Detecting Mental Disorder on Social Interactions in Social Networks

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***Abstract*—In online world, for expressing opinions and interacting with other people Social networks are a very popular way. We know that every good things have some part of bad thing that effects on human life. So we are trying to saves human life from social addiction. Social addicted persons are identifies by using Support Vector Machine Algorithm by classifying in stress or non-stress class. Also to improve our system goal, we further create a mobile app that give user's monthly activities perform on application in mobile and suggest such user about their usage to prevent from social addiction. Here we are trying to prevent user from unnecessary usages of application.**

Keywords: Support Vector Machine, mental disorder, social network, classification.

I. INTRODUCTION

In Social Networks data mining, extraction of patterns and analysis and trends representation is based on social network data processing. According to World Health Organization, 2001 an estimated 300 million people suffer from depression. The prevalence of life reports show a large variation, with 17% in the United States at 3% reported in Japan. Increasingly uses of social media platforms, like Twitter, Facebook, Instagram to communicate and share their thoughts and opinions with another users or friends. Social networks are the main sources of capturing behavioral characteristics that are relevant to a person's thought, activities, mood, communication and socialization [1]. Using such critical information we can saves one's life, because mentally affected or stress one may take wrong decision. Almost all young generation is on social network for interactions.

Rest of this paper is arranged as follows. Section II gives literature survey. Section III gives proposed architecture with algorithm uses for our system. Further section IV gives experimental results and discussion. And at last section V concluded system with future scope.

II. LITERATURE SURVEY

Liang et al. [2] Significant societal events are prevalent in multiple aspects of society, e.g., economics, politics, and culture. To accommodate all the intricacies involved in the underlying domain, event forecasting should be based on multiple data sources but existing models still suffer from several challenges. They proposed a novel group-Lasso-based feature learning model that characterizes the feature dependence, feature sparsity, and interactions among missing values. To ensure global optima proposed parameter optimization. Extensive experiments on 10 real-world datasets with multiple data sources demonstrated that the proposed model outperforms other comparison methods in different ratios of missing values.azzaq

In Germon et al. [3], they study from community engagement on the indicators of Instagram and the role of user-generated content. Images from Instagram with different engagement levels produced by online travel agencies are analyzed. They observed that instead of specially created images, user-generated content has a higher success for the online travel agencies community, and that is especially the case with AirBnB. The engaging photographs mostly depicted landscapes and contained calls for action in the description: calls such as like, tweet, retweet or comment. From Instagram users and non-Instagram content the most successful bloggers sharing their experiences. Even though on Instagram content in community management current dataset is limited, it already shows the importance of user-generated.

Anandkumar et al. [4] use tensor decomposition that works in overcomplete regime. Latent variable models on the overcomplete regime guarantees for learning, where the observed dimensionality exceeds the latent space dimensionality. Especially, they consider sparse coding models, ICA and multiview mixtures. In the semi-supervised setting, to get a rough estimate of the model parameters they exploit label information, and then on unlabeled samples with the help of tensor method refination process takes place.

They compare 3 emoticon preprocessing methods and emoticon-weight lexicon method on the base Twitter aware tokenizer and NB Model Wegrzyn-Wolska et al. [5]. Hinge et al. [6] identify potential users on social network with social network mental disorder. Anandkumar et al. [7] specify which overcomplete models can be identified given observable moments of a certain order.

III. PROPOSED METHODOLOGY

Our system objectives are,

1) To design social interactions on social networks contain useful cues for mental disorder detection

2) To identify users from social network suffering from mental stress and

3) To increase accuracy of detection of mental disorder in social networks.

A. Architecture

In System, there are three main parts that are as follow:

- Data Preprocessing: System relevant data from user profile and posts fired to/from friends. Contains name, friend list, mail Id, likes etc. [11],
- Features extraction: Features which denotes that user is suffering from mental stress.
- Attribute Categorization: To address the issue of stress recognition.

B. Algorithms

Support Vector Machine:

Support vector machine is classification technique mainly use in machine learning. Main task of this algorithm to give large and middle margin between two classes or have high accuracy of classification using attributes. Maximize margin i.e. to the classifier whose decision boundary is further away from any data point. Separate hyper-plane in terms of any data points that are closest to the boundary. And such point are called support vectors.

Algorithm for detecting account holder is in stress or not,

Input: user_id, posts, likes, unlikes, friends

Output: classification of account

1. get *post id, story, link, caption, description, message, users comments.*

2. add all features in vector x

3. **for** attribute in x **do**

4. $h_{w,b}(x) = g(z)$ here $z = (w^T x + b)$

5. **if** $(z \geq 0)$

6. assign g(z)= 1;

7. **else** g(z)= -1;

8. **end if**

9. **end for**

A decision hyper-plane can be defined by an intercept term b and a normal vector w which is perpendicular to the hyper-plane [8]. In the machine learning literature this vector is commonly referred to as the weight vector. We denote the intercept term b, to weight vector among all the hyper-planes that are perpendicular to the normal vector. Were as it is clear that, the hyper-plane is perpendicular to the normal vector, so all points x on the hyper-plane satisfy eq I,

$$w^T x = -b \text{ ....I}$$

Now suppose that we have a set of training data points i.e. data points which we take for learning patterns for classification. D = {(xi, yi)}, where each data points is a pair of a point xi and a class label yi corresponding to it.

$$g(z) = (w^T x + b) \text{.........II}$$

1 For SVMs, instead than 1 and 0, the two data classes are always named +1 and −1. Explicitly intercept terms are always represented by b, by involving an extra always on feature. A -1 value represented as one class, and a value of +1 the other class.

C. Methodology

1. Modules: Data Acquisitions / Data collection

To lead perceptions and assess our successive model, we initially gather a set of data sets utilizing diverse naming techniques, Cyber-Relationship Addiction, Net Compulsion and Information Overload techniques are used.

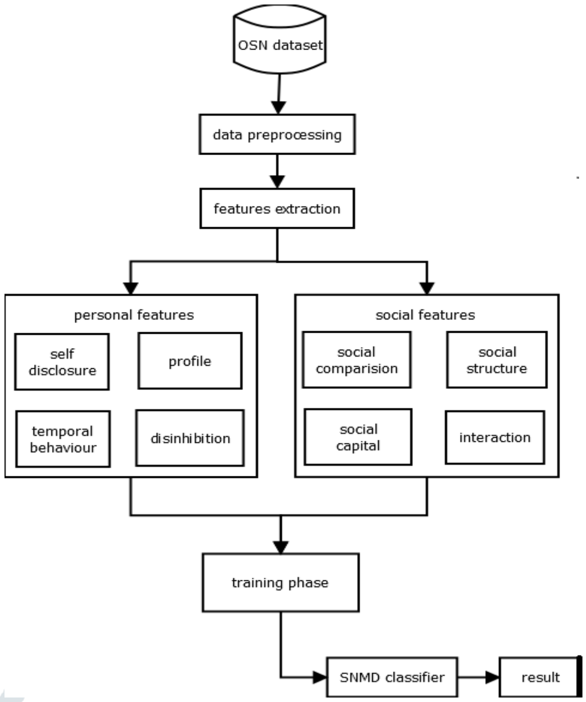


Fig. 1. System Architecture on detection of mental disorder in social interactions.

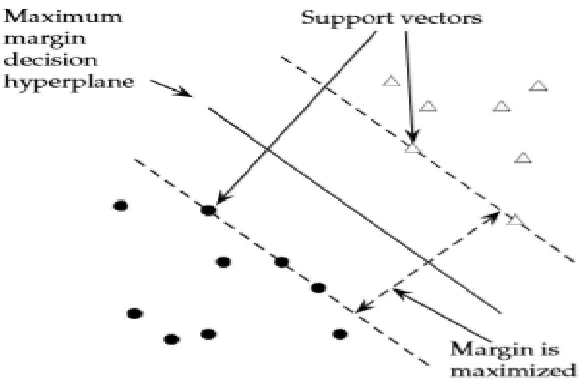


Fig. 2. Support Vector Machine with marginal classifier

2. Modules: Feature Extraction for design of mental disorder detection we focus on extracting discriminative and informative features.

(a) Addictive users: To detect mental disorder, an intuitive idea is to simply extract the usage or time of a user as a feature for training mental disorder detection.

(b) Multi-application learning with the mental disorder characteristics: We should have to exploit user data from their mobile desktop social networks.

3. Modules: Social Interaction Features

To capture the user behavior, we have to extract a number of social interaction features on social network.

(a) Social comparison based features: Although most literature indicates that the majority of the newsfeed updates is positive, recent studies manifest that users who are exposed to positive posts from others on Facebook are inclined to feel envy and depressed due to social comparison.

(b) Social diversity based features: Researchers have observed that diversity improves the depth of people thinking for both majority and minority.

(c) Temporal behavior features: These features are related to personal behavior with respect to social media. In that states like relapse, tolerance are included.

D. Set Theory

- s={I,P,O}
- I=Input, P=process, O=Output I={I0,I1,I2,I4,I5}
- I0=tweeter user id(ID0,...IDn)

- I1=tweeter data set
- I2=temporal behavior of user
- I3=social features
- I4=personal features
- I5=external knowledge P={P0,P1,P2,P3,P4,P5}
- P0= load tweeter dataset
- P1=Data preprocessing
- P2=extract personal features
- P3=extract social features of user
- P4=train the dataset
- P5=testing of OSN dataset O={O0,O1} O0= OSN user is mentally disorder
- O1=OSN user is mentally normal

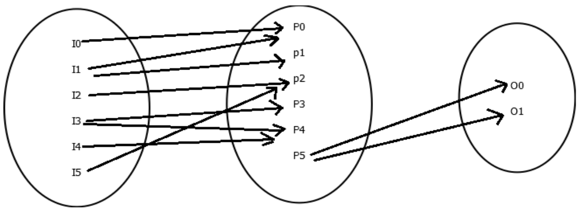


Fig. 3. Venn Diagram

IV.REQUIREMENT SPECIFICATION

A. Hardware Specifications:

- Processor : Intel i5
- CPU Speed : 1.1 GHz or Higher
- RAM : 2 GB or Higher
- Hard Disk : 256 GB or Higher

B. Software Specifications

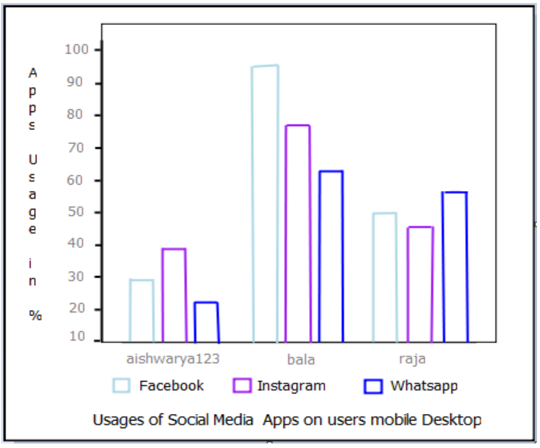
- Operating System : Windows 7 and above
- IDE : Netbeans, Android Studio
- Programming Language : Java
- Database : MySQL 5.5
- Toolkit : JDK 1.8

C. Advantages

- System prevent user from excessive usage of social media.
- Detect users with mental disorder like stress or depression.

V. RESULT AND DISCUSSION

In system we have create web-based graphical user interface to accept information from users at the time of creating account.



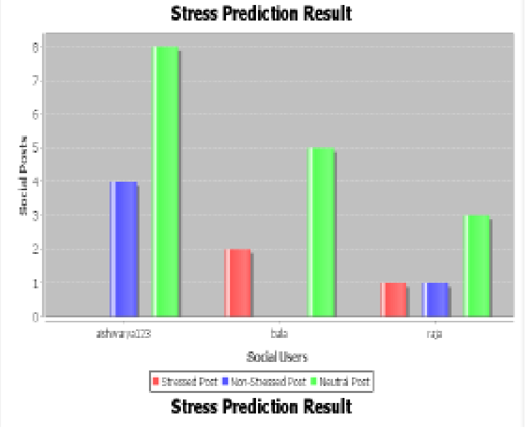


Fig. 4.Usage of Social Media Apps on users mobile Desktop

Fig. 5.Stress Prediction Result

From that admin get document posts by users. We use posts to find out for classification of users under stress and non-stress users features and attributes with the help of given algorithm.
Fig. 5 shows stress prediction result of three users. Further improving to reach near system goal we create mobile app which extract data from log files of users. Log file content information of each application present in user's desktop status per month or may be another, but we use per month status of each user desktop application. Fig. 4 Give result of usage of mobile application on user's desktop in percentage. From that we identify usage of application for social, entertainment, business, knowledge. If user is social addicted then such user have high chances to suffer from stress or depression.

VI. FUTURE SCOPE AND CONCLUSION

We conclude in our system that, users suffers from mental disorder are identifies by applying support vector machine algorithm in social interactions environment. Also we create mobile application that give usage of application on users mobile desktop, from that social addicted users are identify and suggest them cross line of excessive use of social networks. Future scope of our system is use for further development to prevent users from addiction in potential stage and we use for informing to relatives in social network by using friend relationship based network structure.

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