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## A Review On Analysis Of Suicidal Notes Sentiment Rich Data

<sup>1</sup>FARZIZ AKTAR AHMED

Student

Faculty of Engineering and Technology

Assam Down Town University

Guwahati, India

Email: farzizkhan786@gmail.com

<sup>2</sup>JUNUMONI KHAKHLARI

Student

Faculty of Engineering and Technology

Assam Down Town University

Guwahati, India

Email:

junumonikhakhlari608@gmail.com

<sup>3</sup>NITUMANI SARMAH

Assistant Professor

Faculty of Engineering and Technology

Assam Down Town University

Guwahati, India

Email: nitumani.s@inurture.co.in

**Abstract**— Every year 703000 people committed suicide globally because of different reasons. Uses of smartphone has rapidly increased, and people are interacting with others using social media and other platforms has increased as a result. These social media data can be use as raw data to perform sentient analysis to understand the sentiment. In recent few years sentiment analysis has gain so much of popularity. Many studies have been done already to analyze and understand sentiment behind a statement. And there are still many research in progress to analyze the sentiment. This paper acknowledged that many researchers have done their works by using Machine learning and Natural Language Processing (NLP). This research work explored a various numbers research paper related to sentiment analyze of suicidal statements and the methodology they have used and trying to find out the more possibilities to improve the possible outcome with more accuracy. This paper included a table [ Table - 1] of past work. All the works has been done by the researchers on sentiment analysis in different field, but the accuracy of the result is, yet a problem need to be solved. This research work witnesses that there are very rare works done by using Ensemble Model. To solve this problem, this research work prefers to implement ensemble model to improve the accuracy. So, using this model, we can achieve a great level of accuracy. So, this is the field need to be explored more, also to find out the best algorithm in existing work and to improve the same.

**Keywords**—Sentiment Analysis, Suicide attempts, Ensemble Model, Machine Learning. Decision Tree. SVM, Naïve Bayes.

### I. INTRODUCTION

Suicide becoming a leading issue in healthcare sector around the world. Due to many reasons every year 703000[1] of peoples themselves end their life globally and most of them are youth, ages in between 19-25 [1] as per 2019 (World health organization, Updated as on 17 June 2021) data. Among them 77% [1] of the people belong to the countries where people's incomes are in between middle-

lower level. Out of 100 more than one (1.3%) people commit suicide 2019 [2]. A study published recently on depression and anxiety, 67000 college students of more 100 institutions, where one out of five have had thought of suicide at least for once [3]. Among them 9% students making an attempt and 20% of them are reported a self-injury and one out four reported that they are diagnosed with a mental illness. In another recent survey from US "Youth Risk Behaviours Survey 2019" showing that 8.9% of youths with grades 9-12 made a suicide attempt in last 12 months [4]. Among them American Indian or Alaska native students reported 25% and white students reported 7.9% of suicide attempt. Risk factor for these suicide victims vary individual to individual.

Here are some risk factors that have been identified are A prior suicide attempt, A sense of isolation and lack of support, Access to a suicide method, Impulsivity issues, Major depression, Physical illness, Poor coping skills, Serve Personality disorder, Substance use issues, Traumatic or stressful life events [3].

Suicidal behaviours are a complex process that can vary from suicidal ideation (communicated verbally or nonverbally) through planning, attempting, and, in the worst-case scenario, committing suicide. Interacting biological, genetic, psychological, social, environmental, and situational factors influence these behaviours [47]. Inequity, social marginalisation, and socioeconomic disadvantage have all been associated to suicide [48]. It is a massive problem that is generating unneeded human pain and tremendous societal costs. These are some of the major reasons, which lead people to suicidal ideation, attempting phase and at the end it leads people to committed suicide.

These suicide attempts can be prevented if it could be able to know the mental health and conditions of those suicide victims. In most of the cases suicide victim's mental health reflects through their actions. Now a days almost every person has a access to internet and social media, and most the people's posts, message and comments are simply a reflection of their emotions and Mental health. If a person is felling happy and another person is feeling sad and depressed then their posts, message and comments are respectively going to be positive and negative. In 10% to 43% of the

times suicide victims leave a suicide note behind [5]. There are some clinical notes also written by psychiatrists at the time of admission and discharge that includes patients background, mental health, family history, current circumstances and many more to know the patients' mental conditions, and this is very helpful to know the mental health of a patients. As mentioned above these social media's message, comments, posts, tweets, suicidal notes, clinical notes can be used to know the sentiments of a patients using Sentiment Analysis method.

The other name of Sentiment Analysis is called as opinion mining or Emotion AI. Sentiment Analysis is used to extract the emotions of a text or a block of texts. Sentiment analysis is useful in decision making. It uses Natural Language Processing (NLP) & Machine learning to analyse a statement sentence whether the statement is Positive, Negative or Neutral. In addition, Sentiment analysis also analyse the emotions of a sentence whether the statement is happy, sad, angry etc. It's used in different domains like psychologically, socially, machine learning etc. The source for Sentiment Analysis is mostly social communications, mental people's communication.

#### A. Sentiment Analysis.

Sentiment analysis is a machine learning tool which is used to extract the sentiments/emotions from a specific block of texts. It identifies the emotions behind the texts. Sentiment analysis explains the filtering the people's emotions like depressed, happy, sad, along with the positive, negative, or neutral state. Also, it can recognize the mental state of the depressed people. It is also known as "opinion mining" which is used in different domains such as machine learning, psychologically, socially, etc. From the data of social platforms this paper can analyze the mental state of that person whether he/she is happy sad or angry.

It has different field like Machine learning (ML), Natural language processing (NLP), Computational Linguistics, Bags of words.

This strategy is another technique which presents a Redesign of Bags-of-words model to address major Inadequacies of the Bag-of-words model in assessment Appraisal. It depends upon the word level of feeling examination in one branch of knowledge. In addition, this research work can isolate components and expressions of the space to arrange sentiments reviews and show up at the exactly meaning of each review. The proposed strategy in like manner can introduce deals with any consequences regarding feeling assessment to additionally foster position.

It also has three major levels-

- i. Word level.
- ii. Sentence level.
- iii. Document level.

The three level of the sentiment analysis determines the task required for the process. The first level which is word level it is the most difficulty level in carrying out the analysis, whereas the second level and the third level of sentiment analysis which is sentence level and documents level is very similar respectively. Two major techniques which are used for the review of sentimental analysis are Machine learning and Semantic-based Analysis.

And our work is related to analyze the sentiment of all the individuals, those who are posting, sharing, commenting negative statements or it is reflecting that their mental health is not good and they've a thinking for suicide at least for once. In this case sentiment analysis, a major tool to identify those people, who are posting such type of negative post, comments, messages, tweets or anything related suicidal indication.

#### B. Sentiment Analysis on Suicidal notes.

Suicide is one of the most common death reasons in youth around the globe. All the people who have already committed suicide or all those who're going to commit suicide almost all of them are trying to express their feeling through various method. Some of them use to leave suicide notes, and some people try to express their feeling by posting sad or depressed posts on social platforms, also some of them are trying to communicate with their closest one through messaging. In all these methods, suicide victims are expressing their state of mind to others via communications. Twitter is one of the most popular social media platforms where billions of people share their feelings, opinions, thoughts, incidents happening their life on daily basis. If there's any such statement which is a suicidal indication it can be detect with the help of sentiment analysis. Also, Sentiment Analysis can detect or classify, whether the sentiment of that statement of the victim is negative, positive or neutral.

Sentiment analysis can be done with methods like Machine learning (ML), Natural Language processing (NLP) in order to get the sentiment of any statement. The key purpose of using use NLP techniques, especially semantics and word sense disambiguation, to extract the opinions more accurately. Determining the meaning of a word in NLP is the ability to determine what word meaning is activated by using the word in a given context.

Two major approaches to extract the sentiment automatically of a particular context are Lexicon-based approach and machine-learning approach [7][8].

##### i. Lexicon-based approach

Lexicon-based approach uses a predefined collections of word where each and every word associated with a specific meaning. This technique calculates the sentiment orientations of the entire document or set of sentences(s) from semantic orientation of lexicons. The dictionary of the lexicon can be prepared in both ways manually as well as automatically. The wordnet dictionary is the most popular and mostly used dictionary among the researchers.

##### ii. Machine-learning approach

Machine learning mostly rely on supervised classification approach, where detection of sentiment is represented as binary which are positive or negative [9]. To train the classifiers machine-learning approaches needs labelled data.

There are various types of techniques and complex algorithms to extract the emotions from a particular statement of a suicide victims. Some of the algorithms proved to give best performance with maximum accuracy such as Naive Bayes (NB), Max Entropy (MaxEnt) and Support Vector Machines (SVM) [6]

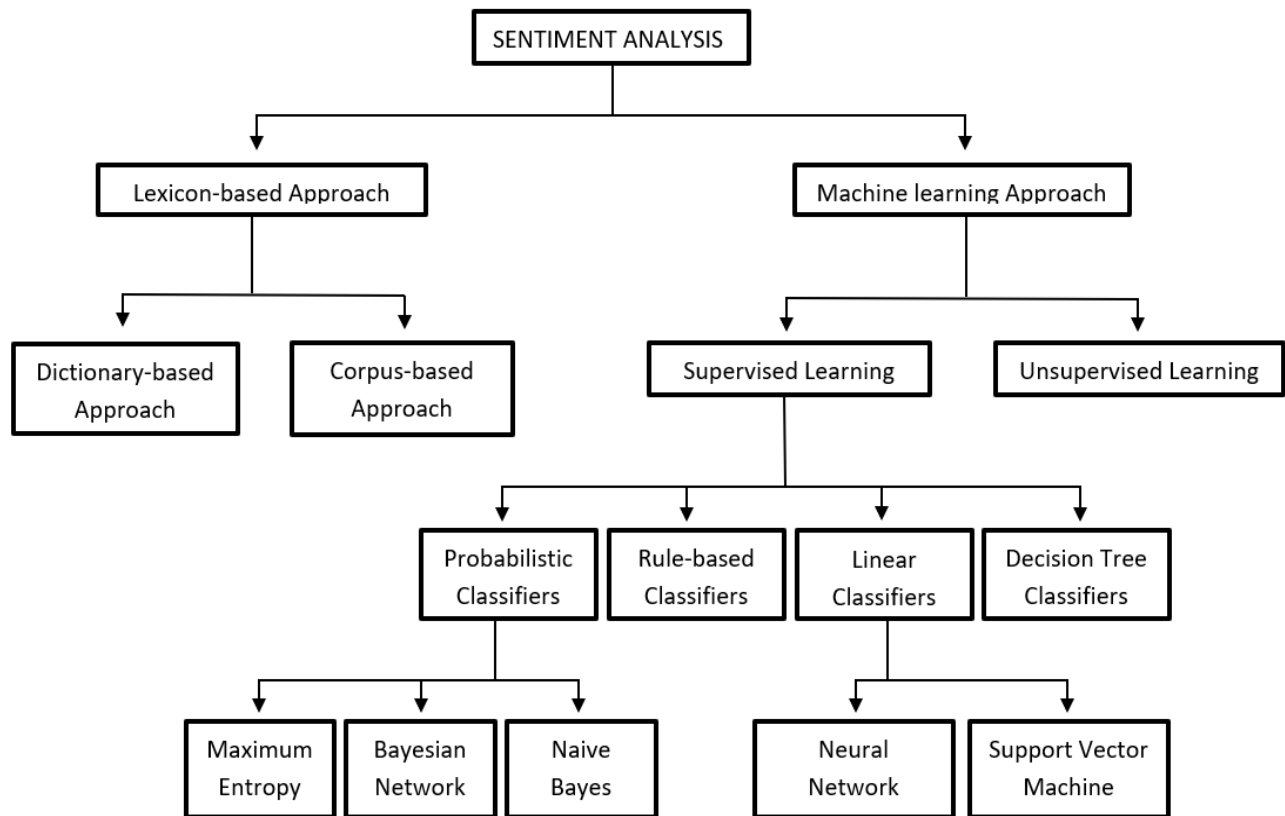


Figure 1: - Classifications of Sentiment Analysis [44]

## II. RELATED WORK

The use of social media has grown unexpectedly in these last few years. Almost all the people are connected through social media those who are using smartphone. In various social media platform people are communicating through messages, expressing their opinion through comments and also, they are sharing their day-to-day life incidents. In case of one, two or for few statements are possible to analyse the sentiment manually but when the opinion, comments, texts messages are in huge numbers like in billions it becomes impossible to analyse the sentiments of those data manually and here the concepts arise to analyse the sentiments of people that what actually they want to express. Are their statement is reflecting positive sentiment, negative sentiment, or neutral sentiment. It is also possible to recognise their emotions whether their emotions are happy, sad or angry.

There have been many studies and research done on this that to analyse the sentiment of an individual's statement or a huge number of opinions that people are generating through social media. There are many different ways to analyse the sentiment of peoples and they are achieved a great accuracy.

Different researchers use different methods to analyse the sentiment more and more accurately. Such as Naïve Bayes, Support Vector machine (SVM), Decision Tree, Know your neighbour (KNN), Random Forest, Logistic Regression etc. These are some most popular algorithms for sentiment analysis among the Researchers, and using these algorithms they are able to achieve a quite good accuracy in their research.

Go et.al.[10] in the journal paper "Twitter Sentiment Analysis" stated that they have performed a sentiment analysis on a set of twitter data to analyse the sentiments of user. They collected their own data using twitter API, all those twitter messages that have emotions. They have used Naïve Bayes classifiers which they have built from scratch

and Third-party library were used for Maximum Entropy and Support Vector Machine (SVM). Using these methods, they are able get an accuracy of 73.913% with Support Vector Machine and with Naïve Bayes they get a accuracy of 44.9% and for Maximum Entropy its didn't contribute much to get a higher accuracy.

Qaiser et. al. [11] in their research paper "Sentiment Analysis of Impact of Technology on Employment from Text on Twitter" they tried to analyse the sentiment of people about the impact of technology on unemployment and technical advancements. In these studies, they have found that 65% of the people have a negative sentiment about the impact of technology on unemployment and technical advancement. They used twitter data related to their topic keywords. In this paper they have they have trained Naïve Bayes machine learning classifier to classify the data according to the users' sentiments. Using Naïve Bayes and Support Vector Machine (SVM), they able to be achieved an accuracy of 87.18% and 82.05% respectively.

Pak et. al. [12] in their studies "Twitter as a Corpus for Sentiment Analysis and Opinion Mining" they have showed an automatic collection of corpuses that they can use to train sentiment classifier. For this method they have used twitter data and through the use of Twitter API they collected data for their sentiment analysis. In this paper they have used multinomial Naïve Bayes classifier that uses N-gram and POS-tags as features to classify the content. Also, they have used TreeTagger for POS-tagging to observe the difference in distributions among positive, negative, and neutral sets.

Altrabsheh et. al. [13] in their paper "SA-E: Sentiment Analysis for Education" they have done research on a new topic sentiment analysis on education. For this they have collected students' feedbacks from social media like twitter, to analyse the sentiments of students to understand whether the students are positive, negative or having any other emotions. In this study this paper they tried to present that Naïve Bayes and Support Vector Machine (SVM) can be combined to analyse the students' feedback in Real-time, and



it holds a great potential. Along with this they have introduced a new system architecture termed as System Analysis for Education (SA-E).

RamyaSri et. al. [14] in their work "Sentiment Analysis of Patients' Opinions in Healthcare using Lexicon-based Method" they have done research on sentiment analysis. Which includes analysing the sentiment of patients based on their opinion to improve the healthcare services. To perform this, they have used patients' opinion data from 92 web pages which contains patients' opinions on Southern California Orthopaedic Institute which is located in California, USA. To perform sentiment analysis on this data they have used Lexicon Based method. Sentiment analysis tools like "VADER" and "TextBlob" are used for classifications. Using these methods, they are able to achieve an accuracy of 71.9% in VADER lexicon-based approach and 73.0% in the TextBlob lexicon-based approach. But on performing comparative analysis considering precision, recall, and F1-score they have found that VADER lexicon-based approach performs better than the TextBlob lexicon-based approach.

Munezero et. al. [15] in their paper "Exploiting Sentiment Analysis to Track Emotions in Students' Learning Diaries" mentioned that they present a functional system for analysing and visualising students emotions expressed in their diaries. This system allows the instructors to extract the emotions expressed in students' diaries. They used a dataset of students Diaries from the Newman. Also, they have used "Stop word removal procedure", "Potter's stemming algorithm".

Graves et. al. [16] in their paper "Use of Sentiment Analysis for Capturing Patient Experience from Free-Text Comments Posted Online" says that they used NHS Choices Datasets to analyse the sentiment of people. They have applied machine learning techniques to all 6412 online comments about hospitals on the English National Health Service website in 2010 using Weka data-mining software. They have compared the results which were obtained from the sentiment analysis with their paper-based national inpatient survey results at the hospital level using Spearman rank correlation for all 161 acute adult hospital trusts in England. In this paper researcher have used Naïve Bayes multinomials, Decision Tree, Bagging, Support Vector Machine (SVM) algorithms. By studying this paper [16] we came to know that using Naïve Bayes Multinomials algorithm they got the accuracy of 88.6% and using Decision trees the accuracy they got is 80.8%. Using Bagging they got the accuracy 82.5% and lastly by using SVM they got 84.6%.

Saif et. al. [17] in the paper "Semantic Sentiment Analyse of Twitter" the researcher has used Stanford Twitter Sentiment Corpus (STS), Health Care Reform (HCR), Obama-McCain Debate (OMD) Datasets to classify the sentiment of people. In their paper, they have introduced an approach for adding semantics as an additional feature into their training set for analyzing the sentiment of the people. For each extracted entity (e.g., iPhone) from the tweets, which were they added its as semantic concept (e.g., "Apple product") which as an additional feature, and for measuring the correlation of the representative concept with positive, negative, or neutral sentiment of the people. They have applied this approach for the prediction of sentiment for different Twitter datasets. Also, they have approach for Naïve Bayes algorithm to perform their analysis on sentiment. In this research paper by performing Stanford Twitter Sentiment Corpus, they got accuracy of 80.7%, with Health Care reform they are able to get the accuracy 71.1% and also by approaching to Obama-McCain method the researcher is able to get the accuracy of 75.4%.

Neri et. al. [18] in this journal paper "Sentiment Analysis on Social Media" the researcher has used the dataset as 1000 posts-by focus crawling of Facebook. In this journal paper the researcher have used Recall and Precision algorithm to filter the sentiment of the comments which are posted in social media by the people to recognize which are positive, negative, or neutral. They have performed their Sentiment Analysis over various Facebook posts about newscasts, comparing the sentiment for Rai - the Italian public broadcasting service - towards the emerging and more dynamic private company La7. Their study maps study the results with observations made by the Osservatorio di Pavia, which is an Italian institute of research specialized in the media analysis at theoretical and empirical level, engaged in their analysis in the mass media of political communication. Their study also takes in account the data provided by Auditel regarding newscast audience, correlating the analysis of social media, of Facebook in particular, with measurable data, available to public domain. The researcher got 87% accuracy by using recall algorithm and they got accuracy of 93% by using Precision algorithm.

Sarlan et.al. [19] the paper named "Twitter Sentiment Analysis" stated that they have used twitter data as dataset, also they used Natural Language Processing (NLP), Case-Based Reasoning (CBR), Artificial Neural Network (ANN), Support Vector Machine(SVM) algorithm to extract the data of sentiments whether its positive, negative or neutral. By using Support Vector Machine (SVM) they got the accuracy as 81.3%.

Aladağ et.al. [20] in their journal paper "Detecting Suicidal Ideation on Forums: Proof-of-Concept Study" they said that they have used the dataset as Reddit dataset (2008 - 2016). In their paper they have said that they have used Logistic regression, random forest, SVM, Baseline ZeroR algorithms to perform the classification of sentiment of the people whether the sentiment of the comment is happy, sad, or angry. They have used method as a total of 508,398 Reddit posts were posted between 2008 and 2016 on SuicideWatch, it has longer than 100 characters in their posts. In their paper Depression, Anxiety, and ShowerThoughts subreddits were downloaded from the publicly available in Reddit dataset. 10,785 posts were randomly selected and 785 were manually annotated as suicidal or non-suicidal in their paper. Some features were extracted using term frequency-inverse document frequency, linguistic inquiry and word count, and sentiment analysis on post titles and bodies. Logistic regression, random forest, and support vector machine (SVM) classification algorithms were applied on resulting for performance evaluation of corpus and prediction. The researcher has got the accuracy of 80% by using Logistic regression, using random forest they got the accuracy as 92%, they got the accuracy of 50% by using Support Vector Machine (SVM), lastly by using baseline ZeroR algorithm they got the accuracy of 66%.

McCart et. al. [21] in their studies "Using Ensemble Models to Classify the Sentiment Expressed in Suicide Notes" in their journal they have used the dataset consisted of 900 suicide notes collected over a 70-year period (1940–2010). Their team have explored multiple approaches combining regular expression-based rules, statistical text mining (STM), and an approach that applies weights to text while accounting for multiple labels. Their best submission used an ensemble of both rules and STM models to achieve a micro-averaged F1 score of 0.5023, slightly above the mean from the 26 teams that competed (0.4875). Also, they have used algorithm as Decision trees, KNN, SVM to filter

out the sentiment of the people from various statement which are posted in different social media platforms.

Pestian et. al. [22] in their paper “sentiment Analysis of suicide notes: A shared Task” stated that they have used 1319 people suicide notes (1950-2011, CHRISTINE) as a dataset in their paper. They have done their research using a shared task in Biomedical domain which includes two features one is the Anonymized clinical texts and annotated suicide notes and the other one is it requires categorization large set of labels. In this paper they have describe about the challenges to classify the emotions found in notes left behind by those who have died by suicide in 2011. In total 106 scientists who have comprised 24 teams responded to the call for the participation. This paper’s results were presented at the Fifth i2b2/VA/Cincinnati Shared-Task and Workshop: Challenges in Natural Language Processing for Clinical Data in Washington, DC, on October 21–22, 2011, as an American Medical Informatics Association Workshop.

George et. al. [23] in their research paper “Application of Aspect-based Sentiment Analysis on Psychiatric Clinical notes to Study Suicide in Youth” they said that they have used 1559 suicidal notes (H18-01402; June 2018) as a dataset in their paper. They propose to address the lack of terminological resources related to suicide by a method of constructing a vocabulary associated with suicide. For a better analysis, they used Weka as a tool of data mining that can extract useful information from Twitter data collected by Twitter4J. Also, they said that they have used Logistic regression, Random Forest algorithm to classify the sentiment of the people by the suicidal notes.

Birjali et. al. [24] in the paper named “Machine Learning and Semantic Sentiment Analysis based Algorithms for Suicide Sentiment Prediction in Social Networks” that they 892 TWEETS (Using Twitter4J API) used as a dataset to classify the feelings of people. Also, they have used algorithm IB1, J48, CART, SMO, NAÏVE BAYES.

Mbarek et. al. [25] in the paper “Suicidal Profiles Detection in Twitter” in this journal paper the researcher have stated that they have used 115 suicidal profiles, 172 not suicidal profiles (Using TWITTER HEREAFTER Site) as a dataset. They have used Random Forest, BayesNet,

Adaboost, J48, SMO these algorithms to figure out the statement which are positive, negative, or neutral. By using Random Forest algorithm, the researcher has got 77% accuracy, using SMO the researcher has got 74% accuracy.

Sohn et.al. [26] in this journal paper “A Hybrid Approach to Sentiment Sentence Classification in Suicide Notes” the researcher has used datasets as 600 actual suicide notes. The researcher has used two algorithm named as NAÏVE BAYES and RIPPER.

Ji et.al. [27] in this paper “Suicidal Ideation Detection: A Review of Machine Learning Methods and Applications” the researcher have stated that they use datasets as TEXT DATA (Reddit, Twitter, ReachOut), EHR, Mental Disorders (questionnaires III-A suicide notes III-C suicide blogs III-C electronic health records III-B online social texts III-D). Also, they have used algorithm as Machine Learning and DEEP LEARNING to extract the sentiment of the data which are available in social platform.

Glenn et.al. [28] in the paper named “Can Text Messages Identify Suicide Risk in Real Time? A Within-Subjects Pilot Examination of Temporally Sensitive Markers of Suicide Risk” the researcher has stated that they have used DIGITAL TEXT DATA (social media) as their datasets. To filter the sentiment of the people from their comments posting on social media platforms they have used Machine Learning algorithm whether the statements are positive, negative, or neutral.

Sharma et.al. [29] in their journal paper named “Analyzing the depression and suicidal tendencies of people affected by COVID-19’s lockdown using sentiment analysis on social networking websites” the researcher has used the Twitter data as a dataset. Also, they have used the algorithm as Machine Learning (Unsupervised) to filter the sentiment of the statement of people which are stated in various social media platforms to classify whether its happy, sad, or angry.

### III. RESULT ANALYSIS OF PREVIOUS WORKS

After reading all our related papers, it is clear that researchers have used many datasets to analyse the sentiment of the people commented on social platforms by using different algorithms. So, this paper mentioned all the data related to our work in the following Table -

SL NO	Topic name	Author name	Datasets used	Algorithms used	Accuracy percentage
1	Twitter Sentiment Analysis	Alec Go, Lei Huang, Richa Bhayani	Twitter API	SVM, Naive Bayes	73.913%, 44.9%
2	Sentiment Analysis of Impact of Technology on Employment from Text on Twitter	Shahzad Qaiser, Nooraini Yusoff, Farzana Kabir Ahmad, Ramsha Ali	wordnet	Naive Bayes, SVM	87.18%, 82.05%
3	Twitter as a Corpus for Sentiment Analysis and Opinion Mining	Alexander Pak, Patrick Paroubek	Twitter API	Naïve Bayes	NOT AVAILABLE
4	SA-E: Sentiment Analysis for Education	Nabeela Altrabsheh, Mohamed Medhat Gaber, Mihaela Cocca	Feedback collected via social media, Twitter	Naive Bayes, SVM techniques	NOT AVAILABLE
5	Sentiment Analysis of Patients' Opinions in Healthcare using Lexicon-based Method	V.I.S. Ramya Sri, Ch. Niharika, K. Maneesh, Mohammed Ismail	patients' opinions on Southern California Orthopaedic Institute	VADER, Text Blob	71.9%, 73.0
6	Exploiting Sentiment Analysis to Track Emotions in Students' Learning Diaries	Myriam Munezero, Calkin Suero Montero, Maxim Mozgovoy, Erkki Sutinen	diaries from the Newman	stop-word removal procedure, Porter's stemming algorithm	NOT AVAILABLE
7	Use of Sentiment Analysis for Capturing Patient Experience From Free-Text Comments Posted Online	Felix Greaves, Daniel Ramirez-Cano, Christopher Millett, Ara Darzi, Liam Donaldson	NHS Choices datasets 2013	Naive Bayes multinomials, Decision trees, Bagging, SVM	88.6%, 80.8%, 82.5%, 84.6%
8	Semantic Sentiment Analysis of Twitter	Hassan Saif, Yulan He, and Harith Alani	Stanford Twitter Sentiment Corpus (STS), Health Care Reform (HCR), Obama-McCain Debate (OMD)	Naive Bayes	80.7%(STS), 71.1%(HCR), 75.4%(OMD)
9	Sentiment Analysis on Social Media	Federico Neri, Carlo Aliprandi, Federico Capeci, Montserrat Cuadros, Tomas By	1000 posts-by-focus crawling of Facebook	Recall, Precision	87%, 93%
10	Twitter Sentiment Analysis	Aliza Sarlan, Chayanit Nadam, Shuib Basri	Twitter data	Natural Language Processing (NLP), Case-Based Reasoning (CBR), Artificial Neural Network (ANN), Support Vector Machine (SVM)	SVM- 81.3%,
11	Detecting Suicidal Ideation on Forums: Proof-of-Concept Study	Ahmet Emre Aladağ, Serra Muderrisoglu, Naz Berfu Akbas, Oguzhan Zahmacioglu, Haluk O Bingol	Reddit dataset (2008 - 2016)	Logistic regression, random forest, SVM, Baseline ZeroR	80%, 92%, 50%, 66%
12	Using Ensemble Models to Classify the Sentiment Expressed in Suicide Notes	James A. Dezon K. Jay Jarman, Edward Hickling, Jason D. Lind2, Matthew R. Richardson, Donald J. Berndt, Stephen L. Luther	dataset consisted of 900 suicide notes collected over a 70-year period (1940-2010)	Decision trees, KNN, SVM	NOT AVAILABLE
13	sentiment Analysis of suicide notes: A shared Task	John P. Pestian, Pawel Matykievicz, Michelle Linn-gust, Brett South, Ozlem Uzuner, Jan Wiebe	1319 people suicide notes (1950-2011, CHRISTINE)	Natural Language Processing (NLP)	NOT AVAILABLE
14	Application of Aspect-based Sentiment Analysis on Psychiatric Clinical notes to Study Suicide in Youth	Amy George, David Johnson, Giuseppe Caronini, Ali Eslami, Raymond Ng, Elodie Portales-Casamar	1559 suicidal notes (H18-01402; June 2018)	Logistic regression, Random forest	(LR-80.70%), (RF-83.69%)
15	Machine Learning and Semantic Sentiment Analysis based Algorithms for Suicide Sentiment Prediction in Social Networks	Marouane Birjalja, Abderrahim Beni-Hssane, Mohammed Erritali	892 TWEETS (Using Twitter4J API)	IB1, J48, CART, SMO, NAÏVE BAYES	NOT AVAILABLE
16	Suicidal Profiles Detection in Twitter	Atika Mbarek1, Salma Jamoussi, Anis Charfi, Abdelmajid Ben Hamadou	115 suicidal profiles, 172 not suicidal profiles (Using TWITTER HEREAFER Site)	Random forest, BayesNet, Adaboost, J48, SMO	77%- RF, 74%-SMO
17	A Hybrid Approach to Sentiment Sentence Classification in Suicide Notes	Sunghwan Sohn1, Manabu Torii2, Dingcheng Li, Kavishwar Waghlikar, Stephen Wu, Hongfang Liu1	600 actual suicide notes	NAÏVE BAYES, RIPPER	NOT AVAILABLE
18	Suicidal Ideation Detection: A Review of Machine Learning Methods and Applications	Shaoxiong Ji, Shirui Pan, Member, IEEE, Xue Li, Erik Cambria, Senior Member, IEEE, Guodong Long, and Zi Huang	TEXT DATA (Reddit, Twitter, ReachOut), EHR, Mental Disorders (questionnaires III-A suicide notes III-C suicide blogs III-C electronic health records III-B online social texts III-D)	ML, DEEP LEARNING	NOT AVAILABLE
19	Can Text Messages Identify Suicide Risk in Real Time? A Within-Subjects Pilot Examination of Temporally Sensitive Markers of Suicide Risk	Jeffrey J. Glenn, Alicia L. Nobles, Laura E. Barnes, Bethany A. Teachman	DIGITAL TEXT DATA (Social media)	MACHINE LEARNING	NOT AVAILABLE
20	Analyzing the depression and suicidal tendencies of people affected by COVID-19's lockdown using sentiment analysis on social networking websites	Sparsh Sharma & Surbhi Sharma	TWITTER DATA	MACHINE LEARNING (UNSUPERVISED)	NOT AVAILABLE

**Table No 1: Comparative study of Sentiment Analysis using different Machine Learning based Algorithms**

#### IV. METHODS

Attempting suicide now a days becomes a global problem. And detection of suicidal sentiment using social media message, comments, posts, suicidal notes has drawn attention of many researchers. Many researchers all over the world trying to build sentiment analysis model to detect the sentiment behind some texts, message, social media posts.

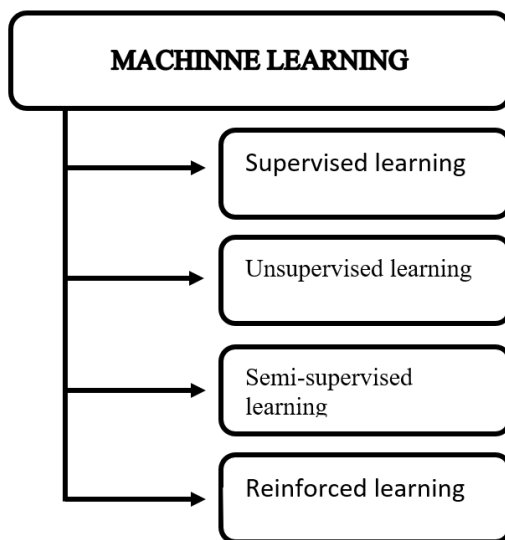
Different techniques are used by the researchers to detect the suicidal sentiment of people. For e.g., clinical methods with patient-clinic interaction [30] and automatic detection from user-generated content (mainly text) [31], [32],[33]. There are many research has been done in this particular field using different models to get more accurate results. Most of the researchers used Machine learning algorithms like Naïve Bayes, Support Vector Machine, Logistic Regression, Natural Language Processing (NLP) etc. But there are very



few works has been done using methods like Ensemble model. This is the field that still need to explore more by the researchers to reach, a step ahead to get more accuracy.

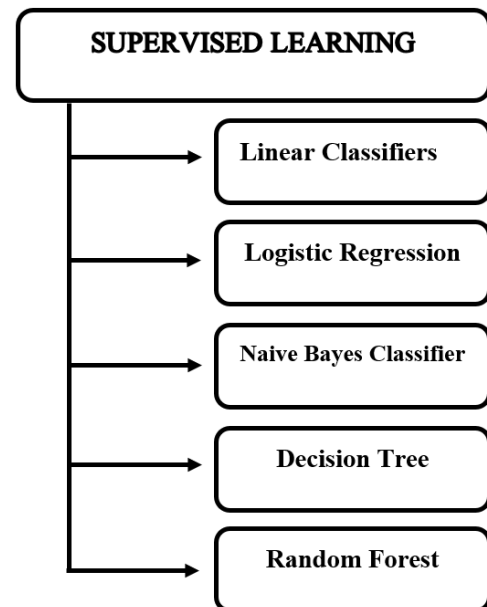
An Ensemble model is a machine learning model which combines two or more than two different models or a model that trained on different datasets to get better accuracy. In this model different algorithms contribute to the ensemble to predict an outcome more accurately. Basically, Ensemble model have two techniques Bagging and Boosting. Bagging also called as Bootstrap Aggregation. Bagging includes Random Forest and in Boosting it has three techniques Adaboost, Gradient Boosting and XGBoost.

**MACHINE LEARNING:** - Machine Learning is the domain of studies of different computer algorithms that can improve through experience. Simon has defined the Machine Learning as “the process of a change and enhancement in the behaviors through exploring new information in time”. It mainly used for to solve the complex problems by using the previous data.[34] Machine Learning can be examined in four parts, shown in figure 2:



**Figure 2: - Classification of Machine Learning [45]**

**SUPERVISED LEARNING:** - Supervised Learning defines the process of providing input data and giving the correct output to the machine learning model. It also helps us to solve various real-world problems. It includes the following classifications which are shown in figure 3: -



**Figure 3: - Classification of Supervised Learning [44]**

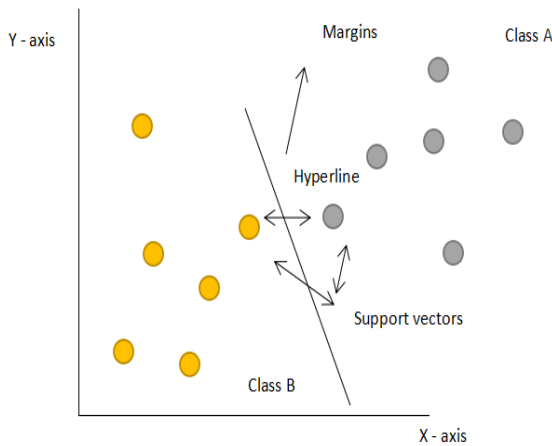
**DECISION TREE CLASSIFIERS:** - It is the most popular method to classify the techniques in data mining.[36] It has the capability to handle the large amount of information. It has several types of Decision Tree algorithms such as:

- Iterative Dichotomies 3 (ID3),
- Successor of ID3 (C4.5),
- Classification And Regression Tree (CART) [38],
- CHi-squared Automatic Interaction Detector (CHAID) [39],
- Multivariate Adaptive Regression Splines (MARS) [40],
- Generalized, Unbiased, Interaction Detection and Estimation (GUIDE), Conditional Inference Trees (CTREE) [41],[42],
- Classification Rule with Unbiased Interaction Selection and
- Estimation (CRUISE), Quick, Unbiased and Efficient
- Statistical Tree (QUEST). [37]

**SUPPORT VECTOR MACHINES:** - Support Vector Machines is related to classical multilayer perceptron neural networks. Support vector machines (SVMs), which were introduced by Vapnik and his coworkers in the early 1990's (Cortes, Vapnik 1995; Vapnik 1996, 1998), these are proved to be effective techniques for data mining (Peng et al. 2008; Yang, Wu 2006).[35][43]. The main motive of SVM is to divide the datasets in to classes to find a maximum marginal hyperplane (MMH).

Important concept in SVM are as follows: -

- Support Vectors:** - Support vectors are all the data points which are closest to the Hyperline.
- Hyperline:** - Hyperline is the decision plane or space which is divided between a set of objects having different classes.
- Margin:** - Margin is the the gap between two lines on the closet data points of different classes.



**Figure 4: - Working graph of SVM [46]**

**SVM KERNEL:** - SVM algorithm is implemented using a kernel that converts the input space into the required form. SVM uses a technique called the kernel trick, in which the kernel allocates a low-dimensional input space and converts it to a higher-dimensional space. In short term, the kernel turns an indivisible problem into a divisible problem by adding more dimensions to it. It makes the SVM even more remarkable, adaptable, and precise. The following are some of the core types used by SVM.

Some types of kernels used by SVM are as follows: -

- i. Linear Kernel: - This kernel used as a dot product between any two observations. Formula for this kernel is as follows: -

$$\text{eq (1): } K(x, x_i) = \text{sum}(x \cdot x_i)$$

In the above formula it shown that the product between two vectors say  $x$  &  $x_i$  is the sum of the multiplication of each pair of input values.

- ii. Polynomial Kernel: - In Polynomial formula it is more generalized form of linear kernel and distinguish curved or nonlinear input space. Formula of polynomial kernel is: -

$$\text{Eq (2): } k(X, X_i) = 1 + \text{sum}(X \cdot X_i)^d$$

In this formula  $d$  is the degree of polynomial, which we need to specify manually in the learning algorithm.

- iii. Radial Basis Function (RBF) Kernel: - In SVM classification, RBF kernel is the mostly used Kernel, maps input space in indefinite dimensional space. Formula for this kernel is: -

$$\text{eq (3): } K(x, x_i) = \exp(-\gamma \cdot \text{sum}(x - x_i)^2)$$

Here,  $\gamma$  ranges from 0 to 1, that need to specify manually it in the learning algorithm. A good default value of  $\gamma$  is 0.1.

**NAIVE BAYES:** - Naïve Bayes is the simplest and most powerful machine learning algorithm which is used to solve classification problem. Basically, it's used for text classification. Naïve Bayes methods are a set of supervised learning algorithms which is based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable. This dataset is divided into two features -

- i. Feature Matrix
- ii. Response Vector

Naive Bayes theorem explains the probability of an event occurring given the probability of another event that has already occurred. The equation of Naive Bayes theorem is given below -

$$\text{Eq (4): } P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Where it defines  $A$  and  $B$  are the events and  $P(B) \neq 0$ .

**K-Nearest Neighbours (KNN):** - K-nearest neighbors (KNN) are a supervised machine learning algorithm, and finds intense application in pattern recognition, data mining and intrusion detection [106]. KNN works by figuring the distance between the target value and the rest of the values, at that point finds the closest k-nearest neighbor values and uses it to decide in favor of the label [110]. The KNN classifier required two boundaries to be set: the k-value, also, the distance metric.

**Random Forest:** - Random Forest, like its name proposes, contains of a large number of individual decision trees that work in coordinates. Each-and-every individual tree in the irregular forest lets out a class forecast and the class with the most votes, which we select as our model for prediction. Random forest comes under Supervised Machine Learning algorithm which is widely used for Classification and Regression problem.

## CONCLUSION AND FUTURE WORK

Prevention of suicide is becoming most important task. By detecting the sentiment of people in early time can prevent suicide. To detect the suicidal sentiment there are several algorithms Naive Bayes, Support Vector Machines, Random Forest, Deep Learning, etc. This research work shown that to detect the sentiment of the people the approach can be made through various model such as machine learning models and ensemble models but finding the best model and having a high accuracy is still a problem that need to be solved. This paper acknowledged that many researchers have done many research by using the datasets in Machine Learning but there is a method called Ensemble model, which is not explored much by the researchers. Using this model this research work can achieve a great level of accuracy. So, this is the field researchers need to explore more.

## REFERENCES

- [1] World health organization. Data 17 June 2021. [Suicide \(who.int\)](https://www.who.int)
- [2] International association for suicide prevention. [WSPD Facts & Figures Infographic \(iasp.info\)](https://www.wspd.org)
- [3] American College Health Association (ACHA). Verywellmind. [Statistics on College and Teen Suicides \(verywellmind.com\)](https://www.verywellmind.com)
- [4] American Foundation for Suicide Prevention. AFSP. [Suicide statistics | AFSP](https://www.afsp.org)
- [5] Sentiment Analysis of suicide notes: A shared Task. John P. Pestian, Pawel Matykievicz, Michelle Linn-gust, Brett South, Ozlem Uzuner, Jan Wiebe.
- [6] SA-E: Sentiment Analysis for Education Nabeela Altrabsheh, Mohamed Medhat Gaber, Mihaela Cocca School of Computing, Buckingham, Building, LionTerrace, Portsmouth, Hampshire, PO13HE, UK E-mail: nabeela.altrabsheh@port.ac.uk, mohamed.gaber@port.ac.uk, mihaela.cocca@port.ac.uk
- [7] M.Taboada, J. Brooke, M. Tofiloski, K. Voll, and M. Stede, "LexiconBased Methods for Sentiment Analysis," Association for Computational Linguistics, 2011.
- [8] S. Sharma, "Application of Support Vector Machines for Damage detection in Structure," Journal of Machine Learning Research, 2008.
- [9] A.Sharma, and S. Dey, "Performance Investigation of Feature Selection Methods and Sentiment Lexicons for Sentiment Analysis," Association for the advancement of Artificial Intelligence, 2012



- [10] Twitter Sentiment Analysis. Alec Go (alecmgo@stanford.edu) Lei Huang (leirocky@stanford.edu) Richa Bhayani (richab86@stanford.edu) CS224N - Final Project Report June 6, 2009, 5:00PM (3 Late Days)
- [11] Sentiment Analysis of Impact of Technology on Employment from Text on Twitter <https://doi.org/10.3991/ijim.v14i07.10600> Shahzad Qaiser Capital University of Science and Technology (CUST), Islamabad, Pakistan Nooraini Yusoff (\*) Universiti Malaysia Kelantan, Kelantan, Malaysia nooraini.y@umk.edu.my Farzana Kabir Ahmad, Ramsha Ali Universiti Utara Malaysia, Kedah, Malaysia
- [12] Twitter as a Corpus for Sentiment Analysis and Opinion Mining Alexander Pak, Patrick Paroubek Université de Paris-Sud, Laboratoire LIMSI-CNRS, Bâtiment 508, F-91405 Orsay Cedex, France alexpak@lmsi.fr, [pap@lmsi.fr](mailto:pap@lmsi.fr)
- [13] SA-E: Sentiment Analysis for Education Nabeela Altrabsheh, Mohamed Medhat Gaber, Mihaela Cocea School of Computing, Buckingham Building, Lion Terrace, Portsmouth, Hampshire, PO13HE, UK E-mail: nabeela.altrabsheh@port.ac.uk, mohamed.gaber@port.ac.uk, [mihaela.cocea@port.ac.uk](mailto:mihaela.cocea@port.ac.uk)
- [14] Sentiment Analysis of Patients' Opinions in Healthcare using Lexicon-based Method V.I.S. RamyaSri, Ch. Niharika, K. Maneesh, Mohammed Ismail.
- [15] Exploiting Sentiment Analysis to Track Emotions in Students' Learning Diaries Myriam Munzero\* School of Computing University of Eastern Finland mmunero@cs.joensuu.fi Maxim Mozgovoy The University of Aizu Aizu-Wakamatsu, Fukushima [mozgovoy@u-aizu.ac.jp](mailto:mozgovoy@u-aizu.ac.jp) Calkin Suero Montero\* School of Computing University of Eastern Finland [calkins@uef.fi](mailto:calkins@uef.fi) Erkki Sutinen School of Computing University of Eastern Finland [sutinen@cs.joensuu.fi](mailto:sutinen@cs.joensuu.fi)
- [16] Use of Sentiment Analysis for Capturing Patient Experience From Free-Text Comments Posted Online Felix Greaves<sup>1,2</sup>, MBChB; Daniel Ramirez-Cano<sup>2</sup>, PhD; Christopher Millett<sup>1</sup>, PhD; Ara Darzi<sup>2</sup>, MD; Liam Donaldson<sup>2</sup>, MD <sup>1</sup>Department of Primary Care and Public Health, Imperial College London, London, United Kingdom <sup>2</sup>Centre for Health Policy, Imperial College London, London, United Kingdom
- [17] Semantic Sentiment Analysis of Twitter Hassan Saif, Yulan He, and Harith Alani Knowledge Media Institute, The Open University, United Kingdom {h.saif,y.he,h.alani}@open.ac.uk
- [18] Sentiment Analysis on Social Media Federico Neri Carlo Aliprandi Federico Capeci Montserrat Cuadros Tomas By Synthema Semantic Intelligence Via Malasoma 24 56121 Pisa - Italy 2.0 Research via Panizza 7 20144 Milano - Italy Vicomtech-IK4 Mikeletegi Pasealekua, 57 Parque Tecnológico 20009 San Sebastián – Spain
- [19] Twitter Sentiment Analysis Aliza Sarlan<sup>1</sup>, Chayanit Nadam<sup>2</sup>, Shuib Basri<sup>3</sup> Computer Information Science Universiti Teknologi PETRONAS Perak, Malaysia aliza\_sarlan@petronas.com.my; [chayanit171@gmail.com](mailto:chayanit171@gmail.com); [shuib\\_basri@petronas.com.my](mailto:shuib_basri@petronas.com.my)
- [20] Detecting Suicidal Ideation on Forums: Proof-of-Concept Study Ahmet Emre Aladağ<sup>1,2</sup>, MSc; Serra Muderrisoglu<sup>3</sup>, PhD; Naz Berfu Akbas<sup>4</sup>, MD; Oguzhan Zahmacioglu<sup>5</sup>, MD; Haluk O Bingol<sup>1</sup>, PhD <sup>1</sup>Department of Computer Engineering, Bogazici University, Istanbul, Turkey <sup>2</sup>Amazon Research, Madrid, Spain <sup>3</sup>Department of Psychology, Bogazici University, Istanbul, Turkey <sup>4</sup>Medical School, Department of Psychiatry, Yeditepe University, Istanbul, Turkey <sup>5</sup>Medical School, Department of Child and Adolescent Psychiatry, Yeditepe University, Istanbul, Turkey
- [21] Using Ensemble Models to Classify the Sentiment Expressed in Suicide Notes James A. McCart<sup>1,2</sup>, Dezon K. Finch<sup>1,2</sup>, Jay Jarman<sup>1,2</sup>, Edward Hickling<sup>2</sup>, Jason D. Lind<sup>2</sup>, Matthew R. Richardson<sup>2</sup>, Donald J. Berndt<sup>1-3</sup> and Stephen L. Luther<sup>1,2</sup> <sup>1</sup> Consortium for Healthcare Informatics Research, <sup>2</sup> HSR&D/RR&D Center of Excellence, James A. Haley Veterans' Hospital, Tampa, FL. <sup>3</sup> University of South Florida, Tampa, FL. Corresponding author email: [james.mccart@va.gov](mailto:james.mccart@va.gov)
- [22] sentiment Analysis of suicide notes: A shared Task John P. Pestian<sup>1</sup>, Pawel Matykievicz<sup>1</sup>, Michelle Linn-gust<sup>2</sup>, Brett South<sup>3</sup>, Ozlem Uzuner<sup>4</sup>, Jan Wiebe<sup>5</sup>, 6 7 8 1 cincinnati children's hospital Medical center, University of cincinnati, cincinnati Oh. 2 American Association of Suicidology, Washington Dc. 3 United States Veteran's Administration, Salt Lake City, UT. 4 University at Albany, SUNY, Albany, nY. 5 University of Pittsburgh, Pittsburgh, PA. 6 University of colorado, Denver, cO. 7 University of Utah, Salt Lake City, UT. 8 The Ohio state University, columbus, Oh. corresponding author email: [john.pestian@ecchmc.org](mailto:john.pestian@ecchmc.org)
- [23] Application of Aspect-based Sentiment Analysis on Psychiatric Clinical notes to Study Suicide in Youth. Amy George, David Johnson, Giuseppe carenini, Ali Eslami, Raymond Ng, Elodie Portales-Casamar
- [24] Machine Learning and Semantic Sentiment Analysis based Algorithms for Suicide Sentiment Prediction in Social Networks Marouane Birjalja, \*, Abderrahim Beni-Hssanea, Mohammed Erritali b a LAROSERI Laboratory, Department of Computer Sciences, University of Chouaib Doukkali, Faculty of Sciences, El Jadida, Morocco
- [25] Suicidal Profiles Detection in Twitter Atika Mbarek<sup>1,2</sup>, Salma Jamoussi<sup>1,2</sup>, Anis Charfi<sup>3</sup> and Abdelmajid Ben Hamadou<sup>1,2</sup> <sup>1</sup>Multimedia Information Systems and Advanced Computing Laboratory (MIRACL), University of Sfax, Tunisia <sup>2</sup>Digital Research Center of Sfax DRCS, 3021, Sfax, Tunisia <sup>3</sup>Carnegie Mellon University in Qatar, Doha, Qatar
- [26] A Hybrid Approach to Sentiment Sentence Classification in Suicide Notes Sunghwan Sohn<sup>1</sup>, \*, Manabu Torii<sup>2</sup>, \*, Dingcheng Li<sup>1</sup>, Kavishwar Waghlikar<sup>1</sup>, Stephen Wul and Hongfang Liu<sup>1</sup> <sup>1</sup> Division of Biomedical Statistics and Informatics, Mayo Clinic, Rochester, MN. <sup>2</sup> ISIS Center, Georgetown University Medical Center. \*Equal contribution. Corresponding author email: [sohn.sunghwan@mayo.edu](mailto:sohn.sunghwan@mayo.edu)
- [27] Suicidal Ideation Detection: A Review of Machine Learning Methods and Applications Shaoxiong Ji, Shirui Pan, Member, IEEE, Xue Li, Erik Cambria, Senior Member, IEEE, Guodong Long, and Zi Huang
- [28] Can Text Messages Identify Suicide Risk in Real Time? A Within-Subjects Pilot Examination of Temporally Sensitive Markers of Suicide Risk Jeffrey J. Glenn<sup>1,2,3</sup>, Alicia L. Nobles<sup>1,4</sup>, Laura E. Barnes<sup>1</sup>, and Bethany A. Teachman<sup>1</sup> <sup>1</sup> Department of Psychology, University of Virginia; <sup>2</sup> Durham Veterans Affairs (VA) Health Care System, Durham, North Carolina; <sup>3</sup> VA Mid-Atlantic Mental Illness Research, Education and Clinical Center (MIRECC), Durham, North Carolina; and <sup>4</sup> Department of Medicine, University of California, San Diego.
- [29] Analyzing the depression and suicidal tendencies of people affected by COVID-19's lockdown using sentiment analysis on social networking websites Sparsh Sharma & Surbhi Sharma To cite this article: Sparsh Sharma & Surbhi Sharma (2020): Analyzing the depression and suicidal tendencies of people affected by COVID-19's lockdown using sentiment analysis on social networking websites, Journal of Statistics and Management Systems.
- [30] V. Venek, S. Scherer, L.-P. Morency, J. Pestian et al., "Adolescent suicidal risk assessment in clinician-patient interaction," IEEE Transactions on Affective Computing, vol. 8, no. 2, pp. 204–215, 2017.
- [31] B. O'Dea, S. Wan, P. J. Batterham, A. L. Calear, C. Paris, and H. Christensen, "Detecting suicidality on twitter," Internet Interventions, vol. 2, no. 2, pp. 183–188, 2015.
- [32] S. Ji, C. P. Yu, S.-f. Fung, S. Pan, and G. Long, "Supervised learning for suicidal ideation detection in online user content," Complexity, 2018.
- [33] Suicidal Ideation Detection: A Review of Machine Learning Methods and Applications Shaoxiong Ji, Shirui Pan, Member, IEEE, Xue Li, Erik Cambria, Senior Member, IEEE, Guodong Long, and Zi Huang
- [34] A Research on Machine Learning Methods and Its Applications Özer ÇELİK (Corresponding author) \* Serthan Salih ALTUNAYDIN \* \* Osmangazi University, Eskişehir, Turkey.
- [35] Algorithms: Classification and Comparison Osisanwo F.Y.\*<sup>1</sup>, Akinsola J.E.T.\*<sup>2</sup>, Awodele O.\*<sup>3</sup>, Hinmikaiye J. O.\*<sup>4</sup>, Olakanmi O.\*<sup>5</sup>, Akinjobi J. \*\*<sup>6</sup> \*Department of Computer Science, Babcock University, Ilesha-Remo, Ogun State, Nigeria. \*\*Department of Computer Science, Crawford University, Igbesa, Ogun State, Nigeria Supervised Machine Learning
- [36] A REVIEW PAPER ON STUDENT PERFORMANCE USING DECISION TREE ALGORITHMS Pratibha V.Jadhav 2Dr.Vaishali V. Patil, 3Dr.S.D.Gore 1Ph.D research scholar 2Assistant Professor, 3Professor 1 JJTU, Rajasthan. 2TC College, Baramati. 3SPPU Pune.
- [37] Classification Based on Decision Tree Algorithm for Machine Learning Bahzad Taha Jijol\*, Adnan Mohsin Abdulazeez<sup>2</sup> <sup>1</sup> IT Department, Technical College of Informatics Akre, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq, bahzad.taha@dpu.edu.krd <sup>2</sup> Presidency of Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq, adnan.mohsin@dpu.edu.krd \*Correspondence: [bahzad.taha@dpu.edu.krd](mailto:bahzad.taha@dpu.edu.krd)
- [38] C. E. Brodley and P. E. Utgoff, "Multivariate decision trees," Machine learning, vol. 19, no. 1, pp. 45–77, 1995.
- [39] G. K. F. Tso and K. K. W. Yau, "Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks," Energy, vol. 32, no. 9, pp. 1761–1768, Sep. 2007, doi: 10.1016/j.energy.2006.11.010

- [40] S. Singh and P. Gupta, "Comparative study ID3, cart and C4. 5 decision tree algorithms: a survey," International Journal of Advanced Information Science and Technology (IJAIST), vol. 27, no. 27, pp. 97– 103, 2014.
- [41] L. Rokach and O. Maimon, "Top-Down Induction of Decision Trees Classifiers—A Survey," Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, vol. 35, pp. 476– 487, Dec. 2005, doi: 10.1109/TSMCC.2004.843247.
- [42] T.-S. Lim, W.-Y. Loh, and Y.-S. Shih, "A comparison of prediction accuracy, complexity, and training time of thirty-three old and new classification algorithms," Machine learning, vol. 40, no. 3, pp. 203– 228, 2000.
- [43] RECENT ADVANCES ON SUPPORT VECTOR MACHINES RESEARCH Yingjie Tian<sup>1</sup>, Yong Shi<sup>2</sup>, Xiaohui Liu<sup>3</sup> <sup>1</sup> Research Center on Fictitious Economy and Data Science, Chinese Academy of Sciences, No. 80 Zhongguancun East Road, Haidian District, Beijing 100190, China <sup>2</sup> College of Information Science and Technology, University of Nebraska at Omaha, Omaha, NE 68182, USA <sup>3</sup> School of Information Systems, Computing and Mathematics, Brunel University, Uxbridge, Middlesex, UK E-mails: 1 tyj@gucas.ac.cn (corresponding author); 2 yshi@gucas.ac.cn; 3 xiaohui.liu@brunel.ac.uk Received 05 September 2011; accepted 19 December 2011
- [44] Source: - [https://www.researchgate.net/figure/Sentiment-classification-techniques\\_fig1\\_261875740](https://www.researchgate.net/figure/Sentiment-classification-techniques_fig1_261875740)
- [45] Source: - <https://litslink.com/blog/an-introduction-to-machine-learning-algorithms>
- [46] Source: - <https://www.kdnuggets.com/2016/07/support-vector-machines-simple-explanation.html>
- [47] Danuta Wasserman, Ellenor Mittendorfer Rutz, Wolfgang Rutz, and Armin Schmidtke. 2004. Suicide Prevention in Europe. Technical report, National and Stockholm County Council's Centre for Suicide Research and Prevention of Mental Ill Health.
- [48] M. Berk and Henry S. Dodd. 2006. The effect of macroeconomic variables on suicide. Psychol Med, 36(2):181–189.

