Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 6s (2024)

Machine Learning based Suicide Analysis in Social Media

Dr. M. Durairaj [1], Rajasekhara Babu L[2]
[12] Bharathidasan University, Department of Computer Science and Engineering, Tiruchirappalli – 620 023, Tamil Nadu, INDIA, Andhra Pradesh - 522502, India.

***Received:** 15-04-2024* ***Revised:** 22-05-2024* ***Accepted:** 10-06-2024*

ABSTRACT

About 800,000 people committed suicide worldwide in 2016, per a WHO report. For those between the ages of 15 and 29, suicide ranks as the second leading cause of death outside of natural causes. This article provides a literature review of the current state of the debate over whether or not machine learning techniques can be used to identify suicides on social media. Goals, data collection methods, development processes, and validation metrics for detecting suicidal behavior on social media are all examined. Arksey and O'Malley's et al method's for performing a scope assessment was used, and the PRISMA protocol was used for selecting the studies that would be included. In order to identify the machine learning techniques used to predict suicide risk from social media posts, this scope review aims to examine all relevant literature. The databases include PubMed, Science Direct, IEEE Xplore, and Web of Science. Half of the studies (8/16) that used data mining methods for object extraction, object detection, or object

Language surveys and word counts were

50%), followed by Dirichlet's latent analysis, latent semantic analysis, and word2vec, each of which was reported by researchers only 25% of the time. The only study that used principal component analysis and non-negative matrix factorization was the 12.5% lowest-quality study. Three out of eight research articles (37.5%) used multiple methods. Ten out of the sixteen studies (62.5%) that used statistical methods also used Supported Vector Machines. The majority of the studies (75%) also use Python to implement machine learning based models.

INTRODUCTION

Nearly 800,000 people commit suicide annually, with 135k (17%) living in India, which is home to 17.5% of the world's population [2]. The suicide rate in India rose from 7.9 per 100,000 in 1987 to 10.3 in 2007 [3], with the southern and eastern states having the highest rates. The National Crime

Records Bureau (NCRB) reports that as of 2014, 56.2% of all reported suicides in India were from the states of Tamil Nadu, West Bengal, Andhra Pradesh, Maharashtra, and Karnataka [4]. Researchers believe that an underestimation of suicide cases in this region [1] accounts for the fact that Uttar Pradesh, the most populous state (16.5% of the population), reports a relatively lower rate of suicide deaths, accounting for only 3.6% of all suicides reported in that country. Using machine learning methods and techniques, this paper explores the factors that contribute to suicide prediction in India. Although ML has been around for a long time in the realm of computers, its use in clinical psychology is relatively new. We then provide a brief overview to help the reader get a grasp on what ML is, why it's preferable to more conventional statistical methods in clinical psychology, and how its efficacy can be evaluated. The purpose of this research is to examine the causes of the rising suicide rate in India, make predictions about that rate, and gain a better understanding of its historical development. the number of people who take their own lives and compile a report that can be used to find a remedy to this tragic trend. This research has both theoretical and practical significance because, once completed, it will be of great assistance to Indian government agencies in taking action and providing solutions to reduce the rate of unemployment. ratio of deaths The annual suicide rate in India continues to rise. The study uses data from India's National Crime Records Bureau detailing the number of suicide deaths in each Indian state between 2001 and 2012. (NCRB). Characteristics of the dataset include sex, marital status, year, age range, suicide tally, code, and classification.What is the primary reason for the dramatic rise in suicide rates and related statistics?

1) Hypothesis: An examination of suicide rates and their correlations with social and economic factors.

Two limitations of the work are noted.

2) The study aimed to predict the causes of suicide in the general population, regardless of age or sex. In conclusion, the purpose of this study was not to rank causes for men and women separately or to predict causation for different age groups.

The suicide rate is one of the most pressing issues in the world today. Every year, more and more people join the ranks of the suicide dead. On average, it is estimated that 800,000 people per year die in suicide attempts [5]. The World Health Organization (WHO) estimates that 17% of the world's suicide victims live in India [5]. Research into the causes, prevention, and treatment of suicidal thoughts and actions has increased in recent years, as reported by the CDC-2015. Despite extensive research and numerous interventions, suicide rates have not decreased [6]. The vast majority of people who attempt suicide do not engage in any kind of premeditated strategy [6]. As a result, it is crucial to improve prediction regarding the people who are likely to act on their suicidal ideation. A researcher proposed an all-inclusive machine learning framework for estimating suicide probabilities. There are three main pieces to the proposed architecture [7]. 1) Extraction of temporal features Risk Management and Regulation Thirdly, we have a feature-selection and ordinal-classification ensemble loop. As a leading cause of death around the world, suicide is widely regarded as a crucial factor influencing people's emotional well-being. As such, it represents a significant barrier to understanding and addressing suicidal ideation. Suicide rates can be estimated using the following sentinel measures [7] to predict the likelihood or probability surrounding a specified future era: 1) Suicide risk cannot be identified during low-risk proceedings. 2) Self-damage or injuries that do not lead to major consequences are examples of moderate-risk actions. Thirdly, serious consequences, including death, are associated with high-risk proceedings. A study was conducted with the intention of identifying the key factors that influence II, and the results were published. An Analysis of the Existing Literature Journal of Computing Research, Vol. 15, No. 2 (July-December 2017) estimates future suicide rates based on past trends and data on how often people in certain Indian districts commit suicide. Authorities in areas with a disproportionately high suicide rate can use this estimate to inform policy decisions [8]. The study's characteristics are representative of the percentage of the population that is distressed primarily as a result of suicides [5]. The Indian government keeps tabs on suicides by keeping a database of all the reported cases across the country. Databases are made available to the public with the goal of conducting analytics on the data that has been logged. In addition to taking into account the number of suicides in each area, demographic data for each state was also taken into account. When creating a model, we split the population into three broad categories: education level, martial arts experience, and regional census data. Karl Pearson's coefficient of correlation was used by the researchers to confirm the features' association and to reveal their correlation with one another. The future suicide rate was predicted using a regression model after the strength of association was determined. The findings were critically important because they identified nine characteristics that were found to have a linear relationship with the reported number of suicides. Using those nine characteristics, we were able to create an estimation model with a 99% confidence interval for the estimated value [5]. It has been suggested by another researcher that a certain method be used to calculate an approximate number of suicides. He suggests estimating the frequency with which people commit suicide using the information collected from recorded suicides. Since social networking systems present substantial information that is gathered and created by the clients/users of the social networking sites, he believes that Sentiment Investigation, one of the most recent experiments developed in machine learning, can play a significant role. By analyzing the thought process mechanism that is dependent on the user's opinion, view, and sentiments, he believes he can profit from the data made available on social networking sites. Harassment, depression, and even suicide have all been linked to the use of social networking sites, so it's crucial that we make every effort to identify potential victims as soon as possible.

LITERATURE SURVEY

Data collection is the starting point for suicide prediction, and sites like Facebook, Twitter, Instagram, and Tumblr are all useful for this purpose. Recent data analysis has shown that a person's tweets can reveal the reasons why they want to end their lives. It has been established by the research community that suicidal ideation and attempts are primarily driven by emotional distress. Data analysis techniques range from text mining and sentiment analysis to network and quantitative data analysis. This paper provides a prognosis and a summary of these approaches and challenges. The paper [1] explains the classification process in detail, breaking it down into manageable chunks. The results of state-of-the-art methods have been presented clearly, and classifiers have been compared in terms of their methodologies. In the paper [2], the author explains how to assess a person's state of depression through a review of their social media activity, taking into account theories of emotion, machine learning methods, and

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 6s (2024)

natural language processing across multiple sites. In this paper [3, we use acoustic

features to train a classification model that can tell if a person is depressed or not. When using the DIAC-WOZ database for training, the SVM algorithm generates a Depression Classification Model with a 93% accuracy rate (DCM). Using Natural Language Processing (NLP) techniques, the authors of paper [4] develop a depression detection algorithm for the Thai language on Facebook in order to gain a better understanding of how people in Thailand who use Facebook to share their thoughts, feelings, and experiences experience depression. A total of 35 Facebook users' behaviours were analyzed to see if they could be used as a predictor of their own levels of depression. Using natural language processing (NLP) on Twitter streams, the research presented in [5] aims to conduct an emotional analysis of depression. A tweet's positivity, negativity, or neutrality can be determined using a depression-specific curetted word-list. Historically, class prediction has made use of both Naive Bayes classifiers and support vector machines. The results have been displayed using prominent classification metrics such as F1-score, accuracy, and confusion matrix. The purpose of this paper [6] is to propose a data-analytic based model for recognizing depressive symptoms in any person. This proposed model makes use of data extracted from social media posts, particularly those made on Twitter and Facebook. Using a user's social media activity, we were able to assess the person's state of depression. In this study, machine learning is used to analyses data stolen from social media users. Depression detection using natural language processing (NLP) and Naive Bayes classification or Support Vector Machine (SVM) may be more efficient and less labor-intensive than current methods. The purpose of this paper

[7] is to offer a high-level overview of the risk factors for suicide attempts on social media. Separating tweets about depression and anxiety is the focus of the paper [8], which employs Multinomial Naive Bayes and the Support Vector Regression (SVR) Algorithm to classify tweets about mental health. In this paper [9], the authors propose an automated system for analysing depressive symptoms and identifying suicidal ideation. Authors have gathered real-time data that has been processed into meaningful data with related features by having students and parents fill out questionnaires. At last, classification

machine algorithms are used to train the data and place it into one of five gradations of depression severity. The highest accuracy was obtained by the XGBoost classifier in this dataset (83.87 percent). In order to determine whether or not a person is suicidal, the authors of this paper [10] propose a depression analysis system. The goal of this study is to apply machine learning techniques to the problem of determining whether or not a Twitter user is depressed. In order to train and evaluate classifiers that can evaluate whether a user is depressed or not, we extracted features from the user's tweeting behaviours. For this purpose, we use classification machine algorithms to teach the machine to distinguish between different levels of depression severity, from 0% to 100%. The study of a set of features and their impact on spotting localized depression is the most novel contribution of this study.

PROPOSED METHODOLOGY

These days, people of all ages go to social networking sites to gain access to information. The authors' emotional and mental states are assumed to be reflected in the language they use in their social media activities. Tens of millions of people worldwide experience depression every year, but only a small percentage of those who need help actually receive it. We tend to investigate the possibility of utilizing social media in the identification and diagnosis of major depressive disorder. In this paper, we adopt a method that is structured in a series of modules. For better implementation, the workflow's constituent parts have been broken down into independent procedures. In this paper, we present a formal model for extracting depression severity from tweet content. Both NLP and ML methods are incorporated into the system. The workflow kicks off with data collection, which in this case involves making use of the Twitter API to produce the dataset. There is a significant improvement over human classification in sentiment analysis when the linguistic communication process is used. Tokenization, stemming, and stop words removal are all part of the data preprocessing module, which runs after the dataset has been created.

Dataset

We drew from a large, publicly available depression dataset suggested by Shen et al. To categorise the tweets, the authors crawled them. There are three parts to the dataset: D1

is the depressed dataset and contains 1.3 million samples labelled as Positive tweets. D2 is the non-depressed dataset and contains
1.3 million samples labelled as Negative tweets. We conducted experiments with the D1 and D2 labelled datasets. In order to perform natural language processing (NLP)
on the dataset, we first preprocess it. The dataset was divided into two parts: a "Training" set (consisting of 80% of the data) and a "Testing" set (cons However, we also report the accuracy to evaluate the proposed model's overall performance.

System Architecture

Using the user's own tweets and the user's Twitter activity, a quantitative study trains and tests a variety of machine learning classifiers to determine whether the user is depressed. The process of how the depression detection model works is shown in the following diagram.

Twitter API

Using the Twitter API, we can look into, learn from, and otherwise interact with Tweets, DMs, and users. With more resources, we can expand, experiment, and innovate at a rapid rate. We are using the Twitter API platform to gain broad access to the public Twitter data that the users have chosen to share with the world. A user can access and modify their Twitter data via the API. The model collects the Twitter account holder's tweets for Sentiment Analysis via the Twitter API. To retrieve tweets from users' accounts, we made use of the Twitter API. By logging in as a developer, we were able to access the API and extract all the data we needed from the user's profile with minimal effort. As a result, we have relied on it to craft tweets, peruse profiles, and gain access to information about our followers as well as a flood of tweets pertaining to selected topics and geographical areas.

Natural Language Processing

As a subfield of artificial intelligence (AI), natural language processing (NLP) aims to make human speech understandable to computers. When it comes to checking the basis and structure of language and creating intelligent systems (based on machine learning and natural language processing algorithms) capable of understanding, analysing, and extracting meaning from text and speech, Natural Language Processing combines the abilities of linguistics and computing. By analysing components like syntax, semantics, pragmatics, and morphology, NLP is used to gain insight into the construction and meaning of the languages we speak. This linguistic information is then converted by technology into machine learning algorithms based on rules, with the potential to address targeted problems and accomplish targeted goals.

Data Pre-Processing

The NLTK (Natural language processing toolkit) is crucial for tweet preprocessing. To prepare the Twitter dataset for further processing, including feature extraction, training, and testing, we employ Natural Language Processing tools. All of the extracted information was first transformed into string form. To ensure that the algorithm does not distinguish between the same words based on case, the entire test was converted to lowercase. The data was then cleaned of any and all embedded hyperlinks. The punctuation in the strings is stripped after the hyperlink elimination process is complete. Next, the strings are cleaned up by removing any stop words that could cause unexpected behaviour if left alone. In order to perform NLP on a smaller data set, stemming and lemmatization are crucial processes. Tokenization is the process of breaking up the posts into smaller, more manageable pieces. Several data preprocessing operations are carried out after reading the CSV file. Natural language processing techniques have been used for the extraction process's preliminary cleaning.

Stop Word Removal

In any language, "stop words" are the most frequently used words. These stop words may not contribute much to understanding the text when used in NLP analyses and model construction. Filtering out "stop words" before or after processing natural language data is common practise in computing (text). Stop words, which are words that occur too frequently to be useful in training, must be eliminated. Otherwise, the training process will be skewed. There is a list of stop-words in the NLTK library that can be used to filter them out of the tweet.

Tokenization

The raw text is tokenized into small pieces. When raw text is tokenized, it is divided into individual words and sentences. These symbols aid in comprehending the setting or creating the model for computer science. By analysing the order of the words, tokenization aids in determining the meaning of the text. In this scenario, tokens are generated from the column in the CSV file that contains the tweet. Tokenizing a sentence into its individual words was a step we took. For improved text classification in the machine learning model, the output of the word tokenization method is then converted to Data Frame. Let's ['Let', "'s", 'see', 'how', 'it', "'s", 'working', '.'] and see how well it's working.

Stemming

Stemming is the process of breaking down a word into its component parts, including prefixes, suffixes, and roots (or lemmas).

There is a strong connection between stemming and NLU/NLP (NLP). Stemming is the process of breaking down words into their simplest components. This would be useful for classifying words into categories. Words like "wonderful" and "amazing" are examples of words that express positive and negative sentiments, respectively, that can be picked up by a sentiment analyzer. If we could do this, we could more easily categorise words into groups.

Lemmatization

Correctly using a vocabulary and morphological analysis of words, lemmatization typically aims to remove inflectional endings exclusively in order to arrive at the base or lexicon variety of a word, which is called the lemma. In the fields of Natural Language Processing (NLP) and machine learning more generally, lemmatization is a popular text pre- processing technique. The goal is to get back to the dictionary form of the word by removing inflectional suffixes and prefixes.

TRAINING

The training set and the text label are the primary inputs needed by the classifier. In this case, the set of tweets that must undergo additional processing before being fed into a classifier constitutes the training set. In order to perform further analysis on the collected tweets, a vectorization step is required. It also receives a vector containing the set of labels for each tweet. Machine Learning for Classification, Part A

Naïve Bayes

In machine learning, Naive Bayes is a model that can tackle both classification and regression tasks. There is a family of classifiers called "naive mathematician classifiers" that uses

Bayes' Theorem as its basis. It is not just one rule but rather a group of algorithms where the common denominator is that the features in the dataset being classified are all distinct from one another. Naive Thomas Bayes is an example of a relatively straightforward supervised machine learning rule, in that it uses the Bayes' theorem to obtain results while making strong independence assumptions between the options. Assuming you have a firm grasp of the world when you don't actually do is naive. The Bayes Theorem offers a principled method for conditional probability, but its application requires a large number of samples (a dataset of extremely large size) and is computationally expensive. Naive Bayes is a common name for the simplified version of Bayes Theorem, which is used frequently in the classification of predictive modelling problems. Given the sentence "I like Harry Potter," our model's Naive Bayes algorithm for sentiment analysis will focus on the words in that sentence rather than the entire thing. The proximity of two words in a sentence affects their meanings, and the order in which words appear in a text is also crucial. However, the algorithm does not distinguish between "I like Harry Potter," "Harry Potter-like I," and "Potter I like Harry." To implement this algorithmic rule, we typically plot all data points in an n-dimensional space, with the value of each feature corresponding to the value of each coordinate.

Support Vector Neural Network (SVNN)

The support for both classification and regression problems makes SVNN the go-to deep learning algorithm (feed-me). Predicting a label or group in classification; anticipating a constant value in regression. In order to perform classification, support vector machines (SVNNs) seek out the hyper plane that best separates the classes we've plotted across n dimensions (where n is the varying of choices you have). The most common way that we classify things is by locating the hyper-plane that most clearly separates the two groups (look at the below diagram). To get to that hyperplane, SVNN reworks our knowledge with the help of mathematical functions, primarily called Kernels. Unit linear, sigmoid, RBF, non- linear, polynomial, etc. are some examples of the many types of Kernels available. For nonlinear problems, the regularization parameter RBF kernel is a general kernel that is used when no prior knowledge of the data exists. The Linear Kernel algorithm is designed for problems with a linear solution. Here, we'll use "linear SVNN" because our model is straightforward (consisting only of positive and negative values).

We have presented machine learning techniques to analyses the tweets in our model, and we have used both classifiers to

compare the two classifiers, the Support Vector Machine (SVNN) and the Nave Bayes (NB), as well as the maximum accuracy of the classifier for calculating the sentiment about the topic. In our testing, Nave Bayes consistently outperformed SVNN.

TESTING

The steps involved in classifier testing are as follows.

Loading saved models

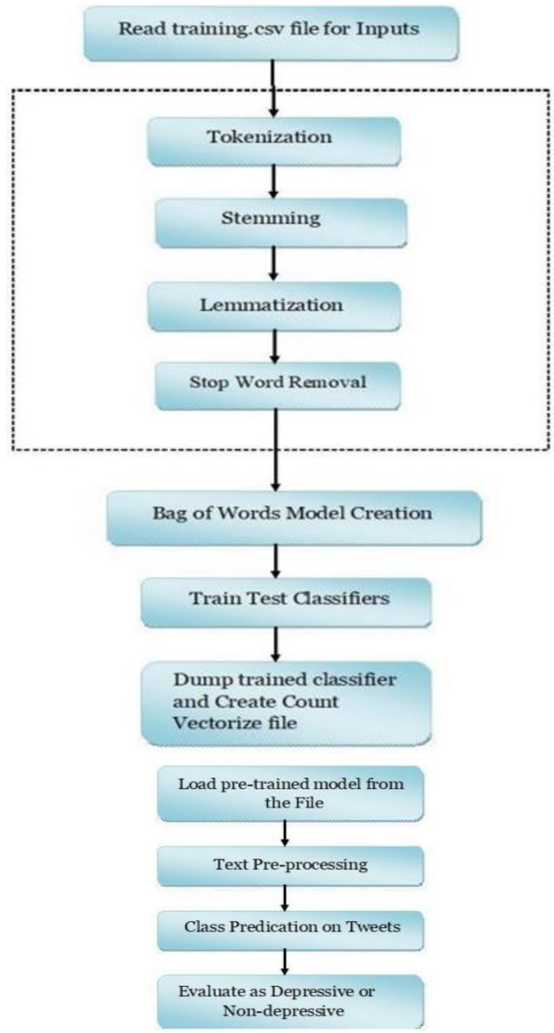
Classification models learned during training are read from a file and applied to a test dataset for prediction.

Data Preprocessing

The same natural language processing (NLP) preprocessing methods used on the training dataset are also applied to the test dataset.

Class Prediction on Test Tweets

After the data has been cleaned and processed, it is then assigned to either the happy or sad category for social media posts or texts.



RESULTS

In the beginning, it takes a single string as input and processes it through all the pre-processing steps, such as removing slang, emoji, hash tags, etc. The tweets are then analyzed using a number of sentiment analyzers, including text Blob and Sent WordNet, before moving on to the feature extraction phase (in python script). The polarity and subjectivity of a sentence are extracted using Text Blob. The sentence's positivity or negativity is determined using data from the sent WordNet dictionary. Text blob and Sent WordNet dictionary, POS tags- POS vector, POS score, and n-grams are used to determine sentiment. To test how well these analyzers work, we use a validation process that ranks tweets on their positive, neutral, and negative sentence score. Both the Multinomial Naive Bayes (MNB) and Support Vector Regression (SVR) classifiers are implemented so that their respective accuracy levels can be compared.

PROPOSED CLASSIFIERS ACCURACY

Naive Bayes 82.22%

Support Vector Neural Network 78.34%

CONCLUSIONS

Machine learning sentiment analysis has been successfully applied to the task of identifying depressive episodes from Twitter data. Predicting depression using text data is difficult for deep learning classification because of this limitation. Further, the Tweets collected before pre-processing have a lot of noise, so about a third of the data is discarded. In this paper, we evaluate SVNN, Naive Bayes, and a custom classifier for measuring depression through sentence-level sentiment analysis. From what we have seen, NB provides superior results compared to SVNN and achieves the highest accuracy in our model.

REFERENCES

[1] N. A. Asad, M. A. Mahmud Pranto, S. Afreen and M. M. Islam, "Depression Detection by Analyzing Social Media Posts of User," 2019 IEEE International

[2] Conference on Signal Processing, Information, Communication & Systems (SPICSCON), Dhaka, Bangladesh, 2019, pp. 13-17, doi:10.1109/SPICSCON48833.2019.90651

[3] K. Katchapakirin, K. Wongpatikaseree, P. Yomaboot and Y. Kaewpitakkun, "Facebook Social Media for Depression Detection in the Thai Community," 2018 15th International Joint Conference on Computer Science and Software Engineering (JCSSE), Nakhonpathom, 2018, pp. 1-6, doi: 10.1109/JCSSE.2018.8457362.

[4] P. Arora and P. Arora, "Mining Twitter Data for Depression Detection," 2019 International Conference on Signal Processing and Communication (ICSC), NOIDA, India, 2019, pp. 186-189, doi: 10.1109/ICSC45622.2019.8938353.

[5] A. U. Hassan, J. Hussain, M. Hussain, M. Sadiq and S. Lee, "Sentiment analysis of social networking sites (SNS) data using

machine learning approach for the measurement of depression," 2017 International Conference on Information and Communication Technology Convergence (ICTC), Jeju, 2017, pp. 138-140, doi: 10.1109/ICTC.2017.8190959.

[6] M. Deshpande and V. Rao, "Depression detection using emotion artificial intelligence," 2017 International Conference on Intelligent Sustainable Systems (ICISS), Palladam, 2017, pp. 858-862, doi: 10.1109/ISS1.2017.8389299.

[7] S. Jain, S. P. Narayan, R. K. Dewang, U. Bhartiya, N. Meena and V. Kumar, "A Machine Learning based Depression Analysis and Suicidal Ideation Detection System using Questionnaires and Twitter," 2019 IEEE Students Conference on Engineering and Systems (SCES) Allahabad, India, 2019, pp. 1-6, doi: 10.1109/SCES46477.2019.8977211.

[8] B. Yalamanchili, N. S. Kota, M. S. Abbaraju, V. S. S. Nadella and S. V. Alluri, "Real-time Acoustic based Depression Detection using Machine Learning Techniques," 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic ETITE), Vellore, India, 2020, pp. 1-6, doi: 10.1109/ic ETITE47903.2020.394.

[9] M. Hooda, A. R. Saxena, D. Madhulika and B. Yadav, "A Study and Comparison of Prediction Algorithms for Depression Detection among Millennials: A Machine Learning Approach," 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC), Mysore, 2017, pp. 779-783, doi: 10.1109/CTCEEC.2017.8455078.

[10] A. Noureen, U. Qamar and M. Ali, "Semantic analysis of social media and associated psychotic behavior," 2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), Guilin, 2017, pp. 1621-1630, doi: 10.1109/FSKD.2017.8393009.

[11] P. Gupta and B. Kaushik, "Suicidal Tendency on Social Media: A Case Study," 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, India, 2019, pp. 273-276, doi: 10.1109/CO MITCon.2019.8862236