Word Segmentation and Sentiment Word Categorization Using Feature Extraction – a Novel Framework

S. Ashika Parvin and M. Sumathi

July 11, 2021

Word Segmentation and Sentiment Word Categorization using Feature Extraction – A Novel Framework

*S.Ashika Parvin[1], M.Sumathi [2]
[1]Sri Meenakshi Government Arts College for Women(A), Madurai,India
[1*]parvinashika@gmail.com
[2]Sri Meenakshi Government Arts College for Women(A), Madurai,India
[2]sumathivasagam@gmail.com

* S.Ashika Parvin
Abstract. Sentiment analysis (SA) is essential for classifying people's thoughts about whatever they submit as reviews online. Because the content on these media is unstructured, the segmentation of the sentiment word, which is critical for detecting attitudes, must be done properly to overcome the problem of missing data, which can lead to erroneous criticism classifications and render the SA approach useless. This study provides a novel approach for automatically segmenting the sentiment word in order to categorise the sentiment of "reviews." This framework contains a pre-processing technique, feature extraction with characteristics such as Terms of presence and frequency (TPF), Parts of speech (POS), Opinion words and phrases (OWP), and Negations, and word segmentation using the RBDT algorithm. Experiments show that our proposed techniques are successful and efficient in segmenting the words necessary for sentiment classification without incurring data loss, with 92% accuracy and a time complexity of 0.0008 ms. Furthermore, with a time complexity of only 0.0006ms, the classification of sentiment words obtained excellent accuracy of 94%

Keywords: **:** Sentiment analysis (SA),data pre-processing, feature extraction, Terms of presence and frequency(TPF), Parts of speech (POS), Opinion words and phrases(OWP), Negations, Segmentation, RBDT algorithm.

1 Introduction

Web 2.0's fast growth has resulted in users creating huge volumes of content online in the shape of views, blogs, tweets, and other forms. This cornucopia of data contains consumer feedback on events, goods, and people. It gives businesses and organizations new ways to better understand their customers, improve product quality, and increase their competitiveness [1]. The study of people's views, sentiments, opinions, perceptions, and emotions based on social media data is known as sentiment analysis, or opinion mining. These topics are more likely to be discussed in reviews. Examining product reviews on the internet to determine how a thing makes you feel or what your overall impression is known as sentiment analysis in reviews [2]. The goal of sentiment analysis is to find new points of view, figure out what emotions they represent, and then categorise them according to their polarity. Sentiment Analysis is a method that may be used to classify data.

Opinion extraction, analysis, categorization, scalability, and summarization are all aspects of an opinion mining system. The initial step in the opinion mining process is to extract all of the views once the user has loaded them all. Each new phase is dependent on the preceding one, and the outcome of the previous step is utilized as an entry in the following step. The first stage is opinion gathering, which lays the groundwork for all subsequent stages. If extraction proves to be ineffective, the method for mining opinions will get modified, and all the extracted characteristics will be not topic-related. [3].

The first stage in sentiment classification is to pre-process the text; this approach turns unstructured internet information with noise into a format that can be classified. Tokenization, stop word removal, lower case conversion, and number removal are all part of the pre-processing procedure. The dataset was pre-processed in one of our earlier papers, which may be found here [4]. The term is then segmented using approaches like Term presence and frequency (TPF), Parts of speech (POS), Opinion words and phrases (OWP), and Negations. The RBDT technique is then used to find the words necessary for sentiment categorization, with no missing data. The segmented words are then divided into five groups: interested, uninterested, sad, happy, and angry.

This study focuses on the problems that emerge while using SA techniques, and an innovative framework is proposed as a solution to the problems stated below.When assessing sentiments, data contains a lot of false information that has to be eliminated. The problem here is deciding which data should be preserved and which should be discarded. The answer might be that all of the data is useful, but just a few are crucial for classifying the clients' feelings. Rather than having all of the information and erroneously categorising the sentiments, just those facts that are irrelevant should be eliminated from classification. Due to a lack of information, inappropriate emotions may be expressed.

As a result, the major goal of this study is to ensure that data is not ignored throughout the categorization process in order to avoid misclassifications of sentiments. The ineffectiveness of the SA process can be attributed to a misunderstanding of emotions To correct the error, a framework has been proposed that pre-processes, segments the sentiment word from the features by gathering all of the sentiment words from the classification table and pruning using the RBDT algorithm with high weighted words to accurately classify the necessary sentiment word rather than having all of the words together.

The other sections of the study are organised as follows: Section II deals with existing literature approaches in the SA field, Section III with suggested method, Section IV with observational data, and Section V with the research's conclusion.

2 Methodology for Literature Review

This section provides an overview of relevant feature extraction work in Sentiment Analysis. We looked at over sixty articles and divided them into categories based on their major approaches and contributions. The methodology of the survey is divided into three categories : 1) Methodology adopted for conducting the survey and 2) Relevant works in the field of SA. This section presents the major feature extraction and modification procedures and approaches identified in the cited papers.Finally, 3) illustrates the motivation to choose this research area and the answer has been justified.

2.1 Methodology of Conducting the Survey

The creation of a clear grasp of our aims should precede a deep dive into the literature. The goal of this study is to demonstrate why it is critical to properly divide the sentiment word. As a result, in section VI, we've clearly framed the questions and described their repercussions in full. The following are the questions that have been formulated:

1. Why is word segmentation necessary?
2. What algorithms were utilized to do the word segmentation?
3. How effective are the results obtained through the use of algorithms?

We compiled a list of all connected publications that answered our research questions using appropriate journal articles. Conference proceedings, books, chapters, survey studies, and other sorts of papers were examined as part of the study. The search terms were "Segmentation in Sentiment Analysis," "word segmentation technique in sentiment analysis," "Feature Extraction in Sentiment Analysis," or a combination of these terms. Alternative additions include the following: 1) Publication in peer-reviewed journals 2) The text is written in English. 3) All articles published in journals in the previous 20 years (from 2001 to 2021).

2.2 Text Segmentation

Text segmentation is an important part of natural language processing. Depending on the level of granularity, the task might be described as segmenting a text into subject pieces or a statement into primitive discourse units[5]. We concentrate on state-of-the-art feature extraction paradigms for sentiment analysis in this paper.

Feature Extraction: Feature-based sentiment analysis [6] includes feature extraction, sentiment prediction, sentiment classification, and optional summarization modules. Feature Extraction deals with the prediction of product features that consumers have remarked on, sentiments related to the products are obtained by the sentiment prediction by assessing the polarity of the sentiments into either positive or negative, and finally the work of compiling the results obtained from the previous two phases are done by summarization module.

Term Presence and Term Frequency (TPF): People are more interested in frequent product features, often known as hot features [6]. In text mining, association rule mining or frequent pattern mining is done using Apriori algorithm [7], is frequently utilized. In conventional Information Retrieval and Text Classification tasks, term frequency has long been deemed crucial. However, Pang-Lee discovered that term presence is more relevant than term frequency in Sentiment analysis. That is, feature vectors with binary values indicating whether a word exists (value 1) or not (value 0) [9].

Part of Speech (POS): To assess a phrase for sentiment properly, it must be split down into components utilising various sub-processes, including POS-tagging, as briefly shown here. Part of Speech tagging [8] is identifying the most important elements of a text, such as verbs, pronouns, adjectives, and adverbs to retain sentence structure and make it obvious which part of speech the word belongs to. After the tokenization procedure, but before the removal of any words(stop words removal) , the POS must be tagged. [10].

Opinion words and Phrases (OWP): Words or phrases that communicate good or negative feelings are referred to as sentiment words and phrases. Good, wonderful, outstanding, excellent, and brilliant, for example, have a positive connotation, whereas terrible, dull, slow, worst, and poor have a negative connotation. Though adjectives and adverbs make up the majority of opinion words, nouns and verbs can also express an opinion. In certain texts, words like garbage (noun), hate (verb), and like (verb) can express a point of view [11].

***Negations* :** Negations are crucial in linguistics because they influence the polarity of other words. Words like no, not, and shouldn't are examples of negatives. When a negation appears in a sentence, it's critical to figure out which words are affected by this phrase. The scope of negation can be confined to the next word after the negation, or it can be expanded to include further words after the negation[12]. Negation processing, which affects virtually every context or domain, since neglecting negations can lead to erroneous implications or false interpretations [13].

2.3 Motivation and Justification

In the twenty-first century, social media sites can collect massive amounts of data. People communicate their thoughts and opinions with the rest of the world via social media platforms such as Twitter, Facebook, and others. In this competitive climate, companies utilize the same technique to understand their market position. Thoughts or assessments are used to communicate feelings, which helps businesses come up with a variety of more enticing offers. Unwanted records may also exist in the views, which must be pre-processed in a timely manner. Text segmentation or word segmentation is necessary after data pre-processing to identify the correct sentiment word, and only then can the mis-classification problem be rectified. As a consequence, I suggest that word segmentation has to be improved because it causes sentiment misclassifications.

An unique approach is presented in this study with the objective of resolving the research problem of missing crucial data while segmenting a word from a sentence. The recommended approach takes considerable care in data segmentation, guaranteeing that no data is lost. this framework considers all sorts of words, short and long, and employs the aforementioned features to generate all weighted words, which are then put through the RBDT algorithm [4] to get segmented sentiment words, which are then classified into one of five categories. The section III delves into the structure in further depth**.**

3 Proposed Methodology

The suggested sentiment word segmentation phases are depicted in Fig. 1, which are utilised to carry out the whole segmentation procedure.

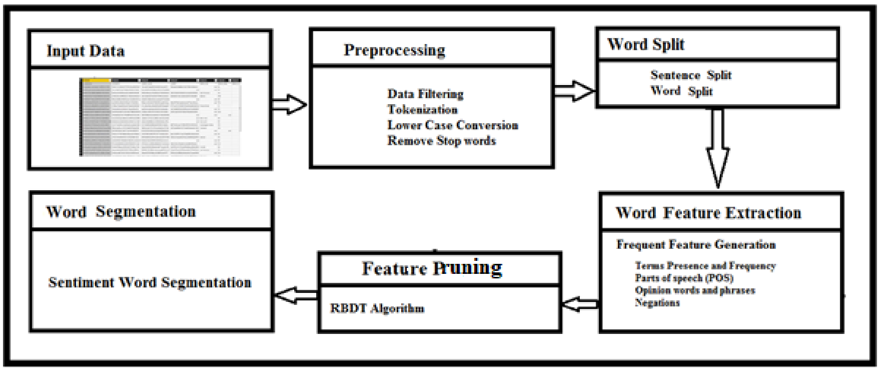

Fig.1 Framework of the Proposed Sentiment Word Segmentation

3.1 Data Description

The sentiment word segmentation and categorization dataset was taken from Kaggle, an open source platform. It contains 1000 records of Amazon reviews, as well as data for training and testing. The link to the webpage may be found here: https://www.kaggle.com/bittlingmayer/amazonreviews.

3.2 Word Feature Extraction

The following are the feature extraction techniques used in this paper**.**

TPF: It's the most basic approach to express features, and it's widely used in both information retrieval and sentiment analysis. As features, it counts the frequency of individual sentences or a list of n sequential phrases in the shape of a n - grams [14].In traditional text classification jobs, it is regarded as critical. However, term presence is more significant than term frequency in sentiment analysis since the presence of a single phrase can occasionally affect the polarity of the entire sentence. The words are either binary weighted or called frequency weights [15]. In addition, frequency weights are used to reflect a word's relative importance. This characteristic is used in our suggested technique to calculate both the existence and frequency of a word before assigning a weight to it. Similarly, the whole dataset was analyzed, and the number of words counted by this characteristic was tabulated for future analysis.

POS: Finding descriptive words/adjectives in the material since they are key point of view identifiers. The meaning of subjective words must be captured in order to properly classify texts by emotion. Adjectives (words like "excellent," "horrible," "awful," "amazing," and so on) are often used to forecast mood. Subjective text analysis and SA research [16, 17, 18, 19, 20, 21] support this viewpoint. Nouns [21, 22], verbs [20, 21], and adverbs [17, 21, 23] are other open Parts-of-Speech (POS) categories that have been related to SA. Each word's syntactic role in a phrase has an impact on how it is interpreted. Components of speech are another name for syntactic roles. The verb, the noun, the pronoun, the adjective, the adverb, the preposition, the conjunction, and the interjection are the eight parts of speech in English. Nouns and pronouns, for example, are typically devoid of sentiment in our proposed technique. When used as an adjective, distinguishing words that may be used in multiple parts of speech, for as "enhanced" as a verb, may have a distinct amount of sentiment, thus these circumstances should be treated with caution. The final word count for this feature is recorded for future trimming.

OWP: Words and phrases that communicate good or negative feelings are known as opinion words (or sentiment words). Regular opinions might be expressed in a direct or indirect manner. For example, Quality of the book is excellent. It directly refers to a feature of "book quality" in this case, implying a direct opinion."My skin absolutely broke out after using the lotion."In this case, the entity "cream" is used to indicate a negative judgement of the attribute "skin." It's easier to digest direct opinions. To determine the polarity of indirect opinions, one must be familiar with the data source domain. Unlike regular opinions, they may express different opinions for same entity There are two types of comparative opinions: explicit and implicit. Explicit comparisons are easy to analyse since they offer a single, positive or negative judgement. For example, Intel 5 has a faster CPU than Intel 3. The element of CPU speed is specifically contrasted here, and Intel 5 comes out on top. The term "implicit comparison" refers to an objective statement in which opinions are expressed in an indirect and oblique manner. For example, programme x takes longer to execute than programme y. In this case, a longer execution time indicates that programme x's performance is inferior to programme y's. As a result, an unfavourable view about programme x is conveyed. This feature collects all of the opinion words that are either explicitly or implicitly known in this suggested approach, and weights are assigned to these terms. The words that were counted based on weights are then tabulated for the trimming procedure.

Negations: Negation scopes are difficult to detect because they are latent, unobservable, and extremely subjective, even among specialists . Anecdotal data shows that even for very basic phrases, this can result in divergences. In the sentence "this mobile is not nice but it functions correctly," for example, the scope of negative is only limited to the next word after negation. The scope of negation is extended to the conclusion of the phrase in another sentence, as in “the battery does not work for a long time.” These examples show how the scope of negation varies based on linguistic features like as conjunctions, punctuation marks, and the negation's part of speech (POS), among others. Furthermore, the presence of a negation phrase does not guarantee that the entire sentence's polarity-carrying words will be inverted. The two forms of negation are clear negation (with obvious indicators such as not, no, etc.) and implicit negation. At the highest structural level, there are two types of negations: morphological and syntactic negations. A suffix (e.g., ir-, non-, un-, etc.) or a prefix (e.g., ir-, non-, un-, etc.) modifies the root word (e.g. -less). In syntactic negations, explicit negation signals are used to flip a single word or a series of words. Negations may occur implicitly in complex settings, such as irony, without the presence of explicit words in the sentence. In this recommended technique, which analyses all types of negations, the words are gathered and tallied.

3.3 Feature Pruning

Pruning the feature set for emotion categorization on a sentence-by-sentence basis may result in the loss of critical information for new instance classification and the omission of uncommon features (multiple occurrences). As a result, for accurate prediction, the model must be capable of identifying strong opinion sentences concerning the relationship between the features of each category, as well as adjust the weights of less frequently used features in order to expand the opinion indicators of sentiments with strong indications. For this aim, RBDT algorithm was introduced in our prior paper for efficient sentiment word segmentation.

RBDT algorithm: This algorithm has been proposed by this author which can be found here [4].The main advantage of this algorithm is that it combines the advantages of Rule Based (Apriori) and Decision Tree algorithms into a single algorithm rather than utilizing them individually. There are no data holes since every sort of word is considered, whether it is short or lengthy. The term is predicted with a high accuracy of 90% and minimal time complexity, and no data in the supplied input text is missing. The final phase in the framework described in this study is feature pruning, which is accomplished using this algorithm by gathering the amount of words extracted by feature extraction algorithms. With a high accuracy of 92% and a low time complexity of 0.0008 ms, the pruning is done in such a way that just sentiment words are segregated without any data loss.

The pseudocode for this framework has been stated below:

Input: Text Data (TD)

Output: Segmented Sentimental Words (SSW) are collected

Step 1: Input Text Data (TD)

Step2: RNV= Extra characters and Numerical values from the supplied text are removed.

Step3: RSW= RNV's stop words are removed.

Step4: SW= RSW's words are splitted

Step5: EF=**Proposed** Extract the Features from SW

Step6: SWE= Feature Pruning from EF based on RBDT method

Step7: SSW=Extract Segmented Sentimental words from SWE

4 Experimental Analysis

4.1 Word Segmentation Accuracy

The words are gathered independently from the tabulation from all of the above-mentioned features. The algorithms then prunes these data such that just the necessary sentiment words are identified, eliminating all other data. This procedure is carried out with great care to ensure that no data is overlooked. With a sample of 20 input text files, the experimental findings are reported in Fig.2. Our suggested framework has obtained excellent accuracies in segmenting the emotion words, as shown in Fig.2.

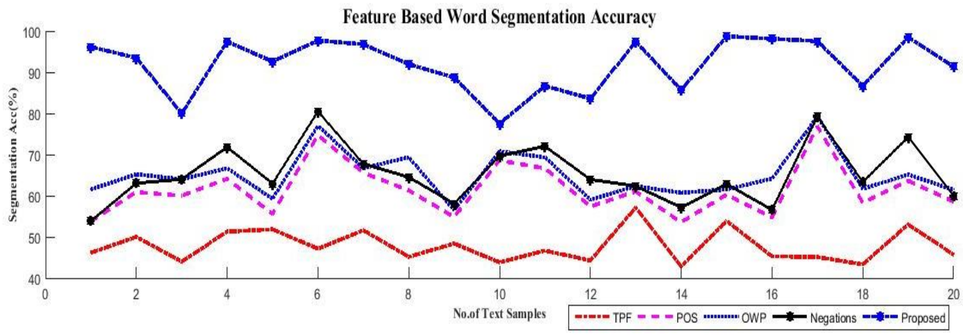

Fig.2 shows the Word Segementation Accuracy rates in % using features

4.2 Sentiment word Categorization

Following the RBDT algorithm's sentiment word trimming, the sentiment words are classified into one of five categories: interested, not-interested, happy, sad, or angry. In the Table.1, the number of words categorised into categories are summarised for only 3 input text files . This procedure is demonstrated for each of the above-mentioned groups. Table.1 shows that the suggested technique has achieved excellent accuracies in sentiment word categorization.

Table.1 shows the Percent Accuracy of Sentiment Word Categorization

Samples	TPF	POS	OWP	Negations	Proposed
			Interested		
Text 1	46.15	53.85	61.54	53.85	96.15
Text 2	51.61	65.59	66.67	67.74	96.77
Text 3	45.16	61.29	69.35	64.52	91.94
			Happy		
Text 1	50.00	60.87	65.22	63.04	93.48
Text 2	51.28	64.10	66.67	71.79	97.44
Text 3	43.82	68.54	70.79	69.66	77.53

			Not Interested		
Text 1	44.00	60.00	64.00	64.00	80.00
Text 2	44.26	57.38	59.02	63.93	83.61
Text 3	57.14	61.04	62.34	62.34	97.40
			Sad		
Text 1	51.85	55.56	59.26	62.96	92.59
Text 2	47.13	74.71	77.01	80.46	97.70
Text 3	53.85	60.26	61.54	62.82	98.72
			Anger		
Text 1	46.67	66.67	69.33	72.00	86.67
Text 2	53.03	63.64	65.15	74.24	98.48
Text 3	44.62	70.77	78.46	73.85	89.23

4.3 Overall Performance

Table.2 shows the overall accuracy rates in % and the time complexity of the word segmentation procedure for the whole dataset. The findings reveal that the proposed framework segmented the sentiment word with 92 % and a time complexity of just 0.0008ms.

Table.2 shows the Overall Accuracy Rates in % and Time Complexity (ms) of Sentiment Word Segmentation

Measurement	TPF	POS	OWP	Negations	Proposed
Word Segmentation (%)	47.90	61.86	65.76	66.09	**91.96**
Time Complexity (ms)	0.0012	0.0177	1.0793	0.0416	**0.0008**

In terms of accuracy rates in percent, the overall classification of emotion words in each of the five categories is given in Fig.3. The results reveal that the category of sad emotion words has a high accuracy rate of 94%, whereas the category of not interested emotion words has a low accuracy rate of 89%.

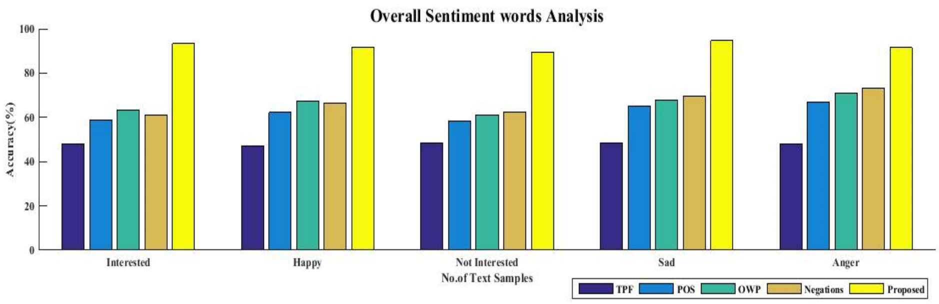

Fig.3 shows the Overall Sentiment Word Accuracy rates in %

Finally, a Table.3 depicts the overall time complexity of sentiment word classification. The findings reveal that the category of angry and interested has a low time complexity of 0.0006 ms and the category of not-interested has a high time complexity of 0.0010 ms.

Table.3 shows the Overall Time Complexity for Sentiment Word categorization in ms

Sentiments	TPF	POS	OWP	Negations	Proposed
Interested	0.0008	0.0156	0.8931	0.0348	**0.0006**
Happy	0.0008	0.0197	0.7396	0.0573	0.0008
Not Interested	0.0009	0.0173	1.1301	0.0478	**0.0010**
Sad	0.0024	0.0172	1.6576	0.0326	0.0007
Anger	0.0009	0.0176	1.0549	0.0168	**0.0006**

5 Conclusion

The segmentation process is the difficult task in the sentiment analysis which is an open challenge for the upcoming researchers can still contribute to this research area. To overcome our research problem, a unique framework has been proposed for the purpose of both sentiment word segmentation and classifying the sentiment words according to their category. There are five categories used in this paper where the experiment results shows that the proposed framework outperforms in all the aspects in segmenting the sentiment word effectively rather than using the feature extraction method individually. Then the classification of sentiment words are also done effectively in such a way that no data is missed in the given input text files. Experiments show that our proposed techniques are successful and efficient in segmenting the words necessary for sentiment classification without incurring data loss, with 92% accuracy and a time complexity of 0.0008 ms. Furthermore, with a time complexity of only 0.0006ms, the classification of sentiment words obtained excellent accuracy of 94%\

References

1. Zhi-Hong Deng, Kun-Hu Luo, Hong-Liang Yu,: A Study of Supervised Term Weighting Scheme For Sentiment Analysis. Expert Systems with Applications: An International Journal. Volume 41, Issue 7, pg.3506-3513, June (2014).
2. Ming Hao, ChristionRohrdantz, HalldorJanetzko,: Integrating Sentiment Analysis and Term Associations with Geo-Temporal Visualizations On Customer Feedback Streams. In SPIE Proceedings.Vol. 8294, 25 January (2012).
3. RamandeepSandhu, Rahul Mehta,: Applying Opinion Mining to Organize Web Opinions. International Journal of Computer Science, Engineering and Applications (IJCSEA). Volume 1, No. 4, pg.82-89, August (2011).
4. M. Sumathi and S. A. Parvin,: Nuances of Data Pre-Processing and its Impact on Business. In 5th International Conference on Intelligent Computing and Control Systems (ICICCS). pp. 1006-1012, doi: 10.1109/ICICCS51141.2021.9432376,(2021).

5. J. Li, B. Chiu, S. Shang and L. Shao,: Neural Text Segmentation and Its Application to Sentiment Analysis. In IEEE Transactions on Knowledge and Data Engineering. doi: 10.1109/TKDE.2020.2983360, (2020)
6. Hu, M., and Liu, B,: Mining Opinion Features in Customer Reviews. AAAI'04, (2004).
7. R. Agrawal and R. Srikant, :Fast algorithms for mining association rules. In 20th Int. Conf of Very Large Data Bases, VLDB. 1215:487–499, (1994).
8. What is Sentiment Analysis and How Does it Work? (bitext.com)
9. Mukund Shenoy K, P Sameer Varma, P Sameer Varma, Sachinkumar Kulkarni,: Sentiment Analysis. A Project Report Submitted To The National Institute Of Engineering. (2014).
10. A Game of Words: Vectorization, Tagging, and Sentiment Analysis | by Madeline McCombe | Towards Data Science
11. Chandra Sekhar Reddy Mukkarapu , Dr V.Jaya Rama Krishnaiah Vemula,: Opinion Mining and Sentiment Analysis: A Survey. International Journal of Advanced Trends in Computer Science and Engineering. Vol.3, No.5, Pages : 498- 502 (2014).
12. Umar Farooq, Hasan Mansoor, Antoine Nongaillard, Yacine Ouzrout, Muhammad Abdul Qadir,: Negation Handling in Sentiment Analysis at Sentence Level. Journal of Computers. Volume 12, Number 5, doi: 10.17706/jcp.12.5.470-478, September (2017).
13. Nicolas Pröllochs, Stefan Feuerriegel, Bernhard Lutz, Dirk Neumann,: Negation scope detection for sentiment analysis: A reinforcement learning framework for replicating human interpretations. Information Sciences. Volume 536,Pages 205-221,ISSN 0020-0255,https://doi.org/10.1016/j.ins.2020.05.022, (2020).
14. Marouane Birjali, Mohammed Kasri, Abderrahim Beni-Hssane, : A comprehensive survey on sentiment analysis: Approaches, challenges and trends. Knowledge-Based Systems.Volume226, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2021.107134, (2021).
15. ChetanKaushik, AtulMishra,: Comparative Analysis of Sentiment Analysis Techniques. ITSI Transactions on Electrical and Electronics Engineering (ITSI-TEEE). Volume -2, Issue -1, ISSN (PRINT) : 2320 – 8945, (2014).
16. J. M. Wiebe,: Learning subjective adjectives from corpora. In Proceedings of the National Conference on Artificial Intelligence. pp. 735-741,(2014)
17. V. Hatzivassiloglou and J. M. Wiebe,: Effects of adjective orientation and gradability on sentence subjectivity. In Proceedings of the 18th Conference on Computational Linguistics. Volume 1, pp. 299-305, (2000).
18. V. Hatzivassiloglou and K. R. McKeown,: Predicting the semantic orientation of adjectives. In Proceedings of the Eighth Conference on European Chapter of the Association for Computational Linguistics. pp. 174-181, (1997).
19. M. Hu and B. Liu,: Mining opinion features in customer reviews. In Proceedings of the National Conference on Artificial Intelligence. pp. 755-760, (2004).
20. P. Chesley, B. Vincent, L. Xu and R. K. Srihari,: Using verbs and adjectives to automatically classify blog sentiment. AAAI Spring Symposium on Computational Approaches to Analysing Weblogs (AAAI-CAAW 2006). vol. 580, pp. 233, (2006).
21. J. Yi, T. Nasukawa, R. Bunescu, W. Niblack, I. B. M. A. R. Center and C. San Jose,: Sentiment analyzer: Extracting sentiments about a given topic using natural

language processing techniques. In Third IEEE International Conference on Data Mining (ICDM 2003). pp. 427-434, (2003).

22. E. Riloff, J. Wiebe and T. Wilson,: Learning subjective nouns using extraction pattern bootstrapping. In Proceedings of the 7th Conference on Natural Language Learning (CoNLL-2003). pp. 25–32, (2003).
23. F. Benamara, C. Cesarano, A. Picariello, D. Reforgiato and V. Subrahmanian,: Sentiment analysis: Adjectives and adverbs are better than adjectives alone. In Proceedings of the International Conference on Weblogs and Social Media (ICWSM), (2007).