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DETECTING SUICIDAL TENDENCY USING MACHINE LEARNING

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Abstract: Suicide is an essential issue in contemporary-day society. There are numerous elements which could cause a suicide for instance, stress, depression, failure, disappointment, pessimism, unemployment, etc. The destructive consequences of suicide in our modern society are not only emotional however additionally economic. A recent study in United State of America estimated that the economic toll of suicide on society is tremendous and the estimated cost caused by suicides and suicide attempts to the nation is around $70 billion each year. Detecting and preventing suicide attempts therefore becomes crucial for the authorities of the land and should be addressed in order to save people's lives and preserve a sociable community. Early detection tends to be the effective and efficient way to prevent suicide attempts. Traditional modes of detection rely upon primarily on interplay among probable suicidal people and an expert, or a psychiatrist. A recent investigation has shown that people are likely to write down their feelings than to express it verbally to an expert. In order to prevent suicide more effectively, the ideation must be detected as early as possible, this can be done by analyzing users' posts for suicidal related content. The main goal behind this research is to present a robust system that automatically recognize posts with suicidal ideation using machine learning techniques. Nowadays online platform becomes a way for people to express themselves and thus may be used to convey suicidal tendencies, as a result we focus on social networking website Twitter. To achieve that goal, we integrated different Machine Learning such as Naïve Bayes, Support Vector Machine and Decision Tree which can accurately recognize residing Suicidal Tendency of a Twitter's content.

Index Terms: Suicides, Suicidal Detection, Machine Learning, Earlier detection, Tweets.

I. INTRODUCTION

Every year nearly 800,000 death are due to suicide and still many who attempt suicide. Every single suicide is a very sad situation that impacts families, communities and the entire nation and has everlasting effect to those who left behind. Suicide is probably the maximum diagnosed motives for loss of life on the news across the world. The motives that human beings devote suicide are complicated, people with despair are probably to take their lives, however many without despair also can have suicidal thoughts. Based on the research done by American Foundation for Suicide Prevention (AFSP), self-destruction factor is classified into three categories: fitness factors, environmental factors, and ancient factors.

Suicide has been an intractable public fitness hassle no matter advances in the analysis and remedy of most important intellectual disorders. A developing area is a good option for the improvement of suicide screening technology via gaining access to and reading social media content. A recent research has shown that adolescent can easily reveal their suicidal planning in electronic means than to express it orally, hence using machine learning approach we developed a robust system that identifies posts containing suicide behavior on Twitter social networking. In this study we primarily focus on detecting suicidal posts and then make intervention in the hope that suicide can be prevented timely and effectively. Detecting suicidal post is a text classification-based model which requires powerful method to be integrated before getting the work completed. Therefore, we have selected three algorithms which are proven to be best for text classification. The three implemented algorithms are support vector, naïve bayes and decision three.

Online platform with its growing suicidal text became an area for text-based model classification. It gives a valuable studies platform for the improvement of latest technological strategies and upgrades which could convey a novelty in suicide detection and in addition suicide prevention (Marks, M, 2019). Psychiatric and experimental studies were carried out by a large number of researchers (V. Venek, et al., 2017) and answers to questionnaires that have been classified (D. Delgado-Gomez, et al., 2011) to identify suicidal ideation. Artificial intelligence (AI) and machine learning techniques can predict people's probability of suicide based on their social media data (G. Liu, et all., 2019), allowing for a greater understanding of people's intentions and the possibility of early intervention. Feature engineering (B. O'Dea, et al., 2015), (H.-C. Shing, et al 2018), sentiment analysis (F. Ren, et al, 2016), (L. Yue, et al., 2018), and deep learning (A. Benton, et al., 2017), (S. Ji, et al., 2018), (S. Ji, et al., 2019) are all used to detect social posts. Recent studies have shown that social network information can be crucial to detect feelings of depression that can also play a significant role in order to prevent suicide effectively and efficiently (M. Birjali, et al.). Recent development of Machine learning and Neural Network which may be a branch of computing (AI) contributed a lot for numerous forms of sentiment analysis (Shickel, et al., 2017). There are also alternative tools for sentiment analysis like SentiWordNet, WordNet (A. Esuli, et al., 2006). Polarity identification on text may be done through TextBlob that comes with basic options of linguistic communication process. Various forms of sentiment analysis basing on these tools have already been done that is picture box workplace prediction, election outcome, scrutiny quality of politicians and so.

To implement machine learning we first pre-process the data that was extracted from Tweeter using tweeter API. This pre-processing is also called feature extraction of the text document. During the preprocessed we adopted Term Frequency Inverse Document Frequency (Tf-idf) and Count Vectorization (CV). We used PyCharm as development platform to write our code. We selected Python as it's proven to be the most powerful tool for implementing machine learning algorithms and also provides powerful library that supports better and easier implementation. To assess our model performance, we considered 10-fold cross validation, accuracy score, precision, recall and F1 scores. In this research paper section 2 highlights the literature review, section 3 mainly focused on proposed methodology, section 4 emphasized on experimental results and section 5 illustrates conclusion and future works.

II. LITERATURE REVIEWS

Many studies have focused on sentiment analysis, and they have tried a variety of methods (Esuli et a.,2006).Sentiment analysis is often used to detect suicidal intent. Since we're concentrating on Twitter, some tweets contain surprising information, such as suicidal intent (M. Hu, et al., 2004). A real-life precedent can be found in two American rappers Freddy E. and Capital Steez who have both tweeted about their plans before taking their own lives (D. V. Kasturi, et all.,2014). According to an article published by the World Health Organization (WHO), one death occurs every 40 seconds, and by 2020, the rate is expected to rise to one death every 20 seconds, which is surprising. Suicide has risen by 60% globally in the last 45 years, and it is now one of the top three causes of death for those aged 15 to 44 years (R. Li, et a., 2012).

The severity of this crisis is immense. About 800,000 people commit suicide each year, with many more attempting suicides. Suicide is a disaster that impacts whole families, nations, and countries, as well as the individuals that are close to them. Suicide affects people of all ages, and it was the world's second leading cause of death among 15–29-year-olds in 2016. It is a major public health issue that affects people all over the world and is influenced by a variety of factors. We're trying to figure out how social networks influence suicidal behavior. In one of the most well-known incidents, the suicide of Phoebe Prince, it is commonly assumed that cyberbullying played a role in her decision to commit suicide. Cyberbullying is a major issue that has been attributed to a rise in suicide rates (Mason, 2008). One theory is that there is a cause and effect associated between suicides advertised on social media and the younger generations who are affected by them.

According to information retrieved from the World Health Organization's World Cause of Death Statistics in June 2013.In 2011, there were 797,823 suicides worldwide, accounting for 1.5 percent of overall mortality and about 16 percent of injury mortality, with a global suicide incidence rate of 11.5 per 100,000 people (WHO, 2013). Though Asian countries account for roughly 60% of all suicides worldwide. In different papers, the rates presented indicate that suicide rates in South Asia are high countries comparatively to the rest of the world. Suicides can be prevented. For effective national interventions, an improved working suicide prevention strategy is necessary. Restricting access to the most popular means of suicide and suicide attempts, such as poisons, weapons, and some drugs, are an effective method for preventing suicides and suicide attempts.

III. METHODOLOGY

The proposed methodology in this research study begins by identifying destructive terms, which are then used to retrieve data from Twitter through Twitter Application Programming Interface (API). The extracted data is then pre-processed before it proceeds to its training stage. The dataset is then subjected to Support vector machine, Decision Tre, Naïve Bayes with three types of weight optimizers, and the model is assessed using accuracy, precision, recall, and F1 score, we also implemented 10-fold cross validation. The aim of this study is to use various machine learning algorithms and natural language processing techniques to improve the effectiveness of the model and text analysis for predicting suicidal behavior in tweeter social networks. For this proposed method, we chose supervised learning from the three forms of machine learning techniques. The following is a flow diagram that depicts the proposed system:

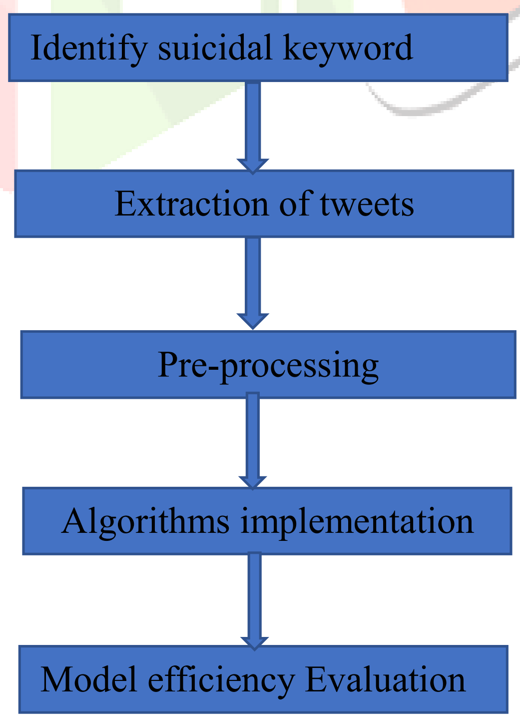

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Fig.1 Steps used in our proposed work.

The suggested methodology is broken down into five sections. These sections include identifying suicidal keywords, information extraction, Pre-processing, integrating Decision Tree, Naïve Bayes Support Vector Machine, and Model efficiency Evaluation.

3.1 Identify suicidal keyword

We needed to define a collection of words that were likely to recognize destructive behavior throughout text before we could gather and process suicidal conversation on Twitter. Under this regard, a study that gathered texts from a variety of sources and examined them to recognize keywords that are commonly used in suicidal notes was extremely useful. The keywords were then analyzed further by three specialists in the area of suicidal behavior prediction, resulting in a list of 62 parameters used in suicidal notes (G. B. Colombo,2016). These keywords were used to retrieve tweets from Twitter.

3. 2 Extraction of tweets

Twitter provides a public API that allows for programmatic gathering of tweets as they occur, filtered according to unique criteria. In order to begin using the Twitter API, For, we used Python's Tweepy package to navigate the Twitter API, which provides us real-time access to publicly accessible Twitter information for a given request. we used python package Tweepy and an API Key (Consumer Key) given to use by Tweeter to extract tweets. Since tweeter contain different post with various content but for our case, we required only specific text. To extract tweets as per our convenient we used keywords such as "depression, anxiety, mental health, suicide, stress, sad, suicidal; suicide; kill myself; tired of life.

3.3 Pre-processing

Pre-processing is the mechanism of filtering a textual data in order to improve accuracy of a proposed system by removing unnecessary features before studying word embedding. It is implemented by utilizing a number of filters to Tweeter posts in order to translate raw data into a format that learning models can understand. We implemented Natural language toolkit (NLTK) to pre-process the datasets before moving on to the training phase in our research. From the original dataset, duplicate sentences are removed. To divide the Tweeter posts into individual tokens, we employed tokenization as based on the data filtering and transforming process. After that, we used a single whitespace to cover all URL addresses, redundant white spaces and contractions. We deleted brackets, colons, dashes stop words, and all newline symbols, which if left alone may cause inconsistent results. As a result, the posts are lowercased and stored as individual text documents. We use lemmatization to guarantee that the word endings are not discarded carelessly, which may result in meaningless word pieces like stemming.

3.4 Support Vector Machine, Naïve Bayes and Decision Tree

Support Vector Machine comes under supervised learning that perform well for text-based classification and produce good results. In an N-dimensional space, we plot every data item to find a hyperplane. Our objective is to find a plane that has the maximum margin We implemented classification by locating the hyperplane that best distinguishes the 2 classes. Support Vector Machine fits our specification because we have a classification task. We supplied our cleaned dataset into the algorithm for training and testing stage.

We have used Decision Tree because it gives good results in complex problems. It's a greedy algorithm that follows recursively top-down greedy approach. It selects the attribute with the highest information gain. Since decision trees comes under supervised learning, they must be trained on annotated data. As a result, the basic concept is the same as it is for every text classification: The algorithm will measure how much each word corresponds with a particular label given a collection of documents (for example, defined as TFIDF vectors) and their labels. It can be discovered, for example, that the word "happy" occurs frequently in positive documents, while the word "suicide" appears frequently in negative documents. It creates a model that can add a mark to any document by integrating all of these observations.

Finally, we have implemented Naive Bayes which is based on the Bayes Theorem. It is a collection of algorithms that having a similar concept, namely where each pair of features being classified is independent of the others, since each input variable is assumed to be independent. Naive Bayes classifier is a probabilistic classifier that divides data into categories based on event possibilities. It is often used in text categorization. Despite its simplicity, it works well in a variety of text classification problems. Naïve Bayes and Decision Tree enables us to show dependencies among features and classes (Chen, 2016) The main goal of the decision tree is to build a training program that will use the prediction class or the value of the input parameters by analyzing the pattern based on historical data, while Nave Bayes assigns a class to a document based on the posterior likelihood of the label, which is based on where the document's word representation is handled.

3.5 Model efficiency Evaluation

The accuracy score is one way to assess model performance. We did this by dividing the dataset into two parts: training and testing stages. We then employed k fold cross validation to evaluate the model because the train and test split is not always enough to determine a model's performance. Train/test indices are given by k fold cross validation to break data into train/test sets. Divide the dataset into k folds in a row. Each fold is then validated once, with the remaining k - 1 folds forming the training collection. The value of k in this situation is 10. Precision, recall, and f1 scores were added for further review. The value computed by dividing true positive by the sum of true positive and false positive is known as precision. Recall, but from the other side, is the value obtained by adding true positive and false negative to somehow get true positive. A true positive in a classification model is a result in which the system accurately predicts the positive class. A true negative is a result in which the model accurately determines the negative class, while a false positive is an outcome in which the system forecasts the positive class inaccurate.

We use assessment metrics like accuracy of estimations (Acc.) Equation (1) and F-score (F1) Equation (4), which are composed of precision (P) and recall (R), to test the baseline with our conceptual machine learning classification model. It is based on a confusion matrix that incorporates data from each test sample prediction outcome. Precision calculates the number of clearly identified samples; recall approximates the proportion of correctly identified positive samples; F1 score is a cumulative mean of precision and recall; precision estimates the number of positively identified samples (2); recall closely resembles the ratio of properly completed positive samples (3).

The most powerful classification evaluation score is accuracy, which is described as follows:

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\textbf{Precision} = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$\textbf{Recall} = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$\textbf{F1 Score} = \frac{\text{precision.recall}}{\text{precision and recall}} \tag{4}$$

V. RESULTS

Our model was assessed on the basis of five variables: accuracy ,10-fold cross validation, recall, f1 score, and precision.

5.1 Results of classification results using features based on tweets.

When we use only features based on tweets, Table 5.1 shows the accuracy, precision and recall, and Completion Speed of our model in recognizing suicidal posts on tweeter. A 10-fold cross validation was used in the experiments. Table 5.1 shows that the Decision Tree classifier achieves the best accuracy of 97.89%, precision of 97.89%, recall 97.38% and Naïve Bayes classifier complete a speed of 5.35 second which is the fastest speed among the remaining algorithms.

Table 5.1: Classification results using features based on tweets.

Algorithms Implemented	**Accuracy**	**precision**	**recall**	**Completion Speed (unit in second)**
Support vector Machine	**92.89%**	**93.53%**	**91.41%**	**1105.52**
Decision Tree	**97.89%**	**97.89%**	**97.38%**	**18.70**
Naïve Bayes	**93.29%**	**89.23%**	**89.04%**	**5.35**

Fig:1 Confusion Matrix for Décision Tree Classifier

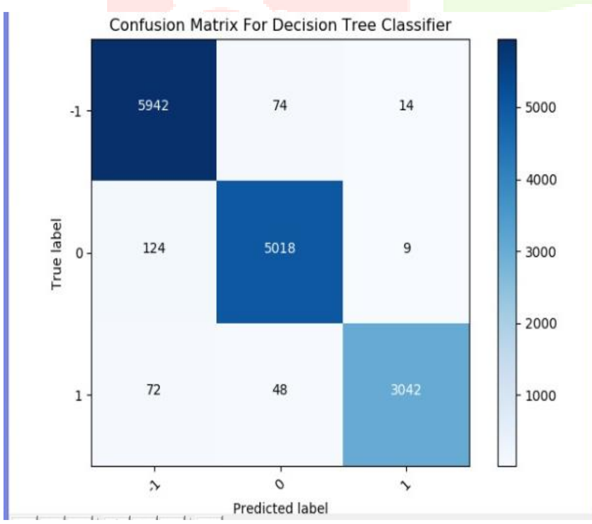


Fig:1 Confusion Matrix Naive Bayes Classifier

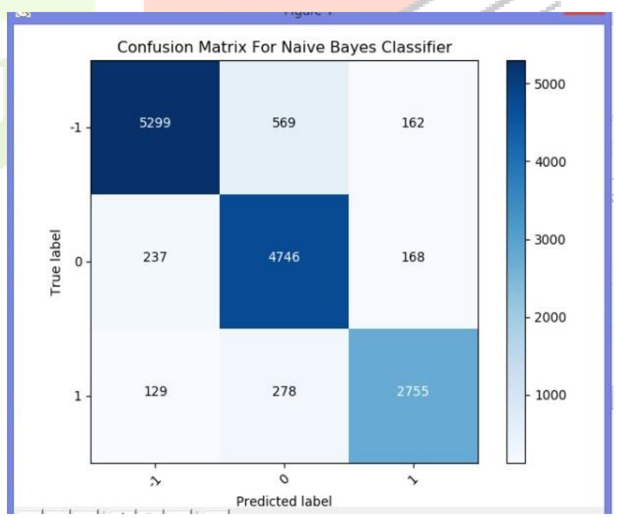
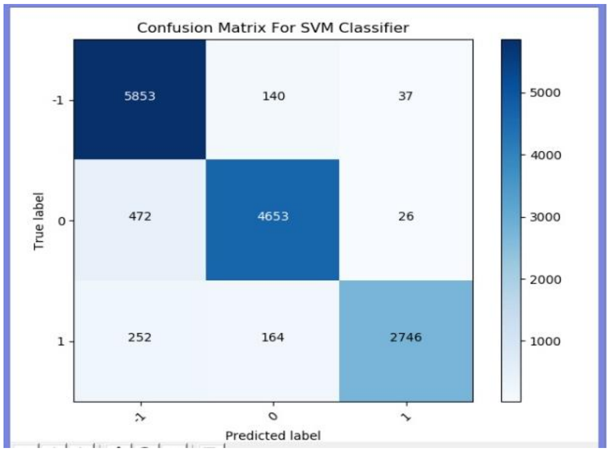


Fig :3 Confusion Matrix For Support Vector Machine Classifier

Fig :4 Performance Comparison



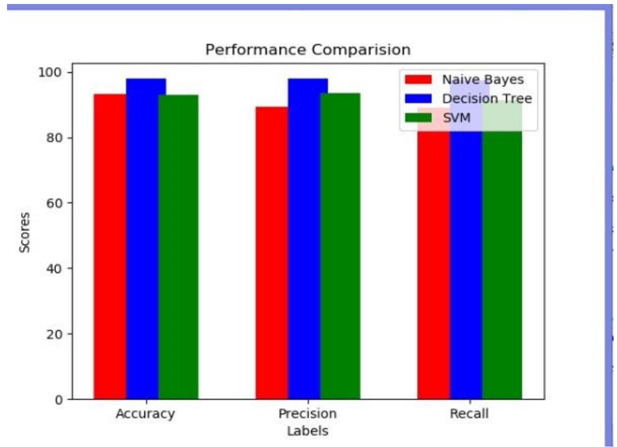


Fig:5 Time Evaluation

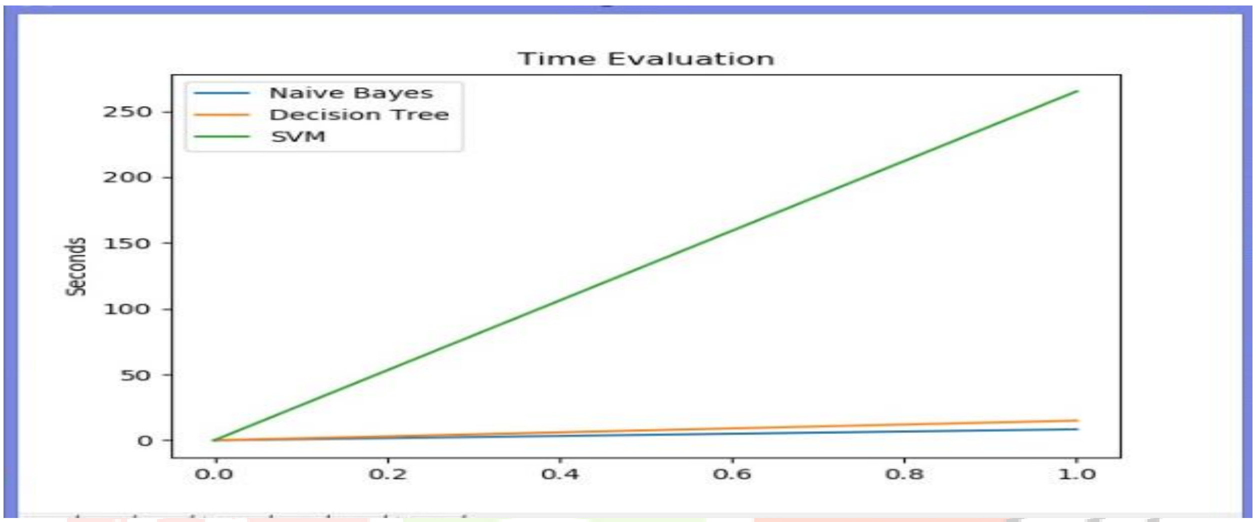


Fig 1,2 and 3 are confusion matrix of the three implemented algorithms decision tree, Naïve bayes and support vector machine. A confusion matrix is a description of classification problem prediction output. The number of accurate and inaccurate predictions is totaled and subdivided by class using count values. The trick to the uncertainty matrix is that when it makes predictions, it is perplexed. The three figures 1,2 and 3 shows an N x N matrix which is used to evaluate the efficiency of a classification model, where N is the number of target groups. The matrix compares the real goal values to the machine learning model's predictions. This provides us with a comprehensive picture of how well our classification model is doing and the types of errors it makes.

Fig 4, demonstrates the performance comparison between decision tree, naïve bayes and support vector machine based on accuracy, precision, and recall of our model in identifying suicidal posts on Twitter. In the experiments, a 10-fold cross validation was used. Fig 4 reveals that the Decision Tree classifier has the highest accuracy (97.89%), precision (97.89%), recall (97.38%), where Support vector machine gave us accuracy (92.89%), precision (93.53%), recall (91.41%) and Nave Bayes obtained an accuracy (93.29%), precision (89.23%), recall (89.04%) classifier has the fastest speed (5.3).Fig 5 shows the completion speed of the three algorithms per second, support vector machine complete a speed of 1105.52 seconds, Decision Tree complete 18.70 seconds and Nave Bayes complete a speed of 5.35 seconds.

From the results obtained by both figures 4 and 5 we can conclude that Decision Tree classifier has the highest accuracy (97.89%), precision (97.89%), recall (97.38%), and Nave Bayes classifier has the fastest speed (5.3).

IV. CONCLUSION AND FUTURE WORKS

In this study, we used a machine learning technique to detect people with suicidal ideation in tweeter. Decision tree provides best results among the three algorithms implemented. When predicting suicide ideator in the test set, decision tree showed a good performance with an accuracy of 97%. Based on our experiment, the proposed decision tree model considerably improves the accuracy of text classification. Existing methods used classification algorithms, which provided less accurate predictions of a system. The proposed system aims to build a more efficient and accurate model to detect suicide thoughts on social media. Although the results of our research reveal that applied classification algorithms performed quite well, the exact value of the metrics indicates that this is a difficult issue that merits additional investigation.

Our study does have some drawbacks. We concentrated mostly on Twitter and the English language. We hope that access to various social networking sites, as well as multilingual support, should be available in the near future. Several initiatives, such as the creation of an annotated Corpus for multiple languages and the development of new machine learning models, particularly in languages other than English, can be undertaken as future work. Suicide is never the remedy. With the rising mortality rate in recent times, it is hoped that the proposed model would help to reduce the number of deaths as a result of suicide.

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