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Identifying Suicidal Ideation Through Natural Language Processing and Machine Learning

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ABSTRACT
Numerous suicide studies estimate that 800,000 people commit suicide annually, and it is still challenging to identify suicidal people. The use of social media has grown, and we've observed that people freely share their plans and attempts at suicide on these sites. Through the identification of suicidal profiles on social networks, this study aims to prevent suicide. In order to extract various elements, including account features linked to the profile and features related to social media data, we first analyze social media profiles. Second, we describe how we use machine learning techniques to use Twitter data to find suicidal profiles. Next, we use a profile data set of people who have already taken their own lives. The accuracy and recall of our method in detecting suicidal traits are confirmed by experimental results. Lastly, a Python-based prototype that shows the recognition of suicidal traits is used to illustrate our research.

Index Terms: Machine learning Algorithms, Suicidal Dataset, Python Based Prototype, Natural Language Processing and tKinter.

INTRODUCTION

According to data from the World Health Organization, over 800,000 people commit suicide each year, making suicide prevention efforts crucial at this time. According to the same data, the Russian Federation is among the top five countries in terms of the number of suicides per 100,000 citizens. Since the Internet is the most practical medium for spreading suicidal content in the form of numerous websites devoted to suicide, numerous organizations are attempting to address this problem. Consider the popular social network Facebook, which has the ability to recognize posts with suicidal content and suspicious profiles of users who are at risk of suicide. A solution is being sought by federal agencies**.** Search engine rankings on this topic are probably impacted by the rules that Roskomnadzor in Russia created in 2016 for the media's distribution of information about suicide cases. Furthermore, there is a single register that contains a list of websites that have been blocked in the Russian Federation since 2006. However, blocking does not happen right away. Dangerous websites are accessible to certain individuals. It is rarely effective to manually filter suicide websites in order to stop the spread of suicidal content. Juvenile suicides in Russia have significantly increased as a result of these barriers for a number of years. The ability of websites with suicidal content to create their own copies, or mirrors, may be one of the causes**.**

EXISTING SYSTEM

Context uses social network user profiles to find publicly accessible data, including name, gender, location, and other specifics. However, these current works are weak because user attributes are often hidden by privacy settings. A number of researchers also discuss the problem of suicide. Even though tweets are a great source of information that can be used to identify users, they occasionally omit crucial details that could be included in the user's public profile characteristics and improve the accuracy of suicide detection. Unlike many earlier studies that ignore semantic features to identify users, we analyze tweets and extract as many of them as possible. Second, the process of identifying suicide is advanced when account features are included in the user's tweeted messages.

PROBLEM STATEMENT

The current system is designed to understand the network and correspondence characteristics of Twitter users, whose responsibility it is to create content that is arranged by a human expert as having easonable expectations of self-destruction or what is commonly referred to as self-destruction. • Inadequate data mining performance. • A decrease in efficiency. • The outcome is inaccurate.

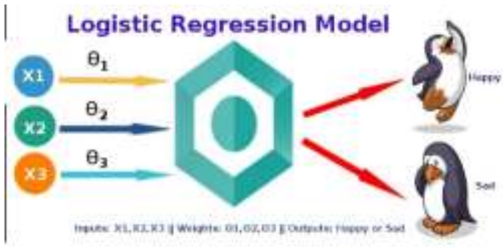
PROPOSED SYSTEM

In This System we propose a method for determining suicidal profiles. First, we evaluate several profiles from the social network using as much of the data as is practical. We then use several criteria to distinguish between profiles that are suicidal and those that are not. These features can be inferred implicitly or explicitly from the user profile using a variety of data mining techniques. Here, we focus on sentiment analysis and emotional traits, which offer hints about the mental health of suicidal profiles. We also use account features to identify individuals based on the shared information on their profiles. Lastly, an integrated vector of every feature that each user has utilized is displayed.

IMPLEMENTED ALGORITHMS

Logistic Regression

One machine learning technique for resolving classification problems is logistic regression. It is a method of predictive analysis founded on the concept of probability. The likelihood of a categorical dependent variable is predicted using the classification algorithm known as logistic regression. In logistic regression, the dependent variable is a binary variable with data coded as 1 (yes, true, normal, success, etc.). or 0 (false, failure, anomalous, etc.). Finding a relationship between traits and the probability of a particular outcome is the aim of logistic regression. For instance, the response variable has two values: pass and fail when predicting a student's exam score based on the amount of time spent studying. Although a logistic regression model uses a more complex cost function also referred to as the "Sigmoid function" or "logistic function" instead of a linear function, it is comparable to a linear regression model.



Many people might wonder if logistic regression is a regression category or a classification. According to the logistic regression hypothesis, the cost function should only have values between 0 and 1. Because it may have a value greater than 1 or less than 0, which is not possible according to the logistic regression hypothesis, linear functions are unable to adequately describe it. 3637 In order to respond to this query, logistic regression is also regarded as a regression model. this particular model.

Natural Language Processing

NLP, or natural language processing, is an exciting area that lies at the nexus of linguistics, computer science, and artificial intelligence. It centers on the use of natural language in communication between computers and people. The ultimate objective of natural language processing (NLP) is to make it possible for computers to comprehend, interpret, and produce meaningful and practical human language.

key Components of NLP:

1. **Tokenization**: Breaking down text into smaller units, such as words or phrases.
2. **Part-of-Speech Tagging**: Identifying the grammatical parts of speech in a sentence.
3. **Named Entity Recognition (NER)**: Detecting and classifying entities like names, dates, and locations within text.
4. **Sentiment Analysis**: Determining the sentiment or emotional tone behind a series of words.
5. **Machine Translation**: Automatically translating text from one language to another.
6. **Speech Recognition**: Converting spoken language into text.

Libraries

i) Beautiful soup: A Python package called Beautiful Soup is used to extract data from HTML and XML files for web scraping. From page source code, it generates a parse tree that can be used to extract data in a more readable and hierarchical way. • It is a full framework for crawling or web-scraping. A parsing library called Beautiful Soup also does a respectable job of retrieving contents from URLs and enabling you to easily parse specific portions of them. It simply retrieves the contents of the URL you provide before ceasing. • One technique for gathering information from websites is web scraping, also known as web data extraction. The majority of this data is unstructured and in HTML format; it is subsequently transformed into structured data in a database or spreadsheet for use in a variety of applications. • By contrasting Beautiful Soup with Selenium, you can see that Beautiful Soup is easier to use, enables you to pick things up more quickly, and makes it simpler to start web scraping smaller tasks. Conversely, Selenium is crucial when the target website's code contains a large number of Java elements.

ii) Tkinter: Tkinter is a popular Python library for creating graphical user interfaces. Using Tkinter to create a GUI is incredibly simple and even faster. A variety of widgets are available in Tkinter for use in GUI development. ML necessitates constant data processing, and Python libraries enable you to access, handle, and modify data. Examples of these include buttons, radio buttons, checkboxes, etc. These are some of the most popular libraries for machine learning and artificial intelligence: Scikit-learn for handling simple machine learning algorithms such as classification, regression, linear and logistic regressions, clustering, and others. • Tkinter provides access to the widgets' geometric configuration, which arranges the widgets in parent windows for data science in Python. There are primarily three geometry manager classes available. • Python's default GUI library is called Tkinter. Combining Python and Tkinter makes creating GUI applications quick and simple. Tkinter offers the Tk GUI toolkit a robust object-oriented interface. The dot. To the GUI application, add one or more of the aforementioned widgets.

WORKING OF MACHINE LEARNING ALGORITHMS

Machine learning follows a structured process: First, raw data is collected and preprocessed to clean and standardize it. Then, the dataset is split into training and testing sets. The model is trained using the training data, adjusting parameters to minimize prediction errors. After training, the model's performance is evaluated using the testing data to measure its accuracy and generalization. To refine the model, different algorithms and preprocessing techniques can be applied iteratively for improvements.

i)Supervised Learning: Supervised machine learning algorithms learn from labeled data to make predictions. Classification handles categorical outputs (e.g., "disease" or "no disease"), while regression predicts continuous values (e.g., "weight" or "price"). Applications include recommendation systems and time series forecasting. Common algorithms are linear regression for regression, random forests for both classification and regression, and support vector machines for classification.

ii)Un Supervised Learning: Unsupervised learning algorithms analyze raw data without labels, identifying patterns for tasks like image recognition and speech processing. They fall into clustering (grouping similar data) and association (finding relationships between items). Common methods include k-means for clustering and the Apriori algorithm for association rule learning.

SYSTEM ARCHITECTURE

Data collection: The first step in designing the suggested system for suicidal content detection using NLP and machine learning techniques is gathering data from a variety of sources, including blogs, forums, and social media platforms, where users may express suicidal thoughts. To preserve user privacy, this data should be gathered in a morally and securely responsible manner.

Data Preprocessing: To eliminate noise and unnecessary information, the data must be preprocessed after it has been collected. This includes lemmatization, stemming, stop-word removal, tokenization, and text normalization.

Feature Extraction: Next, pertinent features from the preprocessed text must be extracted. Word embeddings, TF-IDF, and bag-of-words are some methods that can be used for this.

Model Selection: Choosing a
suitable machine learning model comes next, following feature extraction. To find the most accurate model, a number of models can be assessed, such as logistic regression, decision trees, random forests, and neural networks.

Training and Testing: The labeled data must be used to train the chosen model. There are both suicidal and non-suicidal content examples in the labeled data. To assess the model's performance after training, fresh, untested data must be used.

Model Deployment: Following testing and optimization, the model can be made available as a web service or API. After that, users can communicate with the system by sending text data, and the model will give them a preview.

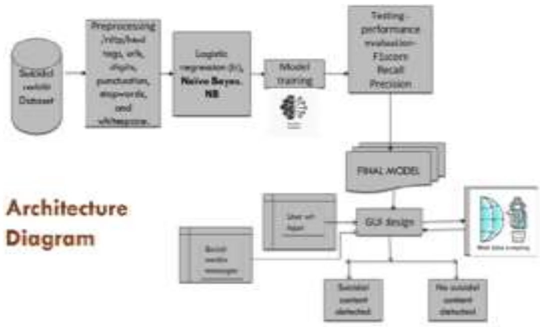


Fig:2 System Architecture Diagram

RESULT ANALYSIS

The learning process of algorithms on a training set is depicted by a ROC diagram. The presented detailed metrics of the trained algorithms allow us to conclude that the SGD algorithm exhibits the highest accuracy, while the Naive Bayes algorithm displays the lowest. findings from evaluating the algorithms on the websites that made up the control group. Drawing from the data collected, we can infer that algorithms generally identify dangerous websites with a high degree of accuracy; however, occasionally they misclassify safe websites as dangerous. Additionally, a threshold of 50% yields satisfactory detection results, whereas a threshold of 10% considerably reduces detection accuracy. Therefore, machine learning algorithms identify dangerous websites correctly on average 46 out of 50 instances when given a threshold of 50%, which is a satisfactory outcome.

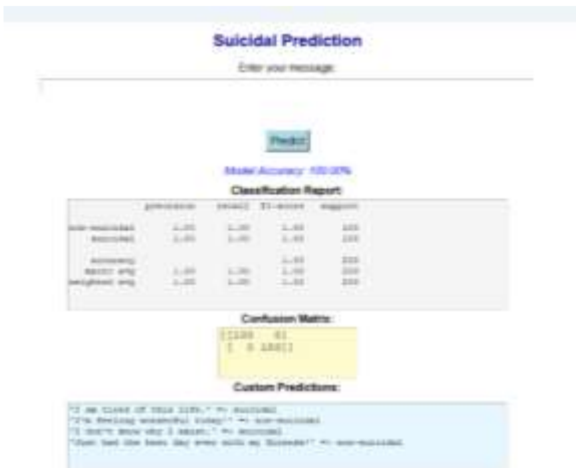


FIGURE A.1 DEMO SCREEN

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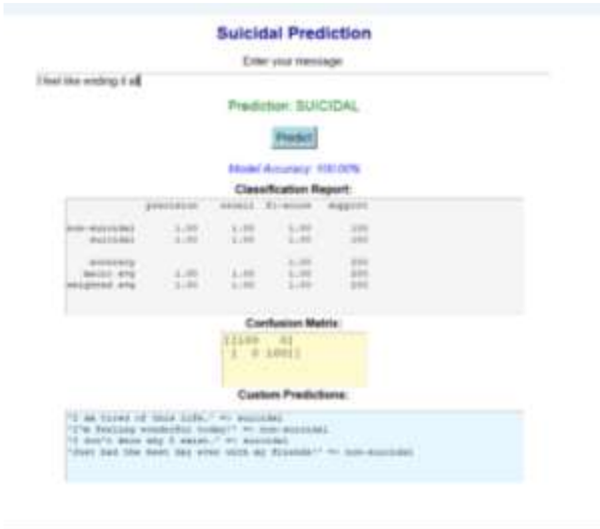

FIGURE A.2 DEMO SCREEN

FIGURE A.3 SUICIDAL CONTENT DETECT

FIGURE A.4 NON-SUICIDAL CONTENT DETECT

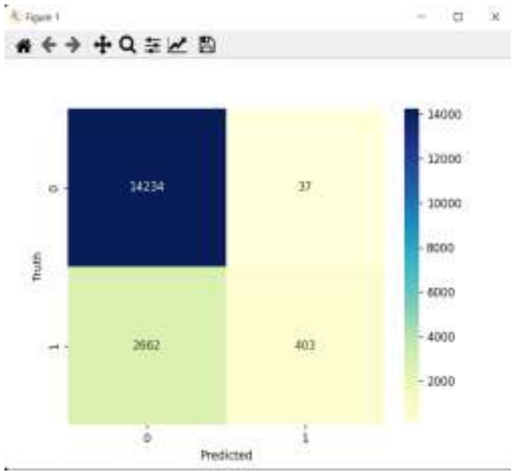

FIGURE A.5 PREDICT MODEL

CONCLUSION AND FUTURE ENHANCEMENT

This work included the presentation of a machine learning-based technique for identifying risky websites with suicidal content. We can infer from the experimental findings that the technique outlined in this article can identify harmful websites. The control group detection results are deemed satisfactory, indicating the potential for real-world application of the method. We plan to upgrade the system that checks websites for suicidal content in the future, specifically. 1. Verify the images because they might be suicidal or contain death group symbols. The final one might be a sign that the website that has it is part of this group. 2. Verify the page's links since they might lead to pertinent websites. 3. Check for suicidal instructions as well. In the future, we plan to refine this approach by examining additional machine learning algorithms and text processing libraries. To increase the precision of identifying harmful websites, more research in this field is worthwhile.

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