Detecting and Terminating the Mental Disorders by Enhanced Multiple Classification in Social Network

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Abstract: The rates of diagnosing depression and mental illness during the last few decapods, a number of cases prevail unheard-of. Symptoms linked to mental illness are detectable on Twitter, Facebook and web forums and automatic methods are more and more able to locate inactivity and other mental disease. In this paper, latest studies that planned to detect depression and mental illness by the use of social media are surveyed. Mentally ill users have already been pointed out the use of screening surveys, their community distribution of analysis on twitter, or by their membership in online forums, and that they were detectable originating at regulate users by patterns in their language and online activity. Various automated detection methods can help to detect depressed people using social media. In addition a number of authors experience that various Social Networking Sites activities may be linked to low self-confidence, particularly in young people and adolescents.

Keywords: Depression, Mental state, Social Media, Machine Learning, Deep learning.

I. INTRODUCTION

Elvis Saravia et al.,mention in his paper that the people that is suffering from mental illness usually wants to alone, and because of that they seek Social media as a platform to share their feelings and illness [1].Maryam Mohammed Aldarwish, Hafiz Farooq Ahmed put in the picture that the comprehensive use of social media could provide opportunities to help detect the depression which is undiagnosed. From the activities of the user in social media, we get the actions and behavior of mentally depressed patients and the way of thinking[2]. Social networking sites such as Twitter and Facebook modified the ways that other people describe their opinions, be in contact with others and share their experience. This result in the continuous flow of large amount of data containing important information related to sentiments and opinions of people’s.

Being so regular Social Media platforms make massive quantities of compilations. Priya Nambisan et al., mention that studies related to depression suggests that persistent thoughts and deliberating behavior are the two main symptom characteristics [3].Social media platforms are normally consistent and provide users to access the internet. Traversely Conventional media requires a lot of time for compilation of information for publication. Even though Social Media is generated in real time.Various researches have been done in this field and the rate of depressed users is increasing day by day and this also sometimes led to suicidality. According to social media statistics the total Worldwide population is 7.6 billion and the internet has 3.5 billion users and among that 3.03 billion active social media users. Facebook has its own 2.072 billon users and it adds 500,000 users every day and Twitter has 330 million users. Facebook Messenger and Whatsapp handle 60 million messages a day.

Studies up to now either consider to predict how, using Social networking sites correlates with mental illness or attempted to detect depression by analyzing the sentiments and opinions of users. In this review we focus only on the detection of mental state of users such depression using social media. In this paper we want to understand how individuals. We consider Depression because in today’s world Depression affects most of the people over Worldwide leading to Suicide. Since Social media are somewhat latest aspect that power the relation among their use and feelings of aloneness and depression has not yet been accordingly researched. Most of the analysis on problem dated published in the last few years.

II. DEPRESSED RATE IN INDIA AND OVER THE WORLD: ACCORDING TO WHO

WHO reports that approx.5 crore people suffer from Depression. The WHO report estimates that about 322 million people are suffered from depression over worldwide and nearly half of the populations are lived in South East Asian and Western Pacific Region. The total number of people that are living with depression are estimated increase by 18.4% between 2005-2015.

WHO report in September 2012suggests that 75% suicides are committed in low and middle income countries. Lancet report in 2012 reports that India has the highest suicide rates in youth, age between 15-29. National Crime Records Bureau reports in 2013, 2471 students commit suicide because of failure in examination. The rate is high due to the lack of happiness and also patience in the individuals.

It is noted that students with happy families has no depression. Seeing that failing in exams and not able to cope up with academics is the primary reason for suicide. The Depression is a state that should be cured as soon as possible, because today in India Suicides rates are increasing day by day.

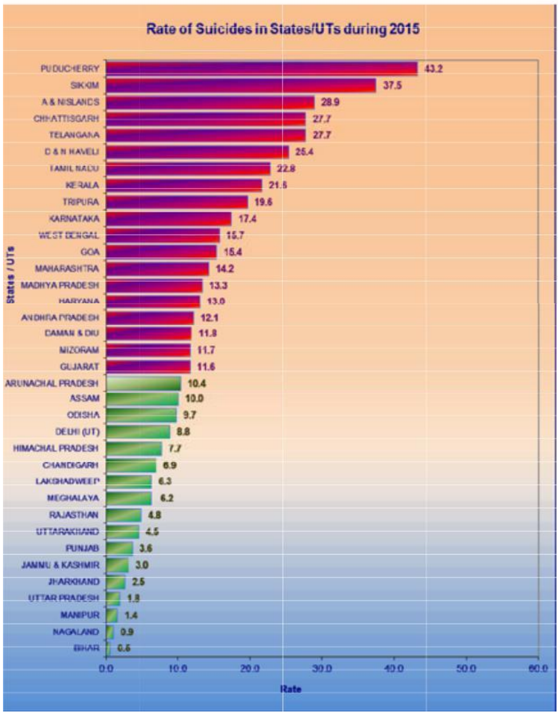

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Figure 1: State wise Rates of Suicides.(Lancet, 2015).

The leading cause for suicide are, the highest rate family problems, illness, drug addiction etc.Lancet report, in 20 12 reports that –A Student Commit Suicide Every Hour in India‖. WHO in his report –Depression and other common Mental Disorders-Global Health Estimates‖ mentioned that overall 7,88,000 people died because of suicide, and he number of suicides of students is approx. 8934 in 2015. In the leading five years 39775 students killed themselves and many of the suicides are unreported

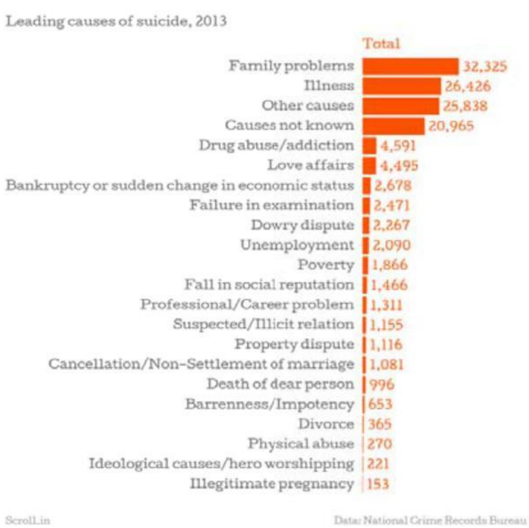

Figure 12 : (National Crime Record Bureau, 2013)

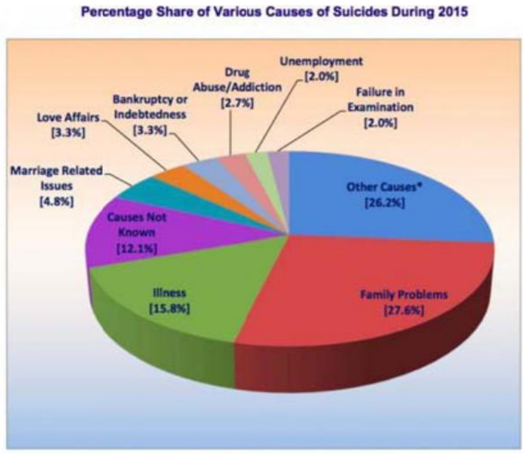

Figure 3: Different types of causes of Suicides.
(Lancet Report,2015).

From the above graph, he Lancet report show the percentage share of various causes of suicides. And by studying the above graph it seems that maximum number of suicides occurred due to family problem

A. Predicted number of Social Media use s from 2010-2021 World Wide (According to Statistic Portal)

The stats show s the total of social media users around the world starting with 2010-2016 including projections upto 2 021. In 2019 its far predicted that one there'll be about 2.77 billions social media users a ll over the World. Social Media is very popular in North America. It occupies the first rank a cording to Statistic Portal.

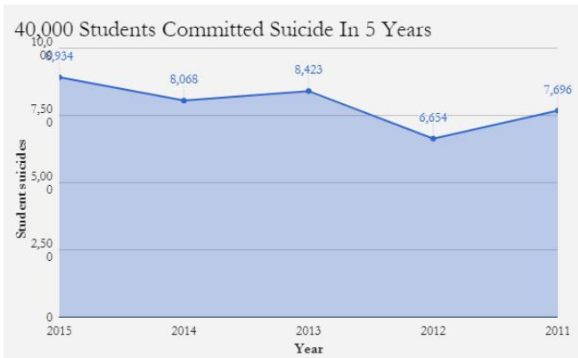

Figure 4: The number of Suicide Attempts
(National Crime records Bureau,2015)

III. RELATED WORK

Many of the studies are do ne in the field of mental illness a d many of the methods are applied by the researchers predict the mental state of users using social media. Th rates of Depression among the individuals are increasing day by day, so it is necessary to predict mental state of user (i.e Depression) and suicide rates. Social media platform such as twitter allow users to broadcast their opinions,sentiments,news and information to other people.

Min Hane Aung et al., mention two methods to access the behaviour related to mental illness, first one is measuring real-world behaviour through sensors and the second is measuring behaviour intercede through technology.[4].Munmun de Choudhury etal., tells in his paper that over the arriving two decades,depression is projected ultimate the prominent explaination for disability in profitable nations. Taking Social media as a reliable tool to predict depression.[5]For the prediction of mental state of a user data is, collected from various social media sites that a user joined them.

Shararth Chandra Guntuku et al., mention two methods for collecting the data, by recruiting the participants to do a Depression survey to share their Facebook and Twitter data, or by collecting the data from public online sources.[6]

A. Prediction through Traditional Methods

As above Shararth Chandra untuku et.al.,2017 mention in his study one of the methods that prediction can be done by conducting a Depression Survey by collecting the data from public online sources[6].We have noticed that most of the researchers like Seung W. Choi et al., predict the mental states by using questionnaires(like Depressive Symptom Inventory-Suicide Subscale(DSI-SS),Beck Depression Inventory(BDI), Center for Epidermologic studies(CES-D))[7]. Scott R. Braithwait et al., examined Depressive Symptom Inventory-suicide subscale, Interpersonal needs Questionnair(INQ) and Acquired Capability for suicide scale(ACSS) for their research[8]. Munnmun De Choudhury et al., uses CES-D Questionnair as a primary tool to predict the depression levels in the crowdworkers. The participants who are giving CES-D test answered on a Likert-type 4-point scale[9]. Liu Yi Lin et al., calculate the depression using a 4-item Scale that is developed by Patient-outcomes Measurement Information System(PROMIS)[10]. Sharth Chandra Guntuku et al., tells in his study that online forums and websites in which users make discussions are also a source of data collection related to mental health.[6]Centers for Disease Control and Prevention(CDC) tells in his report that Depression is a common and serious illness, affecting 1 out of 10 women 18-44 years. Feeling of postpartum depression are more LQWHQVH DQG ODVW ORQJHU WKDQ used to describe the worry,sadness and tiredness. About 1 in 9 women experience symptoms of postpartum depression.Postpartrum depression is also a major disorder that mostly women suffer after child birth.Munmun De Choudhury et al.,2014 examined the Facebbok to predict the postpartrum depression using Patient Health Questionnair (PHQ-9). This questionnair takes the responses from the last two weeks, based on experiences[9]. Postpartum Depression is the most important mental illness that a women faces after birth. Munnmun De Choudhury et.al., mention in his paper that according to CDC it is estimated about 10-20% of recent mothers faces a mood disorder). Various machine learning algorithms are used for the prediction and prevention of depression, so at what extent these algorithms are benificial against the suicide prevention.To do that Scott R Braithwaite et al., adopted various questionnairs, Depressive symptom Inventory-Suicide sub scale(DSI-SS), Interpersonal Needs Questionnaire(INQ),Acquired Capability for Suicide Scale(ACSS) [8].By adopting the questionnair pattern Psychiatrist fails to receive the whole information of the depressed patient. Social media overcome this limitation.

B. Prediction through Social Media

Munmun De Choudhury et al., opts the croud sourcing technique to extract the data from twitter and build a SVM classifier to predict the accuracy of depresssion [5]. Keumhee Kang et al.,uses crawling technique to collect the data form twitter and saves it into their database using open API. And crawling is done using keywords or real time streaming [11].Maryam Mohammed Aldarwish and Hafiz Farooq Ahmed developed a Web Application that characterize the social media users into one out of four Depression levels(Minimal, Mild, Moderate and severe).They colect the data from Facebook and Twitter and use the BDI-II questionnaire and analyze the collected data XVLQJ VHYHUDO 7H[W DQDO\VLV $3, ed GDWD IRFXV RQ WKH ZRUGV WKDW comments and status[2], and for that Elvis Saravia et.al. and Peter Burmap et.al.uses (Term Frequency-Inverse Document frequency) TF-IDF and Pattern of Life Features(PLF) to capture the repetative words that a patient used and predict the emotions and behaviour of the patients [1][12].

Munmun De Choudhury etal., performs a learning based analysis by considering forms and structures of sentences including words related to the human moods, and uses Support Vector Machine (SVM) to understand the relationship among them [5]. Min Hang Aung et al., in his study access the behaviour of human using mobile sensing, Supervised Learning method is used [4]. Munmun De Choudhury et.al. used Six different performance metrices(accuracy, precision and recall,F1, specificity and area under curve AUC) to calculate the performance of the SVM classifier. Linguistic Inquiry :RUG &RXQW /,:& DUH XVHG WR FDWHJRUL]H ³QHJDWLYH´ DIIHFWV /,:& lysis the text that DOVR H[WUDFWV LQIRUPDWLRQ WR FDOFXODWH based on the words in the dictionary[9]. Scott R Braithwaite et al.,done a analysis in python that predicts the mental state using scikit-learn library [8]. Glen Coppersmith et.al. uses two Language Models, first is the Traditional 1-gram LM (ULM) that calculates the each word as a whole, and second is the Character 5-Gram LM (CLM) that derives the sequences upto 5 characters [13]. Maryam Mohammed Aldarwish and Hafiz Faroq Ahmed build a depression model using RapidMiner and test the two classifiers i.e., SVM and Naïve Bayes classifier, and their system has the best precision and minimal accuracy and recall. [2] Braithwaite et al., build a model using Decision tree learning because it can provides a model with accuracy for many applications, and they used the leave-one-out cross validation(loo-cv) to estimate the accuracy of the decision tree [8]. Pete Burmap et al.,built a number of baseline classifiers by using features that is extracted from twitter, and by using the Weka Learning Libraries they conduct the baseline experiments. They they build an ensemble classifier with the help of Rotation Forest Algorithm [12]. Quan Hu et al., predicts the depression in users using the Sina Weibo data and it uses WKH &KLQHVH WH[W DQDO\VLV VRIWZD

;LQ´IRU SURFHVVLQJ WKH WH[W)RU)H applied Greedy Stepwise algorithm and build a classification model using Logistic Regression method and conclude that it is practical to predict a whether users depressed or not by means of Social media [14].

Yoshihiko et al., developed smartphone application ³8WVXUHNR´ WR FROOHFW WKH GDWD IURP XVHUV DQG XVHG WKH SRZHU of Deep Learning to build a depression detection model, and the results shows that their framework are able to predict the severe depression using individual histories gives high accuracy [15].In Social media people are connected to each other. It makes a bond. Eric Gilbert et al., predicts the Tie Strength with social media by using Firefox extension Grease monkey to collect the data and use LIWC to do analysis. SMDI(Social Media Depression Index are used and they conclude that SMDI can intently depict Centers for Disease Control and Prevention(CDC) explained stats on Depression.[16]. Today the personality of a user is most important. Personality poses the exact expression infront of RWKHUV 8VHU¶V SHUVRQDOLW\ FDQ EH SUHGLFWHG E\ WKHLU face book status, comments, images, pages they liked ,by analyzing their behaviour etc.

Heather Cleland Wood et.al. mentioned in his study that using Nighttime social media and emotion investment can affects the sleep quality and levels of Depression Since by using social media at night time may adversely affects sleep in adolescence.[17] Heather Cleland Wood et al., findings conclude that the use of social media specially at bedtime is a major factor that affects adolescence sleep quality, and levels of anxiety, ie. Poorer sleep quality and increased anxiety and depression [17]. Kimberly A. Van Orden etal., study recommended that women might probabily experience many risks that shows the presence of thwarted belongingnessandperceivedburdensomness [18].

C. Mental Health Detection using Deep Learning

Since Deep Learning is a method, with its beginning in Artificial nural Networks, is emerging in recent times as an imperessive tool for Machine Learning, encouraging to customize the field of Artificial Intelligence. George Gkotsis et al., National Language Processing of Electronic Health Recods is more and more getting used to learn about insnity and jeopardize behaviours in so much closer analyze than previously. In the study Author addressed the diffeculty of characterizing and commnly classifying user generated data on social network site Reddit for the prediction of mental health contitions. They manually researched data generated from a number of subreddits to gather the posts within the underline Theme. The obtained grouping of posts into Themes was furthermore evaluated by apply the Topic Detection Algorithms, and results indicates that the Theme based grouping is suthentic. Then they applied two classification studies, a Binary classification to determine whether or not post contains mental health relevant data, and multiclass classification to discover the mental health condition, and they conclude that by applying Convolutionary Neural Network (CNN) in binary classification, they attain a accuracy of 91.08% [19].Richard Socher et al., in his study they introduced a Recursive Neural Tensor Networks and Stanford Sentiment Treebank. And the combination produces a system for sentiment detection of a single sentence, which pushes state of the art by 5.4% for sentence classification. They compare their model to a number of models such as Recursive Neural Network, matrix-vector RNN etc.and they noticed that RNTN acquired a highest accuracy of 80.7%.[20]. Huijie et DO LQ KLV SURSRVHG ZRUN blog KD\ data and present a user-level mental stress detection and to do that they collect the ground truth data, and from the XVHU¶V WZHHW¶V they present a set of low-level content attributes, statistical attributes, and a convolutional Neural Network is designed with cross auto encoders to accumulate these attributes and generate a user-scope attributes and they apply a deep neural network model to understand the higher level of attributes and predict mental stress. They test their model with four different data sets and their results shows that the model efficiently detect the mental stress of users by using micro blog data. [21]. For message-level Twitter sentiment classification. Duyu Tang et al., developed a Deep Learning system Cooooll. Cooooll composed of two parts first is sentiment specific word embeddings(SSWE) and second is the state-of-art-handcrafted features for feature representation. The efficiency of the system Cooooll is verified. Cooooll yields a position 2 on Twitter 2014 test set among 45 systems of SemEval 2014 Task 9.[22].

Table 1: Some posts that indicate Depession.

Depression Indicative posts
³+H\ EUR ZKDW KDSSHQ LV HYHULWKLQJ ILQ GRQ¶W XQGHUVWDQG ZK\ RQO\ PH ZK\ SHRSO
(YHU\RQH WDXQWV RQO\ RQ PH« of this. :K\" , P IHG
, ZLVK , KDYH VRPHRQH WKDW FDUHV IRU PH sad.
, ORVV P\ LQWHUHVW LQ DOO DFWLYLWLHV ,
:K\ , P QRW D ILUVW SULRULW\ IRU D SHRSOH«
How is that poisVLEOH KRZ , FDQ IDLO , GRQ¶W NQR UHDVRQ IRU PH WR DOLYH«
I diagnosed with Depression last week.
, P IHG XS RI DOO WKLV ZK\ FDQ¶W SHRSOH O all the time.

In the above table we mentioned some of the coments that indicates Depression, and that are used by the people when they are not mentally well, and that and taken E\ WKH UHVHDUFKHUFKHUV WR SUHG ([DPSOH Hey bro, what happen , is everithing fine or not ?´ 1R« 1RWKLQJ LV ILQH , GRQ¶W XQ me..why people always cheat only «me7KLV FRPHQW indicates that a person is very disturbed and are close to Depression.³+RZ LV WKDW SRVVLEOH KRZ , FDQ IDLO L GRQ¶W know what to do..there is no reason for me to alive« ´WKLV coment indicates the Suidality.

Table 2: Comparitive analysis of most commonly used approaches used for precticting depression

Author	Topic	Aim	Methods	Results
Munmun De Choudhury et al.,(2013)	Social Media as a Measurement tool of Depression in populations	Measuring Depression	SVM classifier, Center for Epidemiologic studies Depression scale(CES-D), social media depression index(SMDI), Principal Component Analysis(PCA),	SMDI can nearly reflect CDC characterised insights on depression
Richard Socher et al.,(2013)	Recursive Deep Models for semantic compositionality over a Sentiment Treebank	Sentiment Prediction	Recursive Neural Tensor Network (RNTN), Matrix-Vector- RNN (MV-RNN()	RNTN obtains 80.7% accuracy
Munmun De Choudhury et al.,(2014)	Characterizing and Predicting Postpartum Depression from Shared Facebook Data	Detect, Characterize and Predict Postpartum Depression	Patient Health Questionnair (PHQ-9), LIWC	Postpartum Depression was best predicted.
Pete Burmap et al.,(2015)	Machine Classification and Analysis of Suicide-Related Communication on Twitter	Identification and classification related to suicide	Term Frequency inverse document frequency (TF-IDF), Linguistic Inquiry and Word Count(LIWC), Principal Component Analysis, Support Vector Machines(SVM), Rule Based, Naïve Byes, J48 DecisionTree, Rotation Forest	Results achieved an F-Measure of 0.728 overall. 0.69 for suicidal ideation class.
Scott R. Braithwaite et.al.,(2016)	Validating Machine Learning Algorithms for Twitter Data Against Established Measures of Suicidality	To validate the machine learning algorihms to predict suicide risks.	Depressive Symptom Inventory-Suicide Subscale(DSI-SS), Interpersonal Needs Questionnair(INQ), and Acquired Capability for suicide Scale(ACSS), LIWC: updated 2015 version, Scikit-learn library, Decision tree Learning	Their results shows that it can be easily characterised the people who are at suicide risk and who are not with the help of Machine Learning Algorithms.
Elvis Saravia et.al.,(2016)	MIDAS: Mental illness detection and analysis via social media	Predicting Depression	Center for Epidermologic studies depression scale, TF-IDF,PLF, Sentiment 140API, Random Forest Clasiifier: a main learning model	They built an online system that extracts the features of a user by concidering two mental disorders, and their system gives the minimal results,that can be used in future to predict the user behaviour more efficiently.
Keumhee et.al.,(2016)	Identifying Depressive users in Twitter using Multiodal analysis	Extracts Tweets from Twitter thatindicate Depression..	SVM based Learning, Built a Lexicon by using Visual Sentiment Ontoloy and Sentistrength dictionaries, LIWC, K-means Clustering Latent Fusion	The results shows that a multimodel that is developed has high accuracy as compared the existing methods, and can efficiently SUHGLFWV WKH XVHU

Maryam Mohammed Aldarwish et.al.,(2017)	Predicting Depression Levels using Social Media Posts	Classification of users according to Mental Illness.	BDI-II Questionnaire, create a depression model using Rapid Miner, SVM and Naïve Bayes classifiers	The performance of the model is calculated a they got the best precision and minimal accuracy and recall
Adrian Benton et,al.,(2017)	Multitask Learning for Mental Health Conditions with Limited Social Media data.	Predicting Depression	Multitask Learning approach(MTL), Logistic Regression, Feed forward multilayer perceptron Single task Learning(STL),	Results shows that the proposed model performs better compared to LR models.
Yoshihiko Suhara et.al.,(2017)	Deep Mood Forecasting Depressed Mood Based on Self-Reported Histories via Recurrent Neural Networks	Predicting Depressed moods.	Long short term memory recurrent neural networks, Utrsureko: a smartphone application, Ecological momentary assesment (EMA) Approach	The results shows that the developed framew to predict the severe depression based on th individual histories is efficient and gives high accuracy.

Table 2.summarises the different approaches used by researchers to predict the Mental state of users, most of the approches are based on the uses of basic questionnaires (CES-D, PHQ-9, INQ, DSI-SS, BDI) to get the input from the users, then different machine learning algorithms were used to analyses the mental states of the users based on their input information. Later on some researchers have done the analysis of the mental states based on the input given by the users through mobile apps. T approaches are more efficient compare to the earlier approaches as they collect the user input during various phases of the day.

IV. EXISTING SYSTEM

It investigate the association of sleep quality and suicide attempt of Internet addicts. On the other hand, recent research in Psychology and Sociology reports a number of mental factors related to social network mental disorders. An NLP-based approach to collect and extract linguistic and content-based features from online social media to identify Borderline Personality Disorder and Bipolar Disorder patients. It extract the topical and linguistic features from online social media for depression patients to analyze their patterns.

The analyze emotion and linguistic styles of social media data for Major Depressive Disorder (MDD). However, most previous research focuses on individual behaviors and their generated textual contents but do not carefully examine the structure of social networks and potential Psychological features.

DISADVANTAGES

- Although previous work in Psychology has identified several crucial mental factors related to SNMDs, they are mostly examined as standard diagnostic criteria in survey questionnaires.
- To automatically detect potential SNMD cases of OSN XVHUV H[WUDFWLQJ WKHVH IDFWRUV WR DVVHVV XVHUV¶ RQOLQH mental states is very challenging. For example, the extent of loneliness and the effect of disinhibition of OSN users are not easily observable
- The developed schemes are not designed to handle the sparse data from multiple OSNs.
- The SNMD data from different OSNs may be incomplete due to the heterogeneity.

V. PROPOSED SYSTEM

We argue that mining the social network data of individuals as a complementary alternative to the conventional psychological approaches provides an excellent opportunity to actively identify those cases at an early stage.

In this paper, we develop a machine learning framework for detecting SNMDs, which we call Social Network Mental Disorder Detection (SNMDD). We propose an SNMD-based Tensor Model (STM) to deal with this multi-source learning problem in SNMDD.

We propose an innovative approach, new to the current practice of SNMD detection, by mining data logs of OSN users as an early detection system. We develop a machine learning framework to detect SNMDs, called Social Network Mental Disorder Detection (SNMDD). We also design and analyze many important features for identifying SNMDs from OSNs, such as disinhibition, Para sociality, self-disclosure, etc. The proposed framework can be deployed to provide an early alert for potential patients.

ADVANTAGES

- The novel STM incorporates the SNMD characteristics into the tensor model according to Tucker decomposition; and

- The tensor factorization captures the structure, latent factors, and correlation of features to derive a full portrait of user behavior.
- We further exploit CANDECOMP/PARAFAC (CP) decomposition based STM and design a stochastic gradient descent algorithm, i.e., STM-CP-SGD, to address the efficiency and solution uniqueness issues in traditional Tucker decomposition.
- The convergence rate is significantly improved by the proposed second-order stochastic gradient descent algorithm, namely, STM-CP-2SGD.
- To further reduce the computation time, we design an approximation scheme of the second-order derivative, i.e., Hessian matrix, and provide a theoretical analysis.

VI. ALGORITHM

To explore data mining techniques to detect three types of SNMDs

1) Cyber-Relationship (CR) Addiction, which includes the addiction to social networking, checking and messaging to the point where social relationships to virtual and online friends become more important than real-life ones with friends and families.

2) Net Compulsion (NC), which includes compulsive online social gaming or gambling, often resulting in financial and job-related problems.

3) Information Overload (IO), which includes addictive surfing of user status and news feeds, leading to lower work productivity and fewer social interactions with families and friends offline.

We present a Stochastic Gradient-Descent Algorithm for CP decomposition of the SNMD-based Tensor Model, namely, SGD-CP-STM. To iteratively improve each element in the matrices according to the corresponding gradient. We present a stochastic gradient-descent algorithm for CP decomposition of the SNMD-based Tensor Model ,namely, SGD-CP-STM, to iteratively improve each element in the matrices according to the corresponding gradient. Specifically, let T (í ,V,W) be a matrix obtained from T by contracting V and, i.e.,

where T (í ,V,W) ÐRN×R (the same as U). The following lemma first derives the gradient of each iteration. Lemma 1. The gradient of L with regard to U, i.e., ÏUL(T ,U,V,W), is equal to íT (í ,V,W) + U +V,W) + I 5 LaU, where +V,W) is the Hadamard product of V_V and W_W, i.e., +V,W)ij = (V_V)ij (W_W)ij, and I R is the identity matrix of size R. Proof. The objective function L(T ,U,V,W) is comprised of three terms, and the derivative of 2_U_2 with regard to U is I R. For the first term, the CP gradient can be solved by the following equation according to

) R U W K H V H F R Q G U W_a t U, the gradient for U W U is

If the weighted adjacency matrix A is symmetric, Equation F D Q E H I X U W K H U L aU, and ÏUL(T,U,V,W) is R equal to

Therefore, the stochastic gradient descent algorithm updates U at the t-th iteration as follows.

U(t) = U(t í1) í WT (t í1)(í ,V(t í1),W(t í1))
+U(t í +V(t í1),W(t í I 5 LaU(t í1))

Based on equation the gradient for V and W can be derived in the similar way as follows:

ÏVL(T ,U,V,W) = íT (U, í ,W) + V +U,W)
ÏWL(T ,U,V,W) = íT (U,V, í) +W +U,V).

Note that V(t) and W(t) are also updated similarly in each iteration.

VII . DATAFLOW DAIGRAM

VIII. MODULES

- Data Collection
- 'HWHFW ORFDWLRQ RI XVHU¶V
- 'HWHFW WLPH RI XVHU¶V SRV
- 'HWHFW PHQWDO GLVRUGHU X
- Suggestion to block user

A. DATA COLLECTION

Data collection is the systematic approach to gathering and measuring information from a variety of sources to get a complete and accurate picture of an area of interest. Data collection enables a person or organization to answer relevant questions, evaluate outcomes and make predictions about future probabilities and trends. you'll learn the many ways to import data into Python:

(i) from flat files such as .txts and .csvs;

(ii) from files native to other software such as Excel spreadsheets, Stata, SAS and MATLAB files;

(iii) from relational databases such as SQLite & PostgreSQL. This course teaches you to fetch and process data from services on the Internet. It covers Python list comprehensions and provides opportunities to practice extracting from and processing deeply nested data.

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Look for the gray location tag listed at the end of the post. Facebook posters can let their friends and followers know their location by posting a status update and selecting the icon to "add a location to post." The GPS or wireless connection attached to the device where the post was made determines city and state, or sometimes the exact venue. Get a history of the cities, countries, and other places a user has visited, as longas they took a picture there. Is possible anywhere to obtain this huge database of states/cities/regions? Would be interesting to have something similar in our app, but I don't know, where those lists get

C. '(7(&7 7,0(2) 86(5¶6 3267

Social media is one of the best ways to amplify your EUDQG DQG WKH JUHDW FRQWHQW \RX¶UH EUHDWLQJ %XW LW LVQ¶W enough to just post content to social whenever you feel like it. Some times are better than others.

So, what are the best hours to post on each social media channel?

Unfortunately, there's no perfect answer. People browse each social network differently, and businesses may find different days and times work best for them. For example, while Twitter sees tweets perform well at hours like 3 p.m., Instagram sees certain posts perform well as late at 2 a.m. You worked really hard on those social media posts for an upcoming campaign, but do you have any idea how many people will engage? Learning the best times to post on social media is more than just turning a few clicks into a dozen. This data lets you understand your audience inside and out.

D. DETECT MENTAL DISORDER USER

It's widely recognized that psychiatric conditions like depression and anxiety disorders are based in the brain. Scientists have even started to discover which brain areas are involved in different conditions. For example, post-traumatic stress disorder (PTSD) seems to involve excessive activity in the amygdala, which is involved in processing fear, as well as low activity in certain parts of the frontal lobes.

Much of the evidence for the role of specific brain areas in psychiatry comes from "brain imaging," which involves various ways of looking at the brain. Some technologies like PET imaging and functional MRI can measure the activity of the brain either at rest or while a person does certain tasks. Other technologies, like traditional MRI, measure the brain's structure³ its size and shape.

E. SUGGESTION TO BLOCK USER

:H JLYH D VXJJHVWLRQ WR EOR current social media. The blocking is based on reducing their time of usage in social media. We reduce the time of usage to 3hrs-6hrs according to their usage patterns, these are all don through the feedback area of the particular social media.

IX. CONCLUSION

The Lifestyle of people nowadays leads depression even in young generation. As the study indicates that the depression rate is increasing day by day. The reports of WHO and other organizations reflects that the consequences ar worse, even lead to suicide. Our aim is to study the techniques used by the researchers so far to predict Mental State of th public. The study shows that most of the work is based on the input collected from the clients using questionnaires. It is observed that the usage pattern of Social Media users including their time of usage, their posts, and other social activities reflects the mood of the user which can be very helpful to analyses the Mental State of the users and predictin depression.

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