AN EFFICIENT MODEL TO DETECT SOCIAL NETWORK MENTAL DISORDERS USING MACHINE LEARNING TECHNIQUES

[1]Astha Srivastava, [2]Rohit Miri, [3]Raj Kumar Patra

[1]Ph. D. Scholar, Department of Computer Science and Egineerig, Dr C V Raman University, Kota, Bilaspur, India
[2]Professor, Department of Computer Science and Egineerig, Dr C V Raman University, Kota, Bilaspur, India
[3]Professor, Department of Computer Science and Egineerig, CMR Technical Campus, Hyderabad, India

Abstract

Today, social network users around the world are rising significantly. This forum is useful for exchanging information, debating different topics, and even much of the time they spend on social media such as Twitter, Facebook, etc.Because of these physical human relationships, website users are reliant on regular Facebook updates, Twitter, etc.The latest studies indicate a relationship between mental health and the actions of the social network and how mental illness and social networks respond to each other is still unclear.This article attempts to use the data analysis of social network research to find a pattern for mental disorders without consulting the patient by using a Naïve Bayes classifier algorithm.

Introduction

The social network is essentially a web-based software program, allowing family members, colleagues, co-workers, and clients to share information such as images, videos, notes, documents, locations, etc. Even the average man, uneducated people can also easily use such social media. Here the exchange of information is very fast with no information in time anywhere in the world can touch. Specific forms of social media on the consumer market are shown in the following figure1.

Figure1: Social media in the current market

This platform has multiple benefits, such as allowing people around the world to communicate in real-time and to exchange knowledge that helps internally to create individual social power. The role of social media in business is growing at high speed. With more and more people entering and using social networking sites on a regular/efficient basis, the social media industry is expected to rise ever larger.With such exponential growth, every company today needs to exploit appropriate social media platforms such as Facebook, Twitter, LinkedIn, etc. in the best way possible. This is not because it's the "across content" but because its target audience is located in the popular social networks. And they collaborate with and interact with, their favourite brands on various levels.According to an infographic published by Ambassador, 71 percent of clients recommend products to those with strong social media experience.A fascinating study reveals that a person spends 2 hours and 22 minutes per day reading messages in his social media account.As more and more companies experiment with digital ads effectively, they recognize that the direction of social media advertisement is entirely fair because of the parameters low cost, targeted reachability, and real-time performance analysis.

The educational institutions today are well equipped with online and social media information. Activities such as webinars and online discussion groups can promote partnerships and conversations and enable the sharing of ideas. The students will review web pages, videos and other interesting social media material, and get more knowledge about it. Social media is the easiest way for students to build their network in college and will help to get updates about the news. We can also look after the job openings, new technology developments, entertainment and news updates around the world.This has brought learning beyond textbooks and classroom lectures by promoting discussion and sharing of ideas. Where the students can also submit their assignments, quizzes, and other examinations through online mode. When we use social media wisely, the scenario of education in the country can be revolutionized.Students use social media to address the topic by raising the percentage of their productivity because of peer learning.

Social networks are helping senior citizens to meet their old friends, and recent studies have shown that social networking groups are forming very quickly among users over 65 years of age.Political leaders also make very effective use of social networks for their election campaigns, polling on certain social issues, and resolving grievances in real-time using the social network.

Several studies have shown that social media networks such as Facebook are addictive in nature. This is no surprise because the popularity of a social network depends on how much people spend on the site.The average American spends about a quarter of his workday on social networking, with people spending on the entire planet about 70 productive hours a month.The social media is an assassin of profitability, given its importance as a marketing device. Social media interference has a direct effect on job efficiency, according to experts, and may decrease productivity growth. There should be no ignoring either the possibility of misunderstanding or loss of sensitive data.As a result, regular activities that are to be carried out at a biological time do not take place in time such as in-taking of food, waking up at sunrise, and sleeping at night, feeling upset, depression, social annoy, waking up at the middle of the sleep etc. causes on the human brain life cycle.

Literature Survey

Recent times the research on mental disorders receives increasing attention Among them, content-based textual features are extracted from user-generated information (such as blog, social media) for sentiment analysis and topic detection. Many research works in Psychology and Psychiatry have studied the important factors, possible consequences, and correlations of such type of mental disorders. On the other hand, recent research in Psychology and Sociology reports several mental factors related to social network mental disorders. Research indicates that young people with narcissistic tendencies and shyness are particularly vulnerable to addiction with OSNs. However, the below review explores various negative impacts and discusses potential reasons for Internet addiction and mental disorders.

Choudhury et al [1] in this paper he proposed a model which helps to find out a depression in a person by performing analysis on web-based social networking posts, behaviour, login log off frequency, comments on other posts, various issues rising by persons and checking for various kinds of anti-depression medicines based on these data analysis his model can able to identify weather person having depression or not. To achieve this they have used support vector machine classifier and PCA for feature selection.

Choudhury et al.[2] contributed a good effort to identify postpartum depression from newly born mothers. In this work, they are collecting data from twitter specifically from newly born mothers. To identify newly born mothers they have adopted patterns as described in table 1.

Table 2: List of queries for identifying birth events on Twitter

(1) birth, weigh*, pounds/lbs, inches, length/long, baby/son/daughter/boy/girl
(2) announc*, birth/arrival of, son/daughter/brother/sister
(3) are the parents of, son/daughter/boy/girl/baby

(4) welcome* home by, brother/sister/sibling*
(5) is the proud big brother/sister
(6) after, labor, born
(7) it's a boy/girl, born

Once tweets are identified they are labelled as various classes saviour, mild, low then data trained to SVM, K-NN classifiers and build the model and results are evaluated.

O' Dea et al.[3] have build a model to detect the suicidal tendency of depressive users by analysing their tweets. In this, they have taken 2.5k tweets and used decision tree classifier to build the model. Once the model was built it was tested with testing set and evaluated its performance around various parameters like precision, recall, F-Score etc with this model patients can alert in advance to take proactive decisions to come out from life risk events.

Aldarwish et al.[4] was a good researcher who performed analysis on Social network sites for understanding depression levels by using user-generated content at different social networks once data is collected from different sources that data is trained to SVM classifier once the model is built it is used to perform multi-class classification based on the results from the content analysis.

Facebook data shared voluntarily by 165 new mothers as streams of evidence to characterize their post-natal experiences and multiple actions, including activity, social capital, emotion, and linguistic style, in pre-and post-natal Facebook data. In Eric Horvitz et al. [5], we spoke about statistical methods, identification and prediction of major behavioural, language and impact changes from the postpartum of Twitter results.

Sho Tsugawa et al.[6] investigated how useful the various features extracted from the Twitter user history are to detect depression and the degree of accuracy with which active depression can be detected by using these features. We aim to establish a method by which the analysis of large-scale users' activity records in social media and depression can be recognized by users with an accuracy of approximately 69%.

Glen Coppersmith et al.[7] presented a novel method for collecting data on a range of mental illnesses quickly and cheaply, then focus on the analysis of four in particular: post-traumatic stress disorder (PTSD), depression, bipolar disorder, and seasonal affective disorder (SAD).

Adrian Benton et al.[8] have estimated the risk of suicide and mental health in the context of deep learning. By modelling multiple conditions, the system learns to make predictions about suicide risk and mental health at a low false-positive rate. Conditions are modelled as multi-task learning (MTL) tasks, with gender prediction as an additional auxiliary task our best

MTL model predicts potential suicide attempts, as well as the presence of atypical mental health with AUC > 0.8.

Moin Nadeem[9] have discussed the potential of social media to predict major depressive disorder (MDD) in people online even before it began. We use a crowdsourced method to compile a list of users of Twitter who are professing to be diagnosed with depression. Using a corpus of 2.5 M tweets, we achieved an accuracy rate of 81 percent in the classification, with a precision score of 86.

Nguyen et al. [10] proposed a model to differentiate depressive users and normal users of the twitter by using statistical procedures,temperament and understand their behaviour by analysing their social behaviour through various linguistic approaches using LIWS features. In this paper, they have also used 132 labelled mood tags.

Park et al. [11][12] have interviewed two groups of people depressed and non-depressed then they also performed a content analysis on the tweets of interviewed users and their friends. To analyse them they used LIWC where the emotion of each word and sentiment is identified based on that count estimated depression levels.

Bachrach et al. [13] proposed a model by analysing facebook data by considering users and their friend's profile, the relationship between friends, posts they have posted responses they have given to the posts posted by other users, number of times they have attended to the gatherings, number of times their photos are tagged based on this data they have identified weather user is suffering from depression or not for that they have used SVM machine learning model to perform classification between a normal user and depressive user.

Ortigosa et al. [14] proposed a model to find out sentiment of the user posts posted in Facebook into three classes like positive, negative, neutral they can able to detect emotional changes using this analysis. To implement this they have used a hybrid approach such as a combination of linguistic and machine learning and got an accuracy 83.25.

By contrast, this paper proposes data analysis of social network research to find a pattern for mental disorders without consulting the patient by using a Naïve Bayes classifier algorithm.

Proposed model

In this paper, we suggested a model that uses Twitter's API data and these tweets are identified manually as depression and regular tweets. Data are obtained from the Twitter API using the following information:

API key:7jGvCfujLeZk3i6DMWZ6Qd3yz

API secret key: FNacdg7Om3uz1MPRmGcRTD8ty8ZXZUj5UBXo4piUCfmrkqGNCM

Access token: 4264466365-vOBTa66uUySaWAJwAtHNR1cSMolPIAfreXPpBsM

Access token secret: MU7bYu6Xt6vv089gAzNChTLbCfQEKeXxbA8xpLnjw959z

Access Level: Read and write

In the present data have been collected from twitter and the data has been manually labelled into two classes one is depressive and other is normal. The data pre-processing has been performed, and then it is divided into training and testing sets. The training data set have been used to build the model by using Naive Bayes classifier to learn from the data. The building model has been tested with the testing dataset and obtained results with high Accuracy around 92.3. So usually doctor needs to find metal disorders they will fire some questions to the patient based on that doctor detects mental illness but in this model, we can able to detect mental disorders without consulting patient based on their social network behaviour analysis.The format of the data appears as shown in the following table 2, and a sample tweet data shown in the figure 2.

Table 2: The format of the source data

Target	Ids	Date	Flag	User	Text
This field consists of polarity includes{positive, Negative, neutral}	The identity number of the tweet	The date when that tweet was posted	It contains a query if no query then it returns NO_Query	It contains the user details who posted that tweet	It contains the text message posted

Figure 2. A snapshot of the tweeter in Twitter data

Once data are obtained, multiple steps are performed, as seen in Figure 3 below. Every tweet is first identified manually as regular and depressed. Different symbols are then sent to data cleanup. The number is calculated from a .. z, A ... Z and all data are extracted from the source.

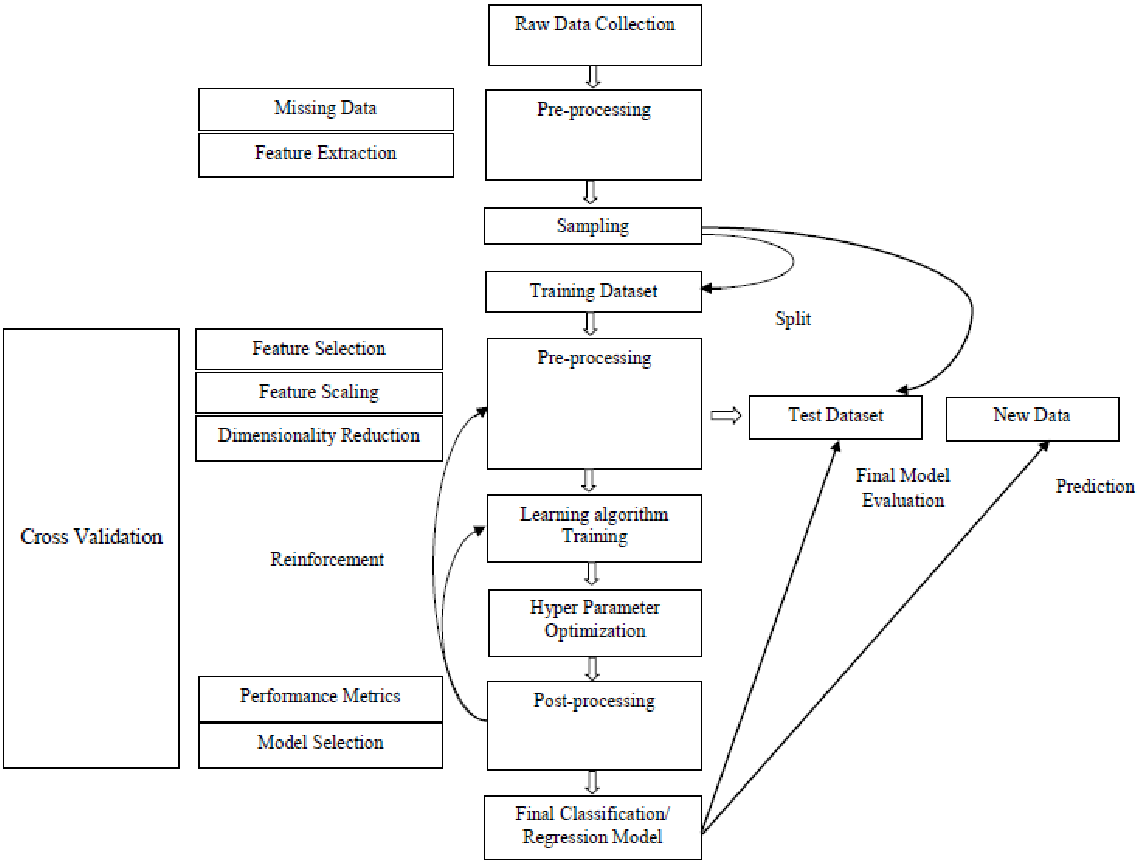

Figure 3: Architecture Tweet Classification

The second phase of the algorithm is tokenization used to split the data into various full meanings of words, but all full grammatical constructions are not appropriate for making decisions, so in the majority of cases only the names and verbs are useful. The third stage eliminates terms such as {is, and, etc.} by using the preset stop word corpus available in the natural language NLTK python toolkit.The tag is then used to put each word into its rootlike motion, then the text is turned into a bag of words matrix e.g., loving as love and actions as action. The entire data is divided into 70 and 30 percent for training and testing. The results were very effective and accurate about 92.3% and experimented using Naïve Bayes classifier in Python environment.

Algorithm – NaïveBayes:

1. List of tweets collected from Twitter API=[T1,T2,…Tn]
2. Remove Special SymbolTweet= re.Sub[a-z,A-Z]
3. Tokenization
4. Stem the tweets bringing every word to its parent word

5. Remove Stop words by Comparing with NLTK stopwords
6. Convert Bag of Words
    a. Build Naïve Bayes Classifier
7. $p(\frac{A}{B}) = \frac{P(\frac{B}{A})p(A)}{P(B)}$

Where P(A)-*P*(*A/B*) is the posterior probability,*P*(*A*) is the prior probability(*B*|*A*) likelihood probability, *P*(B) prior probability of *predictor*.

Results &Discussion

After the model was designed, it was tested with a test set and provided results with very good accuracy of about 92.3 percent compared to existing machine learning techniques. According to the adoption of advanced pre-processing and transformation, we can achieve good results with Naïve Bayes and equate analysis with existing algorithms and is shown below the table 3, the comparative table gives the current method with existing algorithms is in the following table 4.

Accuracy = $\frac{TN+TP}{TN+TP+FP+FN}$

TP: True positive, TN: True Negative, FP: False Positive, FN: False Negative

Table 3: Comparision of the proposed method with other methods

S.No	Model	Accuracy
1	Proposed Naïve Bayes	92.3
2	Random Forest	48.52
3	SVM	50.0
4	KNN	81.46

The following figures figure 4 to figure 9 have represented the positive & negative word classification, top 25-word samples frequencies, log words frequency, and generated word cloud.

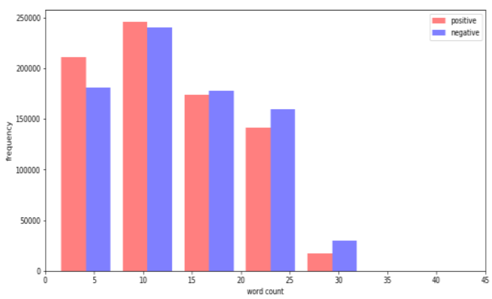

Figure 4

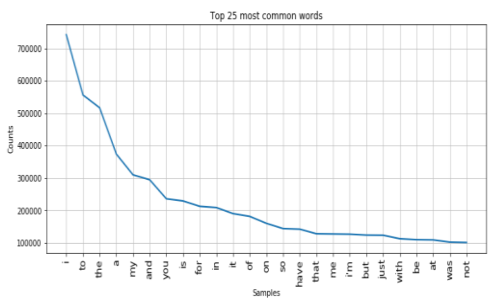

Figure 5

Figure 4 represents the classification of words both positive and negative with their frequency of occurring in the bag of words. Mental disorders comprise words like depression, bipolar disorder, schizophrenia and other psychoses, dementia, and developmental disorders including autism. Out of the classification of words, topmost samples with its frequency count shown in the figure 5.

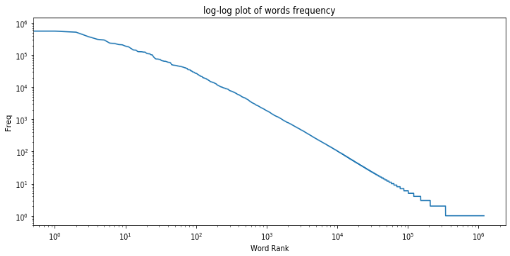

Figure 6

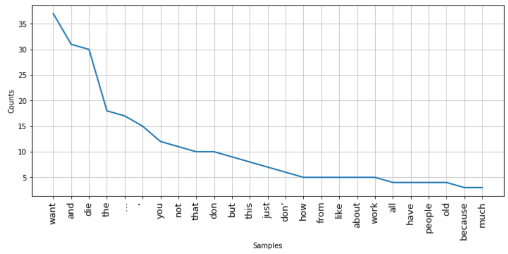

Figure 7

Figur 6 shows the log of words, frequency list is a sorted list of words with frequencies, which typically means the number of word count in the specific corpus from which the location in this list may be the rank. Whereas figure 7 describes ranking words most frequently used in mental disorder.

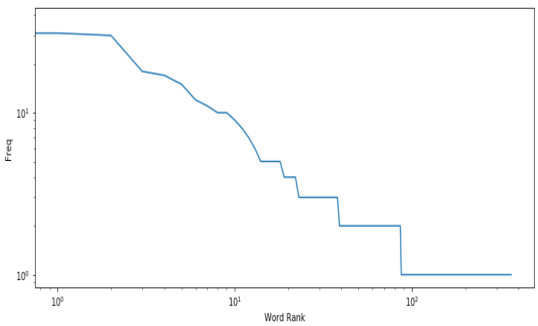

Figure 8

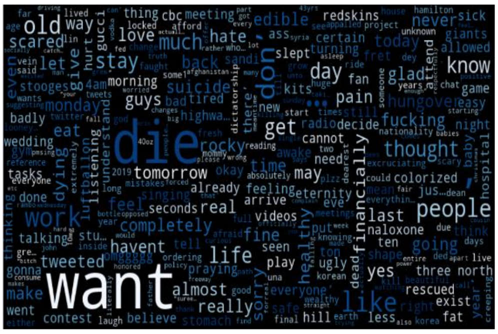

Figure 9

The figure 8 explains about the ranking of words and its count in a specific time of patients. Finally, the list of words and its count is represented as a word cloud in figure 9.
The proposed method performance compared with other methods for accuracy is depicted in the following table 4.

Table 4: Performance of the algorithms

Reference	Data Source	Algorithm used	Quality Metrics	Performance
[1]	Twitter	PCA,SVM	Accuracy	72%
[5]	Facebook	Logistic Regression	Pseudo-R2	36%
[6]	Twitter	SVM	Accuracy	69%
[7]	Twitter	Log-Linear Classification	Precision	76%
[8]	Twitter	Neural Networks	AUC	77%
[9]	Twitter(Self Declared)	Naïve Bayes	AUC	70%

For better visualization, the above results are shown in the following graph figure10.

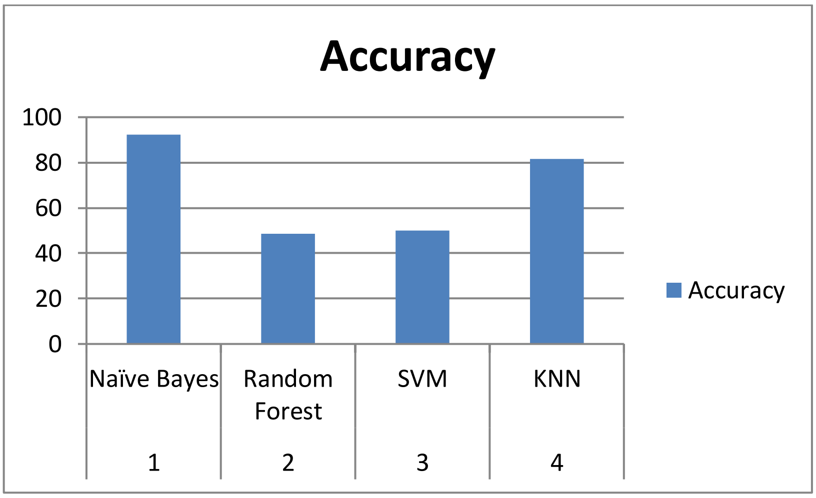

Figure10: Comparative analysis among various machine learning algorithms

Conclusion

In this paper, we have conducted Deeper literature survey and implemented an optimized naïve Bayes model for analysing tweets to detect whether a specific user is suffering from depression or not we have used tweeter API to collect tweets and are manually labelled as two classes depression and normal using python we have implemented the model and able to achieve good accuracy around 92.3% with testing set and effectively able to detect mental disorders through social media.

References

1. De Choudhury, Munmun, et al. "Predicting depression via social media." *Seventh international AAAI conference on weblogs and social media*. 2013.

2. De Choudhury, Munmun, Scott Counts, and Eric Horvitz."Predicting postpartum changes in emotion and behaviour via social media."*Proceedings of the SIGCHI conference on human factors in computing systems*.ACM, 2013.

3. O'Dea, Bridianne, et al. "Detecting suicidality on Twitter." *Internet Interventions* 2.2 (2015): 183-188.

4. Aldarwish, Maryam Mohammed, and Hafiz Farooq Ahmad. "Predicting depression levels using social media posts." *2017 IEEE 13th international Symposium on Autonomous decentralized system (ISADS)*. IEEE, 2017.

5. Munmun De Choudhury et al, "Characterizing and Predicting Postpartum Depression from Shared Facebook Data"; CSCW '14: Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing; February 2014; Pages 626–638; DOI:10.1145/2531602.2531675.

6. Tsugawa, Sho, et al. "Recognizing depression from twitter activity." *Proceedings of the 33rd annual ACM conference on human factors in computing systems*.ACM, 2015.

7. Coppersmith, Glen, Mark Dredze, and Craig Harman. "Quantifying mental health signals on Twitter." *Proceedings of the workshop on computational linguistics and clinical psychology: From linguistic signal to clinical reality*. 2014.

8. Adrian Benton et al. "Multi-task learning for mental health using social media text." *arXiv preprint arXiv:1712.03538* (2017).

9. Nadeem, Moin. "Identifying depression on Twitter." *arXiv preprint arXiv:1607.07384* (2016).

10. Nguyen, Thin, et al. "Affective and content analysis of online depression communities." *IEEE Transactions on Affective Computing* 5.3 (2014): 217-226.

11. Park, Minsu, David W. McDonald, and Meeyoung Cha. "Perception differences between depressed and non-depressed users on twitter." *Seventh International AAAI Conference on Weblogs and Social Media*. 2013.

12. Wee, Jieun, et al. "The influence of depression and personality on social networking." *Computers in Human Behavior* 74 (2017): 45-52.

13. Bachrach, Yoram, et al. "Personality and patterns of Facebook usage." *Proceedings of the 4th annual ACM web science conference*. ACM, 2012.

14. Ortigosa, Alvaro, José M. Martín, and Rosa M. Carro. "Sentiment analysis in Facebook and its application to e-learning."*Computers in human behaviour* 31 (2014): 527-541.