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Dual-channel Chinese Implicit Sentiment Analysis Model Based on Context Information

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Abstract. *In some social media platforms, users tend to use implicit emotional expression with implicit euphemism. Therefore, implicit sentiment analysis is of great significance to the management and guidance of public opinion. Due to the lack of obvious emotional words and sparse emotional information in implicit sentiment sentences, and the strain of traditional explicit sentiment analysis methods is not strong, it is difficult to be competent for implicit sentiment analysis tasks. We propose a context-based dual-channel implicit sentiment analysis model (CBSA). This model combines the semantic features between the contexts of implicit sentiment sentences with the local features of implicit sentiment sentences in the form of two channels, enriching and enhancing the semantic features of sentiment sentences. The CBSA model first expands the text boundary by integrating context information into Chinese implicit sentiment sentences to enrich and enhance the semantic features of Chinese implicit sentiment texts. Secondly, the dual-channel form uses the local features of implicit emotional text and the semantic features between contexts. On this basis, the model introduces self-attention mechanism to optimize the feature vector. On the dataset SMP-ECISA, the method achieves a Macro-F1 of 0.7687, which is 0.11 higher than the baseline model, indicating that the CBSA model can effectively improve the effect of Chinese implicit sentiment classification.*
Keywords: Chinese implicit sentiment, Contextual semantic feature, Dual-channel, Attention mechanism

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1. **Introduction.** Sentiment analysis [1, 2] is to automatically analyze the text content of user reviews to get the users' feelings, attitudes and opinions about products, services, people, events and topics, which has important theoretical and practical value. With the diversification of people ' s expression needs and ways on social platforms, Chinese implicit sentiment expression is widely used in practical scenarios. Implicit sentiment expression in Chinese is implicit and euphemism, but it can also reflect the speaker ' s emotion, attitudes and opinions. Therefore, the analysis of Chinese implicit sentiment can effectively grasp the public opinion trend of hot events and obtain public attitudes and opinions. Due to the diversity and complexity of implicit sentiment expression in Chinese, there is no effective general theory and method for implicit sentiment analysis. Therefore, in-depth research of Chinese implicit sentiment expression plays an important role in the development of natural language processing tasks.

At present, the task of Chinese implicit sentiment analysis is still facing many difficulties. Due to the lack of sentiment words in Chinese implicit sentiment text, the traditional explicit sentiment analysis method based on sentiment dictionary [3] cannot be well applied to Chinese implicit sentiment analysis tasks. Because the use of Chinese implicit sentiment words is relatively objective and neutral, and the expression is more implicit, obscure and euphemism, the text feature extraction method based on bag of words model is not effective, and the text representation and semantic understanding are more complex, which brings great difficulties to Chinese implicit sentiment analysis tasks. At the same time, implicit sentiment in Chinese is closely related to the subjective cognition and common sense of emotional holders, and there is a lack of unified definition standard.

Chinese implicit sentiment expression depends on context information, such as the emotional sentence ' today has haze ', no explicit emotional words, but through the above information ' air quality is too bad ' can judge the implicit sentiment sentence tend to be negative, so the context information can assist the polarity judgment of Chinese implicit sentiment sentence. A dual-channel Chinese implicit sentiment analysis model CBSA based on context information is proposed. Firstly, context information is integrated into Chinese implicit sentiment sentences to enrich and enhance the emotional information and semantic features of implicit sentiment sentences. Secondly, the dual-channel form composed of CNN and Bi-LSTM is used to extract the local features of Chinese implicit sentiment sentences and the semantic features between sentiment sentences and their contexts, and the multi-head attention mechanism is introduced to identify the key emotional information. Finally, this model integrates the local semantic features of Chinese implicit sentiment sentences and the semantic features between sentiment sentences and context, and analyzes Chinese implicit sentiment sentences.

The arrangement of this paper is as follows : in Section 2, the relevant work is reviewed ; in Section 3, the research questions are defined and the Chinese implicit sentiment analysis model is proposed ; the experimental results are described in Section 4 and the model is evaluated. In Section 5, the work of this paper is summarized, and the possible research directions in the future are given.

2. **Related work.** Text sentiment analysis, as a natural language processing task, has attracted wide attention of many researchers, and has been explored and studied from methods and contents. The research method has experienced from the method based on sentiment dictionary and rules to the machine learning method based on feature construction classifier, and then to the mainstream sentiment analysis based on neural network. On the research content, scholars gradually pay attention to Chinese implicit sentiment analysis from explicit sentiment analysis. This section briefly reviews the related work of implicit sentiment analysis.

According to whether there are obvious sentiment words in the text, the text sentiment can be divided into explicit sentiment and implicit sentiment [4]. Table 1 shows examples of implicit affective sentences. Sentences example 1 uses the sentiment word 'bad' to express negative feelings about haze weather, belonging to the explicit sentiment category. The sentiment sentence example 2 does not contain obvious sentiment words, which belongs to the implicit sentiment category, but also expresses negative sentiment for haze weather. Implicit sentiment can be divided into two categories, namely factual implicit sentiment and rhetorical implicit sentiment [5]. Fact-based implicit sentiment expresses sentiment by declaring objective facts. Rhetoric-based implicit sentiment expresses sentiment by rhetoric, such as irony, questioning and metaphor/metaphor. In the sentiment sentence example 3, the negative sentiment is expressed by stating the facts of the game failure, which belongs to the fact-based implicit sentiment. In the sentiment sentence example 4, 'smile' is compared to 'flower' to express positive sentiment, which belongs to rhetorical implicit sentiment. It can be seen that implicit sentiment is one of the important ways of human sentiment expression, which can enrich and accurately express the user ' s sentiment.

Most corpus resources are built for explicit sentiment analysis tasks [6, 7, 8]. Chen and Chen [9] constructed a double recessive corpus. They aim to identify aspects and polarity of opinion statements that do not contain sentiment words or aspect terms, and they observe that implicit sentiment and their adjacent explicit sentiment tend to have the same aspects and polarity. Liao et al. [10] constructed a small implicit fact sentiment corpus and proposed a multi-level semantic fusion model.

For the factual implicit sentiment text, although it only states an objective fact, it contains positive or negative sentiment. To solve this problem, Greene and Resnik [11] identified implicit sentiment by establishing semantics for topics and implicit sentiment and calculating topic similarity. Chen and Chen [9] studied the dual implicit problems in opinion mining and sentiment analysis. Firstly, opinion words and aspect words are extracted from Chinese hotel reviews for clustering, an implicit opinion corpus is constructed and aspect class labels and sentiment polarity are annotated. The results show that the linear kernel support vector machine has strong robustness in implicit sentiment polarity recognition. Liao et al. [10] studied the implicit sentiment recognition of implicit facts

Table 1. Examples of emotional sentences

Example	Sentiment text	Sentiment sentence type	Sentiment orientation
Eg.1	This smog day is really too bad.	Explicit sentiment	Negative
Eg.2	Visibility is less than 20 meters on a smog day.	Factual implicit sentiment sentence	Negative
Eg.3	Liu Xiang lost the game due to injury	Factual implicit sentiment sentence	Negative
Eg.4	Her smile is like a rose.	Rhetorical implicit sentiment sentences	Positive

at the sentence level, and proposed a multi-level semantic fusion method based on representation learning to learn the features used for recognition. This method can effectively identify sentences with implicit factual sentiment.

The use of rhetoric is also an important means of implicit sentiment expression. Based on the pre-trained convolutional neural network model, Ptáček et al. [12] extracted the sentiment features of irony, and then used the support vector machine (SVM) to classify the extracted features. The commonly used expression in ironic rhetoric is to use extreme opposite sentiment to express the emotional contradictions before and after. Luo et al. [13] only started from the structure of the sentiment sentence itself, without considering the context of the sentiment sentence, and calculated the attention scores between any two words to find the key words of irony. Deng et al. [14] designed six features for microblog corpus, and verified the effectiveness of the features by information gain. Finally, different classifiers were used to ironically identify microblog comments. Gao et al. [15] proposed an end-to-end neural network model based on ELMo vector to detect the use of metaphor in context. The model shows good performance in predicting the metaphor of words in a text.

For implicit sentiment analysis in Chinese reviews, Fang et al. [16] proposed a feedback-based opinion analysis model to determine the polarity of implicit opinions in feature and review layers. The experimental results show that the model is superior to SVM model and CNN model. Wei et al. [17] proposed the Bi-LSTM model of multipole orthogonal attention for implicit sentiment analysis. Compared with the traditional single attention model, the use of multi-polar attention mechanism can identify the differences between words and sentiment tendencies. Zuo et al. proposed a context-specific heterogeneous graph convolution network model [18], which combines the context representation to fully reflect the semantic information in implicit sentiment text, so as to achieve the purpose of identifying the target sentiment of sentences. For implicit sentiment in literary texts, Su et al. [19] obtained the characteristics of implicit sentiment through semantic mapping method and long-term and short-term memory network, and could identify 12 implicit sentiment. Mu Wanqing et al. [20] proposed a parallel sentence recognition method based on convolutional neural network and similarity calculation, which was applied to college entrance examination appreciation problems and achieved good results. Wang et al. [21] incorporates knowledge information in text through hierarchical knowledge augmentation to alleviate the "weak feature" problem. Chen et al. [22] proposed an implicit sentiment text preprocessing method for deep learning by converting text data into word frequency maps. Zhuang et al. [23] proposed a multi-feature neural network model for implicit sentiment polarity judgment.

With the in-depth study of text sentiment analysis, how to identify and judge the polarity of Chinese implicit sentiment text has become a very worthy problem. Based on the above analysis, compared with explicit text sentiment, Chinese implicit sentiment analysis faces the following challenges :

(1)There is no obvious emotional word in Chinese implicit sentiment, which makes the traditional sentiment analysis method and bag of words model ineffective. Therefore, semantic information needs to be mined when analyzing Chinese implicit sentiment sentences. At the same time, Chinese implicit sentiment is usually closely related to emotional target, background and so on. It needs to combine target, knowledge, common sense and context background analysis and reasoning to obtain the semantics of Chinese implicit sentiment.

(2)Chinese implicit sentiment is rich in expression forms, and it is difficult to find uniform features in different forms of implicit sentiment expression. Therefore, there are few general Chinese implicit sentiment recognition analysis methods.

(3)Chinese implicit sentiment tendency is closely related to the subjective experience and common sense of sentiment holders, and there is a lack of unified definition standard in the identification process, which makes the construction of Chinese implicit sentiment text corpus more complex.

3. **Chinese Implicit Sentiment Analysis Model.** This section introduces the structure of Chinese Implicit Sentiment Analysis Model (CBSA), and details the functions of each step.

3.1. **Task definition.** For Chinese implicit sentiment sentences S = $\{s_1, s_2, \ldots, s_m\}$ and sentiment tendency tag Y = $\{y_1, y_2, \ldots, y_m\}$ in Chinese implicit sentiment corpus, the purpose of Chinese implicit sentiment analysis task is to obtain a text classifier whose input is the feature representation of Chinese implicit sentiment sentences $S_i = \{w_1, w_2 ,\ldots, w_n\} \in$ S. In the training phase, the text classifier tries to minimize the difference between the actual sentiment orientation label and the predicted sentiment orientation label.

3.2. **Model description.** Context-based dual-channel implicit sentiment analysis model uses dual-channel form for feature extraction and feature fusion of implicit sentiment text. The text information in the context is used to enrich and enhance the emotional information of implicit sentiment sentences, so as to improve the accuracy of implicit sentiment analysis. The structure of context-based dual-channel implicit sentiment analysis model is shown in Figure 1. The left channel of the model aims to extract the local semantic features of implicit sentiment sentences (the left channel), and the right channel of the model is the semantic feature learning method between contexts (the right channel). The purpose is to extract the semantic relationship between implicit sentiment sentences and contexts, so as to enrich and enhance emotional information. Chinese implicit sentiment analysis model (CBSA) is mainly composed of four parts, namely, text representation layer, coding layer, feature fusion layer and output layer. The text presentation layer represents the Chinese implicit sentiment sentences and context information after data preprocessing by word vector. The encoding layer encodes the word vector representation of the text representation layer to capture the local text features and context semantic features of Chinese implicit sentiment sentences. The feature fusion layer fuses the local text features of Chinese implicit sentiment sentences and the sentiment information in the context semantic features. The output layer calculates the sentiment label category through the fused semantic features.

Input layer: (1)Vector representation of implicit sentiment text set context. There is no obvious emotional words in Chinese implicit sentiment sentences, and the use of words is objective and neutral. At the same time, Chinese implicit sentiment sentences

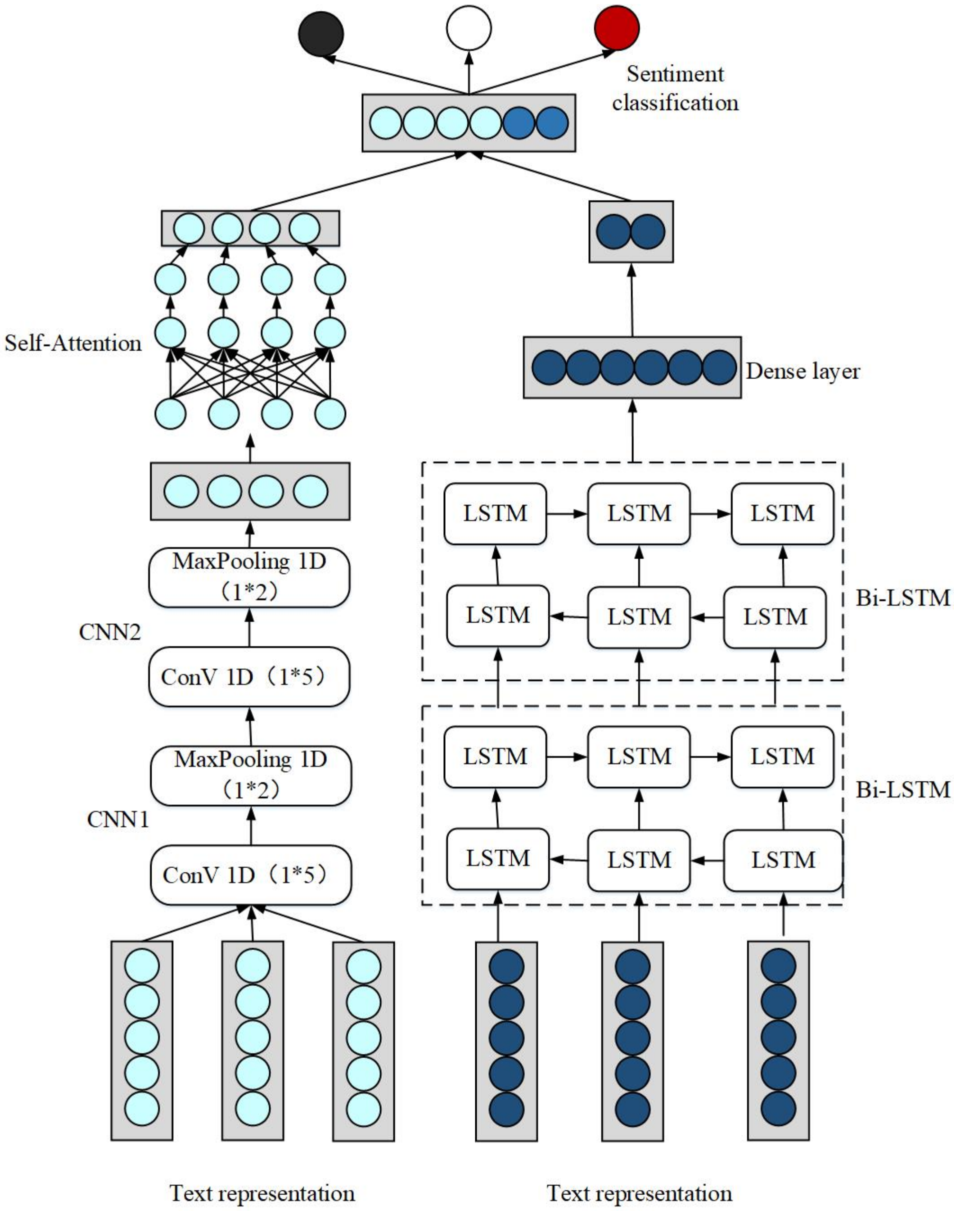

FIGURE 1. CBSA Model structure

are more euphemism and implicit in practical application scenarios. Therefore, the semantic features of Chinese implicit sentiment sentences no longer have obvious emotional information. Due to the particularity of Chinese implicit sentiment text, it is difficult to judge the sentiment tendency of sentiment sentences, but the sentiment information in sentences can be captured through the semantic information provided by the context statement. Therefore, this paper first extracts Chinese implicit sentiment sentences from Chinese implicit sentiment corpus, and integrates the context information into Chinese implicit sentiment sentences, so as to enrich and enhance the emotional information in word vector, thereby improving the recognition accuracy of Chinese implicit sentiment text.

(2)Text preprocessing. There are a lot of noise information in the text data used in sentiment analysis tasks, such as conjunctions, prepositions, adverbs and other auxiliary words. Such words do not have obvious semantic features in sentences, and have a negative impact on the judgment of sentiment tendencies. Chinese implicit sentiment corpus comes from social networking platforms such as Weibo, so there are dirty data such as user ID, redundant punctuation marks, emoticons, English texts and '& quot' symbols in text data. In order to ensure the classification effect of Chinese implicit sentiment analysis model, this paper conducts text preprocessing operations such as data cleaning and character filtering on Chinese implicit sentiment sentences and context information.

(3)Segmentation and removal of stop words. In this paper, jieba word segmentation tool is used to process Chinese implicit sentiment sentences and context information. After word segmentation operation, use HIT stopword list to remove stop words in word segmentation.

(4)Word vector representation. In this paper, we use Word2Vec [24] language model to express implicit sentiment sentences and context, and obtain a fixed dimension feature vector. The Word2Vec model considers the context of words and can learn semantic and grammatical information. At the same time, the word vector dimension obtained by the model is small, which saves storage space and computing resources. In this paper, the feature processing method of text length specification is used to input the features of Chinese implicit sentiment text into the training model to enhance the performance of the model. The maximum length n of Chinese implicit sentiment sentences is set. The implicit sentiment sentences with length less than n are complemented, and the implicit sentiment sentences with length greater than n are truncated.The processing flow of implicit emotional sentences is shown in Figure 2.

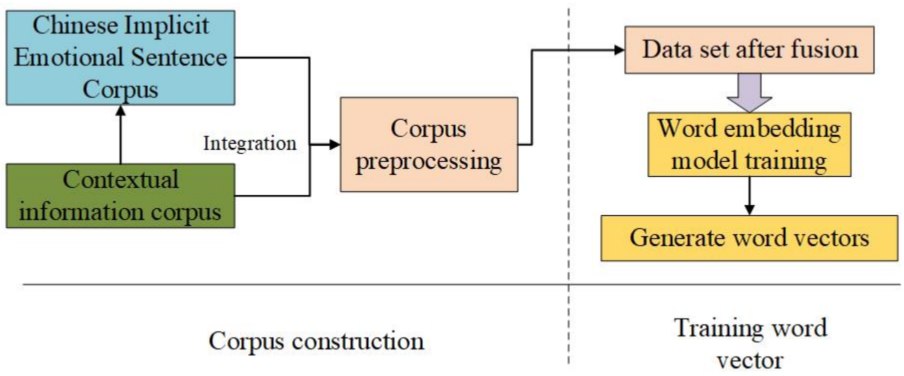

FIGURE 2. Text Data Processing

Coding layer: The coding layer of Chinese implicit sentiment analysis model is mainly composed of convolutional neural network (CNN), bidirectional long-short neural network (Bi-LSTM) and self-attention mechanism.

(1)Extracting local semantic features of implicit sentiment text

In order to extract the key emotional information of Chinese implicit sentiment sentences, the model adds convolutional neural network to capture and extract the local semantic features of sentiment sentences. The results of a convolutional neural network mainly include input layer, convolution layer, pooling layer and full connection layer. In the convolution layer, the convolution kernel is used to extract the local semantic features in the text. After the convolution layer, the pooling operation is used to reduce the dimension of the text feature vector and retain the main semantic features. The pooling layer selects Max Pooling to optimize the feature vector, and selects the largest eigenvalue in the region as the feature of the region, which effectively retains the most obvious semantic information in the text and enhances the characteristics of implicit sentiment sentences.

After the convolutional neural network, the model adds the self-attention mechanism to assign different weights to different sentiment information. The essence of attention mechanism [25] is a resource allocation mechanism, which allocates more attention to key information. It is similar to the selective attention mechanism of human beings, and its main goal is to screen out more critical details from the current information to optimize the task results. In addition to the field of image processing, attention mechanism is also widely used in natural language processing research [26, 27, 28, 29] . After two layers of CNN network, the self-attention mechanism is introduced to give different weights to different sentiment information. The effect of self-attention mechanism is better than the traditional attention mechanism. The self-attention mechanism needs to calculate the attention scores of each word and all words, and can ignore the distance between words to calculate the dependence directly, so it can capture long distance dependence. The calculation process of attention mechanism is shown in Formulas (1-3).

$$e_t = \tanh\left(W_j h_t + b_j\right) \tag{1}$$

$$\alpha_t = \frac{exp(e_t)}{\sum_t e_t} \tag{2}$$

$$s = \sum_t \alpha_t h_t \tag{3}$$

In Formulas (1-3), W_j and b_j are weight and bias values, respectively ; α_t is the attention weight, s is the weighted eigenvalue.

(2)Extract context semantic features

The pooling layer of Convolutional Neural Network (CNN) loses a lot of valuable information and ignores the links between local and global. In order to make up for the defects of convolutional neural network, Bi-directional long-short-term memory neural network (Bi-LSTM) and attention mechanism are used to capture the semantic features between Chinese implicit sentiment sentences and their contexts.

As a variant of LSTM, bidirectional long-short term memory neural network consists of forward LSTM and backward LSTM, which is essentially two independent long-short term memory neural networks (LSTM). In the bidirectional long-term and short-term memory neural network, the calculation of time t depends on the calculation results of time(t-1) and time(t+1), so the bidirectional long-term and short-term memory neural network can capture the semantic features of the two directions before and after the context information, and effectively improve the effect of Chinese implicit sentiment analysis. The structure of the Bi-LSTM neural network is shown in Figure 3, and its representation is shown in formula (4-5). LSTM is composed of a storage unit (cell), an input gate i_t, a forgotten gate f_t, and an output gate o_t. The gate structure can control the information in the storage unit, selectively enabling some information to increase and delete information . The positive LSTM calculation formula is shown in Formulas (6-11).

$$\overrightarrow{h_t} = \overrightarrow{LSTM}(x_t, \overrightarrow{h_{t-1}}) \tag{4}$$

$$\overleftarrow{h_t} = \overleftarrow{LSTM}(x_t, \overleftarrow{h_{t+1}}) \tag{5}$$

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{6}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{7}$$

$$\widetilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_i) \tag{8}$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{9}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = o_t * tanh(C_t) \tag{11}$$

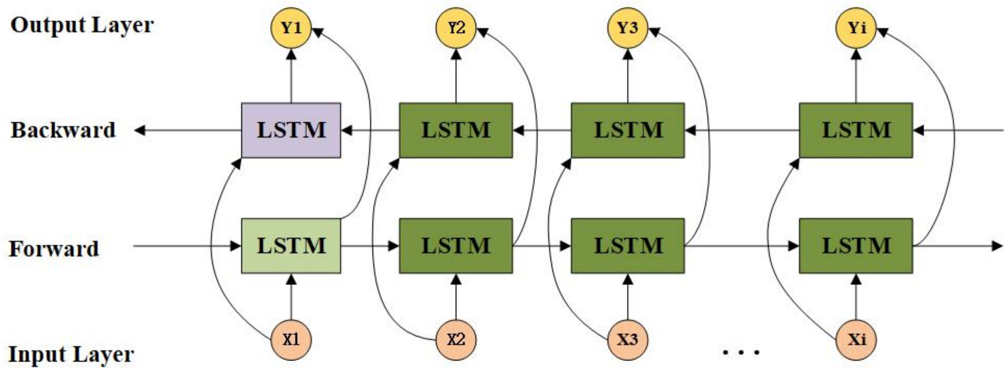

FIGURE 3. Diagram of the structure of Bi-LSTM

3.3. **Model parameter.** The details of some parameters of the context-based dual-channel implicit sentiment analysis model in this section are shown in Table 2. In this model, the two convolution layers are sampled by one-dimensional convolution kernel with a size of 1 × 5 and the step length is 1. The input dimension and output dimension of the first one-dimensional convolution operation are 128 and 64 respectively, and the input dimension and output dimension of the second one-dimensional convolution operation are 64 respectively. Both convolution layers adopt ReLU activation function. The two pooling operations of the model adopt one-dimensional maximum pooling operation, and the maximum eigenvalue in the region is selected as the feature of the region. The kernel size of the one-dimensional maximum pooling layer is 1×2. The input dimension of self-attention mechanism is 64. The number of neurons in the two-layer Bi-LSTM network in the model is 10, the input and output dimensions of the first-layer Bi-LSTM are 128 and 20, and the input and output dimensions of the second-layer Bi-LSTM are 20.

4. **Experimental process and results analysis.** In this section, the data set, experimental process and results are described in detail. Firstly, the optimal number and size of convolution kernels, convolution layers and neurons are determined by parameter comparison experiments. Secondly, the classification performance of the model is verified by comparing experiments with multiple baseline models.

TABLE 2. Context-based two-channel implicit sentiment analysis model parameters

Model	Accuracy	Macro-P
ConV1D-1(128,64,1×5)	ReLU()	Maxpooling1D-1(pool size=2)
ConV1D-2(64,64,1×5)	ReLU()	Maxpooling1D-2(pool size=2)
Self-Attention(64)	ReLU()	—-
Bi-LSTM-1 (20)	ReLU()	—-
Bi-LSTM-2 (20)	ReLU()	—-

4.1. **Data set.** The data set in this paper adopts the Chinese implicit sentiment evaluation SMP-ECISA text data released by SMP2019 of the Eighth National Social Media Processing Conference. Data sources include microblogging, tourism sites, product forums and other social networking platforms, involving areas such as Spring Festival Gala, haze, LeTV, national civil service exams, tourism, Dragon Boat Festival.

The dataset has filtered out all text containing display emotional words through a large emotional dictionary. Text data without sentiment words are labeled as sentences with commendatory implicit sentiment (label 1), derogatory implicit sentiment (label 2) and sentences without sentiment tendencies (label 0). The statistical results of training dataset and validation dataset are shown in Table 3. A total of 12664 articles were included in the training dataset, of which 14774 were annotated, 3828 and 3957 were complimentary and derogatory implicit sentiment sentences, and 6989 were not included. A total of 4391 articles were included in the validation set, of which 5143 sentences were annotated, 1232 and 1358 sentences were complimentary and derogatory implicit sentiment sentences, and 2553 sentences were not included.

TABLE 3. Chinese Implicit Sentiment Corpus

Data set	Chapters	Positive sentences	Negative sentences	Neutral Sentences	Total
Training set	12664	3828	3957	6989	14774
Validation set	4391	1232	1358	2553	5143

4.2. **Data preprocessing.** Based on the fixed rules, this paper obtains Chinese implicit sentiment sentences and context information in SMP-ECISA Chinese implicit sentiment corpus, and embeds the above information and the following information into Chinese implicit sentiment sentences to obtain text data sets with context semantic features. Since Chinese implicit sentiment corpus mainly comes from microblog and other network platforms, the text needs to be cleaned to remove dirty data. After text data cleaning, segment and remove stop words.

4.3. **Evaluation Index.** In the experiment, the three values of Macro-Precision, Macro-Recall and Macro-F1 were used as the evaluation indexes of the performance of Chinese implicit sentiment analysis model. Firstly, the accuracy (P), recall (R) and F1 value (F1) of the three categories of positive implicit sentiment sentences, neutral implicit sentiment sentences and negative implicit sentiment sentences were calculated, and then the average values of the three indexes were calculated. F1 value is the harmonic value of accuracy and recall rate, which can reflect the overall effect of the model. The calculation formula of each evaluation index is shown in Equations (12–17).

$$P = \frac{TP}{TP + FP} \tag{12}$$

$$R = \frac{TP}{TP + FN} \tag{13}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{14}$$

$$Macro - P = \frac{P_{positive} + P_{neutral} + P_{negative}}{3} \tag{15}$$

$$Macro - R = \frac{R_{positive} + R_{neutral} + R_{negative}}{3} \tag{16}$$

$$Macro - F1 = \frac{F1_{positive} + F1_{neutral} + F1_{negative}}{3} \tag{17}$$

4.4. **Experiment parameter.** In order to test the influence of the number and size of CNN convolution kernel, the number of convolution neural network layers and the number of Bi-LSTM neurons on the model effect, the above parameters are compared and the experimental results are shown in Figures.4–5.

In order to make the convolutional neural network (CNN) better capture the local features of Chinese implicit sentiment sentences, several experiments are carried out on the number of convolution kernels in the CNN module. The experimental results are shown in Figure 4. By analyzing the experimental results, when the number of convolution kernels (Filters) is 64, the Chinese implicit sentiment analysis model can show good classification results.

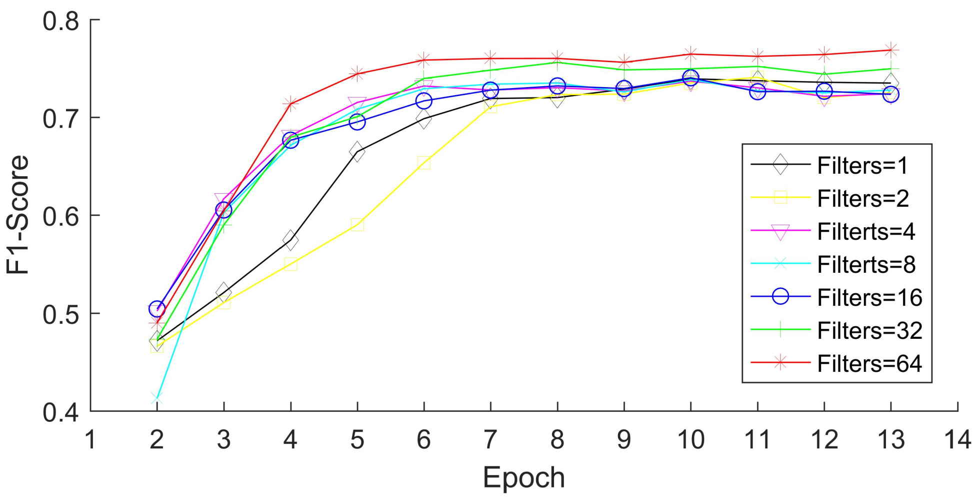

FIGURE 4. Convolution kernel number comparison experiment result

The experiment compares the size of one-dimensional convolution kernel to determine the optimal value of convolution kernel size. The experimental results are shown in Figure 5. By analyzing the experimental results, when the Filters-size is 5, the classification effect of Chinese implicit sentiment analysis model is the best.

In the experiment, the convolution layers are compared to determine the optimal value of convolution layers. The experimental results are shown in Figure 6. By comparing

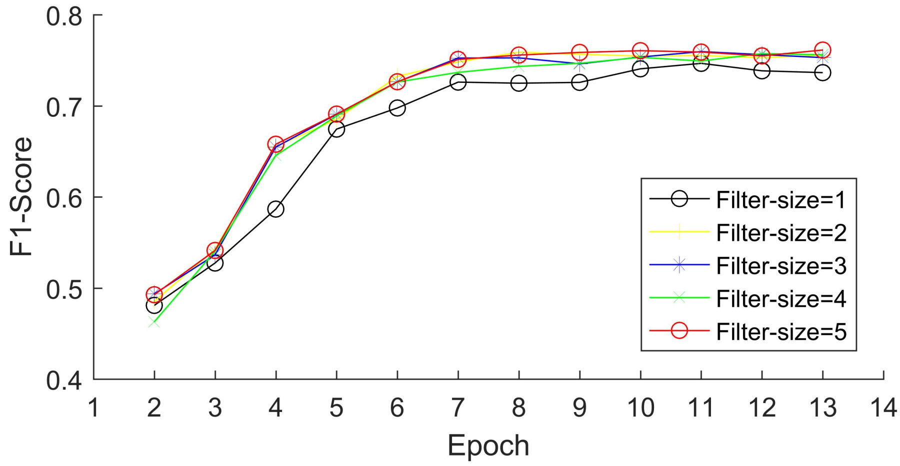

Figure 5. Convolution kernel size comparison experimental results

and analyzing the experimental results, when the convolution layer is 5, the classification effect of Chinese implicit sentiment analysis model is the best.

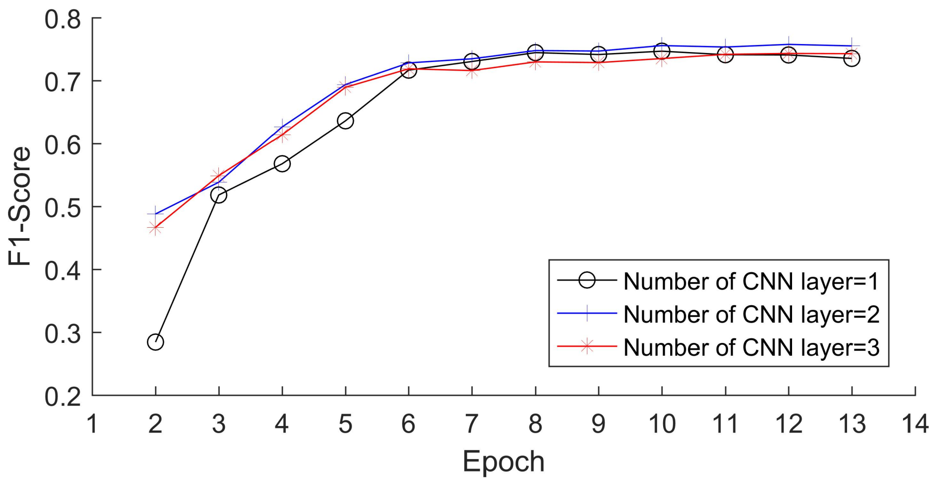

Figure 6. Convolutional layer number comparison experiment results

In order to ensure the effect of semantic features between contexts captured by bidirectional long-term and short-term neural network (Bi-LSTM), the number of bidirectional long-term and short-term neurons was repeatedly tested in the experiment results are shown in Figure 7. By comparing the experimental results, when the number of bidirectional long-term and short-term memory neural network neurons is 10, the Chinese implicit sentiment analysis model can show good classification effect.

The parameters of implicit sentiment analysis model are set as shown in Table 4. The number of convolution kernels (Filters) is set to 64, the size of convolution kernel is set to 5, the number of convolution layers is set to 2, and the number of Bi-LSTM neurons is set to 10. The effect of implicit sentiment analysis model is better. The experiment sets the word vector dimension to 128, the maximum length of the statement to 300, and the dropout rate to 0.2 to prevent overfitting. The optimizer uses Adam and sets the learning rate to 0.001, and the batch size to 64. The convolution layer of the convolutional

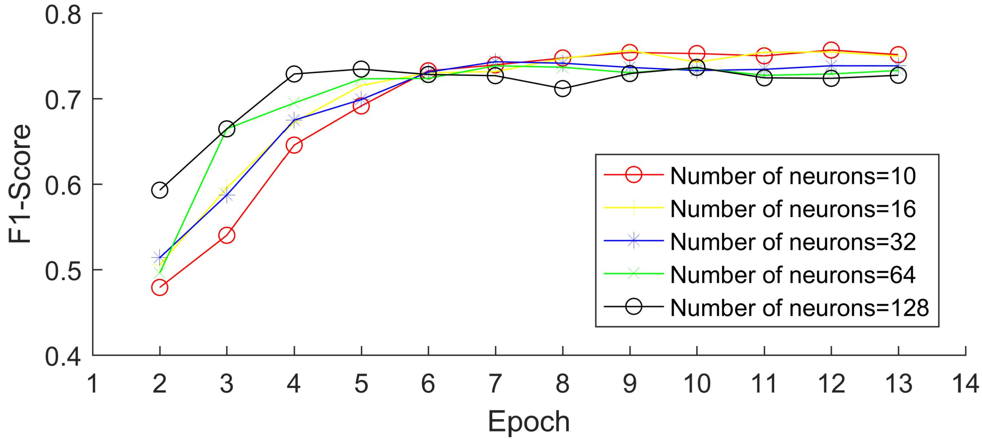

FIGURE 7. Bi-LSTM neurons number comparison experiment results

neural network uses ReLU as the activation function, and the pooling operation selects the maximum pooling operation.

TABLE 4. Model parameter values

Parameters	Value	Parameters	Value
Word vector dimension	128	Batch size	64
Maximum sentence length	300	Filter	64
Number of CNN layer	2	Filter size	5
Number of neurons	10	Learning rate	0.001
Number of Bi-LSTM layer	2	Optimizer	Adam
Dropout	0.2	—-	—-

4.5. **Comparative experiment and result analysis.** In order to evaluate the proposed model, we compare it with the classification performance of the baseline model. The baseline models include CNN, LSTM, Bi-LSTM, C-Bi-LSTM and CNN-Bi-LSTM. The loss values and Macro-F1 values of each model are shown in Figure 8.

(1) CNN: Use convolutional neural network to learn the semantic features of Chinese implicit sentences and establish Chinese implicit sentiment analysis model.

(2) LSTM : The long-term and short-term memory neural network is used to capture the semantic features of Chinese implicit sentiment sentences, and the baseline model of Chinese implicit sentiment analysis is established.

(3) Bi-LSTM : Bi-LSTM neural network adds reverse operation on the basis of LSTM, so that the model can consider the context information in the training process.

(4) C-Bi-LSTM : In this method, CNN and Bi-LSTM are used to extract the semantic features of Chinese implicit sentiment in a single channel, and then the Chinese implicit sentiment analysis model is established.

(5) CNN-Bi-LSTM:This method uses CNN and Bi-LSTM to extract local semantic features and semantic features between contexts of Chinese implicit sentiment sentences in two-channel form.

By analyzing the results of the comparative experiment (Table 5), the following conclusions can be drawn : (a) By comparing the experimental results of CNN, LSTM and Bi-LSTM models, the Macro-F1 value of Bi-LSTM model is increased by 2.38 % and 3.37 % respectively compared with the former two models, indicating that the bidirectional

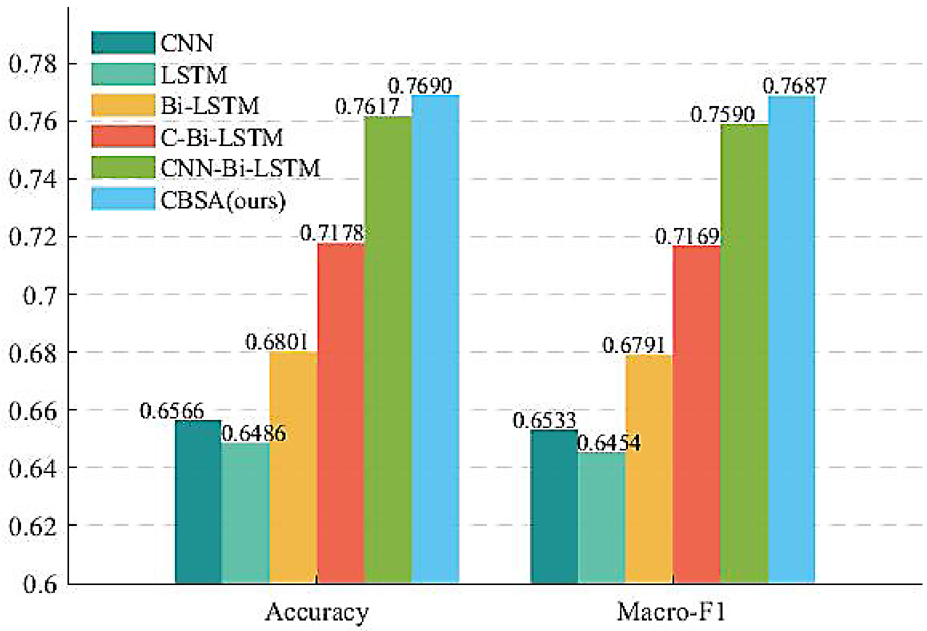

Figure 8. Comparison chart of rating index results

Table 5. Experimental results contrasting

Model	Accuracy	Macro-P	Macro-R	Macro-F1
CNN	0.6566	0.6606	0.6502	0.6553
LSTM	0.6486	0.6541	0.6371	0.6454
Bi-LSTM	0.6801	0.6868	0.6716	0.6791
C-Bi-LSTM	0.7178	0.7797	0.7141	0.7169
CNN-Bi-LSTM	0.7617	0.7779	0.7412	0.7590
Ours model	0.7690	0.7691	0.7682	0.7687

long-short term memory neural network can effectively learn the forward and backward dependencies and improve the classification effect of the model.

(b) By comparing the experimental results of CNN, Bi-LSTM and CNN-Bi LSTM models, the Macro-F1 value of CNN-Bi LSTM model is increased by 10.37 % and 7.99 %, respectively. It shows that integrating Chinese implicit sentiment sentences into context information and extracting semantic features between contexts can enrich and enhance the sentiment information of implicit sentiment sentences and improve the performance of the model.

(c) By comparing the experimental results of C-BiLSTM and CNN-Bi LSTM models, the Macro-F1 value of CNN-Bi LSTM model is 4.21 % higher than that of C-Bi LSTM model, indicating that the dual-channel form can better extract and fuse Chinese implicit sentiment features and semantic features between context information.

(d) By comparing the experimental results of CNN-Bi LSTM and CBSA model, the Macro-F1 value of CBSA model is 0.97 % higher than that of CNN-Bi LSTM, which indicates that the ability of multi-headed self-attention mechanism to capture long-term dependencies is effective in Chinese implicit sentiment analysis.

5. **Conclusions.** In view of the problem that implicit sentiment lacks sentiment words, which makes the traditional sentiment analysis method based on sentiment dictionary unable to effectively discriminate the sentiment tendency of Chinese implicit sentiment text, this paper proposes a dual-channel Chinese implicit sentiment analysis model based on context information. Experimental verification on SMP-ECISA public data set can prove that : (1) Context information can effectively enrich and enhance the semantic features of implicit sentiment expression, and improve the accuracy of implicit sentiment analysis. (2) The dual-channel form adopted in this paper can better extract and integrate Chinese implicit sentiment features and semantic features between context information, and further improve the effect of Chinese implicit sentiment analysis.

Experimental verification was carried out on the SMP-ECISA public data set and compared with the existing baseline model. The experimental results show that the proposed model is better than the baseline model, and the Macro-F1 value is increased by 0.11. At the same time, we find that irony in rhetorical implicit sentiment sentences affects the performance of the model to a certain extent. The reason is that irony implicit sentiment sentences use contradictions to express sentiment, and their sentence structure and language characteristics are more complex. At the same time, due to the development of social media, the user ' s expression has the characteristics of colloquialism and non-standardization. For example, the use of buzzwords and homo phonic words in comments affects the effect of Chinese implicit sentiment classification task to a certain extent. In the future, the influence of special expressions such as irony on implicit sentiment analysis will be considered in the following work, so as to improve the effect of Chinese implicit sentiment analysis, and further comprehensively consider the influence of Chinese implicit sentiment on comment texts.

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