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DETECTION OF MENTAL DISORDERS FROM ONLINE SOCIAL BEHAVIORS USING MINI BATCH GRADIENT DESCENT ALGORITHM

Kodali Rahul[#1] and Ramani S[*2]

[#] *School of Computer science and Engineering, Vellore Institute of Technology,Vellore, India*

[*] *Assistant Professor (Senior), School of Computer science and Engineering, Vellore Institute of Technology,Vellore, India*

***Abstract*— Curiosity to predict personality, behavior and need for this is not as new as invent of social media. Personality prediction to better accuracy could be very useful for society. There are many papers and researches conducted on usefulness of the data for various purposes like in marketing, dating suggestions, organization development, personalized recommendations and healthcare to name a few. In this study, we propose a mini batch gradient descent algorithm which manages the data via batch based system. The social data has been collected from the Online Social Networks (OSNs). The behavior of the social users are observed and collected for developing classification models. The observed features are then preprocessed to remove the irrelevant noise of the data. Then, a latent matrix is created for each batch of users. Depends on latent matrix, the data is organized and then features are trained. The trained features are further for classifying the data. Experimental analysis proves the efficiency of the systems.**

***Index Terms*— Online social networks; Mental disorder, batch based systems; Classification and Latent matrix.**

I. INTRODUCTION

The tremendous growth in social networking apps has become a part of human life. Most of the researchers extract the social data in order to predict the behavior of the social users. Mental health problems are mostly developed by the social networks. The survey states that, by 2030, the costs of global mental health disorders will beat the cost of cancer, diabetes and respiratory disorders [1]. Ample amount of research have been conducted to study about the factors that causes mental health issues. This evidence-based movement has led to substantial improvements in mental health care. At the same time, however, there is a consensus that improvements should be made to more effectively address the global burden of mental health conditions. E-Mental health [2] using application of information technology for the prevention and treatment of psychological disorders yields different healthcare solutions. A number of online treatments are available in increasing and can provide assistance for untreated.

Dealing with mental disorders can be physically, economically and emotionally demanding [3]. Work impairment and social networks are the factor that causes mental illness. Different sorts of data has been partially collected when the involvement of users ensures the online based treatment. These sorts of data are partially collected and it's useful for online based treatment [4]. It assists the users in both situational and personalized environment. In order to analyze the fine –grained type of data, the traditional approaches are insufficient. Social networking sites provide excellent sources of data for studying collaboration relationships, group structure, and who-talks-to-whom. The most common graph structure based on a social networking site is intuitive; users are represented as nodes and their relationships are represented as links. Users can link to group nodes as well.

Normally by making the account on social networking site like Facebook people gives the right to collect their information; based on this data Facebook research team try to monitor the user behavior. Many features and attributes of these social networking sites are useful for personality assessment. Researchers have proved this and were able to assess the personality traits by the use of social media such as Facebook [6] and Twitter. Based on social behavior toward friends and based on structural information like number of friends, groups joined and likes etc. can be used to successfully predict some of the personality traits. In this paper we will try to cover the researches done to predict the personality traits using social media data, algorithm used, limitation and results.

The rest of the paper is organized as follows: Section II presents the related work; Section III presents the proposed work; Section IV presents the experimental analysis and finally concludes in Section V.

II. RELATED WORK

This section presents the related work studied on mining social behaviors to detect the factors causing mental disorders. DTREE [7], an expert system, helps in diagnosing DSM-IV Axis I disorders by the use of Decision Tree. Yap RH and Clarke DM [8] have developed an expert system 'Monash Interview for Liaison Psychiatry' using constraint-based reasoning for systematic diagnoses of mental disorders based on DSM-III-R, DSM-IV and ICD-10. Constraint Logic Programming (CLP) language was applied for the development of the system. In [9], introduced latest approaches for the classification and Data-mining of mental problems by using Brain Imaging data. They also offered the mental health Diagnostic Expert System for the assistance of psychologists to diagnose and treat their mental patients. Three artificial techniques viz., Fuzzy Logic, Rule-Based Reasoning and Fuzzy Genetic Algorithm were applied in diagnosing and suggesting the treatment plans.

In [10], they developed the decision supporting system for diagnosis of schizophrenia having accuracy up to 66-82%. They developed a neuro-fuzzy approach for categorizing of adult depression. The supervised Adaptive Network Based Fuzzy Inference System and Back Propagation Neural Network and unsupervised Self Organizing Map neural network learning techniques were utilized and compared. It was observed that Adaptive Network Based Fuzzy Inference System, a hybrid system performed far better than Back Propagation Neural Network. In [11], they applied depth first search algorithm with the backward search approach for diagnosing dementia. An expert system was developed by them taking in consideration patient's behavior, cognition, emotions and the results of neuropsychological tests. In [12], the authors compared several classification techniques; Multilayer Perceptron, Bayesian Network, Single Conjunctive Rule Learning, Decision Trees, Neuro-Fuzzy Inference System and Fuzzy Inference Systems using various data mining softwares like TANAGRA ,WEKA and MATLAB [13] for diagnosing diabetes. They observed that accuracy levels are different for different techniques on different accuracy measures such as Kappa Statistic and Error rates.

In [14], the authors observed tried finding efficient techniques for the classification of MMPI profiles of patients having mental problem. They found that Attribute Extension methodology improves classification accuracy in case of discretized data. In [15], they applied Multi-Layer Perceptron with Back Propagation Learning for diagnosing Parkinson's disease efficiently with selected attributes. Information Gain from all attributes is taken as a measure for the reduction of attributes [16]. In [17], the authors studied about data mining techniques to find Genome wide Association in Mood Disorders. Six classifiers Support Vector Machine, Bayesian Network, Logistic Regression, Radial-Basis Function, Random Forest and Polygenic Scoring method [18] were being compared. It was found that a simple polygenic score classifier performed much better than others and they also found that all classifiers performed worse with small number of Single Nucleotide Polymorphisms in brain expressed set compared to whole genome set. In [19] the authors detected depression in structural MRI scans for diagnosing mental health of the patients. They compared performances of four Feature Selection Techniques; Information Gain, OneR, SVM and Relief. They found that the SVM Evaluator along with the combination of Expectation Maximization classifier and the Information Gain evaluator along with the combination of Random Tree Classifier give highest accuracy [20].

III. PROPOSED WORK

This section presents the proposed work of the systems. The proposed algorithm, named, "Mini batch gradient descent model" works on basis of batch system. It processes the group of data in iteration based models. Each batch is denoted as m and it composes of variant sort of data. The proposed model composes of three phases, namely,

1.1 Data collection:

Data collection is the first step of the proposed model. Initially, we extract the behavioral features of the social users. The extracted features are discussed as follows:

a) Parasocial relationship: It is generally denoted as |aout|/|ain| in which |aout| denotes number of action users takes and |ain| denotes number of action friends take to the users.
b) Interaction ratio between online and offline: It is denoted as |aon| (Online activities) and |aoff| (Offline activities). The login and log out activities of the users are processed.
c) Social capital: The social theory of the users is described in two forms, namely, bond strengthening and information seeking. The bond strengthening depicts the OSNs events to strengthen the relationship and the information seeking represents the use of data to discover the knowledge.
d) Social searching vs. browsing: Different sorts of addictive behavior is find from social users. It shows social searching develops more interest than social browsing.
e) Personal features: The time period, self-disclosure based features and temporal behavior features are obtained from the personalized user's environment.

1.2 Feature extraction:

Regarding offline behaviors, there are clear definitions in depression criteria, which have been widely used in depression diagnosis. On the other hand, we harvested the social media and found some common online behaviors. With references in computer science and psychology, we finally defined and extracted six depression-oriented feature groups to comprehensively describe each user, presented in our data-released website for more details.

a) Social network feature:

It was found that depressed users are less active in social networks and depressed individuals perceived Twitter more as a tool for social awareness and emotional interaction. Therefore, the social network features were worth considering, such as: 1) Number of tweets. We extracted the number of tweets posted historically and recently by the given user to assess the user's activeness. 2) Social interactions. We considered the social interaction features such as the number of the user's followings and followers to describe users' online social behaviors. 3) Posting behaviors. We also extracted the different posting behaviors of users to reflect the state of their lives, such as the posting time distribution.

b) User profile feature

The user profile features refer to users' personal information in social networks. It was found that people having a college degree or a regular job are less likely to be depressed. However, there is quite little personal information returned by Twitter APIs.

c) Visual feature:

Visual features were proved effective in cross-modal problems and modeling sentiments and emotions in social networks. Compared with texts, images are more vivid, freer, and pass more complex message.

d) Emotional feature:

Emotional status of depressed users differs from that of common users, so the emotional features are beneficial in depression detection. The topics concerned by depressed users and non-depressed users are likely to be significantly different, and topic models had been found to be effective in predicting depression on social media.

1.3 Training:

The extracted features are then framed for N users with M sources. A three mode tensor T ∈ RN×D×M is used to extract the latent feature matrix U. The matrix U depicts the valuable information of the social users. Matrix U effectively estimates a deficit feature (e.g., a missing feature value unavailable due to privacy setting) of an OSN from the corresponding feature of other OSNs, together with the features of other users with similar behavior. Based on Tucker decomposition on T, we present a new SNMD-based Tensor Model (STM), which enables U to incorporate important characteristics of SNMDs, such as the correlation of the same SNMD sharing among close friends.

1.4 Classification:

Finally, equipped with the new tensor model, we conduct semi-supervised learning to classify each user by exploiting mini batch gradient descent algorithm. Mini-batch gradient descent is a variation of the gradient descent algorithm that splits the training dataset into small batches that are used to calculate model error and update model coefficients. Mini-batch gradient descent seeks to find a balance between the robustness of stochastic gradient descent and the efficiency of batch gradient descent. Finally predict the type of disorder.

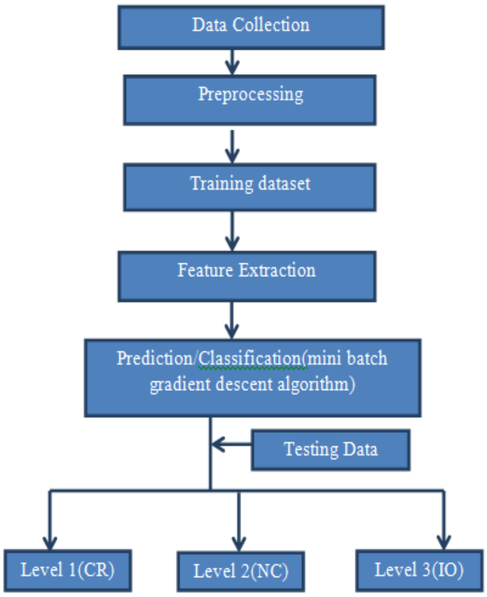

Fig.1. Proposed workflow

IV. EXPERIMENTAL RESULTS

This section presents the experimental analysis of our proposed study.

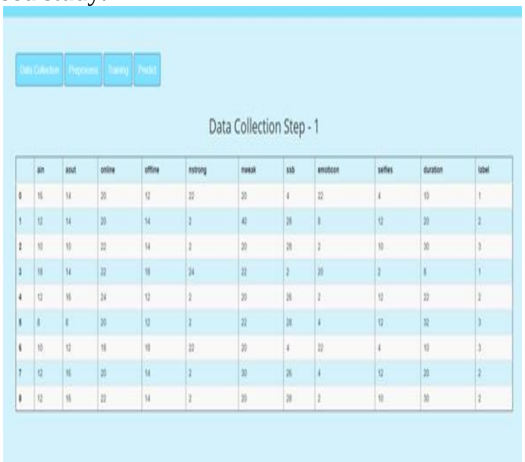

Fig.2. Collecting the data

The fig.2 presents the collecting the data from the social users. The behaviors of the social users are observed and the features are observed to find the different behaviors of the users.

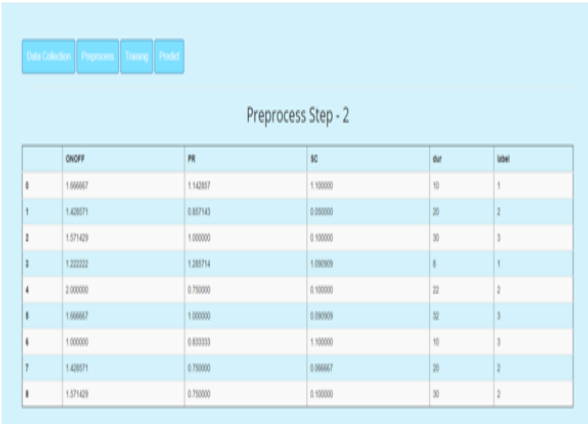

Fig.3. Preprocessing the data

The fig.3 presents the preprocessing of the data. The collected data may subject to the accumulation of irrelevant noise.

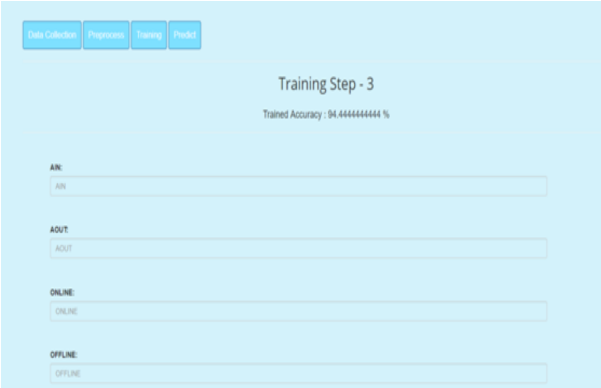

Fig. 4. Training step

The fig.4 presents training step of the proposed model. The preprocessed data is then used for developing the classification model. The selected features are used to develop the training classes.

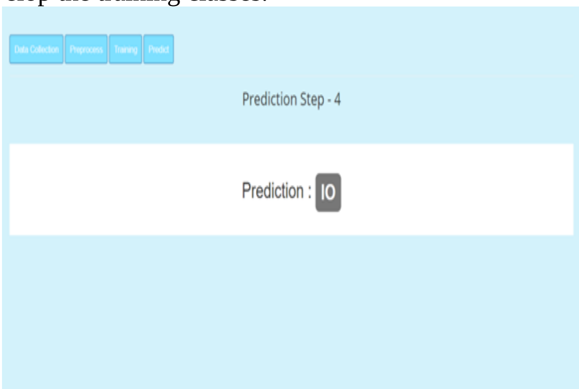

Fig. 5. Classification and prediction

The fig. 5 presents the classification and prediction of the systems. With the help of training model, the type of mental disorder is predicted.

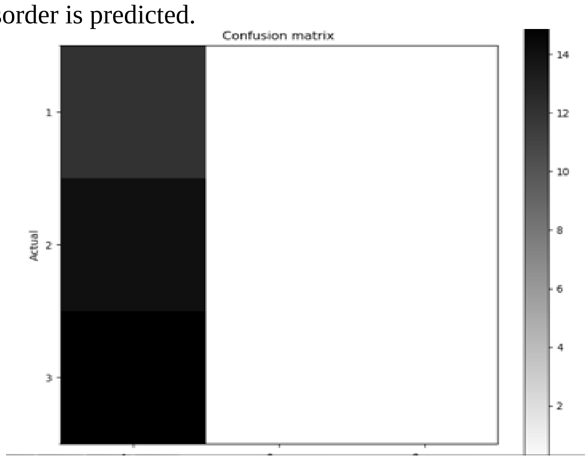

Fig.5. Confusion matrix for detecting the mental disorders

The fig.5 presents the performance analysis on detected mental disorders. The testing data will be given as input to the training and then the data are classified.

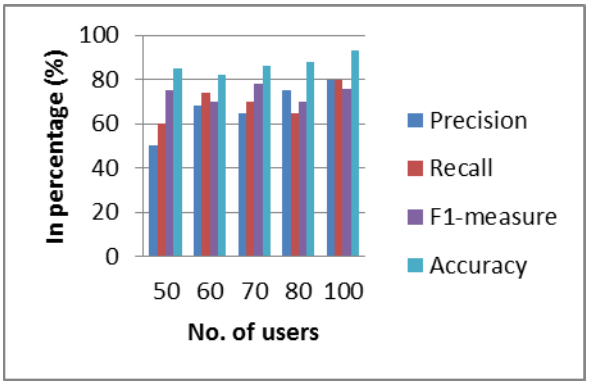

Fig.6. Performance analysis

The fig.6 presents the performance analysis of our proposed framework. The results show that the proposed model achieves better precision, recall, accuracy and F1 measure.

V. CONCLUSION

With the explosive growth in popularity of social networking and messaging apps, online social networks (OSNs) have become a part of many people's daily lives. Most research on social network mining focuses on discovering the knowledge behind the data for improving people's life. This paper aims to make mental disorder detection via harvesting social media. With the benchmark depression and non-depression datasets as well as well-defined discriminative depression-oriented feature groups, we proposed mini batch gradient descent algorithms which detect the depressed users. We then analyzed the contribution of the feature modalities and detected depressed users on a large-scale depression-candidate dataset to reveal some underlying online behaviors discrepancy between depressed users and non-depressed users on social media. Since online behaviors cannot be ignored in modern life, we expect our findings to provide more perspectives and insights for depression researches in computer science and psychology. As future work, we will study about the features extracting from multimedia contents using NLP and computer vision technologies. We also plan to work compromising user engagement by collecting the data from different service providers like face book and instagram.

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