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Suicide ideation detection from online social media: A multi-modal feature based technique

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ABSTRACT

According to an estimate of World Health Organization, each year approximately 700,000 people die by suicide, with many more contemplating suicide. Early detection of suicidal ideation and proper treatment are two of the most effective techniques to preventing suicide attempts. People who are depressed or suicidal are increasingly using social media to express themselves. The main aim of this research is to provide early detection of suicide ideation by evaluating online social media. A well-labeled dataset of suicide thoughts was created on Reddit and Twitter and six feature groups were identified that included not just clinical suicidal symptoms but also online behaviors on social media. A multimodal model is proposed using these feature groups for identifying suicidal thoughts on social media. An accuracy of 87% was obtained using the Logistic regression classifier which outperforms other baselines. According to the study, effective feature selection and combination aids in obtaining greater performance.

1. Introduction

Suicide is one of the most serious social health issues confronting modern society. Suicidal activities can be influenced by a range of personal and social factors, such as trauma or negative experiences, physical or mental illness, social isolation, hopelessness, anxiety, and so on. According to the World Health Organization (WHO), over 700,000 individuals committed suicide in 2019, accounting for one out of every 100 deaths, prompting WHO to release new guidelines to assist nations in improving suicide prevention and care (World Health Organization 2021). Suicide attempts, particularly among young people, were seen to outweigh suicides. Suicidal ideation, also known as suicidal thoughts, refers to people's plans to commit suicide and may thus be used to predict suicide risk. Suicidal thoughts can range from brief to substantial, and may include significant planning, role-playing, and failed attempts. Suicidal ideation is seen in a large percentage of patients, particularly adolescents. As a result, detecting suicide ideation early is one effective technique for preventing such deaths.

Since the introduction of social media, people have been increasingly using online forums, tweets, and blogs to communicate their suicidal tendencies (Park, Cha, and Cha, 2012; Bathina et al., 2020). Some people, particularly teenagers, use social media to express suicidal intentions, seek advice on how to commit suicide in online forums, and even participate in suicide pacts. Anonymity is provided via online communication, allowing people to openly communicate their worries and tensions that they experience in the current world. These internet sites enable early suicide detection and prevention. Twitter is quickly becoming one of the most popular social media venues for sentiment analysis studies. Research indicates that examining social media posts can aid in the detection of depression and other mental health concerns. These online actions prompted them to develop new forms of prospective health care solutions and early suicide detection systems. This is accomplished by detecting suicidal ideas in user postings using machine learning techniques and Natural Language Processing (NLP) methodology. A number of researchers extracted numerous single set feature groups, such as N-grams (Wongkoblap & Curcin, 2017; Benton & Hovy, 2017), Bag-of-Words (Nadeem, 2016; Paul, Jandhyala, & Basu, Aug. 2018), Linguistic Inquiry Word Count (LIWC) (Coppersmith, Dredze, Harman, & Hollingshead, 2015; Maupomés & Meurs, Sep. 2018), or Latent Dirichlet Allocation (LDA), for diagnosing depression in user messages. Other studies compared the performance of these individual features using other machine learning techniques (Resnik et al., 2015; Preotiuc-Pietro et al., 2015; Nguyen et al., Jul. 2014; Schwartz et al., 2014). Some current research work has focused on improving the accuracy of detection by combining some of these features. The authors in (Tsugawa et al., Apr. 2015) combined N-Gram+LIWC to improve the accuracy of detection over single set features. Similarly, in (Wolohan et al., 2018), the authors used advanced text preprocessing and used a combination of Bag of Words, LDA, TF-IDF, and Convolutional Neural Networks (CNN) to increase the performance. According to a study by Tadese et al. (Tyshchenko, 2018), the use of combined features can result in higher performance. They compared the performance of single feature such as bi-gram with Support Vector Machine (SVM) classifier to reach 80 percent accuracy. They demonstrated the effectiveness of a combined feature (LIWC+ LDA+ bi-

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gram) with Multilayer Perceptron (MLP) to attain an accuracy of 91%. Over the last few years, there has been a growing body of literature that deals with the early detection of mental illness by utilizing social media information. (Tadesse, Lin, Xu, & Yang, 2019; Benamara et al., 2018; Song, You, & Park, 2018; Cacheda, Fernandez, Novoa, & Carneiro, 2019).

Although a substantial amount of progress is being made in this field, there are still some challenges to overcome. The aim of the authors of this research is to explore suicide ideation detection using online user-generated material in order to comprehend and detect suicidal ideas from user-generated content. In particular. we have attempted to address the following research questions in this analysis:

Define suicide ideation and the common factors leading towards suicide ideation.

What are the factors that we must look at for suicidal ideation detection from Twitter posts?

How to extract these features from Twitter posts?

What is the relationship between these features and suicidal attitudes?

What is the most effective machine learning algorithm for detecting suicidal ideation from user posts?

In the context of the above mentioned challenges, this work includes a thorough assessment of language preferences, emoticon usage, posting time, and topic descriptors for understanding suicidal ideation from user posts. A variety of characteristics were retrieved from the data, and four learning algorithms were utilised to predict suicidal thoughts. Statistical analyses of the postings were also done in relation to the extracted features, and some interesting facts like tweet length, emoticon usage, and language usage were discovered. Suicidal and non-suicidal writings frequently discuss a wide range of topics that enable us to understand the two types better. LDA is used to extract a set of latent topics from normal and suicidal writings. In addition, this paper aims to study the effects of personality traits on users who have suicidal ideation. With this aim, the authors also attempted to identify a subset of personality traits using relevant features that can be an indicator of suicide risk. Furthermore, we established a metric for sentiment analysis of user posts. Finally, these feature sets are combined with classification approaches to detect suicidal thoughts in user postings. The performance of each individual feature as well as their various combinations is investigated.

The main contributions of the work are summarized as follows:

i) Linguistic, Topic, Emoticons, Temporal and Sentiment features are chosen for the research problem, and their predictive power is successfully proved.
ii) A sentiment value metric is defined for assigning a numerical score to each user based on the sentiment value of their tweets.
iii) Statistical analysis of each type of feature is performed and their effectiveness in suicide ideation detection is identified.
iv) The impact of the user's personality attributes on suicidal thoughts is determined.
v) Various machine learning techniques are employed to demonstrate the advantages of combining different features for achieving high performance in depression detection.

This paper is organized as follows: Section 2 discusses related literature about suicide ideation analysis and detection. The problem statement is given in Section 3. Section 4 introduces the methodology for dataset preparation, feature extraction, and classification model. Experimental analysis and discussion are given in Sections 5 and 6 respectively. Section 7 concludes the paper with future directions.

2. Related work

Gender disparities in the suicide ideation among young people are investigated in (Dholariya, 2017). The study also shows which gender has a higher likelihood of attempting suicide. Another study discovered several elements depending on scenarios that are linked to suicidal inclination among students based on worldwide data among students (Pandey et al., 2019). Anxiety, insecurity, and loneliness were identified by the authors as key elements that might impact students' mental health. They also proposed relevant coping elements to avoid similar situations. The writers of (Nock et al., 2008) outline the many sorts of suicidal behaviour in an article. The authors investigated the epidemic, the risk of suicidal behavior, and the protective variables. Another investigation (Bilsen, 30 October 2018) identifies distinct risk factors for this issue among kids. Suicidal behaviour is one of the world's most serious issues. The authors in (Klonsky, May, & Saffer, March 2016) discuss some facts about suicide, suicide attempts, and suicidal ideation. The authors of (Fernandes, Dutta, & Velupillai, 2018) used NLP to address suicide ideation and suicide attempts, which is another excellent article on the subject. They developed a rule-based technique for defining suicidal thoughts and utilised a hybrid machine learning model to identify suicide attempts in a psychiatric clinical database. Another study looks closely at suicidal behavior in psychiatrically hospitalized teenagers using machine learning and NLP on electronic health information (Nock et al., 2008). The authors of (Ji et al., Feb. 2021) used machine learning to assess suicidal ideation and identification. Specific applications of suicidal ideation are examined using various data sources, such as suicide notes, surveys, and online user content. In (Cook et al., 2016), the authors addressed NLP and machine learning strategies for predicting suicide ideation and symptoms in people released from psychiatric units. The authors of (Mbarek, Jamoussi, & Charfi, 2019) address this issue by mining Twitter for suicide profiles. They used information taken from tweets as well as user profiles to identify people with suicidal intent. In (Ji et al., 2018), a method is described for assessing user language preferences and subject descriptions from online platforms such as Reddit and Twitter. Several important variables were collected from user messages, and four supervised classifiers and two neural network models were employed to predict suicidal thoughts.

The authors of (Ramírez-Cifuentes et al., 2020) proposed a method for measuring the suicide risk of Spanish-speaking social media users by analyzing behavioral, relational, and multimodal data from many social platforms and building algorithms to identify users with suicidal intent. (O'Dea et al., 2015) used both human coders and a machine learning classifier to see if the level of concern in a suicide-related tweet could be determined only by the wording of the tweet. The authors of (Shen et al., 2017) created a multimodal depression dictionary learning model that may be used to diagnose sad Twitter users by mining six feature groups made up of depression-related criteria from clinical and online social behaviors using Twitter tweets. According to the authors of (Kumar & Arora, 2019), anxiety-depression is connected with agitation, sleeplessness, and abnormal mental processes. They suggested a model for predicting anxious sadness based on real-time tweets and posting patterns, as well as linguistic signals. The authors of (Lora, Sakib, Antora, & Jahan, June 2020) employed a variety of machine learning approaches to discern between positive and negative emotions reported by Twitter users and compared the results to deep learning methods. (Rao, Kompalli, & Kompalli, 2020) created datasets on depression using Twitter conversations and used the Naive Bayes classifier to categorize the data. (Sharma & Churi, 2022) investigates persuasive concerns such as social comparison, colorism, and mental health in connection with Instagram use, with an emphasis on young adults in India. Structural Equation Modeling failed to find a positive and significant link between age and social concerns with control factors such as Instagram frequency and time spent. Furthermore, it was shown that social comparison might lead to colorism and mental health problems. Sentiment analysis was also performed in (Neogi, Garg, Mishra, & Dwivedi, 2021) from Twitter data using Bag of Words and TF-IDF and algorithms such as Naïve Bayes, Decision Trees, Random Forest, and Support Vector Machine. (Naredla & Adedoyin, 2022) uses the BERT model to perform processing of data.

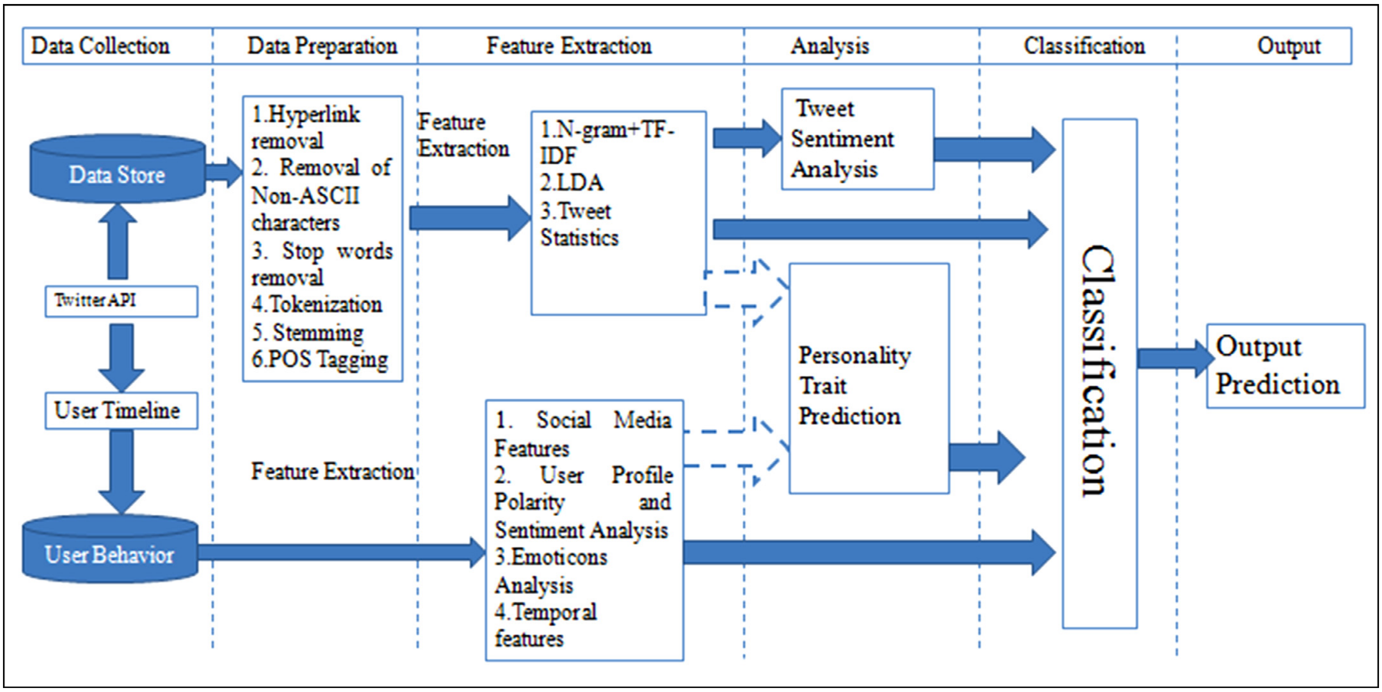


Fig. 1. Methodological Framework of Twitter Data for Suicide Ideation detection.

The authors in (Ji, Li, Huang, & Cambria, 2021) used improved text representation with lexicon based sentiment scores and latent topics and proposed relation networks for detecting mental disorders and suicide ideation with related risk indicators. The relation module also has an attention mechanism to prioritize more important features. The authors of (Ansari, Ji, Chen, & Cambria, 2022) conducted an experimental study to demonstrate how the ensemble and hybrid methods improve depression detection performance. Several experiments were performed on each of the three datasets using different sentiment lexicons and logistic regression as a classifier. In deep learning approaches, they utilised long short-term memory (LSTM) and attention LSTM for conducting experiments for automated depression detection. The authors of (Mahdikhani, 2022) employed BOW, TF-IDF, topic analysis, document embedding, and supervised learning algorithms to develop a prediction model for identifying public opinion from Twitter data during the COVID-19 pandemic. The significance of this feature set may also be appreciated from (Kumar, Kar, & Ilavarasan, 2021) (Chintalapudi et al., 2021), where it has been investigated in relation to its application in service management for doing social media analysis and digital health systems. In (Neogi, Garg, Mishra, & Dwivedi, 2021) (Ahn, Son, & Chung, 2021) (Sharma & Churi, 2022), the authors used these feature sets and supervised learning algorithms for performing analysis on Twitter and Instagram data.

All of the cutting-edge works discussed above aimed to improve the performance of the research by combining features. There are several shortcomings in the existing literature, despite the fact that some of the above-mentioned work has considered sentiment, linguistic, and topic analysis for suicide ideation detection. Only a few studies have focused on using sentiment and emotional analysis of user profile features separately, but no well-known studies have combined user profile features, personality traits, and linguistic features and applied them to the same dataset to observe the deviation in the results. Furthermore, earlier studies did not address statistical analysis of each feature set. This study builds on previous research on depression detection and suicide ideation detection published in (Chatterjee, Samanta, Kumar, & Sarkar, 2022; Kumar et al., 2022). Here, we aim to address these shortcomings by attempting to detect suicide ideation from Twitter comments using a combination of user profile and linguistic features. Various machine learning approaches and various feature combinations are used for detecting individuals who have suicidal ideation.

3. Problem statement

Let $A^{U}=\{\alpha_1, \alpha_2 \ldots \alpha_n\}$ be set of social media sessions of user U where n denotes the number of sessions and i^{th} session is denoted by α_i. Each social media session $\alpha \in A^{U}$ consists of a sequence of posts denoted by P_α and a variable indicator θ_α. $\theta_\alpha = [0,1]$ where $\theta_\alpha = 0$ specifies a normal session, θ_α=1 is an indicator of suicidal tendencies.

The sequence of posts is given by:

$$P_s = \left\{ < p_1^\alpha, t_1^\alpha >, < p_2^\alpha, t_2^\alpha > \ldots\ldots < p_m^\alpha, t_m^\alpha > \right\}$$

Each post $p_i^\alpha \in P_s$ is associated with a timestamp t_i^α denoting the time at which the post was published on social media.

Given a social media session A^U for a particular user U, our objective is to decide whether U is suicidal or not by processing as few sessions from the set A^U as possible. Therefore, we aim to learn a function $Y\{\theta_{\alpha i} \mid \alpha_i\}$ that will receive as input the posts $\{<p_1^\alpha, t_1^\alpha>, <p_2^\alpha, t_2^\alpha> \ldots <p_m^\alpha, t_m^\alpha>\}$ belonging to session α_i and it will return two values {0,1} where 0 specifies a normal session, 1 specifies that the user U possess suicidal tendencies.

4. Proposed methodology

Due to the variety of user behaviours on social media and the complexity of their posts, the authors propose using machine learning models on a specified feature set to classify individuals with suicidal ideation. The model requires two inputs for each user. The first input represents the tweets of each user using a set of linguistic features. Using a collection of linguistic attributes, the first input represents each user's tweets. To assess the personality of each user, we did a word-by-word sentiment and emotional analysis of the tweets, which serves as a second input to our model. Both features' outputs are combined and supplied into our prediction model. Datapreparation, feature extraction, analysis, fusion, classification, and output are all depicted in Fig. 1.The following sections describe our approach.

Table 1
Dataset Statistics.

Description	Suicidal dataset	Non-Suicidal dataset
Number of Twitter users	445	724
Number of tweets	74125	114579
Mean number of tweets per user	166.57	158.25
Mean tweet length	142.89	120.77
Mean number of emoticons per user	30.84	42.80

4.1. Data collection

The proposed work uses Twitter and Reddit data to train the algorithm for suicide ideation detection. Initially, a list of suicide-related statements from subreddits devoted to suicide were compiled where users sought support from the online community. These posts are usually written by people who have suicidal inclinations, hence they can be considered as suicide-indicative statements. In addition, standard posts from other subreddits related to friends, family, or entertainment are also collected. The suicide-indicative posts were reviewed manually to create a subset of phrases which were then used as search terms on Twitter.

Using Twitter APIs, a total of 188,704 English-language tweets containing these search terms were collected from 2000 users. Out of these tweets (37740/188704), tweets corresponding to 400 users were set aside for testing purposes. The rest of the tweets were manually annotated to create two datasets, one for suicide-indicative and one for non-suicidal users. Initially, the tweets containing the maximum number of suicides-indicative keywords corresponding to a particular user were selected. These tweets were then manually labelled to categorize users in two data sets. The suicide dataset features users who appear to be depressed based on their tweets. The normal user dataset includes people whose tweets did not appear to reflect depressive thinking, users who did not refer to their personal ailments, and users who reported news or comments about depression.

For every Twitter user, a simple set of statistics were collected about their profile as well as their tweets for a period of three months starting from an anchor tweet. For the hashtags, links, replies, and @mentions, the authors used the numbers and took the average per tweet. A social media session consists of a tweet and the replies and comments associated with it. In this work, each tweet is considered a post for a session instead of merging all the tweets for a particular user. The proposed work aims to work on each tweet individually and determine whether a user is depressed or not by processing as few tweets as possible. In addition, working with individual tweets allows one to merge tweets easily up to a fixed point, i.e., k. The statistics for the dataset are given in Table 1.

4.2. Data preparation

Data collected from online social media cannot be directly used for feature extraction due to the presence of various noises that are prevalent in the raw data. This causes problems in word matching and semantic analysis. The problem is more exaggerated as data from online social media may contain grammar and spelling mistakes, emojis, and other unwanted characters. Therefore, the data needs to be preprocessed to ensure that the computational model accomplishes reliable predictive analysis. The following data preprocessing procedures are carried out on the data:

- URL links present in user posts are removed as a part of preprocessing because they do not convey any meaning or polarity.
- Stop words like 'a', 'an', 'the', etc. are removed as they are not discriminative or useful for our model.
- To improve text quality, non-ASCII characters are removed.

Table 2
Description of social media features.

Features	Description	Source of feature
#followers	Number of followers	Tweet metadata
#following	Number of profiles followed by the users	Tweet metadata
#friends	Number of friends	Tweet metadata
Polarity of profile description	Polarity value calculation of user profile description.Gives a floating point value between [-1,+1] indicating negative or positive polarity.	Using Python TextBlob function on profile description obtained from Tweet metadata.
Subjectivity of profile description	Subjectivity value calculation of user profile description. Gives a floating point value between [0.0 to 1.0] indicating subjective or objective context.	Using Python TextBlob function on profile description obtained from Tweet metadata.

Table 3
Emoticons feature description.

Emoticons measures	Description
Total emojis /user	# emojis used by a particular user.
Total emojis/user per post	# emojis used by a user per post
# of unique emojis used	# unique emojis used.
Most used emojis	The most frequently used emojis by a user. Indicates the user's consistent state of mind.
# of Emoji belonging to a specific subgroup (love, sad etc.)	The number of emojis that belong to a certain subgroup.

- Tokenizing is the process of changing sentences into a collection of single words.
- Stemming is performed to change each word into its root word.
- POS (part of speech) tagging is performed to reduce ambiguity while interpreting the words.

Data preprocessing and noise removal result in the removal of noisy content from the data and produce a high-quality and reliable dataset that can be used in this study. In addition, the data preprocessing step reduces the computational complexity of the model as the research only has to deal with useful data that will eventually be used in the model.

4.3. Feature extraction

Feature extraction is an important step in gathering detailed information about users in order to provide high accuracy in suicide ideation detection. Several characteristics were retrieved from tweets in this study, including social media features, emoticons, sentiment analysis, TF-IDF, statistics, topic-based features, and temporal features.

4.3.1. Social media features

This feature category includes information expressly taken from a user's profile, such as the user's name, language, number of friends, profile description, country, profile creation date, time zone, profile photo, number of followers, and following. These characteristics can be used to generate other features such as profile polarity and subjectivity. The polarity value of the user profile description reflects the individual's persona and can be used as an important component in the classification process. Table 2 lists the social media features used in the analysis.

4.3.2. Emojis/Emoticons Sentiment

Emojis are used by users to communicate their emotions through nonverbal elements and simple images. Emojis can help us understand the emotion of a text or tweet and differentiate between positive and negative sentiment content. Tweets from users generally include lots of new emoticons that may be categorized as positive, negative, or neutral. Table 3 lists the numerous metrics utilised in emoticon analysis.

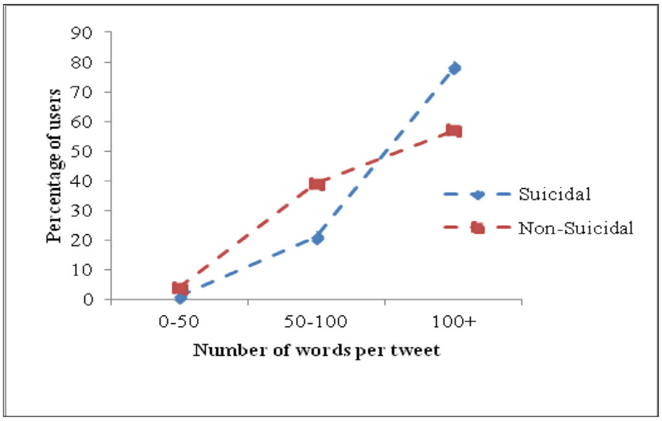


Fig. 2. Mean length of tweets for Suicidal and Normal users.

Several statistical metrics were also employed to calculate a user's emoji usage. Several facts about the use of emoticons were discovered while analysing suicidal ideation messages. Suicidal people, on average, use fewer emoticons, and the quantity of emoticons used in suicidal messages was shown to be significantly lower than in non-suicidal ones. Folded hands, expressionless face, begging face, loudly sobbing face, dissatisfied face, face screaming in dread, bewildered face, and a face without a mouth are the most frequently used emojis among suicidal-tendency users. In the case of non-suicidal inclination users, the most frequently used emojis are: face with tears of joy, loudly weeping face, rolling on the floor laughing, red heart, clapping hands, winking face, and smiling face with heart eyes. Based on this data, it can be concluded that suicidal-tendency users employ negative emoticons more frequently than non-suicidal users.

4.3.3. Tweet statistics

This feature category contains statistical measures derived from user tweets. Simple, brief phrases are used in certain communications, whereas complicated sentences and large paragraphs are used in others. The following metrics are taken into account: the number of tweets and their durations; the number of suicide-related tweets per user; and the ratio of suicide-related posts to total posts per user. Fig. 2 depicts the average length of tweets for suicidal and non-suicidal users. The findings indicate that the mean text length of users with suicidal intentions is much greater than that of non-suicidal users. This is because users who have suicidal thoughts are more likely to have a mental condition or social issues, which is reflected in their messages.

4.3.4. User biography sentiment analysis

Sentiment Analysis is a useful tool for detecting emotional content in user tweets. This method is most effective when a text has subjective content, such as depression. In general, sentiment analysis classifies emotions as either positive, negative, or neutral. We may use this function to predict if a person is feeling positive, negative, or neutral depending on their profile status. Python's SentiWordNet (Baccianella, Esuli, & Sebastiani, 2010) module is used to assign positivity, negativity, and objectivity ratings to each word in a tweet for sentiment analysis.

4.3.5. User tweet sentiment analysis

This is the most effective approach for determining the user's mindset. Here, the user's tweets are examined to determine the type of emotion displayed by the individual on Twitter. Python's SentiWordNet module is used to give positivity, negativity, and objectivity values to each word in a tweet.

Each tweet is given a score based on an Eq. (1).

$$\mathrm{TW}^{\mathrm{k}}_{\mathrm{Sc}} = \frac{\prod_{i=1}^{n} Sc(i)}{nwords} \tag{1}$$

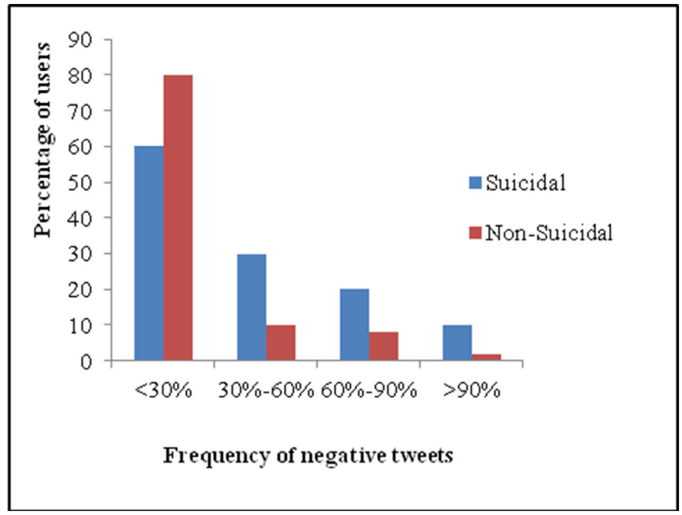


Fig 3. Frequency of negative tweets for suicidal and normal users.

Where Sc(i) represents the positive or negative scores of each word in the tweet and nwords is the number of words in the tweet. Taking the product of each word's score allows to keep the positivity or negative indicator. Because multiplying the scores may provide huge values, the scores are normalized using Eq. (2).

$$\forall_{\mathrm{k}} Norm\left(\mathrm{T}^{\mathrm{k}}_{\mathrm{Sc}}\right) = \frac{\mathrm{T}w^{\mathrm{k}}_{\mathrm{Sc}} - \min\left(\mathrm{Tw}w^{\mathrm{k}}_{\mathrm{Sc}}\right)}{\max\left(\mathrm{T}w^{\mathrm{k}}_{\mathrm{Sc}}\right) - \min\left(\mathrm{T}w^{\mathrm{k}}_{\mathrm{Sc}}\right)} \tag{2}$$

The score for each user is obtained by taking the mean of all the normalized score over all tweets. The equation for calculating the scores for each user is given in Eq. (3). Here n is the number of tweets for each individual user.

$$\forall_{\mathrm{j}} \mathrm{User\_score}_{\ \mathrm{j}} = \frac{\sum_{k=1}^{n} Norm\left(\mathrm{Tw}^{\mathrm{k}}_{\mathrm{Sc}}\right)}{\mathrm{n}} \tag{3}$$

Sentiment analysis of user tweets of both the datasets reveals that most of the users in the suicidal dataset have a sentiment score between -0.5 to -1 compared to normal users where most users have a sentiment score above -0.5. Fig 3 shows the graph of the frequency of negative tweets used by suicidal and normal users.

4.3.6. Personality trait extraction

Every single user in the dataset has a distinct personality. It represents the various qualities of personality for a given trait. From here, it can be determined whether the person is an introvert or an extrovert. For each user, the polarity of the user's tweets as well as some statistical factors are calculated to derive that user's personality attributes. We look at five major personality traits: agreeableness, optimism, active sociality, neuroticism, and spectatorship. For determining the values of the different personality traits for each user, first the polarity of the suspected set's entire corpus is first determined. Each user's tweet's polarity was then compared to the corpus. If a user has the most positive tweets, he is classified as optimistic; otherwise, he is labelled as neurotic. Similarly, the polarity of an agreeable user's tweet is usually the same as the overall polarity of the corpus. When the overall polarity of the corpus is neutral, the polarity of a tweet from an active and sociable user is positive.

This study is considered in the present research to determine the prevalence of personality disorders and understand the traits of users who have posted suicidal ideation and depressive posts on social media. The research aims to examine the association between personality traits and suicide ideation in users. Analysis of the dataset reveals that personality traits were found to be strongly linked to suicidal thoughts. People having low scores in agreeableness and high scores in neuroticism are

Table 4
Generated text using the LDA feature on the depression dataset.

Topic 1	like, love, know, one, want, sorry, sad, cry, sick, hate, die, friend, know, cut
Topic 2	Think, want, Feel, ignore, understand, listen, notice, need, nothing, understand
Topic 3	fat, people, someone, something, never, pain, break, away, smile, sorry, alone
Topic 4	hurt,annoy,one, life, always, care, mean, lose,back,stay,leave, tire,try
Topic 5	Day, really, night, anyone, shit, really, break, better, sleep, bed

found to be associated with increased suicide ideation in 56% of the suicidal dataset. In the normal dataset, users normally have higher scores of agreeableness and optimism. These findings reinforce the notion that personality traits should be considered as a serious risk factor for suicidal ideation. The results are also in correlation with the results obtained in (Na et al., April 2020) and (Duberstein et al., 2000).

4.3.7. *Topic features*

Topic distribution, also known as topic modelling, is a type of statistical modelling technique used to discover abstract subjects in a collection of text documents Vayansky (2020). This method can be used to comprehend, organize, and summarise textual information from a corpus. It also aids in discovering hidden patterns in a document based on the number of topics specified a priori by the user. This method can be used to find latent topical information in any collection of documents represented by a group of words (themes). Using LDA, a topic model is created to extract the hidden topics from the depressed dataset. The LDA requires indicating the number of topics that must be created. The categorization accuracy is determined by the number of topics specified. The authors experimented with different numbers of topics for the study and concluded that 10 was a suitable value. By selecting 10 topics and combining them with additional features using Logistic Regression, an accuracy score of 86 percent is obtained. Table 4 lists some of the topics generated using LDA.

4.3.8. *N-gram and TF-IDF*

To extract unigrams and bigrams, the Tf-Idf vectorizer from the Scikit-learn Python module is utilized. The stop words were eliminated from the dataset, and the term–document matrix was limited to the most frequent unigrams and bigrams. Our entire training dataset is classified in order to discriminate between suicide-indicative and standard message lexicons. For each post category, the frequencies of all bigrams and unigrams are computed and the top 100 unigrams and bigrams are selected. According to the findings, negative emotions, feelings, self-obsession, depressive thoughts, hostility, rage, negative words, hopelessness, interpersonal processes, meaninglessness, and the present tense are lexical terms that are predictive of suicide-ideation. Suicide-indicative posts may also include lexicons about bodily symptoms like weariness, insomnia, low energy, or hyperactivity. Regular post lexicons, on the other hand, include terms that describe earlier events, social interactions, and family-oriented words.

The stop words were eliminated from the dataset, and the term–document matrix was limited to the most frequent unigrams and bigrams. For each type of post, the top 100 unigrams and bigrams are selected. This is depicted in Fig. 4. Both figures indicate the words that appeared with a high frequency.

4.3.9. *Temporal features*

By looking at temporal characteristics, we can better understand how people publish information on Twitter at different times of the day, such as in the morning or evening. According to an analysis of the datasets, the AM value appears more frequently in the depressive data set than in the non-depressive data set. Depressive and suicidal thoughts are more common at night and in the early morning hours due to loneliness, a break from work, a lack of energy, and shifts in communication between light and darkness and the neurological system.

A study of the suicidal dataset reveals that approximately 73% of users having suicidal ideation were active during the time between 6 pm and 6 am, whereas only 27% were found to be more active between 6am and 6pm. In comparison, only 58% of users in a non-suicidal dataset were found to be active between 6 p.m. and 6 a.m. Another research revealed that only 6% of users with suicidal intentions were active between the hours of 12pm and 6pm, compared to 21% of non-suicidal users.

4.3.10. *Classification model*

The detection of suicide ideation posts on social media is a supervised learning classification problem. Given a dataset of tweets $x_{i=1....n}$ and their corresponding labels $Yi_{=1...n}$, a supervised classification model is trained to learn the function, y_i=F(x_i) where y_i=1 indicates a suicidal text and y_i=0 indicates otherwise. Four classical learning algorithms are employed for solving the suicidal ideation classification task. The classifiers utilized in the model's development include Logistic Regression (Peng, Lee, & Ingersoll, 2002), Random Forest (Breiman, 2001), Support Vector Machine (Cristianini & Ricci, 2008), and XGBoost (Chen & Guestrin, 2016).

i) Logistic regression (LR). Logistic Regression is a classification technique that uses machine learning. In the case of a binary classification issue, the procedure is used to predict the value of a predictive variable y, where y might be either 0 or 1. The negative class is denoted by 0 while the positive class is denoted by 1.

A hypothesis h(θ)= θ^TX is constructed for categorizing the two classes, and the classifier output threshold is set to hθ(x) =0.5. If the hypothesis hθ(x)>0.5, the classifier predicts the value of y as 1, indicating that the text is suicidal. If the hypothesis hθ(x) < 0.5, the classifier predicts the value of y as 0, indicating that the text is not suicidal.

Hence,the prediction of logistic regression under the condition 0< hθ(x) ≤ 1 is done. The sigmoid function for logistic regression can be written as follows:

$$\mathrm{h}\theta(\mathrm{x}) = \mathrm{g}\left(\theta^T(X)\right) \tag{4}$$

Where g (z) = $1/(1+x^{-z})$ and hθ(x) = $1/(1+x^{\theta^T X})$

Similarly,the logistic regression cost function can be written in Eq. 5 as follows:

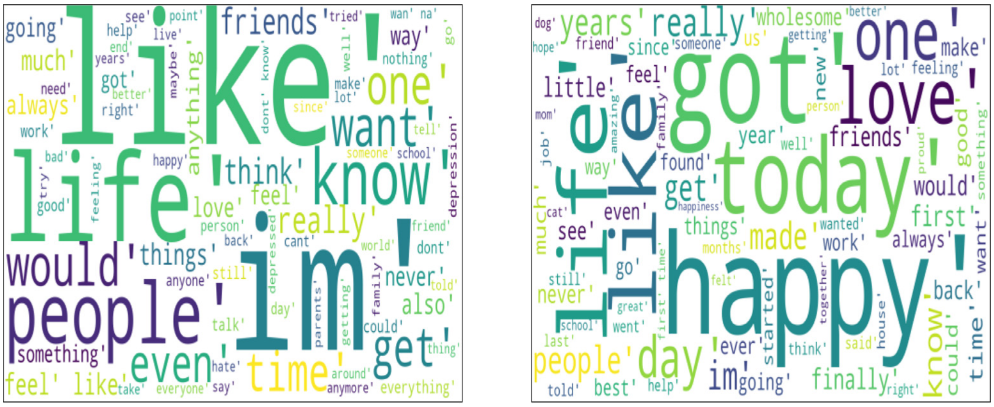
$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} cost\left(\mathrm{h}\theta\left(x^{(i)}, y^{(i)}\right)\right) \tag{5}$$

ii*)* Random Forest (RF). Random Forest is a supervised machine learning algorithm that is based on the concept of ensemble learning methods. It is a combination of a number of simple decision trees bagged with a randomly selected set of features at each split. Bagging enables selection of random samples from the training set and fitting the trees to these samples. Each tree in the random forest makes a prediction, and the prediction with the most votes is the final prediction. The random forest predictor is given as:

$$\mathrm{F(x)} = argmax_i\left\{\sum_{b=1}^{B} T\left(A\left(B, \theta_b\right)\right)\right\} \tag{6}$$

Where the F(x) is the random forest model, B is the number of subtrees, and θ_b characterizes the both random forest trees.

iii) Support Vector Machine (SVM). SVM is one of the most popular classification models for binary and multiclass classification problems. It is a supervised learning algorithm and is based on the key concept that the instances are distinctly separated into N-dimensional space by a hyperplane (where N is the number of features). For a binary classification problem, the hyper plane separates the instances in such a way that w^T +b =0, where w is a weight vector normal to the hyper-plane.The data points are represented by x and b is the bias term which is offset from



(a) (b)

Fig 4. Word Cloud (a) Suicidal data (b) Non Suicidal data.

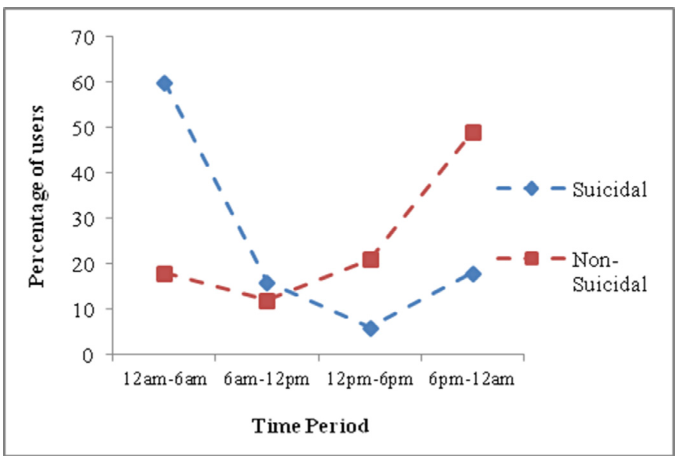


Fig 5. Temporal Analysis of Suicidal and Non Suicidal datasets.

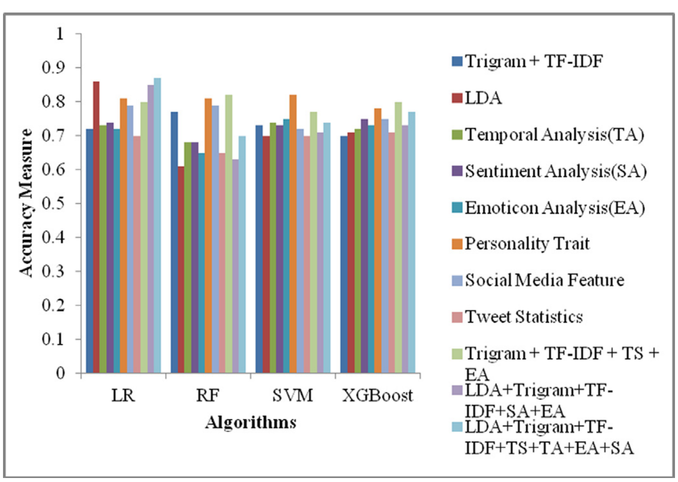


Fig. 6. Accuracy Measure on depression data set of different classifiers.

the origin.The main task of SVM is to determine the values of w and b. In case of linear classification. Langragian function is used to solve w.The support vectors are the data points that are on the maximum border. The solution of w is expressed mathematically as follows:

$$\mathrm{W} = \sum_{i=1}^{n} \alpha_i Y_i x_i \tag{7}$$

where n denotes the support vectors. Y denotes the target class label and the samples are denoted by x. In the nonlinear case, decision function of n,w and b and the kernel trick is expressed as follows:

$$\mathrm{f(x)} = \mathrm{sgn}\left(\left(\sum_{i=1}^{n} \alpha_i Y_i K\left(x_i, x\right) + b\right)\right. \tag{8}$$

The polynomial kernel is given by

$$K\left(x, x_i\right) = \left(\left(x^{\top} x_i\right) + 1\right)^d \tag{9}$$

iv) XGBoost. XGBoost or **Ex**treme **G**radient **B**oosting is a supervised decision tree ensemble algorithm using a gradient boosting framework. An ensemble learning method integrates many machine learning algorithms to create a more accurate model. A gradient boosting decision tree (GBDT) is a decision tree ensemble learning approach used for regression and classification that is similar to random forest. At iteration t, the objective function,that needs to be minimized is as follows:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t\left(x_i\right)\right) + \Omega\left(f_t\right) \tag{10}$$

Where y_i is the real value known from the training data set, l is function of learners which is a sum of the current and previous additive trees and $\Omega(f_t)$ is the regularization term.

5. Empirical evaluation

The goal of this study is to determine whether or not a user is depressed and contemplating suicide by examining their remarks. Each of the features was studied with emphasis on their ability to identify suicide ideation from texts. Several statistical measures were used to analyze the tweets in this study. Text classification algorithms are applied to the entire dimension feature space of the dataset.

Four essential classifiers are employed to determine the significance of the different features collected from the dataset. Each classifier used all of the feature categories. Evaluation metrics are used to assess the performance of the aforementioned strategies. It can be computed in four different ways: True Positive (TP): Suicide ideation cases that are both positive and predicted to be positive. True Negative (TN): the cases of suicide ideation that are negative and predicted as negative. Cases of suicidal ideation that are actually negative but predicted to be positive Suicide ideation cases that are positive but are predicted to be negative. This study considers the following assessment metrics: i) Accuracy, ii) Precision, iii) Recall, iv) F-measure, v) Kappa Statistics. These metrics are based on the information in the confusion matrix, which includes the expected outcome for each test sample. The evaluation metrics are defined as follows (Chen & Guestrin, 2016):

Accuracy is the proportion of the outcomes that are correctly predicted.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

Precision is the proportion of true positive to the cases that are predicted as positive.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{12}$$

Recall is the percentage of true positives to the cases that are actually positive.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{13}$$

F-Measure is the average of precision and recall.F-Measure is calculated as follows:

$$\text{F} - \text{Measure} = 2 \cdot \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

The investigations into all levels of testing data are examined using 10-fold cross validation.

We used classifiers to examine the performance of the linguistic characteristics and observed an improvement in prediction. The LDA with the LR classification model has an F1-score of 0.85 and an accuracy of 86 percent (86 percent, 0.85). With 77 percent accuracy, Trigram + TF-IDF with RF classifier comes in second. When using SVM, temporal analysis as a single feature achieves 74% accuracy. Sentiment Analysis works effectively as a standalone function. Using the XGBoost model, it has a 75% accuracy (75,0.74). The Emotional Analysis (EA) score is a feature that depicts the user's current state of mind by evaluating the emoticons he employs while uploading content. As a result, EA is an important metric for determining users' mental states. Although EA alone is insufficient to offer satisfactory accuracy (72%, 0.71), it performs well when paired with other classifiers. When combined with other characteristics, the SVM model obtains an accuracy of 87 percent (87,0.87).

The purpose was to investigate which combination of linguistic, thematic, statistical, temporal, and emotional variables worked best in terms of accuracy for tweet categorization of suicidal thoughts. Linguistic characteristics were used in combination with sentiment analysis and temporal features. In our study, the LDA + Trigram + TF-IDF + Tweet Statistics + Temporal + Emoticons + Sentiment Analysis feature performed best for detecting suicidal thoughts. Using a Logistic Regression classifier, it outperformed other feature combinations with an accuracy of 87 percent and an F1-score of 0.81. This is followed by LDA + Trigram + TF-IDF + Sentiment Analysis + Emoticons, which has an accuracy of 85% and an F1-score of 0.83. Table 5 contains a full examination of the findings for the combined attributes. The table shows that when more characteristics are incorporated, the performance of all techniques increases. This discovery verifies the usability and usefulness of the features gathered. The individual contribution of each attribute, on the other hand, varies, resulting in varied outcomes for the various techniques.

The AUC-ROC curve is used to compare the performance of the models in Fig. 7. The higher the AUC, the better the model is able to discriminate between positive and negative tweets. The Receiver Operating Characteristic Curve (or ROC curve) is a depiction of sensitivity vs. 1-specificity various threshold levels. The ROC curve is used to compare the performance of various Machine Learning models by taking the shape of the curve into consideration. A curve that is near to the x-axis and away from the y-axis indicates that the model is performing well. The Area under the ROC (or AUC) measures how well a model can distinguish between classes. The AUC combines the ROC curve's performance information into a single quantitative statistics.

6. Discussions

Text or multimedia (picture and video) based information retrieval, has become a vital aspect of most study fields in the analytics domain during the previous few years (Kushwaha, Kar, & Dwivedi, 2021). Social

Table 5
Performance metrics of machine learning classifiers based on linguistic, statistical, sentiment, topic, emoticons and temporal features.

	LR	RF	SVM	XGBoost
Trigram + TF-IDF				
Accuracy	0.72	**0.77**	0.73	0.7
Precision	0.72	**0.79**	0.71	0.7
Recall	0.72	**0.74**	0.73	0.79
F1-Score	0.72	**0.75**	0.75	0.7
Cohen Kappa	0.727	0.713	0.722	0.70
LDA				
Accuracy	**0.86**	0.61	0.70	0.71
Precision	**0.85**	0.30	0.70	0.69
Recall	**0.85**	0.50	0.70	0.69
F1-Score	**0.85**	0.38	0.70	0.71
Cohen Kappa	**0.81**	0.478	0.69	0.686
Temporal features				
Accuracy	0.73	0.68	**0.74**	0.72
Precision	0.72	0.70	**0.74**	0.71
Recall	0.71	0.56	**0.73**	0.72
F1-Score	0.71	0.55	**0.75**	0.72
Cohen Kappa	0.714	0.52	**0.74**	0.695
Sentiment Analysis (SA)				
Accuracy	0.74	0.68	0.73	**0.75**
Precision	0.73	0.70	0.74	**0.77**
Recall	0.73	0.67	0.76	**0.72**
F1-Score	0.72	0.69	0.74	**0.74**
Cohen Kappa	0.762	0.57	0.676	**0.71**
Emoticons Analysis(EA)				
Accuracy	**0.72**	0.65	0.75	0.73
Precision	**0.75**	0.72	0.73	0.76
Recall	**0.76**	0.56	0.74	0.73
F1-Score	**0.71**	0.52	0.75	0.77
Cohen Kappa	**0.732**	0.476	0.67	0.68
Personality Trait(PT)				
Accuracy	0.81	0.81	**0.82**	0.78
Precision	0.7	0.7	**0.67**	0.73
Recall	0.56	0.53	**0.55**	0.78
F1-Score	0.81	0.81	**0.77**	0.75
Cohen Kappa	0.82	0.817	**0.74**	0.68
Social Media Feature(SMF)				
Accuracy	0.79	**0.79**	0.72	0.75
Precision	0.41	**0.41**	0.41	0.71
Recall	0.5	**0.5**	0.55	0.75
F1-Score	0.55	**0.74**	0.45	0.73
Cohen Kappa	0.49	**0.51**	0.43	0.40
Tweet Statistics				
Accuracy	0.70	0.65	0.70	**0.71**
Precision	0.69	0.57	0.70	**0.71**
Recall	0.71	0.65	0.70	**0.71**
F1-Score	0.70	0.59	0.70	**0.71**
Cohen Kappa	0.64	0.53	0.7	**0.65**
Trigram + TF-IDF + TS + EA				
Accuracy	0.80	**0.82**	0.77	0.80
Precision	0.77	**0.81**	0.79	0.77
Recall	0.78	**0.8**	0.8	0.75
F1-Score	0.73	**0.79**	0.81	0.75
Cohen Kappa	0.76	**0.74**	0.69	0.78
LDA+Trigram+TF-IDF+SA+EA				
Accuracy	**0.85**	0.63	0.71	0.73
Precision	**0.84**	0.31	0.71	0.68
Recall	**0.82**	0.51	0.71	0.68
F1-Score	**0.83**	0.39	0.71	0.72
Cohen Kappa	**0.69**	0.43	0.58	0.71
LDA+Trigram+TF-IDF+TS+TA+EA+SA				
Accuracy	**0.87**	0.7	0.74	0.77
Precision	**0.83**	0.69	0.73	0.72
Recall	**0.82**	0.72	0.75	0.71
F1-Score	**0.81**	0.75	0.71	0.75
Cohen Kappa	**0.78**	0.66	0.72	0.74

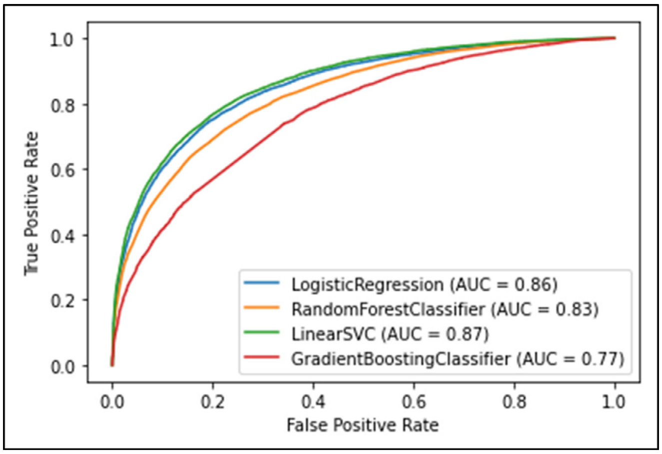


Fig 7. AUC-ROC curve for different classifiers.

media analysis is frequently used to generate insights for enhancing performance and productivity across a variety of applications. The diversity of social media is rising, and there is a need to understand the trends and strategies comprehensively. Several studies (Kushwaha, Kar, & Dwivedi, 2021; Rathore and Ilavarasan, 2017; Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018; Islam et al., 2018) have found that Twitter is the most widely used social media for analysis. This analysis process can be time-consuming, if performed manually. As a result a number of analytical tools are used, with classification and regression being the most common. The proposed work demonstrated the possibility of utilizing Twitter and Reddit as a method for assessing and diagnosing suicide ideation among its users. The work focuses on analyzing text based data derived from the tweets and the posts of the users in social media. A number of research problems were discussed at the beginning of this work to offer a clear comprehension of the proposed approach. The research is supplemented by the analysis done on the selected datasets.

6.1. Contributions to literature

Suicide Ideation has several symptoms and signs, such as inability to focus on any work, inability to complete assignments or enjoy any activity. People having suicidal ideation have feelings of being disappointed, annoyed, worried and consider themselves unlucky and blameworthy. They have thoughts of being unlucky, unfortunate and have a feeling that nothing good will happen to them. They feel tired, ill, have headaches, and suffer from depressive thoughts. Based on these factors, several signs and symptoms were identified in the dataset and certain features were extracted related to emotional variables (sad, positive, negative, anxiety, depression, anger), use of linguistic and temporal features. To extract these factors, several feature extraction methods like sentiment analysis, emoticon analysis, temporal analysis, and personality trait extraction were applied. Each tweet is processed line by line sequentially and each hidden feature is extracted.

A study of the suicidal dataset reveals that approximately 73% of users having suicidal ideation were active during the time between 6 pm and 6 am, whereas only 27% were found to be more active between 6am and 6pm. In comparison, only 58% of users in a non-suicidal dataset were found to be active between 6 p.m. and 6 a.m. Another research revealed that only 6% of users with suicidal intentions were active between the hours of 12pm and 6pm, compared to 21% of non-suicidal users. According to an analysis of the datasets, the AM value appears more frequently in the depressive data set than in the non-depressive data set. Depressive and suicidal thoughts are more common at night and in the early morning hours due to loneliness, a break from work, a lack of energy, and shifts in communication between light and darkness and the neurological system.

The relationship between the above mentioned features and the attitude towards suicide ideation is explored throughout the text and several studies related to sentiment analysis, emoticon analysis, temporal analysis, and tweet statistics are performed to find a relation between attitude towards suicide ideation and the feature used.

We utilised various machine learning algorithms to evaluate the execution learned by the extracted features. The purpose was to investigate which combination of linguistic, topic, statistical, temporal, and emotional variables worked best in terms of accuracy for tweet categorization of suicidal thoughts. Linguistic characteristics were used in combination with sentiment analysis and temporal features. It can be observed from the results that the logistic regression classifier gives the best performance using the combination of all the features. The 2nd best performing classifier is the SVM.

6.2. Implications for practice

Suicidal ideation, often known as suicidal thoughts, is the act of contemplating or planning suicide. Suicidal ideation is present in a significant proportion of patients, particularly teenagers. As a result, early detection of suicidal ideation is one effective method for averting such deaths.

People who are depressed or suicidal are increasingly using social media to express themselves. Twitter is quickly becoming one of the most popular social media platforms for conducting sentiment analysis research. According to researchers, looking at social media posts can help identify depression and other mental health issues. So, they were inspired to create new types of potential health care solutions and early suicide detection systems as a result of these online behaviours. This is performed via the use of machine learning techniques and natural language processing (NLP) methodology to detect suicidal thoughts in user posts. The present work aims to provide a better understanding of the general idea behind suicidal ideation found in online user posts. Each feature extracted from the dataset (linguistic, temporal, sentiment, emotions, persona analysis, topic modelling) was able to successfully classify the dataset and produce the desired outcome. It is hoped that the current work has laid the foundation for future work on the discovery of additional information, such as the detection of the causes of depression and suicidal ideation and their possible implications.

7. Conclusion and future work

The purpose of this work is to acquire a better understanding of the prevalent perspective on suicide by examining suicide-ideation materials published by people online. Data from Twitter is gathered and evaluated in order to supplement our understanding of suicidal thoughts and behavior. Several features are extracted from the data set, including linguistic, topic, sentiment analysis, personality analysis, TF-IDF, and temporal, and it is proved experimentally that all of the features are successful in separating suicidal postings from regular ones. Based on the findings of this study, it is possible to attain excellent prediction performance by carefully selecting characteristics.

Despite the method's effectiveness, there is still a need for additional study and development in this area. Despite the fact that this study investigates temporal data, we have simply divided the day into four time periods (12PM–6AM, 6AM–12PM, 12PM–6PM, and 6PM–12AM). It is meant to divide the day into multiple time slots in order to learn more about the pattern of the user's posting time and how it links with suicidal thoughts. More feature sets, such as timely information and word embedding, may enhance the accuracy of detecting suicidal thoughts. It is anticipated that this research will serve as a foundation for future work in this area.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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