Improving Sentiment Analysis of Arabic Tweets

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Abstract. Twitter popularity grew rapidly the last years and become a place where people express their opinions, views, feelings and ideas. This popularity and the vast amount of information triggered the interest of companies as well as researchers on sentiment analysis trying to export meaningful results from this information. Even if there is a tremendous amount of work on Latin originated languages, such as English, there is not much research available on native languages such as Arabic, Greek etc. This research aims to develop a new system able to bridge the gap in Arabic users and sentiment analysis by providing a novel dictionary able to classify Arabic Tweets with different Arabic dialects and emotions, as positive, negative or natural. The study provides a quantitative analysis to gain an in-depth understanding of the phenomenon under investigation and the findings of the study show that the designed system is very promising.

Keywords: Sentiment analysis · Security · Arabic language · Twitter · Lexicon · Bots

1 Introduction

Nowadays, social networks offer powerful platforms where millions of people can easily share their thoughts, feelings and opinions about a wide variety of topics [17]. A recent report by Twitter Inc affirms that there are over 326 million of monthly active users involved with Twitter in 2019, where 46% of them use the platform daily, sending over 6,000 tweets every second, which corresponds to over 350,000 tweets per minute and 500 million tweets per day [13]. On the other side, Facebook boasts 2.7 billion monthly active users, 74% of them visit the platform daily, with 4.75 billion pieces of content shared daily and 510,000 comments posted every 60 s [23].

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The inherent capability of these platforms in exchanging information in the form of opinions, sentiments, and emotions, makes them an ideal place for consuming and spreading negative and extremist beliefs that promote terrorist activities for the achievement of political, economic, religious, or social goals [16]. For instance, the stunning mass-shootings in Christchurch were planned to get huge attention, leveraging Facebook, YouTube, Twitter, and Instagram platforms to make sure that a lot of people would hear about the deaths and the hate underpinned them. Official authorities had reported that before the attack, a Twitter account was used to post a racist message in which the attackers identified the mosques that were later attacked [19]. Other criminal activities that followed these tactics include the Mumbai terrorist attack on 29 November 2008, Virginia shooting in 25 august 2015, the Brussels airport bombing on 22 Mar 2016, Manchester Arena bombing on 22 May 2017 and London Bridge attack on 3 Jun 2017. In all these cases, attackers used social media to spread their radical thoughts and criminal activities before the attacks. A study conducted in [22], affirm that nearly 1 million accounts that promote terrorism and spread extremist thoughts were identified on Twitter, in the last two years. Further, it is estimated there are over than 100,000 tweets of hate, racism and ethnic generated daily on Twitter [27]. This new reality means that governments, police forces and others involved in public safety, should pay attention to social media valuable content to track these criminal's activities, and determine how to react effectively before they become a real problem [29]. Previous studies have argued that these platforms have the hidden potential to reveal valuable insights when analysis techniques are applied to their unstructured data. In this context, Sentiment Analysis (SA) or Opinion Mining (OM) [20] is one of the key emerging technologies that help to navigate the large volume of sentiment rich data generated by users on social networking websites. SA is defined as a process that automates extracting of opinions, attitudes and emotions from a piece of text, through Natural Language Processing (NLP) methods [12,20]. It involves detecting whether the text expresses a positive, a negative, or a neutral opinion toward an entity (e.g., individual, organisation, event, topics, etc.) [17]. Unlike traditional data mining methods, sentiment analysis deal with unstructured data which is usually textual and messy such as documents, emails, user posts and comments on social media [24]. In the last years, Sentiment Analysis techniques have been intensively exploited to identify user's interests or behaviours through the information extracted from social media, especially towards the distorted beliefs and negative sentiments [5,11,25,30]. Most of the proposed approaches in this area showed promising results and high accuracy in classifying negative user's sentiments and opinions. However, most of these studies deal with English texts, while other languages, especially Arabic, have received less attention. Despite being one of the fastest-growing languages in term of users on social media, the field of Arabic NLP is rather not mature compared to English and other Latin originated languages, for various reasons such as language complexity, variety of related dialects where insufficient number of research publications and datasets gathered and analysed for such purpose [6]. Therefore, effective and more accurate Arabic sentiment analysis becomes the fundamental demand for analysing the vast amount of Arabic data available on social media and detect suspicious behavior.

This paper aims to bridge the gap in research concerning Arabic sentiment analysis, which can lead to a better understanding of the driving changes in different Arab countries and their impact on a global scale. To this end, we build a lexicon that contains positive and negative tokens (words). For the purpose of this study, a corpus of 500 mix feelings tweets is collected from random tweets regarding the Saudi-Qatari conflict [26]. The conflict led to relation cut off between the two countries until the writing of this paper. Most of the conflict was waged through social media platforms, especially Twitter, where a huge number of Arabic tweets were spreading hate and negative thoughts through fake accounts known as "bots" trying to manipulate the public opinion, according to a BBC Arabic investigation [26]. The hate tone in these tweets created a big tension between people in those two countries. The main contribution of this paper is to understand to what extent the existing publicly available systems and algorithms are able to classify a given Arabic tweet polarity. In addition, a more comprehensive lexicon of Arabic tokens is developed and evaluated based on manual annotation of the tweets from 6 native Arabic speakers. The results are then compared with other well-known systems and algorithms in order to demonstrate the efficacy and efficiency of our lexicon.

The rest of the paper is organised as follows. Section 2 presents a review of current state-of-the-art literature on opinion mining and sentiment analysis of Twitter data. Section 3 describes the process of collecting the corpora from the Twitter platform. Then, the generated mixed lexicon and the linguistic analysis of the obtained corpus are presented in Sect. 4. Section 5 presents the experimental results of the study and the findings are discussed in Sect. 6. Finally, Sect. 7 reviews the content of the paper, presents the conclusions and outlines the future work.

2 Related Work

In recent years, sentiment analysis becomes one of the fastest-growing research areas. In this context, many studies have been applied to effectively improve the understanding of user opinion on diverse challenging issues. For instance, authors in [25] used the sentiments expressed by the Turkish people in tweets to understand the public opinion towards the Syrian refugee crisis. Similarly, in [11], the authors exploited the sentiment analysis of Twitter data to provide graphical visualisations about potential terrorism scenarios. The study demonstrated that social media and sentiment analysis technologies can play a critical role in the effective response to terrorism physical activities. In another recent work [5], authors proposed a sentiment analysis approach to classify the user-generated posts on Twitter as extremist and non-extremist. This approach achieved 90% of accuracy in the classification of the user's sentiments. In [30], the authors focused on studying the influence of hate tone on the behaviour of twitter users. They reached 78.4% accuracy in detecting whether a tweet is hateful or not.

With regard to the Arabic language, there is a lack of research that addresses the sentiment analysis in this language, especially for detecting and classifying distorted beliefs and extremist sentiments [25,30]. The proposed studies in this area used two main approaches for sentiment analysis; Machine learning and lexicon-based approach. The Lexicon-based Approach is an unsupervised method that relies on a sentiment lexicon [17], which is a lexicon of known and pre-compiled sentiment terms, phrases and even idioms. It matches the words in the lexicon with the data to determine the polarity [17,25]. In this approach, sentiment scores are assigned to the opinion words describing how positive, negative and neutral the words are, based on the lexicon [6,17]. Lexicon-based approaches can be classified into lexicon-based approaches [17] and corpus-based approaches [20]. The later relies on human experts to annotate a set of data that can be used to train a classification model. The trained model can then be used to classify any new data item [17]. Machine learning techniques like Naive Bayes (NB), Maximum Entropy (ME), and Support Vector Machines (SVM) are usually used to classify the data into different classes [6,17,20].

The first interesting method for sentiment analysis(SA) of Arabic documents was proposed in [2]. In this study, the authors used a hybrid method for sentiment analysis. First, a lexicon-based approach is used to classify some documents, which will be used as a training dataset for the method, which subsequently classifies some other documents. Then, the k-nearest model is used to classify the rest of the documents. To validate this approach, authors used a dataset that was collected from 1,143 posts which contained 8,793 opinions expressed in Arabic from three different domains: “education”, “politics” and “sports”. Authors reported an accuracy equal to 80.29% on detecting negative and positive statements. In one of the few attempts of Arabic extremist SA, authors considered a binary (positive or negative) SA approach of English and Arabic hate/extremist web forum posts [1]. This approach focused on feature selection by using a wide array of English and Arabic stylistic attributes, including lexical, structural, and function-word style markers. For efficient feature selection for each sentiment class, they also developed an Entropy Weighted Genetic Algorithm (EWGA). The effectiveness of this approach was evaluated on two small datasets, each consisting of 1,000 posts written in English or Arabic. This approach achieved accuracy over 91% on both datasets. The main drawback of this approach was the extreme lack of pre-processing which is crucial for Arabic text.

Given the cultural and linguistic differences across the Arab world, inducing variations in semantics, some studies focused on developing SA for the different Arabic dialects used in the social media [9,10,14]. According to [31] there are four dominant dialects in the Arab world: Egyptian, Levantine, Gulf, Iraqi and Maghrebi. In this context, authors in [10] introduced a sentiment model for the Levantine dialect (ArSenTD-LEV)[1]. The proposed model used a corpus composed of 4,000 tweets retrieved from Levantine countries (Jordan, Lebanon, Palestine and Syria). For each tweet, the corpus specifies its overall sentiment and topic, the target to which the sentiment was expressed and how it is expressed

[1] The ArSenTD-LEV corpus is available at http://www.oma-project.com.

(explicitly or implicitly). The experimental results confirmed the relevance of these annotations at improving the accuracy of SA classifiers. Other works in this direction proposed a lexicon-based technique to deal with dialectal Arabic [9]. In this approach, the authors used an online game[2] that enables users to annotate large corpuses of text in a fun manner. For the text analysis and classification, they used the sentimental tag patterns and the sentimental majority approach. Authors reported 60.50% of accuracy for the sentimental majority approach while the sentimental tag patterns reached the lower accuracy of 60.32%. In [14], authors discussed in details the challenges faced by SA of dialectal Arabic on social media, especially the Egyptian dialect. Later they proposed a method for automatically constructing sentiment lexicon for Egyptian dialect [15].

Some other studies focused on the scarcity of available datasets by providing new resources to support research advances in Arabic SA [20–23]. In [28], authors introduced the Opinion Corpus for Arabic (OCA), one of the earliest public Arabic corpus for SA. The dataset contains 500 movie reviews collected from different web pages and blogs in Arabic, 250 of them considered as positive reviews, and the other 250 as negative opinions. While AWATIF [3] was the first corpus for Arabic SA that employed both regular and crowd-sourcing annotation techniques. AWATIF contains 5342 sentences taken from 30 Wikipedia talk pages, Twitter and 2532 threaded conversations taken from seven Arabic forums. Later, the authors proposed SANA [4], a large-scale, multi-domain, multi-dialect, and multi-genre lexicon for sentiment analysis of the Arabic language and dialects. The lexicon automatically extends two manually collected lexicons HUDA (4,905 entries extracted from chat records in the Egyptian dialect) and SIFFAT (3,325 Arabic adjectives). In [21], authors prepared a sentiment analysis dataset gathered from Arabic tweets, called Arabic Sentiment Tweets Dataset (ASTD). ASTD consists of 10,000 tweets which are classified as objective, subjective positive, subjective negative, and subjective mixed. The authors constructed a seed sentiment lexicon from the dataset. In [8] authors presented an Arabic lexicon-based tool called Arabic Opinions Polarity Identification (AOPI). This tool relies on domain-specific lexicon approach for extracting opinions in posts written in Modern Standard Arabic (MSA) and dialectal Arabic. They compared it with SocialMention[3] and SentiStrength[4]. Their results showed that AOPI is more accurate than other tools. Studies in [7,18] showed that most of SA tools are inefficient for extracting opinions in reviews written in MSA or in dialectal Arabic.

From the state of the art, it can be concluded that despite the speedy growth in the volume of Arabic opinionated posts on social media, Research in the area of Arabic SA is progressing at a very slow rate compared to English and other languages. Moreover, most of the available resources in this area are either of limited size, domain-specific or not publicly available. In addition, most of them

[2] http://kalimat.afnan.ws/.
[3] SocialMention: http://www.socialmention.com/.
[4] SentiStrength: http://sentistrength.wlv.ac.uk/.

had issues in terms of the quality of its content and annotation, which limits advancement in Arabic sentiment analysis. Moreover, there is no study that compares publicly available sentiment analysis algorithms on limited Arabic text (tweets) with Lexicon and human opinions of both male and females.

3 Corpus Collection

The corpus samples were collected manually by three different people from the Twitter platform. The reason that corpus was collected manually instead of using an automated API, is because this research uses the Saudi-Qatar political conflict as a case study. The use of API with pre-defined keywords would have resulted many unrelated samples that would needed to be filtered later on. Also, there were no specific selection criteria followed, instead, the collectors were asked to browse Twitter platform in which they tag any tweet that they found related to the matter (Saudi-Qatari politic conflict). In total, 500 tweets were collected during the period from 1 to 8 January 2019 and the focus of this research was to evaluate the lexicon that was constructed. Table 1 provides some statistical information about the collected corpus.

Table 1. Corpus statistics

Item	Corpus overall stats						
	Mean	Std	Min	25%	50%	75%	Max
Token	21.30	10.47	1	16	20	24	55
Char	139.48	63.18	3	110	124	145	305
Special char	0.22	0.88	0	0	0	0	13
Link	0.44	0.54	0	0	0	1	2
Hashtag	1.65	1.59	0	1	1	2	10
Emojis	0.23	0.76	0	0	0	0	7
@	0.18	0.55	0	0	0	0	3

The table shows the mean (average), standard deviation, min, max and quartiles of the listed items for the corpus tweets. The token expresses any single word, term, or symbol exist in a tweet that is separated by white space. However, the definition of the token can be controversy. In this paper context, the above definition is what we followed. For example; the tweet below has five tokens.

"#محمد بن سلمان طموحنا عنان السماء SA"

1. #محمد بن سلمان: means: *person*: Mohammed bin Salman
2. طموحنا: means: *noun*: Our ambition
3. عنان: means: *noun*: highest

4. السماء: means: *noun*: sky
5. SA: means *acronym*: Saudi Arabia

The given translation is not very accurate as is word by word instead as a whole sentence in which the English meaning is not well expressed. From the table, it can be seen that the average tweet has around 21 words. The char indicates any single character in a tweet, for instance, the word طموحنا has the following characters: ط، م، و، ح، ن and ا. Since October 2018, Twitter allows a max of 280 characters per tweet from the initial of 140 characters. The averaged tweet in the collected corpus has around 139 characters. The special char expresses exclamation (!) and question marks (?). The existing of such marks in a tweet could express a type of feeling. For example, the exclamation mark in a short sentence could express very strong feeling, while the existing of question mark could indicate that the tweet is a question in a way that the author do not agree with the context or the point expressed by someone else. From the table, the existing of these marks in the corpus tweet is around 0.22 per tweet, which means that one in every five tweets could include such mark. Finally, "@" indicates the existence of "@" in the corpus tweets whether it belongs to a username or email or any type of context. Table 2 lists the most common tokens in the collected corpus.

Table 2. Most frequent tokens

Token	English translation	Frequency	Token	English translation	Frequency
في	In	245	من	From	212
على	On	117	# محمد بن سلمان	That	73
# ولي العهد	crown prince	71	# السعودية	Saudia	65
أن	That	63	بن	Son	62
و	And	60	مع	With	59
سلمان	Salman	56			

It can be seen that most of the listed word are stop words and name of the crown prince of Saudi Arabia as well as the king of the country.

4 Lexicon Generation

In this study, a mixed lexicon was used since the current literature review did not provide a suitable Arabic lexicon that could fulfil the aims of this study. The lexicon created was a combination of "AraSentiLexicon V 1.0" made by Nora Al-Tweiresh in 2016, along with an Arabic translation of Bing Liu's Lexicon. The translated Bing Liu lexicon has been manually edited and numerous sentiment words added in order to include all cases of sentiments in the Arabic language for male, female, past, present, future, formal, informal as well as other cases that can cause differences in the Arabic language. In the end, the positive lexicon produces was consisted of more than 61,600 positive words and the negative lexicon consisted of more than 77,900 negative words. The generated lexicon includes words that belong to different Arabic dialects which makes it a comprehensive lexicon.

Both lexicons can be downloaded from the link below[5]. Table 3 lists the most common usernames in the corpus from which the tweets were collected. Any user who has four or more tweets is included in the figure along with their number of tweets. Those 22 users (out of 202) from 44% of the total percentage of tweets in the corpus. While 157 tweets out of 500 tweets (total corpus samples) belong to only the top seven accounts most of which are news accounts.

Table 3. Most accounts in the corpus

Screen name	Count of tweets	Screen name	Count of tweets
@AJABreaking	30	@TurkiShalhoub	6
@mshinqiti	30	@m3takl	6
@Benguennak	29	@AjelNews24	5
@hureyaksa	25	@spagov	5
@ELHAMBADER1	15	@AlkhaleejOnline	4
@DrMahmoudRefaat	8	@HashKSA	4
@AJArabic	7	@MALHACHIMI 4	4
@GamalSultan1	7	@MBNsaudi	4
@Saudi_24	7	@aa_arabic	4
@Raed_Fakih	6	@jamalrayyan	4
@SaudiNews50	6	@saudibus222	4

5 Experimental Analysis

In order to measure the performance of the examined approaches, two aspect were considered; word aspect and general overview aspect. The word aspect is when the matching is based on the words within a tweet, with the lexicon been applied in order to find the negative and positive words within a tweet. This also includes how comprehensive are the positive and negative lexicon. The other aspect is the general polarity aspect which is how accurately can the method/software understand the general sentiment of the tweet and be able to

[5] Abduallah Arabic Lexicon: http://shiaeles.net/datasets/Arabic_Lexicon_Abduallah.7z.

classify it. The corpus tweets were classified and annotated into one of three classes; positive, negative or neutral. This is done by requesting 6 adult people (3 males and 3 females) speak different Arabic dialects to perform a manual annotation of the 500 tweets in order to be use as a reference point and validate the accuracy of our lexicon system developed. The annotators ages were between 20 and 40 years old. There were no specific protocol used for the recruitment, however, having different backgrounds and nationalities and mix gender was taken into consideration. The raw tweets were used in the analysis without performing typical pre-processing steps such as removing stop-words, normalisation and root words etc. This is because this study focuses on evaluating how the developed dictionary would perform in comparison to publicly available tools and classifiers without modifying the raw data. Also, the polarity of the tweets were classified by the developed lexicon that this study used. Table 4 presents the overall corpus sentiment polarity. It can be seen that, the developed lexicon positive sentiment rate is close to the human based rate, while the negative and neutral sentiment is different.

Table 4. Corpus sentiment polarity

Sentiment	Method	
	Lexicon	Human
Positive	43%	41%
Negative	33%	14%
Netrutal	25%	45%
Total points	1,330	N/A

In comparison with publicly available sentiment analysis algorithms, such as SentiStrength, uClassify and Vader, the developed Arabic dictionary (lexicon) has higher accuracy to human annotation results as illustrated in Fig. 1. However, this also shows that the problem of analysing Arabic sentiment is not an easy task as the results are significantly vary among the tested approaches. Moreover, it does not only vary among the examined algorithms but also among those required human annotators. As illustrated in Fig. 2, around 75% percentage of the corpus has an agreement with 4 or more annotators, while the rest agreed with three or less people. This reveals how human can interpreted differently written tone feelings, proving that a sentiment analysis system is not a simple task.

To fairly evaluate and compare those selected approaches and systems with human annotations, we filtered the corpus to have only those tweets where there is an agreement among the human annotators of minimum 4. This resulted in a reduction on the samples to 379 tweets (out of 500) which means that 121 tweets have three or less agreements among the annotators. Table 5 presents the agreements as percentage and number of those tweets for each approach and the developed lexicon along with that of the 4 human agreement.

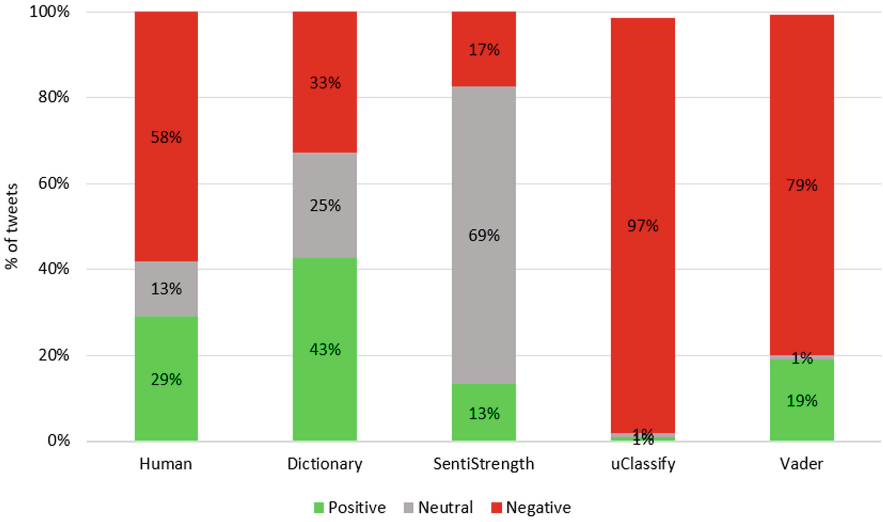

Fig. 1. Overall corpus sentiment polarity

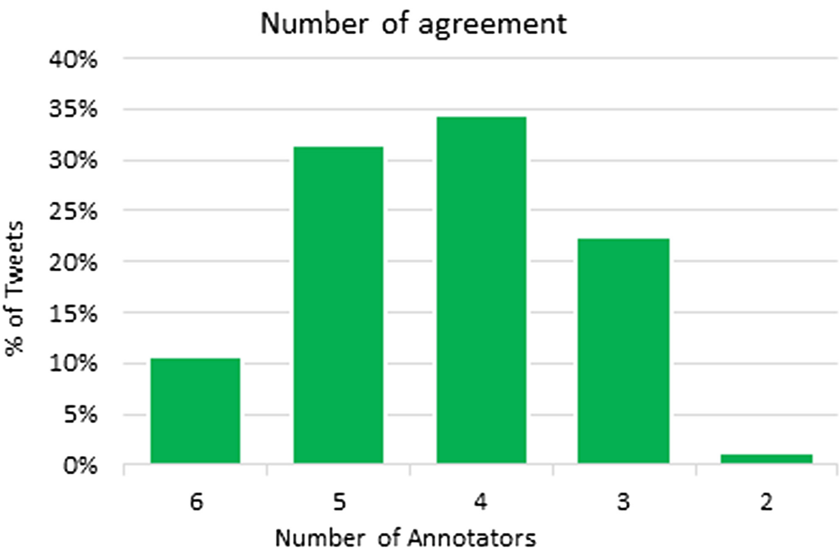

Fig. 2. Human annotation agreements

Table 5. Agreement of tools with human annotations

Sentiment	Method			
	Lexicon	SentiStrength	uClassify	Vader
Positive	83% (29)	23% (8)	0% (0)	1% (1)
Negative	57% (40)	24% (17)	94% (66)	71% (49)
Natural	20% (4)	75% (12)	0% (0)	6% (1)
Overall	60% (70)	30% (37)	54% (66)	42% (51)

6 Discussion

According to the presented results, it can be concluded that the lexicon performance is better than other methods proposed. However, it is noteworthy that sometimes the results were wrong due to the absence of words from our lexicons. Another reason is because a tweet carries mixed opinions and sentiment which can cause miss-classification. Moreover, the nature of the Arabic language itself can lead to miss-classification as well, as there are several vocals such as نَ، نُ، نِ and many other vocal. In this example, the letter ن is called "Noon" which is similar to the letter N in English. However, the letter ن was written with different vocals which will make the sound different in each case. In the first case where the letter was نَ, the letter sounds "Na", in the second case the letter نُ sounds like "No", and in the last case of the example the letter نِ sound like "Ni". There are more vocals in the Arabic language and these vocals can apply to Arabic letters in every word and sometimes it can be the same word with different vocals, and hence it can refer to different meanings. An example of this the word سِلْم and the word سُلَّم, the first sound like "Silm" which means peace, the second word sounds like "Sollum" which means a ladder, now both of the words have the same letters with just different vocals. The issue is in about 95% from the Arabic posts on the internet, as Arabs do not usually use the vocals because it is easy for them to know the intended word by the context, but when it comes to the computer, it is an issue to understand the exact meaning the user refers to.

7 Conclusion

This research dealt with the significant problem of the lack of comprehensive Arabic lexicon. The results of the sentiment analysis of the 500 Arabic tweets in respect to the examined subject showed that there are is high agreements between the developed lexicon and the human annotators. However, the results are still around 75% accurate comparing to the human annotators, therefore, there is a strong need to investigate other approaches such as machine learning and deep learning-based methods along with the lexicon, more able to capture the latent meaning and feelings of the tweets.

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