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Predicting Depression Levels Using Social Media Posts

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***Abstract*— The use of Social Network Sites (SNS) is increasing nowadays especially by the younger generations. The availability of SNS allows users to express their interests, feelings and share daily routine. Many researchers prove that using user-generated content (UGC) in a correct way may help determine people's mental health levels. Mining the UGC could help to predict the mental health levels and depression. Depression is a serious medical illness, which interferes most with the ability to work, study, eat, sleep and having fun. However, from the user profile in SNS, we can collect all the information that relates to person's mood, and negativism. In this research, our aim is to investigate how SNS user's posts can help classify users according to mental health levels. We propose a system that uses SNS as a source of data and screening tool to classify the user using artificial intelligence according to the UGC on SNS. We created a model that classify the UGC using two different classifiers: Support Vector Machine (SVM), and Naïve Bayes.**

Keywords—User Generated Content (UGC), Social Network Sites (SNS), Support Vector Machine (SVM).

I. INTRODUCTION

Social media can be exploited due to the sheer amount of information, which refers to user behavioral attributes. Getting advantage of that information to predict the social media users' mental health level can help psychiatrist, family or friends to get the right medical advice and therapy on time to the depressed user.

According to World Health Organization (WHO) [1], approximately 350 million human-being are affected by depression today. WHO ranks the depression as one of the most devastating diseases in the world. In addition, about two-thirds of depressed people do not seek appropriate treatments, which lead to major consequences. The medical science relies on asking the patients questions about their situations, which does not diagnose the depression in a precise way [2]. The patient has to attend more than one session during a period of two weeks. The classification of a not depressed condition as a depressed is a False Positive problem [3]. However, researchers found that the Electronic Health Record (EHR) systems are not optimally designed to handle integrating behavioral health and primary care. EHRs lack to support documenting and tracking data for behavioral health conditions such as depression [4].

A statistic made by eMarketer [5] has shown the number of social media users in 2015 is almost 2 billion and it is increasing day by day. Most of the people use social media to express their feelings, emotions, and what are they doing on their daily routines. Rich bodies of work have been approved that social media is an open area for many people to express their negative emotions by sharing information which reflects those emotions [6]. Many researchers have been successfully proving that social media has been successfully used to maintain people's mental health. By mining the social media posts of users, we may get a complete image of the user natural behavior. From user's profile in Social media, we can collect all the information that relates to person's mood, activities, sleep hours, thinking style, interactions, guilt feeling, worthlessness, loneliness, and helplessness. Retrieving such behavioral attributes, show symptoms of depression on the social media users, which could be used to predict if the user is depressed or not. Psychiatrist, parents, and friends, could track the user depression by the proposed tool, which will save the time before the depressed user could get into major depression phase.

II. BACKGROUND

Depression is a mood disorder that causes a continuous feeling of sadness and loss of interest. There are many different types of depressive disorders, and each type has it is own unique symptoms. The most common type of depressive disorder is called Major Depressive Disorder (MDD), which interferes most with the ability to work, study, eat, sleep and having fun. Frances A, et al. [7] has shown that to diagnose major depressive episode, the patient will have five or more of the following nine symptoms during the period of two weeks and nearly every day. The first symptom is having depressed mood most of the day. The second is losing interest in almost all activities. The third symptom is weight loss or weight gain and sleeps too much. The fourth symptom is body agitation or retardation. The fifth is feeling tired or loss of energy. The sixth is feeling of guilt or worthlessness. The seventh symptom is finding concentration, thinking, or making a decision becomes a difficult task. The eighth symptom is trouble having sleep or sleep too much. The ninth and last symptom is the only symptom that does not have to exist nearly every day, the symptom is thinking about death, suicide attempt, or planning to commit suicide. Relying on asking the patients questions about those symptoms does not diagnose the depression in a precise way, which approve that the medical science is not

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100% sure about the techniques used to diagnose the depression [2].

The use of Social media is increasing nowadays especially for the younger generation. Users can access their SNS from their Smartphones, PCs, or laptops at anytime and anywhere. The availability of SNS allows users to express their interests, feelings and share daily routine. Collecting user-generated content (UGC) from any SNS could be used in health-related human behaviors. Many types of research proved that using UGC in a correct way might help to maintain people's mental health or diagnose at an early stage. By mining the social media posts of users UGC, we may get a complete image of the user natural behavior, which could help to predict the depression. By applying methods that classify social media user's depression phase according to their personally written text, we might get a precise result of the user mental health. One of the methods has been developed by Husain J [8], which starts with collecting the UGC from Facebook social media. Then they labeled words that refer to either the user is depressed or not depressed in the training phase. After training the classifier, Support Vector Machine (SVM) text classification algorithms applied to assign a text to one of the classes. Tokenization, lower case conversion, word stemming and words removal are preprocessing operators performed on the text before converting into the vector space. Vector space indexed every term as training dictionary index. Term-frequency (tf) has been computed to measure term occurrence in the vector space. Depending upon the tf value the user will be considered as depressed or not depressed. The developed tool is limited to the Facebook users. The tool does not consider all the depression symptoms which mean the final result is not 100% correct and it depends on depression symptoms only.

III. METHOD

Predicting Depression Model is created using RapidMiner [9]. The model consists of a number of processes to test both of classifiers, SVM classifier, and Naïve Bayes classifier. The model consists of two datasets, and seven main operators. The first dataset is the training dataset which contains the manually trained 2073 depressed posts and 2073 not-depressed posts. In addition, it consists of three columns, the first one is binominal sentiment (Depressed, Not-Depressed), the second column contains the depression category (One out of the nine category in case of depressed sentiment), and the third column contains the trained post. The second dataset consists of the patient SNS posts and it is changed for every individual to test the prediction of the model.

The first operator is the Select Attributes which selects which attributes of the training dataset should be kept and which attributes should be removed. The second and the third operators are the Nominal to Text, this operator changes the type of selected nominal attributes to text, also it maps all values of the attributes to corresponding string values, it is used in the training dataset and the test set. The fourth and the fifth process are Process Documents and it is used in the training dataset and the test set which generates word vectors from string attributes and it consists of four operators.

The four operators of Process Document operator are Tokenize, Filter Stop-words, Transform Cases, and Stem. The Tokenize operators splits the text of a document into a sequence of tokens. The filter Stop-words filters English stop-words from a document by removing every token which equals a stop-word from the built-in stop-word list in the RapidMiner. The Transform Cases operator transforms all characters in a document to lower case. The Stem operator stems English words using the Porter stemming algorithm intending to reduce the length of the words until a minimum length is reached. The sixth operator is the Validation operator which contains which applies on the training dataset which consists of two main sections, training, and testing. Training section contains the classifier operator, and we change the classifier model from SVM (Linear) to Naïve Bayes Classifier (Kernel) each time we test patients. The testing section consists of Apply Model operator which applies the trained model on the supervised dataset and the Performance operator used for performance evaluation. The seventh and last operator is Apply model which connect the test dataset and training dataset to give us the final result of the prediction using one of the classifier in the patients.

The accuracy of the classification depends on the training set used to run the classifier. It is extremely important to select sample training nodes that represent edge cases that belong in or out of a class and not only obvious examples of a class. It is, therefore, good practice to get as many different kinds of samples in the training set as possible. For that purpose, we have collected, organized, and manually trained supervised dataset. The posts of the dataset were collected out of three SNS, Facebook, LiveJournal, and Twitter. The dataset manually trained to (Depressed, and Not Depressed), in the case of Depressed sentiment we categorized the depressed post into one out of the nine depression symptoms defined by the American Psychiatric Association Diagnostic and Statistical Manual (DSM-IV). Table 1 summarize the number of posts in the trained dataset, we have 6773 posts, where 2073 posts are trained as a depressed post, and 4700 posts are not-depressed post. Table 2 summarize the number of posts that rely on each depression symptom in the supervised dataset. Table 3 shows a sample of posts from the supervised dataset with each depression symptom.

TABLE 1 NO. OF POSTS IN THE SUPERVISED DATASET FOR EACH SNS

SNS	Posts	Depressed Posts		Not-Depressed Posts
LiveJournal	2132	758		1374
Twitter	2354	489		1865
Facebook	2287	826		1461
	6773	2073		4700

TABLE 2 NO. OF POSTS FOR EACH SYMPTOM IN THE SUPERVISED DATASET

Symptom	LiveJournal	Twitter	Facebook
Sadness	281	365	549
Loss of Interest	14	1	0
Appetite	9	5	0
Sleep	4	31	32
Thinking	83	13	196
Guilt	193	41	0
Tired	6	25	46
Movement	5	1	0
Suicidal ideation	163	7	3

TABLE 3 SAMPLE POSTS IN THE SUPERVISED DATASET FOR EACH DEPRESSION SYMPTOM

Symptom	Post
Sadness	I just found out my mom never wanted me in the first place.; That just ruined my day.
Loss of Interest	What, if anything, is there to live for?
Appetite	I was a little depressed that I ate so much last night there were no leftovers today
Sleep	It was a sleepless night
Thinking	I can't concentrate.
Guilt	I feel bad for doing it
Tired	too worried and tired to post tonight
Movement	I think I just gave myself permission to be lazy.
Suicidal ideation	I did it again. I don't know what I was thinking. I cut a star-like design into my upper left arm, and then took a whole bunch of pills and strong scotch. life is not going well.

The supervised dataset used in the two classifiers where created in Excel file using three columns, the first one is the sentiment (Depressed, or Not-Depressed), the second one is the depression category which consists of one of the nine depression categories, and the third one contain the manually trained posts. However, the not-depressed posts where eliminated randomly from 4700 to 2073 posts to be equal with the depressed posts in the training set. In case of not equal posts between the depressed and not-depressed posts the final result will not be accurate.

IV. PERFORMANCE METRICS

To analyze the performance of our proposed model, we calculated accuracy, precision and recall. The accuracy gives us the percent of the correct prediction, the precision gives us the percent of the positive (Not-Depressed) correct prediction, and the recall give us the percent of the positive (Not-Depressed) correct cases caught. The performance was tested with 30 individuals, 15 of them are assign as depressed after answering the BDI-II questionnaire [9], and the other 15 are not depressed. Table 4 shows the value for each True Positive, True Negative, False Positive, and False Negative of SVM classifier in depression prediction.

TABLE 4 THE CONFUSION MATRIX OF SVM DEPRESSION PREDICTION

		Predicted	
		Depressed	Not-Depressed
Actual	Depressed	7	8
	Not-Depressed	5	10

Equation (1) calculate the accuracy of SVM classifier, where the sum of correct classification depression level divided by the total number of classification.

$$Accuracy\ of\ SVM = \frac{7+10}{30} = 0.567 = 57\% \quad (1)$$

Equation (2) calculate the precision of SVM classifier, where the true positives divided by the sum of true positives and false positives.

$$Precision\ of\ SVM = \frac{10}{10+5} = 0.667 = 67\% \quad (2)$$

Equation (3) calculate the recall of SVM classifier, where the true positives divided by the number of true positives and false negatives.

$$Recall\ of\ SVM = \frac{10}{10+8} = 0.556 = 56\% \quad (3)$$

Table 5 shows the value for each True Positive, True Negative, False Positive, and False Negative of Naïve Bayes classifier in depression prediction.

TABLE 5 THE CONFUSION MATRIX OF NAÏVE BAYES DEPRESSION PREDICTION

		Predicted	
		Depressed	Not-Depressed
Actual	Depressed	4	11
	Not-Depressed	0	15

Equation (4) calculate the accuracy of Naïve Bayes classifier, where the sum of correct classification depression level divided by the total number of classification.

$$Accuracy\ of\ Naïve\ Bayes = \frac{4+15}{30} = 0.633 = 63\% \quad (4)$$

Equation (5) calculate the precision of Naïve Bayes classifier, where the true positives divided by the sum of true positives and false positives.

$$Precision\ of\ Naïve\ Bayes = \frac{15}{15+0} = 1 = 100\% \quad (5)$$

Equation (6) calculate the recall of Naïve Bayes classifier, where the true positives divided by the number of true positives and false negatives.

$$Recall\ of\ Naïve\ Bayes = \frac{15}{15+11} = 0.577 = 58\% \quad (6)$$

Evaluating the system comparing with related works in Table 6 where we compare the performance metrics of the proposed system and the related works. Our proposed system got the best precision and the least in accuracy and recall.

TABLE 6 COMPARATIVE ANALYSIS OF RELATED WORK PERFORMANCE METRICS

Research Name	Accuracy	Precision	Recall
SNS Based Predictive Model for Depression [2]	77%	78%	85%
Predicting Depression via Social Media. [8]	~70%	70%	61%
Proposed System	63.3%	100%	57%

The reasons behind getting lower accuracy and recall are finding depressed individuals which are active in Twitter or

Facebook in the same time, is challenging task. In addition, all the depressed patients from Saudi Arabia where all their tweets and SNS posts in Arabic using slang Arabic words which give different meanings.

CONCLUSION

The key idea of our study is to find out the association among SNS users' activities and mental health illness. We assume that SNS activities can reveal the mental illness at initial states. Using the traditional questioner techniques, the psychiatrist cannot get the complete information from the depressed patient. The SNS based system can overcome the problems regarding self-reporting. From user's social activities, we may get closer to the natural behavior of the depressed patient and his/her way of thinking, and better classify the mental levels. We proposed a web application that can classify SNS user into one out of four depression level, which could be used by psychiatrists, family, and friends of the depressed patient. The web application collects the UGC from the patient's Twitter and/or Facebook. After that, it collects depression answers about the patient from the user the answers are based on BDI-II questionnaire [9]. Next, it analyzes the UGC using several text analysis APIs. Finally, it classifies the patient into one out of four levels (Minimal, Mild, Moderate, or Severe depression. After that, we have created a predating depression model using RapidMiner to test two classifiers (SVM, and Naïve Bayes Classifier). Using the same patients' data that have been added to the proposed web application and depending on a training dataset have been manually classified using 2073 depressed post and 2073 not-depressed post. The performance has been calculated for the three results, the sentiment results, the SVM results, and the Naïve Bayes results.

REFERENCES

[1] Marcus, M., Yasamy, M., Ommeren, M., Chisholm, D., & Saxena, S. (2012). Depression: A Global Public Health Concern. WHO Dataset.

[2] Hussain, J., Ali, M., Bilal, H., Afzal, M., Ahmad, H., Banos, O., & Lee, S. (2015). SNS Based Predictive Model for Depression. The 13th International Conference on Smart Homes and Health Telematics, ICOST 2015, Geneva, Switzerland, 349-354.

[3] Wakefield, J., Schmitz, M., & Baer, J. (2010). Does the DSM-IV Clinical Significance Criterion for Major Depression Reduce False Positives?. The National Comorbidity Survey Replication. American Journal of Psychiatry AJP, Washington, DC, United State, 167(3): 298-304.

[4] Rowe, J. (2015, October 16). For behavioral health, researchers cite need for new IT. Retrieved October 18, 2015, from http://www.himssfuturecare.com/blog/behavioral-health-researchers-cite-need-new-it

[5] Social network users in 2014 and 2018 | Statistic. (2015). Retrieved October 20, 2015, from http://www.statista.com/statistics/278341/number-of-social-network-users-in-selected-countries/

[6] Jalonen, H. (2014). An Arena for Venting Negative Emotions. International Conference on Communication, Media, Technology and Design, Istanbul, Turkey, 224-230.

[7] Frances, A., Pincus, H., & First, M. (1994). Major Depressive Episode. In Diagnostic and statistical manual of mental disorders: DSM-IV. (4th ed., pp. 326-327). Washington, DC: American Psychiatric Association.

[8] De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting Depression via Social Media. The Seventh International AAAI Conference on Weblogs and Social Media (ICWSM), Dublin, Ireland, 128-137.

[9] Alberta, E. (2011). Community-University Partnership for the Study of Children, Youth, and Families. Review of the Beck Depression Inventory 2nd Edition (BDI-II), Canada.