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Sentiment Analysis in the Era of Web 2.0: Applications, Implementation Tools and Approaches for the Novice Researcher

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Nowadays, people find it easier to express opinions via social media-formally known as Web 2.0. Sentiment analysis is an essential field under natural language processing in Computer Science that deals with analyzing people's opinions on the subject matter and discovering the polarity they contain. These opinions could be processed in collective form (as a document) or segments or units as sentences or phrases. Sentiment analysis can be applied in education, research optimization, politics, business, education, health, science and so on, thus forming massive data that requires efficient tools and techniques for analysis. Furthermore, the standard tools currently used for data collection, such as online surveys, interviews, and student evaluation of teachers, limit respondents in expressing opinions to the researcher's surveys and could not generate huge data as Web 2.0 becomes bigger. Sentiment analysis techniques are classified into three (3): Machine learning algorithms, lexicon and hybrid. This study explores sentiment analysis of Web 2.0 for novice researchers to promote collaboration and suggest the best tools for sentiment data analysis and result efficiency. Studies show that machine learning approaches result in large data sets on document-level sentiment classification. In some studies, hybrid techniques that combine machine learning and lexicon-based performance are better than lexicon. Python and R programming are commonly used tools for sentiment analysis implementation, but SentimentAnalyzer and SentiWordnet are recommended for the novice.

Keywords: Sentiment Analysis, Web 2.0, Applications, Tools, and Novice.

1. Introduction

Web 2.0, popularly known as social media, encourages people to share knowledge, thoughts, views on social, political, economic and other matters. Social media platforms such as Facebook, Twitter, blogs, forums, wikis, review sites and likes, provide such means for sentiments expression for both individuals and groups (Mukhtar, Khan, and Chiragh 2018). This implies that Web 2.0 has significantly transformed peoples' interactions. Thus, influencing their social, political and economic perception of things. Freedom of expression, availability of smartphones and cheapness of data bundles have made Web 2.0 accessible and promising to everyone, having a voice to boost human collaboration capabilities globally. Individuals can share opinions through user's generated content. Such opinions gather to form big data set, which requires efficient tools and approaches for analysis for managerial decisions. These tools and approaches could be effectively used to understand sentiment analysis properly.

Sentiment analysis is a new field in Computer Science under Natural Language Processing (NLP), aiming at detecting subjectivity in text from different sources (Mukhtar, Khan, and Chiragh 2018).

Sentiment analysis is also called opinion mining (Prakash and Aloysius 2020) and (Ahmad et al. 2017). Sentiment analysis proves to be effective in analyzing big data people's opinions collected from Web 2.0 on political matters, education, health (Prakash and Aloysius 2020). As such, students, teachers, academics and likes do create social media accounts for collaboration, orientation and data collection for research work. Consequently, peoples' opinions collected via social media platforms amount to a vast data set-making it challenging to analyze using traditional tools. This implies the need for special tools and approaches for efficient and accurate analysis of people's opinions. And this is the work of sentiment analysis. The polarity of an opinion could be positive, negative or neutral. Polarity is a sentiment analysis that examines people's feelings, opinions, attitudes, evaluations, assessments, and emotions about services, goods, individuals, organizations, issues, themes, and events, as well as their characteristics. (Archana and Kishore 2017).

This work aims to provide a novice researcher with a fundamental acquaintance on tools, approaches and applications of Sentiment analysis concerning the emergence of Web 2.0 in collecting peoples' opinions. However, this work has the following objectives:

- To introduce sentiment analysis as a research area in computer science for novice researchers.
- To explore methods, tools and approaches suitable for sentiment analysis of Web 2.0.
- To highlight some of the applications of Sentiment Analysis for collaborative research.

The scope of this study is sentiment analysis for the novice researcher, specifically from social media data (Facebook, WhatsApp and Twitter) on two sentiment classes/polarities: positive and negative. The language used for collecting the sentiment is the English language. However, the study has the following limitations:

- Cannot provide a solution for the ambiguity in natural languages
- Subjectivity classification is considered out of scope
- Other forms of data such as audio, video and image data are not covered.

2. Problem Background

Sentiment analysis deals with categorizing people's thoughts from various sources, such as social media and extracting their polarity. Positive, harmful, or neutral polarity is represented by +1, 0 and -1, respectively. (Mukhtar, Khan, and Chiragh 2018).

There are many studies on sentiment analysis of Web 2.0, especially Facebook and Twitter. Still, most of them are meant for researchers in Computer Science with a good background in sentiment analysis((Andrea, Ferri, and Grifoni 2015). Moreover, most of these articles are broad and too comprehensive for a novice in other fields of study to comprehend quickly. Consequently, this study intended to provide novice researchers from another discipline with the basic knowledge of sentiment analysis for collaborative work. Web 2.0 is chosen for novice researchers because of its popularity and ease of use with less restriction in expressing opinions.

This study explores reviews on sentiment analysis of Web 2.0, Sentiment analysis, the suggestion of best tools, techniques and approaches for the novice researchers to develop their interest in this area for teamwork.

Sentiment analysis domain includes social, online reviews, media and product, movie, news, political, stock and financial (refer to the business domains). But its commonly used domain is social media, as reported by (Prakash and Aloysius 2020). Studies show that the traditional tools currently used for data collection (online surveys, students evaluation of Teachers, etc.) and analysis are time-consuming, restrict user freedom of expression, and lack accuracy as data becomes bigger (Stieglitz et al., 2018). Machine learning approaches tend to give better results regarding large data sets on document-level sentiment classification. Hybrid techniques combine machine learning and lexicon-based and perform better than lexicon(Prakash and Aloysius 2020).

The standard tools currently used for data collection(online survey) and analysis limit respondents in the expression of opinions (unlike the Web 2.0 that allows faster reaction with good efficiency) to the researcher's surveys and could not generate massive data called big data as the one produced by Web 2.0 (Stieglitz et al. 2018).

Sentiment Analysis performs mainly two tasks: classification and prediction(Aldowah, Al-Samarraie, and Fauzy 2019). Therefore, this study focuses on classification.

3. Methodology

The proposed work of this study is to introduce sentiment analysis to novice researchers concerning Web 2.0. Therefore, the methodology here comprises reviews on sentiment analysis, classification criteria, the suggestion of suitable tools, approaches and techniques for the novice researcher.

According to Andrea et al. (2015), Sentiment analysis classifies sentiments or opinions (specifically in text form) based on the following criteria:

- the polarity (positive, negative, or neutral) of the expressed sentiment;
- the outcome's polarization (e.g., improvement versus death in medical texts)
- express your opinion on a topic by agreeing or disagreeing (e.g., political debates)

- whether it's right or wrong
- positive or negative feedback
- Pros or cons

The first sentiment criterion above is suggested for the novice: i.e., polarity-*Positive, Negative* or Neutral (Srividya & Sowjanya, 2017) and (Umar et al., 2020). These authors conducted sentiment analysis work on small data is in English using two sentiment classes, namely positive and negative.

Sentiment analysis is a multi-step procedure that analyzes sentiment data in five ways (Andrea, Ferri, and Grifoni 2015). These steps are:

- data collection: the initial stage in sentiment analysis is to gather information from user-generated content on blogs, forums, and social media sites. There are also benchmark data set from UCI, Kaggle, IMDB and likes(Kotzias et al. 2015) for sentiment analysis. However, for novice researchers,s social media data, especially from WhatsApp, Facebook, and Twitter, are easier to collect sentiments than online surveys.

- Text preparation: this entails cleaning the data before analyzing it. Contents that aren't textual and aren't related to the analysis are identified and removed;

- Sentiment analysis: extracting phrases from reviews and remarks. Contents that aren't textual and aren't related to the analysis are identified and removed;

- Sentiment detection: sentences from reviews and opinions are extracted and analyzed. Sentences containing subjective expressions (opinions, beliefs, and perspectives) are kept, whereas sentences containing objective communication (facts, factual information) are removed.

- Sentiment classification: in this step, subjective sentences are categorized as positive, harmful (simple category for the novice), sound, or poor; like, dislike, or many points;

- Performance Evaluation and Result Visualization: this is the presentation of output. Performance evaluation is done using evaluation metrics which are also called F-measures. The goal is to evaluate the accuracy of two or more algorithms selected by a researcher. These include sensitivity, specificity, positive predicted value, accuracy rate, error rate etc. They are computed based on the output of the confusion matrix viz; True Positive (TP), False Positive(FP)-making Type I error, True Negative (TN), and False Negative(FN)-Type II error (Umar et al. 2020). A confusion matrix is shown in Table 1 as reported by (Umar et al. 2020).

Table 1 Confusion Matrix(Umar et al. 2020)

		ACTUAL CLASS	
		Negative	**Positive**
PREDICTED CLASS	**Positive**	True Negative (TN)	False Negative (FN)
	Negative	False Positive (FP)	True Positive (TP)

- The main goal of sentiment analysis is to turn unstructured text into relevant content. The text results are displayed on graphs such as pie charts, bar charts, and line graphs once the analysis is completed. That is called the presentation of output. The sentiment analysis result can be visualized using special tools called word cloud. Figure 1 is a word cloud from sentiment analysis result visualization of WhatsApp data-Opinion mining of Computer Science Department Staff Forum Regarding the Payment of EAA using the lexicon-based approach.

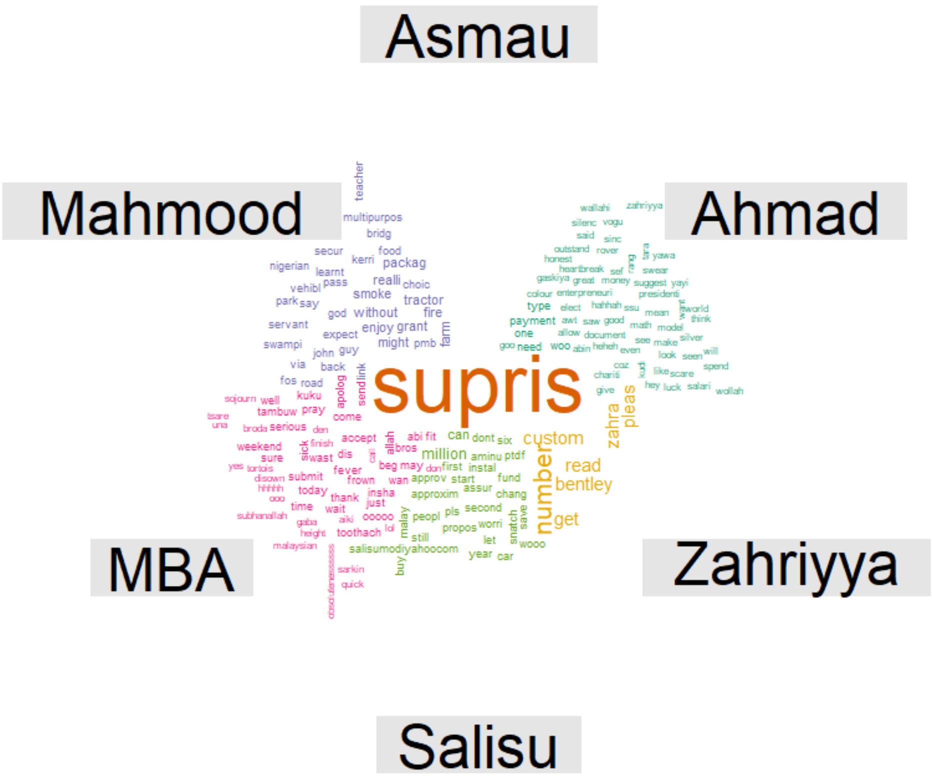

Figure 1. Sentiment Analysis of WhatsApp Data from Computer Science Staff Forum

4. Sentiment Analysis

Sentiment classification is selected for the novice because of sentiments polarity chosen in section 3. Sentiment classification classifies a target unit in a document into positive (favorable) or negative (unfavorable) classes. There are three main classification stages viz: aspect level, sentence level and document level (Ozturk, Cicek, and Ergul 2017):

- document level: identifies whether a document expresses a positive or negative sentiment (Prakash and Aloysius 2020). It considers the entire document a single unit of basic information (one topic). Document-level is better because of its efficiency in giving good results, primarily when written by an individual (Srividya and Sowjanya 2017).
- Sentence-level classification: categorizes the sentiments expressed in each sentence. If the sentence is subjective, it is categorized as either excellent or negative.

Aspect-level classification: categorizes sentiment in terms of specific features of entities. Aspects refer to the words/opinions of users. Users may have differing viewpoints on several elements of the same entity.

4.1 Sentiment Analysis Tools

Many studies reported sentiment analysis tools (Archana and Kishore (2017). Some were developed by private companies in Web services that incorporate functionalities related to Sentiment Analysis(Serrano-Guerrero et al., 2015). In addition, Archana and Kishore (2017) report that RStudio Compiler for R programming, Python and Natural Language Toolkit has also been used as sentiment analysis tools.

Table 2 displays the commonly used sentiment analysis tools and their corresponding Websites according to Serrano-Guerrero et al. (2015) and Archana and Kishore (2017).

Table 2. Sentiment Analysis Tools

Tool	Web sites	Application Area
AlchemyAPI	http://www.alchemyapi.com/	Linguistic analysis
Sentimetrix	http://www.sentimetrix.com	Commercial tool
Repustate	https://www.repustate.com/	Facebook, Twitter
Semantria	http://semantria.com/	Facebook, Wordpress, Twitter
sicmetric	http://www.musicmetric.com/	Social networks &

		blogs
Wingify	http://wingify.com/	E-commerce Websites
SentiRate	http://sentirate.com	Emotion detection
Opendover /SentiSearch	http://opendover.nl/	Twitter and blogs
Openamplify	http://www.openamplify.com/	Social Media Marketing
Opinion Craw	http://www.opinioncrawl.com/	Search Engines
SocialMention,	http://socialmention.com	E-commerce Websites
TweetFeel,	http://www.tweetfeel.com	Twitter
SenticWordNet	http://senticWordnet	Dictionary for Lexicon
Luminoso.	http://luminoso.com	
SentimentAnalyzer	http://sentimentanalyzer.appspot .com/	Web service
Lymbix	http://www.lymbix.com/	Social media analysis
SentiStrength	http://sentistrength.wlv.ac.uk/ Download	We service
Linguistic Inquiry and Word Count	http://www.liwc.net/	Natural language processing

4.2 Sentiment Analysis Approaches/Techniques

Social media data is significant, and that is why there are many techniques to analyze data, including machine learning techniques and hybrid techniques (which combine lexicon-based and machine learning techniques)(Ahmad et al., 2017). A machine learning approach is practical and reliable for opinion mining and sentiment classification. However, machine learning techniques and technologies nowadays come in various variations and expansions. This study explores the best sentiment analysis-machine learning techniques to identify their importance and develop novice researchers' interest in this area.

4.2.1 Machine Learning

Machine Learning algorithms or techniques for sentiment analysis will be briefly analyzed for the sake of novice researchers. In a study by (Ahmad et al. 2017), machine learning techniques in sentiments are implemented based on Unigrams (single words), Bigrams (dual words), and N-grams (multi-words). In general, machine learning techniques are used for binary classification and sentiment prediction as positive or negative. The following categories are used to categorize machine learning algorithms:

Supervised: In these algorithms, a training dataset with pre-labeled classes is provided, and the inputs are labeled with the output class/result based on this trained dataset. These methods use a trained classifier to classify the incoming data set. The training data comprises several instances with an input object and the intended output. Then, an inferred function is constructed using supervised learning methods to analyze training data, mapping additional incoming data, commonly known as test data. The Supervised technique is commonly used in machine learning techniques. It can be divided into two types of methodologies: classification and regression. Linear Regression, Random Forest, and Support Vector Machines are the most common supervised machine learning techniques.

Un-supervised: Unlike supervised learning, these forms of machine learning algorithms accept unlabeled input data and utilize various methods to uncover latent structure/patterns. Unlike supervised learning, this methodology does not employ pre-labeled data to train the classifier. Clustering and association are two types of unsupervised machine learning. Clustering is the most prevalent type of unsupervised machine learning.

Semi-Supervised: These algorithms deal with both labeled and unlabeled data sets. Mukhtar, Khan, and Chiragh (2018) examined various lexicon-based tools and procedures, comparing features and accuracy outcomes of various lexicon techniques.
Machine learning techniques perform better than other approaches on extensively labeled data sets in English (Ozturk, Cicek, and Ergul 2017). On the other hand, lexicons are better than machine learning algorithms on large data in the Urdu Language based on Accuracy, Precision, Recall, F-measure and even economy of time and efforts used (Walasek 2018). The best three machine learning algorithms on large data are Support Vector Machines, Naïve Bayes and MaxEnt(Ozturk, Cicek, and Ergul 2017).

4.2.2 Lexicon-Based Technique

The sentiment lexicon is a collection of words (or phrases) conveying feelings (Han et al., 2018). Entry in the sentiment lexicon has a sentiment orientation and strength. The sentiment orientations of entries in the lexicon can be split into positive, negative, and neutral categories. A lexicon-based approach does not require any

prior training to mine the data. Instead, it employs a predefined list of phrases linked to a specific sentiment known as a sentiment lexicon. Examples of such are SWN, Multi-Perspective Question Answering (MPQA), General Inquirer (GI), and Opinion lexicon (OL).
The lexicon-based technique calculates the ultimate sentiment tendency value by evaluating the sentiment tendency of each word or phrase inside the review. Furthermore, positive words are given a score of +1, while negative words are given a score of -1, reversing the mood value. Therefore, if there is a shortage of tagged data, the lexicon-based method is preferable. (Han et al. 2018).

4.2.3 Hybrid-Based

According to Ahmad et al. (2017), hybrid techniques combine lexicon-based and machine learning approaches. In a study by Hassan et al. (2019), a hybrid-based algorithm comprising of Naïve Bayes (NB) and Whale Optimization Algorithm (WOA) was used to predict the minor features. It was said to have yielded the best sentiments prediction accuracy. A hybrid approach is utilized, which includes sentiment lexicon, semantic rules, negation handling, and ambiguity management(Mukhtar, Khan, and Chiragh 2018).

5. Application of Sentiment Analysis

The different approaches and tools analyzed in this study can be applied in different fields such as education, business, politics, public actions, finance, science and technology. However, literature shows that many sentiment analysis works have been developed in business (i.e., reviews of consumer products and services) more than science and technology, which implies more studies on its applications in other areas, especially science and technology for collaborative research in multidisciplinary.

5.1 Role of Sentiment Analysis in the Context of Research Optimization

The research activities carried out in any institution are a visible reflection of the institution's legitimacy. Good research attracts funding from the government and other organizations, boosting the institution to prominence (Archana and Kishore 2017). Sentiment analysis of the faculty and students involved in the research project provides an estimate of teamwork feelings toward one another and aids in understanding the pace of the research project. Academia and Research Gate are two academic, social networks that provide a platform for researching research work. Sentiment Analysis can assist in determining the study environment. If the initial phase appears to be unsatisfactory, then further research can be considered; otherwise, the required resources, both human and non-human, and the time frame can be determined. In recent years, the focus of sentiment analysis has shifted from online product reviews to social media texts from Twitter and Facebook. Beyond product reviews, sentiment analysis is used in various areas, including stock markets, elections, disasters, medicine, software engineering, and cyberbullying(Mäntylä, Graziotin, and Kuutila 2018).

5.2 Role of Sentiment Analysis in Education

Recruiting the most talented students has become a difficult task in recent years. Universities and colleges are increasingly relying on social media for marketing and advertising. They use blogs and other discussion forums to interact with students who share similar interests and to assess the quality of potential colleges and universities. Personal characteristics, academic excellence, campus amenities, socialization, financial aid, and policies are key factors that students primarily focus on before the enrollment process. Research conducted at the University of New Hampshire reveals that 96 % of students use Facebook, 84 % use YouTube, 20 % use blogs(forum) and 14 % use Twitter. Application of Sentiment Analysis techniques would work wonders if applied to the student enrolment process(Archana and Kishore 2017).

Sentiment analysis of social media data can assist universities in better structuring courses and increasing student retention. Examining student parents' feedback is also essential for institutions to establish a welcoming environment where students can be better shaped by making them feel at ease. (Rani and Kumar 2017).

According to Terán and Mancera (2019), students are matched with courses that best suit their abilities through course recommendation systems called Degree Compass. Tableau, Quibble, and Qlike are examples of educational data analysis tools. However, data mining in higher education (which employs sentiment analysis techniques) is still in its infancy and requires greater attention.(Aldowah, Al-Samarraie, and Fauzy 2019).

5.3 Role of Sentiment Analysis in HealthCare

Sentiment analysis shows good performance in analyzing patients' feelings and emotions. SentiHealth-cancer is an excellent example in this regard. All the experiments conducted in sentiment analysis using SentiHealth-cancer tools are far better than other tools, especially in the cancer context(Prakash and Aloysius 2020).

5.4 Role of Sentiment Analysis in Business

In the business domain, sentiment analysis is used for an online advertisement using Twitter and Facebook; this area is popularly known as e-commerce. Companies adopt these techniques to protect their brand reputation. For example, Tweetfeel is an application that performs real-time analysis of tweets that contain a given term (http://www.tweetfeel.com)(Andrea, Ferri, and Grifoni 2015). Recently, applications of sentiment analysis depend on microblogging (using YouTube) for the advertisement of products by the companies to identify customers' interest-satisfaction or dissatisfaction. Another application of sentiment analysis in the business domain is online commerce (Medhat, Hassan, and Korashy 2014) (Andrea, Ferri, and Grifoni 2015).

5.5 Role of Sentiment Analysis in Politics

In politics, sentiment analysis is applied using voting advice applications (Terán and Mancera 2019). The author further reports that campaign managers also used voting advice applications to track the emotions of voters about different issues in politics. Furthermore, sentiment analysis is also used to clarify politicians' positions on political matters. Thus, enhancing the quality of information that voters have access to (Andrea, Ferri, and Grifoni 2015).

5.6 Role of Sentiment Analysis in Public Domain

In this area, Ahmad et al. (2017) report that Twitter sentiment analysis is used for the early detection of earthquakes. Thus, monitoring real-world events. Linguists at UT Austin also use sentiment analysis to get critical information about earthquake locations and magnitude riot locations in the middle east. Stieglitz et al. (2018) conducted similar studies regarding communication to detect an earthquake in Japan. The monitoring helps policymakers minimize damage in areas expected to be affected next by such events. Another critical application of sentiment analysis is monitoring people's opinions about government policies for managerial decisions (Zhang et al., 2018).

5.7 Role of Sentiment Analysis in Finance

Concerning the finance domain, sentiment analysis is used to aggregate sentiments about news items, articles, blogs, and tweets from public companies. This is as a result of financial news circulating on the Web. For example, the Stock Sonar is a Web service that graphically shows the stock's daily positive and negative sentiment. In addition to that, sentiment analysis helps in monitoring financial risk. Andrea, Ferri, and Grifoni (2015) report that the sentiment lexicon models sentiment information and financial risk relations.

5.8 Role of Sentiment Analysis in Science

Sentiment analysis can be applied in science for evaluating people skills. Academics' opinions on a particular topic can be collected via online forums and social media platforms for analysis. Such analysis can predict trending issues, topics, techniques and innovation. Crossley et al. (2018) conducted a similar study in mathematics, where Math Success is predicted through modeling Math identity using Sentiment Analysis and Linguistic Features. Math identity here refers to self-concept, interest, and value. It helps people self-evaluate themselves via an online survey. The study compares performance on basic math skills within an online math tutoring system to student language (as captured in emails to a virtual pedagogical agent) and surveys Math Identity measures.

6. Conclusion

Based on the literature review, this paper introduced sentiment analysis concerning Web 2.0 (social media that gives big data and is easy to use) from the grassroots for the novice researcher. This study provides basic knowledge of sentiment analysis, sentiment classification level, Tools, approaches concerning features/techniques. The sentiment classification approaches are classified into three (3), namely (i) machine learning, (ii) lexicon-based, and (iii) hybrid approaches. The machine learning approach is used to predict the polarity of sentiments based on trained and test data sets. While the lexicon-based approach does not need any prior training to mine the data. It uses a predefined list of words, where each word is associated with a specific sentiment. Lastly, the hybrid approach- a combination of machine learning and the lexicon-based approaches- can improve the sentiment classification performance.

This study also listed 15 tools used for sentiments analysis and their corresponding Websites viz: AlchemyAPI, Lymbix, Musicmetric, Openamplify, Opinion Crawl, Opendover, Repustate, Semantria, SentimentAnalyzer, SentiRate, Sentimetrix, Uclassify, ViralHeat and Wingify.

All the tools, approaches and techniques discussed in this study can be applied in different fields such as education, business, politics, public actions, finance and science.

The main challenge of sentiment (of Web 2.0) approaches and tools is handling ambiguity in the natural language that expresses different opinions. So, an evolution of approaches and tools is required to overcome this limitation. Besides, there are sufficient studies on sentiment analysis in science areas such as Chemistry, Physics, Biology, etc. Therefore, there is a need for collaborative work in that regard.

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Conflict of interest

The authors declare no conflict of interest.

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