

DETECTION OF MENTAL HEALTH USING SOCIAL MEDIA: REVIEW¹B. Lalithadevi, ²Dhruvraj Singh, ³Ritik Raj, ⁴Anant Sinha¹ Assistant Professor, SRM Institute of Science and Technology, Chennai, India^{2,3,4} SRM Institute of Science and Technology, Chennai, India

Abstract-Detection of mental illnesses and their correlation with social media usage has gained traction in recent years. The availability of symptoms associated with mental illnesses on Facebook, Twitter, Instagram and other online platforms has long been established. In this paper recent studies that aimed to predict mental illness using social media are reviewed. Some of the serious (loopholes) such as the lack of a cyber psychological approach, and the limitedness of variables considered to find mentally sick individuals have been addressed.

I. INTRODUCTION

Increasing rates of social media usage and the strong tendency of these platforms to reflect upon users' mental and social health status can be leveraged to find and help individuals with currently under-diagnosed conditions such as depression, anxiety, PTSD etc. These symptoms become detectable online even before patients receive their diagnosis[1]. Various methods have been proposed and used to detect mental health issues such as identifying markers of depression in Instagram photos[2], using twitter data to forecast mental illness[1]

II. DATA SOURCES

Data can be collected from a large variety of sources. Some studies such as the one authored by Andrew Reece, Andrew Reagen, Katharina Lix, Peter Dodds, Christopher Danforth and Ellen Langer titled "Forecasting the onset and course of mental illness with Twitter data"[1] used twitter data to forecast the onset of mental illness. Others such as the one titled "Instagram photos reveal predictive markers of depression"[2] claim to have found correlations between the Instagram posts of users and depression. The paper titled "Fine-Grained Sentiment Analysis of Social Media with Emotion Sensing"[3] uses text messages as the primary source of data for its analytics engine which can classify text messages into sentiment categories (positive, negative, neutral and mixed)

III. VARIABLE SOURCES

Predictive models need to be built for automated analysis of social media. These models need to find relations across a diverse set of variables. Some of these variables include the frequency of using certain words and the time of posts.

IV. DATA COLLECTION

Collection of users' social media data must be performed responsibly and with their express consent. The paper "Forecasting the onset and course of mental illness with Twitter data"[1] used Amazon's Mechanical Turk (MTurk), a crowd-work platform. This study used survey responses as well as users' previous Twitter data. However it only contains data from people living in the United States. While this restriction was added to ensure better quality data (stating that "MTurk data collected from outside the United States are generally of poorer quality") the data clearly failed to represent a diverse audience. Moreover since the data collected was of users who worked on MTurk it would have a greater number of participants from similar socio-economic backgrounds. The paper titled "Social Media and Health-Related Information: Surveys Development and Validation"[4] used four self administered surveys to gather data. Another paper aimed at extracting fine grained emotions from informal messages (M.Sykora et al 2013) divided messages into segments on the basis of punctuation. Using O'Connor et al's (2010) emotional matching rules the researchers were able to use a tweaked version of Potts (2011) [6] regex based tokeniser.

V. ASSESMENT CRITERIA

Several strategies have been utilised for acquiring web based life data with the related information about the clients' psychological condition. Volunteers are either enrolled to take a short overview and offer their Facebook or Twitter data, or information is gathered from existing open online sources. These sources incorporate hunting open Tweets down watchwords to recognise (and acquire all Tweets from) clients who have shared their emotional wellness condition, client dialect on psychological instability related discussions, or through gathering open Tweets that say dysfunctional behaviour catchphrases for explanation. The strategies that utilise open data have the preferred standpoint that considerably bigger examples can, on a basic level, be gathered quicker and more inexpensively than through the organisation of studies, however review based assessment for the most part gives a higher level of legitimacy.

We first contrast contemplates that endeavour with recognise rationally sick clients from neutotypical controls.

VI. SIZE AND STRUCTURE OF SOCIAL NETWORK AND SOCIAL NETWORKING SITES

The extent of the SNS kinship system and its relationship with depression and anxiety has likewise yielded mixed findings. Fernandez et al and Weidmann and Levinson[7] discovered very important negative connection among social anxiety and the number of friends, and Park et al [8], Park et al[9], Rae and Lonborg[10], and Rosen[11] et al discovered this equivalent relationship directions when examining depression. Rae and Lonborg [10] discovered that a more vital number of companions on Facebook was connected with higher general beneficial outcome and life fulfilment, when use of the site was convinced by taking care of associations. Whatever is left of the examinations displayed no noteworthy associations.

Specific friend categories have also been examined. Tsai et al [12] discovered that clients tolerating the companion demand of an ex-accomplice have a tendency to have more elevated amounts of characteristic nervousness and misery seriousness than the individuals who dismiss the demand. Mota-Pereira[13] demonstrates that for people with treatment-safe Major Depressive Disorder (MDD) presently taking antidepressants, the utilisation of Facebook over a 3-month time span fundamentally diminished depressive manifestations, contrasted and a no-Facebook control, and the expansion of a "therapist as a companion" demonstrated essentially quicker change in depressive side effects. Such discoveries propose an expansive gainful effect of SNS utilise when treatment is expanded by companions from a client's system.

VII. PREDICTION METHODS

Mechanised examination of internet based life is refined by building prescient models, which utilise 'highlights,' or factors that have been removed from online life information. For instance, usually utilised highlights incorporate clients' dialect encoded as frequencies of each word, time of posts, and different factors. Highlights are then regarded as autonomous factors in a calculation (e. g. Linear Regression [4] with built in variable selection [5], or Support Vector Machines (SVM)) [6] to anticipate the reliant variable of a result of intrigue (e.g. clients' psychological wellness). Prescient models are prepared, utilising a calculation, on part of the information and after that are assessed on the other part to abstain from overfitting — a procedure called cross-validation. The forecast exhibitions are then revealed as one of a few conceivable measurements.

VII. SOCIAL SUPPORT AND SOCIAL COMPARISON

Social help plays a blended and differed job inside the SNS condition. Studies recommend that people with higher depressive side effects see their SNS companion arranges as furnishing them with less social help than they really get [14] and that SNS social help looking for may fuel discouraged inclination for a few people [15]. Impression of help seems, by all accounts, to could really compare to genuine help. Crosswise over 2 thinks about, Park et al [14] demonstrated that in the all inclusive community more noteworthy depressive manifestations were related with more genuine social help on announcements that contained negative feeling. Interestingly, saw bolster was adversely connected with wretchedness, and higher depressive manifestations were related with a more prominent inconsistency among real and saw social help. Frison and Eggermont [15] also found that discouraged disposition expanded in young people when social help was looked for on Facebook however saw to not happen. Other research has likewise exhibited the defensive job of apparent social help in improving the effect of SNS peer exploitation on sadness [16].

Social examination of any heading (upward, nondirectional, or descending) may likewise in a roundabout way intercede the relationship between the time spent on Facebook and dejection. Crosswise over 2 thinks about, as people invest more energy in Facebook they participate in more regular adverse (upward) and nondirectional social correlation and more negative (descending) social examination, which thusly identifies with more depressive side effects [17]. Jealousy possibly assumes a dangerous job in uninvolved Facebook utilise (eg, review or perusing profiles; see Table 1). Where Facebook envy is high, more noteworthy recurrence of detached Facebook utilise is related with more prominent depressive indications, and where Facebook envy is low (or not present), uninvolved Facebook utilise is related with diminished depressive side effects [18]. Without a doubt, examination into Instagram (a photograph sharing SNS) [19] has demonstrated that more positive (descending) social correlations are related with diminished depressive indications. Informal community arrangement, also, may direct the connection between successive Instagram utilise and increments in depressive side effects by means of social correlation [19].

IX. PREDICTION BASED ON SELF-DECLARED MENTAL HEALTH STATUS

Various investigations utilise freely open information. 'Selfdeclared' psychological sickness finding on Twitter (distinguished through explanations, for example, 'I was determined to have melancholy today') is one such wellspring of openly accessible information. We survey seven investigations of this kind. Encouraging investigations of this kind, a Computational Linguistics and Clinical Psychology (CLPsych) workshop was begun in 2014 to cultivate collaboration between clinical analysts and PC researchers. 'Shared assignments' were intended to investigate and contrast distinctive arrangements with a similar expectation issue on similar informational collection.

On a common dataset like the 2015 CLPsych workshop, the forecast of uneasiness was enhanced by considering notwithstanding 10 comorbid conditions [24]. Different examinations have utilised mental lexicons (Linguistic Inquiry and Word Count; LIWC) [20] to portray contrasts between psychological instability conditions [21], with some achievement. On the equivalent dataset, Preotiuc-Pietro et al. [22] saw that assessing the period of clients satisfactorily recognised clients who had self-proclaimed a PTSD conclusion, and that the dialect prescient of misery and PTSD had vast cover with the dialect prescient of identity. This recommends clients with specific identity or statistic profiles shared their emotional wellness finding on Twitter, and along these lines that the aftereffects of these investigations (for the most part, expectation correctnesses) may not sum up to different wellsprings of self-portraying content.

X. ETHICAL QUESTIONS

The achievability of internet based life based appraisal of dysfunctional behaviour brings up various moral issues. Protection is a progressing concern. Managers and insurance agencies, for instance, may utilise these against the interests of those torment from psychological instability. As dysfunctional behaviours convey social shame and may cause segregation, information security and possession systems are expected to guarantee clients are not hurt [23]. Barely any clients understand the measure of psychological well-being connected data that can be gathered from their computerised follows. Straightforwardness about which wellbeing markers are inferred by whom and for what reason is basic. From a psychological well-being point of view, clear rules on commanded announcing are required. There are open inquiries around the effect of misclassifications, and how inferred emotional well-being pointers can be dependably coordinated into frameworks of consideration [23]. Dialogs around these issues ought to incorporate clinicians, PC researchers, legal advisors, ethicists, strategy producers, and people from various financial and social foundations who experience the ill effects of dysfunction behaviour.

XI. CONCLUSION

Social media can prove to be an extremely handy tool in detecting and preventing mental health issues in a quick, effective and economic way. While many have attempted this approach a unified solution to the problems faced is required. The data that is collected for research purposes must be from more diverse sources for effective conclusions to be drawn.

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