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A SYSTEMATIC STUDY ON PREDICTING DEPRESSION USING TEXT ANALYTICS

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ABSTRACT

Social Networking Sites (SNS) provides online communication among groups but somehow it is affecting the status of mental health. For adolescents with limited social media friends and using internet for communication purposes predicted less depression, whereas non-communication desire reveals more depression and anxiety disorder. Social media posts and comments provide a rich source of text data for academic research. In this paper, we have discussed various text analytical approaches to predict depression among users through the sharing of online ideas over such websites. This paper presents a comprehensive review for predicting depression disorder by various text analytics approaches. This paper also presents the summary of results obtained by some researchers available in literature to predict Major Depressive Disorder (MDD). In future research, enable self-monitoring of health status of each individuals which may help to increase well-being of an identity.

Keywords: Social Networking Sites; Sentiment Analysis; Machine Learning; Support Vector Machine.

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1. INTRODUCTION

Social Networking Sites (SNS) allow connecting worldwide with the sharing of information, interests and experiences. But on the other hand, it has proven to be most addictive activity found in teenagers. A study reported that Emotional instability mainly occurs during transitional period of childhood and adulthood referred as adolescent age [1]. According to Pew Research Centre, new study reported that over 80% adolescent tends to use social media and check their profiles before they sleep and as they wake up. Insomnia, a sleeping disorder now a common problem faced by seven out of ten peoples using excessive social networking profiles[2]. Social media profiles are now proved to be most commonly used data collection approach to predict mental health status of individuals. Among all SNS, Facebook, Twitter, Instagram etc. are one the most common platforms served by users. Suicidal behaviour is also influenced by social media leads to a phenomenal risk at early stage [3]. By monitoring the status updates, posts, photos sharing, text content, usage limit and other related activity, it becomes easier to identity status of mental health [4]. Mental ill people have been identified using surveys, questionnaires, diagnosis of public sharing on SNS, online membership forums and they can be easily distinguishable from control users through patterns found in their language and online activity [5]. Various automated detection methods are used to serve this purpose such as machine learning techniques, natural language processing, classification techniques, data analysis approaches and more.

In this paper, we have discussed various text analytical approaches to predict depressive symptoms from healthy and ill individuals, methods to predict emotions using text analytics from several recorded responses. Several tools for identifying the onset of major depression are discussed here which may help health care departments and provide health checks and updates for those suffering from depression to get more cautious about their mental health. We are just dealing with beginning phase to examine the ways social media can help us to detect depression but it is interesting to think that in future, our social media use would be an early detection tool for all kinds of mental illness.

2. BACKGROUND AND RELATED WORKS

Balahur et al. [6] analyzed the techniques of parsing texts with opining mining to gather information from web articles. Li et al.[7] presented polarity calculating techniques to categorize the positive and negative sentiment through opinion mining system. Both were presented visually and the experimented results were found feasible and effective. Later on, Jin et al. [8] also proposed a system for sentiment mining that visualize in real world data set and resulted in to an experiment that contrast between positive as well as negative opinions effectively. Veeraselvi et al. [9] used Genetic Based Machine Learning technique that classifies the semantic orientation of phrases after being evaluated. Khan et al. [10] proposed a technique that used machine learning methods based on opinion mining to get opinions from the text documents. Asad et al. [11] presented C4.5 and PART classifier algorithm to extract features from the information. Liu et al. [12] that makes use of IMDb movie reviews dataset that models and predict the information from online reviews. Steinberger et al. [13] proposed a technique that creates sentiment dictionaries to distinguish between polarities of sentences that may be positive or negative sentiment of identities. Ye et al. [14] made comparisons between machine learning methods such as Naive Bayes classifier, Support Vector Machines and N-gram model that perform sentiment classification on online articles and reviews. Experiments proved that SVM and N-gram performed better over NB classifier with 80% accuracy results. Stede et al. [15] presented argument mining technique that shows pictorial representation through argument diagrams to display the mining text results. Zhang et al. [16] performed sentiment analysis over Chinese blogs and online reviews. Cho et al. [17] evaluated a study with Korean twitter posts and perform sentiment analysis by analyzing Korean tweets grammatically built polarity dictionaries through SVM. Experimented results showed the temporal and spatial images of respective identities through text analytics approaches.

Here, Table 1.1 shows the Summary of comparison of reviews that have been reviewed from the existing literature. The table listed the author's name with their corresponding published paper year and the methods or algorithms used for sentiment analysis, opinion mining, and Support vector machines as text analytics approaches.

Table 1. Summary of Literature Reviews

Author's Name	Year	Algorithm
Khan et al.	2009	ML methods based on Opinion Mining
Balahur et al.	2008	Syntactic Parsing
Li et al.	2010	Semantic Role labelling and Polarity computing method
Ji et al.	2010	Opinion Miner System
Ye et al.	2009	Naive bayes classifier, SVM and N-gram model comparison
Cho et al.	2014	Sentiment analysis framework with Twitter Korean posts.
Stede et al.	2013	Argument mining
Steinberger et al.	2012	Sentiment dictionaries algorithm
Veeraselvi et al.	2014	Genetic based learning algorithm
Asad et al.	2013	C4.5 and PART classifier
Liu et al.	2008	IMDb movie review dataset
Zhang et al.	2008	Chinese blogs dataset

3. TEXT ANALYTICS METHODS FOR MDD PREDICTION

Social media is the most commonly used platform searched over Smartphone. It facilitates the communication between parties, sharing information, ideas, and career interests over the web. Facebook, a largest using SNS across the world, and conclude symptoms of depressed users diagnostics and Major depressive episode (MDE) through disclosures of feelings via 'Status Update' features available on Facebook [18].

Psychologists have claimed that SNS has become most powerful and easiest data collection tool for detecting mental illness around the world. Hussain et al. [19] thoroughly studied that the Major Depressive Disorder (MDD) can be identified among populations through their behavioural attributes in the content posted over social network. Ensemble learning techniques are used classify depressed among non-depressed individual. Using questionnaire techniques of Patient Health Questionnaire (PHQ) investigated by Jelenchick et al. [20], Beck Depression Inventory (BDI) and Centre for Epidemiologic Studies Depression Scale Revised (CESD-R), a tool has been developed to diagnose and provide alerts for depressive disorder. CESD-R scale measure symptoms of depression as defined by the American Psychiatric

Association Diagnostic and Statistical Manual, fifth edition through symptoms as Sadness(Dysphoria), Loss of Interest(Anhedonia), Appetite, Sleep, Thinking / concentration, Guilt(Worthlessness), Tired(fatigue), Movement(Agitation) and Suicidal ideation.

A web based tool has been proposed named as *Socially Mediated Patient Portal (SMPP)* to perform depression test over Facebook to predict depression among individuals. This model based on DSM-V criteria studies content analytics and provides feedback over mental state of an identity [21]. Data can be collected from user profiles from various social media platforms such as Facebook, Twitter or Instagram posts and tweets. A depression test has been conducted through a Patient Health Questionnaire PHQ-9 that shows some signs of depression through various CESD-R categories. Experimented results showed in Fig. 1.2 reveals 54% shows sadness, 14% shows sleeping disorder, 6% exhausted and others shows restlessness in their activities.

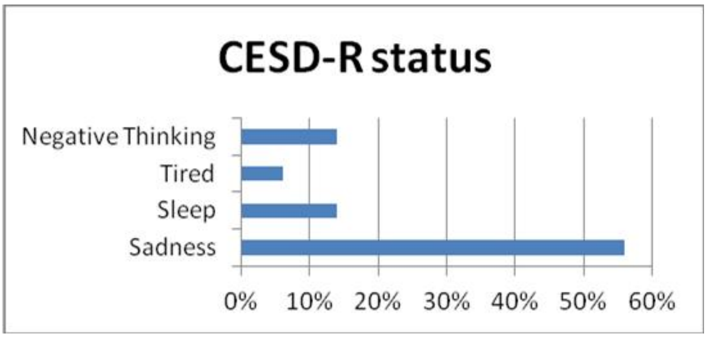

Fig.1. CESD-R categories and CESD-R results based on user posting

In a new study of Moreno et al. [22] **,** after collecting relevant information, Diagnostic and Statistical Manual (DSM) criteria were applied and negative binomial regression analysis model was used to find the link between depression disclosures and site usage. Some statistical measures were conducted with the use of Bi-variate analysis to explore the relationship of valid or invalid depression disclosures. Through these disclosures, psychiatrist are considering most powerful data collection tool as Facebook which can diagnosed depressed identities over time. Since, Facebook shows various advertisements by the side of every profiles, this could be taken into account for health services usage through clinical experts [23].

The basic idea was proposed by Hu and Liu (2012) [24] that follows three basic steps to process textual information over SNS profiles. Phrase extraction from original text corpus, generation of semantic features and feature space construction. Numerous existing approaches exist to represent text in social media such as Natural Language Processing, Sentiment Analysis or Opinion Mining, Text analytics and Machine learning. Data can be created from various principal sources such as Social network media, News data, Public data and programmable interfaces. Settani et al. [25] investigates the relationship between text corpora shared on SNS and self report measures of emotional well-being. This study examines the difference among age groups through emotional textual content with the use of positive or negative emoticon that correlates with higher levels of depression, stress and anxiety. Automated textual analysis were performed by Linguistic Inquiry and Word Count (LIWC) emotion coding software on shared posts and comments for four trimester over social network. A set of t-tests has been applied to calculate mean differences between two age groups. Using Pearson correlation and Fisher's r-z transformation, significant correlation was analyzed to test the correlation differences among the age groups. It is observed that when comparing two age groups revealed no significant differences in the proportion of published posts. Young adults tend to use more negative emoticon when compared with others. Overall, this study supports the feasibility and validity of studying emotional well-being through examining profiles of individuals. However, the sampled data was limited in number, so the study shows some limitations as well. Future research can be carried over large data sets and specialized data mining techniques to obtain more refine results across worldwide.

3.1 Sentiment Analysis

User Sentiment analysis for online social activities are analyzed to cluster behavioural and psychological tendencies of the individual. Later on, Dinakar et al. [26] performed sentiment analysis of online tweets of users over Twitter, a popular social networking site. In this approach, textual analysis has been performed and polarity of tweets was identified. After discovering, the polarity can be categorized into positive, negative and neutral. Further clustering of negative content was done to isolate most common posted words by the user. Grading was done over negative content and score was provided. Using this score, overall percentage of negativity can be calculated. The accuracy of sentiment analysis was performed by calculating precision and recall over negativity scores.

A model for detecting depression can be created that perform sentiment analysis in micro-blog online network proposed by Wang et al. [16]. First collect all input data from each user's micro blog as a sentence and the method of sentence segmentation and word segmentation can be applied which results into sub-sentences. Some linguistic rules can be then applied over each sub-sentence to count the polarity and its corresponding positions that calculates the polarity of sentence (S) as either positive or negative. A positive polarity means positive sentiment of a user and negative polarity means contrary [27]. Psychologists say depressed user makes use of more negative words and less positive emoticons. Now, the polarity can be checked via three magnitudes as micro-blog content, interaction with others and user behaviours. Psychological researchers have given ten features of depressed user which are then sampled as considered aspects in this research [28]. A regression analysis technique with Binary logistic through Statistical Product and Service Solution (SPSS) was applied to perform significance analysis of each feature in this model. Two parameters say, *time of mentioning others* and *time of being forwarded* in the selected post were considered as most powerful feature to distinguish depressed among non-depressed user. Lastly, an application *Mental Health Testing* were then developed to monitor mental health online which also provide fruitful suggestions from psychologists to depressed individuals.

Not only this, there exists previous sentiment algorithm for Chinese blogs which achieves higher accuracy but lower efficiency[16]. The author analyzed the flaws and produced an optimized algorithm that is more efficient than the basic algorithm. It is observed that basic algorithm spends 1296 seconds with efficiency of 79.3 blogs per second to analyze data whereas optimized algorithm takes only 11 seconds with efficiency of 7980.8 blogs per second (100 times to basic). For real time sentiment, a platform is also developed that offers useful APIs of the analyzed result to communicate with other applications [29], [30]. In future, sentiment analysis can be additively used to make it more efficient.

1.2 Machine Learning Techniques

A survey of machine learning based approaches to predict Parkinson's disease (PD) among individuals was carried out. Tiwari (2016) [31] presented a comprehensive review and corresponding results of researchers that includes type of approach used, data description and the performance ratio to distinguish healthy people from disease affected people. Zhang et al. [32] worked over multiple sclerosis detection with the help of machine learning techniques. For the detection, a two level stationary wavelet entropy (SWE) is used which helps to extract features from images of brain. In the experimental study, K-nearest neighbours (KNN) performs best out of decision tree (DT) and Support Vector Machines (SVM). Extreme Learning Machine (ELM) outperforms over traditional machine learning algorithms when compared with others are Naïve Bayes, Kernel biased AIS, AWAIS, Logistic regression and K*. Over all, it works best when there is limited number of hidden neurons [33].

High frequency posted users showed high signs of depression and wrote more about topics related to health [34]. Language of high and low frequency Facebook post users was compared with different topics that show most positively correlated words i.e. hurts, killing, headache, stomach, sleepy etc. and negatively correlated words i.e. happy, wishes, birthday, celebrate, party etc resulted into the fact that low frequency posted users make use of negatively correlated words and are less adhere to depression [35]. There exist a numerous challenges for social network use and text mining in e-health care applications and medicine [36].

Depression, can be estimated with the use of phone sensor data (GPS sensing, sleep markers i.e. bed time/ wake time, proximity sensor etc.), social media usage (posts, status updates, last account activity etc). Personal sensing with the use of sensors to detect human behavioural markers and mental health conditions provided an overview of various sensing methods [37] . For that translation of raw sensor data into knowledge and then converted to features to identify behaviours, moods and stress. Over 28,000 Facebook users, a large data set, gone through a personality survey and found that posts showed features that are equally likely related to depressive moods and severity [38]. Fu et al. [39] perform feature selection over biomarkers associated with diagnosing depression and its treatment response. Using sensor data from personal sensing, the study shows feasibility for various challenges of clinical deployment.

A machine learning approach based on “support vector machines” to differentiate depressed from healthy individuals based on multiple brain network properties. Pattern recognition approach such as Support Vector Machine (SVM) classifies the groups of various identities according to their brain activities and structure [40]. SVM can be used to diagnose neurological and psychiatric disease, prediction for treatment onset and response [41] . Using structural and functional imaging, SVM technique used supervised learning to classify the group of patient and healthy controls. It investigats three studies for possible disorders of Alzheimer's disease, bipolar disorder, major depression, Parkinson, schizophrenia and others. (1) By comparing the diagnostic value of neuro-imaging data. (2) Comparing the brain scans of individuals of both non-healthy and healthy individuals. (3) Comparing the brain scans of patients who respond to treatment of not. It then compares the accuracy, sensitivity and specificity of patients with healthy individuals which clearly identify the neurological and psychological disorder.

4. DISCUSSION

Several past studies explored the models for predicting depression and the treatment of response. A quick glance of the past studies presented in Table 1.2 and 1.3 focuses on studying depression and its treatment response. As an initial, Sample size used across all previous studies was limited in size to minimize the variance in calculation of accuracy, specificity and sensitivity. Based on learning method, validation measures may be varied based on type of frameworks used. The accuracy measure classifies how accurately the predictive model classifies the test data. The specificity and sensitivity measures how accurately the model classifies each label of test data. In short, Accuracy measures overall classification accuracy. The Specificity measures the percentage of depressed patients identified whereas, Sensitivity measures the percentage of non depressed patient identified. This shows an attempt to evaluate methods from past studies.

Table 2. Past studies diagnosed Depressive Disorder

Author	Year	Patient Sample	Machine learning method	Results
Costafreda et al.	2009	37 depressed 37 non depressed	Support Vector Machine	Accuracy: 67.6% Specificity: 70.3% Sensitivity: 64.9%
Marquand et al.	2008	20 depressed 20 non depressed	Support Vector machine (linear kernel)	Accuracy: 68% Specificity: 70% Sensitivity: 65%
Hahn et al.	2011	30 depressed 30 non depressed	Single Gaussian classification and decision tree integration Support Vector machine (linear kernel)	Accuracy: 83% Specificity: 87% Sensitivity: 80%
Mwangi et al.	2012	30 depressed 32 non depressed	Relevance Vector machine Support Vector Machine (non linear Gaussian kernel)	Accuracy: 90.3% Specificity: 87.5% Sensitivity: 93.3%
Rondina et al.	2013	30 depressed 30 non depressed	Support Vector Machine (linear kernel)	Accuracy: 72% Specificity: 67% Sensitivity: 77%
Rosa et al.	2015	Dataset 1: Fu et al. (2008) 19 depressed 19 non depressed	Sparse L1-norm SVM (linear kernel)	Accuracy: 78.95% Specificity: 89.47% Sensitivity: 68.42%
		Dataset 2: Hahn et al. (2011) 30 depressed 30 non depressed	Non sparse L2-norm SVM (linear kernel)	Accuracy: 85.00% Specificity: 86.67% Sensitivity: 83.33%
Zeng et al.	2012	24 depressed 29 non depressed	Support vector Machine (linear kernel)	Accuracy: 94.3% Specificity: 89.7% Sensitivity: 100%

Table 3. Previous studies predicting treatment response for Depressive Disorder

Author	Year	Patient Sample	Machine learning method	Results
Costafreda et al.	2009	9 responders 9 non responders	Support Vector Machine	Accuracy: 88.9% Specificity: 88.9% Sensitivity: 88.9%
Marquand et al.	2008	9 responders 9 non responders	Support Vector machine (linear kernel)	Accuracy: 69% Specificity: 52% Sensitivity: 85%
Liu et al.	2011	17 responders 18 non responders	Support Vector machine (linear kernel)	Accuracy: 82.9%
Nouretdinov et al.	2011	9 responders 9 non responders	SVM with general probabilistic classification method	Accuracy: 83.3% Specificity: 88.9% Sensitivity: 77.8%

In the meantime, it become valuable to continue conducting machine learning approaches with available data set of sample sizes to better refine the predictive models for diagnosing depressive disorder.

5. CONCLUSION

In this paper, we have presented a comprehensive review to pre identify depression through various text analytics approaches on the basis of the data available on Social Networking Sites such as Facebook and Twitter because the user tend to disclose their feelings of loneliness, anxiety, stress and obsessive behaviour. The summary of results obtained by various researchers available as existing literature is also presented. In future research, enable self-monitoring of health status of each individuals which may help to increase well-being of an identity. Various application functions can be introduced over smart phones or social media profiles to take an advantage of several techniques including gaming apps and principles of applied behaviour analysis.

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