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Sentiment Analysis of Chinese Comments using CNN Combined with BiLSTM Model based on Attention Mechanism



Abstract: - This article proposes a Chinese comment sentiment analysis model based on attention mechanism, which combines CNN with BiLSTM, to address the issue of insufficient utilization of contextual information in text sentiment analysis. This model captures emotional words and contextual information in comment texts by combining CNN with BiLSTM structure, and then uses attention mechanism to weight important information in comments. And comparative experiments were conducted on two Chinese comment datasets (one takeout comment dataset and one product comment dataset) to verify the advantages of this model compared to several commonly used deep models. At the same time, ablation experiments were conducted to verify the impact of different modules of the model on this model and the effectiveness of the proposed combination mode.

Keywords: CNN Combined with BiLSTM; Attention Mechanism; Sentiment Analysis .

I. INTRODUCTION

The high-speed development of computer hardware, software technology, and network technology has led to significant changes in people's lifestyles and also affected their consumption patterns, shifting from offline consumption to online consumption dominated by e-commerce. While users consume online, they leave behind a large amount of comment information, including evaluations of product quality, service, and other aspects. Studying comment information is beneficial for understanding user consumption habits and preferences. More and more users are checking product reviews before purchasing online, which to some extent can affect the final purchasing decision of consumer users. By analyzing comments on electronic products, we can understand the satisfaction of different age groups with the performance and appearance of electronic products, and help manufacturers develop new products; By evaluating and analyzing the service provided by staff, we aim to help them better serve consumers. With the popularization of the Internet and the arrival of big data, there are tens of thousands of comments on the products of brands on major e-commerce platforms every day. With the accumulation of time and customer traffic, the amount of data becomes increasingly large. The use of manual recognition of the emotional polarity of comments alone is no longer sufficient to meet the requirements. How to achieve automatic and efficient analysis of these comments and the sentiments contained in the text has become a hot topic of concern.

II. RELATED RESEARCH

Sentiment analysis was first proposed by Pang Bo in 2002. It is the process of using advanced computer technology to recognize, extract, and analyze the sentiments contained in text corpus with sentimental features. From the perspective of research methods, it can be divided into rule-based methods[1], traditional machine learning methods [2], and deep learning methods [3].

The rule-based methods first constructs an sentiment lexicon, divides the text to be classified into words, matches the segmented entries with the sentiment lexicon, and then calculates the sentiment score through a certain calculation method, compares it with the set threshold to achieve text classification. In the construction of sentiment dictionaries, foreign countries started earlier than domestic ones, and the most commonly used ones include SentiWordNet [4], OpinionFinder, GI (General Inquirer) [5], NTUSD [6], HowNet of CNKI, and Dalian University of Technology's sentiment vocabulary ontology library [7]. Wu et al. used LDA topic model extraction and word clustering in constructing sentiment dictionaries, and applied them to dynamic texts [8]. Wang et al. utilized semantic disambiguation to automatically construct sentiment lexicons [9]. Xu et al. used grounded theory and semi-automatic methods to construct a sentiment dictionary about Weibo comments, which contains 2964 words [10]. CHEN et al. used a feature fusion based fine-grained sentiment lexicon construction method to construct

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a corpus in the field of education, which includes 39138 emotion words [11]. The method based on sentiment lexicons has relatively accurate classification results, but building sentiment lexicons manually requires a high cost. It is necessary to read a large amount of information, study existing sentiment dictionaries, extract words with sentimental tendencies, and label them differently based on their sentimental polarity and intensity. However, at present, the network is developing rapidly, and many new network words have emerged. If the sentiment dictionary is not expanded in a timely manner, it cannot achieve good recognition results; The analysis of Chinese is relatively complex, and the same word may also express different emotions in different contexts, so the effectiveness of emotion lexicon based methods in cross domain and cross language contexts may not be ideal; The sentimental color of a word in a text often depends on contextual semantics, but this cannot be taken into account when using sentiment dictionaries for sentiment classification, which can also affect the final classification performance.

Based on traditional machine learning methods, a large amount of annotated or unlabeled corpus is used to extract features using machine learning algorithms, and sentiment analysis and result output are performed. Traditional machine learning methods include supervised, semi supervised, and unsupervised methods. Sentiment analysis is achieved by combining different classifiers, and different combinations have a different impact on the results. However, this method often fails to fully utilize of the contextual information of the contextual text when performing sentiment analysis on text content, and will also have a certain impact on the accuracy of classification. The early use of SVM algorithm achieved good performance in processing text sentiment analysis tasks [12]. Ahmad et al. used SVM to perform sentiment polarity multi classification tasks on three tweet datasets and achieved good results [13]. Huq et al. used SVM and nearest neighbor nearest neighbor classification algorithm (KNN) to extract emotional labels from Twitter posts, in order to identify and analyze positive and negative comments [14]. Wang et al. conducted sentiment analysis on emoticons in texts using naive Bayesian methods [15].

Deep learning-based methods use neural network technology in the process of sentiment analysis. In existing research, a variety of methods have been used to build models, such as single neural networks, hybrid neural networks, networks introducing attention mechanisms, and pre-trained models. Compared with rule-based methods and traditional machine learning methods, when neural network technology is introduced into the process of sentiment analysis, the effect of text feature learning has been greatly improved. It can actively learn features and analyze the information of words in the text. Actively retain, so as to better extract the semantic information of the corresponding words to effectively achieve emotional classification of text. Adding an attention mechanism to the process of sentiment analysis for research on sentiment analysis tasks can better capture the key information in the text, improve the impact of key semantic information, prevent the loss of important information, and effectively improve the accuracy of text sentiment analysis. However, deep learning-based methods require the support of a large amount of data, are unsuited for small-scale datasets, and generally take a long time to work. And the training time depends on the depth and complexity of the neural network. Li et al. proposed a bidirectional LSTM model with multi-channel features, in which a self-attention mechanism was used, and it was applied to five public English datasets for sentiment polarity in binary classification, emotion judgment in five classification, and non binary classification tasks. From the experimental results shown in the paper, it can be seen that the accuracy of classification was highly correlated, and the performance of the model was not stable [16]. Wang et al. combined the GRU model and the Attention mechanism, in order to improve the extraction of contextual semantic features in text data [17]. Fang et al. integrated Stacking ensemble learning and deep learning to construct a model, and tested it on the user comment dataset of JD products. Compared with the baseline model, The results showed that the proposed model can effectively improve the accuracy of comments text sentiment polarity classification tasks [18]. Zhang et al. constructed a model based on text sentiment value weighted fusion word vector representation, and validated the model through online comment datasets on online platforms. The results showed that word vector fusion has a stronger ability to extract semantics, and sentiment value weighting can consider the emotional information contained in the text itself, which also improves the ability of sentiment classification [19]. Xu et al. built a method of sentiment classification based on the integration of local and global features. The sentiment dictionary and BiLSTM neural network model were used to extract text features based on word vectors, the text features based on local weighted word vectors and the text topic features based on the neural topic model were concatenated. The results showed that the neural network features in this model were more abundant, Effectively improving the accuracy of sentiment classification [20]. Aiming at the problems existing in entity-level sentiment analysis tasks in the financial field, Zhu et al. constructed a million-level corpus and annotated more than 5,000 financial sentiment words to form a sentiment dictionary. Based on this dataset, a fine-grained sentiment analysis model for financial texts was proposed that combines financial sentiment dictionaries and attention mechanisms. In order to verify the effectiveness of the model, comparative experiments were conducted and ideal experimental

results were obtained.[21].In view of the lack of ability of simple neural networks to capture contextual semantics and extract important information within text,Yang et al. built a model named FFA BiAGRU, which combines attention mechanism and gating unit. And conducted experimental verification on public data sets to prove the algorithm. Better results can be achieved on these data sets[22]. XIE et al. proposed a knowledge enhanced dual channel multi head graph convolutional neural network and validated it on three publicly available benchmark datasets, with significantly better results than the baseline model [23-24]. Ding et al. constructed a multimodal model of sentiment analysis named CM-SAIR based on cross modal Transformer for semantic alignment and information refinement to address the issues of heterogeneous and semantic gaps, as well as the inability to effectively integrate modalities in multimodal sentiment analysis. Their advantages were demonstrated on popular sentiment analysis datasets [25]. Tang et al. constructed a syntax aware latent graph using dependency labels and designed an emotion refinement strategy to guide the network in capturing important emotional clues [26-27].YANG et al. proposed a graph attention neural network model integrates graph walk information, which can obtain the word weight coefficients of sentences during the execution of graph walks in grammar quotients. The model is combined with graph attention networks to highlight the weight of target aspect words, and has achieved better experimental results in this experiment [28].

III. METHODOLOGY

A. Bi-directional Long Short-Term Memory

This full name of BiLSTM is Bi directional Long Short Term Memory, which consists of forward LSTM and backward LSTM. The design of long short-term memory networks is aimed at solving the conundrum of long-distance dependencies, and on many tasks, using LSTM structures may perform better. LSTM can be seen as a special cyclic structure with three gates and one memory unit in its structure. The structure of the "gate" is actually a fully connected layer, using an activation function named sigmoid that allows information to selectively affect the state at each moment in the neural network. If W is the weight vector of the gate, b is the bias, the gate can be represented as:

$$g(x) = \sigma(W_x + b) \quad (1)$$

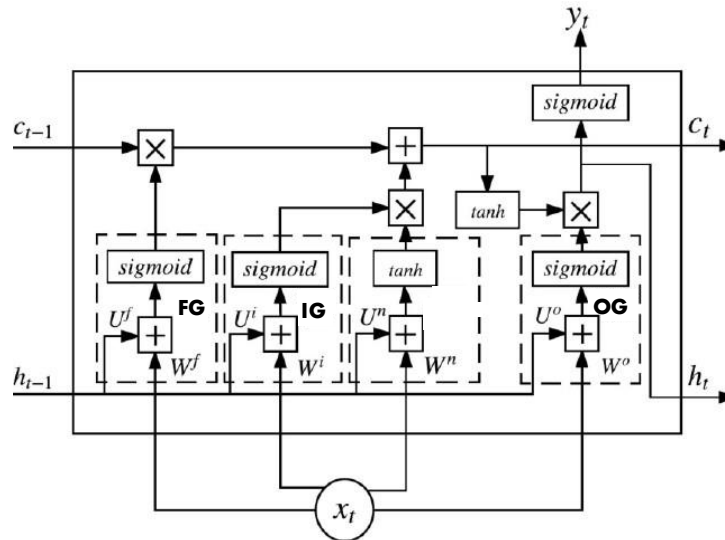


Figure 1. Long Short Term Memory Structure Diagram

There are three gate settings in the LSTM mechanism, namely input gate, output gate and forget gate. x_t is the input of the network at this moment. The input gate indicates how much of it is saved into c_t ; how much of the unit state c_{t-1} of the previous moment is retained into the unit state c_t of the current moment is determined by the forgetting gate; the output gate determines the current moment. How much of the unit state c_t is output to the current output value h_t of the LSTM. The threshold is implemented through a sigmoid activation function, and the input and memory unit states are usually converted using tanh. The memory unit can be defined by the following formula:

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

$$f_t = \sigma(W_f \cdot [h_{t-1}, w_t] + b_f) \quad (3)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, w_t] + b_o) \quad (4)$$

Input transformation:

$$c_{\text{new}_t} = \tanh(W_c \cdot [h_{t-1}, w_t] + b_c) \quad (5)$$

Status update:

$$c_t = f_t \otimes c_{t-1} + i_t \otimes c_{\text{new}_t} \quad (6)$$

$$h_t = o_t \otimes \tanh(c_t) \quad (7)$$

Among them, $\otimes$ stand for the matrix lattice operation, σ represents sigmoid activation function, W_i , W_f , W_o are the weight matrices of input gate, forget gate, and output gate, b_i , b_f , b_o are the biases of input gate, forget gate, and output gate.

Bi-LSTM (Bi-directional Long Short Term Memory) is an improvement of this LSTM model, which adds a bidirectional structure in the light of the long short-term memory network, allowing the model to encode from back to front, and preserve the original statement information to a greater extent, thereby enabling the model to obtain more reliable and useful contextual information. From the figure 2, it can be seen that concatenating the three vectors $\{h_{L0}, h_{L1}, h_{L2}\}$ in the forward LSTM_L, and the three vectors $\{h_{R2}, h_{R1}, h_{R0}\}$ in the backward LSTM_R, yields the final vectors $\{h_0, h_1, h_2\}$, where h_0 is $[h_{L0}, h_{R2}]$, h_1 is $[h_{L1}, h_{R1}]$, and h_2 is $[h_{L2}, h_{R0}]$.

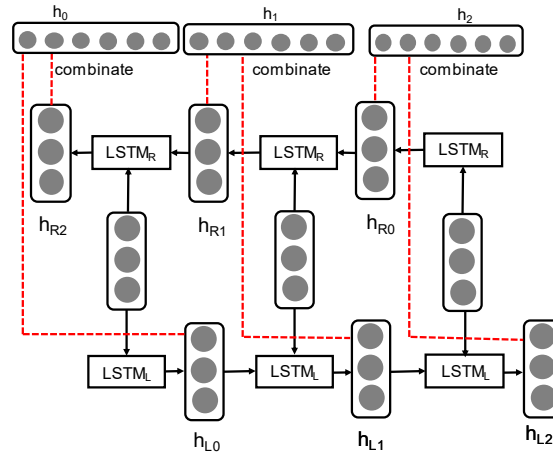


Figure 2. Bi-directional Long Short Term Memory Encoding Principle Diagram

B. ATTENTION

The attention mechanism is an imitation of the human visual and cognitive system. By introducing this mechanism, the model can learn autonomously and focus on important information. Attention first calculates the similarity between each output and all inputs, obtaining a similarity score (weight), and then weighted and summed all inputs based on this weight. The calculated similarity score is a scalar, which is mapped through a softmax to become a weight between 0 and 1, and finally output. Attention is the weighted sum of the weights of input data x , and its calculation method is shown in formula (8). Based on this, the attention obtained describes the corresponding relationship between the target output and the source input. For different outputs (y_i), it is necessary to calculate different "context vectors". By modeling the hidden state h_i at each moment in the Encoder, the attention probability distribution of each word in the input sequence for the output is calculated. Based on this probability distribution, the corresponding semantic encoding c_i is calculated. Finally, decoding operations are performed according to different semantic encoding.

$$\text{ATTENTION} = \sum_{i=1}^n \text{softmax}(f(x_i, y)) * x_i \quad (8)$$

IV. CNN COMBINED WITH BiLSTM MODEL BASED ON ATTENTION MECHANISM

A. Model Design

The model proposed in this article includes input layer, a three-layer CNN layer, a BiLSTM layer, an attention layer, and a classification output layer. Input layer uses Word2vec model to train the word vector features of comments. CNN layer and BiLSTM layer combine to obtain local feature information and contextual relationships of sentimental words during training. Attention layer focuses on the calculation between emotional words, and finally, the extracted features are input into the Softmax layer to get sentimental polarity. The structure diagram of the CNN combined with BiLSTM model based on the ATTENTION mechanism is designed in Figure 3.

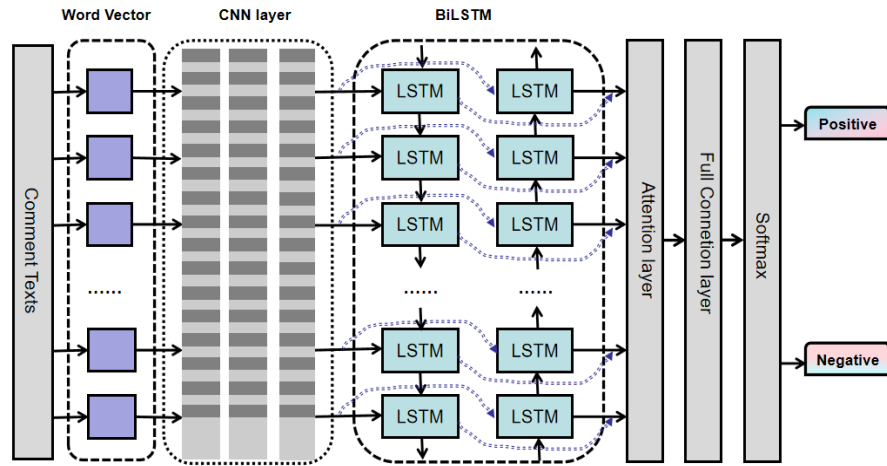


Figure 3. Model structure diagram of CNN combined with BiLSTM based on ATTENTION mechanism

1) Input layer

When applying deep learning methods to the processing of text sentiment analysis tasks, the text data is preprocessed first, through processes such as data cleaning, segmentation, and removal of stop words. After training with the word2vec model, a vector matrix containing text features is obtained. If the input text is represented as $S=\{W_{11}, W_{12}, \dots, W_{mn}\}$, where m is the m -th word in this text, and n represents the number of the sequence, the word vector matrix C can be obtained through the input layer.

$$C = \begin{bmatrix} W_{11} & W_{12} & \dots & W_{1n} \\ W_{21} & W_{22} & \dots & W_{2n} \\ \dots & \dots & \dots & \dots \\ W_{m1} & W_{m2} & \dots & W_{mn} \end{bmatrix}$$

2) CNN-BiLSTM layer

In this layer, the Chinese comment data is first serialized into text, and then vectorized through the embedding layer. The vectorized matrix is input into the CNN layer and BiLSTM layer for text feature extraction.

This layer is divided into two parts. The first part is a three-layer CNN, it is used to extract local information of the text. In the calculation process, the convolution kernel size is set to 5, and the convolution kernel slides on the feature window. After the convolution operation, the maximum pooling operation is performed on each vector to get the output value of the CNN network as the input of the next layer network. The second part is the BiLSTM layer, which can obtain semantic information of the context at a deeper level from the front and back directions, Obtain implicit dependencies in textual data. Using this structure can better capture local and global information of this text, and can also effectively process longer comment texts.

3) ATTENTION layer

The attention mechanism is the Encoder Decoder structure, which can mask unimportant information and focus the computation on useful information. This model introduces an attention mechanism, focusing the calculation on the relationship between the target word and other words. In addition, the attention mechanism will assign greater weight to useful information, enhance the importance of useful data, and obtain better experimental results in the absence of sufficient textual data, which can also improve data processing efficiency to a certain extent.

4) Output layer

After concatenating the eigenvalues obtained in the network, a vector matrix is obtained. Through a fully connected layer, the probability of belonging to a certain category i is calculated using P_i . X_i is the vector matrix obtained by concatenating the eigenvalues, W_0 is the weight matrix parameter of the final output layer, b_0 is the bias term matrix parameter of the output layer, and T is the number of categories for sentiment classification. Choose the category Y with the highest probability as the sentiment polarity, and ultimately complete the sentiment analysis of the comments.

$$P_i = \frac{\exp(W_0 X_i + b_0)}{\sum_{i=1}^T (W_0 X_i + b_0)} \quad (9)$$

$$Y = \operatorname{argmax}(P_i) \quad (10)$$

B. Experiments and Result Analysis

1) Experimental Dataset

There are two datasets for the experimental data in this article. The first dataset is the comment dataset of the food delivery platform, with a total of 11987 comment data, including 7987 positive comments, labeled with 1; 4000 negative comments, marked with 0. The second dataset is a self built dataset, which comes from user comment data of multiple products on JD.com. Based on user ratings of products, positive and negative labels are annotated, resulting in 70761 comment data, including 36047 positive data with a label of 1; 34714 negative data with label 0. The data set is divided into training set, test set and verification set according to the ratio of 8:1:1. Figure 4 and 5 show the word cloud corresponding to positive and negative feedback data for two datasets.

TABLE 1
DATASET COMPOSITION

Dataset	TOTAL	POSITIVE	NEGATIVE
Dataset1	11987	7987	4000
Dataset2	70761	36047	34714



Figure 4. Positive Review Word Cloud



Figure 5. Negative Review Word Cloud

2) Evaluation indicators

In the evaluation of classification results, a confusion matrix is used, presenting the true categories in the dataset, and the predicted categories by the classification model in matrix form. In the confusion matrix, TP represents the number of positive class samples predicted as positive class, FN represents the number of positive class samples predicted as negative class, FP represents the number of negative class samples predicted as positive class, TN represents the number of negative class samples predicted is the number of negative classes. According to the statistical results of the confusion matrix, Accuracy, F1 score, Recall, and Precision are used to evaluate the final effect of the model.

The Accuracy indicator can be used to indicate the accuracy of the model and is a commonly used classification performance indicator. The higher the value, the better the effect of the model; Precision represents the proportion of positive samples identified by the model that truly belong to the positive class; Recall represents the prediction rate of the model for positive samples. The larger the value, the more positive samples can be correctly predicted, and the better the performance of the model; F1 score is the harmonic average of precision rate and recall rate, Its value is between 0-1, and the closer to 1, the better.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \quad (11)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (12)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (13)$$

$$\text{F1-score} = \frac{2 * \text{precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

The use of confusion matrix can provide a deeper understanding of the performance of classification models. It can summarize the records in the dataset in the form of a matrix based on two criteria: the true category and the predicted category of the classification model. The row data of the matrix represents the true value, the column

data represents the predicted value, the number of correct classifications on the diagonal is the number of incorrect classifications outside the diagonal. Figure 6 shows the confusion matrix corresponding to dataset 1, which correctly predicts 2113 and incorrectly predicts 285, with an accuracy of 88.12%. Figure 7 shows the confusion matrix corresponding to dataset 2, with a correct prediction of 13015 and an incorrect prediction of 1138, resulting in an accuracy of 91.96%.

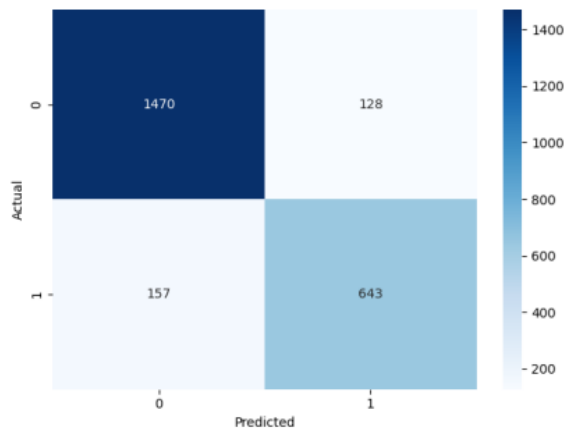


Figure 6. Confusion matrix diagram for dataset 1

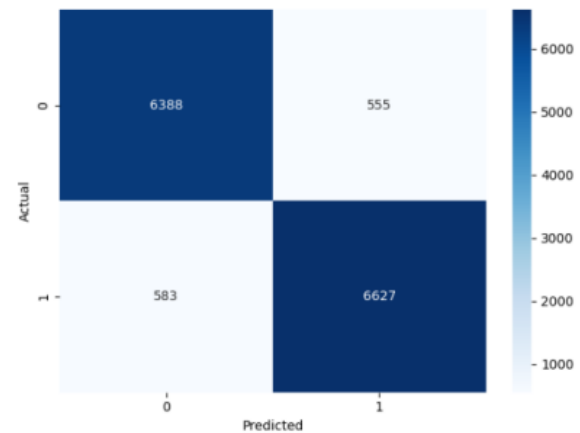


Figure 7. Confusion matrix diagram for dataset 2

3) Comparative experimental design and experimental results

For the purpose to verify the effectiveness of the model proposed in text sentiment analysis tasks, this paper conducted comparative experiments between the CNN-BiLSTM-ATTION model and several deep learning models such as TextCNN, GRU, BiLSTM, MLP, CNN, CNN-LSTM, and CNN-BiLSTM. The results of each model obtained in the experiment are shown in table 2. The bar chart of the classification effect in figure 8 and figure 9 provide a more intuitive observation of the model's performance.

TABLE 2
RESULTS OF SENTIMENT ANALYSIS OF EACH MODEL

	MODEL	ACCURACY	RECALL	F1	PRECISION
Dataset1	TextCNN	0.7677	0.7274	0.7324	0.7393
	GRU	0.8499	0.8306	0.8310	0.8314
	BiLSTM	0.8515	0.8309	0.8323	0.8338
	MLP	0.8590	0.8340	0.8390	0.8450
	CNN	0.8465	0.8193	0.8245	0.8307
	CNN-LSTM	0.8479	0.8381	0.8426	0.8620
	CNN-BiLSTM	0.8557	0.8299	0.8351	0.8413
	CNN-BiLSTM-ATTION	0.8812	0.8618	0.8651	0.8687
Dataset2	TextCNN	0.7839	0.7850	0.7836	0.7876
	GRU	0.9081	0.9081	0.9081	0.9080
	BiLSTM	0.9086	0.9085	0.9086	0.9087
	MLP	0.9038	0.9040	0.9038	0.9039
	CNN	0.9048	0.9049	0.9048	0.9048
	CNN-LSTM	0.9055	0.9059	0.9055	0.9060
	CNN-BiLSTM	0.9098	0.9097	0.9097	0.9098
	CNN-BiLSTM-ATTION	0.9196	0.9197	0.9196	0.9196

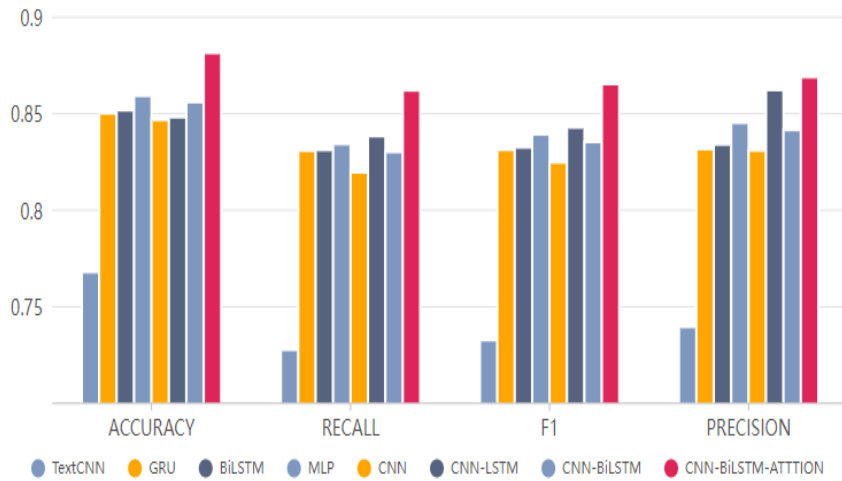


Figure 8. Dataset1 Comparison Experiment Effect Bar Chart

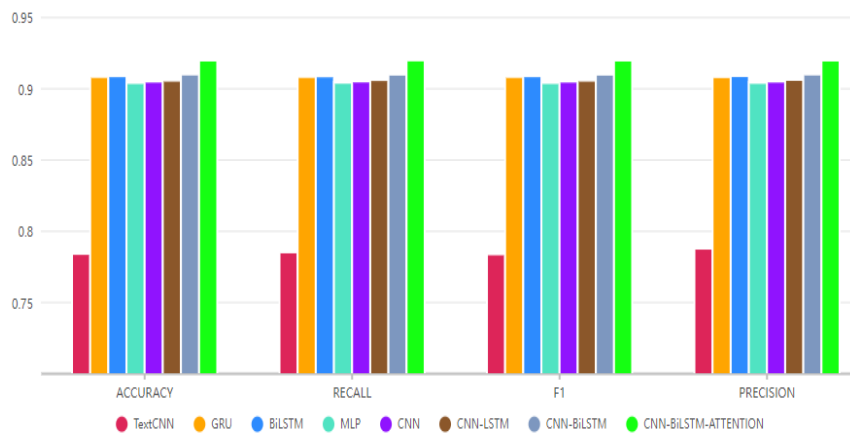


Figure 9. Dataset2 Comparison Experiment Effect Bar Chart

Through data analysis, it can be seen from Figure 8 and 9 that under the same experimental environment, the algorithm proposed in this paper was validated on dataset 1, with an accuracy of 88.12%. Compared with MLP, CNN, GRU, and BiLSTM algorithms, its classification accuracy increased by 2.22%, 3.47%, 3.13%, and 2.97%, respectively. Compared with the CNN-LSTM and CNN-BiLSTM combined models, its classification accuracy increased by 3.33% and 2.55%, respectively. Verified on dataset 2, its accuracy reached 91.96%. Compared with MLP, CNN, GRU, and BiLSTM algorithms, its classification accuracy improved by 1.58%, 1.48%, 1.15%, and 1.10%, respectively. Compared with the CNN-LSTM and CNN-BiLSTM combination models, its classification accuracy improved by 1.41% and 0.98%, respectively. The analysis performance of emotional orientation is slightly higher than that of basic machine learning and neural network algorithms, which can effectively verify the research significance of the algorithm proposed in this article.

4) Ablation Experiment Design and experimental results

In order to explore the impact of each component module of this model on the results, ablation experiments were conducted in this paper. The proposed model was compared with CNN, CNN-BiLSTM, and CNN-ATTENTION models, and the experimental results are shown in Table 3. Figures 10 , figure 11 present the experimental results in the form of bar charts. The design of the CNN and CNN BiLSTM models in this experiment is slightly different from that in the comparative experiment. The CNN and CNN BiLSTM models in the comparative experiment are single-layer CNNs, while in this experiment they are three-layer CNNs.

TABLE 3

	MODEL	ACCURACY	RECALL	F1	PRECISION
Dataset1	CNN	0.8453	0.8246	0.8255	0.8265
	CNN-BiLSTM	0.8455	0.8327	0.8283	0.8245

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Dataset2	CNN-ATTENTION	0.8753	0.8450	0.8552	0.8695
	CNN-BiLSTM-ATTTION	0.8812	0.8618	0.8651	0.8687
	CNN	0.9033	0.9031	0.9032	0.9035
	CNN-BiLSTM	0.9060	0.9064	0.9060	0.9067
	CNN-ATTENTION	0.9142	0.9147	0.9142	0.9151
	CNN-BiLSTM-ATTTION	0.9196	0.9197	0.9196	0.9196

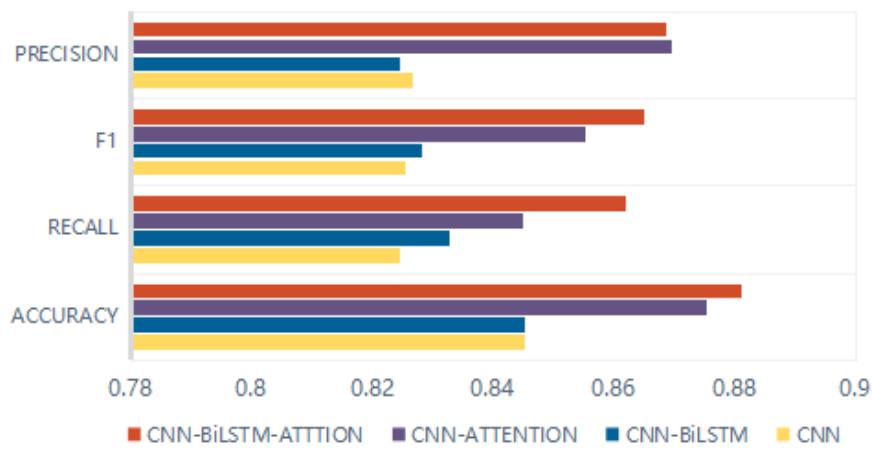


Figure 10. Dataset1 Ablation Experiment Results Bar Chart

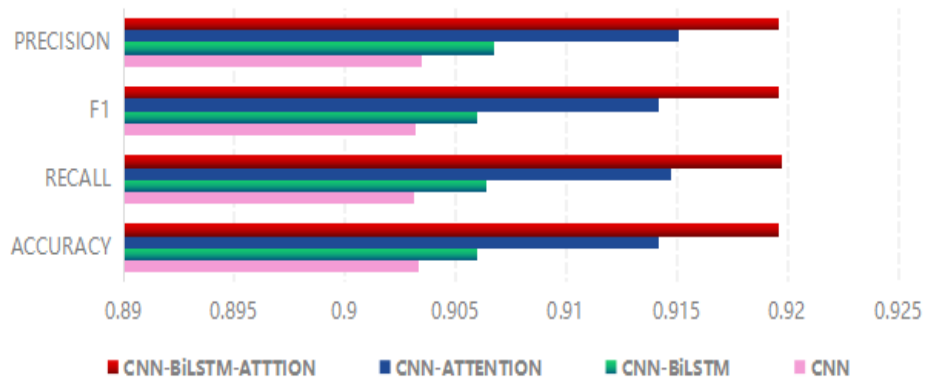


Figure 11. Dataset2 Ablation Experiment Results Bar Chart

In this paper, ablation experiments were conducted on two datasets, and the results of CNN, CNN-BiLSTM, CNN-ATTENTION, and CNN-BiLSTM-ATTTION models were compared. The classification accuracy on dataset 1 was improved by 3.59%, 3.57%, and 0.59%, respectively. On dataset 2, the classification accuracy was improved by 1.63%, 1.36%, and 0.54%, respectively. From the experimental results, it can be seen that the model proposed in this article has the best accuracy in the experiment. From the results, it can be seen that attention mechanism has been added to the design of the model, which gives important emotional words higher weight and can better improve the accuracy of text sentiment classification.

V. CONCLUSION

In this paper, an attention mechanism based CNN combined with BiLSTM model is proposed to handle sentiment analysis tasks. On the one hand, the structure of CNN combined with BiLSTM is used to capture key

emotional words and contextual information in the comment text. On the other hand, attention mechanism is used to further filter irrelevant sentence semantic information. Then, it was validated on two datasets and achieved good results. The contribution of each module was tested in the ablation experiment, and the main contributing modules were verified. When tested on the second dataset, good experimental results can be achieved. The first dataset has a small amount of data, and its testing effect is slightly lower than the second dataset. However, it can also verify the effectiveness of the model proposed in this paper.

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