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Analysis of Suicidal Tweets from Twitter Using Ensemble Machine Learning Methods

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***Abstract*—Suicidal ideation is basically to think about taking one's own life and is related to mental health problems, but people with mental disorders, insecurity, stress and a sense of losing control receive no treatment for their condition due to the limited accessibility to mental health care facilities, awareness or social support. Social media like Facebook, Twitter, Reddit, Instagram is our most preferable area to express our feelings, stress and gratitude. The main challenge is to prevent suicidal cases and detect a suicidal note from one's status, or tweet which will help to provide proper mental support to that person. The main motive of this paper is to anticipate whether a person's tweet contains suicidal ideation or not with the help of machine learning. To attain the objectives, we have used an accurate ensemble classifier that can identify content on Twitter that may potentially hint towards suicidal activity. In this research, we have also used several sets of word embedding and tweet features, and we have compared our model among twelve classifiers models. The results from our study reflect that our proposed model can accurately predict the target outcome and come up with an excellent standard for suicidal ideation prediction on active social media such as Twitter.**

***Index Terms*—Suicide, Suicidal Ideation, Suicide Prediction, Social media, Machine Learning, Ensemble Method**

I. Introduction

Suicidal ideation means thinking, considering, or planning suicide [1]. It is a symptom of certain mental illnesses, and it may even happen in the absence of a mental illness in response to a traumatic incident [2]. It can vary from brief thoughts to thorough preparation, according to suicide risk scales. Passive suicidal ideation is just wish to die but not eager to do suicide whereas active suicidal ideation refers to thinking of it frequently and plan to execute it [3] [4]. The average suicide rate was 39.6/100,000 population/year in 2016 in Bangladesh, with the most prevalent age group aged under 40 years [5]. According to some study from 2008 to 2015, suicidal ideation has increased among both girls and boys with a percantage of 0.14% and 0.10% respectively [6]. From a report by World Health Organization, every year around 800,000 people commit suicide. Around 79% of them belong to a low or middle-income country like Bangladesh [7]. The line between active ideation and passive ideation is very thin [8]. Even though all who think of suicide don't end up dying, it can be considered as a risk factor.

Suicidal ideation can be measured in various scale [9] [10]. According to various reports, there are several factors such as depression and self-destructive syndrome, personal debt, and mental health are responsible for suicidal thoughts [11]. Though none of the scale can measure the accurate rate of suicidal ideation, social media can help to find the pattern to some extent. Suicide is a considerable public health problem, and social media is fueling it and putting off the fire at the same time [12]. In this fast-moving world, where everything is on social media, this mental health epidemic can be detected from social media feeds. More people with mental health problems can be connected on social media and, a vast amount of data is available there. This data can help to detect individuals' intentions and their mental health condition.

Previously, doctors and psychologists could consult with patients for treating their problem which was only possible if the patients decided to visit a doctor. Yet in our social environment, especially in a developing country, mental health is not treated as an illness [13]. So many are discouraged to visit a consultant. However due to the popularity of social media, people seek help there with their situation or sometimes just post about their frustration, depressions, and mood swing. Nowadays with the help of artificial intelligence and technology, online detection of suicidal posts has also become a great option in order to provide medical assistance [14]. Data is very precious from the medical perspective to learn more about any diseases and illness [15]. So if technology can help detect with accuracy, medical advice can be delivered effortlessly [16].

The objective of this research is to improve the existing suicide prediction algorithm's performance, and to introduce a new algorithm. The paper is organized into a number of subsequent sections. Section II gives an idea of related works relevant to this topic. In Section III, the methodology is discussed which involves collecting the data, processing the data, work flow and the proposed algorithm. Section IV presents the results of the study. Finally, Section V concludes the paper with future works.

II. Literature Review

Suicide and suicidal ideation have become more and more of a concern as we learn more about mental health [11]. This section presents the relation of social media with suicidal ideation, approaches of suicide prediction in a psychological approach, and related work in this field along with the technology involved.

Even though many of them think about dying but end up overcoming their thoughts, some of them can't. So early detection can help them having mental awareness and treatment for their betterment. If the symptoms or risk factors are detected early, seeking help can be possible [17]. Upto 90% adolescents don't visit professional for their distress and 62% of all people don't consult professional either [18]. If a mental illness can be detected early, it can be treated and controlled to help prevent suicide attempts [19]. Schizophrenia caused by psychosis can be detected before their social behavior and can be accurately estimated from their past history [20].

Few research has been conducted in this field applying a variety of methods. One of them was concerned with neural network having an accuracy of 77.32%, and the cross validation score was 75.24%. They worked with 3,055 English and 2,119 Filipino tweets [21]. Another group used Chinese microblogs as data. They divided them into lexicons and applied the Support Vector Machine classifier to get precision which is 78.1% [22]. Some used machine learning and deep learning for more deep understanding. Ji Shaoxiong and P. Shirui along with other researchers show the methods mainly used in the machine learning approaches [23]. They only showed the data collection and cleaning process along with the visualization process [24].

R. Sawhney, P. Manchanda along 2 others applied some models like Linear regression, Random Forest, Boosting Decision tree, LSTM. They found Random Forest the best fit with 85.8% accuracy, 84.2% precision, and 84.4% F1 score [25]. According to Bridianne O'Dea, Stephen Wan, Philip J.Batterham, Alison L.Calear, Cecile Paris, Helen Christensen's study, "SVMs with TFIDF no-filter" is the best performing algorithm with 80% precision value for 'strongly concerning'. The study also get 76% precision value for 'possibly concerning' and 75% precision for 'safe to ignore' [26].

In summary, through the literature review, it can be observed that some ML techniques used for predicting suicidal notes in social media. Some research was based on pattern finding, and some were related to machine learning. So, this study is focused on proposing the best ML algorithm for finding out the suicidal notes.

III. Proposed Suicidal Note Prediction Algorithm

Our proposed suicidal note detection algorithm consists of Data Set Information, Prepossessing, and the Proposed Machine Learning Algorithm.

A. Data Set Information

The dataset that has exploited in our study was obtained from Twitter through a public API named "tweepy" by providing proper API credentials such as consumer key, consumer secret, access token, and access secret and also by using some keywords and English phrases consistent with suicidal ideation like - "kill myself", "wrong with my life", "my suicide note", "end my life", "never wake up", "suicide fact", "die alone", "wanna die", "why should I continue living", "to take my own life", "can't go on", "want to die", "better off without me", "go to sleep forever", "quit my life", "cut my wrist", "hate myself", "jump off the roof", "feel sorry for myself", "slit my throat", "can't do this anymore", "die in my sleep", "don't want to exist" etc. The keywords and phrases that are used are illustrated in Fig 1.

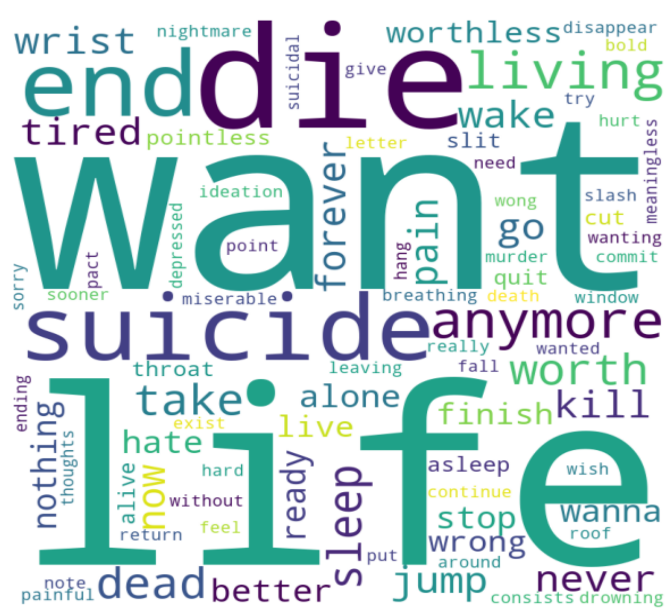

Fig. 1. Suicidal keywords WordCloud

The dataset used in our research was labeled by ourselves and crosschecked multiple times to avoid confusion. After proper preprocessing the tweets were labeled as "suicidal" and "non-suicidal" in other words as 0 and 1.That means if a post contains suicidal ideation related meaning, the post was labeled as 1 and if not the post was labeled as 0. A dataset consisting of 3998 suicide-alarming tweets and 5121 non-suicidal tweets was used. Examples of some suicidal and non-suicidal text from our dataset are shown in Table I. To identify, we have implemented the proposed model by exploiting these data. Data have been split into train and test after stacking the data to the system. The first 80% of the data has been exploited for training the model and the last 20% is for testing the training data. After splitting into train and test, we have standardized the train data and split it into two parts for training the model.

TABLE I
EXAMPLES OF OUR TWITTER POSTS

Suicidal Post	Non-suicidal Post
I wish i could just fall asleep and never wake up	The problem with sleeping is I can never fall asleep and when I do I wake up constantly
I want to stop breathing. I want to close my eyes forever.	I might get tired in 2-3 hours and fall asleep.
Note to myself: My whole existence is a joke and I am planning to Kill myself	i'm so tired of being single but i don't wanna flirt cuz guys i'm tired thinking we will die alone
Why should I continue living? I am rejected so many times from the interview board	I set my alarm in-case i fell asleep for my 3:00, well i never heard it go off
I have nothing to live for and ready to die	I haven't wanted to kill myself in a long time that's pretty cool i guess
I can't take it anymore and ready to jump off the roof	I seriously wanted you to die

B. Pre-Processing

The tweets we extracted from Twitter using the API are not in a structured form as they contain short messages, different signs, emojis, hashtags, URLs, mentions, grammatical errors and linguistic mistakes, redundant information, a lot of HTML entities like '>', '<', '&' etc. which Twitter users use for casual discussions posted as their timeline posts, comments. All these need to be cleaned from the dataset to get it into a structured format.

For preprocessing and data cleaning Natural language toolkit(NLTK) is used in our study. Firstly, a python preprocessing library namely" tweet-preprocessor" is used to remove URLs, hashtags, mentions, emojis, and smileys. Secondly, all digits are removed, and all the texts are made into lower-case texts. Thirdly, Tokenization is done using" TweetTokenizer" from the NLTK library to break the texts down into words. Fourthly, Lemmatization is performed to normalize the words using "WordNetLemmatizer" from the NLTK library as well. Fifthly, to remove punctuations a regular expression library is used. Lastly, stop words are removed from our dataset using English stop words from the NLTK library. Finally, the cleaned dataset is ready for vectorization fit.

C. Proposed Machine Learning Algorithm

In this research, some classifier ML models are used namely Support Vector Machine, Decision Trees, Logistic Regression, Naive Bayes, K-Nearest Neighbors , and various ensemble ML models namely AdaBoost, CatBoost, XGBoost, Gradient Boost, Bagging, and Voting Classifier are also used.

These models were developed on the preprocessed tweet-data; afterward, their performances were evaluated and compared. Out of them, an ensemble model named voting classifier provides the best accuracy while Support Vector Machine Classifier, Decision tree, and Logistic Regression are used as estimators.

Algorithm 1: Proposed Suicidal Tweets Prediction Algorithm

```
Preproceess the given data as described in [A] ;
Train the machine with DATA ;
Test the trained machine ;
pred_LogReg = prediction class from Model with
  Logistic Regression ;
pred_DTree = prediction class from Model with
  Decision Tree ;
pred_SVC = prediction class from Model with
  Support Vector Classifier ;
pred_final Will be result of voting classifier while
  voting = hard
    pred_final ← EMPTY_STRING
    if pred_LogReg = pred_DTree then
      pred_final ← pred_LogReg
    else if pred_DTree = pred_SVC then
      pred_final ← pred_DTree
    else
      pred_final ← pred_SVC
    end if
```

Ensemble methods are a combination of several base models to deliver one ideal prescient model [27]. The procedure used for predicting suicidal ideation posts is the Voting classifier. It is a machine learning model where some classification models are used as estimators and based on the highest majority voting a output class is predicted. Multiple classifiers are employed to get accurate predictions and a class based on the most frequent one is selected. A single machine learning model is generated in this study that predicts the output based on the cumulative majority of votes for each output class. The chosen classifier casts a vote for a class, and the class with the most votes is chosen.

A data flow of voting classifier mechanism is illustrated in Fig 2 and an algorithm is also outlined 7.

Three classifiers were used in voting classifier- a Logistic Regression, a Decision Tree Classifier, and a Support Vector Machine Classifier. Logistic regression is a statistical technique for describing and explaining relationships between one dependent binary variable and one or more independent variables. Decision Tree is used to construct a training model that can be used to predict the class or value of the target variable. The Support Vector Machine Classifier aims to find the best line or decision boundary for categorizing n-dimensional space into classes so that new data points can be conveniently placed in the correct category in the future.
Default parameters were used to initialize the estimators for Logistic Regression, Decision Tree, and Support Vector Machine models. Afterward, to get the desired result, an object is created. Estimators and voting are the two basic hyperparameters of the voting classifier. A list is created for the object by the estimators' hyperparameter. We set the voting hyperparameter to hard. So the voting classifier will make

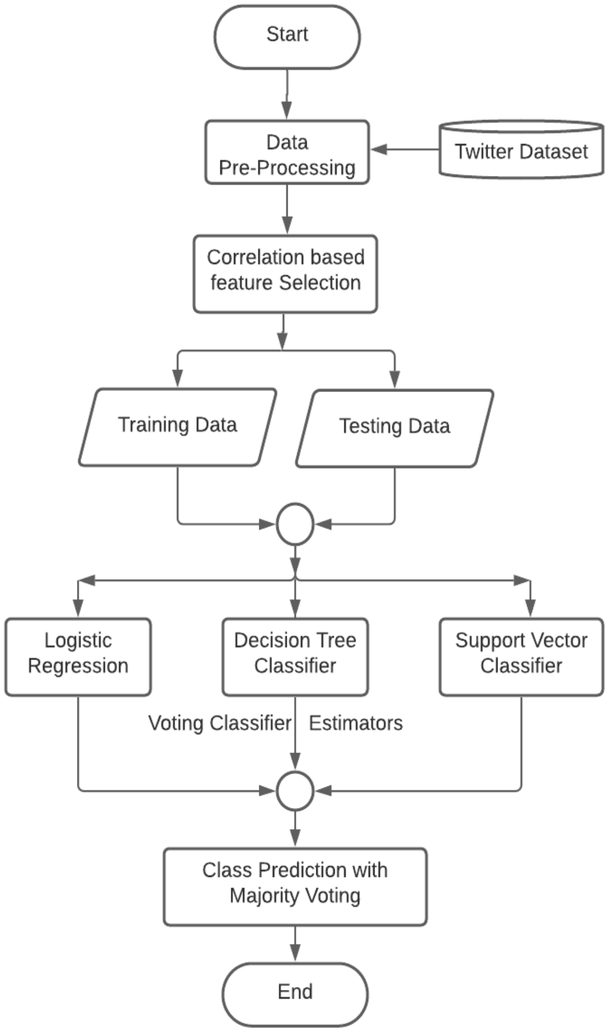

Fig. 2. Flow Diagram of Voting Classifier

judgments based on the predictions that appear the most. Again, to fit the independent variables of the training dataset with the dependent variables the voting classifier is used. After the successful fitting of the dataset, the model's accuracy is calculated based on its prediction result.
In this case, three classifiers have been merged to classify the training dataset and testing dataset sample as per this structure: Let, our 1st classifier chooses class 0 (Non-Suicidal), 2nd classifier chooses class 1 (Suicidal), 3rd classifier chooses class 1 (Suicidal). Our voting classifier will choose the suicidal class because in our prediction it received the most number of votes. So our model will classify the sample as "class 1(Suicidal)".

IV. Experimental Result

The train dataset is used to generate different machine learning prediction models. Then these models are used on our test dataset. We evaluated these models' performances for both the train set and the test set and compared between them. Each of the results of applying the algorithms on train and test dataset are outlined in Table II. Fig. **??** and fig. **??** has the performance of the developed machine learning models. Among all ML algorithms, we decided to choose the Voting Classifier as the most accurate one. It is based on the train data we labeled for the system. In connection with total accuracy as well as the precision, we examine recall and F1 metric for each of the models.

Accuracy is determined by how close the deliberate value to a true value. That implies the nearer the deliberate value to the true worth, the better is the accuracy. Precision refers to the closeness of two or more measurements to each other. It is characterized as the percentage of items effectively arranged into a specific class by the calculation. Recall really computes the number of the actual positives our model catch through the labeling it as positive (True Positive). So, Recall demonstrates the level of the classification that was effectively classified. F1 is the consonant mean of the two and addresses a harmony between the two. The scope of the precision, recall and the F1

TABLE II
Accuracy, Precision, Recall and F1_score of ML models

Model	**Train**				**Test**			
	Accuracy	**Precision**	**Recall**	**F1_score**	**Accuracy**	**Precision**	**Recall**	**F1_score**
Voting Classifier	**0.957**	**0.963**	**0.952**	**0.956**	**0.904**	**0.913**	**0.895**	**0.90**
CatBoost Classifier	0.965	0.970	0.961	0.964	0.901	0.907	0.894	0.898
XGBoost Classifier	0.948	0.955	0.942	0.947	0.903	0.912	0.894	0.900
Gradient Boosting Classifier	0.941	0.949	0.934	0.939	0.866	0.856	0.811	0.829
Logistic Regression	0.953	0.958	0.948	0.952	0.893	0.899	0.885	0.890
Bagging Classifier	0.922	0.936	0.913	0.919	0.895	0.912	0.883	0.891
Multi-layer Perceptron(MLP)	0.997	0.997	0.997	0.997	0.899	0.897	0.898	0.897
Decision Tree Classifier	0.885	0.903	0.872	0.880	0.854	0.874	0.839	0.846
Support Vector Machines	0.863	0.967	0.959	0.962	0.885	0.889	0.878	0.882
AdaBoost Classifier	0.903	0.909	0.896	0.900	0.884	0.890	0.876	0.881
K-Nearest Neighbor(KNN)	0.692	0.737	0.659	0.648	0.655	0.689	0.618	0.599
Naive Bayes Classifier	0.898	0.916	0.885	0.893	0.860	0.864	0.852	0.856

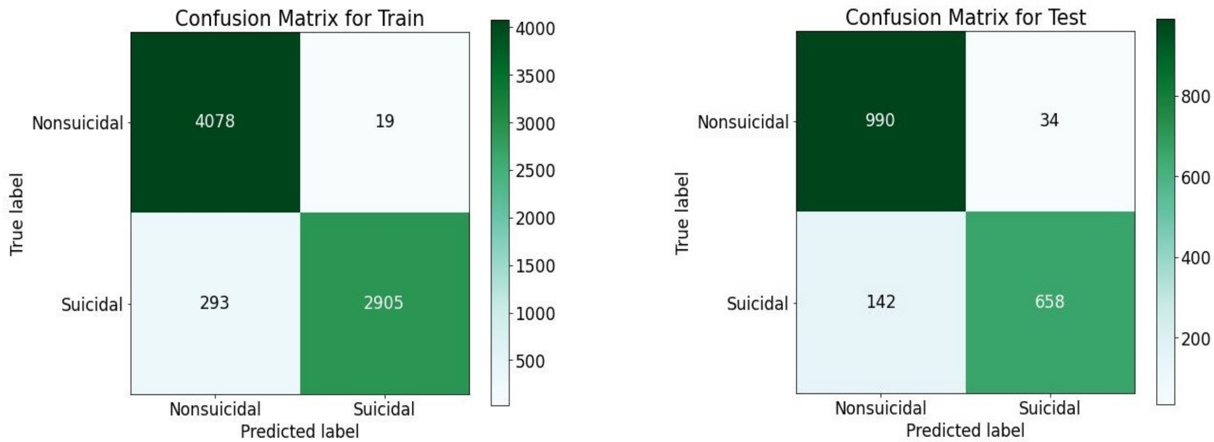

Fig. 3. Confusion matrices for the developed model

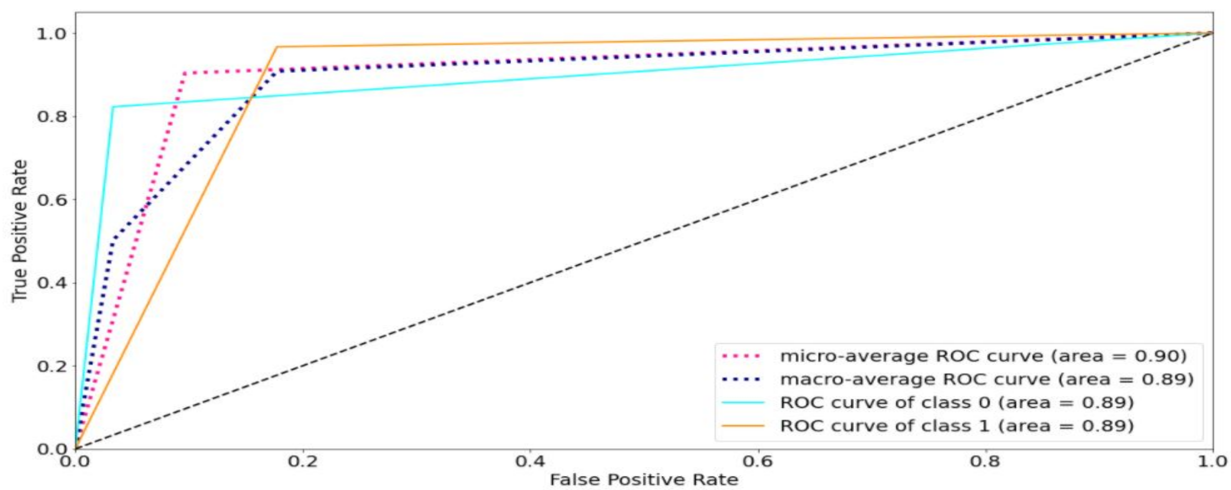

Fig. 4. ROC Curves for the developed model

measurements are completely limited somewhere in the range of 0 and 1, of which a higher worth shows better execution.

These measurements are characterized as:

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

$$\text{precision} = \frac{TP}{TP+FP}$$

$$\text{recall} = \frac{TP}{TP+FN}$$

$$\text{F1\_score} = 2 \times \frac{precision \times Recall}{precision + Recall}$$

where,
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

A confusion matrix is used to represent the false positive and false negative values. Those values were minimized to avoid the error. The confusion matrix of the chosen voting classifier algorithm for our train and test data is portraited in fig. 3; 990 correct results out of 1024 of nonsuicidal data was achieved and 658 correct suicide prediction out of 800 suicidal data was achieved from the test data of the voting classifier. As the suicidal data is less in the whole dataset the machine has less confidence in the suicidal data. That's why suicidal data is less accurately detected than nonsuicidal data. For our dataset, we got the best accuracy for the voting classifier.

For the voting system, as an estimator, we chose the combination of Logistic Regression, Support Vector Machine, and Decision Tree Classifier as it gives us the best results among all the combinations. We tried some other combinations along with those and got the best result with these basic ML models. According to some research papers, they are commonly used for the better result of a voting classifier.

From Table II, the accuracy score of Logistic Regression, Decision Tree, Support Vector Machine of train data are

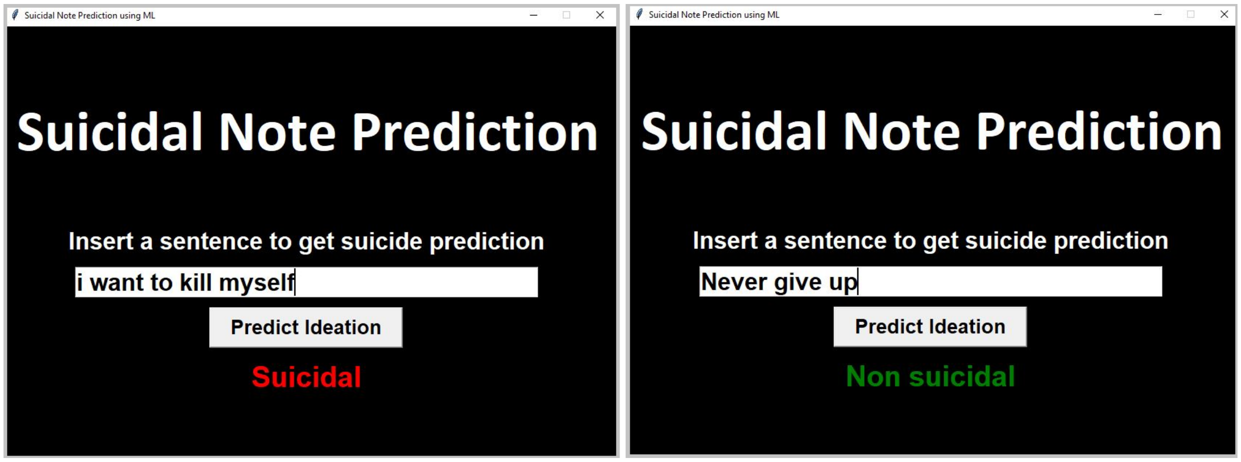

Fig. 5. Single Tweet Prediction

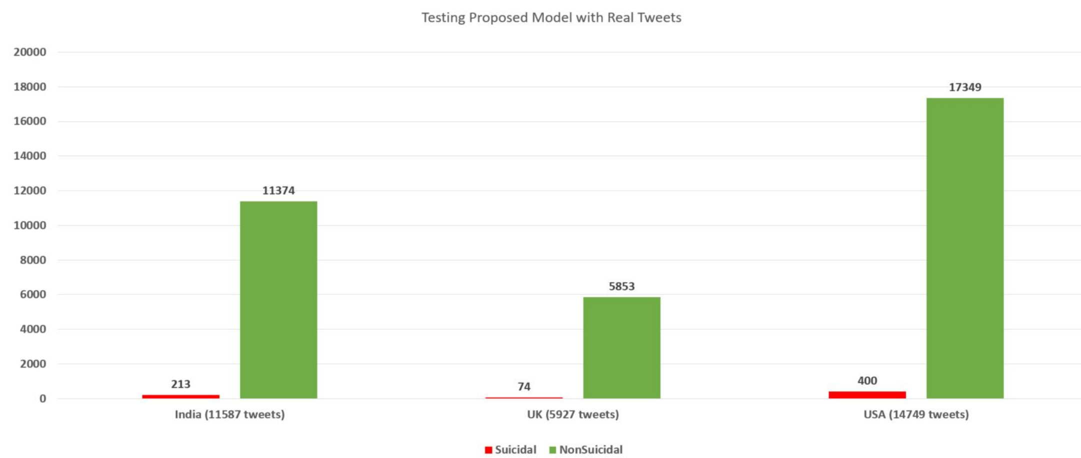

Fig. 6. Testing on region based Tweets

95.3%, 88.5% and 86.3% accordingly and for the test data they are 89.3%, 85.4% and 88.5% accordingly. But when these three are merged into the voting classifier the training accuracy becomes 95.7% and testing accuracy becomes 90.4%. So in the test accuracy of the voting classifier model, we get significant improvement. The precision and Recall and F1 score of both train data and test data got significant improvement compared to the logistic regression model, decision tree model, and support vector machine model. A ROC area under the curve for the Voting classifier model is shown in fig. 4 which is a graph plotted between sensitivity and false-positive rate.

A simple interface is made to test the single tweets prediction potraited as suicidal or non-suicidal using Tkinter is illustrated in fig. 5. Tkinter is the standard Python interface to the Tk GUI toolkit. Another dataset was used to test the accuracy of predicting the suicidal or non-suicidal entities. We have collected three individual Twitter datasets which are differentiated by country. The dataset was not labelled. From the fig. 6 the ratio of suicidal and nonsuicidal posts are visible those datsets.

V. Conclusion, Limitations and Future works

Our research provides a model to predict suicidal alarming tweets. By making a dataset fed into multiple classifiers and then using voting classifiers, the model chooses the highest getting vote for identifying Suicidal Ideation using Machine Learning. The primary focus of this research is to enhance the voting classifier's accuracy compared with other classifiers. The models were trained and tested using accuracy score, precision score, recall score, F1 score, confusion matrix, and ROC curve for evaluation. It also indicates that identifying suicidal posts from tweets plays the most crucial role in this study compared to the other published works.

Although throughout the research, it is strictly tried to be kept as accurate as possible in collecting data, analyzing error factors, and predicted results, there have been some unavoidable limitations. Professional dataset labeling can give more accuracy, i.e., if the dataset is labeled by psychiatrists, then tweets labeling could be more accurate and give higher accuracy. Another limitation faced is that in this research Twitter dataset is used, which is restricted to only 180 characters. If the input text is more than 180 characters, the performance of our model could be less. So, for larger datasets like Reddit or Facebook, accuracy may fall.

Currently, the research is only based on either suicidal or non-suicidal posts. So for future work and further research, we will try to implement such kind of machine learning model which can predict not only suicidal or non-suicidal but also predict another level of mental illness like anxiety, depression, frustration, etc. Again, if the person has previously posted the same category texts, we should mark them as vulnerable and find their Twitter information. That means we will check the suspicious user's previously posted tweets for suicide ideation, and based on this, we will predict if the post is suicidal or not. Due to COVID-19, unemployment, identity crisis, loneliness, and relationship problem have become paramount, which induces depression and frustration, leading to a person taking a suicide attempt. Social media is one of our preferable platforms for sharing our feelings and lifestyle. However, despite having many friends on social media, we feel alone [28]. So with the help of Twitter status, we can analyze people's behavior who needs help. Our primary research goal is to identify those negative feelings from social media to offer mental support to those people.

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