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Review

Sentiment Analysis of Twitter Data

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Abstract: Twitter has become a major social media platform and has attracted considerable interest among researchers in sentiment analysis. Research into Twitter Sentiment Analysis (TSA) is an active subfield of text mining. TSA refers to the use of computers to process the subjective nature of Twitter data, including its opinions and sentiments. In this research, a thorough review of the most recent developments in this area, and a wide range of newly proposed algorithms and applications are explored. Each publication is arranged into a category based on its significance to a particular type of TSA method. The purpose of this survey is to provide a concise, nearly comprehensive overview of TSA techniques and related fields. The primary contributions of the survey are the detailed classifications of numerous recent articles and the depiction of the current direction of research in the field of TSA.

Keywords: sentiment analysis; text classification; natural language processing; Twitter

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1. Introduction

Due to the recent explosive rise of Social Networking Services (SNS), an enormous amount of user-generated data, such as comments and reviews, is being created consistently [1]. People's opinions and feelings are expressed in the information, which is mostly based on a common object of interest. These data have become treasure troves of information, giving several chances for analyzing people's reactions, which is particularly beneficial in forecasting the sales of products [2], trends in the stock market [3], and results of political elections [4]. There are more than 300 million active Twitter users [5], making it one of the most popular micro-blogging services [6]. In light of its significance in the perception of people's thoughts and attitudes, Twitter-based Sentiment Analysis (TSA) has consequently attracted a great deal of attention [7,8].

The topic of SA has been the subject of a great deal of writing, and more recently, significant attention has been paid to TSA. Obviously, this therefore calls for a survey article that may provide an overview of the current techniques and directions in the field of study. Pang and Lee [9] provided an extensive and in-depth review of SA through experimental works by using different kinds of data. However, the most up-to-date methods were not shown in the article due to the fact that it was released a while ago. In addition, comprehensive coverage of core concepts and topics concerning SA was introduced by Liu et al. [10], in which the examination of application-centric methods was performed to explain the basic ideas of SA. Adwan et al. [11] offered a survey providing a brief introduction to the techniques of TSA. Nevertheless, only a few publications were mentioned. Although there is also a most recent survey related to TSA [12], in which only the machine-learning-based methods were investigated. According to our knowledge, there is a lack of comprehensive studies focusing on TSA. Thus, as a fundamental, a thorough overview of the concepts of SA, and a more concise description of the ideas and terminologies of TSA was illustrated in this survey. Recent advances and discoveries in TSA were also presented. Moreover, tables were used to properly classify the published papers, which allows for a more straightforward comparison among various methods.

The chosen articles in the present survey have a significant impact on TSA research and related topics. Particularly, the state-of-the-art technologies available today have been incorporated to exhibit the most current findings of TSA, while the traditional approaches were selected as a comparative standard. In addition, the central section of the survey is structured with three primary components: machine-learning-based, lexicon-based, and hybrid approaches, all of which are in keeping with the current trends in TSA research. More effort has also been devoted to machine-learning-based solutions since those techniques can produce a better performance of prediction accuracy for TSA tasks. Specifically, TSA is extensively discussed in this survey, and it is broken down into the following subsections: Section 2 introduces the role and the structure of Twitter. Section 3 illustrates the background and basic concept of sentiment analysis. The representation of the feature for TSA is explained in Section 4, and Section 5 shows the different levels of analysis. In Section 6, the approaches and recent achievements in Twitter sentiment analysis are presented. Section 7 presents several survey-related discussions. Finally, the survey is concluded in Section 8. Table 1 displays the abbreviation descriptions mentioned in this paper. To gain a better understanding of the TSA, several research questions are raised as follows.

Table 1. The description of abbreviation.

Abbreviation	Description
TSA	Twitter-based Sentiment Analysis
SNS	Social Networking Service
SA	Sentiment Analysis
OM	Opinion Mining
NLP	Natural Language Processing
NB	Naïve Bayes
SVM	Support Vector Machine
POS	Part of Speech
BN	Bayesian Network
ME	Maximum Entropy
DAG	Directed Acyclic Graph
NN	Neural Network
PSO	Particle Swarm Optimization
3NN	3-Nearest Neighbors
PCA	Polarity Classification Algorithm

RQ1: What is the major difference between sentiment analysis and opinion mining?

Sentiment Analysis (SA) and Opinion Mining (OM) are two promising fields of study that are both employed to learn about the feelings and opinions of people regarding certain topics. As a result, both SA and OM can be used interchangeably to convey the same concept in many cases. However, other scholars have argued that they are different since they were developed to solve different problems. For instance, Tsytsarau et al. [13] claimed that OM is designed to assess whether or not a given piece of text contains an opinion and is used to address the subjective analysis problem. On the other hand, SA refers to the analysis and prediction of the sentiment polarity of text data [14].

RQ2: Why was Twitter selected as the primary target platform for the study of SA?

Twitter has a significant number of active users, and Twitter API makes it simple to collect vast quantities of opinionated text data. In addition, the users come from a variety of backgrounds, including common individuals, celebrities, politicians, etc. In addition, the collected corpus includes a wide range of distinct materials from several domains, which allows easy access to textual information in a variety of languages [15].

RQ3: What are the challenges that TSA is facing?

TSA has several significant challenges. Given that a tweet can only be a maximum of 140 characters long, text length is an extremely crucial one. Different from previous research on evaluating the long text of the document, analyzing the sentiment of short length text presents a new challenge for TSA. Topic relevance is another difficulty, which refers to the categorization of tweets into certain topics. This contributes to the efficiency of the fine-grained TSA tasks. In addition, text pre-processing techniques are also essential for TSA. Preprocessing the raw dataset is a prerequisite for model creation, therefore various methods, such as removing punctuation, stop-word removal, stemming, and lemmatization, etc., have been introduced accordingly [14].

2. Twitter

Various microblogging platforms like Twitter, Facebook, and Instagram were born out of the emergence of SNS [14]. Twitter is a widely used SNS that allows users to exchange 140-character messages (referred to as "tweet") [16]. More than 300 million people have signed up to use Twitter, which generates over 500 million updates each day [6,17]. Because of the ease with which it can be shared, Twitter has grown to be one of the most important sources of user-generated data. The following is a list of the most important features of Twitter.

Tweet: A tweet is a 140-character maximum data unit that can be transmitted using Twitter. Its content ranges from how people feel or what they think about certain events, to photos, videos, and links, etc., all of which can be easily shared with the users' contacts.

Handle: This refers to the behavior of tweet updating or public messaging to other users. It is written as "@username," and the @ symbol is used to refer to the person or organization with whom the tweets are connected [14].

Hashtag: Hashtag is a kind of metadata tag used in various SNS that allows users to adopt dynamic, user-generated tags to make it easier for others to find the tweets related to a specific topic [18].

Follow: This is an activity of registered users to pursue people, companies, or any organization that they are interested in and to receive updated tweets in real time. Twitter is more than just a tool for staying in touch with friends and sharing one's own daily activities, its true strength lies in the dissemination of information and the following of others.

Retweet: It is one of the most useful tools for disseminating information on Twitter, in which users are allowed to re-post the tweets they are interested in. Here, the original tweets generally remain unchanged, followed by the abbreviation of the original username of the authors [14].

Search: This powerful feature allows users to search keywords and phrases on Twitter to find updated tweets about their interests in real time [19]. People are more likely to join Twitter because of this search function, which facilitates the discovery and dissemination of relevant content.

Table 2 shows an example of a tweet from the user, BaskFan. It is worth noting that the tweet contains some of the features above. @Strive indicates that the tweet is a reply to the user of Strive, and the user, NBA, has also been mentioned. Meanwhile, the hashtag shows that it is related to the topic of lakers.

Table 2. One example of a tweet including user opinions.

Source	Username	Post
Twitter	BaskFan	@Strive: I LIKE watching basketball @NBA game especially LAKERS GAMES. #lakers

3. Sentiment Analysis

Opinion mining is a subfield of linguistics and natural language processing that deals with sentiment analysis. It evaluates the degree of polarity of words and phrases to examine and extracts views and feelings from textual data [20,21]. Various studies and advances have been carried out by organizations or individuals that are interested in finding out how people feel about a given issue [20]. The term of sentiment was firstly coined by Das and Chen [22] and Tong [23] in 2001, who evaluated the sentiment of the market by automatic analysis of the text [9]. Turney [24], Pang et al. [25], and Nasukawa and Yi [26] were some of the first to discuss sentiment analysis and the Natural Language Processing (NLP) methods that go along with it in their following publications. In addition, a great deal of work has been carried out on more application-oriented approaches. As an example, Liu et al. [27] proposed a sentiment-based approach to forecast sale patterns. The models presented by McGlohon et al. [28] to estimate product and merchant quality were statistical and heuristic. Chen et al. [29] used sentiment analysis techniques to find hidden relationships between subjects and opinionated phrases in the political realm, where novel opinion scoring models were developed. Yano and Smith [30] sought to identify links between the number of comments and political sentiment using statistical modeling. Furthermore, evaluating Twitter conversation has emerged as a promising area of study. As the conversation offers a wealth of discriminative information relevant to various topics, it can facilitate the understanding of the feelings of people. Optimistic and pessimistic emotions expressed in Twitter conversations were analyzed by using a novel deep learning approach [31]. It integrated emotion detection with conversation reconstruction modules to discover sentiment polarity in social media posts. Tamar Ginossar et al. [32] evaluated the cross-platform spreading of information by analyzing Twitter conversations. Rabindra Lamsal et al. [33] developed forecasting models to predict the prevalence of virus using the workload of Twitter conversations, which employed a latent variables-based searching technique.

Sentiment analysis has also been applied to business and social studies. Companies like Google and Microsoft have recently built their own sentiment analysis systems to assist in their industrial and commercial activities [34]. TSA attempts to address the difficulty of evaluating the hidden meaning of tweets posted on Twitter, which is considered a new subject of sentiment analysis. There exist some challenges to TSA, the most significant of which is the restriction on message size. Due to the fact that a tweet contains no more than 140 characters, it is difficult to glean the sentiment contained within such a little amount of text. Meanwhile, the irregular textual representation on Twitter intensifies the complicatedness. Therefore, several concerns need to be addressed by the suggested TSA procedures [14]. Figure 1 shows the general operation flow of TSA.

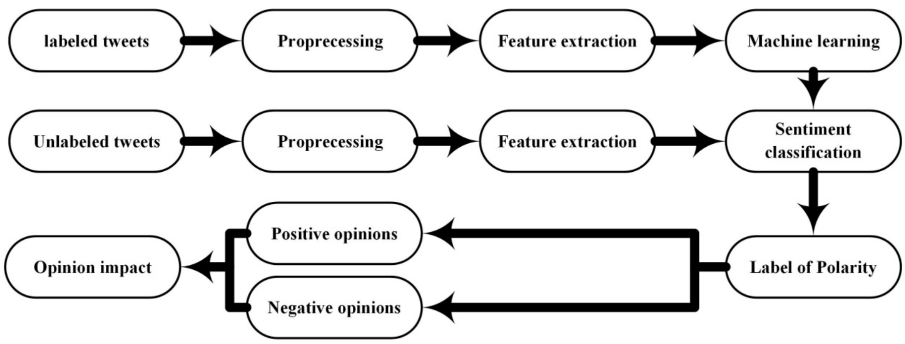

Figure 1. The operation flow of Twitter sentiment analysis [14].

A sentiment analysis system often receives data from a variety of sources, such as blogs, comments, reviews, etc., in a variety of forms, such as XML, HTML, and PDF [35]. Techniques like tokenization, steaming, and stop-word removal are used to standardize and transform the data from the corpus into training datasets in text format. In sentiment analysis, selecting a collection of relevant features to train the text classifiers is a critical stage since different combinations of features have a significant impact on the final performance of sentiment analysis tasks. Then, the polarity label of the tested data is determined, relying on a text classifier which is trained and built up by the machine learning technique [14].

4. Representation of Feature

Feature representation is a preprocessing step in sentiment analysis that involves turning text content into a feature vector [9]. The following are the most common ways of expressing the feature in sentiment analysis:

N-gram: It identifies a single feature in a given text or speech corpus as a continuous sequence of n terms. Unigram refers to the n-gram of the size of one, and bigram refers to the size of two. Specifically, the term frequency based unigram is the most often used representation in which a single word is considered as a feature and its occurrence frequency is tallied as the feature value [36].

Part of Speech (POS) tagging: As another essential syntactic feature representation, this method assigns a POS tag (verb, adverb, adjective, etc.) to every word in a text or corpus. The well-known Penn Treebank POS tags are shown in Table 3 [34,37].

Table 3. Penn treebank POS tags.

Tag	Description	Tag	Description
CC	Coordinating conjunction	PRP$	Possessive pronoun
CD	Cardinal number	RB	Adverb
DT	Determiner	RBR	Adverb, comparative
EX	Existential there	RBS	Adverb, superlative
FW	Foreign word	RP	Particle
IN	Proposition or subordinating conjunction	SYM	Symbol
JJ	Adjective	TO	
JJR	Adjective, comparative	UH	Interjection
JJS	Adjective, superlative	VB	Verb, base form
LS	List item marker	VBD	Verb, past tense
MD	Modal	VBG	Verb, gerund, or present participle
NN	Noun, singular or mass	VBN	Verb, past participle
NNS	Noun, plural	VBP	Verb, non-3rd person singular present
NNP	Proper noun, singular	VBZ	Verb, 3rd person singular present
NNPS	Proper noun, plural	WDT	Wh-determiner
PDT	Predeterminer	WP	Wh-pronoun
POS	Possessive ending	WP$	Possessive wh-pronoun
PRP	Personal pronoun	WRB	Wh-adverb

Negation: This is an important linguistic feature that greatly influences the polarity of a sentence. The location of the negative words is critical to rapidly establish the breadth of the word's impact. A statement like, "I like playing basketball but I am tired today", is impacted by the negative term because of the word following "basketball" [38].

5. Different Levels of Analysis

Classification at the document, sentence, and aspect levels are the three main types of classification for sentiment analysis.

5.1. Document-Level Sentiment Analysis

Negative or positive opinions are typically classified at document-level sentiment analysis. It treats the opinion expressed in a document as a single entity [34,39]. Two primary approaches to sentiment analysis at document level are supervised and unsupervised learning. To determine the polarity of a document, supervised learning divides the documents into certain groups and generates specialized training datasets. Semantic orientation is used by unsupervised learning approaches to detect the polarity of test documents by measuring the degree of particular phrase polarity in the documents. The test document is regarded as positive if the average value of semantic orientation is above the threshold, and it is considered as a negative one if it is not [35].

5.2. Sentiment-Level Sentiment Analysis

A single sentence is evaluated as an independent entity, and its entire tone is examined. The pre-judgment stage is necessary for the sentiment level of sentiment analysis. Only the subjective instances are analyzed further, while the objective ones are often deleted [35].

5.3. Aspect-Level Sentiment Analysis

In contrast to the previous two levels of analysis, a fine-grained analysis is conducted in aspect-level sentiment analysis. It typically comprises three steps: identification, categorization, and aggregation. Here, not only the overall sentiment of an item, but also the sentiments of all its components are examined. The stage of identification identifies the target pairs in the provided content that are relevant to the sentiment, and classification classifies their sentiments based on the predetermined sentiment values. Aggregation is the process of integrating the sentiment values of all components for a comprehensive perspective [40].

6. The Approaches for Twitter Sentiment Analysis

The methodologies for sentiment analysis can be generally divided into three main categories: machine learning-based, lexicon-based, and hybrid-based approaches. The taxonomy of sentiment analysis is shown in Figure 2 [41].

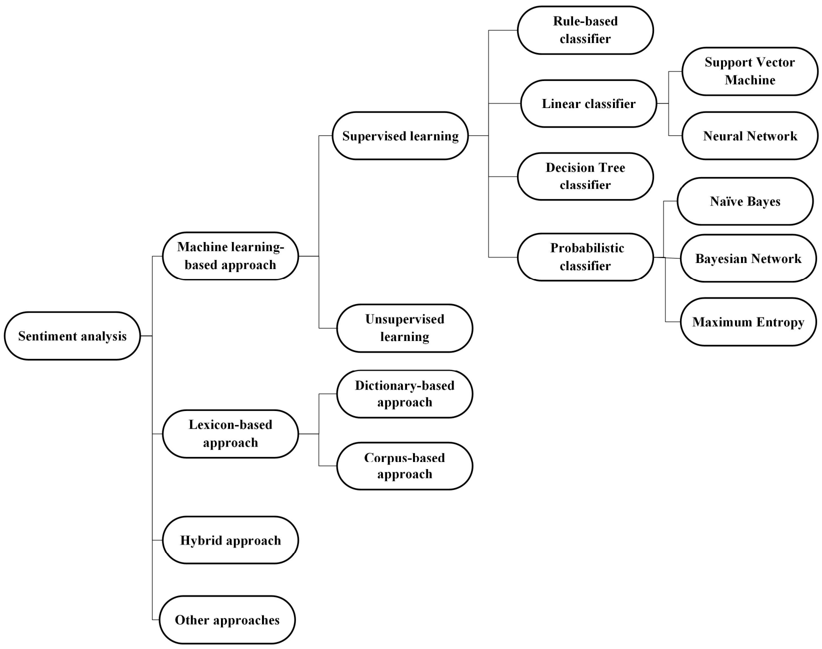

Figure 2. The taxonomy of sentiment analysis.

6.1. Machine Learning-Based Approach

The classification stage in sentiment analysis uses a classifier that is trained using machine-learning techniques. This approach can be broadly split into two types: supervised learning and unsupervised learning. An overall publication using machine learning techniques is provided in Table 4. The training dataset and linguistic characteristics are utilized for automatic text categorization in supervised learning, and primary supervised learning methodologies are outlined as follows.

6.1.1. Probabilistic Classifier

Mathematical models are used to predict the categorization based on the input [42]. Probabilistic classifiers such as the Naïve Bayes classifier (NB), Bayesian Network (BN), and Maximum Entropy classifier (ME) are often used in data analysis [43,44]. To determine the best class match, the Bayes theorem-based NB classifier is one of the most extensively used techniques. BN is another probabilistic model that employs Bayesian inference to calculate probability. Directed Acyclic Graph (DAG) is used to depict the variables and their conditional interdependencies [45]. The probability of a feature belonging to a specific category is computed using ME.

Table 4. The list of machine learning-based approaches for sentiment analysis.

Ref	Objective and Algorithm Used	Data Scope	Dataset
[46]	Feature selection, particle swarm optimization (PSO), CRF	Restaurants and laptop reviews	SemEval-2014
[47]	Feature subset selection, discrete PSO, logistic regression model	Financial, spambase, Nursery, etc.	UCI ML Respository
[48]	Feature selection, Binary PSO, CART, NB, SVM	Handwritten digits	UCI benchmark datasets
[49]	Selecting emotional features, multi-swarm PSO, SVM	Course review	Datasets from MOOC
[50]	Feature weighting, optimization-based weighted voting scheme, NB, SVM, LR, Bayesian logistic regression, linear discriminant	Camera, doctor, drug, radio, TV, etc.	Datasets extracted from websites
[51]	Binary classification, SVM	Movie review	Own
[52]	Feature weighting, adaptative Kullback–Leibler divergence score, SVM	Movie review, newspaper article,	Polarity dataset, Subjectivity dataset, MPQA dataset
[53]	Feature selection and weighting, NB, SVM	Movie review	IMDb
[54]	Supervised term weighting, SVM, kNN	Newsgroup message, Economic news	20 Newsgroups, Reuters-21578, TanCorp
[55]	Feature selection, dynamic relevance, and joint mutual information maximization, SVM with RBF kernel, NB, 3-Nearest Neighbors (3NN)	Vehicle, Madelon, USPS, etc.	UCI Repository
[56]	Feature clustering, divisive algorithm, NB, SVM	News message, HTML documents	20 Newsgroups, data from open directory project
[57]	Discriminatively weighted NB, NB, IWNB, BNB, DNB	wide range of domains	UCI datasets
[58]	Adaptive feature weighting approaches, MNB, CNB, OVA	wide range of domains	Datasets in WEKA
[59]	Improved NB text classifier, feature weighting, SVM, MNB	Economic news, Newsgroup message	Reuters 21578, 20 Newsgroups
[60]	Feature weighting and ranking, SVM, kNN, RBF	wide range of domains	UCI ML Respository
[61]	Content-based recommendation system, feature weighting,	Movie review	IMDb
[62]	Iterative RELIEF for feature weighting, kNN	wide range of domains	UCI and Microarray datasets
[63]	Effective feature weighting, improved NB, GRFWNB, RFWNB, DTFWNB, CFSFWNB, CFSNB, and DFWNB.	wide range of domains	UCI ML Respository

Table 4. *Cont.*

Ref	Objective and Algorithm Used	Data Scope	Dataset
[64]	Imbalanced text classification, probability-based term weighting, SVM, NB	Archive of engineering technical papers, Newsgroup message	MCV1 and Reuters 21578
[65]	ITD and ITS based supervised term weighting, SVM	Movie review, product review	Cornell movie review, product reviews from Amazon, Stanford large movie review data set
[66]	Comparative study of feature weighting, SVM	Economic news	Reuters 21578
[67]	Concept-based linguistic methods, Naive Bayes, Neural Network	Tweet	Manually annotated dataset
[68]	Decision tree, logistic regression, multinomial naive Bayes, support vector machine, random forest, and Bernoulli Naive Bayes	Tweet	Manually collected dataset

6.1.2. Linear Classifier

The linear classifier is generally used to determine which class a feature belongs to. The classification decision is made based on linear predictor functions, which linearly combine feature values. Support Vector Machine (SVM) and Neural Network (NN) are another two widely used implementation methodologies.

6.1.3. Rule-Based Classifier

This is effective to represent the information of the feature space using a set of rules of "IF-THEN" for the classification, and the decision is made to classify the features into predefined classes.

6.1.4. Decision Tree Classifier

This is a non-parametric approach of supervised learning, in which the feature space is continually partitioned into sub-feature spaces for classification and regression. The goal of this approach is to use decision rules to forecast the class label of the feature.

The supervised learning-based method is efficient for sentiment analysis; however, it is difficult to manually prepare labeled data for the classification system. An unsupervised learning-based approach has been developed to solve the problem, which identifies the degree of polarity by subjective indicators generated from the sentiment lexicon [9].

6.2. Lexicon-Based Approach

The lexicon-based method makes use of a sentiment lexicon to gauge the strength of the feelings expressed. To create a sentiment lexicon, a set of preset words is widely used. Dictionary-based and corpus-based methods are the two most common techniques to build a sentiment lexicon. Note that lexicographical information, such as a dictionary, is used in the dictionary-based technique to define sentiment words, whereas the corpus-based method typically employs scenarios of co-occurrence along with already established sentiment terms [69]. Table 5 lists the publications that use the lexicon-based sentiment analysis approach [14,41].

Table 5. The list of lexicon-based approaches proposed for sentiment analysis.

Ref	Objective and Algorithm Used	Data Scope	Dataset
[70]	Classification of text using fine-grained attitude labels, semantic, lexicon created by own	User-generated personal story	Dataset from Experience Project website
[71]	Lexicon-based approach, document discourse structure, sentiment classifier, semantic, lexicon created by own	Movie review	IMDB
[72]	Lexicon-based comments-oriented news sentiment analyzer, NLP, PMI-IR, taxonomy lexicon	News information	N/A
[73]	Comparative analysis of emotion detection, supervised and lexical knowledge-based approach, SVM	Corpus of emotions	ISEAR, Emotinet
[74]	Affect-based search, emotion lexicon by crowdsourcing	Emails, fairy tales, Novels, etc	Corpus of enron email
[75]	Unsupervised system of SSA-UO, rule-based classifier	Unlabeled Twitter message, SMS message	SemEval
[76]	Rule-based pattern matching system, rule-based classifier	Message of Twitter and SMS	SemEval
[77]	Unsupervised sentiment analysis with emotional signals, sentiment lexicon	Tweet message	STS, OMD
[78]	Entity and tweet-level sentiment analysis, generic sentiment lexicon	Tweet message	OMD, HCR, STS-Gold
[79]	Detection of connotative polarity, connotation lexicon	Tweet message	SemEval-2007, Sentiment twitter

6.3. Hybrid Approach

For this approach, the machine-learning and lexicon-based methods are combined. It has been shown that the hybrid approach improves the performance of classification, and the publications using this approach are summarized in Table 6 [14,80].

Table 6. The list of hybrid-based approaches proposed for sentiment analysis.

Ref	Objective and Algorithm Used	Data Scope	Dataset
[81]	Neural-network-based hybrid approach, sentiment classifier	Blogger comments and product reviews	Datasets collected from LiveJournal, Review Centre
[82]	Comparative study of ensemble technique for sentiment analysis, NB, SVM, maximum entropy	Movie review, product review	Cornell movie-review corpora
[83]	A system for subjectivity and sentiment analysis (SSA), manually created polarity lexicon	Chat messages, Arabic tweets	multi-domain sentiment dataset from Amazon
[84]	Rule-based multivariate feature selection, linear kernel SVM	Online review	DAR, TGRD, THR, MONT
[85]	Hybrid method combining rule-based classification and machine learning, SVM, SBC, RBC, GIBC	Movie review, product review, and MySpace comment	Epinions, Edmunds, Movie review [15]

Table 6. *Cont.*

Ref	Objective and Algorithm Used	Data Scope	Dataset
[86]	Entity-level sentiment analysis method, opinion lexicon, SVM	Tweet message	Polarity dataset
[87]	Supervised feature reduction using n-grams, Twitter-specific lexicon, SVM	Tweet message	Dataset extracted from Twitter API
[88]	Large-scale distributed system for real-time Twitter sentiment analysis, lexicon builder, lexicon-based classifier, adaptive logistics regression	Tweet message	Dataset extracted from Twitter API
[89]	Polarity Classification Algorithm (PCA), EEC, IPC, SWNC	Tweet message	Dataset extracted from Twitter API

6.4. Other Approaches

It is worth noting that some methods described in TSA literatures do not fit well into any of the aforementioned categories, part of which could be categorized as "graph-based approaches" [14]. The methodology seeks to build a connected social graph for effective label propagation with the assumption that people are mutually influential. Such approaches were initially developed by Speriosu et al. [90] for TSA, in which various objects (tweets, hashtags, unigrams, etc.) were utilized as nodes to create the graph. Additionally, Cui et al. [91] introduced another label propagation method based on the extraction and analysis of emotion tokens. Recently, a graph-based technique was presented by Cambria et al. [92] where reasoning tasks were performed by developing a morphology-aware concept parser. Since construction of the social graph is time-consuming, and the availability of the graph is greatly dependent on the diversity of the corpus, this area of study requires further investigation.

7. Discussion

In light of the above, it is clear that the machine-learning-based approach to TSA is the most popular. By this method, conventional machine learning algorithms are trained using a subset of available features to predict the sentiment polarity of a given piece of text. It is worth noting that the performance of the combination of multiple classifiers generally yields better experimental results than the use of an individual one. Nonetheless, the approach has its limits. Firstly, the size of the training dataset has a significant impact on the classification performance of TSA. In order to train the models, most machine-learning algorithms need a huge number of manually annotated tweets. However, due to the high cost of human annotation of tweets, creating such data becomes a tedious task. Although research such as distant supervision has looked into techniques to generate a huge number of annotated tweets, annotation in poor quality has a negative impact on the efficiency of TSA. Secondly, domain dependence is another limitation of machine learning-based approaches. Specifically, the prediction accuracy of the TSA task is highly dependent on the classifiers that were taught by the target domain [14].

Lexicon-based approaches relying on sentiment lexicons are introduced to categorize TSA tasks. Its advantage is that it does not require annotated tweets; nevertheless, the words that are not in the lexicon might reduce the performance. Context independence is another drawback of the lexicon-based approaches, which ignores the relationship between the sentiment and context of words. Hybrid approaches are proposed to address the weaknesses of the machine-learning-based and lexicon-based approaches, which produce superior performance in specific domains of the dataset but require a high computational cost [14].

8. Conclusions

In recent years, researchers have become increasingly interested in analyzing tweets based on the sentiments they represent. This interest comes from the fact that a great number of tweets are posted on Twitter, which provides vital information on the sentiments of the public on a variety of subjects. The goal of this survey is to introduce the basic concepts and techniques for sentiment analysis of tweets, and more than 60 publications were evaluated and classified to exhibit the most recent developments in the field. It is also beneficial to learn sentiment analysis by looking at the most recent applications of TSA. It is believed that TSA will be a rapidly developing research field during the next few years. More studies on TSA will be conducted in the future.

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References

1. Zimbra, D.; Abbasi, A.; Zeng, D.; Chen, H. The State-of-the-Art in Twitter Sentiment Analysis: A Review and Benchmark Evaluation. *ACM Trans. Manag. Inf. Syst.* **2018**, *9*, 5. [CrossRef]
2. Rui, H.; Liu, Y.; Whinston, A. Whose and What Chatter Matters? The Effect of Tweets on Movie Sales. *Decis. Support Syst.* **2013**, *55*, 863–870. [CrossRef]
3. Bollen, J.; Mao, H.; Zeng, X. Twitter Mood Predicts the Stock Market. *J. Comput. Sci.* **2011**, *2*, 1–8. [CrossRef]
4. Wang, H.; Can, D.; Kazemzadeh, A.; Bar, F.; Narayanan, S. A System for Real-time Twitter Sentiment Analysis of 2012 U.S. Presidential Election Cycle. In Proceedings of the ACL 2012 System Demonstrations, Jeju Island, Korea, 10 July 2012.
5. Statista. Available online: https://www.statista.com (accessed on 15 November 2022).
6. Reyna, N.S.; Pruett, C.; Morrison, M.; Fowler, J.; Pandey, S.; Hensley, L. Twitter: More than tweets for undergraduate student researchers. *J. Microbiol. Biol. Educ.* **2022**, *23*, e00326-21. [CrossRef] [PubMed]
7. Meng, F.; Xiao, X.; Wang, J. Rating the crisis of online public opinion using a multi-level index system. *Int. Arab. J. Inf. Techn.* **2022**, *19*, 597–608. [CrossRef]
8. Khan, I.U.; Khan, A.; Khan, W.; Su'ud, M.M.; Alam, M.M.; Subhan, F.; Asghar, M.Z. A review of Urdu sentiment analysis with multilingual perspective: A case of Urdu and roman Urdu language. *Computers* **2022**, *11*, 3. [CrossRef]
9. Pang, B.; Lee, L. Opinion mining and sentiment analysis. *Found. Trends®Inf. Retr.* **2008**, *2*, 1–135. [CrossRef]
10. Bing, L.; Lei, Z. A survey of opinion mining and sentiment analysis. In *Mining Text Data*, 1st ed.; Charu, C.A., ChengXiang, Z., Eds.; Springer: New York, NY, USA, 2012; pp. 415–463.
11. Adwan, O.; Al-Tawil, M.; Huneiti, A.; Shahin, R.; Zayed, A.A.; Al-Dibsi, R. Twitter sentiment analysis approaches: A survey. *Int. J. Emerg. Technol.* **2020**, *15*, 79–93. [CrossRef]
12. Kulkarni, S.; Nadaph, A.; Narang, G. Survey on Twitter Sentiment Analysis using Supervised Machine Learning Algorithms. *Int. J. Res. Trends Innov.* **2022**, *7*, 2456–3315.
13. Tsytsarau, M.; Palpanas, T. Survey on mining subjective data on the web. *Data Min. Knowl. Discov.* **2012**, *24*, 478–514. [CrossRef]
14. Giachanou, A.; Crestani, F. Like it or not: A survey of Twitter sentiment analysis methods. *ACM Comput. Surv. (CSUR)* **2016**, *49*, 28. [CrossRef]
15. Pak, A.; Paroubek, P. Twitter as a corpus for sentiment analysis and opinion mining. In Proceedings of the Seventh International Conference on Language Resources and Evaluation, Valletta, Malta, 17–23 May 2010.

16. Swathi, T.; Kasiviswanath, N.; Rao, A.A. An optimal deep learning-based LSTM for stock price prediction using twitter sentiment analysis. *Appl. Intell.* **2022**, *52*, 13675–13688. [CrossRef]
17. Bose, D.; Aithal, P.S.; Roy, S. Survey of Twitter Viewpoint on Application of Drugs by VADER Sentiment Analysis among Distinct Countries. *Int. J. Manag. Technol. Soc. Sci.* **2021**, *6*, 110–127. [CrossRef]
18. Djenouri, Y.; Belhadi, A.; Srivastava, G.; Lin, J.C.W. Toward a Cognitive-Inspired Hashtag Recommendation for Twitter Data Analysis. *IEEE Trans. Comput. Soc. Syst.* **2022**, 1–10. [CrossRef]
19. A Step-By-Step Guide to Getting Started on Twitter. Available online: http://img.constantcontact.com/docs/pdf/getting-started-on-twitter.pdf (accessed on 16 March 2021).
20. Jose, A.K.; Bhatia, N.; Krishna, S. *Twitter Sentiment Analysis*; Seminar Report; National Institute of Technology Calicut: Kozhikode, India, 2010.
21. Kouloumpis, E.; Wilson, T.; Moore, J. Twitter sentiment analysis: The good the bad and the omg! In Proceedings of the International AAAI Conference on Web and Social Media, Barcelona, Spain, 17 July 2011.
22. Das, S.; Chen, M. Yahoo! for Amazon: Extracting market sentiment from stock message boards. In Proceedings of the Asia Pacific Finance Association Annual Conference, Bangkok, Thailand, 22–25 July 2001.
23. Tong, R.M. An operational system for detecting and tracking opinions in on-line discussion. In Proceedings of the Workshop on Operational Text Classification, Bangkok, Thailand, 22–25 July 2001.
24. Turney, P.D. Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. In Proceedings of the Association for Computational Linguistics, Philadelphia, PA, USA, 6 July 2002.
25. Pang, B.; Lee, L.; Vaithyanathan, S. Thumbs up? Sentiment classification using machine learning techniques. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, Philadelphia, PA, USA, 6 July 2002.
26. Nasukawa, T.; Yi, J. Sentiment analysis, Capturing favorability using natural language processing. In Proceedings of the Conference on Knowledge Capture, Sanibel Island, FL, USA, 23 October 2003.
27. Liu, Y.; Huang, X.; An, A.; Yu, X. ARSA: A sentiment-aware model for predicting sales performance using blogs. In Proceedings of the ACM SIGIR Conference on Research and Development in Information Retrieval, Amsterdam, The Netherlands, 23 July 2007.
28. McGlohon, M.; Glance, N.; Reiter, Z. Star quality: Aggregating reviews to rank products and merchants. In Proceedings of the International Conference on Weblogs and Social Media, Washington, DC, USA, 23–26 May 2010.
29. Chen, B.; Zhu, L.; Kifer, D.; Lee, D. What is an opinion about? Exploring political standpoints using opinion scoring model. In Proceedings of the AAAI Conference on Artificial Intelligence, Atlanta, GA, USA, 11 July 2010.
30. Yano, T.; Smith, N.A. What's Worthy of Comment? Content and Comment Volume in Political Blogs. In Proceedings of the International AAAI Conference on Weblogs and Social Media, Washington, DC, USA, 23–26 May 2010.
31. Blanco, G.; Lourenço, A. Optimism and pessimism analysis using deep learning on COVID-19 related twitter conversations. *Inf. Process. Manag.* **2022**, *59*, 102918. [CrossRef]
32. Ginossar, T.; Cruickshank, I.J.; Zheleva, E.; Sulskis, J.; Berger-Wolf, T. Cross-platform spread: Vaccine-related content, sources, and conspiracy theories in YouTube videos shared in early Twitter COVID-19 conversations. *Hum. Vaccines Immunother.* **2022**, *18*, 1–13. [CrossRef]
33. Lamsal, R.; Harwood, A.; Read, M.R. Twitter conversations predict the daily confirmed COVID-19 cases. *Appl. Soft Comput.* **2022**, *129*, 109603. [CrossRef]
34. Liu, B. *Sentiment Analysis and Opinion Mining*; Synthesis lectures on human language technologies; Morgan & Claypool Publishers: San Rafael, CA, USA, 2012.
35. Feldman, R. Techniques and applications for sentiment analysis. *Commun. ACM* **2013**, *56*, 82–89. [CrossRef]
36. Zhu, E.; Zhang, J.; Yan, J.; Chen, K.; Gao, C. N-gram MalGAN: Evading machine learning detection via feature n-gram. *Digit. Commun. Netw.* **2022**, *8*, 485–491. [CrossRef]
37. Santorini, B. *Part-of-Speech Tagging Guidelines for the Penn Treebank Project (3rd Revision)*; Technical Reports (CIS); University of Pennsylvania: Philadelphia, PA, USA, 1991.
38. Farooq, U.; Mansoor, H.; Nongaillard, A.; Ouzrout, Y.; Qadir, M.A. Negation Handling in Sentiment Analysis at Sentence Level. *J. Comput.* **2016**, *12*, 470–478. [CrossRef]
39. Behdenna, S.; Barigou, F.; Belalem, G. Sentiment analysis at document level. In Proceedings of the International Conference on Smart Trends for Information Technology and Computer Communications, Jaipur, India, 6 August 2016.
40. Schouten, K.; Frasincar, F. Survey on aspect-level sentiment analysis. *IEEE Trans. Knowl. Data Eng.* **2015**, *28*, 813–830. [CrossRef]
41. Medhat, W.; Hassan, A.; Korashy, H. Sentiment analysis algorithms and applications: A survey. *Ain Shams Eng. J.* **2014**, *5*, 1093–1113. [CrossRef]
42. Delgado, R. A semi-hard voting combiner scheme to ensemble multi-class probabilistic classifiers. *Appl. Intell.* **2022**, *52*, 3653–3677. [CrossRef]
43. Zheng, W.; Yin, L. Characterization inference based on joint-optimization of multi-layer semantics and deep fusion matching network. *PEERJ Comput. Sci.* **2022**, *8*, e908. [CrossRef] [PubMed]
44. Zheng, W.; Tian, X.; Yang, B.; Liu, S.; Ding, Y.; Tian, J.; Yin, L. A few shot classification methods based on multiscale relational networks. *Appl. Sci.* **2022**, *12*, 4059. [CrossRef]
45. Hosseini, S.; Ivanov, D. A multi-layer Bayesian network method for supply chain disruption modelling in the wake of the COVID-19 pandemic. *Int. J. Prod. Res.* **2022**, *60*, 5258–5276. [CrossRef]

46. Gupta, D.K.; Reddy, K.S.; Ekbal, A. Pso-asent: Feature selection using particle swarm optimization for aspect based sentiment analysis. In Proceedings of the International Conference on Applications of Natural Language to Information Systems, Passau, Germany, 17 June 2015.
47. Unler, A.; Murat, A. A discrete particle swarm optimization method for feature selection in binary classification problems. *Eur. J. Oper. Res.* **2010**, *206*, 528–539. [CrossRef]
48. Shang, L.; Zhou, Z.; Liu, X. Particle swarm optimization-based feature selection in sentiment classification. *Soft Comput.* **2016**, *20*, 3821–3834. [CrossRef]
49. Liu, Z.; Liu, S.; Liu, L.; Sun, J.; Peng, X.; Wang, T. Sentiment recognition of online course reviews using multi-swarm optimization-based selected features. *Neurocomputing* **2016**, *185*, 11–20. [CrossRef]
50. Onan, A.; Korukoğlu, S.; Bulut, H. A multiobjective weighted voting ensemble classifier based on differential evolution algorithm for text sentiment classification. *Expert Syst. Appl.* **2016**, *62*, 1–16. [CrossRef]
51. Basari, A.S.H.; Hussin, B.; Ananta, I.G.P.; Zeniarja, J. Opinion mining of movie review using hybrid method of support vector machine and particle swarm optimization. *Procedia Eng.* **2013**, *53*, 453–462. [CrossRef]
52. Kummer, O.; Savoy, J. Feature Weighting Strategies in Sentiment Analysis. In Proceedings of the First International Workshop on Sentiment Discovery from Affective Data, Bristol, UK, 24–28 September 2012.
53. O'Keefe, T.; Koprinska, I. Feature selection and weighting methods in sentiment analysis. In Proceedings of the 14th Australasian Document Computing Symposium, Sydney, NSW, Australia, 4 December 2009.
54. Chen, K.; Zhang, Z.; Long, J.; Zhang, H. Turning from TF-IDF to TF-IGM for term weighting in text classification. *Expert Syst. Appl.* **2016**, *66*, 245–260. [CrossRef]
55. Hu, L.; Gao, W.; Zhao, K.; Zhang, P.; Wang, F. Feature selection considering two types of feature relevancy and feature interdependency. *Expert Syst. Appl.* **2018**, *93*, 423–434. [CrossRef]
56. Dhillon, I.S.; Mallela, S.; Kumar, R. A divisive information-theoretic feature clustering algorithm for text classification. *J. Mach. Learn Res.* **2013**, *3*, 1265–1287.
57. Jiang, L.; Wang, D.; Cai, Z. Discriminatively weighted naive Bayes and its application in text classification. *Int. J. Artif. Intell. Tools* **2012**, *21*, 1250007. [CrossRef]
58. Zhang, L.; Jiang, L.; Li, C.; Kong, G. Two feature weighting approaches for naive Bayes text classifiers. *Knowl.-Based Syst.* **2016**, *100*, 137–144. [CrossRef]
59. Kim, S.B.; Han, K.S.; Rim, H.C.; Myaeng, S.H. Some effective techniques for naive bayes text classification. *IEEE Trans. Knowl. Data Eng.* **2006**, *18*, 1457–1466.
60. Jankowski, N.; Usowicz, K. Analysis of feature weighting methods based on feature ranking methods for classification. In Proceedings of the International Conference on Neural Information Processing, Shanghai, China, 13–17 November 2011.
61. Debnath, S.; Ganguly, N.; Mitra, P. Feature weighting in content based recommendation system using social network analysis. In Proceedings of the 17th International Conference on World Wide Web, Beijing, China, 21 April 2008.
62. Sun, Y. Iterative RELIEF for feature weighting: Algorithms, theories, and applications. *IEEE Trans. Pattern Anal. Mach. Intell.* **2007**, *29*, 1035–1051. [CrossRef]
63. Jiang, L.; Li, C.; Wang, S.; Zhang, L. Deep feature weighting for naive Bayes and its application to text classification. *Eng. Appl. Artif. Intell.* **2016**, *52*, 26–39. [CrossRef]
64. Liu, Y.; Loh, H.T.; Sun, A. Imbalanced text classification: A term weighting approach. *Expert Syst. Appl.* **2009**, *36*, 690–701. [CrossRef]
65. Deng, Z.H.; Luo, K.H.; Yu, H.L. A study of supervised term weighting scheme for sentiment analysis. *Expert Syst. Appl.* **2014**, *41*, 3506–3513. [CrossRef]
66. Deng, Z.H.; Tang, S.W.; Yang, D.Q.; Li, M.Z.; Xie, K.Q. A comparative study on feature weight in text categorization. In Proceedings of the Asia-Pacific Web Conference, Hangzhou, China, 14–17 April 2004.
67. Bibi, M.; Abbasi, W.A.; Aziz, W.; Khalil, S.; Uddin, M.; Iwendi, C.; Gadekallu, T.R. A novel unsupervised ensemble framework using concept-based linguistic methods and machine learning for twitter sentiment analysis. *Pattern Recognit. Lett.* **2022**, *158*, 80–86. [CrossRef]
68. Rodrigues, A.P.; Fernandes, R.; Shetty, A.; Lakshmanna, K.; Shafi, R.M. Real-time twitter spam detection and sentiment analysis using machine learning and deep learning techniques. *Comput. Intell. Neurosci.* **2022**, *2022*, 5211949. [CrossRef] [PubMed]
69. Verma, B.; Thakur, R.S. Sentiment Analysis Using Lexicon and Machine Learning-Based Approaches: A Survey. In Proceedings of the International Conference on Recent Advancement on Computer and Communication, Singapore, 12–13 October 2018.
70. Neviarouskaya, A.; Prendinger, H.; Ishizuka, M. Recognition of affect, judgment, and appreciation in text. In Proceedings of the 23rd International Conference on Computational Linguistics, Beijing, China, 23–27 August 2010.
71. Heerschop, B.; Goossen, F.; Hogenboom, A.; Frasincar, F.; Kaymak, U.; de Jong, F. Polarity analysis of texts using discourse structure. In Proceedings of the 20th ACM International Conference on Information and Knowledge Management, Glasgow, UK, 24–28 October 2011.
72. Moreo, A.; Romero, M.; Castro, J.L.; Zurita, J.M. Lexicon-based comments-oriented news sentiment analyzer system. *Expert Syst. Appl.* **2012**, *39*, 9166–9180. [CrossRef]
73. Balahur, A.; Hermida, J.M.; Montoyo, A. Detecting implicit expressions of emotion in text: A comparative analysis. *Decis. Support Syst.* **2012**, *53*, 742–753. [CrossRef]

74. Mohammad, S.M. From once upon a time to happily ever after: Tracking emotions in mail and books. *Decis. Support Syst.* **2012**, *53*, 730–741. [CrossRef]
75. Ortega, R.; Fonseca, A.; Montoyo, A. SSA-UO: Unsupervised Twitter sentiment analysis. In Proceedings of the Second Joint Conference on Lexical and Computational Semantics, Atlanta, GA, USA, 13–14 June 2013.
76. Reckman, H.; Baird, C.; Crawford, J.; Crowell, R.; Micciulla, L.; Sethi, S.; Veress, F. teragram: Rule-based detection of sentiment phrases using sas sentiment analysis. In Proceedings of the Second Joint Conference on Lexical and Computational Semantics, Volume 2: Seventh International Workshop on Semantic Evaluation, Atlanta, GA, USA, 14–15 June 2013; Association for Computational Linguistic: Stroudsburg, PE, USA, 2013; pp. 513–519.
77. Hu, X.; Tang, J.; Gao, H.; Liu, H. Unsupervised sentiment analysis with emotional signals. In Proceedings of the 22nd International Conference on World Wide Web, Rio de Janeiro, Brazil, 13 May 2013.
78. Saif, H.; He, Y.; Fernandez, M.; Alani, H. Contextual semantics for sentiment analysis of Twitter. *Inf. Process. Manag.* **2016**, *52*, 5–19. [CrossRef]
79. Feng, S.; Bose, R.; Choi, Y. Learning general connotation of words using graph-based algorithms. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, Edinburgh, UK, 27–31 July 2011.
80. Ravi, K.; Ravi, V. A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowl.-Based Syst.* **2015**, *89*, 14–46. [CrossRef]
81. Chen, L.S.; Liu, C.H.; Chiu, H.J. A neural network based approach for sentiment classification in the blogosphere. *J. Informetr.* **2011**, *5*, 313–322. [CrossRef]
82. Xia, R.; Zong, C.; Li, S. Ensemble of feature sets and classification algorithms for sentiment classification. *Inform. Sci.* **2011**, *181*, 1138–1152. [CrossRef]
83. Abdul-Mageed, M.; Diab, M.; Kübler, S. SAMAR: Subjectivity and sentiment analysis for Arabic social media. *Comput. Speech Lang* **2014**, *28*, 20–37. [CrossRef]
84. Abbasi, A.; France, S.; Zhang, Z.; Chen, H. Selecting attributes for sentiment classification using feature relation networks. *IEEE Trans. Knowl. Data Eng.* **2011**, *23*, 447–462. [CrossRef]
85. Prabowo, R.; Thelwall, M. Sentiment analysis: A combined approach. *J. Informetr.* **2009**, *3*, 143–157. [CrossRef]
86. Zhang, L.; Ghosh, R.; Dekhil, M.; Hsu, M.; Liu, B. *Combining Lexicon-Based and Learning-Based Methods for Twitter Sentiment Analysis*; Technical Report HPL-2011-89; Hewlett-Packard Development Company: Palo Alto, CA, USA, 2011.
87. Ghiassi, M.; Skinner, J.; Zimbra, D. Twitter brand sentiment analysis: A hybrid system using n-gram analysis and dynamic artificial neural network. *Expert Syst. Appl.* **2013**, *40*, 6266–6282. [CrossRef]
88. Khuc, V.N.; Shivade, C.; Ramnath, R.; Ramanathan, J. Towards building large-scale distributed systems for Twitter sentiment analysis. In Proceedings of the 27th Annual ACM Symposium on Applied Computing, Trento, Italy, 26–30 March 2012.
89. Khan, F.H.; Bashir, S.; Qamar, U. TOM, Twitter opinion mining framework using hybrid classification scheme. *Decis. Support Syst.* **2014**, *57*, 245–257. [CrossRef]
90. Speriosu, M.; Sudan, N.; Upadhyay, S.; Baldridge, J. Twitter polarity classification with label propagation over lexical links and the follower graph. In Proceedings of the First Workshop on Unsupervised Learning in NLP, Edinburgh, UK, 30 July 2011.
91. Cui, A.; Zhang, M.; Liu, Y.; Ma, S. Emotion tokens: Bridging the gap among multilingual twitter sentiment analysis. In Proceedings of the Asia Information Retrieval Symposium, Dubai, United Arab Emirates, 18–20 December 2011.
92. Cambria, E.; Mao, R.; Han, S.; Liu, Q. Sentic parser: A graph-based approach to concept extraction for sentiment analysis. In Proceedings of the 2022 International Conference on Data Mining Workshops, Orlando, FL, USA, 30 November–3 December 2022.