Characterizing Suicide Ideation by Using Mental Disorder Features on Microblogs: A Machine Learning Perspective

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Characterizing suicide ideation by using mental disorder features on microblogs

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Abstract

Suicide ideation is a complicated mental illness that results in a high rate of suicides around the world. Despite the success of psychological and clinical methods, psychological studies have revealed that the number of individuals exhibiting suicide ideation has highly increased. The main challenge of suicide prevention is understanding and detecting the major threat levels and warning signs that may trigger the event. Therefore, this study proposes a new mechanism for characterizing suicide ideation. A total of 54,385 English-language tweets were collected and analyzed, followed by an application of cluster analyses via the hierarchical method. Next, the latent Dirichlet allocation (LDA) algorithm was applied to each cluster to extract the hidden topics. Then, suicidal polarity (positive, negative, and neutral) and emotions (anger, fear, sadness, and trust) were extracted via the SentiStrength, time series, and NRC affect intensity lexicon methods. The results show that suicidal messages contain limited levels of trust, anger, and positive sentiments. In contrast, fear, sadness, and negative sentiments are highly associated with suicidal statements. In addition, our results indicate that the bagging classifier (accuracy of 97.64%) has the best classification result for detecting suicide ideation. The proposed method allows for predictions of suicide ideation via online platforms; a step toward boosting the decision-making process related to characteristic mental disorders by using online texts.

Keywords: suicide ideation, sentiment analysis, topic modeling, Twitter

1. Introduction

Suicide ideation has been identified in the existing literature as an individual's intention to end his or her life. Suicidal behaviors can be generally divided into three streams: suicide ideation, suicide planning, and attempted suicide. Each of these three types of suicide ideation and self-harming behavior are common among adolescents (Robinson et al., 2012). Suicide has also been identified as an individual's intention to develop a plan to kill oneself (Lewinsohn, Rohde, & Seeley, 1996). Despite numerous studies and efforts to better understand suicidal behaviors among people of different demographic backgrounds, the rates of suicide ideation and attempts have remained unchanged (Nock & Banaji, 2007). This can be attributed to the complexity in characterizing suicidal behaviors among a group of people. In addition, the current suicide identification approaches and methods used by health care organizations are mostly shaped by self-reports of suicidal thoughts and intentions. These classical methods can be less effective in identifying and monitoring changes in individual suicidal behaviors, especially in relation to certain events or situations (Sourirajan, Belouali, Dutton, Reinhard, & Pathak, 2020). Furthermore, suicide ideation and suicidal behavior may go unreported in places where health care services are limited. For instance, individuals who are developing plans to commit suicide are less likely to report depression and other mental health symptoms (Spokas, Wenzel, Stirman, Brown, & Beck, 2009). The literature has also showed that certain individuals may even lack an introspective awareness of the thoughts and feelings that drive suicidal behavior and thus lack the ability to inform others of these issues (Nock & Banaji, 2007). Through the latest advancement in social media mining, researchers can benefit from information that is shared across social media networks to better understand people's behavioral and emotional changes in relation to certain events (Bide & Dhage, 2021). The potential of using sentiment analysis as a way to offer timely and effective predictions of online events has been widely addressed in the literature (Rahimi, Naghi Zadeh Kakhki, Winter, & Stevenson, 2019). However, the application of sentiment analysis in suicide detection has yet to reach its full potential (Sarsam, Al-Samarraie, Alzahrani, Alnumay, & Smith, 2021). Based on these observations, this study aims to answer the following questions: 1) 'What are the main topics related to mental disorders and suicide ideation on Twitter?' and 2) 'What are the types of emotions that can best describe suicide ideation on Twitter?'. To answer these questions, this study investigates the potential of using topic modeling and time series analysis to characterize the main topics shared on Twitter in relation to suicide ideation and mental disorders. The study also investigates the predictive capability of certain emotions that are found in tweets in relation to suicide ideation. The findings from this study can offer mental health scientists and organizations a new and effective way to understand changes in people's suicidal behavior in a context-specific setting.

2. Literature review

The process of identifying suicidal behaviors is recognized as an important public health problem that may result in unwanted psychological and economic burdens on a community (Okolie, Dennis, Thomas, & John, 2017; Silverman, 2016). The detection and recognition of suicidal events in Malaysia have been reported to be understudied compared to other risk factors, such as gender, depression or other psychopathological dimensions (Murni & Ibrahim, 2020). This can be mainly attributed to the lack of advanced methods for screening early-stage suicidal behaviors in Malaysia (Ibrahim, Che Din, Amit, Ghazali, & Mohd Safien, 2019). However, the process of developing intelligent detection methods can be a challenging task. This can be attributed to the complexity of linking shared information with certain suicidal events or situations. In addition, the classical reporting methods of suicide ideation (questionnaires and clinical interviews) are not capable of capturing changes in suicide ideation across a population (Siau, Wee, Ibrahim, Visvalingam, & Wahab, 2017). Meanwhile, the current methods provided by health care organizations in Malaysia are limited to the instruments' foreign languages, which need to be translated to the official language of the country (Bahasa Melayu). Although this issue can be resolved through the translation process, producing an efficient meaning for some terms or statements in the questionnaires is not guaranteed due to the multiple translation procedures that may result in different meanings (Victor et al., 2019). Therefore, providing new ways to identify suicidal behaviors in people has proven to be useful in developing effective prevention strategies. The expression of individual sentiment (emotion) is shown to be an effective medium that can greatly contribute to the detection (prediction) process of suicide ideation.

Previous studies, such as Selby, Anestis, Bender, and Joiner Jr (2009), have revealed that people who struggle to regulate their emotions are more vulnerable to suicide attempts. The authors stated that individuals involved in different suicide attempts are likely to overcome their innate biological tendencies toward survival. This may require an effective understanding of the reasons or topics related to the avoidance behaviors that lead a person to experience pain-related fear (Law, Khazem, & Anestis, 2015). According to Abrutyn and Mueller (2014), social emotions can push certain groups of people to commit suicide. The authors looked at the potential benefits of studying the link between emotions and cultural factors in an attempt to understand individual intentions and decisions to commit suicide. In line with this, social media websites can be viewed as a convenient medium for users to express their emotions and feelings regarding different matters (Sun et al., 2018; Wu, Li, Shen, & He, 2020). These emotions can be utilized to provide an early screening mechanism for psychiatric disorders with the help of machine learning. For instance, emotions expressed in tweets can be used to predict suicidal behaviors (Varathan & Talib, 2014). This assumption is supported by Sarsam, Al-Samarraie, Alzahrani, et al. (2021), who studied the potential of how emotions can characterize suicide ideation among people. Therefore, the present study explores a new direction for characterizing suicide ideation in Malaysia with the help of data mining methods (sentiment analysis, topic modeling, and time series).

3. Method

We summarized the implementation procedure in Figure 1. This procedure consists of data collection, data pre-processing, cluster analysis, topic modeling, emotion extraction, and classification technique. The following sections explain the implemented process in detail.

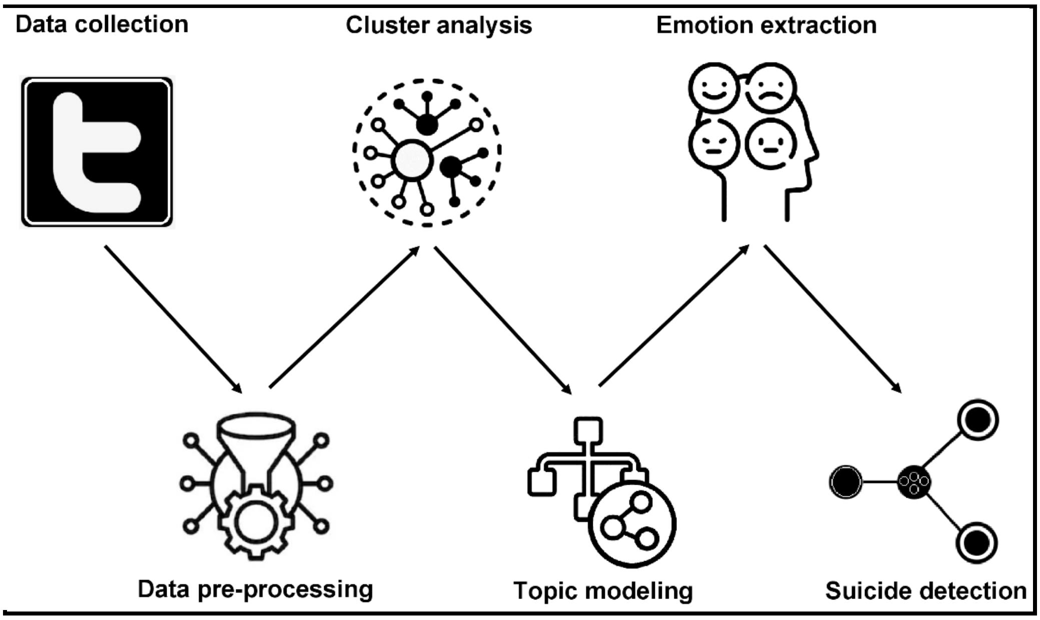

Figure 1: The study procedure

3.1 Data collection

A total of 54,385 English tweets were collected within a time span of six months (September 1st, 2020, till 30th April 2021). We collected the data using the Twitter free streaming Application Programming Interface (API) based on the recommendation of Sarsam, Al-Samarraie, and Omar (2019). The desired tweets were obtained via number of keywords: 'suicide', 'suicidal thoughts', and 'contemplating suicide'. Then, several data preparation steps were considered to enhance the quality and the reliability of tweets, which are extremely essential for the analysis stage.

3.2 Data pre-processing

In this study, several pre-processing methods were used to obtain a solid knowledge out of it. In this context, the bag-of-words model was implemented where and the "Tokenization" technique was utilized to extract the tweets features (words) and build a dictionary of from these features. Then, all these features were converted to a lowercase form before applying the Stopwrods list technique which was used to keep the necessary words in the dictionary and provide relevant information. Finally, the length of the tweets was normalized using the L2 (Sarsam, Al-Samarraie, & Al-Sadi, 2020). This helps to guarantee fair treatment to all the tweets by machine learning algorithms in the coming stages.

3.3 Cluster analysis

After the data pre-processing stage, the hierarchical clustering algorithm was used based on the recommendation of (Sarsam & Al-Samarraie, 2018a, 2018b). Hierarchical clustering was used to create a hierarchical decomposition of the dataset and find the hidden pattern in the data that share similar characteristics. The clustering result produced three groups/clusters.

Finally, topic modeling was implemented on each cluster as a step to extract embedded themes in the tweets.

3.4 Topic modeling

After extracting three clusters from the collected tweets, the Latent Dirichlet Allocation (LDA) algorithm was applied was implemented via the LDAvis system (Jelodar et al., 2019; Sievert & Shirley, 2014) to each cluster to discover the latent topics in these tweets. LDA is unsupervised generative probabilistic method for modeling a corpus. It is the most popular topic modeling method. LDA allows presenting the documents as random mixtures over latent topics where a topic is explained by a distribution over data features (words). It presumes that each document can be represented as a probabilistic distribution over latent topics, and that topic distribution in all documents share a common Dirichlet prior. Therefore, topic modeling to find suicide-related topic as a step towards identifying suicide-related sentiment. To do so, three experts in the public health domain were asked to assess the content of each topic and provide proper label for its cluster (see Section 4.1) as step towards identifying suicide cluster. As a result, the experts suggested to label cluster 3 as 'Suicide' category and both clusters 1 and 2 as 'Non-suicide' category. Finally, sentiments associated with each category was extracted and examined to be used for the classification task, see Sections 3.5 and 3.6.

3.5 Emotion extraction

At this stage, users' sentimental features were extracted from their textual data using NRC Affect Intensity Lexicon (Mohammad, 2017) since textual information is related to users' mental conditions (Al-Samarraie, Sarsam, Alzahrani, & Alalwan, 2019) The NRC consists of a list of English words and their associations that were used to represent six emotions: anger, fear, sadness, and trust. For a given word and emotion X, the scores range from

0 to 1. A score of 1 means that the word conveys the highest amount of emotion X. A score of 0 means that the word conveys the lowest amount of emotion X. Then, the emotional features for each tweet were calculated by adding the relevant associations of the words for a given lexicon. In addition, the polarity of the tweet was extracted using the “SentiStrength” technique via the Waikato environment for knowledge analysis (WEKA) tool (Culpeper, Findlay, Cortese, & Thelwall, 2018; Sarsam & Al-Samarraie, 2021; Thelwall, 2017). For each tweet, SentiStrength assigned scores ranging from ‘+1’ for ‘not positive’ to ‘+5’ for ‘extremely positive’ and ‘-1’ for ‘not negative’ to ‘-5’ for ‘extremely negative’. Based on these scores, we labeled the tweets with +5 as ‘Positive’ tweets, -5 as ‘Negative’ tweets, and -1/+1 as ‘Neutral’ tweets.

3.6 Classification task

Four classification schemes were compared in this study to identify the best suicide classification (detection) method. These classifiers were: K-nearest neighbour (IBk) (Sarsam, Al-Samarraie, & Alzahrani, 2021), multinomial logistic regression (Logistic) (Alafif, Alotaibi, Albassam, & Almudhayyani, 2021), Bagging (Al-Samarraie, Sarsam, & Guesgen, 2016), and decision tree (Yaseen, 2021). These schemes were applied via Weka tool (Waikato Environment for Knowledge Analysis) (Al-Samarraie, Sarsam, Alzahrani, & Alalwan, 2018; Al-Samarraie et al., 2016). In addition, stratified tenfold **cross-validation** method was applied to evaluate the overall prediction process based on the recommendation of (Sarsam, 2019). Several evaluation metrics were implemented to understand the prediction performance of the examined classifiers (see Section 4.3). These metrics are Accuracy, Kappa statistic, Root Mean Squared Error (RMSE), Receiver Operating Characteristic (ROC), and Confusion matrix (Sarsam, Al-Samarraie, Alzahrani, et al., 2021).

4. Results

4.1 Results of topic modeling

Figure 2 exhibits the result of the LDAvis tool for each cluster, where every circle represents a specific topic from the collected tweets, while the size of a circle demonstrates the frequency of a topic. In addition, the distance between circles reflects the similarity between topics. From the figure, we can see that some topics are far apart (independent), whereas some topics are relatively close or even overlap (a high level of similarity).

The results of the topic modeling method implemented on the first cluster reveal that tweets in these groups are mostly concerned about providing advice on preventing suicide. Suicide treatment and prevention topics were discussed often, providing advice to help prevent suicides. For instance, many of these topics proposed engaging in psychosocial interventions, such as cognitive behavioral therapy (CBT). Additionally, some topics discussed accessing collaborative care as a step toward reducing suicidal thoughts. The second cluster, LDA results, shows that the tweets of this cluster focused on presenting statistical information about suicide, for example, that more than eight hundred thousand people die yearly because of suicide (i.e., one person every 40 seconds). Statistical information about the utilized suicide methods was also discussed in this cluster; for example, firearms were the most popular method utilized to commit suicide in the United States, where they annually contribute to more than 50% of all suicide deaths. Additional statistical information about suicide worldwide included, for example, that the suicide rate for men is twice as high as that for women. On the other hand, the LDA results on the third cluster show that these tweets were highly associated with mental disorder topics: (i) “depression”, (ii) “alcoholism”, and (iii) “schizophrenia disorders”. Regarding depression-related topics, the LDA results reveal that some of the people with depression who committed suicide had personal problems, such as the loss of a relationship or job. On the other hand, suicide topics related to alcoholism indicated that individuals with suicidal thoughts often turn to alcohol, which increases suicidal thoughts when individuals drink alcohol before taking their lives. The topics also indicated that people use alcohol as a self-medication to treat, for example, anxiety or a personality disorder and to cope with a trauma. Finally, the topic modeling technique results related to schizophrenia disorders showed that schizophrenia patients are more likely to commit suicide if they have a family history of suicide or suffer from a long-term illness or chronic pain.

Once the topics were extracted from each cluster, we asked three experts in the public health domain to evaluate the content of each topic and provide proper labels for each cluster as a step toward identifying suicidal clusters. As a result, the experts suggested labeling Cluster 3 as the 'Suicide' category and both Clusters 1 and 2 as the 'Non-suicide' category. In light of this categorization, users' sentiments associated with each category were extracted and examined to identify whether sentiments belonged to the suicide/non-suicide category during the classification task (see Sections 4.2 and 4.3).

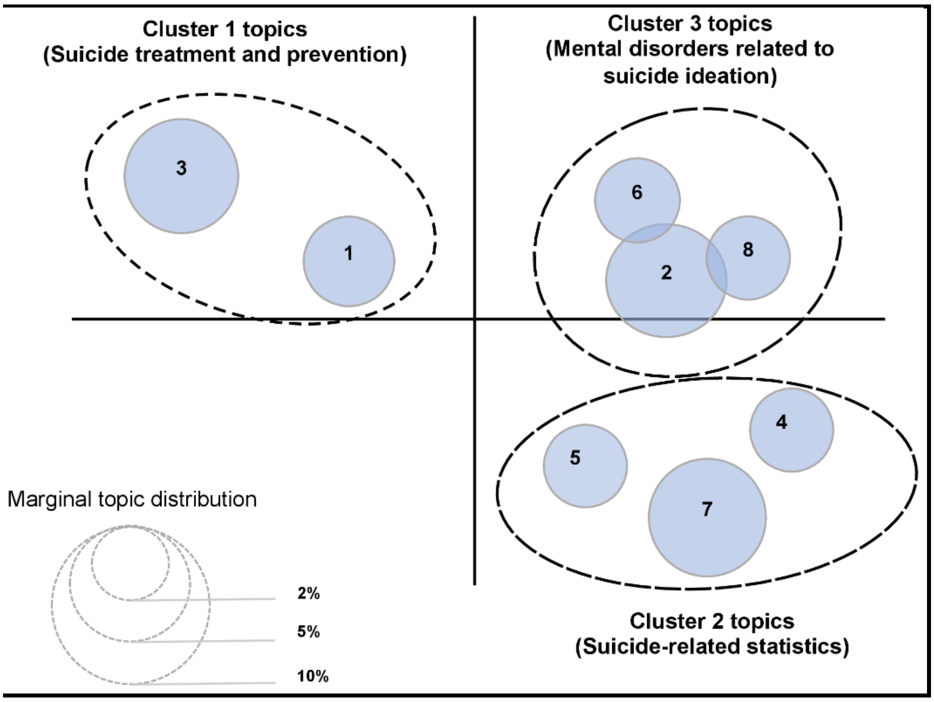

Figure 2: LDA results

4.2 Results of the emotion extractions

To identify suicidal sentiments, suicidal polarity and emotions were extracted from the identified topics. SentiStrength was implemented to extract positive, negative, and neutral polarity types from each cluster. Then, we examined the temporal features of each topic, using the time series method over a period of six months (180 days) (see Figure 3). Finally, four types of emotions (anger, fear, sadness, and trust) were obtained via the NRC affect intensity lexicon method.

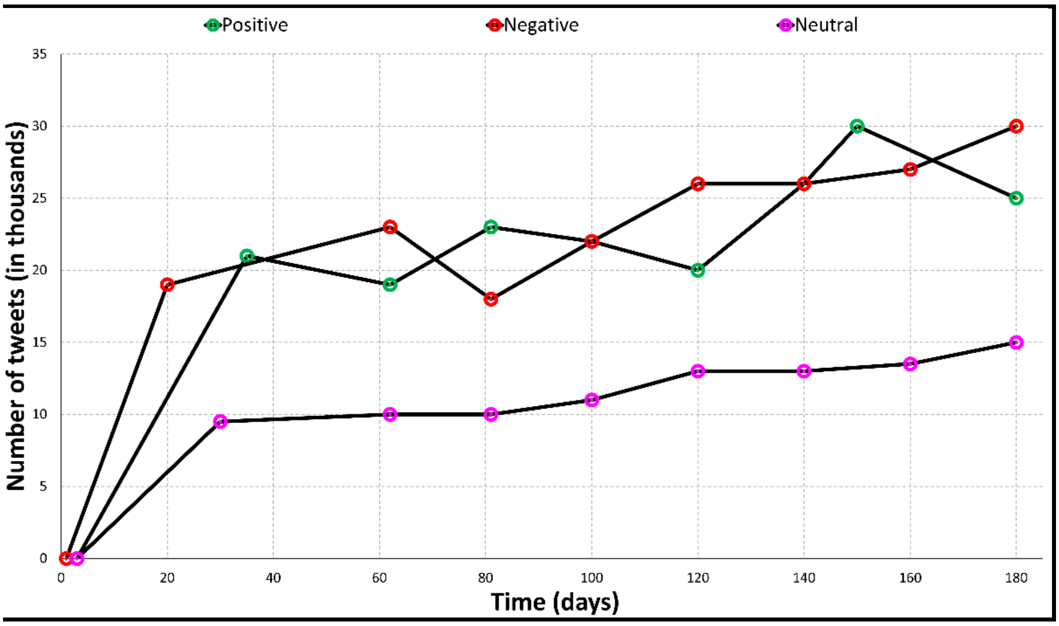

Figure 3: Time series results for users' sentiments in each cluster

From this figure, it can be observed that each cluster has a specific type of sentiment that is dominant—the highest number of tweets carry a specific type of emotion in a particular cluster. We found that Cluster 1 and Cluster 3 contain positive and negative emotions, respectively, while neutral sentiments were found to be dominant in Cluster 2. In addition, the temporal features associated with both positive and negative sentiments are higher than those associated with neutral sentiments. Finally, suicide ideation-related tweets were assessed by three experts (the same experts involved in the topic modeling stage) to assess the relationship between suicide ideation as highlighted in the tweets and their relationship with polarity types. The experts concluded that the tweets that contain neutral sentiments have no relation with suicide ideation; thus, such sentiment was not recommended for identifying suicidal thoughts. Accordingly, we focused on analyzing only positive and negative sentiments via the NRC affect intensity lexicon technique.

Four types of emotions were extracted, including anger, fear, sadness, and trust, via the NRC affect intensity lexicon technique to understand suicidal and non-suicidal sentiments, and these results are summarized in Figure 4. From the figure, tweets from the suicidal group contained higher levels of fear (***M*** = 1.67, ***SD*** = 0.14) and sadness (***M*** = 1.98, ***SD*** = 0.20) than the fear (***M*** = 0.11, ***SD*** = 0.08) and sadness (***M*** = 0.07, ***SD*** = 0.03) in the tweets from the non-suicidal group. In contrast, non-suicidal tweets showed higher levels of anger (***M*** = 0.68, ***SD*** = 0.18) and trust (***M*** = 0.94, ***SD*** = 0.27) than suicidal tweets (anger (***M*** = 0.10, ***SD*** = 0.02) and trust (***M*** = 0.11, ***SD*** = 0.05)). On the other hand, to assess the similarities and differences between tweets related (or not related) to suicidal and non-suicidal tweets, a t-test was utilized, and the results (t = 39.22) showed that there was a significant difference ($p<0.05$) between these two groups. As a result, non-suicidal tweets showed a low level of trust and anger-positive sentiments. In contrast, fear, sadness, and negative sentiments were highly associated with suicidal statements.

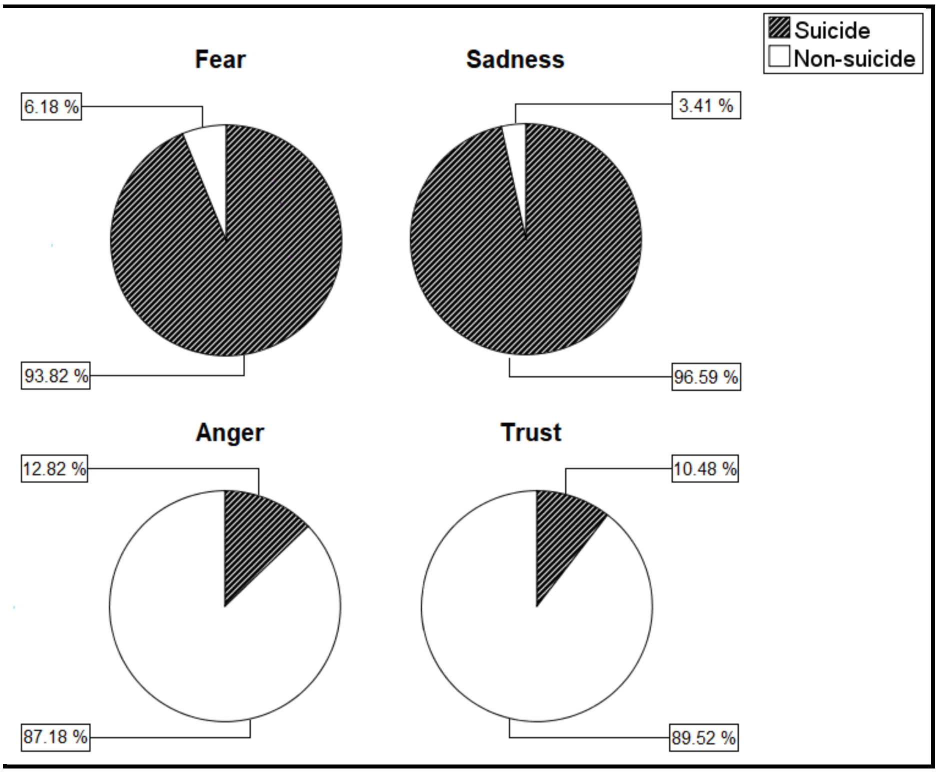

Figure 4: Emotion extractions

4.3 Classification results

Our classification results are summarized in Table 1 and Figure 5, which reveal that the bagging classifier achieved the highest classification accuracy (97.64%), followed by the IBk (64.18%), J48 (56.82%) and logistic (49.43%) methods. Additionally, the classification results show that the bagging algorithm had the highest kappa statistic value (96%) compared to the IBk (68%), J48 (61%), and logistic (55%) methods. In contrast, the logistic classifier produced the highest RMSE value (91%), followed by the J48 (49%), IBk (35%), and bagging (3%) methods.

Table 1: Classification results

Learning algorithm	Accuracy (%)	Kappa statistic (%)	RMSE (%)
Bagging	97.64	96	3
IBk	64.18	68	35
J48	56.82	61	49
Logistic	49.43	55	91

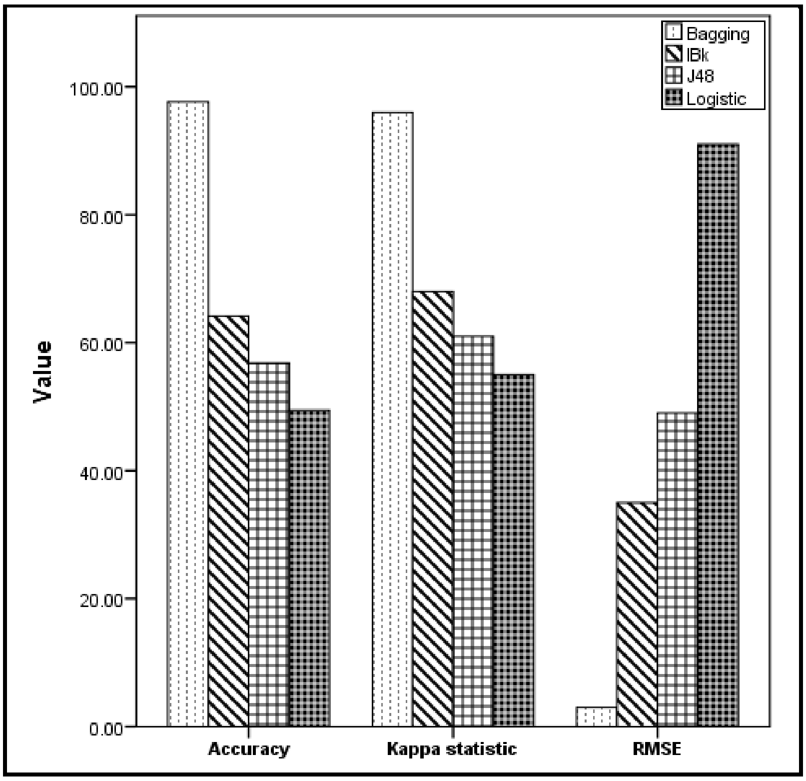

Figure 5: Evaluation metrics of the three algorithms

In addition to the previous evaluation metrics, we used the confusion matrix approach to evaluate our algorithms by measuring the relationship between the predicted and actual instances, based on the demonstrating instances along the diagonal of the confusion matrix. Our results (see Figure 6) reveal that the bagging classifier had the highest predictive capability between actual and predicted classes, i.e., 97.80% and 98%, for the suicidal and non-suicidal categories. In conclusion, the bagging classifier had the best classification performance in detecting suicide ideation on the Twitter platform.

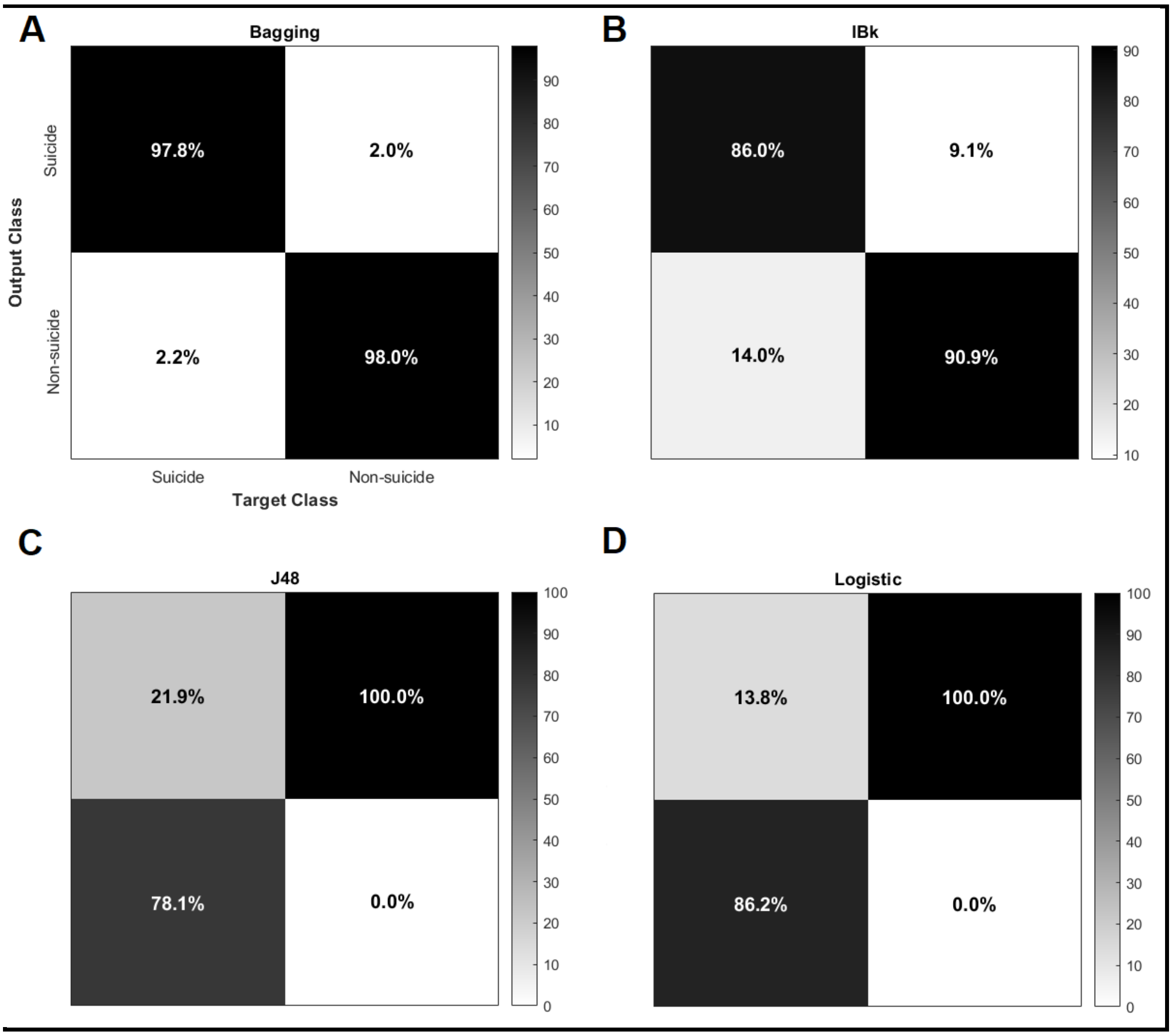

Figure 6: Confusion matrix results

5. Discussion

We have found that the individual emotions embedded in Twitter messages have a great impact on the suicide classification process. Our results show that three main mental disorders, depression, alcoholism, and schizophrenia, are highly associated with suicidal behavior. In addition, our findings indicate that fear, sadness, and negative sentiments are highly linked to suicidal statements, whereas anger, trust, and positive sentiments are found to be related to non-suicidal content. In addition, the bagging classifier showed the highest prediction capability regarding suicidal statements compared to the other machine learning algorithms we examined.

Our LDA results indicate that mental disorder topics in tweets related to depression, alcoholism, and schizophrenia forcefully discuss suicide attempts. This could be attributed to the high probability of committing suicide among people with depression, alcoholism and schizophrenia ; the risk of participating in suicidal and self-harming behaviors have been estimated to range between 5% and 8% for people with these mental disorders (Nordentoft, Mortensen, & Pedersen, 2011). Depression is strongly related to both suicide ideation and attempts; adolescents with depression are six times more likely to commit suicide than nondepressed people (Chen et al., 2020). In addition to depression, suicide risk is correlated with high alcohol consumption, which might be related to the potential role of acute intoxication in increasing the risk of suicidal behavior, impairing judgment by reducing the inhibition of suicidal actions (Borges et al., 2017). In the existing literature, it can be observed that both depression and alcohol consumption are highly associated with suicide risk. According to Overholser, Braden, and Dieter (2012), it is quite possible that the abnormal mental conditions in suicide victims are related to depressive and substance abuse disorders. This could explain our LDA result, which indicates the existence of depression and alcoholism in our data. On the other hand, our topic modeling results show that several Twitter messages that discussed suicide attempts identified schizophrenia as one of the important factors influencing suicide deaths and attempts. The suicide risk among patients with schizophrenia can be related to delusions and hallucinations as well as disorganized thoughts. However, it has been found that suicide risk is considered to be higher among patients with schizophrenia during their first year of illness compared with those with long-term schizophrenia (Ventriglio et al., 2016). The reason behind this could be a loss of trust, together with negative emotions, such as fear and a lack of social support while facing unstable relationships, among patients with schizophrenia.

Our sentiment analysis results show that sadness is the most frequent type of emotion expressed in the relevant tweets (Pestian, Matykiewicz, & Linn-Gust, 2012). This finding confirms the results of previous studies (e.g., (Sarsam, Al-Samarraie, Alzahrani, et al., 2021)), which have found that fearful and negative sentiments are associated with suicidal behavior. This might be the reason for the strong relation between fear and anxiety that was reported among suicide victims.

This study shows the significant role of individual emotions in predicting suicidal behavior on microblogs. Hence, the proposed method greatly contributes to suicide prevention by aiding those clinical decision support systems that implement a temporal risk profile for suicidal behaviors. Finally, the proposed mechanism can be applied to predict other psychiatric disorders on microblogs via the analysis of the user sentiments that are embedded in their online posts.

6. Limitations and future work

Despite the effectiveness of the proposed approach, it has some limitations. Tweets in English were collected and analyzed since it is the most popular communication language in the world. Additionally, specific emotion-related features were extracted in the current work, so in the future, other emotions could be explored, and their relationship with suicide ideation could be examined further. In this work, specific mental aspects were examined, but additional aspects could also be examined. Finally, suicide was used here as an example of a mental health disorder due to its dangerous impact on people and society. Hence, future studies could apply the proposed mechanism to predict other psychiatric disorders by using the content of social media platforms.

7. Conclusion

We proposed a novel approach for suicide detection via users' sentiments existed in Twitter messages. We analyzed several types of users' polarity and emotions embedded in their tweets via SentiStrength, time series, and NRC Affect Intensity Lexicon methods, respectively. Then, Bagging classifier was used to predict suicide-related content. Result showed that suicide messages contained low-level trust, anger, and positive sentiments. In contrast, fear, sadness, and negative sentiments were highly associated with suicide statements. Besides, our result indicated that Bagging classifier (accuracy of 97.64%) has the best classification result in detecting suicide ideation. The proposed method allows predicting suicide ideation from online platforms as a step toward boosting the decision-making process in characteristics mental disorders from online texts.

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