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Suicidal Ideation Detection Using Machine Learning Based Hybrid Techniques

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ABSTRACT

The rapid growth of technology and social media platforms allows everyone to express their opinions and emotions and share them with millions. Online Social Networks (OSN) such as Facebook, Twitter, Instagram and WhatsApp are becoming data-sharing platforms. As the number of people participating in the virtual channel increases, the much-unstructured text is generated. These texts help understand the user's state of mind and predict the level of depression or Suicidal Ideation (SI) of the person. Yet, identifying and understanding patterns of SI can be difficult. Identifying and comprehending the complex risk factors and warning signs that lead to suicide is the most challenging part of suicide prevention. To combat this problem, Machine Learning (ML) based hybrid techniques like Support Vector Machine (SVM), Random Forest (RF) and Prism for suicide ideation prediction on social media posts. Firstly, the preprocessing stage eliminates the unwanted symbols, stemming and tokenization. Then we apply Term Frequency-based Information Gain (TFIG) feature extraction to select essential features of suicidal thoughts. Finally, ML-based Hybrid models with Natural Language Processing (NLP) categorize suicide or non-suicidal tweets. The outcome of the simulation analysis is that the proposed hybrid models achieved higher accuracy by observing people's emotions from their text than other methods.

Keywords: Online Social Networks (OSN), Suicidal Ideation (SI), Natural Language Processing (NLP), pre-processing, feature extraction, classification.

1. INTRODUCTION

Online communication sites like Twitter and Instagram are allowing their users to share their thoughts and communicate with each other using the web-based services provided them. Even though these sites are beneficial, they are creating negative impact on people having suicidal thoughts. Several researches reported the relationship between group of people with suicidal ideation and social networks.

Now-a-days people are killing themselves based on the text received in social media. As per the WHO report, most of members who are attempting to the suicide are users of social media. In this way, these platforms are posing some issues on its users. Social media sites are having large amount of increasing data related to the user personal lives as well as data related to society. With the proper usage of the information in social media, we can identify and prevent most of the suicide attempts.

In order to save the lives of people we need to study the behavior and recent communications performed by them. According to consequences of social media, these are for supporting non-professional users of social media, rather than supporting professional users. In order to measure the efficiency of machine learning algorithms, we conduct a baseline experiment for classifying suicidal and non-suicidal tweets. Then, we perform frequent modifications in training data to check the impact of data manipulation on the results that are generated after classification. Finally, we are aimed to provide this information to the current researches on suicidal ideation in social networks.

The application of prism learning classifier is limited. The Prism rule learning algorithm is developed to identify the problem called replicated sub-tree which generally occurs with the DT classifier.

The Prism classifier is able to select instances depending on the values generated related to a particular category, as it is a rule learning classifier. First it selects an attribute after that learns few rules related to the target attribute, finally it classifies the remaining attributes from the target classes. This procedure is applied to each class by using them as the target attributes.

2. Literature survey

Machine learning is a part of artificial intelligence that gives systems which can naturally detect and use patterns for prediction from information. Raw Data yet important client information is continuously being generated on Twitter stages. This information is, be that as it may, increasingly important when they are mined using distinctive methodologies, for example, machine learning techniques [1].

Classification is a popular task in many application areas, such as decision mak-ing, rating, sentiment analysis and pattern recognition. In the recent years, due to the vast and rapid increase in the size of data, classification has been mainly undertaken in the way of supervised machine learning [2].

The assessment of suicide risk is commonly based on the identification and appraisal of warning signs as well as risk and protective factors that are present. Information relevant to the person's history, chronic experience, acute condition, present plans, current ideation, and available support networks can be used to understand the degree of risk [3].

Although good evidence exists for a few selected characteristics, systematic and large-scale investigations are missing. Moreover, the growing importance of social media, particularly among young adults, calls for studies on the effects of content posted on these platforms [4].

Suicidal behavior is a major public health problem. As it has for decades, suicidere-mains one of the leading causes of death in the western world. This project reviewsthe literature and the latest developments on the research and knowledge of suicidebehav-ior and death from suicide [5].

The study examine quantifiable signals related to suicide attempts and suicidal ideation in the language of social media data. They used data consists of Twitter users who have attempted suicide and age- and gender-matched neurotypical controls and similarly matched clinically depressed users. We apply simple language modeling techniques to separate those users automatically, and examine what quantifiable signals allow them to function, tying them back to psychometrically validated concepts related to suicide [6] [7].

The Evidence-Based Resource Guide Series is a comprehensive set of modules with resources to improve health outcomes for people at risk for, with, or recovering from mental and/or substance use disorders [8].

In this project, we try to find the individual users suicide state and also their suicide levels are closely connected with his/her friend's suicide levels in social media [9]. Initially we try to identify the words which are related to suicide related and tendency and try to add those words into the database (natural language Processing) and try to match each and every tweet with those BOW words. If any tweet is matched with suicide/ related tweet then we can easily separate that tweet as one category and those which are not matched with any suicide related words are treated as Normal tweets.

Our findings investigate both verbal and nonverbal behavior information of the face-to face clinician-patient interaction. We investigate 60 audio-recorded dyadic clinician-patient interviews of 30 suicidal (13 repeaters and 17 non-repeaters) and 30 non-suicidal adolescents [10-12].

3. PROPOSED METHODOLOGY

In this novel, we collect and analyze posts from the Reddit OSN platform to predict whether users who post such texts suffer from depression based on ML techniques. This section contains three stages: i) pre-processing, feature extraction and classification of SI, as presented in figure 1.

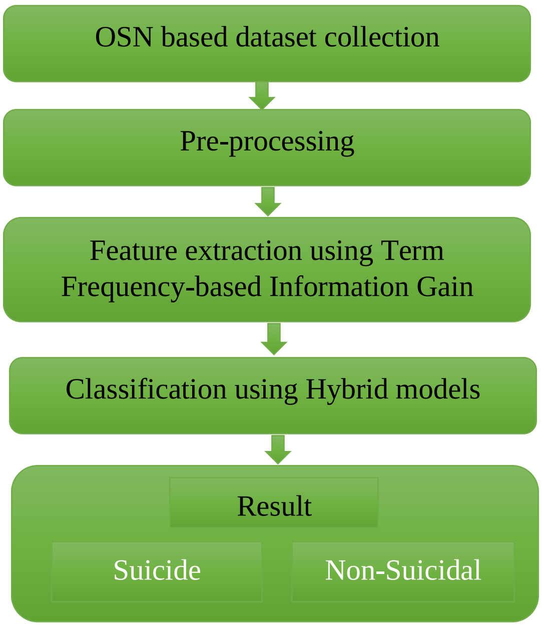

Fig 1: Architecture diagram

Firstly, the preprocessing stage eliminates the unwanted symbols, stemming and tokenization. Then we apply Term Frequency-based Information Gain (TFIG) feature extraction to select essential features of suicidal thoughts. Finally, ML-based Hybrid models with Natural Language Processing (NLP) categorize suicide or non-suicidal tweets. The outcome of the simulation analysis is that the proposed hybrid models achieved higher accuracy by observing people's emotions from their text than other methods.

A. Pre-processing

After data collection from OSN cannot be utilized instantly for feature extraction owing to diverse noises in the raw data. This can generate issues with word matching and semantic parsing. The problem is exacerbated because OSN data may include grammatical and spelling errors and additional undesirable textures. Accordingly, data pre-processing is essential for reliable predictive prediction. This stage's objective is to filter the text posts to remove noise and use feature extraction and embedding techniques to generate word vectors for classification. The following procedure carries out the collected dataset

- First, remove the URL for extracting the meaning sentence.
- To eliminate the stop words such as the, a, is, was, etc.
- Stemming is used to find the root of the word in the text.
- To convert each to lowercase to quickly identify the text.
- Finally, Non-ASCII text is eliminated to enhance the dataset.

Algorithm steps for Pre-processing

Input: OSN dataset
Begin
  Initialize the OSN dataset (DT)
  For each text i do n
    Eliminate stop words, hash tags and URL
    Find the stemming words
    Convert the lower case LC
    $LC = Lower(Text)$
    Identifying the appropriate sentence (A)
    $A = \sum \frac{q*p*LC}{q*p}$
Output: pre-processed dataset A
Stop

The proposed first analysis of each text is based on stemming, tokenization, lowercase, and tokenization for preparing the collective dataset. Let assuming that, p is the training dataset, q is the collected dataset, i presents iteration and n amount of process.

B. Feature extraction

Feature Extraction (FE) is essential in collecting precise details about users to detect suicidal ideation more precisely using the proposed Term Frequency-based Information Gain (TFIG) method. This FE contains details explicitly fetched from user profiles, like usernames, number of friends, a profile description, country, creation day and date, time location, profile picture (pp), number of followers, and subsequent status. Hence this proposed method estimates each user's last month posted images and texts' average likes about which content.

The sequence of OSN posts is expressed by:

$$A = \{(A_1, T), (A_2, T) \dots (A_n T)\} \quad (1)$$

Every post $An \in A$ is related with time T for text was published on OSN. The following equations is used to calculate the user follow ratio$UserF^{Ratio}$, user comments $User^{CoL}$ and user average likes Avg^{L} expressed by:

$$UserF^{Ratio} = \sum \frac{T_{followers}}{T_{following}} \quad (2)$$

$$User^{coL} = \sum \frac{Pos_{images}*(L+co)}{T_{followers}} \quad (3)$$

$$Avg^{L} = \sum \frac{Avg_{co}}{Avg_{L}} \quad (4)$$

Assuming that $T_{followers}$ presents total followers, $T_{following}$ presents total following, Pos_{images} posted images, L denotes Likes, co denotes comments, Avg_{co} presents average comments, and Avg_{L} presents average likes. This method is beneficial for calculating the significance of patterns in user text. Term frequency $F_t$recognizes occurrences of particular words and specifies their likeness as estimated by:

$$F_t(W)_{dc} = \frac{A_w(dc)}{|D|} \quad (5)$$

Where dc denotes single text, and D presents a set of text documents $dc \in D$. For each document is defined as a collection of sentences and words W andA_w presents repeated words W in the text dc. Here we estimating the size of the text document $|D|$ is expressed by:

$$|D| = \sum A_w(dc) \quad (6)$$

The frequency with which a term occurs in a pre-processed dataset is estimated in the equation.

$$I_F(W)_{dc} = 1 + \log\left(\frac{|D|}{|\{dc:D|W \in dc\}|}\right) \quad (7)$$
$$F^{Importance} = F_t(W)_{dc} * I_F(W)_D \quad (8)$$

From equation is used to calculating the corpus important weights for suicidal thoughts. The proposed TFIG algorithm text illustration is a sentiment analysis representation in Natural Language Processing (NLP). Convert individual words and sentences in a given text into a reduced dimensional attribute vector.

C. Hybrid models for suicidal prediction

After getting feature extraction, this section explained the Hybrid techniques for predicting suicide ideation (SI) users' posts from the feature extraction process. The Hybrid techniques like SVM, LR and prism to predict suicidal Ideation and Non suicidal. Feature extraction dataset is ${F_i}^{Importance}$=1, 2...n and their related labels Ri=1, 2...n. Here Ri=f (${F_i}^{Importance}$), assuming that Ri=1 denotes suicidal identification text and Ri=0 denotes non-suicidal text.

$$ET_{score} = \sum_{i=1}^{n} \frac{S({F_i}^{Importance})}{T_R} \quad (9)$$

For each tweet text sentiment score calculating on equation 9. Where S presents suicide and non-suicide score of important features and T_R is the amount of tweets in the feature extraction dataset.

$$N_{ds} = \sum_{i=1}^{n} \frac{ET_{score} - minimum\ (ET_{score})}{maximum(ET_{score}) - minimum(ET_{score})} \quad (10)$$

In equation 10 is calculating the minimum and maximum score of tweets N_{ds}. Then we calculate the individual user text score to identify the suicide or non-suicide from the tweet text.

$$U_{Individual}(score) = \sum_{i=1}^{n} \frac{N_{ds}}{T_R} \quad (11)$$

From equation 11, suicide text score weight between 0 to -1 and non-suicide text score weight 0 to 1.

i) Support Vector Machine

SVM is a considerably widespread classification technique for binary and multiclass categorization issues. The SVM algorithm aims to generate an optimal line or decision boundary that splits the feature extraction dataset into classes so that recent data points can be quickly allotted to the correct class types. Below equation is estimating the decision boundary marginal values expressed by:

$$\omega + bs = 0 \quad (12)$$

Assuming that ω is weight vector and bs denotes bias term.

$$S_{vm} = \sum_{i=1}^{n} \alpha_i P_i(U_{Individual}) \quad (13)$$

In equation is used to find the closest margin values of suicide prediction. Where α_i positive element, P_i denotes target class labels of individual user text score$U_{Individual}$.

ii) Random Forest

It combines many simple decision trees, obtaining each segment's selected set of features. Each tree in the RF produces a prediction, with the most votes being the final prediction. RF is estimated by equation 14,

$$R_f = Argmax\{\sum_{i=1}^{st} P(S_{vm}(st, \theta))\} \quad (14)$$

In equation 14 is used to find the Random forest R_f prediction result P and subtrees st and θ characteristics of decision trees.

iii) Prism

This algorithm predict the categorization of suicidal and non-suicidal text from RF prediction results. For binary classification problems, use this method to estimate the expected value. And this algorithm verifies the data from all angles and categorizes OSN users into suicidal and non-suicidal.

$$Ri = P\left(\theta\left(R_f\right)\right) \tag{15}$$

From equation is used to predict the result as suicide or non-suicide user's text. The proposed classifier threshold values is 0.5. If we obtain $Ri > 0.5$ the proposed getting result is $R = 1$ which denotes the suicidal text. If we obtain $Ri < 0.5$ which denotes the non-suicidal text. Here we calculate the P.

$$P = \frac{1}{1+R_f{}^{-1}} \tag{16}$$

This algorithm efficiently classifies the two classes like suicide and non-suicide text using hybrid techniques like SVM, RF and Prism.

4. RESULT AND DISCUSSION

This section is used to evaluate the proposed implementation compared with previous algorithms. This proposed implementation uses the Anaconda environment and python language version 3.11.1 on the windows 10 operating system with an I7 processor. The dataset gathering from an online kaggle repository, and its name is the suicide tweet dataset. The gathering dataset is split into training (80%) and testing (20%) records.

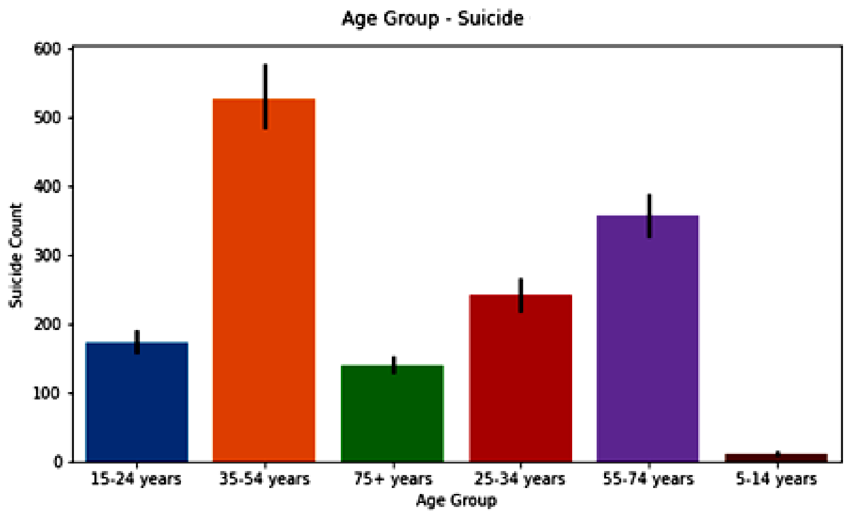

Fig 2: Result for age based on suicide analysis

Figure 2 defines the simulation result for different age group-based suicide attempt texts in the gathering dataset.

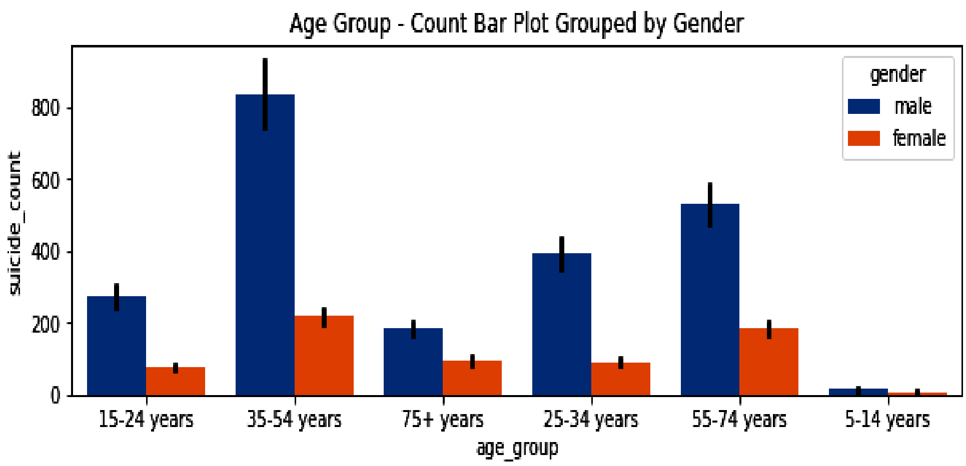

Fig 3: Result for gender based on suicide analysis

Figure 3 denotes simulation result for female and male different age group-based suicide attempt texts in the gathering dataset.

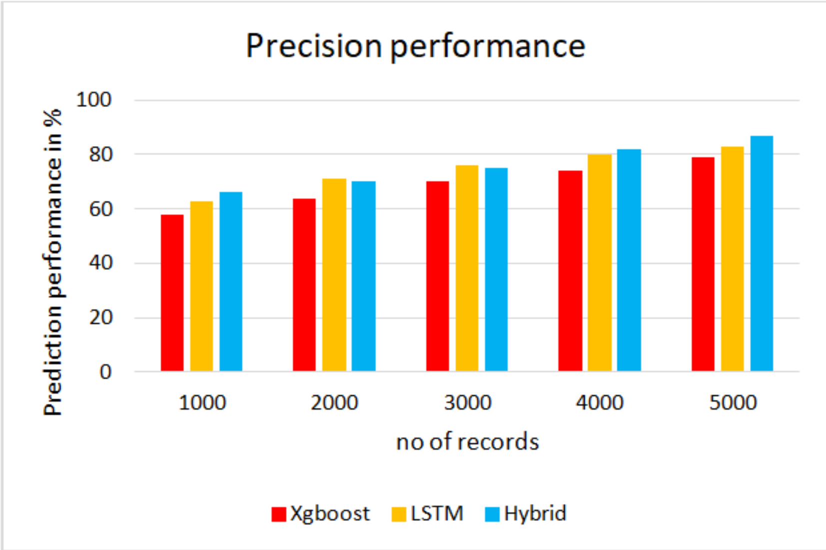

Fig 4: Performance of precision performance result analysis

In Figure 4 explains the precision performance comparative result analysis with various approaches. The proposed hybrid techniques achieved 87% for precision result than other methods.

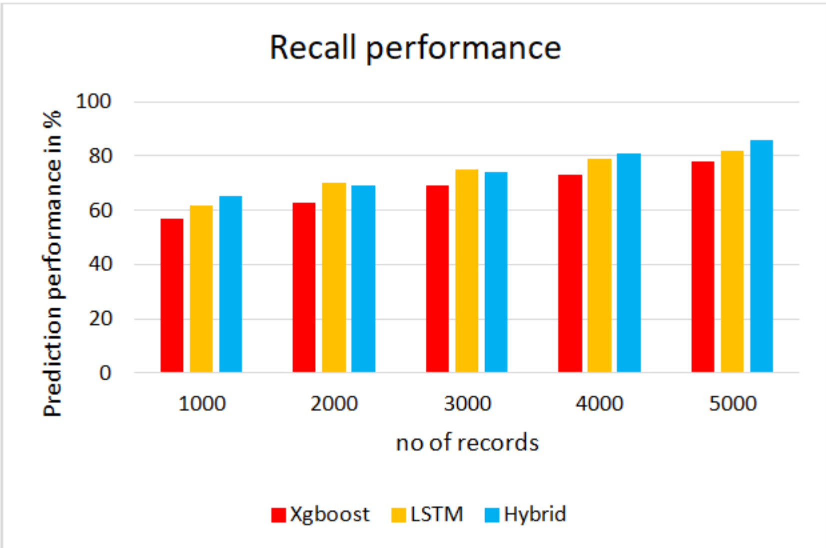

Fig 5: Performance of precision performance result analysis

In Figure 5 explains the precision performance comparative result analysis with various approaches. The proposed hybrid techniques achieved 86% for precision result than other methods.

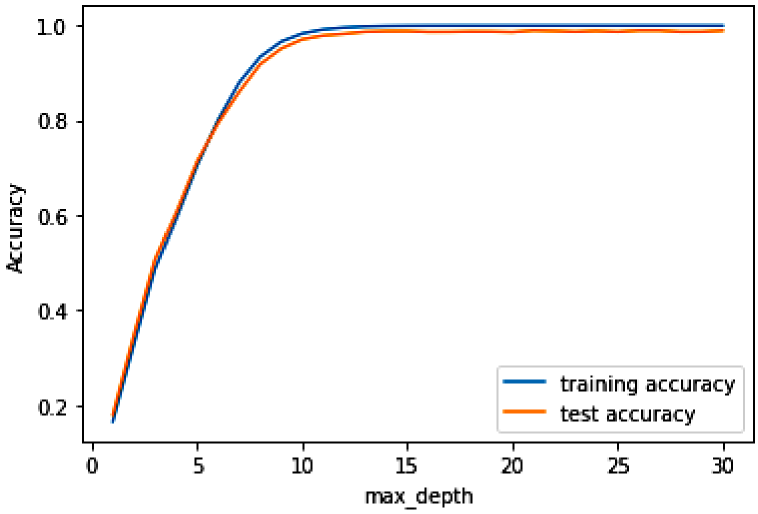

Fig 6: Performance of prediction performance result analysis

In Figure 6 explains the precision performance comparative result analysis with various approaches. The proposed hybrid techniques achieved 90% for prediction performance result than other methods.

5. CONCLUSION

Machine Learning based hybrid Methods like Support Vector Machine (SVM), Random Forest (RF) and Prism for suicide ideation prediction on social media posts. Firstly, the preprocessing stage eliminates the unwanted symbols, stemming and tokenization. Then we apply Term Frequency-based Information Gain (TFIG) feature extraction to select essential features of suicidal thoughts. Finally, ML-based Hybrid models with Natural Language Processing (NLP) categorize suicide or non-suicidal tweets. The outcome of the simulation analysis is that the proposed hybrid models achieved higher accuracy by observing people's emotions from their text than other methods.

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