Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 9
AIDML 2025

# A Survey of Text Aspect-level Sentiment Classification Focusing on Relevance

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**Abstract.** Sentiment classification is an essential part of sentiment analysis. In recent years, it has emerged as a major research area in natural language processing. This field of research has high application value in social media, product reviews, and other areas. With the advent of deep learning, research for sentiment classification is evolving from coarse-grained towards fine-grained approaches. The merge is relatively oriented towards aspect-level sentiment classification. The underlying technologies for aspect-level sentiment classification consist mainly of neural networks and their hybrid models. The text level is the focus of this study, which highlights the relationships between texts. It is a classification of the kinds and methods of text sentiment categorization. It presents a comparative study of currently-available aspect-level sentiment classification techniques. It details the structural features, application mechanisms of different models and quantitative evaluation of experimental data. This yields to an assessment of the pros and cons of various models. Moreover, this study proposes the framework of "aspect relevance.", which gives qualitative evaluation of how well various methods solve textual relations. This study provides some outlooks for research directions on aspect-level sentiment classification in the future. It indicates future models should find the right equilibrium between performance and cost. This study also underlines the need to strengthen generalization abilities and calls for multimodal data representations and new application domains.

**Keywords:** Sentiment classification; aspect-level; deep learning; text level; relevance.

## 1. Introduction

Sentiment analysis, also known as opinion mining or sentiment orientation analysis, is the extraction of emotional information from user-generated content [1]. It processes different types of data such as text, images, audio and video to understand users' emotions, attitudes, opinions, positions and tendencies. It has become a research hot spot of natural language processing (NLP) in the past few years. The core task of sentiment analysis is text sentiment analysis. This mainly involves the analysis, processing, summarization and inference of subjective texts with affective semantics [2]. Sentiment classification is an important subtask of sentiment analysis. Its precapture task is to classify the emotional orientation of texts at the text level, like positive, negative, or neutral [3].

With the rapid development of the internet and social media, user-generated content has experienced explosive growth. Therefore, sentiment classification technology has great application value in social media analysis, product review mining, public opinion monitoring and other scenarios. Not only does sentiment classification technology have its own academic significance, but it even has a wide variety of prospects for commercial applications. For example, in E-commerce platforms, sentiment classification can be employed to evaluate users' feeling about products, thus helping merchants refine their products and services. Sentiment classification in social media can be used for tracking public sentiments regarding particular events or themes, supporting decisions. Instead, in the finance domain, sentiment classification can also help analyze the market sentiment, which aids in making investment decisions.

Although great advancements characterized the use of deep learning technology for sentiment classification, various challenges remain to overcome. The diverse and complex nature of language makes it challenging to generalize the performance of sentiment classification across domains and languages [3]. Meanwhile, aspect-level sentiment classification has made great progress in single-type, single-language environments. However, there is still a lot of room for improvement in cross-domain and cross-language settings. It is of great significance for promoting research and application in the field that summarizes and organizes existing sentiment classification methods in an orderly manner, provides a comprehensive and objective analysis of the advantages and disadvantages of various methods, and predicts future development trends.

In recent years, a large number of research achievements have emerged in the field of sentiment classification. For example, Wang proposed an attention mechanism-based LSTM model (ATAE-LSTM) for aspect-level sentiment classification, which significantly enhanced classification performance [4]. Zhang utilized Graph Convolutional Networks (GCN) to capture the syntactic relationships between words in sentences, further improving the accuracy of the model [5]. Li and Keung proposed innovative solutions for cross-domain and multilingual sentiment classification problems, respectively [6,7]. These studies have laid a solid foundation for the development of sentiment classification technology, while also revealing current methods' shortcomings in generalization ability, computational efficiency, and interpretability.

This study aims to provide related a comprehensive review of methodologies in sentiment classification field. It also tries providing theoretical underpinnings and practical guidance for the usage of this technology in the real world. With the advancement of technologies like pre-trained models or graph neural networks in the coming days, sentiment classification is expected to make differences across the domains.

## 2. Sentiment Classification Framework

Text sentiment classification primarily involves systematically categorizing the emotional information and meanings conveyed by the text. As illustrated in Figure 1, sentiment analysis can be divided into two levels based on granularity: coarse-grained and fine-grained classifications. Corresponding to different levels of granularity, the classification tasks can be categorized into binary classification, ternary classification, and multi-class classification.

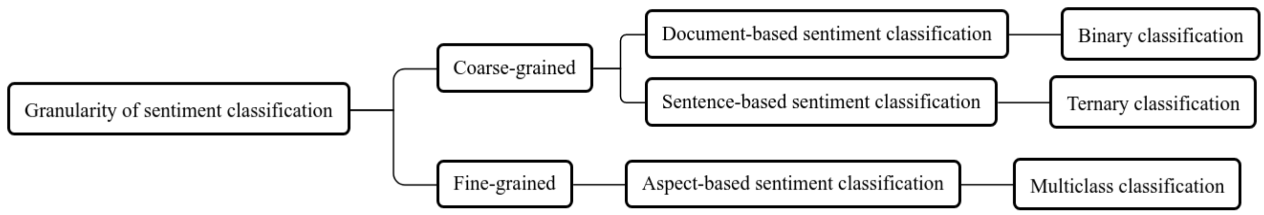


**Fig. 1** Granularity of sentiment classification

Coarse-grained sentiment classification includes document-level and sentence-level sentiment classification. Document-level sentiment classification focuses on determining the emotional polarity of the entire text, which is typically categorized as positive or negative, representing a binary classification task. The goal of this level of analysis is to capture the overall emotional tendency of the text. In contrast, sentence-level sentiment classification is more complex, as it assesses the emotional polarity of individual sentences, usually divided into three categories: positive, negative, and neutral, representing a ternary classification task. Compared to document-level sentiment classification, sentence-level sentiment classification is often more challenging due to the relative brevity of sentences and the scarcity of emotional information. This level of analysis assumes that each sentence expresses a single opinion and emotion; however, this assumption may have certain limitations in practical applications.

Building up such classification, fine-grained sentiment classification pertains to hierarchizing text units that specifies the sentiment orientations of the concerned segments, also known as aspect-level sentiment classification. In this context the emotional trending generally includes various types which fit a multi-class classification task. This analysis generally consists of three key elements:

aspect terms, opinion words, and emotional polarity. Aspect-level sentiment classification requires to consider the interaction between aspect words and emotions. If these elements are considered separately—meaning that aspect information is ignored in emotional evaluation—this may lead to incorrect classifications. This is because the same adjective may convey different feelings when describing different things or when used in different contexts. Aspect-level sentiment classification allows for a more fine-grained classification of the emotional polarity regarding specific aspects, leading to more accurate assessments of text sentiment [3].

## 3. Sentiment Classification Methods

In the research domain of sentiment classification, mainstream methods can be categorized into two major classes based on their technical approaches: traditional methods and deep learning methods. Traditional methods can be further divided into four subcategories: lexicon-based methods, machine learning-based methods, weakly supervised methods, and hybrid methods that combine lexicon and machine learning approaches. Traditional classification methods primarily focus on coarse-grained sentiment classification at the document and sentence levels, typically assuming that the text conveys a single sentiment (e.g. either positive or negative). These methods are limited in their ability to identify sentiments related to multiple aspects within a text [3].

With the models performance enhancing,the granularity of sentiment classification progresses from coarse to fine. Then due to the ability of end-to-end learning without relying on manually defined features,deep learning methods shows obvious advantages in aspect-level sentiment classification.

As illustrated in Figure 2, current major methods for aspect-level sentiment classification can be further subdivided into three main categories: methods that combine sentiment lexicons with deep learning, traditional deep learning methods, and graph neural network-based methods. Traditional deep learning methods include those based on Convolutional Neural Networks (CNN), Memory Networks (MemNN), and Recurrent Neural Networks (RNN). Given that the majority of contemporary mainstream methods are based on deep learning techniques, this study will focus on analyzing the latter two categories of aspect-level sentiment classification methods.

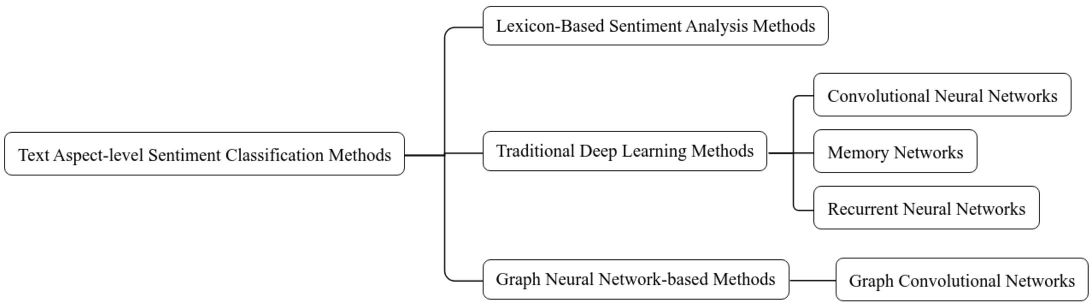


**Fig. 2** Text aspect-level sentiment classification methods

### 3.1. Lexicon-Based Sentiment Analysis Methods

Using sentiment lexicons and linguistic rules to address aspect-level sentiment analysis tasks is closely aligned with traditional sentiment analysis methods that leverage sentiment lexicons. This approach requires the use of annotated sentiment lexicons or linguistic rules to determine sentiment polarity [8].

To adapt to the current fine-grained classification tasks, sentiment lexicons are increasingly not used in isolation; rather, they are combined with deep learning algorithms through knowledge enhancement to improve the performance of fine-grained sentiment analysis [9]. For example, Liang et al. integrated SentiNet with Graph Convolutional Networks to construct a graph neural network that enhances the dependency graph of sentences, achieving promising results [10]. Additionally, Jain et al. incorporated SentiNet into a BERT-DCNN model, enabling it to perform sentiment analysis at the conceptual level [11].

## 3.2. Traditional Deep Learning Methods

### 3.2.1. Convolutional Neural Networks

Convolutional Neural Networks are already widely used in many fields, such as computer vision. It can extract high-level features from raw data through convolution and pooling operations. Therefore, these networks are able to capture rich semantic information without requiring much computation. This method is effective across various domains, including sentiment analysis.

Ye et al. proposed a model called Combining with A Lite Bidirection Encoder Represention from TransConvs and ConvNets (ALBERTC-CNN) for aspect-level sentiment analysis, which attempts to merge the ALBERT network with Convolutional Neural Networks in a creative way [12]. This model primarily focuses on obtaining global semantic information and local sentiment information from a text to overcome the limitations of some intent models for sentiment analysis. Keyword extraction is one of the major challenges in the field of natural language processing. This avoids missing important semantic signals when determining a sentiment. However, since we only use the ALBERT network, it is difficult to obtain the subtle local sentiment features in the text. In order to solve this problem, ALBERTC-CNN model add a convolutional neural network to the output layer, use CNN's local perceptive ability to effectively extract sentiment-related information about a specific aspect of the text. The design allows the models to use and separate the tendency of the sentiment in solving complex problem in emotion. In particular, ALBERTC-CNN model embeds input text into word vectors and then applies ALBERT network to extract global features. Next, the convolutional layer takes this further by allowing the model to capture local features. At last, a linear mapping and a softmax function are applied to output the extracted features as the sentiment classification results.

### 3.2.2. Memory Networks

Chen et al. proposed a memory network with hierarchical multi-head attention (MNHMA), which integrates rotational units of memory (RUM) with hierarchical multi-head attention mechanism [13]. It circumvents the information loss in recurrent units evidenced in recurrent neural networks as these sequential layers unfold to process long sequences, by representing long-distance dependencies in Euclidean coordinates and modeling semantics as the product of unique rotation operations across each layer. The hierarchical multi-head attention mechanism progressively attends to important contextual words associated with the aspects by consolidating aspect embeddings with the input so that the effect of irrelevant vocabulary is diminished. Moreover, nonlinear transformations of the sentiments can be performed after each layer through a fully connected layer after each layer of attention, providing richer contextual representations. This type of method achieves great effectiveness in aspect retention and noise attenuation.

The study proposed by Lin et al. introduced a new model called Deep Selective Memory Network (DSMN) for aspect-level sentiment classification [14]. The main goal of this model is to select contextual memory dynamically using a selective attention mechanism and cross-aspect modeling to enhance the analysis of posted multi-aspect sentiments. Compared with this, DSMN framework is composed of deep memory networks and a multi-hop attention mechanism that allows better learning of contextual information for aspect-level tasks. With the distance-related information, the model chooses different context parts across different layers of the memory network, making it possible to extract rich aspect context information. Moreover, in order to leverage relationships among the different aspects, they devised a cross-aspect modeling module that generates semantic and relational information about nearby aspects that better guides sentiment classification. The innovation of this framework lies in its combination of traditional semantic dependency information with positional dependency information, enabling it to adapt to different types of datasets. Extensive experimental results on multiple benchmark datasets show that DSMN outperforms state-of-the-art methods significantly, especially when learning dynamic patterns and relations of multi-aspect sentiments. By designing selective attention modules, cross-aspect modeling modules and fusion modules, DSMN maximize the benefits of different information sources, which greatly improved the accuracy of aspect-level sentiment classification. Such approaches provide several new insights into the field of sentiment analysis, as well as application potential across varied data types.

#### 3.2.3. Recurrent Neural Network

Recurrent Neural Networks demonstrate the abilities in sequence learning, and many state-of-the-art methods for aspect-level sentiment classification primarily rely on RNN for modeling.

Li et al. proposed a Convolutional Enhanced Recurrent Neural Network (CERNN) [15], which combines the benefits of Convolutional Neural Networks and Recurrent Neural Networks. CERNN tackles the problem of weakened processing to sequential data by RNN through the TextCNN or FastText for text feature enhancement. The convolutional structure The convolutional structure properly extracts local features from the text and highlights important information, while the recurrent structure remains the sequential nature of the text, allowing for long-distance dependencies in the context to be effectively captured. Moreover, CERNN employs its variants which includes LSTM or Bi-LSTM to get better accuracy for text classification and performs better especially in sentiment analysis tasks. This allows for significant improvements in classification accuracy as well as a decrease in training time.

In the study conducted by Aydin and Güngör [16], they proposed a framework that combines Recursive Neural Networks (RvNN) and Recurrent Neural Networks for aspect-level sentiment analysis. They proposed two models of recursive neural networks separately on the outputs of the constituency parsers (CP) and dependency parsers (DP). This model is innovative in adopting a syntactic parser to divide comments into sub-comments that extract sentiment information for specific aspects. By constructing a syntactically-based recursive tree, it can capture the grammatical structure of sentences and the associated sentiment information. Then, the outputs of the recursive trees are fed into the RNN for better sentiment modeling. A crucial advantage of this method is the integration of the benefits of both RvNN and RNN. RvNN can learn the relational and hierachical information among words, performing effectively in processing tree-structured data; on the other side, RNN is better at processing sequential data and learns temporal dependencies. By this combination, the model can not only learn the grammatical and sentiment structures of the text but also capture the propagation and sentiment drift of sentiment within comments. Experimental results show that this framework performs excellently on multiple datasets, and demonstrates its effectiveness in aspect-level sentiment analysis tasks.

### 3.3. Graph Neural Network-based Methods

Yang et al. presented a Bidirectional Graph Convolutional Networks (BiGCN) method for aspect-level sentiment classification with Interactive Attention Mechanism (IAM) [17]. This model is based on the Bidirectional Graph Convolutional Network to extract the syntactic dependency relationship between contextual words and aspect terms, which effectively solves the problem that the traditional model does not pay attention to syntactic information. The model uses the Interactive Attention Mechanism to learn interaction information in context and aspect terms while extracting important sentiment features from context and relevant features from aspect terms that may contribute to classification. It also adds masking layer techniques on aspect term vectors to better represent the aspect term by shielding non-aspect term vector. In this way, the model not only integrates indispensable information in context but also keeps information in aspects.

Wu et al. proposed an interactive memory network that leverages syntactic dependency information [18], where a Graph Convolutional Network embeds an Interactive Memory Networks (IMN) module at its center (IMNGCN). The GCN extracts structured relational features between aspects and context from the syntactic dependency tree, addressing the issue of insufficient utilization of syntactic information in traditional methods. The IMN module enhances the semantic association between aspects and context by dynamically assigning word weights, thereby reducing the interference of irrelevant vocabulary. Meanwhile, the positional relationships between aspect words and context words are enhanced based on positional encoding mechanism, and then is used to promote the sentiment classification accuracy. It gets excellent performance on multi-aspect long sentences.

## 4. Experiments

### 4.1. Evaluation Metrics

In previous experiments of sentiment classification, it is common to use the evaluation metrics including precision (P), recall (R), accuracy (Acc), and F1 score. The formulas for calculating each metric are as follows:

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{1}$$

$$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{2}$$

$$\mathrm{F1} = \frac{2 \times \mathrm{R} \times \mathrm{P}}{\mathrm{R+P}} \tag{3}$$

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

In these formulas, TP represents the number of positive samples predicted as positive, FN denotes the number of positive samples predicted as negative, FP indicates the number of negative samples predicted as positive, and TN refers to the number of negative samples predicted as negative.

### 4.2. Experiment Set

The experiment set on three benchmark datasets: SemEval 2014 Task 4 (Restaurant reviews), SemEval 2014 Task 4 (Laptop), and a general Twitter datasets. These datasets span multiple domains, and therefore provide a thorough evaluation of model performance across multiple text types and language types. For example, the SemEval 2014 Task 4 contains the Restaurant (Rest14) and Laptop (Lap14) datasets with high quality annotations of aspect terms and respective sentiment polarities (i.e., positive, negative, or neutral), and the Twitter datasets presents further difficulties due to the informal language, abbreviations, and noise.

This experiment evaluated a range of models, including ATAE-LSTM [4], ALBERT-CNN [12], MNHMA [13], DSMN-I/II [14], CP+RNN/DP+RNN [16], BiGCN-IAM [17], and IMNGCN-Glove/BERT [18]. Performance was evaluated using accuracy (Acc) and F1 score, as defined in Section 4.1. This setup provides a rigorous framework for comparing model performance and identifying benefits and limitations across different domains and text types.

### 4.3. Experiment Results

Table 1 presents the performances of different models on the Lap14, Rest14, and Twitter datasets. IMNGCN-BERT [18] had excellent performance on all datasets and ALBERT-CNN [12] also achieved high accuracy on the Rest14. In contrast, traditional models such as ATAE-LSTM [4] got a relatively weaker performance. It shows the advantage of pre-trained models in sentiment classification tasks.

However, the performance of all models on the Twitter dataset are relatively lower. For instance, the accuracy of MNHMA [13] and DSMN-II [14] are 73.99% and 73.84%. It reflects the negative impact of noise and informal language present in social media texts on model performance.

In summary, the experimental results reveal the advantages of hybrid model and the domain dependency of performance. It also identifies the technical challenges associated with processing noisy data and informal text.

**Table 1**. Performance of different models on three datasets

| Model | Lap14 | | Rest14 | | Twitter | |
|---|---|---|---|---|---|---|
| | Acc (%) | F1 (%) | Acc (%) | F1 (%) | Acc (%) | F1 (%) |
| ATAE-LSTM[4] | 68.70 | - | 77.20 | - | - | - |
| ALBERTC-CNN[12] | 80.56 | 76.97 | 87.23 | 81.01 | - | - |
| MNHMA[13] | 81.88 | 73.59 | 76.49 | 73.19 | 73.99 | 72.27 |
| DSMN-I[14] | 77.59 | 73.61 | 81.16 | 71.50 | 72.25 | 70.54 |
| DSMN-II[14] | 77.27 | 73.91 | 81.16 | 72.09 | 73.84 | 72.12 |
| CP+RNN[16] | 73.73 | - | 80.27 | - | - | - |
| DP+RNN[16] | 75.75 | - | 80.90 | - | - | - |
| BiGCN-IAM[17] | 76.18 | 71.95 | 81.34 | 72.61 | 72.98 | 71.39 |
| IMNGCN-Glove[18] | 78.56 | 75.54 | 83.98 | 76.24 | 76.07 | 74.80 |
| IMNGCN-BERT[18] | 81.51 | 78.02 | 87.92 | 81.01 | 78.29 | 77.39 |

### 4.4. Experiment Analysis

In sentiment classification tasks, various neural network models have individual characteristics. Convolutional Neural Networks are widely utilized for high accuracy and fast training advantages; however, the complex structure design of the Convolutional Neural Networks also increases the difficulty of implementation, while the pooling operation can also cause the loss of positional information of the text. Memory Networks achieve a high accuracy for those tasks which require long-term memory and are fitted to integrate with others, but easy to cause overfitting issues. The deep structure also adds significant complexity. While Recurrent Neural Networks are good at extracting features from sequential data and are quite robust, they take longer time to train, and the computational cost obviously increases with the length of sequences. As a new model, the graph convolutional networks can well fit topological relationships in text with excellent performance, which is a convenient for graph structure data processing. But they are sensitive to noisy data, and their performance depends on the accuracy of the dependency parsing output.

Overall, each model has its effective scenarios and limitations. Deciding which model to use need careful choice in terms of task and data types. Future research could explore multi-model fusion strategies. For instance, hybridize the local feature extraction capability of CNN with the global structure modeling capability of GCN can take advantage of both models while minimizing their downsides.

## 5. Outlook

### 5.1. Discussion

This study systematically reviews the development of deep learning techniques for fine-grained sentiment classification. It notes that existing methods mainly use architectures like attention mechanisms and Long Short-Term Memory (LSTM) networks, aiming at creating deep interaction between the aspect terms and the contextual semantic spaces. These methods greatly improve the precision of word-level sentiment recognition by strengthening the local context features (e.g. intra-sentence dependency relations modeling) and studying cross-aspect correlations (e.g. cross-attention computations). But with the increasing complexity of the models, there are the technical challenges to model long-distance text associations, filter out useless information and ensure model interpretability. While stacking multiple layers of attention mechanisms partially captures potential relevance between paragraphs, it consumes a large amount of computational resources and drops the balance of model interpretability. Most existing approaches are not even quantitative and admit of no notion of what constitutes an "effective" or "logical" association, thus rendering impossible the separation of random associations due to grammatical disconnects from semantically confirmed associations.

To this end, this study attempts to propose an evaluation metric called "aspect relevance," which consists of three dimensions: (1) The intensity dimension detects the relevance levels either strong or weak. Strong relevance pays attention to semantic dependencies at long distances across paragraphs or texts (such as the distribution pattern of core opinion words in the whole document), and weak relevance focuses on the extraction of local features in sentences or between adjacent sentences. (2) The quality dimension introduces the notion of "over-relevance," specifically addressing the model's response to pseudo-relevance triggered by syntactic disjunction, or semantically irrelevant texts. Noise associations of this kind can create a polarity of wrong sentiment judgement. (3) For logicality dimension, this study construct an interpretable approach allowing syntactic tree parsing and importance scoring to form a linkage between sequencing models while modeling association to satisfy linguistic logic rules and have the ability of ranking feature importance.

This framework provides a theoretical benchmark for balancing model complexity and association effectiveness. Its metrics can guide the improvement of efficient contextual filtering algorithms, optimization of computational resources meanwhile maintaining the accuracy.

### 5.2. Prospect

Sentiment classification still has much development potential. This study provides several important research directions worth exploring in the field of aspect-level sentiment classification.

#### 5.2.1. Model Performance

Current models often have an increase in computational cost and complexity while getting better performance. Future research should explore more efficient model, such as improving the computational methods of attention mechanisms or designing lighter network structures. Moreover, the dynamic context filtering mechanisms could be considered, which would prioritize the processing of text segments closely related to emotional expressions and reduce the computation associated with irrelevant information.

#### 5.2.2. Generalization Ability

The generalization performance of sentiment classification on multilingual textual data and low-resource linguistic scenarios remains inadequate, and there are significant disparities in accuracy for cross-domain classification tasks. Understanding how well sentiment classification models transfer will be a novel and impactful avenue of research. In multilingual tasks, generating a common emotional semantic space might help the quality in low-resource languages. Although they are trained only on one domain, domain adaptation techniques such as adversarial training can help these networks generalize across domains by helping the model adapt between the mismatched data distribution of different domains.

### 5.3. Multimodal Sentiment Analysis

Given the ubiquitous use of multimodal data, sentiment analysis is not tied to a single text modality anymore. Future exploration on audiovisual studies over multimodal data could address the issue of how to align emotional representation across text, image, and audio. Techniques such as building cross-modal emotional relationships via contrastive learning and creating approaches to resolve differences by modalities (e.g. discrepancy in text and picture emotions) would be useful.

### 5.4. Application Domains

Sentiment classification technology has broad application prospects across various fields. In social media analysis, it can be utilized for real-time monitoring of public sentiment changes; in the business sector, it can assist in analyzing fine-grained emotional tendencies in product reviews; and in the medical field, sentiment analysis can aid in the early identification of psychological disorders. Furthermore, to enhance the credibility of models, future research should strengthen model interpretability, especially in high-risk scenarios such as judicial and financial contexts, to ensure transparency in decision-making processes.

In summary, the further development of sentiment classification technology requires collaborative advancement at theoretical, technical, and application levels. By continuously optimizing model performance, enhancing generalization capabilities, expanding multimodal analysis, and deepening application scenarios, sentiment classification technology will provide more intelligent decision support across various sectors of society.

## 6. Conclusion

This study reviews the current state of aspect-level research in the field of sentiment classification. It organizes the  classification logic and framework of this task and systematically summarizes various mainstream methods based on deep learning that have emerged in recent years. Then it compares the performance of various models on an identical datasets on the same datasets and discusses the pros and cons of various methodologies. This research emphasizes the concept of "relevance" and attempts to propose the framework of "aspect relevance", trying introducing a dimension of assessment by which a proper analysis of the methods should be done. This paper also provides a reasonable outlook on the future development directions of sentiment classification in terms of both technology and applications, suggesting that there remains significant potential for growth in this field.

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