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# Fine-Grained Sentiment Analysis Based on SSFF-GCN Model

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**Abstract:** The research on aspect-based sentiment analysis (ABSA) mostly relies on a single attention mechanism or grammatical semantic information, which makes it less effective in dealing with complex language structures. To address the challenges in fine-grained sentiment analysis tasks, this paper establishes a novel model of syntax and semantics based on feature fusion together with a graph convolutional network (SSFF-GCN), which includes a dual-channel information extraction layer by combining syntactic dependency graphs and semantic information, and consists of three important modules: the syntactic feature enhancement module, semantic feature extraction module, and feature fusion module. In the grammar feature enhancement module, this model uses dependency trees to capture the structural relationship between emotional words and target words and adds a dual affine attention module to enhance grammar learning ability. In the semantic feature extraction module, aspect-aware attention combined with self-attention is used to extract semantic associations in sentences, which ensures effective capture of long-distance dependency information. The feature fusion module dynamically combines the enhanced syntactic and semantic information through a gated mechanism; therefore, it enhances the model's ability to express emotional features. The empirical results show that the SSFF-GCN model is generally superior to existing models on several publicly available datasets.

**Keywords:** fine-grained sentiment analysis; feature fusion; graph convolutional network; aspect-based sentiment analysis

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## 1. Introduction

As an important task in the fields of text mining and natural language processing (NLP), ABSA requires in-depth exploration of the emotional polarity of specific aspects or attributes in the text and provides more accurate and specific emotional information. Compared with entire sentiment analysis, ABSA can capture detailed evaluations from reviewers on different aspects of the game, such as gameplay, graphics, sound effects, plot, etc. This fine-grained sentiment analysis not only helps us to have a more comprehensive understanding of players' experiences and preferences, but also provides precise feedback to game developers, and points out the strengths and areas for improvement of the game. The important task of ABSA is to extract sentiment tendencies toward specific aspects in text, involving automatic recognition of aspect words, sentiment words and their polarities, as well as the associations between these elements. The complex relationships between these elements determine the emotional expression of the text, which makes ABSA a challenging yet highly applicable research direction.

Sentiment analysis is usually divided into three levels in the research of NLP: document-level sentiment analysis, which treats the entire document as the basic unit of analysis to identify its whole sentiment polarity; sentence-level sentiment analysis,

which focuses on subjectivity detection and sentiment classification for individual sentences; aspect-level sentiment analysis, which adopts a more fine-grained perspective to recognize sentiment expressions related to specific target entities or their attributes. These granularity sentiment analyses usually classify emotions into three categories: positive, negative, and neutral. ABSA is used to classify whether an entire document, sentence (subjective or objective), and aspect expresses a sentiment (positive, negative, or neutral) [1,2]. ABSA helps to better understand the problem of sentiment analysis because it focuses directly on the sentiment rather than the linguistic structure [3] and therefore determines the sentiment polarity of a particular aspect in a sentence. Figure 1 gives a food evaluation sentence, "Great food but the service was dreadful", where the dependency tags conj: conjunct; amod: adjectival modifier; cc: coordinating conjunction; det: determiner; nsubj: nominal subject; acomp: adjectival complement, the part of speech tags JJ: adjective; NN: noun; CC: coordinating conjunction; DT: determiner; VBD: verb past tense. The purpose of ABSA is to predict the sentiment polarity of food and service aspects, such as "negative" or "positive". Sentiment categorization as an advanced form of sentiment analysis can provide more nuanced information about opinions.

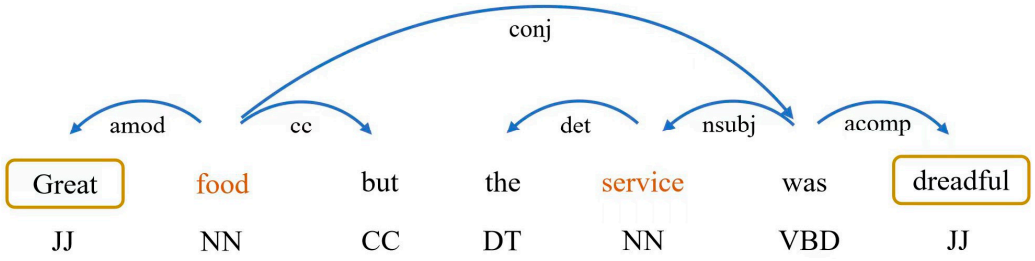


**Figure 1.** Example sentence with dependencies.

In early research, ABSA is mainly based on traditional machine learning models [4]. For example, Zheng et al. [5] combined word frequency inverse document frequency and support vector machine (SVM) to determine the sentiment bias of review texts. Diaz-Garcia et al. [6] proposed a new approach of a non-query-based system that combines association rules, generalized rules, and sentiment analysis in order to catalog and discover opinion patterns in the social network Twitter. Liu et al. [7] extended the word vector model of continuous bag of words (CBoW) and propose a cross domain emotion aware embedding learning model that can capture the emotional information and domain relevance of words. In recent years, a recurrent neural network (RNN) model has shown excellent automatic feature extraction and classification capabilities in ABSA as a neural network model [8]. In order to incorporate emotional information into document-level data for ABSA modeling, Li et al. [9] proposed a framework called a semi-supervised and multi-task learning (SEML) model, which uses embedding and long short-term memory (LSTM) layer.

The key to solving the ABSA task is to establish a link between words "aspects" and "opinion". Ma et al. [10] applied a RNN model with attention mechanisms to generate aspect-specific sentence representations and obtain better results. However, this method often encounters challenges due to the presence of many features and the expression of multiple viewpoints in sentences. As shown in Figure 1, when one considers the aspect of "food", the opinion word "dreadful" may receive more attention than "great", but it is worth noting that "dreadful" actually refers to another aspect, namely "service". Cheng et al. [11] used the syntactic structure of sentences to establish connections in ABSA, an approach that provides comprehensive syntactic information through dependency trees obtained by dependency parsing, which depends on RNN. In recent years, graph neural network (GNN) models, such as graph the convolutional network (GCN) model

and graph attention network (GAT) model, have been used to learn dependency tree representations, among which the GCN model displays the syntactic relationships in sentences by exploiting the dependency tree structure, which enables the model to better capture the dependencies between aspect words and their associated sentiment words. By representing the dependency tree structure of a sentence as a graph, the GCN model can consider each word as a node in the graph, and the edges indicate the grammatical dependencies between words. Such structured information helps the model to accurately capture long-distance dependencies, especially in sentences involving complex grammatical structures. Furthermore, the GCN model can effectively shorten the paths between aspect and emotion words, thus avoiding possible noise interference in the attention mechanism.

The motivation of this article is to improve the accuracy of sentiment analysis. To achieve this goal, we construct a new model based on feature fusion together with GCN, which integrates syntactic and semantic information and improves the accuracy of sentiment classification through the GCN model. The contributions of this article are as follows: Firstly, this study establishes a dual-channel graph convolutional network model that extracts structured information and contextual semantic information from sentences through dependency trees and semantic attention mechanisms, respectively. The model uniquely integrates syntactic dependencies and semantic features and significantly enhances its capability for fine-grained sentiment analysis. Secondly, this paper incorporates a bi-affine attention mechanism to capture complex syntactic dependencies between words and introduces a dynamic threshold fusion mechanism to balance the contributions of syntactic and semantic information. This ensemble method explicitly analyzes syntactic and semantic relationships between words, optimizes the capture of long-distance dependencies, and improves adaptability and robustness across diverse linguistic structures and sentiment expressions.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature. Section 3 constructs a fine-grained sentiment analysis model. Section 4 provides the empirical analysis. Section 5 gives the conclusion and prospect.

## 2. Literature Review

### *2.1. Aspect Sentiment Analysis*

ABSA is a fine-grained sentiment analysis task that aims to determine the emotional polarity of a particular target. ABSA mainly uses manual methods to extract features from sentences; for example, it uses a sentiment lexicon to mark scores to calculate the distance between negatives and adjectives, then trains classifiers such as an SVM based on these features [12]. However, these classification methods largely depend on the quality of the features and are very time consuming. With the advancement of deep learning techniques, deep learning networks have been widely used in studies [13,14]. In deep learning based on ABSA, words in a sentence are segmented and converted into vectors by word embedding. The vectors are then fed into an RNN based on the original order of the words, and finally multiple categories are classified using the softmax function. Models such as LSTM and gated recurrent unit (GRU) have achieved significant performance in sentiment analysis tasks. However, these methods still face many challenges in extracting sentiment-dependent features between aspect and its context; therefore, many studies use neural network methods to overcome these challenges. Zeng et al. [15] proposed a new multi-task learning network for relationship construction, which uses GCN to encode aspect representations. Phan et al. [16] applied contextual information, semantic relationships, and syntactic structures to construct the GCN model. In order to enhance the ability of the current GCN to model emotional dependencies, Zhao et al. [17] introduced an aggregated GCN model. Feng et al. [18] developed a new model aggregated graph and video super

resolution model, which uses variable sentence representations and attention assisted graphics for aspect-based sentiment classification.

### *2.2. Attention Method*

In recent years, various attention-based neural network models have been proposed to capture semantic relationships between aspects and their contexts [19]. For example, Wang et al. [20] proposed an attention-based LSTM for aspect-based sentiment analysis. Feng et al. [21] introduced an attention masking mechanism to ignore irrelevant words in context. Abadal et al. [22] combined GRU and attention mechanisms to model sentences. The integration of sophisticated attention mechanisms with sequence models greatly improves the performance of ABSA. Lee et al. [23] found that the pre-trained language model bidirectional encoder representations from a transformer (BERT) shows good performance in various ABSA tasks. Rietzler et al. [24] trained model adaptation by combining external knowledge with adaptive fine-tuning of the BERT, they adopt self supervised fine-tuning in the target domain, then use supervised training in the source domain. Dominic et al. [25] applied the BERT model to analyze sentiment of social media data, and study the different granularity and their corresponding sentiment dependencies. Fu et al. [26] combined supervised contrastive learning with BERT supervised contrastive learning (BERT-SCL) model, and use a knowledge graph to embed external general knowledge information into text entities, which enriches the text information. These methods are somewhat effective; however, as these methods extract relevant information from attention scores, it becomes difficult to capture long-term dependencies between words.

### *2.3. Method of Graph Neural Networks*

The GCN model not only has the ability to process data on graphs but can also capture the dependency relationships of graph structures and has the ability to process data on general graphs. Thus, it can capture long-distance sentiment relations through syntax or semantics between words. Zhao et al. [27] applied the GCN model together with a dependency tree (DT) model to explore the predict aspect sentiment polarity. Cui et al. [28] used the GCN model to enhance textual representation by considering syntactic graphs. Shen et al. [29] proposed a novel GCN model with an interactive memory fusion mechanism, which fuses local and global structural information, and assigns different weights to modules. However, these methods consider all relations between words, but do not focus on the connection between "aspect" and "opinion". As is well known, one can obtain richer grammatical information by dependency trees, and can capture complex relationships between aspect words and viewpoint words in closer proximity.

### *2.4. Method of Syntax and Semantics*

In the study of grammar and semantics, Zhou et al. [30] incorporated grammar knowledge into ABSA tasks. Zhao et al. [31] reduced the effect of irrelevant words by considering syntactic relative distance. He et al. [32] introduced an attention model and applied syntactic information with dependency trees to calculate attention weights. Li et al. [33] used graph attention networks to learn node representations from neighboring nodes based on syntactic structures. Wang et al. [34] applied a relational graph attention network to construct and encode syntactic dependency trees rooted in the target aspect. Liang et al. [35] used sentiment knowledge from SenticNet to construct graph neural networks to enhance the dependency relationships between aspect words and other aspects. Jiang et al. [36] combined grammar and vocabulary maps to capture co-occurrence information of words.

The GNN model and syntactic dependency trees were shown to be effective in improving the performance of the ABSA model. Based on previous work, this paper introduces an aspect-aware self-attention mechanism to capture semantic information and proposes

a feature fusion-based GCN model, which can effectively capture both syntactic and semantic information. In particular, a multi-layer GCN model is applied to each of the two channels; this approach enables the model to learn local and global dependencies in sentences and better utilizes graph structure information for feature extraction. The extracted syntactic knowledge and captured semantic information are finally aggregated to obtain a comprehensive aspect feature representation.

## 3. Model of Fine-Grained Sentiment Analysis

We next describe in detail the semantic syntactic feature fusion based on the SSFF-GCN model, which is mainly divided into semantic feature layer, syntactic feature layer, GCN layer, and feature fusion layer; this model also includes several modules such as the encoding layer, attention layer, and bi-affine attention mechanism. The framework of the model is shown in Figure 2.

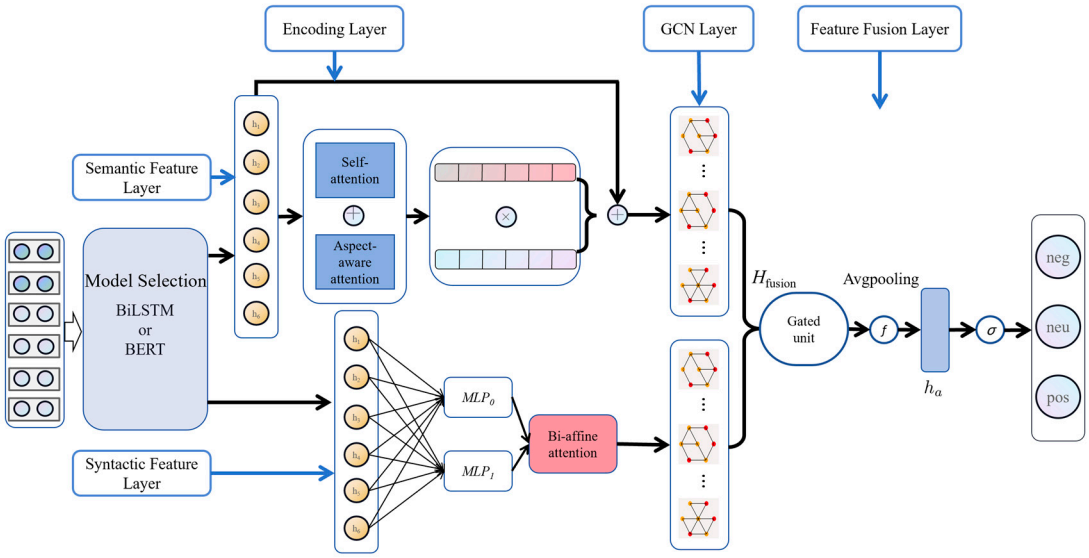


**Figure 2.** Framework diagram of SSFF-GCN model.

Task definition: Given a sentence $S = \{w_1, w_2, \ldots, w_{a_1}, w_{a_2}, \ldots, w_{a_k}, \ldots, w_n\}$, which contains $n$ words, $w_i$ and $w_{a_k}$ denote the $i$-th word and the $k$-th aspect word in the sentence $S$, respectively, and the set of aspect words $a = \{a_1, a_2, \ldots, a_m\}$ is a subset of the sentence $S$; the domain of fine-grained sentiment analysis usually defines the task as determining the sentiment polarity of the aspect word $a_k$ from the sentence $S$.

### *3.1. Input Coding Layer*

Based on the pre-trained lexicon, words in a sentence are mapped into a low-dimensional real-valued vector via the embedding matrix $E \in \mathbb{R}^{|V| \times d_e}$, where $|V|$ is the size of the vocabulary, and $d_e$ denotes the dimensions of the word embedding vectors. The sentence $S$ is converted into a series of word embedding $X = \{x_1, x_2, \ldots, x_{a_1}, x_{a_2}, \ldots, x_{a_k}, \ldots, x_n\}$, followed by sequence modeling extraction using either bidirectional long short-term memory (BiLSTM) or BERT as the sentence encoder. The hidden context representation $H = \{h_1, h_2, \ldots, h_{a_1}, h_{a_2}, \ldots, h_{a_k}, \ldots, h_n\}$, where $h_i \in \mathbb{R}^{2d}$ is the hidden vector obtained by BiLSTM, $d$ is the hidden dimension of the output of a one-way LSTM, and $H_a = \{h_{a_1}, h_{a_2}, \ldots, h_{a_k}\}$ is a subset of $H$. This paper constructs a sentence–aspect pair "[CLS]$S$[SEP]$A$[SEP]" as an input to obtain the hidden representation of the aspect in the sentence, where [CLS] and [SEP] denote the beginning and the end of the sentence, respectively, $S$ denotes the given sentence, and $A$ denotes the aspect word

in the sentence. Finally, the whole hidden representation of the sentence is input to the semantic feature layer and syntactic feature layer, respectively.

In the example sentence in the Introduction, "Great food but the service was dreadful", pre-trained embedding is used to generate word-level embedding, and capture semantic meanings of words like "Great", "food", "service", and "dreadful". The embedding is then fed into a BiLSTM or BERT-based encoder to produce context-aware representations, and reflect relationships between words. Aspect terms ("food" and "service") are separately identified and embedded to ensure their specific representation in the context of the sentence.

### *3.2. Semantic Feature Layer*

To satisfy the requirement of capturing different contexts and relationships for fine-grained sentiment analysis tasks, this study designs an attention layer that combines the self-attention mechanism and aspect-aware attention; the two sub-modules are introduced below.

(1) *Self-Attention Mechanism*

Self-attention is a mechanism used to capture the interaction and dependency between any two words within a sentence, and learns the whole semantic information of the sentence. The classical self-attention mechanism calculates the attention weights by the following formula:

$$A_s^i = \text{softmax}\left(\frac{QW^Q \times (KW^K)^T}{\sqrt{d}}\right) \tag{1}$$

where the matrices $Q$ and $K$ denote query and key of the self-attention mechanism, respectively. $W^Q \in R^{d\times d}$ and $W^K \in R^{d\times d}$ are the weight matrices, and $d$ is the dimension of the input node features. The self-attention mechanism obtains the attention score matrix $A_S$ by calculating the relationship of each word pair in the sentence with all other word pairs, and the score after softmax normalization represents the model's attention to each word. To allow the model to focus on different aspects of the sentence at the same time, self-attention is extended to multi-head attention in the experiments by pooling the aspect representation $h_a$ equally and replicating $n$ times to construct the aspect representation matrix $H_a \in R^{n\times d}$, where $n$ is the number of words in the sentence, each head focuses on a different feature of the sentence, the computed self-attention score is denoted by $A_s^i$,$i$ indicates the $i$-th head of attention, and the outputs of these different heads are then concatenated to generate a final output representation. The formula is as follows:

$$\text{MultiHead}(Q, K, V) = \text{Concat}\big(\text{head}_1, \text{head}_2, \ldots, \text{head}_p\big)W^O \tag{2}$$

where $W^O \in R^{(h\times d_k)\times d_{\text{model}}}$ is the weight matrix, and $d_{\text{model}}$ is the target dimension of the output. The model is able to identify the importance of each word to the aspect term through the self-attention mechanism.

(2) *Aspect-Aware Attention*

In this paper, aspect-aware attention is designed for acquiring local semantic information related to specific aspect terms. The mechanism of aspect-aware attention uses the aspect representation as a query, and the word representation in the sentence as the key and value. The attention score is calculated by the following formula:

$$A_a^i = \tanh\Big(H_a W^a \times \big(KW^K\big)^T + b\Big) \tag{3}$$

where $K$ is equal to the output of the coding layer $H$, and $W^a \in R^{d \times d}$ and $W^K \in R^{d \times d}$ are learnable weight matrices. The score of aspect-aware attention indicates the correlation between the aspect term and each word in the sentence. This model also uses multi-head aspect-aware attention to learn features from inputs in different representation sub-spaces. Each head independently calculates the attention score matrix $A_a^i$, where $i$ refers to the $i$-th attention head, an approach designed to capture relevant information on different semantic dimensions of the sentence. Next, the self-attention score matrix is spliced and merged with the aspect-aware attention score matrix.

$$A^i = A_a^i + A_s^i \tag{4}$$

The integration of the self-attention and aspect-aware attention mechanisms in Equation (4) balances local and whole semantic dependencies. Self-attention effectively captures long-distance dependencies and whole sentence structures but lacks specificity in targeting aspect-related contexts. Aspect-aware attention addresses this by focusing on the relationship between aspect terms and their relevant contextual words and reduces noise from unrelated parts of the sentence.

By combining these mechanisms, one can create a richer semantic representation, where self-attention provides whole context, and aspect-aware attention enhances aspect-specific features. This complementary approach ensures a more accurate modeling of nuanced semantic relationships and improves the model's robustness in handling diverse sentence structures. This fusion ultimately strengthens the model's ability to extract fine-grained sentiment features and contributes to its superior performance in aspect-based sentiment analysis tasks.

When considering the example sentence in the Introduction, the semantic feature layer extracts the relationships between aspect terms and related sentiment words. A self-attention mechanism computes the semantic dependencies among all words in the sentence, such as the strong positive correlation between "food" and "Great". Additionally, an aspect-aware attention mechanism focuses on capturing localized semantic information by treating each aspect term ("food" or "service") as a query. For instance, "food" aligns with "Great" while "service" aligns with "dreadful". The outputs of the self-attention and aspect-aware attention mechanisms are combined to generate comprehensive semantic representations.

### *3.3. Bi-Affine Attention*

Bi-affine attention is a graph-based neural dependency parser specifically designed to handle dependency parsing. In order to enable the model to learn both the semantic relations between aspects and the semantic meaning of the overall sentence, the SSFF-GCN model employs bi-affine attention to learn the syntactic dependencies of the sentence's word pairs and constructs a syntactic dependency graph from the aspects and sentiment words.

The bi-affine attention architecture firstly analyzes each word item in the input sentence in-depth and transforms the high-dimensional hidden state of each word into two types of low-dimensional representations by means of a dimension reduction technique. These two types of representations correspond to the head and tail of potential grammatical dependencies in the sentence, i.e., the start and end points of the dependencies, respectively. To achieve this goal, two distinct multi-layer perceptron ($MLP_0$ and $MLP_1$) are employed. $MLP_0$ processes the head words in the dependency relationship and focuses on encoding global structural information and the broader semantic context that defines the role of the head word. On the contrary, $MLP_1$ specializes in capturing fine-grained syntactic information from the dependent words, and ensures that local contextual nuances and directional relationships are effectively modeled. Each $MLP$ applies nonlinear activation functions to transform the input vectors into lower-dimensional representations and filter out irrelevant

information while preserving features critical for dependency modeling. Furthermore, in this paper, these low-dimensional vector pairs are scored by bi-affine transformations to obtain the weights of each pair of potential dependencies; this process generates two important matrices: an arc scoring matrix that reflects the weights of all possible dependencies in the sentence, and a label scoring matrix that labels the likelihood of each dependency type. Using these scoring matrices, the model is able to identify the dependency tree, which is most likely to express the true grammatical structure among all potential grammatical dependency constructions of the sentence and accurately captures the complex dependencies between aspect and viewpoint words. This approach not only enhances the model's ability to understand grammatical structures but also improves the accuracy of identifying deeper relationships in sentences, thus achieving higher performance in aspect-based sentiment analysis tasks. The model is represented by the following equation:

$$h_i^{\text{head}} = MLP_0(h_i) \tag{5}$$

$$h_j^{\text{dep}} = MLP_1(h_j) \tag{6}$$

where $v_i$ and $v_j$ denote the sequences of hidden representation output from the coding layer, $MLP$ represents the multi-layer perceptron, and $MLP_0$ and $MLP_1$ are used to process the cyclic output vectors of headwords and dependent words, respectively. The main goal of the model to perform dimension reduction and nonlinear transformations for each recurrent output vector is to exclude information that is not relevant to the current decision. This process not only improves the speed of the parsing process, but also effectively reduces the possibility of over-fitting. The following formula is used to calculate the bi-simulation attention score:

$$Q_{i,j} = {h_i^{\text{head}}}^T W_1 h_j^{\text{dep}} + W_2\left(h_i^{\text{head}} \oplus h_j^{\text{dep}}\right) + b^{\text{bam}} \tag{7}$$

$$r_{i,j,t}^{\text{syn}} = \frac{\exp\left(Q_{i,j,t}\right)}{\sum_{k=1}^{q} \exp\left(Q_{i,j,k}\right)} \tag{8}$$

where $W_1 \in R^{d \times m \times d}$ and $W_2 \in R^{2d \times m}$ are learnable weights, and $b^{\text{bam}}$ is the bias term. One can obtain the model by $h_i^{\text{head}}$ and $h_j^{\text{dep}}$, and further obtain the score tensor $Q_{i,j}$. $r_{i,j,t}$ denotes the probability distribution of word pairs $v_i$, $v_j$ with relation type of category $t$, and $q$ is a hyper-parameter. Combining Formulas (6)–(9), one can obtain the following equation:

$$R^{\text{syn}} = \text{Biaffine}(MLP_0(H), MLP_1(H)) \tag{9}$$

where $R^{\text{syn}} \in R^{n \times n \times m}$ denotes the probability distribution graph.

### *3.4. GCN Model*

Inspired by traditional convolutional neural network (CNN) and graph embedding techniques, GCN is a variant of CNN. Graph data consists of nodes and edges, and the GCN model captures the topological relationship between nodes through convolutional operations to obtain local information about the nodes. This paper applies the GCN model to receive the feature outputs from the semantic and syntactic layers, and learns more whole information through the information transfer of the multi-layered GCN model. Some previous studies introduce a neighborhood matrix $A$ to reflect the dependencies; the element $A_{ij}$ in matrix $A$ indicates whether the $i$ node is connected to the $j$ node or not. If the $i$ node is connected to the $j$ node, then $A_{ij} = 1$; otherwise, $A_{ij} = 0$. In the $l$ layer of the model, the hidden state vector $h_i^l$ of the $i$ node is obtained by the hidden state of its neighboring nodes processed by weighting, superposition, and nonlinear activation

function. The hidden state of the node $i$ in $l$-th layer state $h_i^l$ is updated according to the following equation:

$$h_i^l = \sigma\left(\sum_{j=1}^{n} A_{ij} W^l h_j^{l-1} + b^l\right) \tag{10}$$

where $W^l$ represents the weight matrix, $b^l$ is the bias term, and $\sigma$ denotes a nonlinear activation function, such as the ReLU function. In this way, each node not only contains its own feature information, but also integrates information from neighboring nodes, which enables the model to capture the complex syntactic and semantic relationships between words. The deep propagation of information in the multi-layer GCN structure allows the model to capture dependencies between distant words, which in turn enhances the ability to judge specific aspects of sentiment.

In the semantic layer, this paper employs the GCN to model graph-structured data with complex semantic dependencies. This method not only improves the representation of words related to specific aspects but also enhances the accuracy of aspect sentiment classification. The updating process can be represented as the semantic feature representation of the final output of the GCN at layer 1. In the design of the syntactic layer, the syntactic relationship among words can be further refined by parsing the dependency tree output from the coding layer. Furthermore, the GCN is used to perform information aggregation on the syntactic relation graph so that each node fuses information about the words themselves and their neighbors in the syntactic structure. The model can be described by the following equation:

$$h_i^{l-\text{sem}} = \sigma\left(\sum_{j=1}^{n} r_{ij}^{\text{sem}} W^l h_j^{l-1} + b^{l-\text{sem}}\right) \tag{11}$$

$$H^{l-\text{sem}} = \left\{h_1^{l-\text{sem}}, h_2^{l-\text{sem}}, \ldots, h_n^{l-\text{sem}}\right\} \tag{12}$$

$$h_i^{l-\text{syn}} = \sigma\left(\sum_{j=1}^{n} r_{i,j}^{\text{syn}} W^l h_j^{l-1} + b^{l-\text{syn}}\right) \tag{13}$$

$$H^{l-\text{syn}} = \left\{h_1^{l-\text{syn}}, h_2^{l-\text{syn}}, \ldots, h_n^{l-\text{syn}}\right\} \tag{14}$$

where $H^{l-\text{sem}}$ is the semantic feature representation of the final output of the $l$-th GCN layer, and $H^{l-\text{syn}}$ is the syntactic feature representation of the final output of the $l$-th GCN layer.

### *3.5. Feature Fusion Layer*

(1) *Gated Fusion Mechanism*

In models of fine-grained sentiment analysis, feature representations at different layers are crucial for understanding the sentiment tendency of a text. Our model fuses the outputs of the semantic and syntactic layers through a gated mechanism to capture subtle sentiment changes related to aspect terms in a sentence. Specifically, the gated unit serves to dynamically adjust the contribution of the two features and allows the model to automatically learn the integration strategy of semantic and syntactic features based on the contextual content. The gated mechanism helps the model to learn which features are more critical for the prediction task at hand and thus selectively emphasizes or ignores certain information. The gated fusion process can be represented by the following equation:

$$G = \text{sigmoid}\left(W_{\text{sem}} H_{\text{sem}} + W_{\text{syn}} H_{\text{syn}} + b\right) \tag{15}$$

$$H_{\text{fusion}} = G \odot H_{\text{sem}} + (1 - G) \odot H_{\text{syn}} \tag{16}$$

where $W_{\text{sem}}$ and $W_{\text{syn}}$ are the learnable parameter matrices, $G$ is the gated coefficients, $b$ is the bias term, and $H_{\text{fusion}}$ is the final fusion feature representation.

(2) *Model Training*

After the above steps, one can obtain the fusion feature representation $H_{\text{fusion}}$. This paper uses an average pooling operation to retain sufficient information for each aspect word representation $h_a^l$, $h_a^l = f\left(h_{a_1}^l, h_{a_2}^l, \ldots, h_{a_m}^l\right)$; $f(\cdot)$ represents the average pooling function. It is then passed through a fully connected softmax layer and mapped to the probabilistic polarity of the three emotions.

$$p(a) = \text{softmax}\left(W_p h_a^l + b_p\right) \tag{17}$$

Finally, we adopt the cross-entropy loss function as the objective function.

$$L(\theta) = -\sum_{(s,a)\in D} \sum_{c\in C} \log p(a) \tag{18}$$

where $D$ contains all sentence aspect pairs, $a$ denotes the aspect which appears in sentence $S$, $\theta$ represents all trainable parameters, and $C$ is the set of sentiment polarities. During the optimization process, we adjust model parameters $\theta$ to maximize the probability of predicting the correct emotional polarity. The sentiment polarities $C$ include positive, neutral, and negative.

In the example sentence in the Introduction, the feature fusion layer integrates semantic and syntactic information through a gated mechanism. This mechanism dynamically adjusts the contribution of each feature type to the final representation and ensures that critical information is retained. For example, the semantic association between "Great" and "food" is emphasized, while the syntactic dependency between "dreadful" and "service" is prioritized. The fusion feature representation encapsulates both local syntactic structure and the whole semantic context. Finally, in the sentiment classification layer, the fusion feature representation is passed through a fully connected layer and a softmax function to predict the sentiment polarity of each aspect. The model assigns a positive sentiment to "food" and a negative sentiment to "service" and correctly identifies their respective polarities.

## 4. Empirical Analysis

The flowchart of the sentiment analysis is shown in Figure 3.

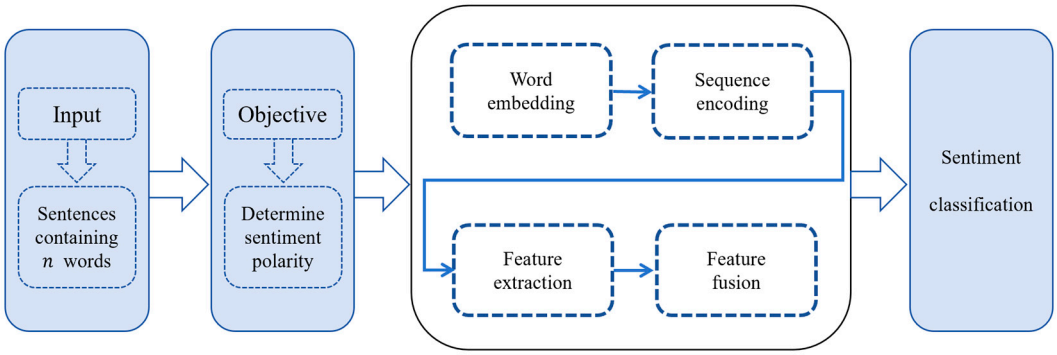


**Figure 3.** Empirical analysis flowchart.

### *4.1. Datasets and Parameter Setting*

In this paper, we conduct aspect-oriented fine-grained sentiment analysis experiments on three publicly available benchmark datasets: Restaurant and Laptop reviews from SemEval 2014 Task 4 [37] and Twitter datasets presented by Dong et al. [38]. Each aspect is labeled by one of three sentiment polarities: positive, neutral, and negative. The statistical information of these three datasets is shown in Table 1.

**Table 1.** Classification of datasets.

| Dataset | Delineation | Positive Number | Negative Number | Neutral Number |
|---|---|---|---|---|
| Restaurant | Training set | 2164 | 807 | 637 |
| | Test set | 727 | 196 | 196 |
| Laptop | Training set | 976 | 851 | 455 |
| | Test set | 337 | 128 | 167 |
| Twitter | Training set | 1507 | 1528 | 3016 |
| | Test set | 172 | 169 | 336 |

Two types of context encoders are used in the experiments: a BiLSTM encoder and a BERT-based encoder. For the BiLSTM-based encoder, 300-dimensional GloVe vectors are used in the experiments to initialize the representation of the words; the size of both the lexical embedding and the positional embedding are set to 30. The input word embedding is given a dropout rate of 0.3, and the model is trained using Adam's optimizer with a learning rate of 0.002, and a multiplicity of attention hyper-parameters for the syntax extraction layer $p = 5$. For the BERT-based encoder, the pre-trained bert-base-uncased English version is used for fine-tuning, where the hidden state dimension is 768, the weights are initialized with a uniform distribution, and the dropout rate of the BERT embedding is 0.1. The batch size of both types of models is 16, and the number of GCN layers is 2. The models are evaluated by accuracy (Acc) and macro-F1 (MF1), these metrics are given as follows:

$$\text{Acc} = \frac{T}{N} \tag{19}$$

$$\text{MF1} = \frac{2 \times P \times R}{P + R} \tag{20}$$

In addition, in order to avoid the insufficient fusion of key information and the insufficient mining of potential semantic relations, which may be caused by relying only on the attention mechanism in the semantic extraction layer, the model introduces the outer product sum operation after the attention layer, which explicitly models the interactions between words to generate the relational feature matrix. Specifically, the feature representation outputs from the attention layer are first passed through two independent linear transformation layers to obtain two new sets of feature representations, then their outer products are computed to generate the relational feature matrix, where each element represents the strength of the semantic relationship among words. The relational feature matrix is then summed at the element level with the original sentence feature matrix, thus combining the output features of the attention layer with the original semantic structure features to obtain the final fusion feature representation. This design can better capture the semantic relationships between words and provide support for model performance improvement. Finally, to further improve the model performance, an early stopping method is used to prevent over-fitting during the model training process. When the performance on the validation set no longer improves, one can terminate the training in advance.

### *4.2. Comparison Experiment*

In order to comprehensively assess the performance of the SSFF-GCN model, this paper introduces some baseline models for comparison experiments as follows:

LSTM: A unidirectional LSTM is used to encode contextual information [39].

IAN: The interactive attention network (IAN) models aspect words and context words separately and interactively learns the relationship between aspects and their context [40].

ASGCN: Actional-structural GCN (ASGCN) learns the grammar information and word dependency relationships of sentiment analysis by constructing a GCN [41].

CDT: A credible decision tree (CDT) model learns representations of sentence features by applying convolutional operations based on dependency tree models [42].

SKGCN: A syntax and knowledge-based GCN (SKGCN) model integrates grammatical dependency trees with commonsense knowledge via graph convolution to enhance the expression of sentences in specific aspects [43].

Kuma GCN: Enhancing the accuracy of aspect-level sentiment analysis by combining linguistic dependency trees and automatically generated aspect-specific graphs [44].

DGEDT: A dependency graph-enhanced dual transformer network (DGEDT) model combines the planar representation learned from the transformer with the graphical representation learned from the corresponding dependency graph [45].

R-GAT: A relational graph attention network (R-GAT) is used to encode new tree structures from ordinary dependency parse trees [34].

BERT: A BERT model is used to generate deep bidirectional linguistic representations fusing left and right contextual information [23].

SKGCN + BERT: An SKGCN model for encoding context by BERT instead of BiLSTM [43].

DGEDT + BERT: A dependency graph-enhanced dual transformer (DGEDT) model for encoding context by BERT instead of BiLSTM [45].

R-GAT + BERT: A relation graph attention network (R-GAT) model with BERT replacing BiLSTM for encoding context [34].

### *4.3. Experiment Results and Analysis*

This paper uses Acc and MF1 as evaluation metrics. According to the experimental results in Table 2, the SSFF-GCN model shows excellent performance in fine-grained sentiment analysis tasks. In the method of GloVe word embedding, the SSFF-GCN model achieves significant advantages on three datasets, Restaurant, Laptop, and Twitter, and the accuracy/F1 values reach 83.75%/75.96%, 77.98%/74.49% and 75.95%/74.43%, respectively. This result significantly outperforms classical models such as traditional LSTM and IAN models, as well as other graph neural network-based methods such as the ASGCN model, and attention-based methods such as the R-GAT model. This is because the SSFF-GCN model can effectively integrate grammatical structures and semantic information, and accurately captures the complex relationships between aspect words and emotion words, therefore avoiding the noise introduced by attention mechanisms when establishing dependency relationships.

**Table 2.** Comparison of evaluation metrics of different models on three datasets.

| Form | Model | Restaurant | | Laptop | | Twitter | |
|---|---|---|---|---|---|---|---|
| | | **Acc** | **MF1** | **Acc** | **MF1** | **Acc** | **MF1** |
| GloVe | LSTM | 78.13 | 67.47 | 69.28 | 63.09 | 69.56 | 67.70 |
| | IAN | 79.26 | 70.09 | 72.05 | 67.38 | 72.50 | 70.81 |
| | ASGCN | 80.77 | 72.02 | 75.55 | 71.05 | 72.15 | 70.40 |
| | CDT | 81.46 | 73.59 | 75.89 | 71.84 | 72.87 | 71.40 |
| | SKGCN | 80.36 | 70.43 | 73.20 | 69.18 | 71.97 | 70.22 |
| | Kuma GCN | 81.43 | 73.64 | 76.12 | 72.42 | 72.45 | 70.77 |
| | DGEDT | **83.90** | 75.10 | 76.8 | 72.30 | 74.80 | 73.40 |
| | R-GAT | 83.30 | **76.08** | 77.42 | 73.76 | 75.57 | 73.82 |
| | SSFF-GCN | 83.75 | 75.96 | **77.98** | **74.49** | **75.95** | **74.43** |
| BERT | BERT-base | 82.68 | 73.54 | 77.74 | 73.30 | 73.70 | 71.50 |
| | SKGCN + BERT | 83.48 | 75.19 | 79.00 | 75.57 | 75.00 | 73.01 |
| | DGEDT + BERT | 86.30 | 80.00 | **79.80** | 75.60 | **77.90** | 75.40 |
| | R-GAT + BERT | 86.60 | 81.35 | 78.21 | 74.07 | 76.15 | 74.88 |
| | SSFF-GCN + BERT | **87.11** | **81.79** | 79.66 | **75.83** | 77.42 | **75.97** |

The basic BERT model significantly outperforms most of the models based on static word embedding, which reflects the advantages of pre-trained language models in capturing semantic information. The model performance is further improved when combining feature fusion and GCN together with BERT. The SSFF-GCN + BERT model achieves the best or near-optimal results on all datasets, especially on the Restaurant datasets, the accuracy and F1 value reach 87.11% and 81.79%, respectively, and this result is significantly better than other BERT-based models. This indicates that the SSFF-GCN model can not only perform the task cost-effectively but also effectively combines with advanced pre-trained language models to make full use of the powerful semantic representation capability of the BERT model and the fine-grained syntactic semantic analysis capability.

The excellent performance of the SSFF-GCN model may be attributed to its design to process input information by combining a semantic module that combines an attention layer with an outer product sum operation and a syntactic module that combines dependency parsing with bi-simulation attention. This approach allows the model to take into account both syntactic dependencies and semantic correlations among words, therefore leading to more accurate recognition and classification of affective tendencies in complex linguistic environments. In addition, the SSFF-GCN model performs well on datasets from different domains, which indicates its good generalization ability and domain adaptability.

### *4.4. Ablation Experiment*

In order to verify the validity of the SSFF-GCN components, ablation experiments are constructed; the results are shown in Table 3. The SSFF-GCN model is taken as the baseline model, we denote “without” by “w/o”, where "w/o arc" means that the arc scoring matrix is removed in the bi-affine module, "w/o label" means that the label scoring matrix is removed in the bi-affine module, "w/o self-attention" denotes the self-attention mechanism is removed, "w/o aspect-aware attention" denotes the aspect-aware attention mechanism is removed, "w/o outer product sum" represents the the outer product sum operation is removed, and "w/o gated mechanism" indicates that the use of splicing method instead in dual channel information fusion.

**Table 3.** Results of ablation experiments.

| Models | Restaurant | | Laptop | | Twitter | |
|---|---|---|---|---|---|---|
| | **Acc** | **MF1** | **Acc** | **MF1** | **Acc** | **MF1** |
| SSFF-GCN | **83.75** | **75.96** | **77.98** | **74.09** | **75.95** | **74.43** |
| w/o arc | 82.33 | 74.20 | 77.05 | 73.01 | 74.00 | 72.76 |
| w/o label | 81.82 | 73.99 | 76.32 | 72.30 | 73.78 | 73.40 |
| w/o self-attention | 82.11 | 73.13 | 76.19 | 72.88 | 74.02 | 72.18 |
| w/o aspect-aware attention | 81.35 | 74.29 | 74.23 | 71.95 | 75.10 | 71.91 |
| w/o outer product sum | 82.14 | 75.05 | 75.69 | 72.09 | 74.80 | 72.84 |
| w/o gated mechanism | 82.84 | 75.11 | 76.16 | 73.31 | 74.91 | 73.15 |

The results of the ablation experiments show that model performance decreases significantly when the arc scoring matrix is removed; the accuracy decreases by 1.42%, 0.93%, and 1.95% on the Restaurant, Laptop, and Twitter datasets, respectively, which highlights the importance of the arc structure in capturing relational dependencies, and demonstrates the importance of the arc scoring matrix in maintaining the integrity of the dependency structure.

Similarly, it leads to significant decline when the label scoring matrix is removed, which shows the importance of label information for the model to understand the grammar and semantics in sentences. The accuracy decreases by 1.93%, 1.66%, and 2.17% on the Restaurant, Laptop, and Twitter datasets.

In addition, the self-attention mechanism and aspect-aware attention mechanism is also essential; the accuracy decreases by 1.64%, 1.79% and 1.93% on the Restaurant, Laptop, and Twitter datasets without the self-attention mechanism. The ability of the model to capture relevant semantics is significantly weakened without aspect-aware attention; the accuracy decreases by 2.40%, 3.75% and 0.85% on the Restaurant, Laptop, and Twitter datasets, respectively. This suggests that the self-attention mechanism and the aspect-aware attention mechanism are crucial for capturing the whole semantics of sentences and the associated aspect words with relevant contextual information.

Additionally, model performance decreases significantly when outer product sum operation is removed. The accuracy decreases by 1.61%, 2.29%, and 1.15% on the Restaurant, Laptop, and Twitter datasets, which indicates the importance of outer product sums in comprehensive relationship characteristics and semantics.

Finally, model performance decreases when the gated mechanism is removed, but its impact is relatively weak. The accuracy decreases by 0.91%, 1.82%, and 1.04% on the Restaurant, Laptop, and Twitter datasets, which indicates that the gated mechanism helps to filter and refine the information flow within the model.

Combining the results of the ablation experiments, it can be concluded that each component of the SSFF-GCN model makes a significant contribution to the whole performance of the model. The accuracy and macro-F1 will significantly decrease if one removes any individual component, which indicates the necessity of each part in implementing aspect-based sentiment analysis in the model.

### *4.5. Performance Analysis of GCN Layers*

This paper analyzes the effect of the number of GCN layers on the performance of the SSFF-GCN model. The number of GCN layers is adjusted from 1 to 8 in the experiments, and the results of the experiments are displayed in Figure 4. The results show that 2-layer GCN outperforms the other layers in terms of whole performance; therefore, the number of GCN layers is set to 2 in the experiments. The SSFF-GCN model with 1-layer does not have satisfactory accuracy and macro-F1 scores on all the three datasets, which indicates that 1-layer GCN is insufficient to take full advantage of the sentiment dependencies of specific aspects of a sentence. In addition, the performance of the model fluctuates as the number of GCN layers increases, and the performance decreases when the number of layers exceeds 2. This may imply that blindly increasing the number of GCN layers will weaken the learning effect of the model with the increase in the number of parameters.

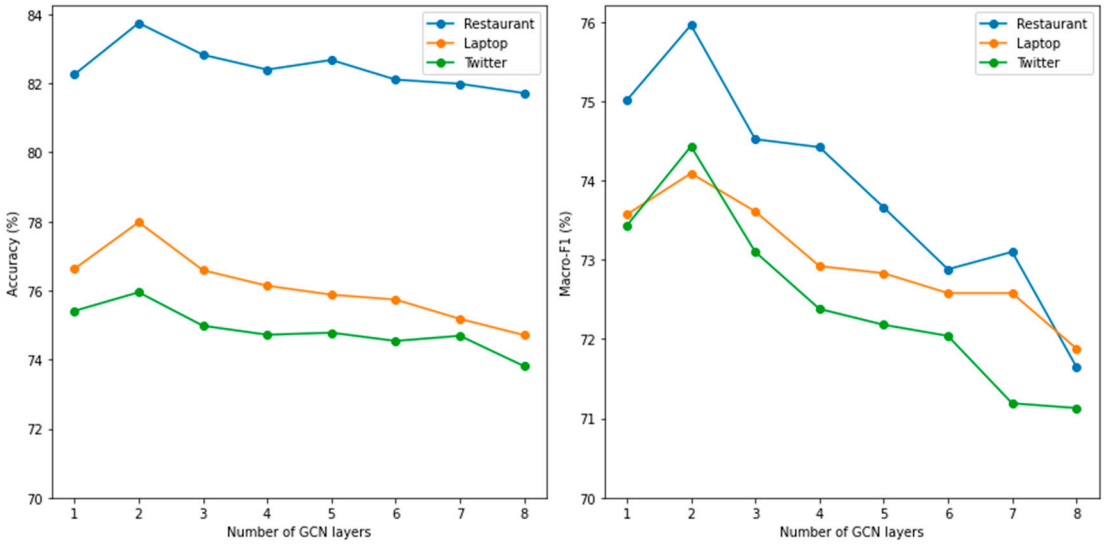


**Figure 4.** Accuracy and macro-F1 of SSFF-GCN model on different GCN layers.

### *4.6. Sample Analysis*

In order to validate the performance of the model, four sample sentences are selected in Table 4. The "Biggest" in the first sentence, "Biggest complaint is Windows 8", may offset the negativity of the opinion word "complaint". This poses a challenge for the model to identify the sentiment category because the R-GAT model misinterprets this negative sentiment as neutral. Both the CDT and the SSFF-GCN models give correct predictions. In the second sentence, "ipad sucks, apple needs to do better", all models correctly identify the sentiment polarity of the aspect word "ipad"; however, there is a disagreement in understanding the aspect word "apple", which is also not correctly identified by R-GAT. For the third sentence, "The food is not as good as the service", there are two inconsistent sentiments: "food" is negative and "service" is positive; both the CDT and SSFF-GCN models perform well and correctly identify the different polarities.

**Table 4.** Experimental results of sample study.

| Sample Statement (Computing) | R-GAT | CDT | SSFF-GCN | Correct Marking |
|---|---|---|---|---|
| Biggest complaint is **Windows 8** | O | N | N | N |
| **ipad** sucks, **apple** needs to do better | N-P | N-N | N-N | N-N |
| The **food** is not as good as the **service** | N-N | N-P | N-P | N-P |
| Try the **rose roll** (not on **menu**) | P-N | O-O | P-O | P-O |

Finally, the fourth sentence, "Try the rose roll (not on menu)", highlights a common challenge where the lack of explicit viewpoint words may confuse the model. However, the SSFF-GCN model still correctly classifies the sentiment, which shows its superiority in handling implicit sentiment.

The results in Table 4 indicate that R-GAT is susceptible to the influence of opposing or interfering opinion markers in sentences; the lack of clear viewpoint words in sentences poses difficulties for CDT to correctly identify emotional polarity. Through these cases, it can be clearly seen that the SSFF-GCN model, which fully utilizes grammatical and semantic information, is more robust in handling complex sentences containing implicit viewpoints or conflicting emotions. In Table 4, "P", "N" and "O" denote "Positive", "Negative" and "Neutral", respectively.

## 5. Conclusions and Prospect

### *5.1. Conclusions*

In this paper, we propose a fine-grained sentiment analysis model based on feature fusion. The model designs a dual-channel parallel information extraction architecture, which captures structured information and contextual semantics in the text through a syntactic feature enhancement module and a semantic feature extraction module, respectively. In terms of syntactic features, the model uses dependency syntactic analysis to construct dependency trees and combines the bi-affine attention mechanism to enhance the learning of syntactic relations between sentiment words and target words. In terms of semantic features, the model effectively captures long-range dependency information by combining the attention layer with the outer product and incorporating both aspect-aware attention and self-attention mechanisms. Both feature channels use graph convolutional networks for in-depth learning and finally achieve dynamic feature fusion through the gated mechanism, which improves the model's ability to express complex emotional features. Experimental results show that the SSFF-GCN model outperforms the existing baseline model on all three publicly available datasets, which shows the effectiveness of the model in fine-grained sentiment analysis tasks. In-depth analysis shows that the success of the model is mainly

due to its effective combination of three aspects, syntactic structure, semantic information and pre-trained language model, which provides an important reference for future related research.

### *5.2. Prospect*

The research of the SSFF-GCN model can continue to deepen in the following directions: Firstly, the internal mechanism of the model can be deeply explored, especially the process of how the gated fusion mechanism dynamically adjusts the feature weights according to different contexts. Secondly, the performance of the model on larger datasets can be investigated to verify its scalability. Finally, the framework of the SSFF-GCN model is considered to be extended to other natural language processing tasks, such as text classification, entity extraction, and other domains. These explorations will help to further enhance the performance and application value of the model.

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