiLSTM model also includes a self-attention layer, a fully connected layer, and a classification layer (Zhu et al., 2023). The self-attention layer improves the model's ability to understand context by allowing each position in the input sequence to focus on information from all other positions to obtain global contextual information. The fully connected layer is used to map input features to output feature space and to perform nonlinear transformations on the output of the self-attention layer to enable the model to learn higher-level abstract features and improve its performance on specific tasks. The classification layer is the last layer of the model output, used to map features to the task-related output space, such as the softmax classifier used for sentiment classification and other tasks, using the confidence of different categories to achieve the classification of positive or negative emotions.

2.1.4 Introduction to the process of BERT-ABiLSTM model

The BERT-ABiLSTM model combines BERT, CNN, and BiLSTM networks for text sentiment analysis. The specific algorithmic process is as follows:

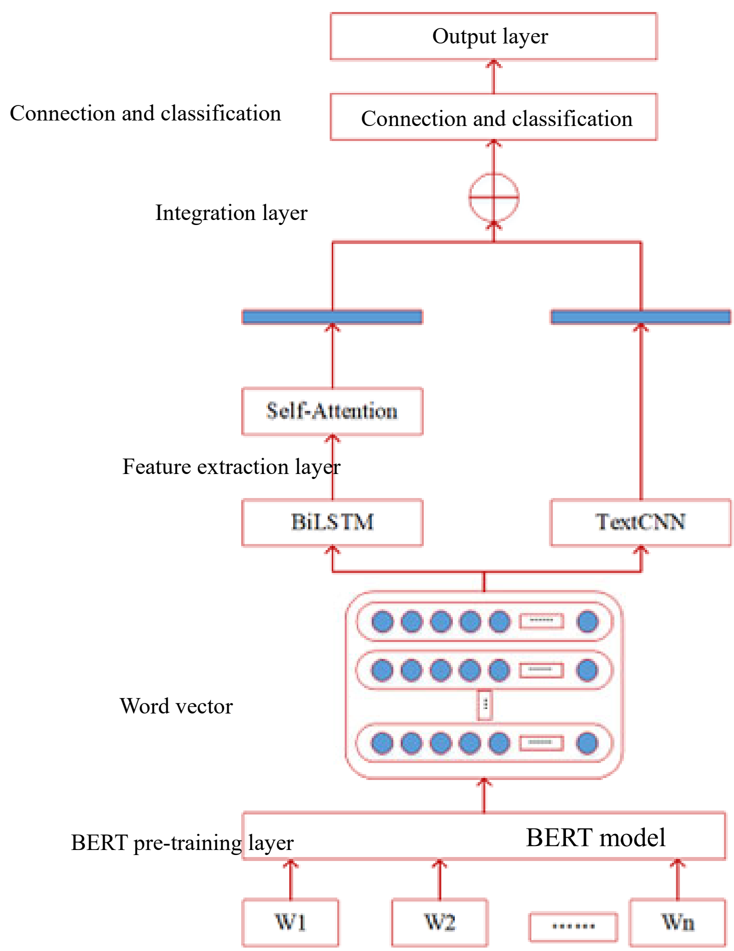
1. Input representation: The text to be analysed is input into the BERT model to obtain word embedding representations for each word. The BERT model can learn the semantic representations of each word in context.
2. Local feature extraction: The output of the BERT model is connected to the CNN module, which performs convolution operations on the text at different window sizes to extract local features. CNN can capture local patterns in the text.
3. Sequence modelling: The output of the CNN module is connected to the BiLSTM module, which uses bidirectional LSTM networks to model the text sequence and capture temporal information in the text. BiLSTM can effectively handle long-distance dependencies in text sequences.
4. Feature integration: The outputs of the CNN and BiLSTM modules are integrated, and the final text representation is obtained through simple concatenation or other methods, containing both local features and temporal information.
5. Sentiment classification: The integrated text representation is passed to the fully connected layer and the classification layer, and sentiment classification results are obtained through softmax function. Typically, sentiment classification can include categories such as positive, negative, or neutral sentiment.
6. Model training: The model is trained using labelled sentiment classification datasets, and cross-entropy loss function or other suitable loss functions for classification tasks are utilised for model optimisation.

2.2 Optimisation of BERT-ABiLSTM

The BERT-ABiLSTM model faces challenges in handling tasks like sentiment analysis due to its design for general language processing. While the BERT model is crafted for universal language comprehension, the BiLSTM layer emphasises bidirectional information processing for long sequences and representation of information memory. However, this emphasis on longer sequences creates a deficiency in extracting local features, necessitating further optimisation of the BERT-ABiLSTM model to enhance its capability in extracting local features from textual data (Wei et al., 2023).

In this study, a TextCNN module is introduced in parallel during the BiLSTM layer and self-attention layer process in the original BERT-ABiLSTM model. This addition enhances the local feature extraction capability of the BERT-ABiLSTM model.

Figure 1 Structural diagram of BERT-CNN-ABiLSTM model (see online version for colours)



Firstly, the TextCNN module can extract multi-level features from input using convolutional kernels of varying sizes. This enables it to capture information at different scales in the text, which in turn enhances the BERT-AbiLSTM model's ability to learn local text features more comprehensively. As a result, the model becomes more sensitive to local text information. Secondly, The TextCNN module can optimise the limitations of BERT's pre-training layer in processing both fixed-length and variable-length input sequences, thus increasing the flexibility of input and output text information (Yang and Kong, 2023). Figure 1 shows the structure diagram of the optimised BERT-CNN-AbiLSTM model.

In the BERT-CNN-ABiLSTM model, the BERT pre-training layer serves as the model input, processing and transforming textual data to generate a two-dimensional matrix containing information on the length of textual sentences and word vectors. This matrix is then utilised as the contextual representation input for the next layer of the model.

The BiLSTM layer and TextCNN module receive word vectors generated by BERT. The TextCNN module employs convolutional neural networks with various convolutional kernels. While keeping the dimensionality of word embeddings constant, these kernels slide up and down the word vector dimensions, extracting local features of the text. To achieve the calculation process, the first convolution kernel of TextCNN is consistent with the word embedding dimension of the two-dimensional matrix of the text, and then multiple and different convolution kernels are performed on the word vectors to make the local features of the text language information more diverse and detailed.

If the word vector of each sentence is Y, the length is n, y_i is each word vector in the sentence, and then the word vector matrix of the text is shown in formula (1).

$$Y = [y_1, y_2, y_3, \ldots, y_n] \tag{1}$$

For the TextCNN model, if the convolutional kernel size is $x * m$ when performing convolution operations on word vectors, each sliding will result in a feature value. Then, the calculation formula is shown in formula (2).

$$z_i = f(W \cdot Y_{i:i+x-1}) + b \tag{2}$$

By continuously sliding on the word vector, a feature vector T consisting of $n - x + 1$ eigenvalues can be obtained, and after max pooling, the maximum value is selected from these eigenvalues. By incorporating the TextCNN module, multiple convolution kernels can be designed according to actual situations to enrich the feature extraction of local semantics. After maximum pooling, the main features can be extracted through feature fusion (Kong and Chen, 2022).

Due to the parallel processing of the TextCNN, BiLSTM, and self-attention layers in the BERT-CNN-ABiLSTM model, it is necessary to introduce a fusion layer to integrate the features of TextCNN and BiLSTM, capturing both local and global characteristics of the text. A feature fusion layer is added to the model to achieve this fusion, combining local and global feature vectors through vector summation. As shown in formula (3), H is the final feature vector and is the feature vector of the TextCNN model and BiLSTM model.

$$H = T^t \oplus T^B \tag{3}$$

3 Result verification of BERT-CNN-ABiLSTM model

The text sentiment analysis model based on the BERT-CNN-ABiLSTM architecture represents an end-to-end process for analysing sentiment in natural language text. Following the model structure illustrated in Figure 1, the algorithmic workflow for text sentiment analysis can be devised. This process involves handling natural language information within the text and deriving corresponding sentiment classification results.

3.1 Optimised algorithm process

The algorithmic process for sentiment analysis using the BERT-CNN-ABiLSTM model is structured as follows: text data undergoes processing through the pre-trained layers of BERT, followed by the extraction of textual features through the BiLSTM layer and TextCNN module. The subsequent processing layers classify the output and determine the final judgment results. The specific algorithm process is as follows:

- First is data cleaning. Use regularisation to clean text data and ensure data validity.
- Second, text segmentation and pre-processing. Use tools such as Jieba to perform word segmentation on text data and use the stop word list to remove stop words from the text, reducing the dimensionality of text data and improving text processing performance and analysis efficiency.
- Third, text word vector transformation. Using the BERT model, process the obtained text sequence to obtain a dynamic word vector representation of the text data.
- Fourth is global feature extraction. The BiLSTM model extracts the global feature vectors of word vectors and uses a self-attention mechanism to set permissions on the feature vectors, making highly correlated features more prominent.
- Fifth is local feature extraction, using the TextCNN module to extract local features from dynamic word vectors and perform internal feature fusion (Yang et al., 2022).
- Sixth, feature fusion. The fusion operation of global and local features ultimately obtains the feature vector text dataset.
- Seventh, result output. After full connection and softmax classifier processing, the final sentiment result of the text is obtained.

3.2 Comparative experiment and result analysis

This study conducted comparative experiments to validate the effectiveness of the BERT-CNN-ABiLSTM model. The models without the TextCNN module and those with the TextCNN module were compared. Additionally, within the BERT-CNN-ABiLSTM model, four TextCNN modules were incorporated, each configured with different convolutional kernels to analyse the model's efficacy further.

To evaluate the effectiveness of the experimental results, three evaluation indicators were calculated after the model experiment, including the accuracy of the predicted results (accuracy), the proportion of positive samples correctly identified as positive categories (recall rate – recall), and the reciprocal F1-value of accuracy, recall, and harmonic mean. As shown in formulas (4), (5) and (6).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

Among them, *TP* and *FP* represent the number of true and false positives; *TN* and *FN* represent the number of true and false positive and negative cases, respectively.

$$F1 = \frac{2\ precision * recall}{precision + recall} \tag{6}$$

Among them, precision is the accuracy rate, which is the proportion of correctly recognised positive category samples.

3.2.1 Experimental comparison of convolutional kernel size setting

For this comparative experiment, we opted for the general dataset provided by the SMP2020 Weibo Sentiment Classification Technology Evaluation Competition.

Select text data samples and set different convolution kernels for sample processing on the four TextCNN modules of the BERT-CNN-AbiLSTM model. Considering that a too-large convolution kernel may introduce too much noise, a too-small convolution kernel may not perform well in extracting local features. Considering the performance of the experimental host, the number of convolutional kernels was set to 128 in this model, and the selected comparison convolutional kernel sizes were (1, 2, 3, 4), (2, 3, 4, 5), (3, 4, 5, 6), and (4, 5, 6, 7) for comparative experiments. The data processing process is shown in the algorithm flow in Subsection 3.1. The comparison of the processing results of BERT-CNN-AbiLSTM models with different sizes of convolutional kernels is shown in Table 1.

Table 1 Comparison of processing results of BERT-CNN-AbiLSTM models with different sizes of convolutional kernels

Experiment no.	*Convolutional kernel size*	*Accuracy*	*Recall*	*F1*
1	(1, 2, 3, 4)	76.1%	70.3%	68.4%
2	(2, 3, 4, 5)	77.4%	70.9%	70.1%
3	(3, 4, 5, 6)	77.4%	70.7%	69.8%
4	(4, 5, 6, 7)	76.4%	69.9%	68.1%

According to the results in Table 1, it can be seen that convolution kernel sizes (2, 3, 4, 5) and (3, 4, 5, 6) have the highest accuracy. In contrast, experimental results with convolution kernel sizes (2, 3, 4, 5) have better recall and F1 values than convolution kernel sizes (3, 4, 5, 6). Therefore, in the model comparison experiment, the BERT-CNN-AbiLSTM model can set the convolution kernel size to (2, 3, 4, 5).

3.2.2 Model comparison

Perform text data processing on the BERT-AbiLSTM model and BERT-CNN-AbiLSTM model using the same data samples, with the BERT-CNN-AbiLSTM model having a convolution kernel count of 128 and a size of (2, 3, 4, 5). Finally, different models' accuracy, recall, and F1 values were calculated to compare their results. The specific results are shown in Table 2.

Table 2 Comparison table of text processing results of different models

Experiment no.	*Verification model*	*Accuracy*	*Recall*	*F1*
1	BERT-ABiLSTM model	77.2%	71.8%	71.0%
2	BERT-CNN-ABiLSTM model	77.9%	72.7%	71.6%

According to the results in Table 2, it can be seen that the accuracy of the BERT-CNN-AbiLSTM model is 77.9%, which is higher than the 77.2% of the BERT-AbiLSTM model. The recall rate and F1 value are also 0.9 and 0.6 percentage points higher, respectively. Therefore, in the current sample data processing results, the optimised BERT-CNN-AbiLSTM model has higher accuracy in text sentiment analysis.

4 Application analysis of the BERT-CNN-ABiLSTM model

The application scenarios of the BERT-CNN-ABiLSTM model encompass tasks in natural language processing (NLP), such as text processing and sentiment analysis. In the information age, social media, e-commerce, and other systems have become a part of our lives. Various media or product reviews are crucial in platform operation decisions, product development, and market decisions. Meanwhile, text transmission remains the main data exchange method in the network, and there is a great demand for text classification or entity name recognition tasks such as person names and place names in different fields or occasions. Finally, text-based online Q&A or chat systems can also provide the BERT-CNN-AbiLSTM model with great potential for application.

4.1 Application scenarios for text sentiment analysis

The BERT-CNN-AbiLSTM model can be applied in fields such as social media monitoring, product review analysis, public opinion analysis, etc., to achieve sentiment analysis of user-generated text data such as social media comments and product reviews. The BERT-CNN-ABiLSTM model provides robust textual representation capabilities for sentiment analysis tasks by integrating various levels of feature extraction and sequence modeling methods. This model accurately captures emotional information within the text, enabling precise classification of sentiments as positive, negative, or neutral in comments or evaluations (Jin et al., 2020). When applying the BERT-CNN-ABiLSTM model to text sentiment analysis, optimisation and adjustment of the model structure are essential. This process should be tailored to different system applications, host performances, and business requirements for optimal results. For example, comparing the effects of using different BERT pre-training models (such as BERT base, BERT target, etc.) to understand the performance of the model under different parameter settings; Analysing different model structure configurations, such as the number of layers and hidden units of TextCNN and ABiLSTM modules, to find the optimal configuration. Meanwhile, in text sentiment analysis, it is also necessary to consider the generalisation ability of sentiment analysis for multilingual texts and texts from different fields to improve the applicability of the BERT-CNN-AbiLSTM model.

4.2 Application scenarios for text classification or recognition

The BERT-CNN-AbiLSTM model can be applied to news classification, legal document processing, medical entity name recognition, and other tasks by modifying the recognition target of the model to text categories or entity names. This study aims to discern the distinctive features of various categories or entities by employing precise category or entity labelling in pre-training. This facilitates the prediction of category or entity labels for each word in a given text or document. It aims to enhance the application performance in document processing and entity name recognition.

In the context of text classification or recognition using the BERT-CNN-ABiLSTM model, special attention should be given to parameter settings within the TextCNN module and the BiLSTM layer. It is crucial to continuously conduct comparative experiments on processing layers, convolutional kernel sizes, and quantities to identify the optimal configuration, thereby enhancing the model's processing performance. To further enhance the processing ability of the BERT-CNN-AbiLSTM model in special fields, labelled training data should be used to train the model, and the model parameters should be updated through backpropagation to better adapt to specific tasks. Especially in special fields such as news, medicine, law, etc. due to a large number of professional terms, specific abbreviations, and fixed formats, the adaptive ability of the model needs to be considered during model training. Enhance data annotation and backpropagation to progressively improve the processing capabilities of the BERT-CNN-ABiLSTM model in specialised domains.

4.3 Intelligent online question and answer retrieval application scenarios

The BERT-CNN-ABiLSTM model can be employed in various domains, such as intelligent question-answering systems, knowledge base retrieval, or online customer service (Cheng et al., 2020). Utilising a similarity computation approach within the model compares the similarity between a given question and each potential answer, determining the matching degree between questions and answers. Consequently, this enables users to receive the most relevant answers from extensive knowledge bases or question-answer repositories.

During the training process of the BERT-CNN-ABiLSTM model, it is crucial to consider the match between questions and answers. This involves utilising the model's loss functions, such as binary cross-entropy, to measure the degree of alignment between questions and answers. Simultaneously, given the specialised nature of questions in the QA system, the training process introduces a domain adaptation strategy. This strategy ensures that the model can meet the diverse Q&A requirements across different professional domains in online QA systems. The online QA system based on the BERT-CNN-ABiLSTM model operates as a dynamic system. Continuous iteration and optimisation of model parameters are essential. Leveraging feedback from answers, adjustments to model parameters or structures are made, allowing the model to dynamically adapt to the QA system. This iterative process ensures that the model delivers optimal answers to users in the QA system.

4.4 Application scenarios of social media public opinion monitoring

The BERT-CNN-ABiLSTM model plays a crucial role in the application of social media public opinion monitoring. Leveraging its strong text comprehension and sentiment analysis capabilities, it achieves rapid positioning of social media public opinion. In social media public opinion monitoring, the model helps the system better understand user-generated content, capture user sentiment, and accurately reflect changes in public opinion, thereby providing effective tools and support for public opinion monitoring and management.

The BERT model, as a pre-trained language model, learns semantic information from large-scale text data, endowing it with powerful contextual understanding capabilities. In social media public opinion monitoring, user-generated text data contain rich contextual information, such as various internet memes, emoticons, and internet slang. The BERT model effectively captures these contextual cues, aiding in better understanding user-generated content.

The TextCNN module efficiently extracts local features from text, such as phrases and word combinations, helping the model capture subtle changes in sentiment expression. In social media public opinion monitoring, user sentiment expression may be influenced by various factors such as topics, events, and personalities. The TextCNN module assists the model in swiftly and accurately capturing these changes, thus improving its understanding of user sentiment.

The ABiLSTM module, being a BiLSTM network, captures long-term dependencies in text sequences, facilitating better understanding of temporal information in text. In social media public opinion monitoring, user comments often form a continuous time series. The ABiLSTM module aids the model in better grasping the temporal features of user comments, thereby more accurately analysing trends in user sentiment changes.

5 Conclusions

The deep learning text sentiment analysis model based on BERT-CNN-AbiLSTM is a dynamic end-to-end text language model that can be used for text sentiment analysis. The BERT model is pre-trained on the Transformer architecture, allowing it to have exceptional contextual understanding and mastery of universal language representation. BiLSTM focuses on processing BiLSTM networks and introduces attention mechanisms to process sequence information. TextCNN can enhance the local feature extraction capability of the BERT-AbiLSTM model by setting convolution kernels of different sizes to achieve multi-level feature extraction, enhance the model’s sensitivity to local text information, and fully connect and classify layers to achieve the output of text sentiment results. After comparing the experimental results, it was found that the BERT-CNN-AbiLSTM model has a higher accuracy in text sentiment analysis and is suitable for scenarios such as text sentiment analysis, text classification and recognition, and intelligent online question and answer retrieval. This enables the processing of natural language text data and more accurately improves the results of text sentiment analysis.

Of course, the BERT-CNN-ABiLSTM model still has some potential limitations or challenges that require further research and improvement:

1 Specific domain limitations: The BERT-CNN-ABiLSTM model did not consider domain-specific knowledge during the pre-training phase, which may result in poor performance in sentiment analysis tasks in certain domains. Therefore, future research can explore how to integrate domain-specific knowledge into the model to enhance its performance in specific domains.

2 Scarcity of data samples: In certain emerging professional fields, sentiment classification data available for training may be relatively scarce. Therefore, in future applications, it is necessary to explore how to use techniques such as transfer learning or data augmentation to fully utilise limited data for model training.

3 Limitations in handling long texts: Due to the input length restrictions of the front-end BERT model, the BERT-CNN-ABiLSTM model may face challenges in processing long texts for sentiment analysis. In future research, it is necessary to further improve the model to handle long texts and ensure its performance in sentiment analysis tasks involving long texts.

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