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Suicidal Ideation Detection: Application of Machine Learning Techniques on Twitter Data

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***Abstract*—The World Wide Web, particularly Twitter, and online social networks have expanded the network connecting people, allowing for the rapid dissemination of information to large numbers of people. There are several instances of this kind of online collaborative contagion, one of which is the development of self-destructive ideas in social media sites like Twitter, which has caused alarm. In this investigation, the implications and findings of several machine classifiers that were applied to the point order of tweets and terms connected to suicide are discussed.The classifier can distinguish between more stressful information, such as suicidal creativity, other suicide-related topics, in-depth suicide-related facts, loyalty, campaign, and support. A simple classifier utilizing emotional, lexical, psychological, and structural characteristics from Twitter is used to link and identifyallusions to suicide. This procedure makes use of clustering, bracketing, association rules, NLP (natural language processing), and numerous machine-learning techniques. This research study explores the restrictions or difficulties in this field and serve as a guide for future research.**

***Index Terms*—Machine Learning, Natural Language Processing (NLP), Data Mining, Classification, Python, Tokenization,Lemmatization, Text Analysis**

I. INTRODUCTION

In today's environment, it is crucial to address mental health disorders like anxiety and depression. The developed nations are particularly suffering from them. These rapidly developing nations are the rising market for profoundly dysfunctional mental illness. Suicidal thoughts and attempts can be eliminated with treatment. Some internet messages are filled with a lot of unpleasant material, which can lead to issues like cyberbullying and stalking online. Social media of some kind is frequently involved in such offensive content. It results in brutality, rumors, and even psychological harm. There is evidence that cyberbullying and suicide are related. Victims who have been subjected to a lot of unpleasant messages and experiences could feel down and irritated. Worse, people occasionally kill themselves. Suicide has a variety of causes. While numerous individuals who aren't depressed might additionally experience suicidal thoughts, those who suffer from depression are more inclined to actually commit suicide. The American Suicide Prevention Foundation (AFSP) has classified the causes of suicide into three groups: environmental, historical, and health-related. According to Ferrari et al., suicide has been linked to mental health issues and drug use disorders. The whole review of the psychology of suicide by O'Connor and Nock was condensed into four categories: personal and individual psychological risks differences, cognitive variables, social factors, and adverse life events.

According to the provided tabular data of the individual or textual material submitted by a person, suicidal ideation detection (SID) assesses if an individual has suicidal thoughts or feelings. A rising number of people are using social media advancements and online anonymity to engage with others online. People are increasingly using online communication platforms to communicate their emotions, pain, and suicidal thoughts. Online channels naturally began to monitor for suicidal thoughts and mine social media for information that may help prevent suicide. Special social phenomena are expanding daily, including online networks that agree on copycat suicide and self-harm.

In this vein, a lot of study has focused on suicide prevention have increased in prominence in recent years. Indeed, one of the most noticeable characteristics of social networks is the benefit they provide in obtaining depressive emotional ideas and sentiments. For this reason alone, a lot of researchers utilize social networking sites to investigate suicide. As an example, With the use of short posts termed as tweets which include semantic expressions like emoticons, hashtags, special characters, etc., millions of users on Twitter continue to communicate their feelings and views. As a result, text mining has access to a wealth of data from Twitter.

Most suicidal human beings utilize social media make their intentions known to others. Such as ”I want to end my life,” ”I hate my life,” ”I have lived long enough,” or ”I’m so tired” may be received from them. Finding these warning indicators along with other hidden signals that have been buried under their posting material is the quickest approach to halt suicide attempts so that you can react to them and take action to stop their deaths. Someone who uses Twitter is often identified by their profile picture and stream of tweets. Name, age, location of residence, and birthday is just a few of the details in a profile that characterize the individual. However, while the fact that tweets include an abundance of data that may be used for recognizing people, they often omit off crucial details that might exist in the user’s public profile traits and help suicide detection become more accurate. In addition to these investigations, both user-shared data—which is described as account features—and tweets in the methodology in an effort to address the issue of suicidal profile detection are leveraged. First, it is challenging to deduce further details about individuals from tweets that have been posted. The most problematic semantic properties are those that are difficult to directly extract from user-posted tweets, such as emotions, emoticons, hashtags, n-grams, stylometry, writing style, etcetera.

The tweets are evaluated and extracted with as many semantic characteristics as possible, as user-posted tweets may represent their habits and traits. The openly accessible tweets are examined properly to glean semantic properties, such as linguistic, emotive, stylometric, etc. These attributes enable us to differentiate between the writing habits of various individuals, making it easier to determine them as suicidal or not. A variety of data mining methods and tools are used for the extraction process. In order to label each user’s tweet as suicide or not, numerous classification methods are employed and a supervised machine learning model is presented to learn its characteristics. This test is performed as a strategy using Twitter data collection that contains profiles of people who either lean towards suicide or have in fact committed suicide.

II. EASE OF USE

A. Existing Design

With the use of the Linguistic Inquiry and Word Count (LIWC) technique, Braithwaite et al. validated an ML strategy to detect depressed people with 92 percent accuracy by analyzing the Twitter accounts of 135 study participants. Using LIWC analysis on Twitter data, O’Dea et al. showed in 2017 that, messages which were strongly concerning suicide had unique linguistic patterns. Additionally, in 2018, Du et al. used ML to create a convolutional neural network that can recognize tweets that are suicidal. An ML classifier created by Burnap et al. can identify people with SI on Twitter with an estimated accuracy of 68–73 percentage. These techniques give possibilities for quick interventions in individuals at risk of attempting suicide by identifying tweets that refer to suicide, and contain the word ’suicide’ in the tweets.

B. Proposed Design

A binary categorization of self-harming individuals is obtained with an accuracy of approximately 85 percent, and one’s message ought not to mention suicide for it to be classified. As previously mentioned, the proposed design demonstrates a refined precision, and a credible classifier is used to categorize posts as suicidal or not homicidal. The analysis, labeling, and prediction of tweets have become quicker, simpler, reliable, and more accurate with the employment of sophisticated tools available, such as the NLTK library in Python programming language and an interactive IDE, like Jupyter Notebook.

III. LITERATURE SURVEY

The project’s main goal is to identify thoughts of self-harm by collecting numerous tweets taken from the Twitter site, parsing and analysing every word, and then rating each tweet as suicidal or not. To do this, a handful of works from experts in the subject were collected and referred to an extensive amount of articles. This research review is centered on the use of sentiment assessment by machine learning as well as natural language processing in analyzing texts, which is partially connected to recognizing potential suicide tweets or not.

When using Twitter data from US airlines, Md Taufiqul Haque Khan Tusar and Md. Touhidul Islam demonstrated a paper on sentiment assessment using NLP and various ML techniques. The main goal of sentiment analysis is to classify the polarity of textual data, whether it is favorable, detrimental, or neutral. By using sentiment analysis techniques, decision-makers may monitor changes in the general public’s or customers’ perceptions of various people, things, activities, technologies, and services. Sentiment analysis can help a corporate organization to swiftly enhance its products and services, as well as helping a political group or nonprofit organization to generate outstanding results. Sentiment analysis has made it simpler to quickly comprehend the general public’s viewpoint. Most of the data used for sentiment analysis comes from social networking websites and is stored in databases referred to as datasets. However, when the datasets are unbalanced, enormous, multi-classed, etc., sentiment analysis becomes difficult. They used Twitter US Airline Sentiment, a sizable, unsteady, multi-class, and real-world dataset, in their investigation. The data was previously pre-processed and vectorized using NLP procedures. Using machine learning methods for classification, the polarity of textual information was then classified. In order to figure out the correct course of action, relevant Machine Learning algorithms and NLP methods were compared.

Separate examinations have been carried out by Arwa Alshamsi (Faculty of Engineering and IT at The British University in Dubai), Reem Bayari (the Research Institute of Sciences and Engineering at the University of Sharjah in Sharjah), and Said Salloum (the School of Science, Engineering and Environment at the University of Salford in Manchester, UK). Social media platforms like Facebook, Twitter, and Instagram provides helpful data that company operators can use to track and study client perceptions regarding their own and rival brands. Furthermore, these useful facts attract decision-makers who desire to enhance the services offered. In order to study the techniques and processes used for text classification, this research article evaluated multiple studies that looked at Twitter's classification of information and analysis for various reasons. Before conducting text classification tests using machine learning techniques and different classifiers, or classification algorithms, the authors of this work sought out open-source datasets. To categorize texts from two versions of datasets, the authors used a variety of classifiers.

From a scientific standpoint, the most prevalent methods for identifying suicidal ideation right now are machine learning and questionnaire-based approaches. In the study by Stephanie et al., scale-based models and evaluation questionnaires to forecast suicidal thoughts and behaviours (STB) are diverse and typically successful. However, because of the growing popularity of social media nowadays, people do post "suicidal" remarks on websites like Twitter, which offers more factual information. The ability to gather semantic information from text and speech has also been made accessible by the broad use of novel approaches in machine learning and natural language processing. This breakthrough yields interesting possibilities for STB prediction from the perspective of language aspects. Suicidal postings relying on online social media data can be identified in order to catch individuals who require assistance. Suicidal ideation detection algorithm based on a machine learning method and implemented to an objectively available microblogging dataset.

IV. ARCHITECTURE AND METHODOLOGY

The different phases for the approaches are as follows:
1) Acquiring information for ML classifier training and testing.
2) Cleansing up the dataset in preparation for further processing.
3) Using NLP for transforming textual data into vector form.
4) Splitting the dataset into training and testing portions. The ML Classifier then learns how to predict the polarity of the experimental data using the training data. Fig. 1. depicts the flow of processing of the analysis and classification.

A. Data Collection

The Kaggle machine learning repository, an open data source for data mining and predictive analytics, contributed to the essential data sets that were employed for the analysis, extraction procedure, and categorization of tweets. The Kaggle website was used to collect and analyze data required for this work, with a pre-existing data set. A CSV file including the username of the Twitter user and the tweets that they published

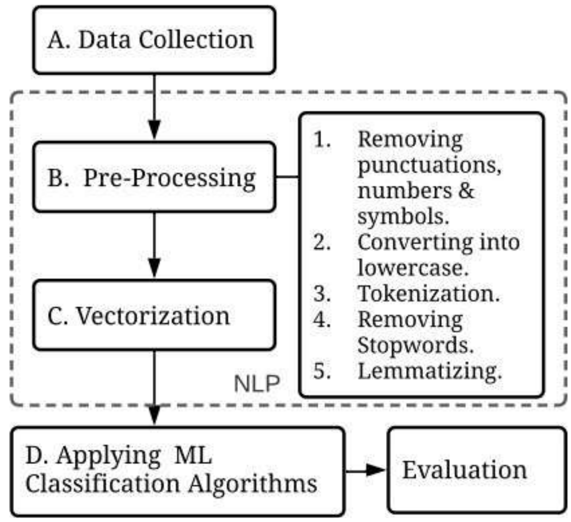

Fig. 1. Flow process of analysis and classification of tweets

on the website was utilized as the data source for the acquisition.

B. Data Cleaning

Considering the data source might contain inconsistent data, it is crucial to examine the CSV file's contents for any missing values, information that is redundant, or contradictory data. Therefore, every variable needs to be reviewed and confirmed using filters, and null values must be removed in order to raise the accuracy level.

C. Pre-Processing

Multiple characters (!, @, etc.), numerals, punctuation, and stop words are permitted in tweets. Stop words are defined as words that lack emotion- like he, she, the, is, and that. The NLTK library is used to perform stopword removal. The Natural Language Toolkit, sometimes called NLTK, is a rich text pre-processing package. A list of stopwords is kept in NLTK in 16 distinct languages. It may be deleted by simply importing the class "stopwords" from this substantial library and indicating the language or words you wish to omit.
As previously said, noisy data in sentiment analysis. Any punctuations, digits, and symbols from the data is removed and changed every single one of the characters to lowercase in order to make it ready for processing. A built-in function in Python allows you to convert an uppercase string to a

Table I
PRE-PROCESSING OF NOISY DATA

Tweet 1	#Delicious #Beef #Cheese #Burger @McDonald Testing CheeseBurger and Hamburger
After Pre-processing	[delicious, beef, cheese, burger, mcdonald, taste, cheeseburger, hamburger]
Tweet 2	#Late Service @McDonald Delicious Hamburger but slow service
After Pre-processing	[late, service, mcdonald, delicious, hamburger, slow]
Vocabulary	[delicious, beef, cheese, burger, mcdonald, taste, cheeseburger, hamburger, late, service, slow]

lowercase one. It additionally pertains to strings that contain both capital and lowercase letters. Strings are converted to lowercase using the ”lower()” function. Tokenization is the technique of breaking down a continuous stream of words into individual tokens or words. Utilizing whitespace as ”delimiter” of words within a string is the simplest method of tokenizing text. The split function in Python may be used to do this, and it served its purpose throughout the tokenization process in this research. The tweet was then broken up into tokens, and the list of tokens was then purged of stop words before being stripped of all of its further meaning. A fundamental form has been converted via lemmatization. The basic versions of each tweet that had been cleaned up and prepared were subsequently stored in a list called tweets. The outcomes of the preprocessing are shown in Table I.

D. Natural Language Processing (NLP)

The aspect of artificial intelligence (AI) referred to as ”natural language processing” (NLP) in computer science is more specifically focused on giving computers the ability to understand spoken and written language in a way analogous to that of humans.

NLP combines rule-based modeling of human language with statistically significant, neural networks, and deep learning models. These improvements allow robots to completely ”understand” whatever is currently said or written, encompassing the intents and mood of the speaker or writer, and to convert human voice into text or audio data.

NLP powers a variety of software applications, including those that translate text across languages, respond to spoken queries, and sum up voluminous volumes of text quickly—even in real-time.

Several NLP operations disassemble voice and text data to help the machine comprehend what is written and the speech data, it is ingesting. These stand for things like named entity recognition, word sense distinction, word segmentation, sentiment analysis, part-of-speech tagging, co-reference resolution, and the creation of natural language, among other things.

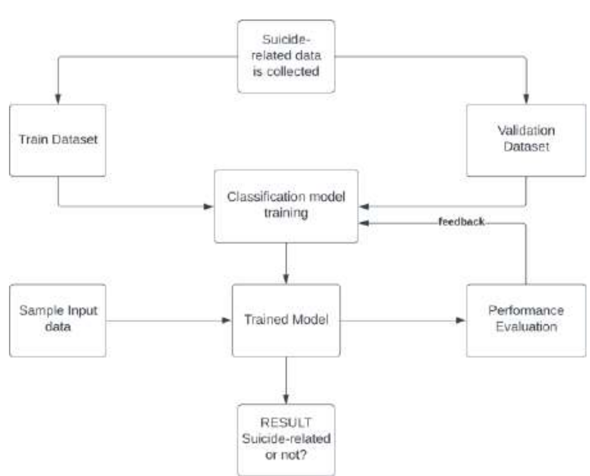

Fig. 2. The system architecture of the proposed design

E. Feature Extraction

In Natural Language Processing, one of the simple stages to be followed for a better comprehension of the context that we are working with, is Feature Extraction. Essentially, the process of converting linguistic information into numbers is called feature extraction. One very easy method for improving con- text understanding in natural language processing is to employ feature extraction. As written information cannot be computed by a machine, it must first be cleaned and normalized before being transformed into its characteristics for modeling. The words are expressed mathematically because they are easy for machines to process. There are several methods for extracting features, including Word Embeddings, Countvectorizer, and TF-IDF Vectorizer.

F. Methodology

As, Python is the programming language employed in this research, it consists of a potential and multipurpose library called NLTK (Natural Language Toolkit) library. This library consists of various classification algorithms, out of which, the most prominent and well-known classifier, Naïve Bayes Classifier, is used.The Naive Bayes technique is a supervised learning approach for problem solving in classification that is based on the Bayes theorem. It is mostly employed in text categorization with a large training set. Being a probabilistic classifier, it makes predictions based on the likelihood that an object will be present.

G. System Architecture

Fig. 2. demonstrates the system architecture in which suicidal data are gathered and acquired, which is subsequently divided into a training dataset and a validation dataset that are provided together for the training of a classification model. The model that was trained is now available for analysis, extraction, and classification of various tweets once the dataset has been trained. As an illustration, a sample set of input data is provided to the trained model. The result of the input data posted on Twitter is known, and therefore the model is tested to see if it achieves the desired outcome. Performance assessment of the trained model is what is meant here. Potentially suicidal posts would be the output, or they wouldn’t be.

V. IMPLEMENTATION

Digital social networking platforms have developed into more available websites where people can share their opinions, regardless they are helpful or terrible. Positive ideas may have a limited audience than negative ones, but the latter may include posts that promote hate speech, self-harm, sadness, or suicide ideation, which shows how willing a person is to express their opinions online. One illustration of this is the usage of the social media site Twitter, which offers users a quick way to share their opinions on a variety of topics. Twitter is connected to other parts of the world, demonstrating its global reach in terms of communication.

The major focus of this study is the dissemination of this kind of negative ideas, including suicide postings or tweets online, as well as the examination and classification of those messages as suicidal or not.

A. Python

Python is a dynamically semantic, object-oriented, high-level, interpreted programming language. Because of its high-level integrated data structures, typing dynamics, and dynamic binding, it is particularly useful for rapid application creation and utilization as a glue language or scripting language to bring existing components together. Python's concise syntax places emphasis on readability and ease of use, which reduces the expense of programming upkeep. Taking advantage of modules and packages, that are supported by Python, encourages modularity and the reuse of code in programs. The Python interpreter and the broad standard library are accessible for free and available in source or binary form for all widely used systems. Python's improved productivity frequently leads to programmers falling in love with it. As there is no compilation process phase, the edit-test-debug cycle moves extremely quickly. Python programs are easy to diagnose because a segmentation failure is never the result ofa bug or bad input. When an error is discovered, the language interpreter throws an error message instead. In the case that the code doesn't catch the exception, the interpreter generates a stack trace. A source-level debugger allows for setting breakpoints, testing arbitrary expressions, inspection of the two global and local elements, line-by-line code navigation, and other features. The debugger, which was developed in Python, can be considered an example of introspection inaction. However, the quickest way to debug a program is to add a few print commands to the code base because of the short edit-test-debug cycle.
Being a versatile language, Python is frequently employed for a variety of uses. Examples of typical applications include:

- Development of web applications utilizing frameworks like Zope, Django, and Turbogears Work on systems management using short scripts
- Using GUI toolkits to build desktop programs, such as Tkinter or wxPython, or, more recently, Windows Forms and IronPython
- Creating Windows apps using Py2exe to produce independent programs and the Pywin32 extension for finished Windows integration.
- Scientific research with the aid of programs like Scipy and Matplotlib.

For this project, a text editor will be used to program in Python. An integrated development environment (IDE) like Thonny, Pycharm, Netbeans, or Eclipse can be used to write Python code. These IDEs are very useful for organizing an immense amount of Python files.

B. Jupyter Notebook

You can create and share documents with real-time code, equations, graphics, and text using an open-source online application called the Jupyter Notebook. A few examples include data cleansing and transformation, computational modeling of statistics, data visualization, machine learning, and other fields. Python programs for data analysis may be written and improved upon with the help of Jupyter notebook. You can create sections of code and execute these one at a time rather than developing and rewriting a full program. Then, in the same window, if you desire to make a modification, you may return, make your edit, and run the program once again.
Jupyter Notebook is built on IPython, an interactive way to run Python code in a terminal window applying the REPL principle (Read-Eval-Print-Loop). The IPython Kernel, which does the calculations, also communicates with the Jupyter Notebook front-end interface. Multiple languages can now be handled by Jupyter Notebook. Jupyter Notebooks give IPython the ability to do tasks like storing the original source code and results and preserving markdown comments.

1) Lauch a jupyter notebook: Open your terminal and go into the directory wherever you want to keep your Jupyter Notebook in order to run it. The program will then launch a local server at localhost:8888 once you run the command Jupyter notebook. (or another specified port). If not, use the address it provides you; otherwise, a browser window containing the Jupyter Notebook UI should open right away. Since the program employs pre-built Docker containers to place notebooks on their own distinct route, each notebook has its own unique token. Press control-C twice in the terminal to shut down the kernel and the server.

2) Jupyter Interface: Now that you're in the Jupyter Notebook interface, you can view every file in the directory you're now in. The notebook representation shown next to each Jupyter Notebook's name serves as a visual cue. Find the Jupyter Notebook you wish to see in the current directory in your files list, and then click it to open it. Go to New and pick Notebook - Python 2 to start a new notebook. You may click Upload and select a different Jupyter Notebook from your computer if you would like to use one of those instead. The icon for active notebooks will be green, while the icon for idle notebooks will be grey. Click the Running tab to obtain a list of all currently active notebooks.

3) Inside the notebook: The first thing you'll notice when you open a fresh Jupyter notebook is that it has a cell. The regions in which the code is written are called cells. It also serves as the framework of notebooks.

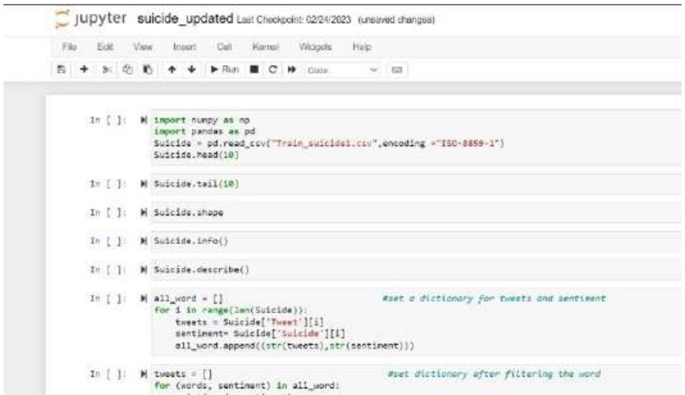

Fig. 3. Various cells displayed in the jupyter notebook when opened

Fig. 3. demonstrates multiple cells shown in Jupyter notebook when the project is opened accordingly. Click the cell to select it, then hit SHIFT+ENTER or click the play icon in the toolbar above to run the code. Additionally, you'll find several options for running cells under the Cell dropdown menu, including running all cells simultaneously or only one cell at a time.

VI. RESULTS AND OUTPUT

In the Jupyter Notebook, all cells in the notebook start running concurrently when you select the Restart and Run all option under the kernel mode. The primary objective of the project is to determine whether or not a tweet is suicidal. Fig. 4. shows us the output of multiple cells holding the source code encompassed in the notebook following an order of computational procedures as accompanied by the code to determine the desired output.

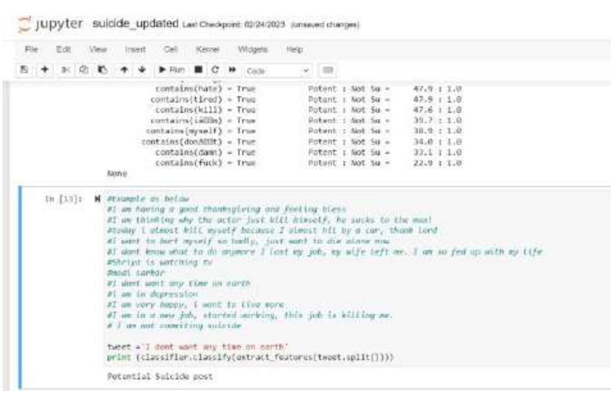

Fig. 4. Result of the cell as a suicidal tweet or not

VII. CONCLUSION

A Machine Learning approach for probable suicidal and non-suicidal tweets was presented in this research. To forecast the outcomes, Natural Language Processing (NLP) together with other machine learning frameworks were employed. These approaches, however, have a limited capacity to forecast suicide intent before it manifests, since the model can only detect suicidal tweets that have already been sent. The future scope of this research is employed to extend this feature to other social media platforms, apart from Twitter; to try and predict minimal/minor symptoms of suicidal thoughts like anxiety, depression, fear, low self-esteem, etc.; and finally, to enable the notification feature in it, so as to collaborate with protection and suicide-related government agencies.

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