Cyberbullying Detection by Sentiment Analysis of Tweets' Contents Written in Arabic in Saudi Arabia Society

Amjad Rasmi Almutairi[1†] and Muhammad Abdullah Al-Hagery[2†],

[1,2] Department of Computer Science, College of Computer
Qasim University, Buraidah, Saudi Arabia

Summary

Social media has become a global means of communication in people's lives. Most people are using Twitter for communication purposes and its inappropriate use, which has negative effects on people's lives. One of the widely common misuses of Twitter is cyberbullying. As the resources of dialectal Arabic are rare, so for cyberbullying most people are using dialectal Arabic. For this reason, the ultimate goal of this study is to detect and classify cyberbullying on Twitter in the Arabic context in Saudi Arabia. To help in the detection and classification of tweets, Pointwise Mutual Information (PMI) to generate a lexicon, and Support Vector Machine (SVM) algorithms are used. The evaluation is performed on both methods in terms of the F1-score. However, the F1-score after applying the PMI is 50%, while after the SVM application on the resampling data it is 82%. The analysis of the results shows that the SVM algorithm outperforms better.

Keywords:
Cyberbullying; Sentiment Analysis; Arabic Tweets; PMI; SVM;

1. Introduction

Nowadays, social media has become part of our daily lives, and global means of communication. Twitter becomes one of a common communication tool. It can be accessed and used easily by everyone, and its inappropriate usage could have much more of a negative effect on young people. One of the widely spread misuses of technology is Cyberbullying. It is a form of online bullying that embarrasses another person. It uses digital devices such as mobile phones, laptops, and tablets to bully others. Now it is harder to control because there are thousands of free sites with millions of user's access anytime from any place. One of the common sites is Twitter that has 330 million active users monthly. It is a free social network site that is accessible and usable, and it allows cyberbullies to target the victims easily [1]. Arabic is not like other languages. It has a very complex morphology. However, in various Arabic language contexts, words have different categories of polarity. Most users in social media used dialectal Arabic rather than using modern standard Arabic and the resources of dialectal Arabic are rare. For this reason, this paper aims to detect and classify cyberbullying on tweets' contents in the Arabic language in Saudi Arabia.

There is one previous research work achieved related to this topic is that investigates cyberbullying among Saudi's higher-education students. Its results showed that cyberbullying is primarily avoided by students. However, 26.5% of the students reported that they once or twice bullied other students online. Furthermore, 57% of students reported that one student face cyberbullies at least once or twice. Finally, this result shows that Saudi Arabia's cyberbullying rate has increased compared to the 2012 Reuters Global survey. This increase may indicate a serious prevailing issue and require additional intervention [2]. Another research was carried out to achieve to detect cyberbullying in the Egypt dialect [3].

Governments can't read every Tweet, post or comments on social media as it generates a large quantity of data at an unprecedented rate. Hence, machine learning approaches can help to detect cyberbullying. To detect the Arabic Tweet conversation, two approaches namely machine learning and lexicon-based have been proposed [4]. However, the Naïve Bayes (NB) and SVM algorithms are used by them to detect the tweet conversation [5]. There is still a gap in which lexicon-based approach and SVM algorithms could be used and comparative analysis can be carried out for cyberbullying detection on Twitter. For this reason, the lexicon-based approach and machine learning algorithm namely SVM are used in this study. Also, Pointwise Mutual Information (PMI) algorithm is used for lexicon generation, while for the classification purpose the generated lexicon used according to the PMI score and the Support Vector Machine (SVM) algorithm is used in this study. It also evaluates compares the performance of machine learning and lexicon-based techniques on a Colloquial Arabic text dataset which is collected directly from Twitter.

The remaining organization of this paper is as follows: Section 2 consists of a literature review. The methodology of this study is discussed in section 3. While results and discussion are presented in section 4. Lastly, the conclusion and future work are presented in section 5.

Manuscript received March 5, 2021
Manuscript revised March 20, 2021
https://doi.org/10.22937/IJCSNS.2021.21.3.15

2. Literature Review

Researchers have faced a lot of challenges to detect cyberbullying in the Arabic context, hence machine learning algorithms are used to detect cyberbullying automatically. Additionally, it helps government agencies to quickly solve the issues, and to create a safe and secure virtual world environment. To detect cyberbullying in Arabic text, text mining and lexicon-based approach are used [4]. To detect the hateful content on Twitter, a supervised machine learning classifier is developed to help decision-makers that track the public response to emotional events. However, it combines probabilistic, rule-based and spatial classifiers to improve the results [6]. To perform the sentiment analysis on the large dataset for Arabic Tweets sufficient language resources are not present. As a result, the Arabic Tweets corpus that is annotated for the sentiment analysis is extracted [7]. Also, a first publicly released annotated corpus that applied sentiment analysis to twitter content is presented [8]. Due to the complex Arabic language and less Arabic text analysis, few scholars have tried to applied different approaches for analyzing the Arabic text. However, there are many limitations in their approaches. Using NB Classifier, the Arabic text web document was classified from the al Jazeera website into 5 classes, and the average accuracy did not exceed 68% [9]. Most of the work on the Arabic language that has standard Arabic resources are used machine learning based on lexical classification [10], [11]. For instance, datasets are prepared by using tagger [12], [13]. In the same way, Token, Word forms, Lemma, POS Tagging standard features (Unique Gender, User ID) with a polarity lexicon for Arabic social media subjectivity and sentiment analysis are used [14]. On the other hand, opinions are extracted from the Arabic document by combining three approaches i.e. lexicon-based, entropy method, and k-nearest method. In every method, the results from the previous are used as a training set [15].

Moreover, the sentiment of tweets that contains emotions related to iPhone and Microsoft is done with the help of NB and decision tree algorithms. However, the results of the decision tree outperform the NB algorithm [16]. To identify the specific natural disasters in the Arabian Peninsula, the colloquial Arabic text dataset, and a plethora of text-based classification methods were used. To identify the specific natural disasters in the Arabian Peninsula, the colloquial Arabic text dataset, and a plethora of text-based classification methods were used. Moreover, the classification techniques SVM, NNET, NB, J48, C5.0, and k-NN have used, and without stemming SVM outperforms the better [17].

The target audience is identified from the list of company followers on Twitter with the help of various methods of text mining, SVM, Fuzzy keyword match, and Twitter LDA (Latent Dirichlet Allocation). However, the Fuzzy keyword match method outperforms others [18]. Using the Twitter streaming API, the training data set is collected from the Twitter messages which contain terms of abuse. However, with the help of the classification technique NB, its accuracy reaches 70% [5]. To analyze the opinions of the students about their e-learning experience, SVM and NB algorithms are used. However, the dataset of Arabic Tweets is collected using rapid miner. The experimental results indicate that the classification of Arabic text using sentiment SVM and N-gram features outperformed NB using positive, negative, and neutral classes [19]. A system called Kuwaiti-Dialect Opinion Extraction System is developed from Twitter (KDOEST) to extract the opinions about "interrogation of ministers by the National Assembly of Kuwait". This system is based on techniques they proposed was it starting with Twitter collector and ends with opinion classification [20]. To discover the Twitter user's feelings, an application of text mining with the help of the NB algorithm proposed. Moreover, it also predicts the emotions of Twitter users [21]. By focusing on the Twitter data, an emotion classifier is built using the SVM to classify the emotion of the person's writing. However, it also explains how a corpus for emotion analysis is collected automatically, and finally, the linguistic analysis of the collected corpus is performed [22]. Due to the need to classify a big dataset of short texts with high accuracy and without manual efforts, an Emotex approach is proposed to classify the messages from Twitter into different emotional classes. For classification, SVM, KNN, NB, and decision tree algorithms are used [23]. However, research has conducted in understanding the problems of engineering students in their educational experience by using their tweets on Twitter. To classify the Tweets that represent the problems of students, multipliable classifiers such as Non-Linear SVM, NB, and linear SVM methods have used. The non-linear SVM classifier outperforms the other methods [24], [25]. A various set of classifiers were employed with text data or different types of data, for instance, those in [26], [27], [28], [29], and satisfying good results.

In addition, to improve the semantic orientation, an optimized approach for mining opinions in Arabic religious decrees using PMI Algorithm is presented. Its value is calculated between words to present the strength of the semantic association and from this association, semantic orientation is inferred [30]. Also, two sentiment lexicons are successfully extracted from the Tweets dataset using various approaches. One of them is by using the PMI approach. It ensures the association strength that is occurring between two words in the Tweets dataset. Moreover, it measures all the positive and negative words in a corpus that subsequently generates the lexicon [31].

3. Methodology

This section explains the overall steps of the methodology used in this paper, which is divided into two stages. The first stage is the dataset stage and it consists of data collection, preprocessing, and manual classification. While the second stage is a tweet classification stage, and two methods namely the lexicon-based approach and the machine-based approach are used. The framework of the proposed methodology is illustrated in Fig. 1.

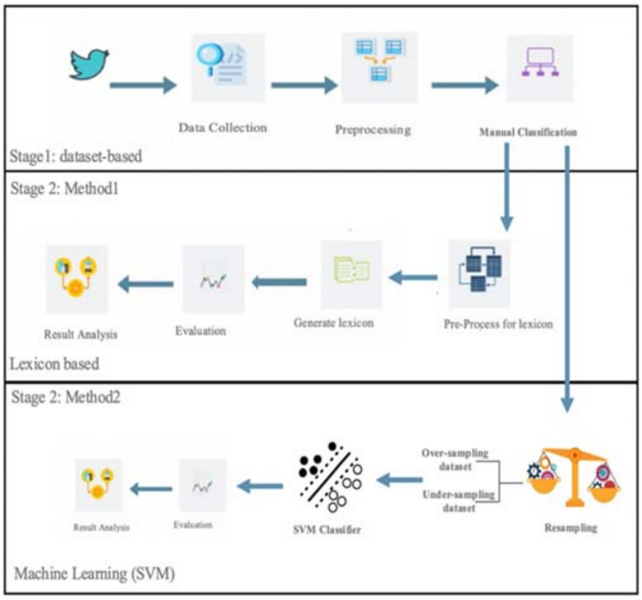

Fig. 1 Framework of the proposed methodology.

2.1 Data Collection

The process of the collection of data using Twitter API involves the following steps. First, log in to the Twitter developer's app, create a new Twitter application, and write the application details. Second, generate the access tokens and the access token secret. Finally, an open-source library package namely tweepy is used in the Python programming language to access the Twitter API. However, with the help of this package, the data is collected for a specific location (i.e. Saudi Arabia) along with a bullying keyword from a Twitter database. All of the data is collected in the JSON file format. These steps are illustrated in Fig. 2.

Table 1 shows the collected data from "twitter.com" that is used in this study including name, number of tweets, and date. The dataset was collected in separated periods from 30 Oct 2018 until 31 May 2020, which is approximately one year and 7 months. These periods include the Saudi's students Exam, Saudi Vacation, and COVID19. However, the total number of tweets that were collected is 8154.

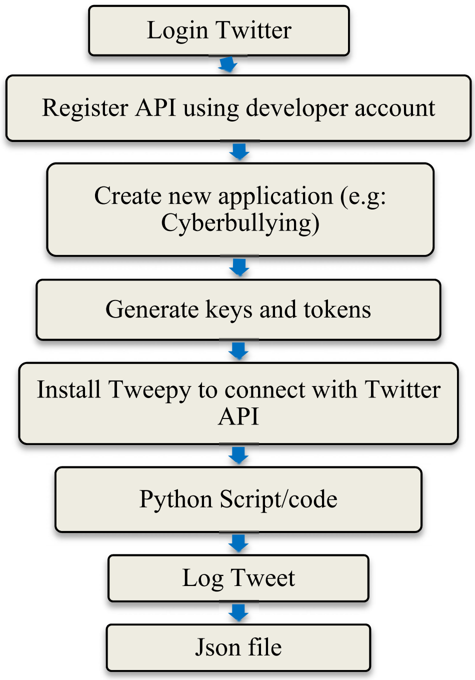

Fig. 2 Data Collection Steps using Twitter API.

Table 1: Collected Data Timeline

Name	No. Tweets	Date
SaudiData1	155	30 Oct 18
SaudiData2	1198	7 Nov 18
SaudiData3	375	14 Nov 18
SaudiData4	38	21 Nov 18
SaudiData5	21	29 Jan 19
SaudiData6	80	7 Feb 19
SaudiData7	1923	17 Feb 19
SaudiData8	1142	25 Feb 19
SaudiData9	632	3 Mar 19
SaudiExamTime	80	21 Apr 19
SaudiExam	409	29 Apr 19
SaudiVacation	393	6 May 19
Covid19	509	21 Apr 20
Covid19plus	101	1 May 20
Ramadan20	425	9 May 20
Ramadan33	75	16 May 20

Eid01	452	24 May 20
Eid02	146	31 May 20
Total	8154	18 times

2.2 Data Preprocessing

In the preprocessing step as illustrated in Fig. 3, the collected data is cleaned by the following steps:

- The JSON file format is converted to CSV file format.
- Attributes such as username, bio, date, etc. except for text attributes, and duplicate tweets are removed using MS Excel.
- Using the command line, all collected CSV files are combined into one file.
- Finally, all tweets are cleaned using Python. In this process, the URL is removed. However, mention hashtags, emoji, newline, numbers, repeated letters, digits, Tashkeel (Arabic Diacritics), English, Arabic punctuation, non-Arabic letters, extra spaces, single letter, and unrelated tweets.

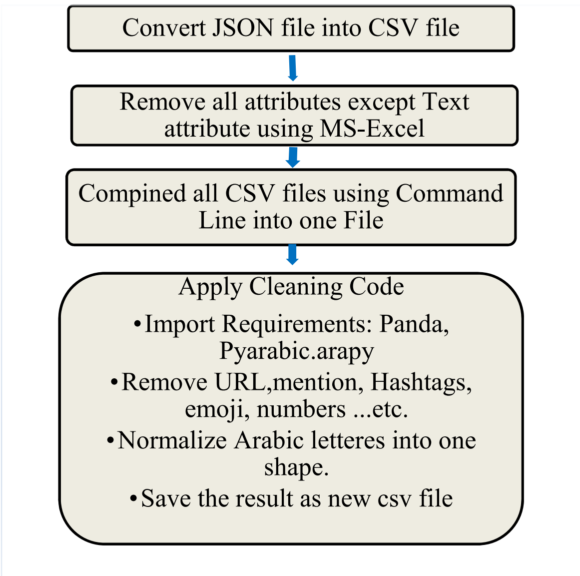

Fig. 3 Data Pre-Processing

2.3 Manual Annotation

In this process, the preprocessed data is manually classified into Cyberbullying or not. This step achieves by three people (annotate) and uses an odd number of people to be the last classification after the majority opinion. However, for cyberbullying, it is classified as 1, and for non-cyber bullying, it is classified as 0. The result of this step is used on both methods lexicon-based and SVM. Table 2 shows our dataset statistics, which contains the number of Tweets and tokens before and after cleaning for both Bullying and non-Bullying Tweets.

Then separated the file into two files, a Bullying file and a Non-Bullying file to be prepared for lexicon. For both files with the whole dataset file, we transformed each Tweet into separated words (tokens) using Python and compute the frequency of each word. The result will be three files BullyingIteration.csv, non-BullyingIteration.csv and allDatasetIteration.csv. Because the PMI is not a good estimator of words with lower frequency, any words that occurred less than five times will be removed in all files. This is done using python code for both split and compute the word iterations. A sample of the data after preparation for the lexicon is shown in Table 2.

Table 2: Sample of data after prepared for lexicon

word	count
كذاب	351
امعه	143
مجنون	261
حقير	105
شعب	18
فاهم	19

2.4 Lexicon Based Approach

It is a corpus-based approach or lexicon-based approach, that is used a corpus to generate a lexicon by creating a seed list of known sentiment words and using different approaches to identify the words of similar or opposite polarity. In this approach, the frequencies of the words in both negative and positive datasets are used to determine the strength of the polarity of each word in the lexicon. There are three most widely used lexicon-based approaches, including High Entropy, Chi-Square Based, and PMI [32].

PMI approach is used in this study based on the good results of existing studies. With the help of PMI, the lexicon is generated from the separate files and the strength of the relation is calculated between the term and a class. For the Tweet score of the selected word, PMI and all non-bullying words are subtracted from PMI and all bullying words. PMI for bullying tweets can be calculated using the given equation (1).

$$PMI(w, Bull) = \log_2 \frac{freq(w,Bull)*N}{freq(w)*freq(Bull)} \tag{1}$$

freq(w, Bull) represent the word *w* frequency in bullying Tweets, *freq(w)* calculates the word *w* frequency in the whole dataset, *freq(Bull)* consider tokens number in the bullying Tweets whereas *N* is the total number of tokens in the dataset. PMI for non-bullying Tweets can be measured using the same method *PMI(w, Non).* For word *w, the* Tweets score can be calculated using equation (2) [7].

$$SentimentScore(w) = PMI(w, Non) - PMI(w, Bull) \quad (2)$$

We write a code on Python that calculate the sentiment score of words and then generate a lexicon. The result is 320 words as shown in Table 3.

While in the text classification step, the summation of the sentiment scores of the tweet terms found in the lexicon is used as bullying detection. However, if the tweet results are greater than or equal to -1, the tweet is classified as non-bullying, otherwise, it is classified as bullying. Finally, these results are used as a reference for comparing and testing with the annotated dataset. The result of classification based on the PMI lexicon is shown in Table 4.

Table 3: PMI lexicon output sample

Word	Score
الناس	0.728234176521078
همجي	-0.05243667282068730
متخلف	-2.0662779625621
طيب	0.411974831720408
انسان	-0.458257293309263
طرش	-2.54995712744607

Table 4: Sample of the lexicon-based approach classification using PMI lexicon

Tweet	Bullying
لاعب فاشل مدرب فاشل رييس فاشل فلا غرابه اذا فشل في انتقاء كلماته فالفشل يحيط به من كل مكان	1
هذا من عينات حدثني احد الثقات والله انه كذاب	1
بالعكس مو مغرور بس مايحب التطبيل علي كل صغيره وكبيره	0
سمعت اخر نكته دامبي فليح يقول الهريفي بتاريخ الهلال يكفي شرف انه اول لاعب في العالم سنتر ضربه البدايه ههه عرفت ليه جمهورهم غبي	1
يمكن فاعل خير يبي يتصدق علي احد لازم كل فعل يطلع شين والغايه منه شينه استر علي ما وجهت وادعي له الله	0

2.5 Machine Learning-Based Approach

In this approach, the SVM algorithm is used. The SVMs have supervised learning models from the theory of computational learning based on the concept of structural risk minimization technique. The SVM is selected in this research based on the strength of this method in Arabic Tweets classification, according to [33]. The idea behind this concept is the identification of hypothesis h having the lowest value of the true error can be assured. When an unseen and random test case is selected then the probability of true error is h [34]. However, it creates one or more hyperplanes that classify the data. And, the optimal margin hyperplane between the two classes is selected [25].

In the classification step, the same data that is collected and cleaned is used. The dataset is converted from string feature into numerical features by using Term Frequency-Inverse Document Frequency (TF-IDF). In Python, the Vectorizer classifier is a part of the sklearn library, which can be used to calculate TF-IDF. This will tokenize the documents by learning their vocabulary. Then, inverse documents weights are learned. After the learning phase, the dataset is splatted into a training and testing dataset.

The kernel is used to implement the SVM algorithm that transforms input data into the desired format. The first kernel we will use is the Linear SVC kernel and compute the performance of this type of kernel. On the other hands, we will use Radial Basis Functions (RBF) which is the well-known kernel used in SVM. RBF is used to semantically map an input into infinite-dimensional space. Also, by using C which is a hypermeter to control error. Low C means less error and large C high error. However, it does not mean that low errors mean we have a good model. This depending on the dataset that how much error dataset consists of. Another hypermeter in SVM is gamma which is used when we use the Gaussian RBF kernel. Gamma decides how much curvature we want in a decision boundary. High gamma means more curvature, while low means less curvature.

Because of the imbalanced dataset which includes 3974 non-bullying tweets and 1153 bullying tweets, and to get high performance of SVM we will be resampling the dataset. Resampling is a technique to deal with highly unbalanced data as it is used to remove ample from majority class called under-sampling or adding features to minority class known as oversampling. Before applying to resample, the Singular-Value Decomposition is used. It is a matrix decomposition method for reducing a matrix to its constituent parts to make certain subsequent matrix calculation simpler. With import Truncated SVC from the sklearn module. After that, resampling is done by using the Python imbalanced-learn module. For oversampling the Synthetic Minority Oversampling Technique (SMOTE) is imported with ratio='minority', and Random Under Sampler for under-sampling.

The dataset after resampling divided into training and testing using the sklearn model selection. Then, the SVM model is applied. Finally, the results of SVM before and after resampling are evaluated based on F1-score, accuracy, precision, and recall.

The dataset after resampling divided into training and testing using the sklearn model selection. Then, the SVM model is applied. Finally, the results of SVM before and after resampling are evaluated based on F1-score, accuracy, precision, and recall.

4. Results and Discussion

After performing the experiments on the Saudi Arabia Dataset, the comparison of different models i.e. PMI, SVM linear SVC, SVM RBF, SVM with SMOT, and SVM with under-sampling are shown in Table 5.

Table 5: Performance Evaluation after applying different approaches

Model	Accuracy	Recall	Precision	F1-Score
Lexicon-Based (PMI)	68	73	38	50
SVM Linear SVC	75	39	25	30
SVM RBF with c=4 and gamma=0.5	74	39	43	41
SVM after application of resampling method (SMOT)	82	84	81	82
SVM after random under sampling	82	83	80	82

To improve the classification performance of the SVM model, Radial Basic Function (RBF), GAMMA, and C hyperparameters are used in this study. RBF semantically map an input into infinite-dimensional space, and a polynomial degree is added to make the features constant. However, GAMMA decides the curvature in the decision boundary. While the error rate is controlled by C. With the help of this, the F1 score reaches 41%, which indicates there is still a need to deal with the imbalanced dataset to improve the performance. Furthermore, to deal with the imbalanced data resampling is used. It removes the samples from the majority class in the case of under-sampling while oversampling is adding samples to the minority class. For this reason, SMOT and random under-sampling are used in this study. In this case, the results that are achieved in terms of F1-Score are 82%. The analysis of the results shows that the application of the SVM algorithm after applying SMOT and under-sampling performs better in terms of F1-Score as compared to other approaches.

The findings of this research paper are very significant, for various reasons; it provides a way for researchers to focus on their desired regions with the usage of Twitter API on the bullying data in the context of Saudi Arabia. It also detects Saudi Cyberbullying in different periods, and classify whether the current data is cyberbullying or not. Moreover, with the help of this, this enables the Tweeter Company to take appropriate decision by closing the account in case if anyone posts harmful tweets repeatedly.

Some limitations of this study are the following: Twitter API has maintained strict policies to access Twitter contents, it needs permission after submitting a survey to know why we need access to Tweets. After we set the location specifically Saudi Arabia and some bullying keywords, we commonly find it difficult to obtain enough dataset. Also, the API search collects only data only for one week, therefor we need multiple permissions for collecting a sequence of data samples. For this reason, the most significant challenge that faced this study was trying to collect data on separated periods for a long time.

To get the weight of Saudi's bullying words was confused and difficult. We tried first to collect and give the bullying words a weight based on a survey that can be distributed to many Arabic Language experts. But we found that this method is time-consuming. For this reason, we started using the PMI lexicon which calculates the required weights based on the dataset.

5. Conclusion and Future Work

In this contribution, we have successfully built the required Tweets dataset through various periods with 5109 tweets, and the number of bullying tweets was 1135. However, on the created dataset of tweets texts written in Arabic.

There are two methods were successfully applied, namely lexicon-based PMI, and machine learning-based SVM for detection and classification purpose. The performance of both methods according to the results is compared in terms of the F1 score. The results of the application of SVM after resampling the dataset outperforms with an 82 % F1-score as compared to the second method so that the SVM method gave the best results. Based on these results, it clear that Cyberbullying is a present problem in Saudi society within social media especially with those who are using the Tweeter platform. Consequently, this needs to pay too much attention to this problem, its roots, and identify all its related factors as a successful step for the reduction of Cyberbullying. The Ministry of Education can contribute to solving this problem by inserting such topics as "Ethics of Social Media" into the early levels classes, this, in turn, can reduce the problem. The results also contribute to help for Anti Cybercrime. Moreover, for future work, the accuracy can be increased by expanding the dataset and used 'celebrities' hashtags to create a lexicon since it has a lot of bullying tweets. Also, the results can be improved by handling the negation in the tweets that may affect negatively the performance of our analysis, besides, the tweets can be categorized based on the type of bullying, such as offensive, religious, and violence, etc., Moreover, the neural network or the deep learning algorithms can be employed for much better results.

References

[1] S. Poland, "Cyberbullying Continues to Challenge Educators," District Administration, 2010.

[2] A. M. Al-Zahrani, "Cyberbullying among Saudi's Higher-Education Students: Implications for Educators and Policymakers," World J. Educ., vol. 5, no. 3, p. n/a, 2015.

[3] D. Farid and N. El-Tazi, "Detection of Cyberbullying in Tweets in Egyptian Dialects," vol. 18, no. 7, pp. 34–41, 2020.

[4] A. H. Alduailej, "The challenge of cyberbullying and its automatic detection in Arabic text," pp. 389–394, 2017.

[5] H. Sanchez, "Twitter Bullying Detection," Homo, 2011.

[6] P. Burnap and M. L. Williams, "Cyber Hate Speech on Twitter: An Application of Machine Classification and Statistical Modeling for Policy and Decision Making," Policy & Internet, vol. 7, no. 2, pp. 223–242, 2015.

[7] N. Al-Twairesh, H. Al-Khalifa, A. Al-Salman, and Y. Al-Ohali, "AraSenTi-Tweet: A Corpus for Arabic Sentiment Analysis of Saudi Tweets," Procedia Comput. Sci., vol. 117, no. December, pp. 63–72, 2017.

[8] H. A.-D. Adel Assiri, Ahmed Emam and International, "Saudi Twitter Corpus for Sentiment Analysis," Int. J. Comput. Inf. Eng., vol. 10, no. 2, pp. 272–275, 2016.

[9] M. El Kourdi, A. Bensaid, and T. Rachidi, "Automatic Arabic document categorization based on the Naïve Bayes algorithm," Proc. Work. Comput. Approaches to Arab. Script-based Lang. - Semit. '04, p. 51, 2004.

[10] M. Oakleaf, "Writing information literacy assessment plans: A guide to best practice," Commun. Inf. Lit., vol. 3, no. 2, pp. 80–90, 2009.

[11] L. Albraheem and H. S. Al-Khalifa, "Exploring the problems of sentiment analysis in informal Arabic," Proc. 14th Int. Conf. Inf. Integr. Web-based Appl. Serv. - IIWAS '12, p. 415, 2012.

[12] Ö. Erdur-Baker, "Cyberbullying and its correlation to traditional bullying, gender and frequent and risky usage of internet-mediated communication tools," New Media and Society, 2010. .

[13] W. A. Al-harbi, "E Ffect of S Audi Dialect P Reprocessing on," Int. J. Adv. Comput. Technol., pp. 91–99, 2016.

[14] "11 Facts About Cyber Bullying," DoSomething.org | Volunt. Soc. Chang., pp. 5–7.

[15] A. El-Halees, "Arabic Opinion Mining Using Combined Classification Approach," Int. Arab Conf. Inf. Technol. ACIT2011, 2011.

[16] S. Wakade, C. Shekar, K. J. Liszka, and C. Chan, "Text Mining for Sentiment Analysis of Twitter Data."

[17] W. Alabbas, M. Haider, A. Mansour, G. Epiphaniou, and I. Frommholz, "Classification of Colloquial Arabic Tweets in real-time to detect high-risk floods," Proc. Int. Conf. Soc. Media, Wearable Web Anal. (Social Media 2017), 2017.

[18] P. B. Dastanwala and V. Patel, "A review on social audience identification on twitter using text mining methods," Proc. 2016 IEEE Int. Conf. Wirel. Commun. Signal Process. Networking, WiSPNET 2016, pp. 1917–1920, 2016.

[19] H. Al-Rubaiee, R. Qiu, K. Alomar, and D. Li, "Sentiment Analysis of Arabic Tweets in e-Learning," J. Comput. Sci., vol. 12, no. 11, pp. 553–563, 2016.

[20] J. Ben Salamah and A. Elkhlifi, "Microblogging Opinion Mining Approach for Kuwaiti Dialect," Comput. Technol. Inf. Manag., vol. 1, no. 1, p. 9, 2016.

[21] R. Sonykrishna, L. Priyanka, K. Vijayalakshmi, and M. Sowmya, "A Text Mining Application Of Emotion Classification Of Twitter ' s Users," no. April, pp. 203–207, 2017.

[22] R. Balabantaray, "Multi-class twitter emotion classification: A new approach," Int. J. …, vol. 4, no. 1, pp. 48–53, 2012.

[23] M. Hasan, E. Rundensteiner, and E. Agu, "EMOTEX: Detecting Emotions in Twitter Messages," ASE BIGDATA/SOCIALCOM/CYBERSECURITY Conf., pp. 27–31, 2014.

[24] F. M. Al-kharboush and M. A. Al-hagery, "Features Extraction Effect on the Accuracy of Sentiment Classification Using Ensemble Models," vol. 10, no. 3, pp. 2019–2022, 2021.

[25] R. Rana and V. Kolhe, "Analysis of Students Emotion for Twitter Data using Naïve Bayes and Non Linear Support Vector Machine Approachs," Int. J. Recent Innov. Trends Comput. Commun., vol. 3, no. 5, pp. 3211–3217, 2015.

[26] M. A. H. Al-Hagery, "Classifiers' Accuracy Based on Breast Cancer Medical Data and Data Mining Techniques," Int. J. Adv. Biotechnol. Res., vol. 7, no. 2, pp. 760–772, 2016.

[27] S. Al-qarzaie, S. Al-odhaibi, B. Al-saeed, and M. Al-hagery, "Using the Data Mining Techniques for Breast Cancer Early Prediction," Symp. Data Min. Appl., vol. 1, no. May, 2014.

[28] A. Abdulrahman Al-Noshan, M. Abdullah Al-Hagery, H. Abdulaziz Al-Hodathi, and M. Sulaiman Al-Quraishi, "Performance Evaluation and Comparison of Classification Algorithms for Students at Qassim University," Int. J. Sci. Res., vol. 8, no. 11, pp. 1277–1282, 2018.

[29] E. I. Al-Fairouz and M. A. Al-Hagery, "The most efficient classifiers for the students' academic dataset," Int. J. Adv. Comput. Sci. Appl., vol. 11, no. 9, pp. 501–506, 2020.

[30] A. M. Misbah and I. F. Imam, "Mining opinions in Arabic text using an improved 'semantic orientation using pointwise mutual information' algorithm," 2012 8th Int. Conf. Informatics Syst. INFOS 2012, pp. 61–69, 2012.

[31] N. Al-Twairesh, H. Al-Khalifa, and A. Al-Salman, "AraSenTi: Large-scale twitter-specific Arabic sentiment lexicons," 54th Annu. Meet. Assoc. Comput. Linguist. ACL 2016 - Long Pap., vol. 2, pp. 697–705, 2016.

[32] C. Stephanidis, "Foreword," Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 10280 LNCS, no. January 2021, p. VII, 2017.
[33] M. AbdullahAl-Hagery, M. AbdullahAl-Assaf, and F. MohammadAl-Kharboush, "Exploration of the best performance method of emotions classification for arabic tweets," Indones. J. Electr. Eng. Comput. Sci., vol. 19, no. 2, pp. 1010–1020, 2020.
[34] T. Joachims, "Text categorization with Support Vector Machines: Learning with many relevant features," pp. 137–142, 1998.

Ms Amjad Rasmi Almutairi received the B.Sc. degree in Information Technology from the Information Technology department, Qassim University, Saudi Arabia, in 2014. Currently, she is a Computer Science Master student at the Computer Science Department, College of Computer, Qassim University.

Dr Mohammed Abdullah Al-Hagery received the B.Sc. degree in computer science from the University of Technology, Baghdad, Iraq, in 1994, the M.Sc. degree in computer science from the University of Science and Technology (USTY), Sana'a, Yemen, in 1998, and the PhD degree in Computer Science and Information Technology (Software Engineering) from the Faculty of Computer Science and IT, University Putra Malaysia (UPM), in November 2004. He was the Head of the Computer Science Department, College of Science and Engineering, USTY, from 2004 to 2007. Since 2007, AL-Hagery has been a Staff Member in the Department of Computer Science, College of Computer, Qassim University, Saudi Arabia. He was appointed as the Head of the Research Centre, Computer College, and a Council Member of the Scientific Research Deanship, Qassim University, from September 2012 to October 2018. He is currently an Associate Professor, has published more than 36 research papers in various international journals. AL-Hagery is teaching master's degree students and a supervisor of many master's dissertations. He is a Jury Member of several PhD and master's thesis as well he is an internal and external examiner in the field of his specialization.