Journal of Organizational and End User Computing
Volume 36 • Issue 1 • January-December 2024

Consumer Sentiment Analysis and Product Improvement Strategy Based on Improved GCN Model

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ABSTRACT

In recent years, the amount of online shopping review data has increased dramatically. Obtaining information that helps business decision-making from such complex and massive reviews has become a difficult and important task for merchants. This paper uses sentiment analysis technology to innovatively introduce the attention mechanism on the LSTM infrastructure of the baseline model, and proposes a word vector structure and a BiGRU structure to build an online user sentiment analysis system based on deep learning. The system includes a user review sentiment classification and sentiment analysis model based on the improved GCN model. The experimental results also show the superiority of our method, which brings 4.73%, 7.84% and 5.72% F1-score improvements to the algorithm respectively. It proves that the two algorithms proposed in this paper can effectively achieve their goals and achieve high performance.

KEYWORDS

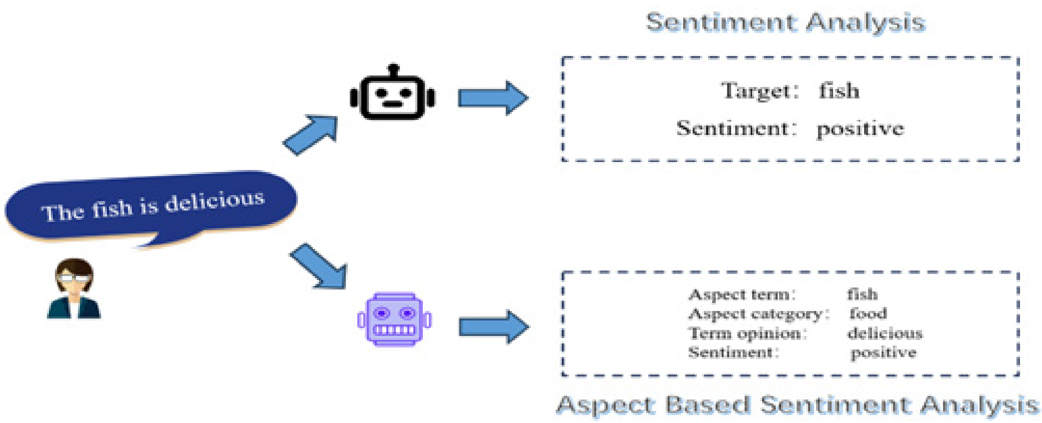
Deep Learning, Aquatic Products, Consumer Review, Online Platform

INTRODUCTION

As online shopping has grown and consumers' buying experiences have increased, the volume of online shopping reviews has also increased significantly. This influx of data makes it harder for shoppers to find information that is useful when making purchasing decisions. It also creates a challenge for merchants to use this data effectively and extract valuable insights from the vast amount of feedback they receive. Nonetheless, the need to effectively leverage review data to provide actionable insights that enhance product quality and customer service is a pressing concern across many industries.

DOI: 10.4018/JOEUC.355238

Figure 1. The difference between ABSA and ordinary sentiment analysis algorithms



Aspect-based sentiment analysis (ABSA) (Nguyen et al., 2021) is a recent and popular technique that aims at discriminating the sentiment polarity of explicitly given aspectual words in a sentence. The difference between ABSA and ordinary sentiment analysis algorithms is shown in Figure 1.

For example, "The service was good, but the food was a bit bad." Given the aspectual words "service" and "food," the sentiment polarity discriminations are "positive" and "negative," respectively. In the field of traditional text sentiment analysis, the comprehensive sentiment polarity of a paragraph or sentence is often given. With the rapid development of e-commerce platforms, people are mostly evaluating a product in multiple dimensions and aspects, such as the product's "quality," "packaging," "date of production," "price," etc. Therefore, the generalized emotional polarity of a paragraph or sentence is no longer in line with the characteristics of the current consumer review text, so it is necessary to discriminate the emotional polarity based on specific aspects.

Past methods in sentiment analysis primarily focused on determining the overall sentiment of a given text. These traditional approaches, such as lexicon-based methods and basic machine learning models, have several limitations. Traditional sentiment analysis methods often provide a holistic sentiment score for an entire text, ignoring the nuances associated with different aspects. This approach fails to capture the multi-faceted nature of product reviews, where users comment on various attributes separately.

Many early sentiment analysis models do not consider the context in which a sentiment word is used. For example, the word "cold" can have different sentiment implications in "cold drink" (positive) versus "cold food" (negative). Lexicon-based approaches struggle with such contextual nuances. Simple sentiment analysis techniques often fail to correctly interpret sentences with sarcasm or negations. For instance, "I don't like the service" may be incorrectly classified as positive if the model fails to account for the negation.

Earlier methods do not inherently identify and differentiate between various aspects of the product. This limitation is crucial because consumers often provide feedback on multiple attributes within a single review, and treating the review as a monolithic block of text can lead to inaccurate sentiment analysis. Traditional sentiment analysis models often rely on predefined dictionaries or rules, which can be labor-intensive to maintain and scale. As the volume of review data grows, these models become less practical due to their static nature. In many cases, user reviews are short and contain colloquial language, which can lead to data sparsity issues. Ambiguities in language, such as polysemy (words with multiple meanings), further complicate the sentiment analysis process. Many early sentiment analysis models were designed for a specific language, predominantly English.

However, e-commerce platforms operate globally, necessitating models that can handle multiple languages with equal efficacy.

To address these limitations, ABSA offers a more granular approach by focusing on the sentiment associated with specific aspects mentioned in the text. This method improves the accuracy and relevance of sentiment analysis in the context of detailed product reviews, providing more actionable insights for both consumers and merchants.

Our paper is organized as follows. “Related Work” introduces related work; “Research on Consumer Sentiment Analysis Based on Deep Learning” elaborates on our work; “Experiments” explains the multiple experiments we conducted to verify the effectiveness of our approach; and finally, “Summary and Next Steps” concludes the paper.

RELATED WORK

Research on Sentiment Analysis Methods

Currently, there are many methods and models designed for sentiment analysis. For example, Lai et al. (date) selected 10 health science videos from the video website, Bilibili, using a sentiment-lexicon-based method combined with the interactive ritual chain theory to analyze the sentiment of the pop-ups in the videos and presented the final analysis results through visualization. Yuping et al. (date) established a semantic categorization dictionary of medical sentiment based on frame semantic theory, as well as an approach that is both definitive and rule-based to perform sentiment semantic analysis of online medical comments, labeling the information of sentiment categories, sentiment themes, polarity, and intensity. Yiping et al. (date) proposed an online review sentiment analysis method that integrated edge sampling and cooperative training, constructed a dynamic pricing model for fresh fruits based on online review sentiment analysis, designed an alternating direction multiplier method that integrated Gaussian back generation to solve the model, and derived the optimal pricing decision for retailers through numerical simulation and sensitivity analysis. Xuechen et al. (date) proposed an index prediction sentiment analysis bidirectional encoder representations from transformers long short-term memory (SA-BERT-LSTM) model based on financial text sentiment analysis to predict the rise and fall of CSI 300 index. Maomao et al. (date) selected Ctrip hotel booking platform and short-term rental platform as the experimental objects, collected 86,635 user comment texts from Beijing-related listings, and combined a latent Dirichlet allocation (LDA) model, a thematic social network, and thematic sentiment analysis methods to analyze the cross-platform comparison of user text comments. Xinrong et al. (date) proposed an algorithm model based on multi-layer attention mechanism BiGRU-SD-Attention. Firstly, the text of clothing e-commerce comments was collected by a distributed crawler, and the text data was cleaned and divided into word-level and sentence-level datasets; the BiGRU network was used to extract the positive and negative sentiment features of the text, and then the attention mechanism was applied to the words and sentences to reweight the sentiment features, respectively, through the multilayered recursive weighting computation, and the final categorization output was the sentiment features of the text of clothing e-commerce tendency. Table 1 shows the main use areas of emotion calculation in this paper's research statistics.

Application of Deep Learning Techniques in Sentiment Analysis

The application of deep learning techniques in sentiment analysis mainly includes Liu et al. (2020) proposed a weighted word to vector (word2vec) convolutional neural network (CNN) and a bidirectional threshold recurrent unit based on attention mechanism (ATT-BiGRU) hybrid neural network sentiment analysis model. Since the word vectors generated by word2vec cannot highlight the role of text keywords, the term frequency-inverse document frequency (TF-IDF) algorithm is introduced to calculate the word weight values. Then, the weighted word vectors are fed into a

Table 1. Main areas of use of affective computing

Fields	Literatures
Education	(Wang & Shi, 2021); (Lanouette, 2022)
Healthcare	(Shanthi et al., 2022); (Uban et al. 2021)
Human-computer interaction	(Svenstrup, n.d.); (Irutia, 2009)
Physiological	(Stappen et al., 2021); (Holm et al., 2021)
Retail	(Alkhodre & Alshanqiti, 2021); (Gokhale et al., 2022)
Social Networking	(Yi et al., 2022); (Wang et al., 2023)
Customer Service	(Kottursamy, 2021); (Song et al., 2021)
Opinion	(Zhang et al., 2022); (Plaza-del-Arco et al., 2021)
Emergency	(Behnke et al., 2021); (Zhu et al., 2021)
Government	(Liu et al., 2020); (Zhao & Sun, 2022)
Library	(Peng, date); (Bo et al., 2022)
Advertisement	(Li, date)

hybrid model CNN and ATT-BiGRU to extract the implicit features. The model extracts text features by CNN and ATT-BiGRU, respectively, to improve the text representation ability. Xie et al. (date) combines bidirectional long short-term memory (BiLSTM) and a GCN to propose a bi-guide-based attention network (Bi-G-AN) and proposes an attribute sentiment analysis model based on a bi-guide attention network (BiG-AN). This improves the model's ability to learn the representation of textual attribute-level sentiment features by focusing on both contextual information and remote dependency information of the text through the mechanism of interactive guided attention.

Yaou et al. (2021) proposed a hybrid model based on embeddings from language models (ELMo) and transformer for sentiment classification. First, the model utilizes ELMo model to generate word vectors. Based on the BiLSTM model, ELMo can further incorporate the contextual features of the sentence in which the words are located into the word vectors and can generate different semantic vectors for different semantics of polysemous words. Then, the obtained ELMo word vectors are input into the transformer model for sentiment classification. In order to realize the classification, the study modified the encoder and decoder structure of transformer. The hybrid model of ELMo and transformer is a combination of recurrent neural network and self-attention, and the two structures can extract the semantic features of sentences from different sides, and the semantic information obtained is more comprehensive and richer.

Guangyao et al. (date) proposed the domain-specific sentiment word attention model (DSSW-ATT). The model establishes two independent subspaces, uses the attention mechanism to extract the features of shared emotion words and the features of unique emotion words, builds the corresponding shared feature classifier and unique feature classifier, and uses the co-training method to merge these two features at the same time.

Liu et al. (2020) proposed an ABSA model, a matched short-term and long-term memory (mLSTM)-GCN, which integrates the mLSTM and grammatical distance. Firstly, the correlation between the aspect words and the context is calculated word by word, and the obtained attentional weights are fused with the contextual representations as inputs to the mLSTM to obtain the contextual representations that are more correlated with the aspect words; then, grammatical distance is introduced to obtain the correlations with the aspect words that are more correlated with the aspect words. Then, the syntactic distance is introduced to obtain the context with higher correlation with aspectual word syntax, so as to obtain more contextual features to guide the modeling of aspectual words and obtain the aspectual representation through the aspectual masking layer; finally, the combination of positional

Table 2. Summary of work related to the research in this paper

Literatures by author	Core Idea
(Liu et al., 2020)	word2vec/attention mechanism/TF-IDF word weighting
(Xie et al., date)	bi-guide attention network/BiLSTM/GCN
(Yaou et al., 2021)	ELMo/transformer
(Zhao & Sun, 2022)	attention mechanisms/synergistic training methods
(Liu et al., 2020)	mLSTM/ABSA/GCN

weights, contextual representations, and aspectual representations are used for the interaction of information, so as to obtain the features used for the sentiment analysis. Table 2 lists some works on deep learning techniques applied to sentiment analysis referenced in this paper.

According to the current research, the main advantage of the application of deep learning in sentiment analysis is that it tries to add various modules, such as attention mechanism, more optimized word embedding algorithms, more efficient sentiment classification models, etc., so the performance of the sentiment analysis algorithms continuously improves. The main shortcoming, however, is that the relevant algorithms are not sufficiently utilizing the lexical information of the vocabulary or the interaction between the vocabulary and the context; therefore, there is still room for improvement of the performance of the model.

In this paper, we take the online comments from the Taobao platform as the object of analysis. By using the Python programming language, we capture the comment data of the products, and with the help of text mining and machine learning algorithms, we construct an online user sentiment analysis system based on deep learning, which contains three algorithmic models, namely, sentiment classification of user comments, sentiment analysis of user comments, and point of view extraction of user comments. The main purpose of building this system is to mine the emotional tendencies of consumers on the platform products and the more concentrated viewpoints on the products through the study of the review data, to assist merchants in exploring the factors affecting the different emotional tendencies of consumers, in order to further make suggestions for the improvement of the products of the merchants, and at the same time, it can also provide potential consumers with the purchasing decision.

RESEARCH ON CONSUMER SENTIMENT ANALYSIS BASED ON DEEP LEARNING

At present, there are many e-commerce platforms, and they all have their own operating characteristics, so this paper comprehensively considers the platform model, user frequency, and platform evaluation structure, as well as other factors. Ultimately, we selected the Taobao platform in a large aquatic company sales of seafood and aquatic as the object of study.

Data Preprocessing

(1) Data Capture Stage

In this paper, four categories of aquatic products, namely, fish, shrimp, crab, and shellfish, are selected, and the comment texts of 17 products under the four categories are selected according to their sales rankings. The specific products are shown in Table 3.

In this paper, we use the Python programming language to write code to collect the comment data. Firstly, we get the URL of each product and set the headers, cookies, and the referrer request header and send the request to the server. Because the comment data of the Taobao platform is a dynamic page, we need to do a conversion into JSON format and save the obtained result as a CSV

Table 3. Subjects selected for review in this paper

Product category	Product subcategories
fish	cutlassfish
	butterfish
	salmon
	sea bass
	yellow croaker
	balsa
shrimp	prawns
	chicken lobster
	white shrimp
crab	Yangcheng Lake hairy crab
	king crab
	Bread crab
	pike
mussel	oyster
	abalone
	scallop
	Arctic shellfish

file to complete the data collection. The commodity data collected in this paper mainly includes the user’s username, commodity attributes, ID, evaluation time, comment score, comment content, etc. Finally, 400,000 comment data are obtained.

(2) Data Cleaning Stage

The first objective of this stage is to de-emphasize the comment data, remove the same repetitive content in the comments, as well as the comment data, such as “this user has not filled in the evaluation content.” The second intent of this stage is to compress the phrases, which will appear in the comments, such as “ha ha ha” In other words, the compression of phrases, such as “ha ha ha ha,” “ha ha, good, ha ha, good,” and other continuous repetitions of comments and redundant verbiage must be reduced to a single word that expresses the meaning of the sentence more succinctly. The next aim phrase deletion when the comment text is too short and the removal of the phrase will not affect the results of the judgment. Generally, text that is six words or less is removed. Next, we remove the invalid text such as English letters, numbers, symbols, etc., which have no significance to the expression of the meaning of the words. After data cleanup, 30,000 comments were obtained.

(3) Chinese Segmentation Stage

Since online comments are unstructured data, computers cannot directly recognize the structural idea of the whole sentence when processing natural language. To transform online comments into structured data that can be recognized by computers, generally a sentence is split into corresponding sub-sequences according to standardized criteria, and the overall meaning of the original statement is unchanged. In this paper, we utilize Python's third-party data package, Jieba (Zeng, 2019), Python’s Chinese word segmentation model, to realize Chinese word splitting. The text splitting in this paper makes use of Jieba's precise patterns. For example, take the following sentence: “在Taobao买东西

Figure 2. Example of Chinese word splitting operation

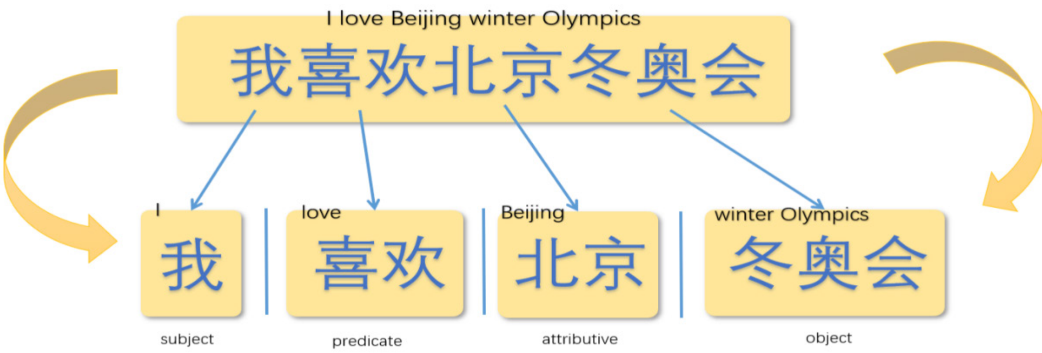
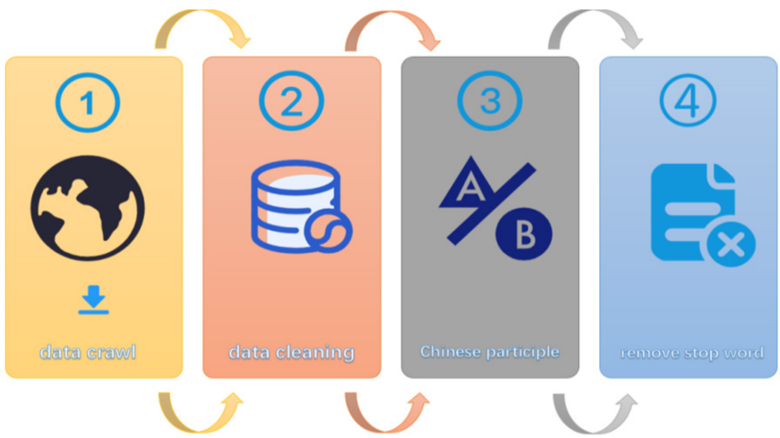


Figure 3. Pre-processing flow of online shopping mall comment data



就是放心质量,没的说,有保证,物流速度快,产品新鲜,日期好". The effect of segmentation is as follows: "在/Taobao/买/东西/就/是/放心,质量/没/的/说/有保证/,物流/速度/快,产品/新鲜,日期/好." The Chinese word splitting operation is shown in Figure 2.

(4) Removal of Deactivated Words Stage

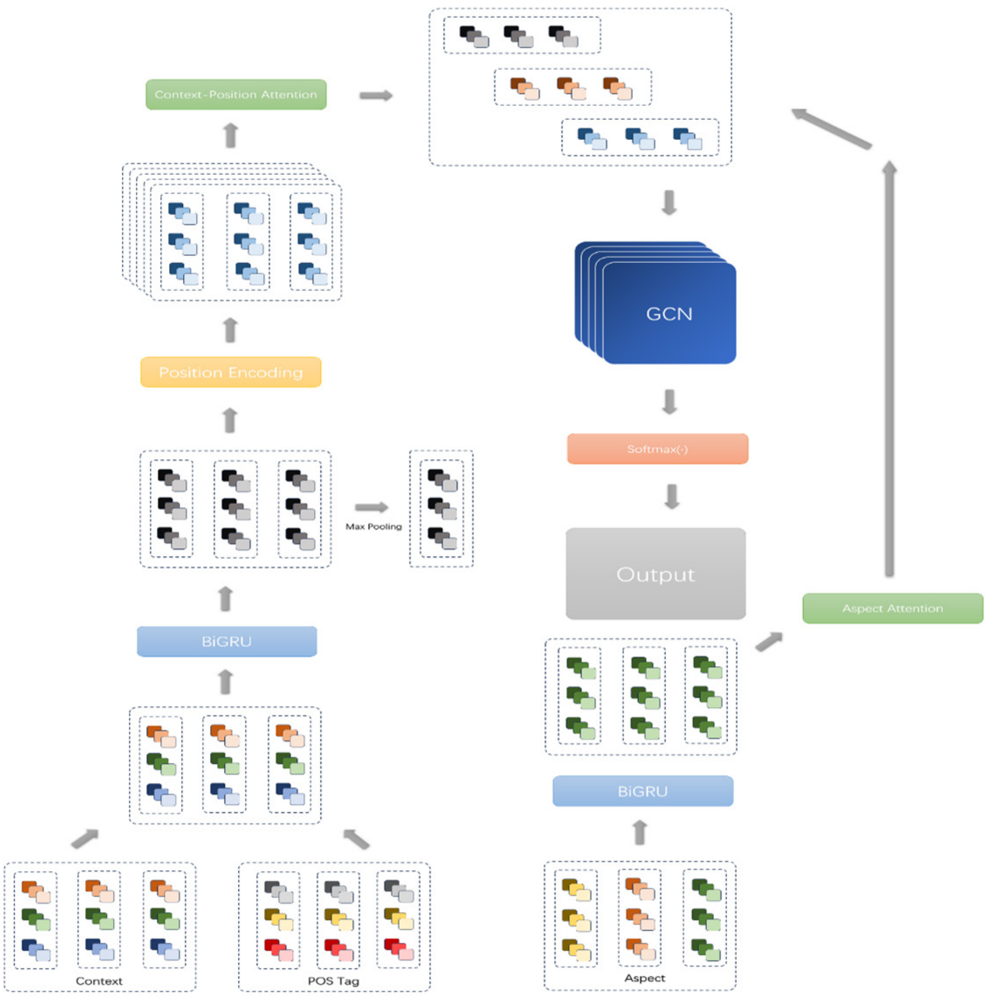
Jieba can support customized deactivation lexicon import, which can be not limited to the thesaurus that comes with Jieba to include deactivated words in the domain.

The whole preprocessing stage is plotted in Figure 3.

Improved GCN-Based Consumer Sentiment Classification and Sentiment Polarity Analysis

In this section, an improved GCN model (Li, et al., 2020) incorporating auxiliary information is proposed for aspectual sentiment analysis of review texts. First, the general architecture of the model is introduced, followed by the text embedding layer (Bollegala & O'Neill, 2022), BiGRU layer, location coding layer, multi-head attention mechanism layer (Fuster et al., 2022), GCN layer, and output layer of the model in turn. The overall structure is shown in Figure 4.

Figure 4. Design diagram of the general architecture of the model



Text Input Layer

Get the comment text S, which consists of a sequence of N consecutive words, as shown in Equation 1.

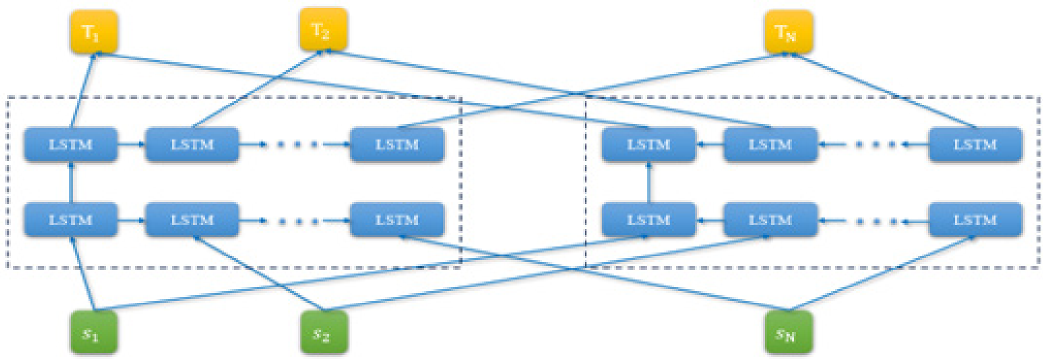
$$S^c = \left\{ s_1^c, s_2^c, s_3^c, \ldots, s_N^c \right\} \tag{1}$$

where s_i^c denotes a sequence of comment text.

In aspect-level sentiment analysis, which is to discriminate the sentiment polarity of a given aspect word, the lexical properties of the words before and after the aspect word may affect the sentiment polarity. So in this chapter, the lexical feature information is used as auxiliary information for obtaining deeper sentiment trait characterization information. According to the acquired text sequences, using the lexical annotation tool, the lexical annotation is performed, and Equation 2 shows the result.

$$S^p = \left\{ s_1^p, s_2^p, s_3^p, \ldots, s_N^p \right\} \tag{2}$$

Figure 5. Schematic diagram of ELMo model



where s_i^p denotes the sequence of lexical annotations of the comment text S.

Assuming that there are J given aspectual words in the comment text S, then the set of aspectual words is denoted as shown in Equation 3.

$$S^a = \{ s^{a_1}, s^{a_2}, \ldots, s^{a_J} \} \tag{3}$$

Each aspect word is a contiguous subsequence in a sentence, and the sequence of individual aspect word is denoted as shown in Equation 4.

$$s^{a_i} = \left\{ s_1^{a_i}, s_2^{a_i}, \ldots, s_{M_i}^{a_i} \right\} \tag{4}$$

where s^{a_i} denotes the ith aspect word in the sequence S^a which contains $M_i \in \left[1, N\right)$ words.

The comment text sequence, S^c, the lexical annotation sequence, S^a, and the aspectual word sequence, s^{a_i}, are obtained, and embedding is performed on them, respectively. Due to the problem of inconsistent semantic representation of the same word in different contexts in actual text expression, ELMo (Liu et al., 2020) is a multi-layer BiLSTM (Rahman et al., 2021) neural network language model, which dynamically adjusts the vector representation by combining with the specific context of the current word and obtaining a dynamic word vector representation by training on a huge amount of corpus representation. Among them, each layer of LSTM can learn different levels of semantic information features, shallow LSTM can capture syntactic and lexical information, and deep LSTM shallow LSTM can capture syntactic and lexical information, while deep LSTM can capture high-dimensional semantic information, so that word vectors have more accurate semantic expression ability. A BiLSTM can capture contextual information, which can solve the problem of multiple meanings of words to a certain extent. The overall model structure of ELMo is shown in Figure 5.

For the sentence $\left(s_1, s_2, s_3, \ldots, s_N \right)$, the language model forward process calculates the probability of occurrence of the sentence as a whole, which can be decomposed into the known $\left(s_1, s_2, s_3, \ldots, s_{k-1} \right)$, predicting the probability of the s_k occurs, and the related computational procedure is shown below. The backward process, on the other hand, knows $\left(s_{k+1}, s_{k+2}, \ldots, s_N \right)$ to predict the probability of the occurrence of s_k, and the related computational procedure is shown below. The ELMo model is used to predict the probability of the occurrence of s_k by combining both forward and backward LSTMs in order to maximize the probability value of the sentence, the process as shown in Equation 5.

$$p(s_1, s_2, s_3, \ldots, s_N) = \tag{5}$$

$$\prod_{k=1}^{N} p\left(s_k \mid s_1, s_2, s_3, \ldots, s_{k-1} \right)$$

$$p(s_1, s_2, s_3, \ldots, s_N) =$$

$$\prod_{k=1}^{N} p\left(s_k \mid s_{k+1}, s_{k+2}, \ldots, s_N \right)$$

$$\sum_{k=1}^{N} \begin{pmatrix} logp\left(s_k \mid s_1, s_2, \ldots, s_{k-1}; \theta_x, \vec{\theta}\ \mathrm{LSTM}, \theta_S + \right. \\ \left. logp\left(s_k \mid s_{k+1}, s_{k+2}, \ldots, s_N; \theta_x, \overleftarrow{\theta}\ \mathrm{LSTM}, \theta_S \right) \right) \end{pmatrix}$$

where θ_x is the vector representation of the word x; θ_S denotes the *Softmax* layer parameter; and the forward vector $\vec{\theta}\ LSTM$ and the backward vector $\overleftarrow{\theta}\ LSTM$ denote the forward and backward LSTM model parameters, respectively.

Therefore, in an ELMo model consisting of a BiLSTM at the L-layer, the vector representation of the word k is $2L + 1$ combination of vectors, and the process is shown in Equation 6.

$$R_k = \left\{ x_k^{LM}, \vec{h}_{kj}^{LM} \mid j = 1, \ldots, L \right\} = \left\{ h_{k,j}^{LM} \mid j = 0, \ldots, L \right\} \quad (6)$$

where x_k^{LM} and $\vec{h}_{kj}^{LM}$ are the word vector representations of the input layer.

The ELMo model is task-dependent and weights the set of vectors to obtain the word k of the vector representation. The process is shown in Equation 7.

$$ELMO_k^{task} = E\left(R_k, \theta^{task} \right) = y^{task} \sum_{j=0}^{L} S_j^{task} h_{k,j}^{LM} \quad (7)$$

where S_j^{task} denotes each layer weight parameter; y^{task} is task-related to the ELMo word vector as a whole parameter that does the scaling and is used to some extent as layer normalization, thus, bringing regularization effects.

The comment text sequence S^c, the lexical annotation sequence S^a, and the aspect word sequence s^{a_i} are obtained, and they are embedding, respectively. The comment text sequence and the aspect word sequence are represented by the ELMo model; the word vector after each word encoding is denoted as $e_t \in \mathbb{R}^{d_{emp} \times 1}$, where d_{emp} denotes the word vector dimension. The lexical labeling sequence adopts discrete representation for word embedding, and the commonly used lexical labeling category is 36. Then, the word vector representation after encoding is denoted as $e_p \in \mathbb{R}^{36 \times 1}$, which has a word vector dimension of 36. Then, the comment text word vector is then spliced with the lexically labeled sequence word vector as a new text sequence word vector, denoted as $e_{tp} \in \mathbb{R}^{d_{(emp+36)} \times 1}$. Finally, after embedding, the text embedding matrix of the left part of the model is denoted as $E^c \in \mathbb{R}^{d_{(emp+36)} \times N}$. The ith aspect word sequence embedding matrix of the input on the right side of the model is denoted as $E^{a_i} \in \mathbb{R}^{d_{emp} \times M_i}$.

BiGRU Layer

Gated recurrent unit (GRU) (Yevnin et al., 2023) networks are a variant of LSTM that possess fewer parameters, reduces the risk of overfitting, and has better performance on small datasets. Based on the LSTM network, the original "input gate," "forget gate," and "output gate" are simplified and combined to "update gate," "rewrite gate," and "reset gate" to control information update. The update gate controls how much information needs to be retained from the history state in the current state and how much information needs to be received in the waiting state. The current state of the hidden layer is updated by the following formula. The formula for updating the current state of the hidden layer is represented in Equation 8.

$$h_t = z_t \odot h_{t-1} + \left(1 - z_t\right) \odot g\left(x_t, h_{t-1}; \theta\right) \tag{8}$$

where x_t is the current t-moment input; $\odot$ is the Hadamard product; h_t denotes the current state of the t-moment, and h_{t-1} denotes the $t-1$-moment state; $z_t \in \left[0,1\right]^D$ denotes the update gate, as shown in Equation 9.

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1} + b_z\right) \tag{9}$$

where $\sigma(\cdot)$ is the sigmoid function; W_z, U_z are the weight parameters; and b_z is the bias term parameter. When $z_t = 0$, the current state state h_t and the previous moment state h_{t-1} exhibit a nonlinear functional relationship; when $z_t = 1$, h_t and h_{t-1} exhibit a linear functional relationship. In the GRU network, $g\left(x_t, h_{t-1}; \theta\right)$ is defined as shown in Equation 10.

$$\widetilde{h}_t = tanh\left(W_h x_t + U_h\left(r_t \odot h_{t-1}\right) + b_h \tag{10}$$

where $\widetilde{h}_t$ denotes the candidate state at the current moment; W_h and U_h are weight parameters; b_h are bias term parameters; $r_t \in \left[0,1\right]^D$ is a parameter for the reset gate, as shown in Equation 11.

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1} + b_r\right) \tag{11}$$

where W_r, U_r are weight parameters; b_r are bias term parameters. By resetting the gate to decide $\widetilde{h}_t$ computation depends on whether $t-1$ time moment on the state h_{t-1}. When $r_t = 0$, the candidate state $\widetilde{h}_t$ is only related to the current t-moment input x_t and is not related to the historical state information; when $r_t = 1$, then $\widetilde{h}_t$ is related to x_t and the historical state h_{t-1}. Finally, the hidden layer state of the GRU network is updated as shown in Equation 12.

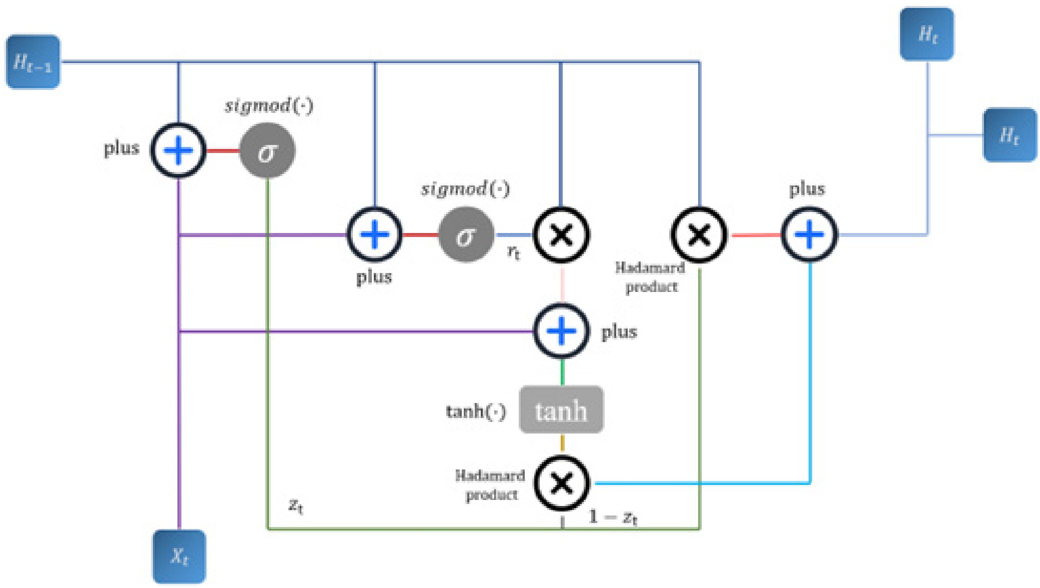
$$h_t = z_t \odot h_{t-1} + \left(1 - z_t\right) \odot \widetilde{h}_t \tag{12}$$

when $z_t = 0, r_t = 1$, the network is a general recurrent neural network; when $z_t = 0, r_t = 0$, the current state h_t is only related to the input x_t; when $z_t = 1$, then we have $h_t = h_{t-1}$, and the current state is equal to the previous moment state and is related to the current moment input, and x_t is not relevant. The structure of the GRU model is shown in Figure 6.

A BiGRU (Yu et al., 2022) network is composed of two GRUs that model sequences. One layer of GRUs is used as forward input for acquiring sentence information in the forward direction, and the other layer of GRUs is used as backward GRUs, and the other GRU is used as backward inputs to obtain sentence information in the reverse direction. Compared with the BiLSTM model, its gated loop unit only contains update gate and reset gate.

In this research, the text word embedding is used as the input to the BiGRU model to obtain the forward hidden layer state, $\overrightarrow{h}_t \in \mathbb{R}^{d_{hid} \times 1}$, and the backward hidden layer state, $\overleftarrow{h}_t \in \mathbb{R}^{d_{hid} \times 1}$, where

Figure 6. GRU layer structure



d_{hid} denotes the number of neurons in the hidden layer in the BiGRU number of elements. Then the hidden layer state at the t-moment is denoted, as shown in Equation 13.

$$h_t = \left[\overrightarrow{h}_t, \overrightarrow{h}_t\right] \in \mathbb{R}^{2d_{hid}\times 1} \tag{13}$$

Based on the text embedding matrix representation, E^c, and the aspectual word sequence embedding matrix representation, E^{a_i}, respectively, we obtain the sentence context hiding layer output $H^c = \left[h_1^c, h_2^c, \ldots, h_N^c\right] \in \mathbb{R}^{2d_{hid}\times N}$ and the ith aspect word hidden layer output $H_i^a = \left[h_1^{a_i}, h_2^{a_i}, \ldots, h_{M_i}^{a_i}\right] \in \mathbb{R}^{2d_{hid}\times M_i}$.

Location Encoding Layer

The distance between aspectual words and other words in a sentence contains important information in user comments. The affective polarity of aspectual words is often influenced by their context. For example, in the sentence "The service was good, but I think the food was a bit bad," "good" affects the sentiment of "service," while "bad" affects the sentiment of "food." To capture this positional context, this chapter designs a positional coding rule to encode the positional information of aspectual words as auxiliary feature information, enhancing the determination of their sentiment polarity.

Given an aspect word, s^{a_i}, which can consist of multiple sequences of consecutive words, in which case it is regarded as a whole, and denote the number of aspect words present in the comment text as J, where $i \in [1, J]$. Then, the relative distance between tth word and the ith aspect word, s^{a_i}, is defined as shown in Equation 14.

$$d_t^{a_i} = \begin{cases} 1, dis = 0 \\ 1 - \frac{mrd}{dis}, dis \neq 0 \end{cases} \tag{14}$$

where dis denotes the distance between the tth word in the sequence and the aspect word s^{a_i} calculated, as shown in Equation 15.

$$dis = |\ index(s^{a_i}) - index(otherword)\ | \tag{15}$$

where $\cdot\cdot\cdot$ denotes taking the absolute value, $index(s^{a_i})$, denotes the index of the aspect word s^{a_i} in the sequence, and $index(otherword)$ denotes the index of the tth word in the sequence.

mrd denotes the maximum relative position of the aspect word s^{a_i} in the sentence, defined, as shown in Equation 16.

$$mrd = max(index(s^{a_i}), N - index(s^{a_i})) \tag{16}$$

where $max(\cdot)$denotes the maximum value, and N denotes the sequence length.

The positional coding layer based on the aspect word s^{a_i} will be output, as shown in Equation 17.

$$p_t^{a_i} = d_t^{a_i} h_t^c \tag{17}$$

$$P^{a_i} = \left[p_1^{a_i}, p_2^{a_i}, \ldots, p_N^{a_i}\right]$$

where h_t^c denotes the hidden layer output of H^C at the tth moment; P^{a_i} denotes the positional encoding based on the ith aspect word s^{a_i}. Eventually, J positional encoding representation will be obtained through the positional encoding layer.

Multiple Attention Mechanism Layer

The model employs an attention mechanism to capture interaction information between context and aspectual words, incorporating the positional coding information proposed in this chapter to better understand the affective impact of the comment context on the aspectual words.

The bidirectional attention layer consists of two parts. The first part, aspect attention, uses the word embedding representation of the aspect word processed through BiGRU to obtain the hidden layer output. This output is then combined with context information through the attention mechanism to get a new aspect word representation. The second part, context-position attention, takes this new aspect word representation and combines it with contextual information including position encoding. This combined information is processed through the attention mechanism to obtain a specific aspect representation that integrates lexical, positional, and contextual information. This integrated representation is then used as input for the GCN network for sentiment classification.

In the aspect attention section, the attention weights are assigned to the aspect words to get the new aspect word representation, computed as shown in Equation 18.

$$f_{aa}\left(\overline{h_{max}^c}, h_t^{a_i}\right) = \overline{h_{max}^c}^T \cdot W_{aa} \cdot h_t^{a_i} \tag{18}$$

$$\alpha_t^{a_i} = \frac{exp\left(f_{aa}\left(\overline{h_{max}^c}, h_t^{a_i}\right)\right)}{\sum_{t=1}^{M_i} exp\left(f_{aa}\left(\overline{h_{max}^c}, h_t^{a_i}\right)\right)}$$

$$m^{a_i} = \sum_{t=1}^{M_i} \alpha_t^{a_i} \cdot h_t^{a_i}$$

where $h_{max}^{\bar{c}} \in \mathbb{R}^{2hid\times1}$ is derived from the sentence context hidden layer output H^c as Max Pooling, $h_{max}^{\bar{c}}{}^T$is the transpose of $h_{max}^{\bar{c}}$; $W_{aa} \in \mathbb{R}^{2hid\times2hid}$ is the weight parameter; $\alpha_t^{a_i}$ is the attentional weight of the hidden layer vector for each aspect word; m^{a_i} denotes the aspect word with a new aspect word representation after the attentional weights are computed.

In the Context-Position Attention section, the aspect word representations are compared with the context with positional coding information and fused lexical information. In the Context-Position Attention section, the aspect word representation is computed with the context with positional encoding information and fused lexical information to obtain a specific aspect word representation. The calculation process is shown in Equation 19.

$$f_{cpa}\left(m^{a_i}, p_t^{a_i}\right) = m^{a_i T} \cdot W_{cpa} \cdot p_t^{a_i} \tag{19}$$

$$\rho_t^{a_i} = \frac{\exp\left(f_{cpa}\left(m^{a_i}, p_t^{a_i}\right)\right)}{\sum_{t=1}^{N} exp\left(f_{cpa}\left(m^{a_i}, p_t^{a_i}\right)\right)}$$

$$z^{a_i} = z_i = \sum_{t=1}^{N} \rho_t^{a_i} \cdot h_t^c$$

where $W_{cpa} \in \mathbb{R}^{2hid\times2hid}$ is the weight parameter; z^{a_i} is the representation of the particular aspect word s^{a_i}. The final obtained aspect-specific aspect word representation, as shown in Equation 20.

$$Z = [z_1, z_2, \ldots, z_J] \tag{20}$$

where J denotes the number of aspect words in the comment text.

GCN Layer

GCNs augment CNNs with the ability to encode local information on unstructured data. They operate directly on graphs and introduce node embedding vectors based on node-to-node dependencies. By leveraging the data transmissibility among nodes in graphs, GCNs are widely used in graph data with rich dependencies. The inputs to GCNs are node feature vectors and the graph structure. For each node in the graph, GCNs encode its neighborhood information into a new feature vector, effectively capturing and utilizing the local and relational information within the graph.

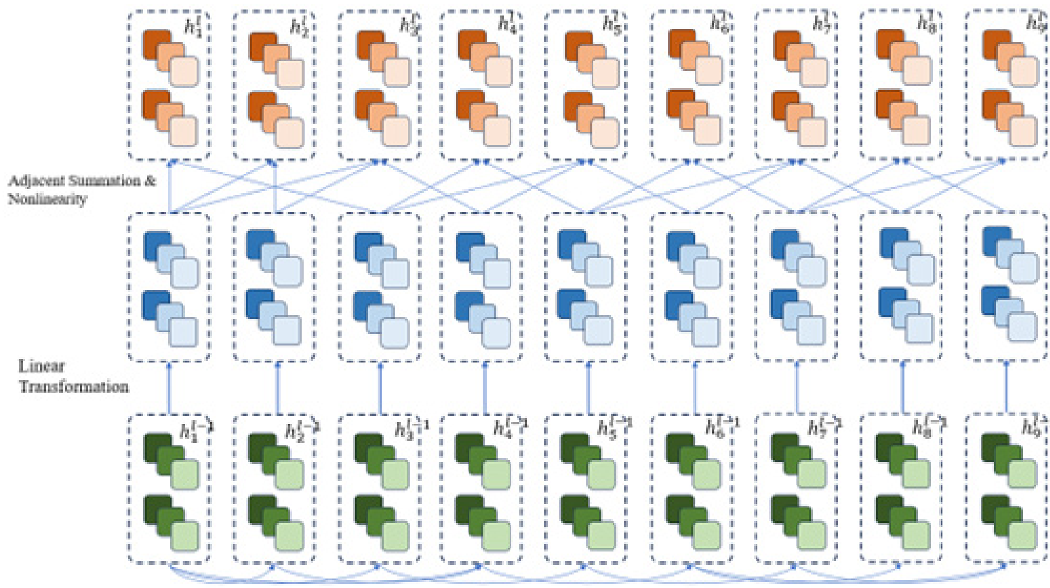
Given a graph with k nodes, the adjacency matrix $A \in R^{k\times k}$ is obtained from the node information in the graph. In this chapter, a multilayer GCN is used in aspect level sentiment analysis. Assuming that the GCN has L layers, where $l \in [1,2,3,\ldots,L]$, the hidden layer output of a node i in l layer is denoted as h_i^l, where h_i^0 denotes the initial state of the node i. Then the hidden layer state h_i^l is computed, as shown in Equation 21.

$$h_i^l = \sigma\left(\sum_{j=1}^{k} A_{ij} W^l h_j^{l-1} + b^l\right) \tag{21}$$

where $\sigma(\cdot)$is a nonlinear function, W^l is the weight matrix, b^l is the bias parameter, $h_j^{l\text{-}1}$ is the hidden layer state of the previous node J. The GCN structure is shown in Figure 7.

This research uses graphs to capture the emotional dependencies between aspects. Specifically, each aspect in a piece of comment text is treated as a node, and then construct edges from these nodes based on whether the aspects are adjacent to each other and consider each edge as an aspect's. Each edge is regarded as the emotional dependency of the aspect, and finally, the graph structure is constructed from these nodes and edges, which is used as the input of GCN.

Figure 7. GCN network structure



In aspect-level sentiment analysis, since the sentiment polarity of aspect words is influenced by context, the sentiment map defined in this chapter is the undirected graph. The graph structure is only related to the number of aspects in a comment and the order between the aspects. If two nodes are connected by an edge, it means that these two nodes are adjacent to each other. That is, given node v, and all neighboring nodes of node v defined as $N(v)$, $u \in N(v)$ means that there is an edge connection between nodes u and v.

In the graph structure constructed in this chapter, the information related to its neighborhoods is encoded into a new representation vector through GCN, and every node represents a vector representation of an aspect. In addition, each node is self-cycling. Initially, nodes are represented in the graph as shown in Equation 22.

$$z_v^1 = \sigma\left(\sum\nolimits_{u\in N(v)} W_{node} z_u + b_{node}\right) + \sigma\left(W_{se} z_v + b_{se}\right) \tag{22}$$

where $\sigma(\cdot)$denotes a nonlinear function, e.g., the ReLu function; $W_{node} \in \mathbb{R}^{dim_m \times dim_n}$, $W_{se} \in \mathbb{R}^{d_m \times d_n}$ is the weight parameter, $b_{se} \in \mathbb{R}^{dim_m \times 1}$, $b_{se} \in \mathbb{R}^{dim_m \times 1}$ is the weight parameter, and $dim_m = dim_n = 2h_{hid}$, z_u is the uth particular aspect denoted, and z_v is the same.

When stacking multiple layers of GCNs, each node state is node updated with the information received from the previous layer. That is, each layer GCN takes the output of the node representation of the previous layer as the input of the current layer, and the node representation between the multi-layer GCNs is updated as shown in the following equation. The update of node representation between multi-layer GCNs is shown in Equation 23.

$$z_v^{l+1} = \sigma\left(\sum\nolimits_{u\in N(v)} W_{node}^l z_u^l + b_{node}^l\right) + \sigma\left(W_{se}^l z_v^l + b_{self}^l\right) \tag{23}$$

where l denotes the number of GCN layers currently in place, $1 \leq l \leq L-1$.

Table 4. Properties of hardware and software used in the experiment

software		hardware	
operating system	**Windows 11**	**computers**	**1**
development language	Python	CPU	intel core i7
development framework	PyTorch	RAM	32G
toolkits	Geometric(PyG)	hard disk	2T

Sentiment dependencies are learned from the information of all neighboring nodes. After training, the GCN can capture a single comment dependency between different aspects in a text, and thus infer the sentiment relationship between multiple aspects.

Output Layer

In this chapter of GCN, the final hidden layer output of each node z_i^L as the ith aspect word in a piece of comment text as a sentiment sentiment classifier. Eventually, this hidden layer output is plugged into a fully connected neural network layer that maps z_i^L to the $C - dim$ sentiment class space, as shown in Equation 24.

$$c_i = W_c z_i^L + b_c \tag{24}$$

where $W_c \in \mathbb{R}^{C \times 2d_{hid}}$ is the weight parameter, $b_c \in \mathbb{R}^{2d_{hid} \times C}$ is the bias term parameter.

Finally, the sentiment polarity of the ith aspect word $j \in [1, C]$ is derived by Softmax and computed as shown in Equation 25.

$$y'_{ij} = \frac{\exp(c_{ij})}{\Sigma_{k=1}^{C} \exp(c_{ik})} \tag{25}$$

The model is trained using the Cross Entropy Loss (CEL) function with L2-regularization, as shown in Equation 26.

$$loss = \sum_{i=1}^{J} \sum_{j=1}^{C} y_{ij} log\left(y'_{ij}\right) + \lambda \parallel \theta \parallel^2 \tag{26}$$

where y_{ij} is the true labeling result, λ is the L2-regularization coefficient, θ is the regularization parameter.

EXPERIMENT

In order to verify the effectiveness of the improved GCN-based consumer sentiment classification and sentiment polarity analysis algorithm proposed in this paper, this study collects the data of seafood and aquatic reviews sold by a large aquatic company on the Taobao platform as a dataset, selects seven indicators and 20 benchmark models for sentiment analysis and designs a comparison experiment and an ablation experiment.

Experimental Environment

The hardware and software environments in which the experiments of this paper are conducted are shown in Table 4.

Table 5. Statistic information on data set

data set		CMN	AWN	Pos	Neg	Neu
fish	cutlassfish	400	114	341	23	36
	butterfish	420	106	288	55	77
	salmon	2316	119	1456	767	93
	sea bass	2624	102	1295	137	1192
	yellow croaker	2143	98	2115	17	11
	balsa	175	93	146	12	17
shrimp	prawns	796	119	660	5	131
	chicken lobster	2198	92	1700	16	482
	white shrimp	2894	107	1397	800	697
crab	Yangcheng Lake hairy crab	1509	103	503	581	425
	king crab	1263	109	989	184	90
	Bread crab	2663	103	1662	196	805
	pike	2307	106	1744	177	386
mussel	oyster	1409	103	438	286	685
	abalone	2750	113	992	955	803
	scallop	1302	104	711	409	182
	Arctic shellfish	2831	112	1136	773	922

It is worth stating that the PyTorch Geometric Library, a graph neural network (GNN) library based on PyTorch, contains many implementations of methods and commonly used datasets from GNN-related papers and provides easy-to-use interfaces for generating graphs, so it is quite convenient to use for conducting experiments.

Datasets

The dataset used in this chapter comes from the review data of seafood and aquatic products sold by a large aquatic company in Taobao between January and August 2023. The review data contains the text of the reviews of a total of 17 products of the aquatic company, and the dataset is divided into 17 copies. Each dataset is sliced into a training set and a test set in the ratio of 7:3. In addition, in order to avoid the interference of invalid data on the model training, some noise data in the dataset are eliminated in this paper. Because this experiment is to discriminate the sentiment polarity of the given aspect words in the reviews, the review texts without aspect words in the dataset were eliminated.

The statistical properties of the dataset are shown in Table 5. The sentiment polarity of aspects in the dataset is categorized into three categories, namely “Positive,” “Negative,” and “Neutral.” After manual screening, each comment contains at least one aspect word. In the table, “CMN” denotes the number of comments, “AWN” denotes the number of aspectual words, “Pos” denotes the number of labels with aspectual sentiment polarity of positive, “Neg” denotes the number of labels with aspectual sentiment polarity of negative, and “Neu” denotes the number of labels with aspectual sentiment polarity of neutral.

Among them, we collected important aspectual words from the dataset, as shown in Table 6. This group of aspectual words has eight categories, divided into four categories of positive and four categories of negative emotions.

Table 6. Important aspect terms in the dataset

Categories	Positive emotions aspect words
Freshness	Nice, fresh, frozen, meaty, tender, likeable
Taste and flavor	Good, texture, flavor, full, fresh, taste
Express	Satisfactory, very fast, cold chain, speed, distribution, delivery
Product value for money	affordable, quality, cost-effective, activity, reassuring
	Negative emotions aspect words
Quality of aquatic products	Dead, smelly, poor, rotten, blackened
After-sales service quality	Complaints, returns, customer service, after-sales, garbage, disappointment
Protective packaging	Defrosted, broken, packaging, ice packs, soft, bad
Price difference	Discrepancy, activity, deception, expensive, caution, price

Table 7. Parameter settings of the model of this paper

parameter name	parameter value
ELMo word vector dimension	768
GRU hidden layer unit number	300
GCN Number of layers	2
Output vector dimension	300
Initialized values for all parameter weight matrices	Random numbers in the range [-0.01,0.01]
Dropout	0.5
Data batch size	64
Learning Optimizer	Adam
Learning rate	0.001

Benchmark Models

Twenty models are selected for comparison with the improved GCN model proposed in this paper. Table 7 lists the parameter settings of the improved GCN models in the comparison experiment. Table 8 lists the basic properties of the 20 baseline models used for comparison in this experiment and their design ideas.

In this study, we investigated in detail the models related to sentiment analysis in recent years and selected 20 models as benchmark models for comparative analysis with the improved GCN model proposed in this paper on the Taobao aquatic product dataset. Some of these models are classical models with relatively high citation rates, and some are relatively new models published in recent years.

Evaluation Indicators

Seven indicators were selected for this experiment to evaluate and compare the performance of the model. The indicators and their meanings are shown in Table 9.

Comparative Experiment Results and Data Analysis

This part lists in detail the result data of the comparison experiment under the seven evaluation indexes and gives reasonable explanations for the key problems and special phenomena.

Table 10 shows the comparison of the accuracy of models. Table 11 shows the comparison of precision rates of models. Table 12 shows the comparison of recall of models. Table 13 shows the

Table 8. Baseline model selection

No.	Model	Publication date	Modeling Ideas
1	Feature-support vector machine (SVM) (Kiritchenko et al., 2014)	2014	The model is a traditional support vector machine approach based on complex feature engineering for aspectual sentiment classification tasks
2	Attention-based LSTM with Aspect Embedding (ATAE-LSTM) (Wang et al., 2016)	2016	The model incorporates aspectual information into word embeddings and uses an attentional mechanism to capture important parts of the sentence.
3	TD (Target Dependent)-LSTM (Tang et al., 2015)	2015	The model splices the target string with word embedding vectors into the LSTM to represent the semantic relationship between the target and the context.
4	MemNet (Tang et al., 2016)	2016	The model utilizes a multi-hop memory network to focus on aspect words in sentences through word and location information.
5	IAN (Ma et al., 2017)	2017	The model uses two attention-based LSTM networks to generate aspect words and contextual representations, respectively, and then connects the contextual and aspectual representations as feature vectors for sentiment prediction to make sentiment polarity discriminations for the aspect word.
6	AOA (Huang et al., 2018)	2018	The model obtains the hidden layer outputs of context and aspect words through BiLSTM, then learns the corresponding representations of context and aspect words through the interactive attention mechanism, and finally, obtains the sentiment polarity distributions through the Softmax layer, which leads to the results of aspect word sentiment classification.
7	AEN (Song et al. 2019)	2019	The model mainly consists of an embedding layer, an attention coding layer, an attention layer for specific aspect words, and an output layer. Meanwhile, in order to solve the problem of not being able to parallelize in the RNN model, the model uses an attention-based encoder to model aspect words and their contexts
8	IARM [55]	2018	The model uses a memory network to merge neighboring aspect-related information into the target aspect information.
9	ASGCN (Zhang et al., 2019)	2019	The model constructs a directed graph on the dependency tree of a sentence and uses a graph convolution network to extract syntactic information and word dependencies.
10	Dual-GCN (Li et al., 2021)	2021	A two-graph convolutional network model that simultaneously considers syntactic structural complementarity and semantic relevance. In particular, the Enriched Syntactic Knowledge module is designed to reduce dependency parsing errors. Self-attention mechanism module is designed to enhance the semantic relevance. In addition, it is required to obtain the semantic correlation between context words by orthogonal and differential regularizes.
11	BERT (Zhao & Sun, 2022)	2018	The model processes sentence text directly using the BERT pre-trained model and fine-tunes aspect-level emotion classification as a downstream.

continued on following page

Table 8. Continued

No.	Model	Publication date	Modeling Ideas
12	InterGCN (Liang et al., 2020)	2020	The model obtains aspect-specific, and aspect-interaction features by constructing aspect-specific and aspect-relationship graphs, respectively.
13	SenticGCN (Liang et al., 2022)	2022	The model constructs a graph neural network by integrating external sentiment knowledge from SenticNet to enhance the dependency graph of sentences.
14	DGCN-SKIA	2023	The model is an aspect-level sentiment analysis model based on two-graph convolutional networks jointly learning sentiment knowledge information and aspect interactions proposed in Chapter 3 of this paper.
15	CDT (Sun et al., 2019)	2019	A dependency tree-based convolutional model that utilizes BiLSTM to learn the representation of sentence features and uses dependency trees and GCN to transfer contextual and dependency information from opinion words to aspect words.
16	DGEDT	2019	By jointly considering planar and graph-based representations, a dual-transformer module is designed based on dependency graphs and bidirectional GCNs, iteratively interacting planar representations with graph representations, and both representations are jointly improved through the Biaffine transformation process.
17	DGEDT-BERT (Tang et al., 2020)	2020	This approach is the same as the DGEDT described above, except that it changes the pre-model of DGEDT by using a pre-trained BERT instead of BiLSTM as the encoder.
18	R-GAT (Wang et al., 2020)	2020	A relational graph attention network based on recoding the dependency tree to link aspects to opinion words and solving the problem of model confusing the link between aspect words and opinion words through syntactic coding can better establish the link between aspects and opinion words and significantly improve the performance of graph attention networks.
19	R-GAT-BERT (Wang et al., 2020)	2020	The methodology is the same as the R-GAT described above, except that the pre-model of the R-GAT is altered to use a pre-trained BERT instead of a BiLSTM as the encoder.
20	BiGCN (Zhang & Qian, 2020)	2020	A new architecture aimed at convolution on hierarchical syntactic and lexical graphs. Global lexical graphs are used to encode word co-occurrence information at the corpus level, conceptual hierarchical construction in syntactic and lexical graphs, and in order to distinguish between each class of dependencies or lexical word pairs, a two-layer interactive GCN is used.

comparison of FNR values of models. Table 14 shows the comparison of FPR values of models. Table 15 shows the comparison of AUC values of models. Table 16 shows the comparison of F1-score values of models. Figure 8 plots Tables 10 through 16 as graphs.

Table 9. Setting of evaluation indicators

Indicator name	Indicator abbreviations	Indicator meaning	Calculation of indicators
True Positive (TP)	TP	Predicting positive classes to positive numbers	--
True Negative (TN)	TN	Predicting positive classes to negative class numbers	--
False Positive (FP)	FP	Predicting negative classes to positive numbers	--
False Negative (FN)	FN	Predicting negative classes to positive numbers	--
accuracy rate	accuracy	Number of negative categories predicted to be negative All predictions correct (both positive and negative) as a percentage of total	$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$
recall rate	recall	Percentage of correct predictions that are positive as a percentage of all actual positive predictions	$Recall = \frac{TP}{TP+FN}$
precision rate	precision	Percentage of all predictions correct (both positive and negative categories) in total	$Precision = \frac{TP}{TP+FP}$
False Negative Rate (FNR)	FNR	Proportion of negative categories with wrong predictions to all positive categories	$FNR = \frac{FN}{TP+FN}$
False Positive Rate (FPR)	FPR	Proportion of incorrectly predicted positive categories to the total positive categories	$FPR = \frac{FP}{TN+FP}$
Area Under Receiver-Operating Characteristic Curve(ROC) (AUC)	AUC	The area under the ROC curve enclosed with the coordinate axes	The area under the ROC curve enclosed with the coordinate axes.
F1-score	F1-score	Harmonized averaging of precision and recall rates	$F_1 = 2*\frac{Precision*Recall}{Precision+Recall}$

(1) The improved GCN model proposed in this paper outperforms the baseline model in both crab and mussel datasets in terms of 1-score and AUC. This result proves that the improved GCN model proposed in this paper has an all-around advantage over the baseline model, although it is not as good as the baseline model in some specific metrics, but the comprehensive performance is the point that researchers should be more concerned with.

(2) Feature-SVM model is the only non-deep learning model among all the above models. This model relies on a large number of manually extracted features and ultimately uses SVM as a classifier to discriminate the sentiment polarity of aspectual words. In early sentiment analysis tasks, this algorithm can achieve good results, but its disadvantage is that it requires a lot of manpower to manually select features. Therefore, in this comparison experiment, the performance of this model performs slightly worse than the effect of other deep learning models.

(3) Similar to the considerations in this paper, the TD-LSTM model works by inputting the contextual information of aspect words into two LSTMs separately, then vector splicing the computation results of the hidden layer and using the spliced feature vectors for the sentiment discrimination of aspects. Like this paper, the model also utilizes the left and right textual feature information of the aspect words, but the model does not consider the interaction information between the

Table 10. Comparison of the accuracy of models

Model	fish	shrimp	crab	mussel
Feature-SVM	74.32%	72.25%	79.40%	61.47%
ATAE-LSTM	63.62%	69.29%	73.83%	70.28%
TD-LSTM	66.04%	79.23%	69.62%	77.54%
MemNet	71.73%	75.57%	70.55%	69.51%
IAN	64.06%	71.51%	60.86%	71.76%
AOA	69.42%	69.06%	61.77%	60.42%
AEN	68.04%	60.39%	67.90%	64.67%
IARM	60.44%	78.38%	72.95%	66.69%
ASGCN	64.40%	60.21%	**79.86%**	69.90%
Dual-GCN	66.16%	71.70%	63.00%	67.89%
BERT	66.66%	68.66%	66.96%	65.99%
InterGCN	69.68%	69.36%	79.64%	73.21%
SenticGCN	72.69%	73.80%	73.93%	61.14%
DGCN-SKIA	73.14%	69.85%	75.77%	71.48%
CDT	61.90%	**79.69%**	76.79%	78.35%
DGEDT	61.08%	67.53%	68.79%	**78.44%**
DGEDT-BERT	68.89%	77.92%	76.76%	76.64%
R-GAT	65.19%	71.65%	73.51%	75.15%
R-GAT-BERT	64.30%	66.47%	72.69%	76.71%
BiGCN	72.19%	72.24%	75.91%	73.02%
Ours	**80.11%**	79.12%	77.82%	78.18%

aspect words and the context as well as the dependency relationship between the texts, so it does not achieve the desired results.

(4) Similar to the considerations in this paper, the ATAE-LSTM model adds the attention mechanism on the basis of the LSTM layer, but the attention mechanism in this model only focuses on the information of the aspect word itself and does not consider the influence of the context on the aspect word, so there is a slight gap in performance compared to the model in this paper.

Product Improvement Strategies Based on Consumer Sentiment Analysis

Tables 17 through 20 list the results of the sentiment polarity calculation of the four major categories of aquatic products obtained after the improved GCN model proposed in this paper. Analyzing the calculation results, this paper proposes some product and service improvement suggestions for this large aquatic company.

Analysis of the Results

(1) As an important aspect word, consumers are highly concerned about the quality of products. Aquatic products are a kind of food, which is closely related to the health of consumers, so consumers are more concerned about the quality of aquatic products.

Table 11. Comparison of precision rates of models

Model	fish	shrimp	crab	mussel
Feature-SVM	61.28%	49.19%	54.08%	43.42%
ATAE-LSTM	42.98%	48.65%	59.04%	**64.18%**
TD-LSTM	41.70%	46.92%	53.70%	60.69%
MemNet	62.60%	44.31%	46.15%	63.43%
IAN	46.93%	**63.31%**	**62.40%**	41.58%
AOA	50.84%	44.36%	43.03%	64.43%
AEN	63.15%	62.10%	62.13%	50.65%
IARM	**63.77%**	44.24%	47.33%	60.17%
ASGCN	60.75%	47.52%	57.89%	63.23%
Dual-GCN	44.32%	49.12%	42.50%	58.76%
BERT	57.13%	49.65%	53.73%	55.27%
InterGCN	44.12%	60.17%	45.12%	54.39%
SenticGCN	56.67%	49.85%	45.96%	59.99%
DGCN-SKIA	48.48%	62.82%	60.20%	41.98%
CDT	42.49%	46.32%	44.41%	47.24%
DGEDT	52.54%	51.47%	48.16%	53.62%
DGEDT-BERT	59.98%	55.89%	63.19%	42.57%
R-GAT	48.68%	49.01%	42.59%	59.10%
R-GAT-BERT	59.35%	52.40%	43.08%	59.67%
BiGCN	59.20%	60.10%	63.60%	59.90%
Ours	59.91%	62.34%	60.21%	60.11%

(2) The emotional tendency of consumer review information on online shopping platforms is mainly positive. This shows that most consumers are basically satisfied with aquatic products in the market at present. If aquatic product suppliers still need to improve their reputation, they can try to invest more resources in after-sales service and further improve consumer satisfaction by perfecting their services.
(3) At present, a lot of dissatisfaction with the merchant is centered on the merchant's untimely feedback of consumers' opinions and lack of attention to consumers' opinions.

Suggestions to the Merchants

(1) It is recommended that merchants control product quality and ensure product freshness. The analysis of the experiment in this paper concludes that consumers are more concerned about the freshness and taste of aquatic products. but some of the fresh aquatic products to the hands of consumers but death, blackening, softening. The merchant should pay more attention to the quality of aquatic products and improve the quality control system of aquatic products to ensure that the provision of aquatic products from qualified, standardized suppliers' sources. In the aquatic products packaging and delivery process, the aquatic products should be checked again for quality control to identify deteriorated, damaged products and remove them to improve the

Table 12. Comparison of recall of models

Model	fish	shrimp	crab	mussel
Feature-SVM	59.18%	66.09%	65.74%	62.07%
ATAE-LSTM	52.27%	69.06%	59.15%	60.61%
TD-LSTM	63.28%	58.22%	60.73%	52.98%
MemNet	56.29%	62.82%	**69.12%**	69.31%
IAN	65.42%	64.50%	56.62%	54.23%
AOA	69.05%	50.52%	55.13%	67.69%
AEN	67.46%	52.91%	50.80%	58.96%
IARM	66.17%	**69.98%**	58.10%	64.82%
ASGCN	69.17%	59.41%	50.32%	52.37%
Dual-GCN	59.25%	58.87%	61.08%	51.43%
BERT	56.40%	53.97%	69.91%	67.48%
InterGCN	53.86%	56.44%	53.77%	53.50%
SenticGCN	63.99%	62.74%	66.59%	67.95%
DGCN-SKIA	63.23%	53.65%	63.20%	60.13%
CDT	**69.24%**	61.63%	61.55%	57.99%
DGEDT	61.66%	56.14%	61.36%	55.07%
DGEDT-BERT	59.45%	66.77%	57.11%	61.52%
R-GAT	68.02%	52.62%	62.79%	70.00%
R-GAT-BERT	56.22%	57.61%	57.23%	60.04%
BiGCN	67.53%	57.07%	54.16%	64.59%
Ours	65.12%	61.21%	67.42%	**71.62%**

supply chain system and ensure that consumers receive safe and fresh aquatic products. In addition, the current consumer is more concerned about the issue of food safety, so in order to dispel the consumers' concerns about food safety, suppliers should realize the quality of aquatic products traceability. Also, consumers can use the WeChat small program and other ways to understand the whole production process of aquatic products in real time, as well as the origin of the product, the date, product number, and other information to achieve openness and transparency and to improve consumer confidence in purchasing and increase the purchase rate.

(2) Merchants should practice advance notice activities, reasonable price optimization, and services improvement. The experimental data in this paper shows that the price difference factors make consumers produce negative emotional attitudes. Therefore, businesses should use a variety of ways to provide advance notice of preferential activities and set reasonable prices. So that consumers can choose the right time to buy products for the activities of high-priced purchase of consumers during the period to provide a price guarantee service, return the difference between the price, the consumer receives a damaged Reasonable compensation for damaged aquatic products received by consumers, to ensure the quality of service, thereby enhancing consumer confidence and satisfaction with the purchase.

(3) In addition, merchants should pay more attention to consumer demand, and provide a variety of aquatic products at a reasonable price, not only to form a differentiated marketing, but also to meet the purchase needs of different consumers.

Table 13. Comparison of FNR values of models

Model	fish	shrimp	crab	mussel
Feature-SVM	31.13%	26.07%	33.02%	27.08%
ATAE-LSTM	20.46%	27.62%	30.06%	32.47%
TD-LSTM	27.04%	**16.80%**	22.61%	32.92%
MemNet	32.48%	28.79%	33.18%	18.00%
IAN	29.85%	31.63%	16.80%	16.04%
AOA	31.33%	28.84%	32.99%	**15.83%**
AEN	19.81%	21.30%	24.21%	32.88%
IARM	28.94%	25.09%	22.25%	21.09%
ASGCN	20.04%	25.94%	34.30%	34.05%
Dual-GCN	17.14%	30.29%	18.66%	19.45%
BERT	26.28%	19.55%	18.15%	25.79%
InterGCN	29.07%	23.49%	27.69%	29.92%
SenticGCN	15.79%	25.45%	21.89%	25.58%
DGCN-SKIA	28.17%	27.41%	**15.41%**	33.50%
CDT	33.88%	31.38%	18.87%	31.33%
DGEDT	31.44%	17.49%	26.27%	27.62%
DGEDT-BERT	26.45%	30.56%	22.36%	26.34%
R-GAT	**15.13%**	21.14%	26.66%	20.93%
R-GAT-BERT	20.06%	34.62%	23.26%	28.76%
BiGCN	16.67%	33.51%	25.70%	25.93%
Ours	25.15%	28.52%	19.24%	16.43%

Ablation Experiment Results and Data Analysis

In order to verify the effect of the improved part of the GCN model proposed in this paper, an ablation experiment is designed, which compares the improved GCN model proposed in this paper with the GCN model, and the difference between the two models is mainly that this paper's model adds a word embedding module based on the ELMo model, a BiGRU layer, and a multi-head attention mechanism. The ablation experiment compares the performance of the algorithms by eliminating one of the three models, respectively.

Table 21 is plotted in Figure 9.

Replacing any of the modules decreases the effectiveness of the improved GCN model proposed in this paper, which shows that several of the proposed improvement modules contribute to the performance improvement of the algorithm. Among them, removing the BiGRU module has a somewhat larger impact on the algorithm performance. Especially on the FNR metric, removing the BiGRU module caused a significant decrease in the algorithm performance.

Application of the Improved GCN Model to Other Datasets

In order to verify the performance of the model of the proposed model in this paper in a real environment, this experiment collects a batch of product review data from another large aquatic company on the Jingdong online shopping platform and tests the model's performance on a new dataset using the aforementioned seven metrics, and the experimental results are shown in Table 22.

Table 14. Comparison of FPR values of models

Model	fish	shrimp	crab	mussel
Feature-SVM	**17.48%**	28.50%	28.07%	20.10%
ATAE-LSTM	33.02%	26.82%	23.52%	22.31%
TD-LSTM	25.37%	27.97%	27.94%	24.45%
MemNet	24.66%	16.84%	26.36%	29.21%
IAN	25.10%	34.01%	32.83%	18.35%
AOA	29.78%	22.48%	18.48%	26.63%
AEN	20.42%	26.24%	18.12%	30.37%
IARM	26.39%	26.29%	16.66%	34.34%
ASGCN	19.13%	30.48%	25.46%	21.38%
Dual-GCN	24.94%	32.44%	20.17%	17.95%
BERT	31.03%	29.57%	22.87%	27.01%
InterGCN	27.00%	25.74%	**15.75%**	22.62%
SenticGCN	18.71%	32.94%	22.55%	17.81%
DGCN-SKIA	18.04%	28.22%	28.66%	24.58%
CDT	29.88%	19.43%	16.02%	26.04%
DGEDT	34.16%	**15.50%**	25.16%	28.62%
DGEDT-BERT	33.14%	18.72%	25.14%	24.10%
R-GAT	28.31%	21.21%	31.25%	**17.80%**
R-GAT-BERT	26.65%	24.74%	30.50%	30.84%
BiGCN	26.98%	16.65%	26.32%	28.45%
Ours	21.43%	19.21%	16.41%	19.53%

Comparing the above table with the performance metrics of this paper's model in the previous comparison experiments, the performance of this paper's model on the Jingdong aquatic dataset is not much worse, which proves the stability of the performance of this paper's model.

In addition, this paper also validates the aforementioned 20 baseline models on the Jingdong dataset, and the results are shown in Table 23.

The performance of each model on the Jingdong dataset is slightly worse than that on the Taobao dataset, but the difference is not obvious, which proves the stability of the performance of the algorithm. Among them, the algorithm proposed in this paper performs better on the AUC metrics compared to other models and is only second to the DGCN-SKIA model on the F1-score metrics. This result further proves the advantage of the performance of the algorithm.

Limitations

Although the ABSA method improves the accuracy and relevance of sentiment analysis, the model in the paper may still be limited by the granularity of sentiment analysis. For example, the model may not be able to accurately distinguish the subtle emotional differences of the same aspect word in different contexts. In addition, with the rapid growth and complexity of text data, the model needs to be able to handle larger and more diverse data. At the same time, in order to improve the practicality and user trust of the model, the interpretability of the model also needs to be improved.

Table 15. Comparison of AUC values of models

Model	fish	shrimp	crab	mussel
Feature-SVM	67.77%	62.43%	75.78%	62.99%
ATAE-LSTM	69.66%	66.38%	**79.65%**	64.99%
TD-LSTM	64.37%	75.48%	65.04%	73.83%
MemNet	67.42%	63.65%	78.88%	71.43%
IAN	68.96%	73.43%	61.74%	60.81%
AOA	73.15%	75.11%	66.98%	70.94%
AEN	76.33%	73.46%	71.63%	71.61%
IARM	63.27%	73.15%	61.51%	61.27%
ASGCN	65.85%	71.49%	68.79%	73.83%
Dual-GCN	73.25%	66.02%	77.59%	65.53%
BERT	76.73%	70.69%	70.94%	79.91%
InterGCN	78.14%	69.08%	75.87%	73.11%
SenticGCN	67.48%	**79.25%**	72.16%	63.68%
DGCN-SKIA	**78.79%**	63.35%	70.95%	78.12%
CDT	70.35%	75.03%	63.52%	66.11%
DGEDT	63.91%	73.07%	73.39%	72.51%
DGEDT-BERT	63.36%	60.31%	64.11%	71.08%
R-GAT	67.12%	69.25%	68.97%	73.30%
R-GAT-BERT	63.98%	76.16%	64.93%	76.68%
BiGCN	67.36%	79.24%	60.23%	78.76%
Ours	71.45%	75.91%	78.93%	**83.14%**

SUMMARY AND NEXT STEPS

Summary of This Research

For merchants, through the analysis of review data, merchants are able to better understand consumers' emotional attitudes and consumption preferences towards goods, so as to continuously improve the quality of products and services and enhance their competitiveness through differentiated marketing with other merchants. This chapter proposes an improved GCN model for the task of aspectual sentiment analysis of consumer reviews for online shopping malls and elaborates on each part of the model. Then, the dataset used in this chapter is introduced and relevant statistical information about the dataset is given. Next, the baseline model is described in detail and an experimental comparison is made between the model in this chapter and the baseline model, with the results proving that the model is superior to the baseline model. Then, through the ablation experiments, the results prove the effectiveness of the fused lexical information, positional coding information, and GCN in this model for the model, and discuss the effects of the number of GCN layers and the number of aspects in the comments on the performance of the model. Comprehensively, it is proved that the proposed method can effectively handle the task of aspectual sentiment analysis.

Table 16. Comparison of F1-score values of models

Model	fish	shrimp	crab	mussel
Feature-SVM	73.80%	60.67%	66.28%	79.32%
ATAE-LSTM	65.55%	73.64%	76.33%	74.92%
TD-LSTM	72.35%	67.08%	69.97%	72.78%
MemNet	75.17%	74.65%	68.73%	77.13%
IAN	71.51%	76.39%	71.90%	74.86%
AOA	65.36%	79.01%	79.13%	69.52%
AEN	65.30%	75.67%	74.99%	77.39%
IARM	71.74%	63.06%	76.26%	79.63%
ASGCN	74.65%	71.01%	61.75%	63.39%
Dual-GCN	65.76%	69.29%	77.12%	65.62%
BERT	66.25%	73.48%	61.00%	70.85%
InterGCN	61.24%	64.94%	74.61%	61.85%
SenticGCN	60.02%	79.24%	79.76%	76.52%
DGCN-SKIA	**79.97%**	63.13%	69.66%	72.32%
CDT	78.02%	75.41%	76.59%	71.66%
DGEDT	76.09%	**79.88%**	73.47%	65.98%
DGEDT-BERT	75.24%	72.42%	62.55%	75.28%
R-GAT	60.82%	71.52%	60.34%	71.84%
R-GAT-BERT	61.07%	68.07%	66.15%	62.57%
BiGCN	66.74%	72.00%	69.79%	60.88%
Ours	68.92%	75.23%	**82.19%**	**81.23%**

Next Steps

(1) In the data preprocessing stage, the emoticons in comments, such as lol, are ignored. And nowadays, user comments may contain a large number of emoticons, which have a very clear emotional tendency, so the influence of emoticons on the sentiment polarity of aspectual words will be further considered in future research.
(2) Nowadays, online shopping platforms generate a large amount of review data every day, but most of these data are unstructured unlabeled data. Therefore, considering the aspect sentiment analysis of user reviews under different domain themes in aspect sentiment analysis is one of the next research directions, which can be solved by using transfer learning to discriminate the sentiment polarity of aspects under different domains.
(3) This paper aims to perform sentiment analysis for aspect words of products in reviews; some reviews do not have aspect words, but there is a generalized description of some aspects of the product in that review, and we refer to this generalized description as an aspect category. In the next study, reviews that do not have specific aspects are identified as an aspect category and the sentiment polarity of that aspect category is given.

Figure 8. Comparative experimental results graph (a) comparison of accuracy (b) comparison of precision (c) comparison of recall (d) comparison of FNR values (e) comparison of FPR values (f) comparison of AUC values (g) comparison of F1-score values

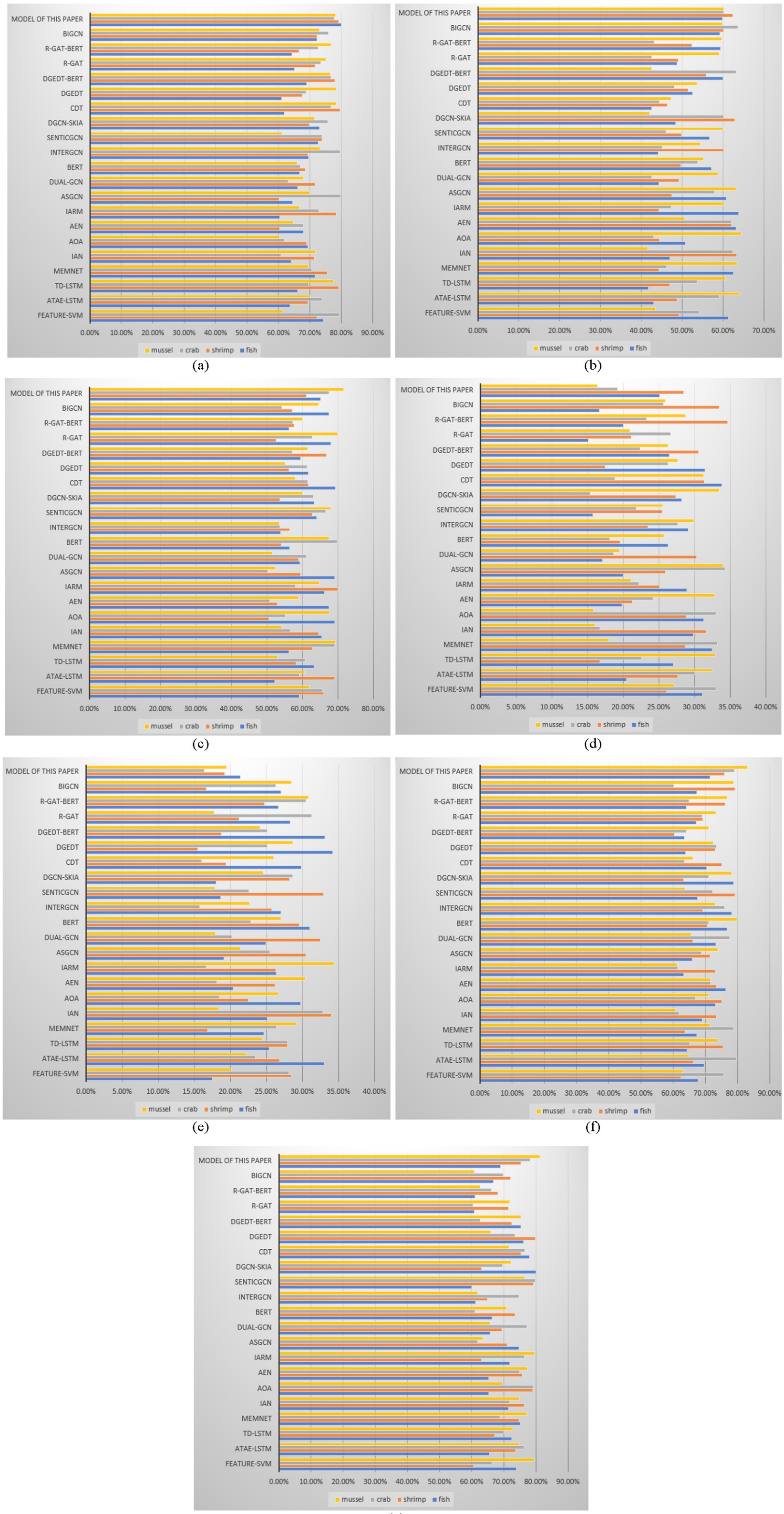


Table 17. Calculated emotional polarity of user comments on fish product

Model	Positive	Negative	Neutral
Feature-SVM	70.38%	6.25%	23.37%
ATAE-LSTM	72.73%	11.31%	15.96%
TD-LSTM	69.79%	9.16%	21.05%
MemNet	66.71%	10.09%	23.20%
IAN	66.87%	1.17%	31.96%
AOA	78.75%	11.40%	9.85%
AEN	67.49%	18.23%	14.29%
IARM	54.39%	15.92%	29.69%
ASGCN	62.30%	2.76%	34.94%
Dual-GCN	79.92%	4.62%	15.46%
BERT	53.10%	10.01%	36.89%
InterGCN	75.26%	19.92%	4.82%
SenticGCN	60.63%	13.51%	25.85%
DGCN-SKIA	56.65%	0.80%	42.55%
CDT	72.13%	4.35%	23.52%
DGEDT	79.73%	0.52%	19.75%
DGEDT-BERT	77.99%	2.90%	19.11%
R-GAT	53.09%	2.28%	44.63%
R-GAT-BERT	59.16%	11.49%	29.34%
BiGCN	63.34%	3.29%	33.37%
Ours	73.10%	11.92%	14.98%

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The authors of this publication declare there are no competing interests. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Funding for this research was covered by the authors of this article. We would like to thank the anonymous reviewers whose comments and suggestions helped improve this manuscript.

PROCESS DATES

August 26, 2024
Received: June 11, 2024, Revision: July 15, 2024, Accepted: August 13, 2024

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Table 18. Calculated emotional polarity of user comments on shrimp product

Model	Positive	Negative	Neutral
Feature-SVM	79.68%	5.06%	15.26%
ATAE-LSTM	77.09%	15.65%	7.27%
TD-LSTM	70.07%	7.60%	22.33%
MemNet	66.78%	8.45%	24.77%
IAN	52.99%	3.03%	43.98%
AOA	78.16%	16.11%	5.73%
AEN	64.23%	13.26%	22.51%
IARM	53.33%	17.55%	29.11%
ASGCN	52.56%	15.00%	32.44%
Dual-GCN	64.37%	11.23%	24.40%
BERT	67.42%	1.50%	31.09%
InterGCN	73.36%	3.09%	23.54%
SenticGCN	70.68%	5.09%	24.23%
DGCN-SKIA	69.39%	9.63%	20.98%
CDT	54.78%	16.09%	29.13%
DGEDT	59.23%	14.64%	26.14%
DGEDT-BERT	72.41%	3.65%	23.94%
R-GAT	78.63%	11.59%	9.78%
R-GAT-BERT	66.76%	11.28%	21.95%
BiGCN	75.66%	16.20%	8.14%
Ours	72.91%	15.10%	11.99%

Table 19. Calculation of emotional polarity of user comments on crab products

Model	Positive	Negative	Neutral
Feature-SVM	70.75%	11.56%	17.69%
ATAE-LSTM	70.76%	9.54%	19.71%
TD-LSTM	50.87%	1.85%	47.28%
MemNet	71.73%	4.15%	24.12%
IAN	62.04%	1.56%	36.40%
AOA	51.23%	7.09%	41.68%
AEN	51.95%	14.21%	33.84%
IARM	71.94%	1.29%	26.76%
ASGCN	57.71%	19.13%	23.16%
Dual-GCN	70.47%	15.87%	13.67%
BERT	62.14%	16.73%	21.13%
InterGCN	72.39%	15.56%	12.05%
SenticGCN	59.93%	15.40%	24.67%
DGCN-SKIA	52.26%	0.56%	47.18%
CDT	74.05%	6.89%	19.07%
DGEDT	79.74%	16.94%	3.32%
DGEDT-BERT	59.73%	16.69%	23.58%
R-GAT	61.10%	10.40%	28.50%
R-GAT-BERT	63.11%	3.23%	33.66%
BiGCN	54.16%	6.77%	39.07%
Ours	82.11%	9.20%	8.69%

Table 20. Calculated emotional polarity of user comments on shellfish product

Model	Positive	Negative	Neutral
Feature-SVM	72.55%	17.77%	9.68%
ATAE-LSTM	60.41%	19.84%	19.76%
TD-LSTM	75.62%	3.93%	20.44%
MemNet	53.20%	17.76%	29.04%
IAN	68.29%	8.01%	23.70%
AOA	71.14%	6.73%	22.14%
AEN	57.98%	9.67%	32.35%
IARM	65.03%	9.92%	25.05%
ASGCN	68.52%	11.94%	19.53%
Dual-GCN	52.43%	12.52%	35.06%
BERT	72.70%	13.86%	13.44%
InterGCN	64.37%	12.40%	23.23%
SenticGCN	69.54%	17.44%	13.03%
DGCN-SKIA	77.37%	15.85%	6.78%
CDT	77.98%	15.00%	7.02%
DGEDT	73.11%	1.75%	25.14%
DGEDT-BERT	67.48%	6.40%	26.12%
R-GAT	71.16%	8.36%	20.48%
R-GAT-BERT	54.58%	3.58%	41.84%
BiGCN	71.31%	1.80%	26.89%
Ours	62.45%	23.20%	14.35%

Table 21. Ablation experiment results

Model	Accuracy %	Precision %	Recall %	FNR %	FPR %	AUC %	F1-score %
Remove the EMLO module	61.71	55.10	57.27	32.93	23.72	75.37	72.25
Remove the BiGRU module	67.98	50.70	57.14	32.22	25.86	72.90	69.14
Removal the multi-attention mechanism module	69.33	53.91	60.57	23.29	22.60	73.94	71.26
Ours	78.80	60.64	66.34	22.33	19.14	77.36	76.98

Table 22. Performance of the improved GCN model in the Jingdong aquatic dataset

Accuracy	Precision	Recall	FNR	FPR	AUC	F1-score
79.21%	51.23%	56.04%	34.12%	20.91%	78.24%	79.83%

Figure 9. Graph of ablation experiment results

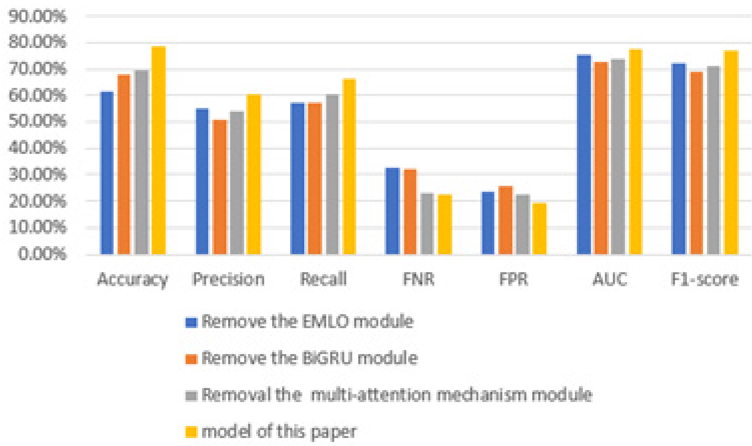

Table 23. Comparison of the performance of baseline models in the Jingdong aquatic dataset

Model	Accuracy %	Precision %	Recall %	FNR %	FPR %	AUC %	F1-score %
Feature-SVM	52.98	30.43	31.90	34.32	22.60	67.56	55.43
ATAE-LSTM	60.71	40.78	57.34	35.80	21.56	75.24	76.82
TD-LSTM	70.00	32.73	56.59	37.57	27.85	56.90	52.29
MemNet	73.89	25.89	43.10	32.20	24.14	54.73	63.73
IAN	52.74	29.03	51.81	29.51	20.48	71.09	58.43
AOA	65.69	37.07	35.47	30.23	22.27	51.70	53.07
AEN	78.62	46.39	56.11	33.69	26.23	67.75	66.98
IARM	66.93	30.53	48.33	34.64	28.35	58.82	72.68
ASGCN	57.35	40.90	42.83	32.28	22.85	56.12	76.42
Dual-GCN	53.00	33.18	37.60	34.61	27.68	54.63	79.78
BERT	54.98	**52.22**	45.35	**29.42**	25.89	67.29	52.15
InterGCN	69.53	51.57	47.71	33.99	29.61	50.43	55.25
SenticGCN	55.50	26.35	32.22	36.54	24.37	75.22	77.03
DGCN-SKIA	77.62	33.03	39.62	30.94	25.64	68.16	**81.37**
CDT	74.16	51.88	47.89	34.61	**20.11**	60.29	79.32
DGEDT	53.67	37.42	38.19	38.55	20.14	69.11	58.84
DGEDT-BERT	57.95	40.91	**58.63**	36.88	29.58	53.65	74.51
R-GAT	68.26	49.62	37.81	31.49	20.21	75.16	64.41
R-GAT-BERT	**79.53**	49.84	46.61	36.19	26.20	59.30	77.26
BiGCN	76.82	39.04	29.40	32.25	25.63	52.25	61.76
Ours	79.21	51.23	56.04	34.12	20.91	**78.24**	79.83

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