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Sentiment Analysis in Online Public Opinion: Trends, Challenges, and Future Directions

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Abstract: The rapid development of the Internet, particularly following the COVID-19 pandemic, has significantly influenced public opinion analysis, a critical field in natural language processing (NLP). This paper systematically reviews recent domestic and international research on online public opinion from an emotional perspective, drawing on sources from the China National Knowledge Infrastructure (CNKI) and Web of Science. The study highlights the importance of sentiment analysis in understanding public opinion, emphasizing the need for advanced machine learning techniques and multimodal content integration to enhance model performance. Future research should explore the inclusion of diverse languages and larger datasets to improve generalization, and consider transforming sentiment detection tasks into multi-classification or regression challenges. This comprehensive review aims to guide future researchers by providing a deeper understanding of current trends and potential advancements in online public opinion analysis.

Keywords: Online public opinion; Emotional analysis; Machine learning; Deep learning.

1. Introduction

According to the 51st Statistical Report on the Development of Internet in China released by the China Internet Network Information Center (CNNIC), as of December 2022, the number of Internet users in China has reached 1.067 billion, an increase of 35.49 million over December 2021, and the Internet penetration rate has reached 75.6%. The development of the Internet is beyond imagination, but it is reasonable. Especially after the COVID-19, the development of the Internet has also opened a channel for people around the world to understand each other and obtain information.

In today's Big data era, various learning technologies have been applied to online public opinion research, aiming to provide more convenient, fast and efficient methods. In addition, various types of information carriers such as images, videos, and voice that exist on the Internet also provide data support for various aspects of online public opinion research. Under these conditions, domestic and foreign researchers have started to study the emotional changes and communication characteristics in online public opinion from an emotional perspective.

This article systematically collects research from domestic and foreign scholars in recent years on online public opinion from an emotional perspective and analyzes its development trends. The discussion in this article is mainly based on the literature provided by China National Knowledge Infrastructure (CNKI) and Web of Science. Through literature analysis, the domestic and foreign studies involved in this article are summarized and analyzed, aiming to provide assistance to future researchers, gain a deeper understanding of the current research status and future trends in this field, and provide theoretical reference for their future research.

2. Overview of literature on emotional based online public opinion research

2.1. Source of research literature

This article mainly uses the literature research method to analyze the current research status of online public opinion both domestically and internationally. Chinese and English literature is selected from the CNKI full-text database and the Web of Science database, respectively. As the online public opinion is mainly caused by emergencies, and considering the online public opinion caused by the outbreak of "COVID-19" in 2020, This paper uses "(subject: online public opinion) AND (subject: emotion) OR (subject: COVID-19) AND (subject: emotion) OR (subject: emergency) AND (subject: emotion)" and "sentient analysis (All Fields) and public opinion (All Fields)" as the retrieval methods of CNKI database and Web of Science database (the retrieval time is June 7, 2023. Since the COVID-19 started in late 2019, many major emergencies occurred in succession, which led to a surge in Internetattention. Internet public opinion began to receive extensive attention and research from scholars, and eventually 522 Chinese literatures and 822 foreign literatures were retrieved.

2.2. Annual analysis of research literature

We calculated the number of relevant literature published in CNKI and Web of Science databases over the years from 2018 to 2023, as shown in Figure 1. On the one hand, this graph can reflect the research trends in the relevant fields described in this article over the years, and on the other hand, it reflects the attention paid by researchers to the field of online public opinion sentiment research.

From Figure 1, it can be seen that the research trend in this field at home and abroad has been increasing since 2021, while in 2023, the gap has narrowed and the number of publications has decreased. From 2018 to 2019, research in this field received little attention in China, and it was not until 2020 that the attention level increased, Starting from the continuous fermentation of unexpected events such as the "7.23 Wenzhou high-speed train accident," "Ya'an earthquake," "flooding disasters in southern regions," and "Shanghai Bund stampede incident" on the internet, more scholars have conducted in-depth research on the evolution and dissemination of network public opinion from the perspective of public opinion emotions. Since 2018, machine learning and deep learning and other technologies have been widely used in the emotional analysis of online public opinion, making more accurate research results on emotional classification and emotional evolution. The "Liangshan Forest Fire Event" in 2019 and the "COVID-19" in 2020 have led to a straight-line increase in attention in this field. Compared to domestic research progress, foreign scholars' research on online public opinion has surpassed domestic research since 2018, and has shown explosive growth since 2020. The COVID-19 that broke out in 2020 has become the fuse to ignite online public opinion. Online public opinion has rapidly generated and continued to spread around the world, making the attention in this field reach the peak, and also stimulating more scholars to pay attention to and study online public opinion.

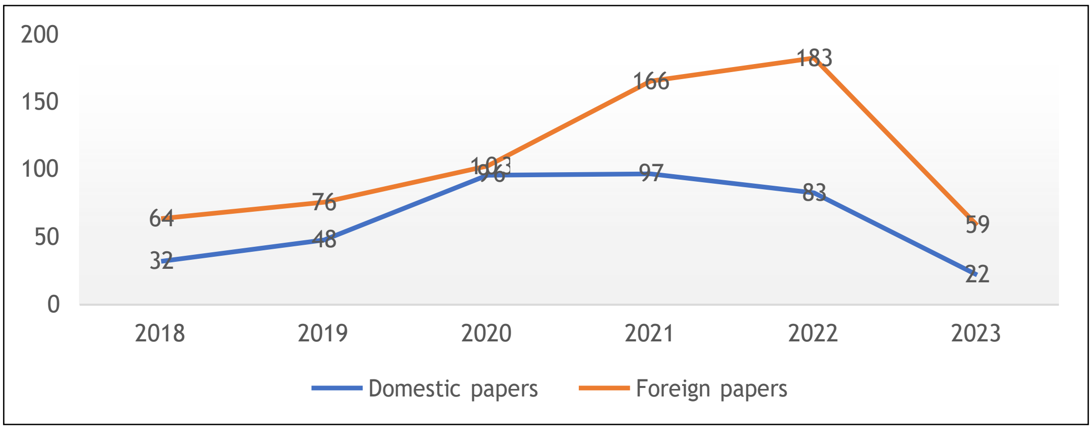

Figure 1. Number of published research papers on online public opinion both domestically and internationally

2.3. Analysis of hot topics of research literature

By studying the themes of literature related to online public opinion and analyzing the changing trends, this trend can reflect the main research directions and theoretical research progress brought by scholars at home and abroad in different time periods. Based on this, this article uses CiteSpace software to draw relevant research at home and abroad, and the resulting timeline is shown in Figure 2 and Figure 3.

Through Figure 2 and Figure 3, it is possible to intuitively reflect the temporal development and research progress of clustering evolution on various topics. Firstly, the temporal order from left to right represents each hot topic word, while from top to bottom represents the decreasing order of clustering information for each word. For example, in the foreign research literature in Figure 2, the clustering nodes related to machine learning and emotion analysis have been a research hotspot since 2018, Several other topics have also been research hotspots in the past five years. In the domestic research literature in Figure 3, online public opinion, emergencies, and sentiment analysis have also become popular research topics for researchers since 2018. In addition, research methods for online public opinion by researchers have also begun to diversify, and technologies such as machine learning and deep learning are increasingly being used for online public opinion research.

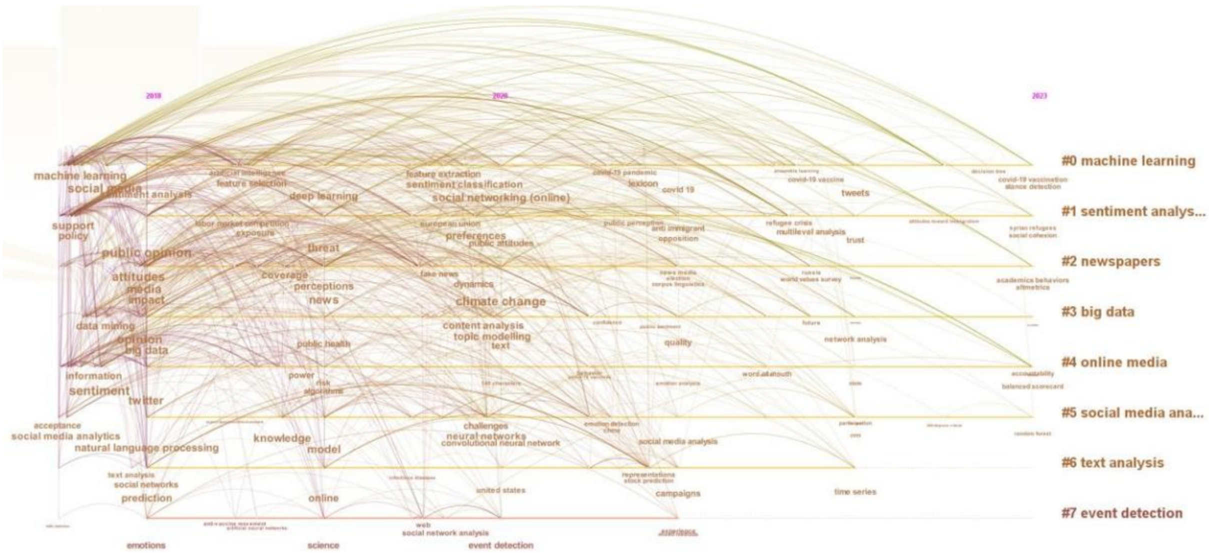

Figure 2. Timeline of Foreign Network Public Opinion Research

Figure 3. Timeline of Domestic Network Public Opinion Research

2.4. Keyword analysis of research literature

In each literature, keywords belong to key information or key tags, which can directly reflect the central viewpoint of the article's content. The statistics of keyword information in domestic literature through CNKI are shown in Figure 4.

From the pie chart, it can be intuitively observed that the top few scholars' research content is related to events in the context of the current period in the context of the overall trend. Due to the lack of statistical function for keywords in Web of Science, no foreign keyword distribution map is provided. However, there is a commonly used data mining method, TF-IDF, which has excellent applicability and robustness. It is composed of word frequency and inverse file frequency, and the importance of a word to an article is determined by the ratio of the frequency of its occurrence in the corpus to the frequency of its occurrence in multiple statements, that is, the importance is directly proportional to the TF-IDF value. This

article compares the top five keywords with TF-IDF values in domestic and foreign literature through statistics and calculations, and the results are shown in Table 1.

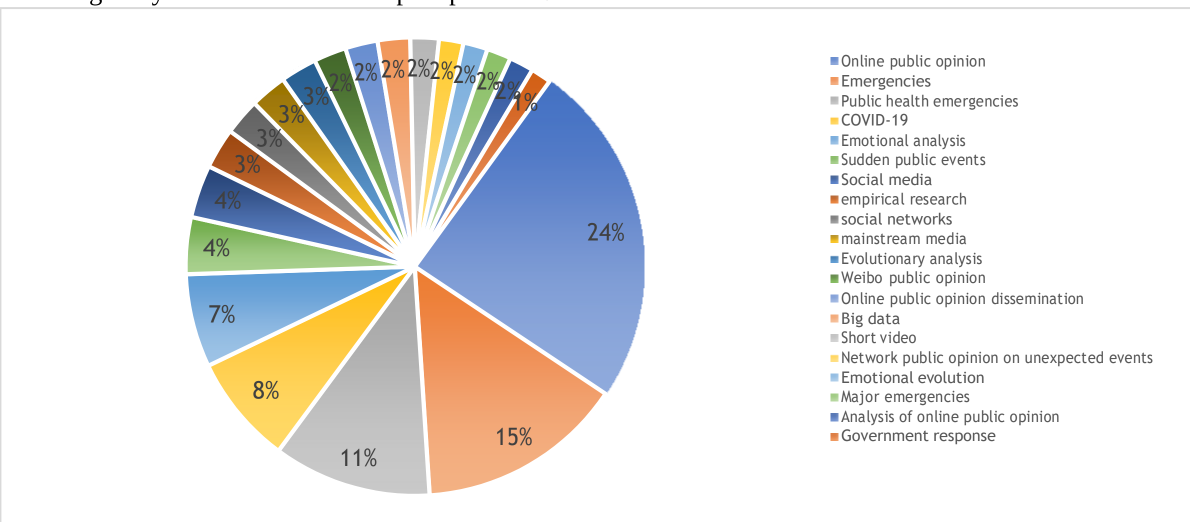

Figure 4. Distribution of Domestic Network Public Opinion Keywords

Table 1. Comparison of keywords in domestic and foreign research literature on online public opinion

Order	Chinese Keywords	English Keywords
1	Online public opinion	Sentiment Analysis
2	Public opinion analysis	Public Opinion
3	Sentiment analysis	Social Media
4	Deep learning	Opinion Mining
5	Machine learning	Deep Learning

From Table 1, it can be seen that domestic and foreign scholars focus more on the emotional aspects of public opinion in their research on online public opinion, and their research methods mostly use deep learning and machine learning. On the basis of adopting deep learning technology, foreign scholars have focused more on the perspective mining of public opinion.

3. A Review of Research on Online Public Opinion at Home and Abroad

3.1. Research on Emotional Analysis of Online Public Opinion in China

The analysis of domestic text data related to public opinion events in the field of Natural language processing can be broadly divided into the following three categories: rule-based emotional dictionary [1], machine learning [2], and deep learning [3].

Research on rule-based sentiment dictionaries: mainly relies on constructing an appropriate sentiment dictionary for rule setting, in order to improve the accuracy of public opinion sentiment analysis on text data. Wu Jiesheng et al. [4] have made targeted improvements and expansions to the public opinion sentiment dictionary, including the construction of degree adverbs, negative word dictionaries, and Weibo domain dictionaries, thereby improving the accuracy of Weibo sentiment analysis. Chen Ke et al. [5] improved the Transformer model by utilizing the feature information of emotion dictionaries, which to some extent improved the classification performance. Li Jidong[6] integrated the basic emotion dictionary, created the online public opinion emotion dictionary, and improved the accuracy of Sentiment analysis of microblog. Li Yuqing[7] proposed a multi category sentiment analysis model for constructing bilingual dictionaries based on existing dictionaries, effectively expanding the problem of single language in existing dictionaries. The majority of scholars improve the accuracy of Sentiment analysis by constantly adding rule dictionary content according to needs, but they need a lot of energy to annotate data and construct dictionaries. Kang Yue et al.[8] proposed the method of building a large-scale emotion dictionary by fusing 100000 emotion dictionaries to handle the emotion classification problem of semantically complex Chinese data. This can effectively solve the problem of polysemy of emotion words in traditional emotion dictionaries, which only judge emotion categories based on emotion words and cannot accurately express the polarity of emotions containing contextual words. HuanhuanYuan et al. [9] proposed weighted word2vec to reduce dependence on manually constructed sentiment dictionaries and highlight the role of keywords in comment texts. They also incorporated attention mechanisms into the Long Short-Term Memory (LSTM) model to fully utilize the role of keywords in sentiment classification, making sentiment words more capable of expressing the original meaning and accurately determining the emotional polarity of the text, However, the influence of contextual structure on emotional polarity was also overlooked. Based on the issues of poor adaptability and complex manual operations in emotion dictionaries, scholars have applied machine learning and deep learning methods to construct emotion dictionaries that can improve the accuracy of emotion classification.

In terms of machine learning, public opinion sentiment analysis based on machine learning mainly involves selecting some features for part of speech annotation, dividing the original dataset into training and testing sets in a certain proportion, and then using classifiers such as naive Bayes [10] and support vector machines [11] for sentiment analysis. In addition, public sentiment analysis based on machine learning can be divided into three categories: Supervised learning [12], Semi-Supervised Learning [13] and Unsupervised learning [14]. Qi Tianmei et al. [15] involved the calculation method of emotional orientation based on four machine learning algorithms, effectively improving the accuracy of emotional orientation and intensity calculation. Sun Jianwang et al. [16] added the positional weight calculation of feature polarity values to the SVM classifier, which to some extent improved the accuracy of sentiment classification for Chinese Weibo texts. Pu Zekun[17] proposed an sentiment analysis model ARAEC based on comment analysis and ensemble classification, and improved the SVM model to the SD-LS-SVM sentiment classification algorithm. The two algorithms were combined to construct a machine learning based e-commerce comment sentiment analysis system. Although many scholars have continuously improved machine learning algorithms by increasing the extraction of emotional features or combining and selecting classifiers themselves, in order to achieve a certain degree of improvement in emotional classification performance. However, when machine learning algorithms perform emotional analysis on the content of text data itself, they often fail to fully utilize the semantic relationships and contextual connections between contextual texts. Therefore, improving the accuracy of machine learning algorithm classification can have a certain degree of impact [18]. Cai Jianping et al. [19] used a naive Bayesian algorithm model to combine contextual features obtained through sentence structure analysis for sentiment classification. Yang Shuang et al. [20] proposed a multi-level sentiment classification method for Weibo based on SVM multi feature fusion, which achieves sentiment classification by fusing semantic features, part of speech features, emotional features, etc. in Weibo text data. From the perspective of classification performance, machine learning performs better in emotion classification than emotion dictionaries, but it also has certain drawbacks. The use of machine learning methods for text classification has a strong dependence on data features, and the quality of extracted features directly affects the extraction of key text information during data fitting, thereby greatly affecting the classification results. The implementation principles of emotion dictionaries and machine learning methods are simple and easy to understand, but their transfer ability is poor, generalization ability is weak, and accuracy still needs to be improved. Compared to deep learning based emotional methods, they are widely welcomed by people.

In terms of deep learning-based sentiment analysis in online public opinion, deep learning-based sentiment analysis can effectively compensate for the shortcomings of computational learning algorithms in contextual text correlation. By analyzing the semantic information between contextual text information, actively learning text features, preserving the relevance of the original text words, and thereby improving the recognition effect of text information, emotional tendency analysis of online public opinion texts can be achieved. Wang Wenkai et al. [21] proposed a way to integrate Convolutional neural network and tree LSTM model to solve the problem of context structure and semantic feature extraction. It can use attention mechanism to recombine feature word vectors, increase the correlation between contextual semantic features, and extract the optimal features layer by layer through CNN convolution layer, which can more accurately complete sentiment analysis tasks. However, the operation process is complex, logarithmic data requirements are strict, and the applicability needs to be improved. Wang Baohua et al. proposed a dual channel deep memory network model to conduct emotional analysis on students' teaching evaluation and effectively explore emotional tendencies in different teaching aspects. On the basis of Convolutional neural network, Jin Zhigang[23] and others gathered Word2vec to calculate the semantic features of texts and emotional features of emoticons, further improving the accuracy of emotional analysis of microblog short texts. Liang Jun and others used recurrent neural networks combined with emotional polarity transfer models to enhance the capture of text relevance to a certain extent. In addition, Word embedding is of great significance in the research of emotion analysis based on deep learning [24]. However, there are some occasional problems in the process of learning word vectors in the Word embedding model, that is, words with similar contexts but opposite emotional meanings (such as "good" and "bad") may be mapped into similar vectors. Although the use of word vectors to replace or combine traditional text features for short Sentiment analysis has achieved some results [25,26], the lack of emotional information will certainly affect the effect of emotion analysis. Therefore, researchers propose word vectors with emotional significance specifically designed for emotional analysis. Tang et al. [27] improved the C&W word vector model, added supervised emotional information to the Loss function of the model, learned emotion related word vectors, and achieved better results than word vectors in the experiment of tweet emotion analysis. Yu et al. [28] used optimization strategies to obtain word vectors with emotional and contextual meanings. Jiang et al. [29] proposed the emoticon space model (ESM), which constructs an emotion space from emoticon word vectors in Weibo text. Based on the cosine values of emoticon word vectors and other word vectors in Weibo text, the word vectors are mapped into the emotion space to obtain word vectors with emotional significance, and support vector machine (SVM) is used as a classifier, Achieved outstanding results in the Chinese Weibo sentiment classification task.

3.2. Research on Emotional Analysis of Online Public Opinion in Foreign Countries

In foreign countries, scholars mostly use deep learning technology for their research on public opinion. The key is that deep learning technology has been widely favored by scholars in recent years, and its efficient advantages are destined to gain more popularity in the field of natural language.

Basiri et al. [30] suggest sentiment analysis based on an attention based bidirectional CNN RNN deep model. This study used past and future backgrounds. This study considered five comments and three Twitter datasets. Jin et al. [31] proposed sentiment analysis based on heterogeneous graphs, network embedding based on variational autoencoders, for learning joint representations of user social relationships. This is encouraged by maintaining structural proximity and attribute proximity separately, and this model outperforms traditional text-based sentiment analysis methods. Pota et al. [32] recommended a bidirectional encoder based on a converter (BERT) to represent a pipeline for Twitter sentiment analysis. This study is interesting because it aims to convert jargon into plaintext, and tweets use Burt classification, but pre-trained on plaintext. This model is applicable to multiple languages. Lu et al. [33] conducted aspect-based sentiment analysis using aspect gated graph convolutional networks. This model utilizes syntactic information and emotional dependencies, and has been experimentally analyzed on multiple semi physical datasets. At the same time, the model has improved accuracy and macro F1 by 2.14% and 1.33%, respectively, compared to the baseline model. Nemes and Kiss [34] conducted emotional analysis on social media based on Covid 19 (comments, tags, posts, tweets). Although the COVID-19 has had an impact worldwide [35,36], the study considered recurrent neural network (RNN) for analysis. Research has concluded that there are more positive tweets on social media. Tubishat et al. [37] relied on the best combination of rules for explicit aspect extraction in sentiment analysis. This algorithm combines 126 aspect extraction rules for formal and informal texts, mainly considering rules based on dependency relationships and rules based on patterns. This study also proposes a whale optimization algorithm for rule selection related issues. Kandasamy et al. [38] proposed another method for sentiment analysis using neutral sets, which allows for the consideration of seven membership functions from the initial three functions [39-41]. The research shows that the multiple refined Masked palm civet collection performs well in analyzing text emotion. Huang et al. [42] proposed sentiment analysis based on attention emotion enhanced convolutional LSTM to solve high-level abstraction problems. The LSTM network in the study was improvised by combining emotional intelligence and attention mechanisms. The model also supports convolution, pooling, and cascading, and exhibits considerable performance. Zhao et al. [43] proposed a combination of CNN and Gated Recursive Networks (GRU) for emotion analysis. The proposed model relies on the local features generated by CNN and the long-term dependency of GRU learning. The robustness of the model was verified through experimental analysis on multiple datasets.

Srividya and Sowjanya[44] recommend using neural attention models for aspect based emotional analysis. The model was trained on datasets REST14, REST15, and REST16, and its performance was evaluated based on accuracy and F-1 scores. Ö zt ü rk et al. [45] collected Türkiye and English Twitter data about the Syrian refugee crisis, and divided the emotional polarity of netizens contained therein into five levels: particularly negative, negative, neutral, positive and particularly positive. At the same time, researchers also classify the emotions of netizens in a specific way. Poria et al. [46] proposed a multi category sentiment data analysis framework to identify the four emotions of netizens: anger, happiness, sadness, and neutrality from videos, audio, and text. At the same time, many scholars have also explored the authenticity of news content in public opinion. For example, Khattar et al. [47] proposed an end-to-end multimodal Variational autoencoder model (MVAE) to explore the distribution rules of Fake news by learning the potential distribution of multimodal features. Some scholars consider improving the model detection performance through external knowledge. Qian et al. [48] added the Knowledge graph module to learn the external knowledge contained in news text entities under the traditional multimodal framework; However, it takes a lot of time to construct knowledge map training on the whole news text. In response to this defect, Mayank et al. [49] proposed a false news detection framework that only targets Headline entities. Under this framework, they use two-way Long short-term memory (LSTM) networks to learn Headline features, and identify and extract Headline entities, build a Knowledge graph to obtain external information features, and finally splice and fuse the two parts of features to do the second classification task. However, throughout the models proposed by these scholars, they have focused too much on finding suitable models to improve the accuracy of extracting text and image features, resulting in the loss of a large amount of task related information during training.Singhal et al.[50] proposed using a pre trained Bidirectional Encoder Representation from Trans formers (BERT) model to learn news text features, resulting in better performance than the benchmark multimodal model. Inspired by this method, this article uses a multi head attention mechanism to extract text features, and a self-attention mechanism model combined with position encoding can extract key information in text sequences. Moreover, the model is relatively simple and causes less information loss during training. The construction method of emotion dictionary based on semantic similarity is used to measure the distance between emotion words and positive and negative labels. According to this method, L et al. Turney et al. [52] proposed a phrase sentiment propensity calculation method for PMI-IR based on PMI, and obtained the average sentiment propensity of text phrases as the result of judging emotional polarity. This traditional emotion dictionary-based calculation method relies heavily on part of speech. Some words in the text contain polysemy or reverse expressions, and the emotions expressed in different contexts will be different. However, in traditional emotion dictionaries, emotion categories are only judged based on emotion words, and the polarity of emotions containing contextual words cannot be accurately expressed. Vaibhavi et al. [53] applied the Bayesian model to sentiment dictionaries and trained sentiment words in text data through naive Bayesian models to reduce the impact of domain independence on sentiment expression. Wikarsa et al. [54] added six emotional features to the calculation of part of speech and expression features during data processing, and used a naive Bayesian model for sentiment classification. The accuracy of classification was improved, and the sentiment classification results also achieved the expected results. Boiy et al. [55] fused multiple machine learning models through a hierarchical system, and experiments showed that the fused model has significant advantages in extracting text features.

The application of machine learning in emotion classification has indeed made significant improvements in feature extraction of text data, and improvements have been made to the situation where contextual features cannot be used in emotion dictionaries. Kim Y et al. [56] combined Convolutional neural network with Word embedding to learn the relevance of context semantic sequence, and the results proved that the accuracy of the model for emotion classification was improved, but the influence of context structure on emotion classification was ignored. Liu Longfei et al. [57] proposed a method of inputting trained unit word vectors into CNN for feature extraction for sentiment analysis. High demand vector input can achieve good training results, but it has significant limitations and strict requirements. For the application of CNN in sentiment analysis, Santos et al. [58] and Bahdanau[59] proposed corresponding text feature extraction methods to improve the correlation of semantic features. The network memory and shared parameters of RNN have natural advantages for learning semantic features of text sequences. In view of the characteristic that Long short-term memory neural network can solve the gradient explosion and Vanishing gradient problem problem, Schuster M et al. [60] proposed a Bidirectional recurrent neural networks model (Bi RNN) to do more in-depth research on gradient problems. Hochreiter S et al. [61] proposed the method of adding control units to Long short-term memory networks; Tang D et al. [62] proposed a simplified version of LSTM GRU; The methods proposed by Eyben F et al. [63] for the bidirectional LSTM model (Bi LSTM) are all used to solve such problems, and have achieved good results in their respective fields. The experimental results also indicate that they can effectively classify text, but there are different problems that need improvement in their respective fields.

4. Conclusion

Online public opinion analysis is one of the hottest research fields in Natural language processing, and has been widely used in various applications supporting smart cities. Previous research has emphasized that sentiment analysis in public opinion is conducted using several traditional and non-traditional methods, including artificial intelligence. In the future, it is hoped that more such hybrid machine learning techniques and other hyperparameter optimization methods can be used to explore this issue. In addition, the dataset under consideration is mainly composed of English words. It is interesting to analyze on a dataset containing sentences from different languages. In the future, we can try to introduce more modal content to improve model performance, such as news comment content, background content of news releases, news video content, etc; Due to the limitations of existing public opinion news datasets, the fitting effect of our model on other data needs to be verified, and the model needs to be trained on larger and different real datasets in different fields to improve its generalization ability; In addition, it is unreasonable to simply classify the task of detecting emotional tendencies in public opinion news as a binary classification problem. Although there are also a few studies that divide emotions at a fine-grained level, there are very few related to public opinion. Subsequent research can continue to increase the analysis of news at a finer granularity. How to convert it into a multi classification task or even a regression task is also a major challenge for future work.

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