A comprehensive study on Mental Health Problems caused by Online Social Networks.

R Vidhya[1], Nysa P Ginu[2], Rishma Mitra Dhar[3]
{vidhyar@srmist.edu.in[1], nysapginu111@gmail.com[2], rishmadhar45@gmail.com[3]}

School of Computing, SRM Institute of Science and Technology, Kattankulathur, Chennai, 603203 Tamil Nadu, India.[1,2,3]

Abstract. With the explosive rise in the development and popularization of social networking apps, Online Social Networks (OSNs) have now become a cornerstone of everyone's daily lives. Although OSNs tend to broaden the capacity of their users to increase social interactions, they may actually reduce users' real-world person-to-person dialogue. This decrease in the actual interaction can cause many mental health problems like Nomophobia, Phubbing, etc. In this paper, we try to learn about all the efforts made in this field to detect these mental health disorders. We review various literature available regarding the Mental Health Problems caused by Online Social networks and the methods used to detect them using Data Mining. These research works have utilized Regression Techniques, Support Vector Machine, Naive Bayes, etc to predict the outcomes. We further investigate their pre-processing, feature extraction, and classification processes throughout this paper.

Keywords: Mental Health, Online Social Networks, Data Mining.

1 Introduction

In the modern world where technology is expanding in an unprecedented way making our lives easier and coining new terms like "A global village" to describe the world which is brought together by the internet or other communication mediums. But as a coin has two sides, with this ease comes an ever-increasing issue of mental health which was not a major problem in yesteryears. The exponential rise in social networking adulation has led to troublesome use.

Studies point out that there could be heavy consumption, depression, isolation, and a myriad of other adverse ramifications of these psychiatric illnesses. These signs are essential components of diagnostic criteria which, resulting in delayed medical interventions, are typically passively observed today. Symptoms include (not limited to) excessive use of social networking sites or applications, typically characterized by loss of time perception or disregard of simple drives, and detachment when computer apps are unavailable. Today, the recognition of these possible mental disorders often passively lies in the hands of supervisors such as parents or educators. However, as there are only a few notable physical risk factors, medical or psychological services are not actively pursued by patients. Therefore, only when their symptoms become serious can patients seek therapeutic intervention.

This paper explores various research works and conference papers to expand our knowledge about the topics surrounding it and also the help that data mining and machine learning can

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provide to it. The technology and models relating to the detection and classification are further discussed. Our main aim is to understand the concepts which are implemented in the research works and gather the required information out of this topic.

2 Review of Literature

We looked up some of the studies done in order to explain the various models used in the prediction, identification, and classification of mental health issues triggered by online social networking sites.

Logistic Regression was used to understand the connection between suicidality and Internet addiction and behaviors in Taiwanese young adults. 9510 adolescent students chosen in Taiwan, with the help of the stratified random sampling strategy, were surveyed by I-Hsuan Lin et al [1]. Their proposal was to use the Chen Internet Addiction Scale to track the internet interactions of the participating students and assess their internet addiction, and then use logistic regression to moderate the impact of demographic attributes, parental support, depression, and self-esteem in order to figure out the correlation between suicidal thoughts and internet compulsion and actions. This research has shown that young adults with internet compulsion are more prone to having suicidal thoughts and actions and various types of internet behaviors often have different suicidal connections. Like online games, chatting, etc elevate the chances of having suicidal ideations while watching online news decreases it. The study had some drawbacks, such as the cross-sectional study design could not validate the causative link between suicidal behavior and internet addiction. Besides, the suicide assessment was based only on what the participants' reported.

Young Min Baek et al. [2] tested the effects of the usage of Social Media Platforms on the psychological health of its users'. Concerning subjective isolation, mutual trust, and SNS addictions, this psychological well-being was measured. They used the Korean national representative survey data to test this. To evaluate the psychological well-being of the users, they used the UCLA loneliness scale, Rotter's interpersonal trust scale, and the Korean Internet addiction scale - all updated and shortened for the SNS scope in Korea. On two forms of Social Media association as well as seven statistical controls, the outcome of the three parameters was regressed. This study distinguished reciprocal relationships from unidirectional ones. It also showed that greater dependence on parasocial SNS relationships is positively linked to isolation and mistrust, which are negatively related to dependence on social relationships. This also indicates that it is simplistic and impractical to take a homogenous view of the consequences of SNSs. This research did not have a psychological state of mediation between reliance on SNS interactions and psychological well-being measures and failed to implement causal terms.

Dhivya Karmegam et al.[3] discussed the practicality of using data obtained from SNS for psychological well-being monitoring as well as the methods used during disasters to deduce that. The Natural Language Processing methods were used for retrieving features in SOCIALmetrics and EMOTIVEmetrics. Moreover, the Multinomial Naive Bayes model was used to classify emotions from texts, and the Support Vector Machine was used to classify sentiments. The study had a few shortcomings. The first is that the entire population is not reflected by the information collected from social media. Secondly, only a sample of tweets was collected due to the rules of Twitter API. Thirdly, the possibility that the place where the disaster happened and the person who tweeted have no connection cannot be ruled out.

A study that concentrated on understanding the different methodologies, ML algorithms, data outlets of Online Social Networks, and types of languages used to identify psychological health in Social Network Apps was presented by Rohizah Abd Rahman et al. [4]. It could be seen that the majority of the studies used Machine Learning Algorithms followed by questionnaires as the methods. Out of all the Machine learning, Naive Bayes, Linear Regression, Support Vector Machine, Random Forest, Decision Tree, Deep Neural Networks were the used machine learning algorithms out of which a vast majority used Support Vector Machine for mental health prediction. It was seen that most studies used the Twitter API as a type of data source and English as the medium used for the prediction of mental health. It was concluded that it has great potential for early mental health identification. The extraction of data from OSNs was difficult due to the account privacy policy enforced by most of the OSNs. This limited the available data for the research.

Thilagavathi P et al.[5] proposed a method for defining the mental stress states of consumers from their social network data on a weekly basis, using the content of tweets and their social interaction. To train the model, they employed Sentiment Analysis. Using real-world social media evidence, they analyzed the connection between psychological stress states and social engagement behaviors.

Quan Guo et al. [6] examined the issue of feature learning at the element and aggressive topic (AS) level for cross-media social data. They implemented CAE to study uniform modality-invariant attributes and suggested phases of At and PT to exploit large samples of cross-media data and train CAE to work on cross-modality correlation in social aspect of cross-media. Furthermore, they used CCAE, which is centered on the CNN system together with the social AS management CAE filters. The learned AS level features and local connection patches in CNN were found to be much less sensitive to outliers. It had a set of drawbacks which included abnormal data, empirical raw features, and unreliable labeling.

Huijie Lin et al.[7] suggested a method for automatically detecting stress using cross-media data from microblogs. To draw up the issue, they created a three-level architecture. Firstly, they rummaged through tweets to get a bunch of low-level characteristics. Then, using psychological and artistic theories, they created middle-level representations. Ultimately, a Deep Sparse Neural Network was developed to understand the stress types that integrate the cross-media properties. For stress detection, this framework was found to be very feasible and effective. This suggested approach can be used to identify psychological stress from virtual communities automatically. The downside was that it was not possible to fully examine the social correlations of psychological stress.

Chun-Hao Chang et al. [8] proposed a data gathering system for gathering patient and non-patient datasets called Subconscious Crowdsourcing. To train classifiers to diagnose mental illnesses, they developed their own linguistic and behavioral characteristics. They collected data from Twitter REST API and gathered the self-reported users. Three groups were then explicitly created for these users: Patient, Expert and Non-related. For pre-processing the data, Sentiment Analysis and Emotion Classifier are applied. Using TF-IDF, LIWC, and PLF, feature extraction is carried out. They selected the Random Forest Classifier quantitatively to be the primary learning model. They found that to achieve reasonable results in the data collection process, a fusion of physical and automated work is required. The immediate drawback of this is that the tweet language chosen is limited to only English and followers are only limited to the self-reported ones i.e. a vast majority of the undetected ones are still left out.

Budhaditya Saha et al.[9] demonstrated that the mental state and involvement of groups related to mental health can potentially be captured by the linguistic characteristics and subjects discussed among online communities. The topics discussed using Bayesian LDA were extracted and the top 50 topics discussed were chosen. With the subject characteristics as the input and the twelve classes as results, they trained the model and then used the LIWC characteristics as the input and 12 interest categories as outputs, and then eventually merged the topic characteristics and LIWC characteristics into one feature set and repeated the procedure. The model's effectiveness against Single-Task Logistic Regression (STL) and Multi-Task Learning System has been assessed (MTL). Both the compared models were outperformed by the proposed model. This demonstrated the value of networking sites and virtual audiences with an interest in depression in the advanced diagnosis and tracking of mental-health-related issues.

Adrian B. R. Shatte et al.[10] extracted machine learning literature and mental health Big Data applications. For publications on the above-mentioned scope, they examined 8 health and information technology research databases. Data on the application of mental health, ML methodology, form of data, and results of the study were collected. With four major application domains, 300 papers were described - identification & diagnosis, prognosis, care & assistance, public welfare, and study & clinical management. The study was found to focus primarily on the identification and projection of psychological health disorders, including depression, Alzheimer's disease, and schizophrenia. In clinical and scientific procedures and produce fresh perspectives into mental health and well-being, ML has shown promise. It had a few limitations. First was some relevant articles may have been missed due to the restrictions in the search methods. Secondly, the effectiveness of ML techniques was not examined for each mental health application.

A research to determine the link between the use of social networking sites and mental health among adolescents has been carried out by Chloe Berryman et al. [11]. A questionnaire was submitted by 471 undergraduate students. The results associated with overall mental health symptoms (BSI), thoughts of suicide, social distress, isolation, and anxiety were all subjected to distinct regression studies. It was inferred that variables from online networking sites were weak determinants of negative effects. An exception to that, which marginally predicted depression and suicidal feelings, maybe Vaguebooking. Time people spend online and the value of social media was not a predictor of any outcome. It was discovered that, in terms of mental health, how people use networking sites is much more important than how much hours they spend on it.

3 Result

After reading so many great works done in this field, we have accumulated knowledge regarding the mental health issues caused by online social media networks. We were able to understand the importance of such models and their application in the real world.

3.1 General Architecture of Mental Health Prediction

Several methods for mental health prediction in OSN have been used in various research studies. According to the researcher, this general architecture will be a common step in implementation for future studies in mental health prediction. Social network analysis, keyword-based data acquisition, data pre-processing, feature collection, machine learning algorithm-based data classification, evaluation, and early mental health detection are all part of the common structure for mental health prediction. The steps corresponding to the input-process-output model of information systems are depicted in Figure 1.

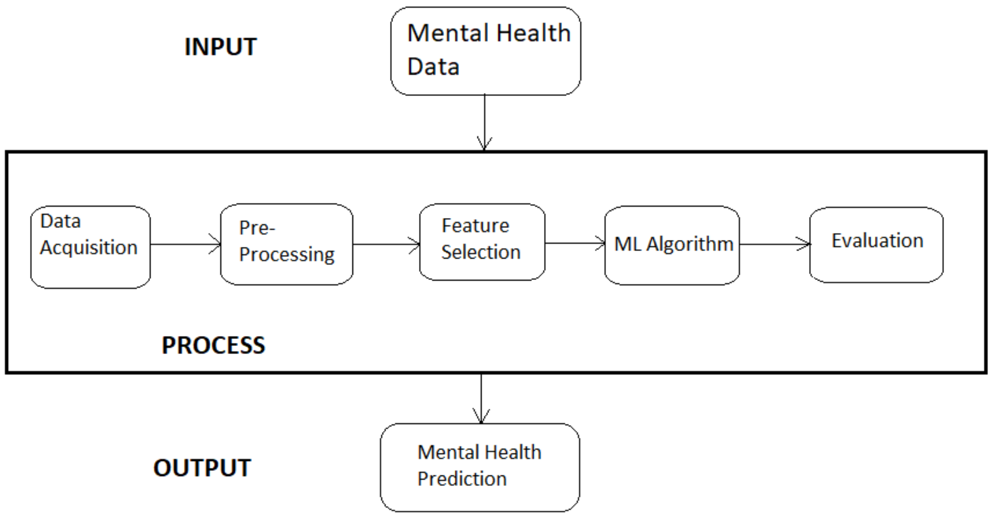

Fig. 1. Common Structure of Mental Health Prediction.

From the studies reviewed above, it could be seen that the Input Mental Health Data was taken from majorly two sources, namely, Questionnaires and Online Social Network APIs (Such as Twitter, Weibo, etc.) with the latter being a more popular choice than the former. After which, for the method, a few steps were introduced, such as keyword-based data acquisition. Before moving on to the feature selection step, it must be pre-processed to eliminate outliers. As a final stage, the data is modeled using a machine learning technique.

3.2 Analysis of Methods used in the Prediction of Mental Health

Table 1. Methods used in the prediction and detection of Mental Health.

Study	Author	Year	Method			
			Machine Learning Algorithm	**Hybrid Algorithm**	**New Method**	**Natural Language Processing**
[1]	I-Hsuan Lin	2014		√		
[2]	Young Min Baek	2013			√	
[3]	Dhivya Karmegam	2020	√	√		√
[4]	Rohizah Abd Rahman	2018	√	√	√	√
[5]	Thilagavathi. P	2018				√
[6]	Quan Guo	2016	√		√	√
[7]	Huijie Lin	2014	√		√	
[8]	Chun-Hao Chang	2016		√		√
[9]	Budhaditya Saha	2016	√		√	
[11]	Chloe Berryman	2018	√	√	√	

Table 1 lists research that has been conducted using various techniques for detecting mental illness. Most of these studies are aimed at highlighting different machine learning algorithms in order to demonstrate a superior technique [1], [3], [4], [6]-[9], [11]. Some researchers used Hybrid Algorithm for prediction [1], [3], [4], [8], [11], while many have created a new method altogether with the help of machine learning algorithms [4], [6], [7], [9], [11]. Natural Language Process also gave very promising results [3]-[6], [8].

4 Conclusion

From the above works, it can be concluded that Mental Health problems caused by social media can be predicted using the data available through their APIs efficiently. This can help in early detection which in turn results in early clinical intervention. A spectrum of different machine learning algorithms was seen that had good accuracies but still had some room left for improvement. For future work, we propose to develop a Social Network Mental Disorder Detection Framework using various machine learning models and validate it using the 10-Fold Cross-Validation to evaluate the precision and recall of each model.

References

[1] **Journal article**: I-Hsuan Lin, Chih-Hung Ko, Yu-Ping Chang, Tai-Ling Liua, Peng-Wei Wang, Huang-Chi Lin, Mei-Feng Huang, Yi-Chun Yeh, Wen-Jiun Chouf, Cheng-Fang Yen. The association between suicidality and Internet Addiction and activities in Taiwanese adolescents. Comprehensive Psychiatry. 2014; 55(3):504-510

[2] **Journal article**: Young Min Baek, Young Bae, Hyunmi Jang. Social and Parasocial Relationships on Social Network Sites and Their Differential Relationship with Users' Psychological Well-being. Cyberpsychology, Behaviour and Social Networking. 2013; 16(7):512-7.

[3] **Journal article**: Dhivya Karmegam, Thilagavathi Ramamoorthy, Bagavandas Mappillairajan. A Systematic Review of Techniques Employed for Determining Mental Health Using Social Media in Psychological Surveillance During Disasters. Disaster Med Public Health Prep. 2020; 14(2):265-272.

[4] **Journal article**: Rohizah Abd Rahman, Khairuddin Omar, Shahrul Azman Mohd Noah, Mohd Shahrul Nizam Mohd Danuri. A Survey on Mental Health Detection in Online Social Network. IJASEIT. 2018; 8(4-2):1431.

[5] **Journal article**: Thilagavathi. P, Suresh Kumar. A, Pushkala K, Yamini. P. Detecting Stress Based on Social Interactions in Social Network. IJERT. 2018; 6(8):page numbers

[6] **Journal article**: Quan Guo, Jia Jia, Guangyao Shen, Lei Zhanga, Lianhong Cai, Zhang Y. Learning robust uniform features for cross-media social data by using cross autoencoders. Knowledge-Based Systems. 2016; 102:64-75.

[7] **Conference proceedings paper**: Huijie Lin. Psychological Stress Detection from Cross-Media Microblog Data using Deep Sparse Neural Network. Proceedings of the *2014 IEEE International Conference on Multimedia and Expo (ICME)*; 14-18 July 2014, Chengdu, China. Place of publication: IEEE; 2014. p. 1-6.

[8] **Conference proceedings paper**: Chun-Hao Chang. Subconscious Crowdsourcing: A Feasible Data Collection Mechanism for Mental Disorder Detection on Social Media. Proceedings of *2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*; 18-21 Aug. 2016; San Francisco, CA, USA. Place of publication: IEEE; 2016. p. 374-379.

[9] **Journal article**: Budhaditya Saha, Thin Nguyen, Dinh Phung, Svetha Venkatesh. A Framework for Classifying Online Mental Health Related Communities with an Interest in Depression. IEEE J Biomed Health Inform. 2016; 20(4): 1008-15.

[10] **Journal article**: Adrian B. R. Shatte, Delyse M. Hutchinson, Samantha J. Teague. Machine learning in mental health: a scoping review of methods and applications. Psychological Medicine. 2019; 49(9):1426-1448.

[11] **Journal article**: Chloe Berryman, Christopher J. Ferguson, Charles Negy. Social Media Use and Mental Health among Young Adults. Psychiatr Q. 2018; 89(2):307-314.