Identify the Deception of the Social Network to Investigate the Relationship between Dependence and Data Mining From Social Networks

Tanvi Hinge, Shweta Jamkhandi, Prof.Mahendra Salunke

Department of Computer Engineering, Pimpri Chinchwad College of Engineering and Research, Ravet, Pune,

Maharashtra, India

ABSTRACT: Mining social networks are the process to represent the analysis and extraction of patterns and trends that can be processed by social network data. Social networks are a very popular way of expressing opinions and interacting with other people in the online world. However, recently there has been a growing amount of cheating on social networks. Mental illness has a profound impact on individuals, families and, by extension, on society in general. This document defines that online social behavior mining offers the opportunity to actively identify social network delusion (SND) at an early stage based on the machine learning framework. We perform analysis of the characteristics and add an opinion score to increase accuracy. We also studied the relationship of social network dependency compared between the different users of the recorded entries of the SND forecast to find a solution to reduce the growing number of cases of SND.

KEYWORDS*: Online social network, mental disorder detection, feature extraction, tensor factorization.

I. INTRODUCTIONS

A. Background:

Most social network extraction research focuses on discovering the treasure of knowledge behind data to improve people's lives. On the contrary, much less attention was paid to remedying the problems caused by the various applications of social networks. In fact, some mental disorders of social networks (SNMD) have recently been observed, such as information overload and network compulsion. Mental illness is one of the leading causes of disability worldwide. An estimated 300 million people suffer from depression (World Health Organization, 2001). Reports on the prevalence of life show a large variation, with 3% reported in Japan at 17% in the United States. UU. In North America, the possibility of having a major depressive episode within a period of one year is 3-5% for men and 8-10% for women (Andrade et al., 2003). However, global dispositions and services for analyzing, supporting and treating mental illnesses of this type have been considered inadequate (Detels, 2009). In general, the diagnosis is based on the patient's self-explained experiences, behaviors reported by relatives or friends and on a mental state exam. In the context of all these challenges, we examine the potential of social media as a tool for identifying and predicting affective disorders in people and the proportion of their addiction. People are increasingly using social media platforms, like Facebook, Instagram, Twitter to communicate and share their thoughts and opinions with their contacts. Social networks provide a means of capturing behavioral characteristics that are relevant to a person's thought, mood, communication, activities and socialization. The emotion and the language used in the publications on social media can show feelings of uselessness, guilt, impotence and self-hatred. In addition, social sites contain the user's large-scale data set that can be used for analysis of the illusion detection and dependency rate survey. Internet addiction could be considered as a model of maladaptation of Internet use behavior that is associated with various psychological and social problems, to solve such problems the research has been the cause of the psychometric properties of Internet addiction. The research has seen personality and individual differences, ie self-presentation and membership in the social network. Research or survey is important to find out the answer, make basic decisions about objective information and compare results for prevention or important decisions. Therefore, the reason for this work is to investigate the relationship between addictions and develop prevention strategies against the increase in the number of SNDs.

B. Problem Statement:

The online social behavior of mining offers the opportunity to actively identify the NDMS at an early stage. It is difficult to identify the SNMD because the mental factors considered in the standard diagnostic criteria (questionnaire) cannot be observed from the registers of online social activities. We have developed a new framework of machine learning (the detection of mental disorders in social networks (SNMDD) that exploits the characteristics extracted from social network data to accurately identify potential SNMD cases. Furthermore, we exploit learning from multiple sources in SNMDD and propose a new SNMD-based tensor model (STM) to improve performance.

C. Goals and Objectives:

1) We use multi sourcing to collect the feature analysis for predicting the SND case with the additional feature 'sentiment score' which explain relationship of user with other individuals to increase accuracy.

2) The prediction results of SND are used for main purpose of this paper that is investigation of the comparative social network addiction ratio among the different user from recorded entries of SND prediction to find solution for reducing the increasing Number of SND cases.

II. RELATED WORK OR LITERATURE SURVEY

1. CHIH-CHUNG CHANG and CHIH-JEN LIN (2011) has represents LIBSVM: A Library for Support Vector Machines [1]. LIBSVM is a library for Support Vector Machines (SVM). We have been actively developing this package since 2000. The goal is to help users easily apply SVM to their applications. LIBSVM has gained great popularity in machine learning and in many other areas. In this article, we present all the implementation details of LIBSVM. Issues such as troubleshooting SVM optimization, theoretical convergence, multi-class classification probability estimates, and parameter selection are discussed in detail.

2. Kun-Lin Liu,Wu-Jun Li, MinyiGuo has developed Emoticon Smoothed Language Models for Twitter Sentiment Analysis [2].The analysis of Twitter sentiment (TSA) has become a hot topic of research in recent years. The goal of this task is to find out the attitude or opinion of tweets, which is usually formulated as a text classification problem based on machine learning. Some methods use manually tagged data to form fully supervised models, while others use noisy tags, such as emoticons and tags, for model training. In general, we can only get a limited amount of training data for fully supervised models because the task of manually tagging tweets requires a lot of work and time. For models with noisy labels, it is difficult for them to get satisfactory performance due to the noise in the labels, although it is easy to get a lot of data for training. Therefore, the best strategy is to use manually tagged data and noisy tagged data for training. However, how to integrate these two types of data perfectly into the same learning framework remains a challenge. In this paper, we present a new model, called the emoticon softened language model (ESLAM), to handle this challenge. The basic idea is to form a linguistic model based on manually tagged data, and then use noisy emoticon data to smooth out. Experiments with real data sets show that ESLAM can effectively integrate both types of data to overcome these methods using only one of them.

3. Ronan Collobert, Fabian Sinz, JasonWeston(2006) has proposed Large Scale Transductive SVMs [3]. We show how the concave-convex procedure can be applied to transductional SVMs, which traditionally requires the resolution of a combinatorial search problem. This provides for the first time a highly scalable algorithm in the non-linear case. Detailed experiments verify the usefulness of our approach.

4. Young Min Baek, Young Bae and Hyunmi Jang has represents (2013) Social and Parasocial Relationships on Social Network Sites and Their Differential Relationships with Users' Psychological Well-being [4].With the advent of social networking sites (SNS), people can efficiently maintain pre-existing social relationships and make friends online without offline meetings. While such technological features of the SNS have a variety of possibilities for individual and collective benefits, some scholars warn that the use of SNS could lead to socially negative consequences, such as social isolation, erosion of social cohesion or dependence on SNS . .

This study distinguishes the types of SNS relationships and investigates their relationships with social isolation, interpersonal trust and SNS dependency. We classify SNS relationships in two types: (a) social relationships based on the reciprocity between a user and his friends and (b) parasocial relations in which a common user knows the activities of a celebrity (for example, famous actors, athletes). and others) but not vice versa. Based on the results obtained in studies on the effect of media and social psychology, we constructed a series of hypotheses and tested them using a sub-sample of SNS users extracted from representative survey data in South Korea. We found that the dependence on social relationships is positively correlated with loneliness, but negatively correlated with interpersonal distrust, whereas dependence on social relationships is negatively correlated with loneliness, but is positively correlated with trust. However, a greater reliance on social and parasocial relationships is positively correlated with SNS dependence. Results-based implications are also discussed.

5. R. Schwartz (2014) has represents Mobility and locative media: mobile communication in hybrid spaces [6].Mobility has become an important framework for understanding and analyzing contemporary social, spatial, economic and political practices. Especially when mobile media integrates seamlessly into transport networks, navigating through urban spaces and connecting with social networks while they are on the move, researchers need new approaches and methods to link mobility with mobile communication and media. Rental. Mobile communication experts have focused on mobile phones, often ignoring wider connections with urban spaces, geography and location. As a result, they emphasized virtual mobility and personalized communication as a way to disconnect from place, location and audience.

6. V. Arnaboldi, M. Conti, A. Passarella, and R. Dunbar (2013) has represents Dynamics of personal social relationships in online social networks: a study on twitter [7]. The author analyzes a series of data from Twitter's communications registers, studying the dynamic processes that regulate the maintenance of online social relations. The results reveal that people on Twitter have highly dynamic social networks, with a large percentage of weak links and high turnover. This suggests that this behavior could be the product of an evolutionary strategy aimed at managing the extremely difficult conditions imposed by our society, in which dynamism seems to be the key to success.

7. K. Wise, S. Alhabash, and H. Park (2010) has demonstrate Emotional responses during social information seeking on Facebook [8].Based on existing research on social networks and on the search for information, it was proposed to conceptualize the use of Facebook.com with two main objectives: passive social navigation (ie news) and extractive social research (ie friends). This study explored whether these categories adequately reflect the use of Facebook and whether they moderate the physiological indicators of emotions. Thirty-six participants navigated on Facebook.com while screen activity and physiological responses associated with motivation and emotion were recorded. The results showed that most of the screens found during the use of Facebook could be classified as dedicated to social browsing or social research. The participants spent more time on social navigation than on social research. Data on skin conductance indicate that sympathetic activation decreases during social research and social research. Facial EMG data indicate that participants experienced more sympathy during social research than they experienced during social navigation. These results are discussed in terms of research on existing social networks and an evaluative spatial model of emotions.

8. E. Ferrara, R. Interdonato, and A. Tagarelli (2014) has represents Online popularity and topical interests through the lens of Instagram [9].Online sociotechnical systems can be studied as proxies of the real world to investigate human behavior and large-scale social interactions. Here we focus on Instagram, an online media exchange platform whose popularity has increased to collect hundreds of millions of users. Instagram presents a mix of features that include social structure, social tagging and media sharing. The network of social interactions among users models various dynamics, including the relationships between followers / followers and the communication of users through publications / comments. Users can upload and tag media such as photos and images and can "like" and comment on any information on the platform. In this article, we

examine three main aspects in our Instagram dataset: (i) the structural characteristics of its heterogeneous network of interactions, to reveal the emergence of self-organization and the topically induced community structure; (ii) the dynamics of content production and consumption, to understand how global trends and popular users emerge; (iii) the behavior of users who label media with labels, to determine how they devote their attention and explore the variety of their current interests. Our analysis provides clues to understand the dynamics of human behavior in socio-technical systems, in particular users and the popularity of content, the mechanisms of user interaction in online environments and how collective trends emerge from the current interests of individuals.

9. G. Wang, B. Wang, T. Wang, A. Nika, H. Zheng, and B. Y. Zhao (2014) has represents Whispers in the dark: analysis of an anonymous social network [10].The author presents the results of the first large-scale empirical study of an anonymous social network, using a complete 3-month track of the Whisper network covering 24 million whispers written by over 1 million unique users. We try to understand how anonymity and lack of social ties influence user behavior. We analyze Whisper from different perspectives, including the structure of user interactions in the absence of persistent social links, the user's commitment and the rigidity of the network over time and the moderation of content in a network with the least responsibility of the user. Finally, we identify and test an attack that exposes Whisper users to detailed location tracking.

III. EXISTING SYSTEM AND DISADVANTAGES

In the existing system, the identification of possible mental disorders often falls on supervisors (such as teachers, employers or parents) who can observe the symptoms mentioned above better than others, but only passively. Because the facts that there are very few significant physical risk factors, patients generally do not actively seek medical or psychological services to reduce these symptoms. As a result, patients should seek clinical interventions with psychiatrists and medical treatment only when their condition becomes very serious. However, a recent study shows a strong correlation between suicide attempt and SNMD for students. In this research, 9510 adolescent students aged 12 to 18 years were tested using a personality inventory and an inventory of Internet addiction. The results indicate that adolescents who suffer from social network addiction have a much higher risk of suicidal ideation than non-addictive users. The research also reveals that social network addiction can deteriorate the emotional state, causing more hostility, depressed mood and compulsive behavior. More importantly, delayed early intervention can lead to mental illness and, therefore, can seriously damage an individual's social functioning. In summary, it is desirable to actively detect potential users of SNMD in OSN at an early stage. Although previous work in Psychology has identified several crucial mental factors related to SNMD as standard diagnostic criteria for the detection of SNMD, they are mostly accessible via survey questionnaires by design. To identify possible cases of SNMD of OSN users, the extraction of these factors to evaluate the mental states of users is very demanding. For example, the degree of solitude and the effect of the distinction of OSN users are not easily observable.

Disadvantages of Existing System:
1. The findings indicate that adolescents suffering from social network addictions have a much higher risk of suicidal ideation than non-addictive users.
2. The extent of loneliness and the effect of distinguish of OSN users are not easily observable.

IV. PROPOSED SYSTEM AND ADVANTAGES

The proposed architecture represents the framework for SNDP for the dependency search system. The architecture consists of three phases which are phase 1, phase two and phase three. The first phase contains the behavior of SND. The behavior of the system is none other than the characteristics that will be extracted. The second phase consists of the learning framework that takes the feature as input and compares it with the threshold database and then provides SND prediction and records it in the database. The third phase is to investigate the relationship of addiction. The steps mentioned above are described in detail in the following way.
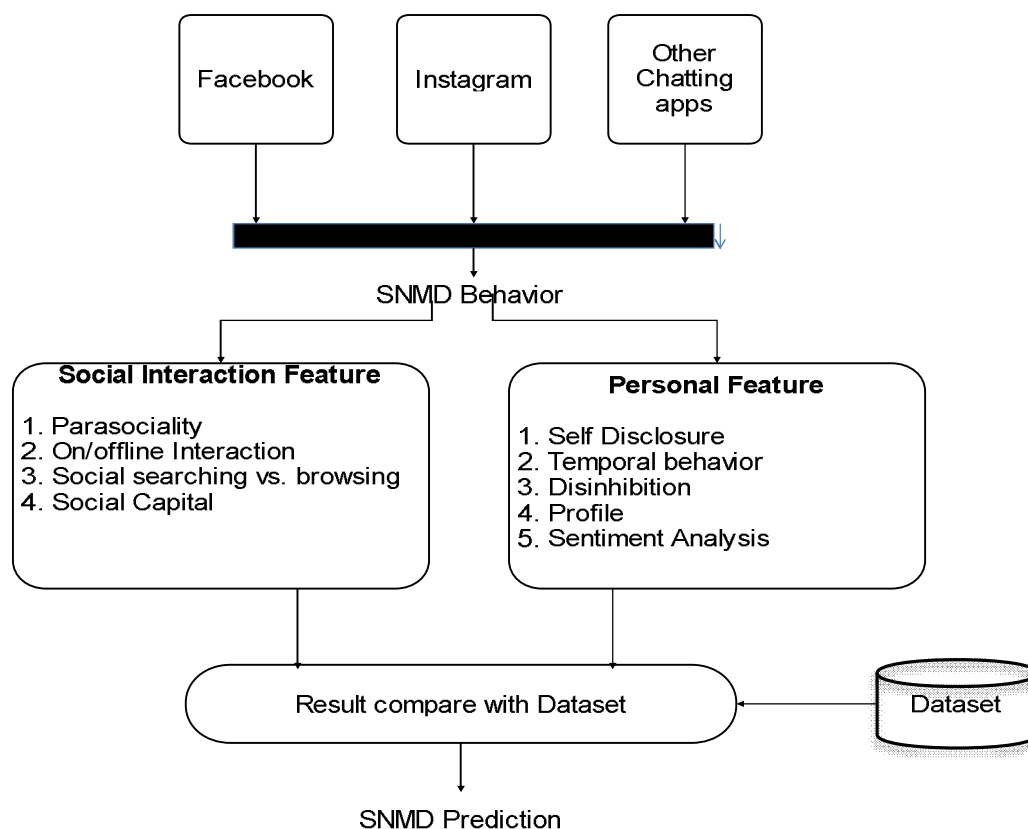
Fig: System Framework

Phase-I:

The behavior of the social network deception prevention system is described at this stage. It consists mainly of analysis of features and extraction from different sources such as Facebook, Instagram and Twitter. The various functions we are considering are based on personnel and on the function of social interaction. The personal characteristic consists in the temporal behavior, in the time of use that shows the relationship of use online a day and the profile showing age and sex. The social interaction function consists of a parasocial relationship that shows the positive and negative score, the online / offline relationship and the social capital that shows the score of the user's sentiment with the others. This phase contains the pre-processing of the characteristics to obtain the labels that will be used in the second phase.

Phase-II:

The characteristics extracted from the first phase are used here to predict the deception of social networks. Here the learning framework is applied to the pre-processed features and compared with the threshold database to predict the SND. The SND is predicted in three categories: normal user, employee and heavy user. The result is stored in the database for each user who will enter the third phase for investigating dependencies.

Phase III:

In this phase we will use the result of SND as input data for the study of the dependency relationship of the different users. The research is mainly carried out by two phases after the extraction of input data which are "user differentiation" and "search and generation of graphs".

Since there are no age limits to use social networking sites and people of different ages can have different behaviors. Therefore, it is important to separate the cases of SND between the different age groups to know the exact proportion. Taking this into account, it is important to differentiate users in the appropriate age range and this activity is carried out in the user differentiation phase. After the user's segregation, it's time to investigate the relationship between addiction and addiction. This will show the volume of the dependency relationship for each age group and generate the dependency graph. It also highlights the oldest dependency group and possible remedies for this.

Advantages of Proposed system:

1. You can apply SNMDD on large-scale real datasets and perform a social network analysis on the detected cases.
2. Collaborative effort between computer scientists and mental healthcare researchers to address emerging issues in SNMDs.

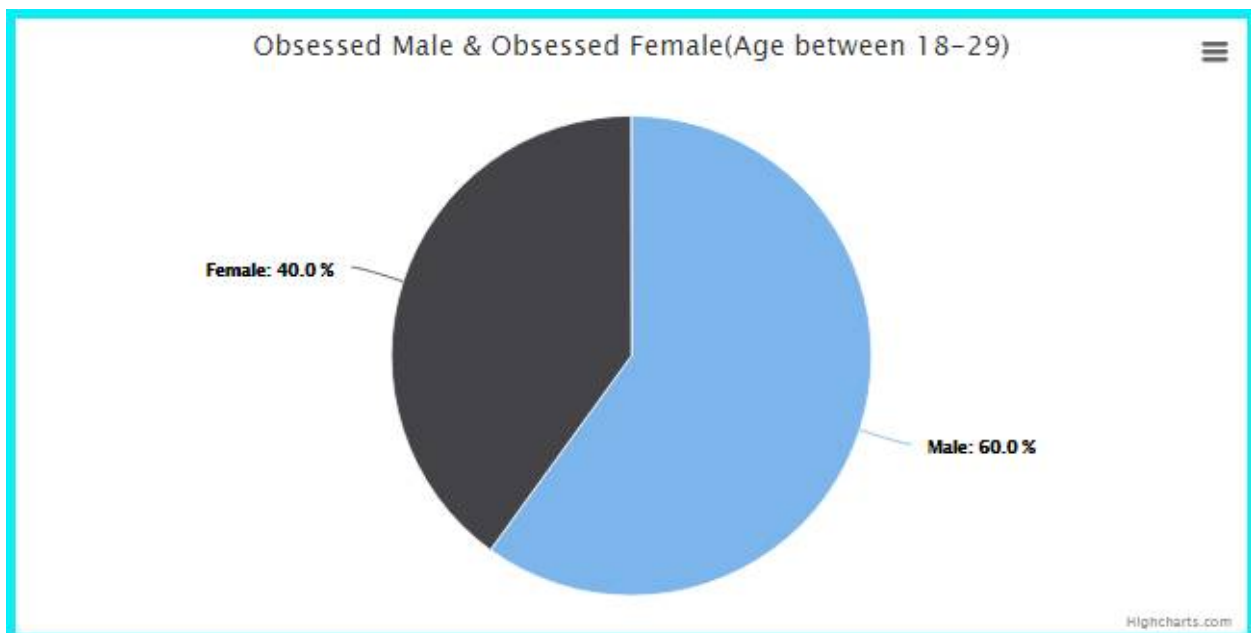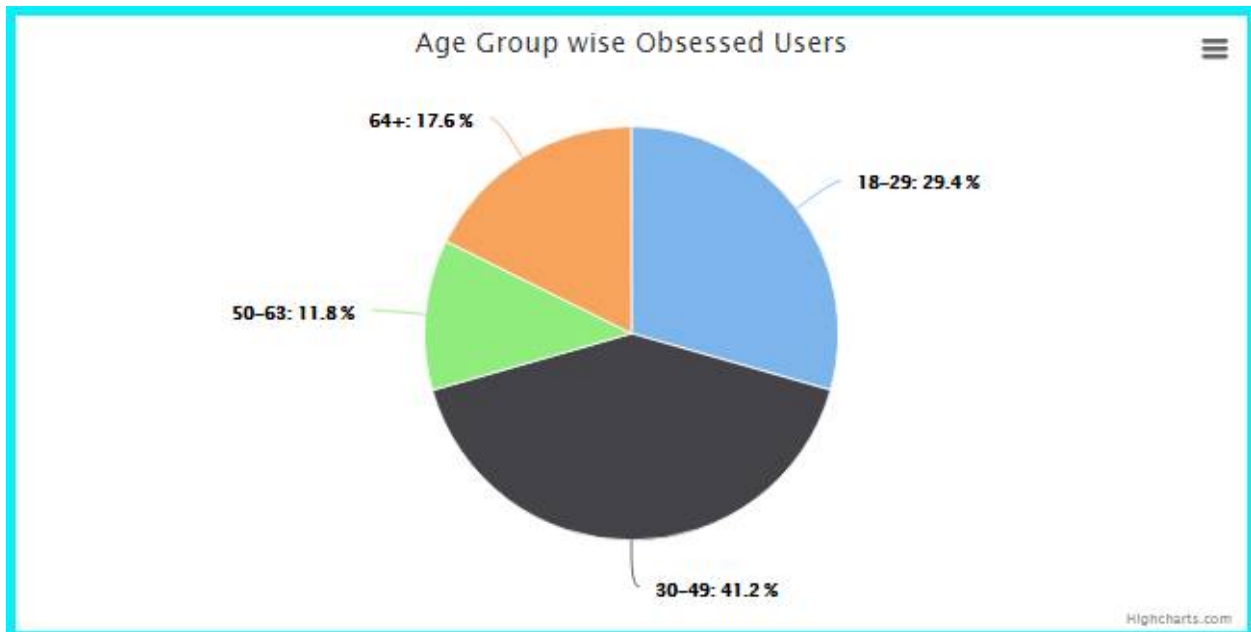## V.   RESULT AND ANALYSIS

Graph:
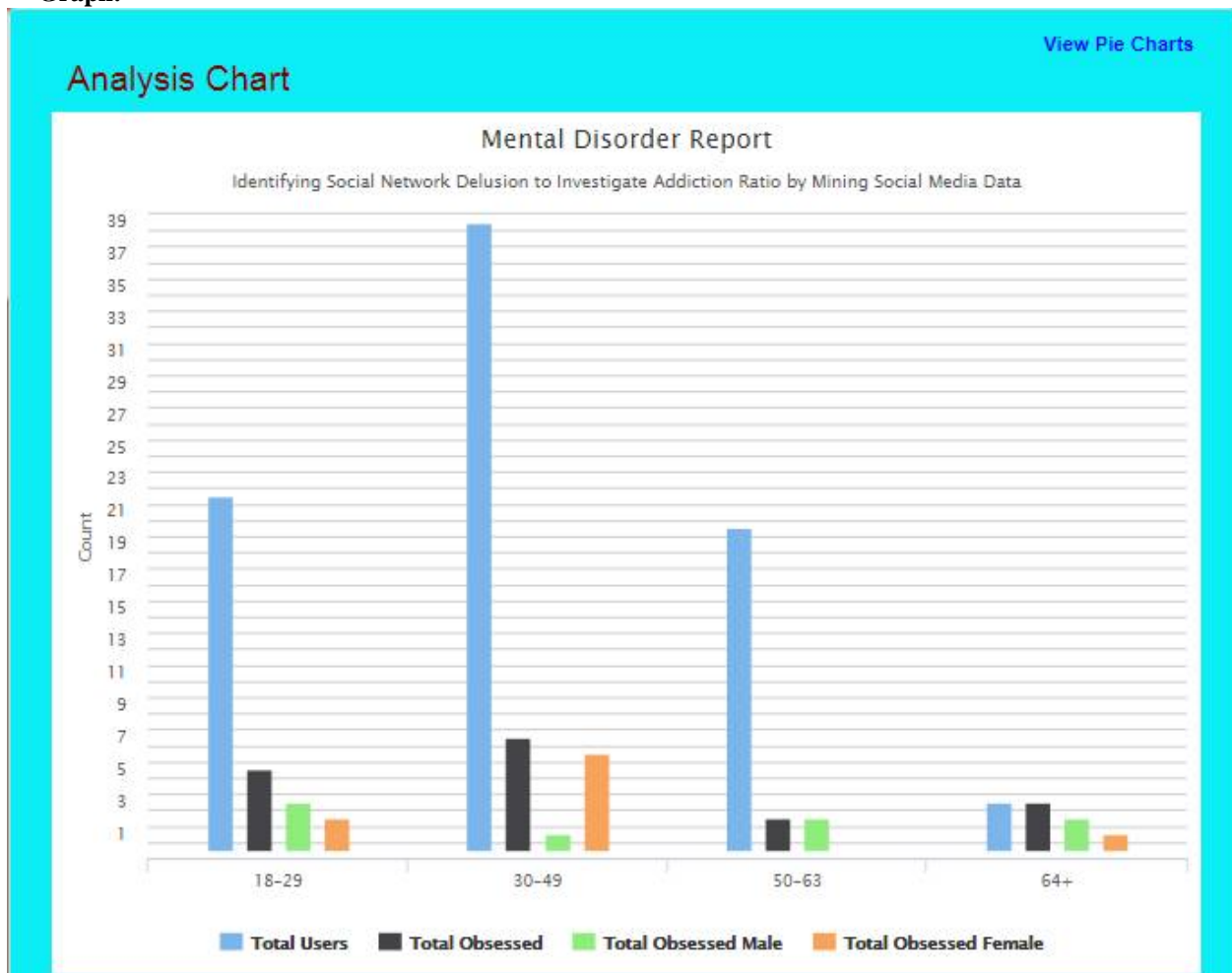
Fig. Age Wise Classification

The above Fig. shows the age wise classification. The X-axis contains the age groups and Y-axis represents the total user Count.

Table:

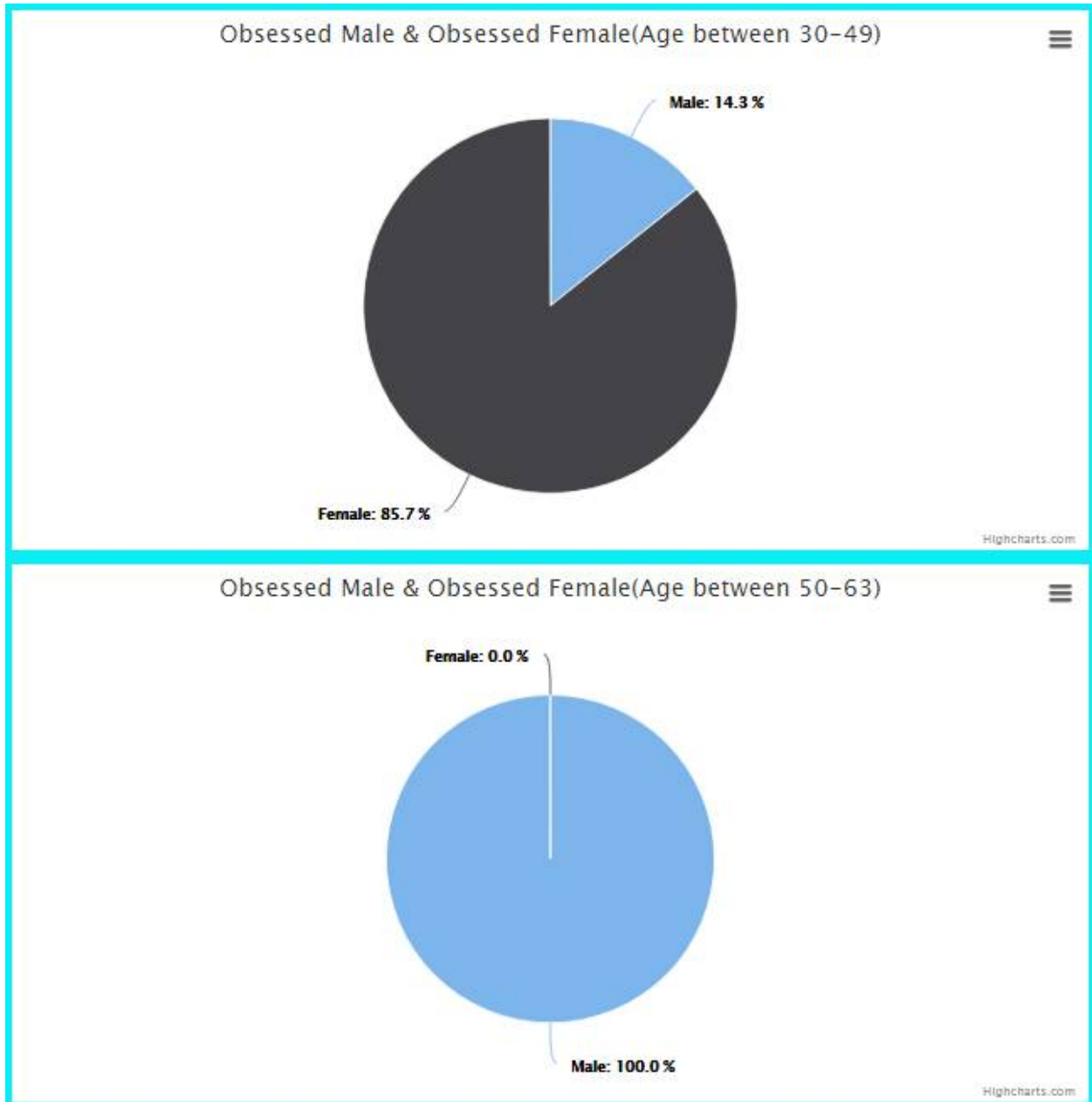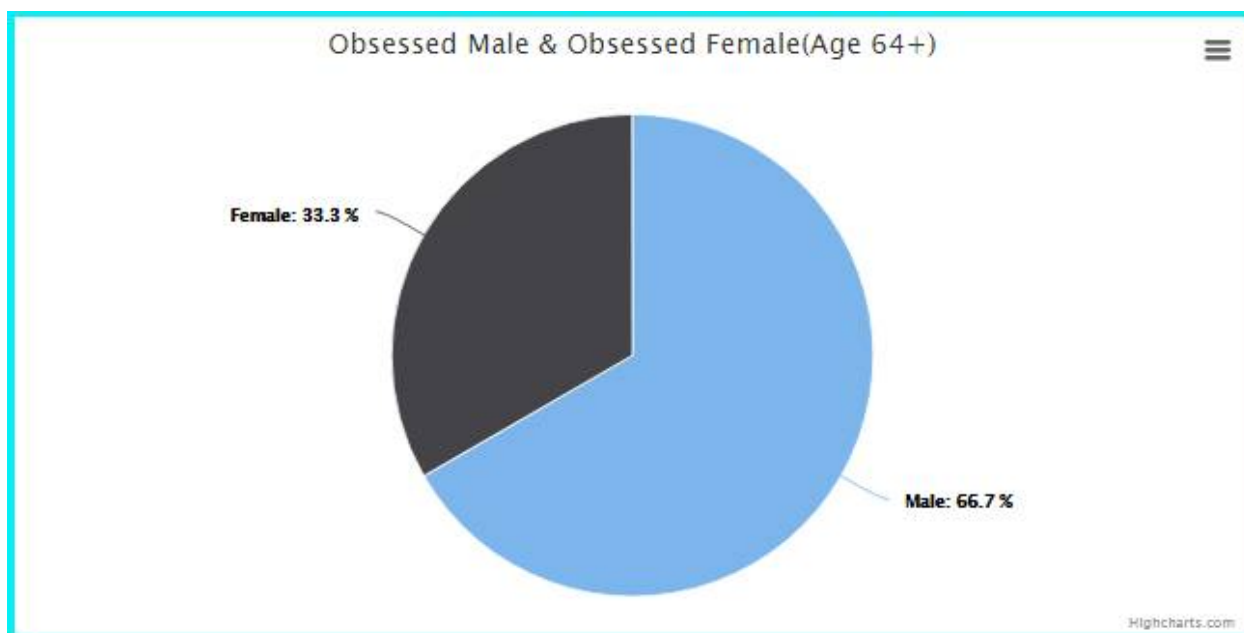## Age wise Result Classification

Age Category	Total Users	Total Obsessed	Total Male	Total Obsessed Male	Male Obsessed Ratio	Total Female	Total Obsessed Female	Female Obsessed Ratio
Adolescent[18-29]	22	5	11	3	60.0	11	2	40.0
Young[30-49]	39	7	24	1	14.285714	15	6	85.71429
Middle Aged[50-63]	20	2	8	2	100.0	12	0	0.0
Elderly[64+]	3	3	2	2	66.666664	1	1	33.333332
Total	84	17	45	8	60.23809	39	9	39.761906

Table: Age Wise Result Classification

V. CONCLUSION

We try to automatically identify potential users online with SNMD. We propose a SNMDD framework that explores various features of an OSN's data records for SNMD detection. This work represents a collaborative effort between computer scientists and mental health researchers to address the emerging problems in the SNMD.Our main contributions in this paper are as follows,

1. We use multisourcing to collect analysis of the characteristics to predict the SND case with the additional 'feeling score' function that explains the user's relationship with other people to increase accuracy.
2. The SND prediction results are used for the main purpose of this document, which is the analysis of the dependency relationship from social networks comparing the different users of the items provided by SND to find a solution to reduce the growing number of users. SND cases.

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