A Review on Prediction of Suicide Related Activity

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Abstract: *Suicide is an alarming public health problem accounting for a considerable number of deaths each year worldwide. In this work, we automatically extracted informal latent topics from online social media twitter and expressing suicidal ideations. We first subjectively evaluated the latent topics and then exhaustively compared them to risk factors proposed by domain experts. As social networking sites have become more common, users have adopted these sites to talk about intensely personal topics, among them their thoughts about suicide. The tweets are important for analysis because data arrive at a high frequency and algorithms that process them must do so under very strict constraints of storage and time. In this work, we extract Emoticons and Synonyms Feature and also used n-gram model which is combination of Unigram, Bigram and Trigram with hybrid dictionary for score calculation. Our Proposed model leveraging the informal topics to predict the urgency of the posts using machine learning algorithms. In this research we also compare different approach like SVM, NB, and RF.*

Keywords: *Twitter, Sentiment Analysis, N-Gram, Emoticons, Synonyms, Acronyms, SVM, ANN, DT, NB.*

1. INTRODUCTION:

In this research, Sentiment analysis on Twitter dataset will perform to predict the suicide on Twitter data and make survey and prediction of attempt and about user’s behaviour. Suicidal ideation is generally associated with depression and other mood disorders. However, it seems to have associations with many other psychiatric disorders, life events, and family events, all of which may increase the risk of suicidal ideation. For example, many people with borderline personality disorder exhibit recurrent suicidal behaviour and suicidal ideation. One study found that 73 % of patients with borderline personality disorder have attempted suicide, with the average patient having 3 or 4 attempts.[16]

Early detection and treatment are the best ways to prevent suicidal ideation and suicide attempts. If signs, symptoms, or risk factors are detected early then the person will hopefully seek for treatment and help before attempting to take his/her own life. In a study of people who did commit suicide, 91 % of them likely suffered from one or more mental illnesses. Nevertheless, only 35 % of those people were treated or being treated for a mental illness. This emphasizes the importance of early detection; if a mental illness is detected, it can be treated and controlled to help prevent suicide attempts. Another study investigated strictly suicidal ideation in adolescents. This study found that depression symptoms using twitter account its tweets. Tweet are process and using machine learning prediction is done using machine learning approach.[12]

Figure 1: Suicide Prediction

2. RELATED WORK :

Over [1], Reilly N. Grant and et. All evaluate suicide related post from user on social media. To analyse the post they use clustering algorithm. A raddit data is feed to a clean words and phrases after that the data is pass to word2vec which is used to create word vector. A k-means clustering technique is used to group together similar words of raddit data in order to discover suicide related activities. This paper attempts to discuss the technical and social perspectives of text mining analysis of raddit data

Previously, [2], Bridianne 'Deaa and et. All proposed social media platform Twitter has been used by individuals to communicate suicidal thoughts and intentions. To understand how Twitter users respond to suicide-related content as compared to non-suicide related content. Using a dataset of suicide and non-suicide related posts, replies, retweets and likes were analysed and compared. The rate of reply to the suicide-related posts was also significantly faster than that of the non-suicide related posts. Mean and standard deviation is used to find the rate of reply.

On [3], Fatima Chiroma and et. All measured the performance of four popular machine classifiers, i.e. DT, NB, RF and SVM, in classifying suicide-related tweets. The results of the experiments showed that the best performance was an F-measure of 0.778 for the suicide-related communication (suicide and flippant classes). To improve the performance of machine learning techniques in classifying suicide-related communication, it is required to further examine and compare the performance of other machine learning techniques with the result of this experiment. Therefore, we intend to investigate the performance of ensemble learning approaches, which could potentially be more accurate and robust, as shown by other research.

In [4], Jingcheng Du and et. All proposed a Suicide has been one of the leading causes of deaths in the United States. One major cause of suicide is psychiatric stressors. The detection of psychiatric stressors in at risk population will facilitate the early prevention of suicidal behaviours and suicide. The first effort to extract psychiatric stressors from Twitter data using deep learning based approaches. Comparison to traditional machine learning algorithms shows the superiority of deep learning based approaches. CNN is leading the performance at identifying suicide-related tweets with a precision of 78% and an F-1 measure of 83%, outperforming Support Vector Machine (SVM), Extra Trees (ET), etc. RNN based psychiatric stressors recognition obtains the best F-1 measure of 53.25% by exact match and 67. 94% by inexact match, outperforming Conditional Random Fields (CRF). Moreover, transfer learning from clinical notes for the Twitter corpus outperforms the training with Twitter corpus only with an F-1 measure of 54.9% by exact match. The results indicate the advantages of deep learning based methods for the automated stressors recognition from social media.

On [5], Shaoxiong Ji and et. All proposed new methods to detect online texts containing suicidal ideation in the hope that suicide can be prevented. To understanding of suicidal ideation and behaviour. Though applying feature processing and classification methods to their carefully built datasets, Reddit and Twitter, they evaluated, analysed, and demonstrated that their framework can achieve high performance (accuracy) in distinguishing suicidal thoughts out of normal posts in online user content.

In [6] Pete Burnap and et all developed a number of machine classification models built with the aim of classifying text relating to communications around suicide on Twitter. The classifier distinguishes between the more worrying content, such as suicidal ideation, and other suicide-related topics such as reporting of a suicide, memorial, campaigning and support. They built a set of baseline classifiers using lexical, structural, emotive and psychological features extracted from Twitter posts. They then improved on the baseline classifiers by building an ensemble classifier using Forest algorithm.

3. METHODOLOGY :

A. API Interfacing: Companies, developers, and users can get programmatic access to twitter data through twitter APIs (application programming interfaces).
In this, User tweets or Twitter datasets API is retrieve from the Twitter to perform sentiment analysis on the dataset to make a prediction geographically about political tweets, movie ratings and making predictions about the results of Products and location of customer.
B. Pre-Processing: Data pre-processing is an abstracts mining address that involves transforming raw abstracts into a barefaced format. Real-world abstracts is generally incomplete, inconsistent, and/or defective in assertive behaviours or trends, and is acceptable to accommodate abounding errors. Abstracts pre-processing is an accurate adjustment of absolute such issues.
In this, first step is applied on Twitter dataset to remove unnecessary words from the tweets, remove stop words, punctuations, and hash tags to get the better accuracy in result of analysis.[13][3]
C. Feature Extraction: Feature extraction refers to the process of extracting useful information or features from existing data or pre-processed data.
In this, from the pre-processed dataset required feature such as emoticons, acronyms, synonyms and the n-gram that is user tweets in the form of combination of words is extracted to makes the prediction more accurate.
Emoticons: Tweets messages holding emoticons are retrieved Eventually Tom's perusing utilizing those twitter apes (”Data accumulation phase”) et cetera they would gathered under two sets: certain situated What's more negative set, holding sure j Also negative l emoticons individually (”Positive/Negative emoticon class formation phase”).
Synonyms: Replacing two or more repeating letters in a tweet by two letters of the same in tweets, sometimes users repeat letters to stress the emotion or feelings. Words with rehashed letters, e.g. “coooool”, are regular in tweets, and individuals tend to utilize thusly to express their slants. For instance, “coooool” is supplanted by “cool”.
N-Grams: The new algorithm will develop that is n-gram which is combining all the features of unigram, 2-gram and 3-gram which is the combination of all pre-processed and required words of tweets. This makes the prediction more accurate.[11]
D. Score Calculation: To achieve better results, word sense disambiguation should be combined with some integer values in positive and negative using Dictionaries.
In this, Affine and Lexicon both dictionaries are used to assign the score to each words of the n-gram. The automatic score is assign using dictionaries to make a multiclass classification.[11]
E. Multiclass Classification: Multiclass alternately multinomial arrangement is those issue of classifying instances under a standout amongst three or that's only the tip of the iceberg classes.[3]

Naive Bayes Classification: Clinched alongside machine learning, credulous bayes classifiers are a crew of basic "probabilistic classifiers" In light of applying bayes' hypothesis with solid (naive) autonomy presumptions between those offers. Credulous bayes classifiers need aid exceedingly scalable, requiring a number about parameters straight in the number for variables (features/predictors) clinched alongside An Taking in issue. Maximum-likelihood preparation might a chance to be carried out Eventually Tom's perusing assessing a closed-form expression, which takes straight time, instead of Eventually Tom's perusing exorbitant iterative close estimation likewise utilized to huge numbers Different sorts for classifiers.

Artificial Neural Network: Simulated neural networks would generally rough electronic networks about neurons In view of those neural structure of the mind. They methodology records particular case in a time, and gain toward contrasting their order of the record (i.e. generally arbitrary) with those known real arrangement of the record. The errors from the introductory arrangement of the principal record is nourished go under those network, what's more utilized on change the networks algorithm to further iterations.

Neurons would sorted out under layers: input, Hidatsa Furthermore yield. The information layer may be created not for full neurons, at rather comprises basically of the record's values that are inputs of the following layer from claiming neurons. The following layer will be those Hidatsa layer. A few Hidatsa layers might exist in you quit offering on that one neural system. The last layer is those yield layer, the place there is particular case hub to each class. An absolute clear forward through the system brings about the work of a quality to every yield node, and the record is allocated of the population hub for the most elevated quality.[8]

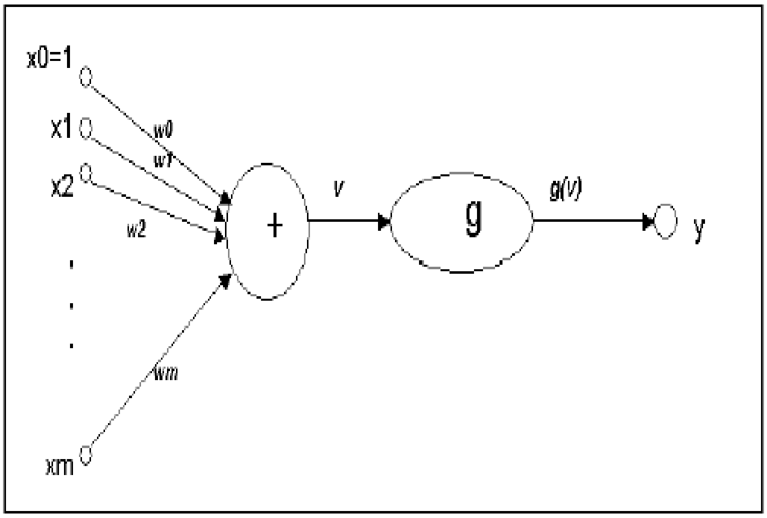

Figure 2: Artificial Neural Network

Support vector machine: Help vector machine is a regulated machine taking in calculation which might make utilized for both order and relapse tests. However, it may be most acicula utilized within arrangement issues. In this algorithm, we plot each information thing Similarly as A perspective on n-dimensional space (where n may be amount for features you have) for the quality about every characteristic constantly the worth of a specific direction. Then, we perform arrangement by finding those hyper-plane that differentiates those two classes delicately.[3][4]

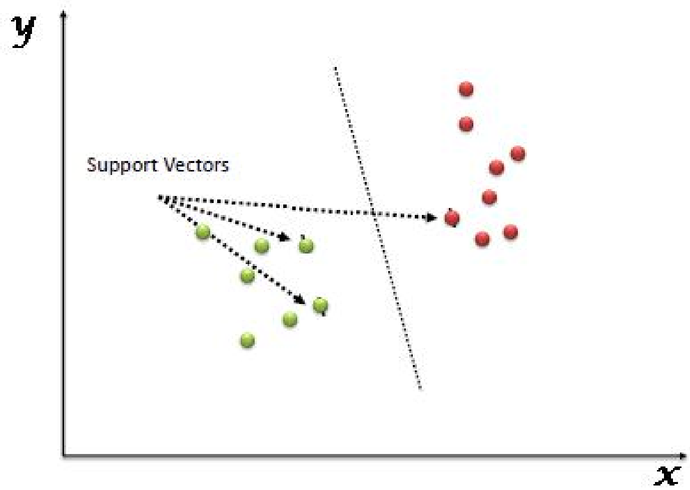

Figure 3: Support Vector Machine

Decision Tree Classification: Choice tree manufactures arrangement alternately relapse models in the type of a tree structure. It breaks down a dataset under more diminutive Also littler subsets same time during those same occasion when a charted choice tree will be incrementally formed. The last come about may be a tree for choice hubs and leaf beet hubs. A choice hub (e.g. Outlook) need two alternately additional extensions (e.g. Sunny, cloudy and Rainy). Leaf beet hub (e.g. Play) speaks to an arrangement or choice. Those top-notch choice hub on a tree which corresponds of the best predictor called root hub. Choice trees camwood handle both unmitigated What's more numerical information.[9]

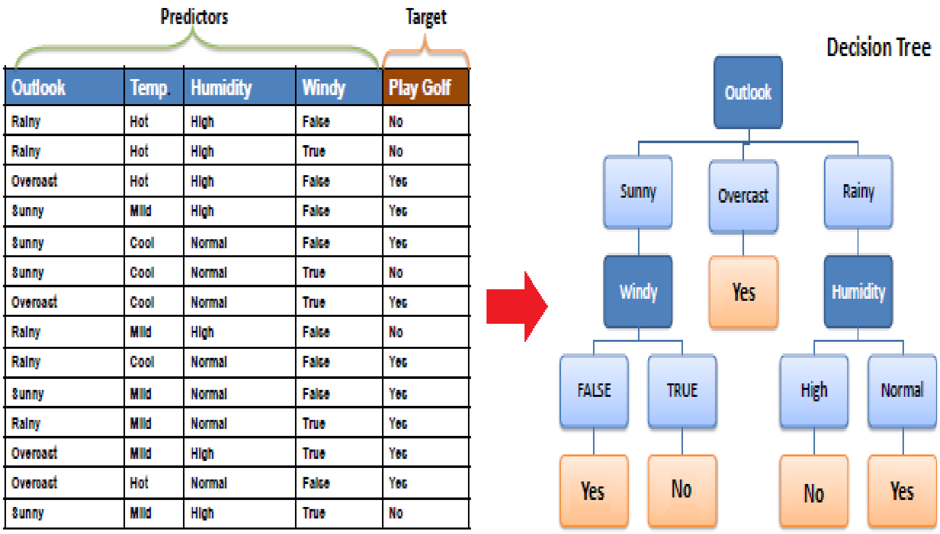

Figure 4: Decision Tree Classifier

K- Nearest Neighbouring: K- closest neighbouring will be a non-parametric, sluggish Taking in calculation. Its reason for existing will be to utilize a database over which those information focuses need aid differentiated under a few classes should foresee those order of a new example perspective.

At we say a procedure may be non-parametric, it implies that it doesn't aggravate whatever presumptions on the underlying information conveyance. KNN may be likewise a sluggish calculation this methods will be that it doesn't utilize the preparation information focuses should do any generalization. Done other words, there will be no express preparing stage or it may be Verwoerd negligible.

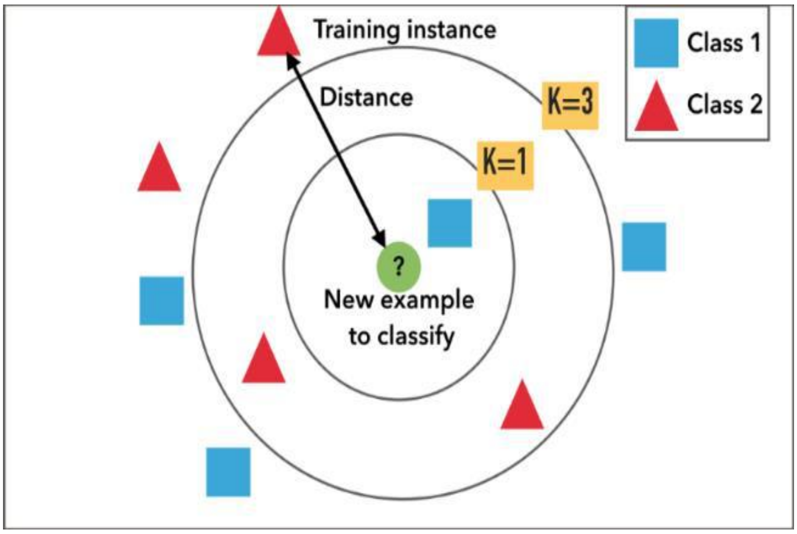

Figure 5: K- Nearest Neighbouring

4. COMPARATIVE STUDY :

Table 1: Example of Unigram, Bigram, Trigram and N-gram

Physician Note	**"Patient has evidence of macular degeneration"**
Unigrams	"Patient", "has", "evidence", "of", "macular", "degeneration"
Bigrams	"Patient has", "evidence of", "macular degeneration"
Trigrams	"Patient has evidence", "of macular degeneration"
N-gram	"Patient has evidence of macular degeneration"

Table 2: Example of Emoticons, Synonyms and Acronyms

Emoticons	 for Excellent  for Good  for Average  for Poor  for Very Poor
Synonyms	Hunggggrryyy, Huuuuuuuuuungry for “Hungry Happpppy, Happyyyyyyyyyy for “Happy” Grrrrreat,Greeeeeat for “Great” Nicccccceeeee, Niceeeeeeefor “Nice” Supppppppperb, Suuuuuppperb, “Superb”
Acronyms	BTW for By The Way KIT for Keep In Touch NYOB for None of Your Business OMG for Oh My God IDK for I Don't Know

Table 3: Comparison of Classification Methods

Method	**Advantages**	**Disadvantages**
NB	-Fast to train. -Fast to classify. -Handles real and discrete data -Handles streaming data well	-Strong feature independence assumption.
ANN	-“Ann can perform tasks which linear program cannot. -When element of neural network fails it continue to work.”	-A lot of chips and a distributed run-time environment is required to train on very large datasets.
SVM	-“SVM is less complex.” -“Produce very accurate classifiers.” -“Less over fitting, Robust to noise.”	-“SVM is binary classifier, to do a multi-classification, pair-wise classifications can be used.” -“Computationally expensive, thus runs slow.”
Decision Tree	-“It reduces overfitting and is therefore more accurate.” -Easy to Implement -“Works with all types of data.” -“Multi classification Support.”	-“It may not work if the dependent variables considered in the model are linearly related. Therefore one has to remove correlated variable by some other technique.”
KNN	-“Robust to noisy training data.” -“Effective if the training data is large.”	-“Distance based learning is not clear which type of distance to use and which attribute to use to produce the best result.” -“Computation cost is quit high.”

5. CONCLUSION :

In this work, we automatically extracted informal latent topics from tweeter which expressing suicidal ideations. We first subjectively evaluated the latent topics and then compared them to risk factors .In future, we will build models which is use to predict the urgency of the posts. Finallyand will extend our analysis to other mental health issues such as post-traumatic stress disorder and depression. From this review, machine taking in method it will make chose that from client internet reviews that which you quit offering on that one may be preferred. Clinched alongside future mixture characteristic and also multi-level arrangement approach may be utilize to Suicide Related examination.

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