Symptomatic Diagnosis and Prognosis of Psychiatric Disorders through Personal Gadgets

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ABSTRACT

Mental disorder has been shrouded as a stigma and disregarded as a secondary issue to physical health. It has become a major contributor to morbidity, disability and at times, fatality.
Through our research, we show that the data generated through our daily interaction with technology has consistent patterns to identify symptoms in prodromal phase of degrading mental health. We propose a methodological data driven system that will help to raise an early alarm on the onset of symptoms of potential psychiatric disorders. The system collects the user's data from different human-computer interfaces to create a fine-grain electronic health portfolio, which can assist doctors in differential diagnosis as well as prognosis.

CCS CONCEPTS

•**Applied computing** → **Consumer health; Health care information systems;** •**Human-centered computing** → *HCI theory, concepts and models; User interface management systems;* •**Computing**

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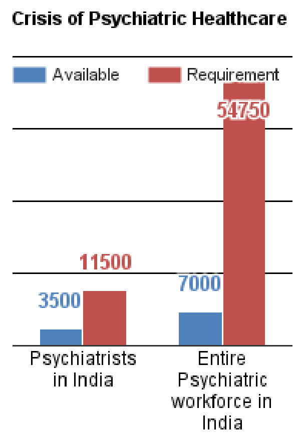

Figure 1: According to the Ministry of Health and Family welfare (India), there are just 3500 psychiatrists for a total of 1.3 billion people. The entire workforce comprising of clinical psychiatrists, psychologists, psychiatric social workers and psychiatric nurses is nearly 7000 while the actual requirement is around 54750 [10].

Sidebar 1: Research Questions

How to utilize the rapidly evolving, immersive ecosystem of human computer interaction to detect and understand some potential symptoms of psychiatric disorders?

How should we structure a framework which is scalable, secure and generalised enough for identifying prodromal symptoms of various mental disorders?

methodologies → *Probabilistic reasoning;* •**Information systems** → Collaborative and social computing systems and tools; Data streaming; Web mining;

KEYWORDS

Mental Health, Data Collection and Processing, Information interfaces, Design Tools and Techniques

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INTRODUCTION

Mental health is an integral and essential component of an individual's health. We studied the current scenario of mental healthcare. In U.S., one in every five adults (i.e. 43.8 million or 18.5%) experiences mental illness in a given year as per National Institute of Mental health [3]. The situation is significantly worse in developing countries (see Figure 1).

International standard classification tools exist, namely Diagnostic and Statistical Manual of Mental Disorders (DSM-5) by the American Psychiatric Association (APA) and International Statistical Classification of Diseases and Related Health Problems (ICD-10) by the World Health Organization (WHO) for diagnosis of psychiatric disorders. Current practice of diagnoses is often largely subjective rather than being evidence based [11]. To support the practice of evidence based psychiatry, we need exhaustive data about the patients, which may indicate prodromal phase or patterns of symptoms.

In our approach, we have first, identified different interfaces where data is generated upon interaction of humans with technology. Second, we developed a scalable Methodological framework for Emotional Journal (MeEJ). The data from different sources is combined to analyse the history of emotions, behavior and experiences. The model learns patterns in data and analyses whether it is different from that of a neurotically normal person. If it does differ, this will raise an 'early alarm' about onset of symptoms of potential psychiatric disorder(s).

RELATED WORK

Research has focused upon automating the process of psychiatric diagnosis over the decades [7]. The process typically followed by practitioners involves an interview, known as a mental status examination, where evaluations are made of appearance, behavior, self-reported symptoms, mental health history, and current life circumstances (see Figure 2). Some hospitals utilize the assistance of clinical decision support systems [2]. Speech-based psychosis detection [1], emotion and disposition recognition [12] and a variety of computational psychiatry approaches have been studied. Computational tools have been used to identify the first episode of psychotic disorder (FEP) [5]. These techniques

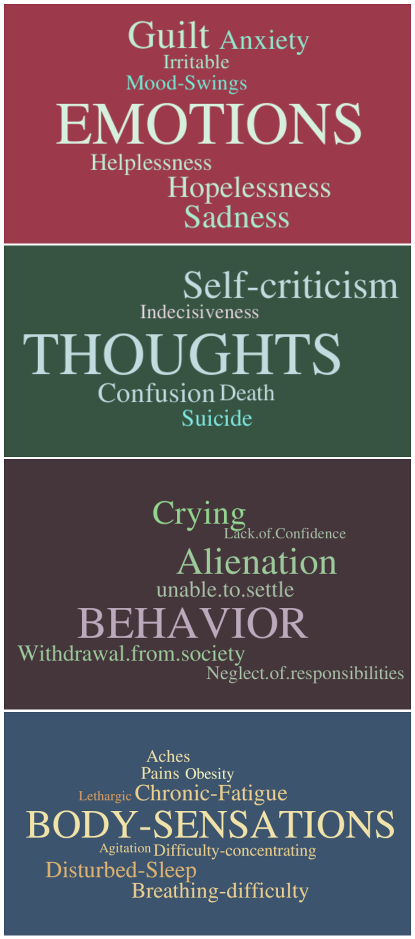

Figure 2: WordClouds depicting how our (a)Emotions (b)Thoughts (c)Behavior and (d)Physical Body Sensations, reveal early symptoms of psychotic disorders

remain relatively confined to highly specialised clinics and hospitals, and are not yet inaccessible for majority of the population.

Accuracy of classification becomes critical to ensure reliability of the automated data driven diagnosis versus a human psychiatric practitioner. Statistical studies such as [9] require sufficient dataset about symptoms to build a robust classification model(s). Web search logs are being explored to identify behavioral patterns which may indicate health conditions of the users [8]. Cognitive healthcare systems like IBM Watson (http://www.ibm.com/watson/health/) are current revolutionary technologies which provide holistic view of a person's health.

MOTIVATION

Delay in detection of psychotic disorder has been a dominant concern in mental healthcare. Psychiatric problems are often neglected, primarily due to lack of awareness, social stigmas and inaccessibility to mental care services. Some of the challenges observed are as follows:

Acknowledge the Problem. A person suffering from psychiatric disorder needs to understand that he/she requires help. Delay in realising and communicating about psychiatric symptoms compounds the problem.

Inaccessibility of Quality Care. Huge number of untreated cases reflect how inaccessible quality psychiatric services are for a majority cases. Those who are able to seek mental health care, often report that "less time spent with doctor" and "heavy medication with side-effects".

Reporting Symptoms and Asking Questions. It is often difficult to share detailed history of all the symptoms for appropriate diagnosis. Social stigmas associated with mental disorders often cause reluctance in visiting a psychiatrist.

Tracking Recovery. Often when patients start to recover, they tend to give up routine-check visits to their doctor. This may cause significantly higher risk of recurrence of the disorder.

Discovering Symptomatic Patterns. Disorders often overlap and have correlation, such as in psychiatry and diabetes , or in schizophrenia and bipolar disorders. Data driven psychiatric support system can help to identify such correlations and customise medication.

DATA DRIVEN ARCHITECTURE

We propose a system to collect patient data to support doctor consultation. Since the development of this system is a crucial step that will shape the interactions between patient-system-doctor(s), we have focussed upon the design for scalable data transmission through the system. We also discuss HCI concerns, the advantages, the limitations and future scope of the system.

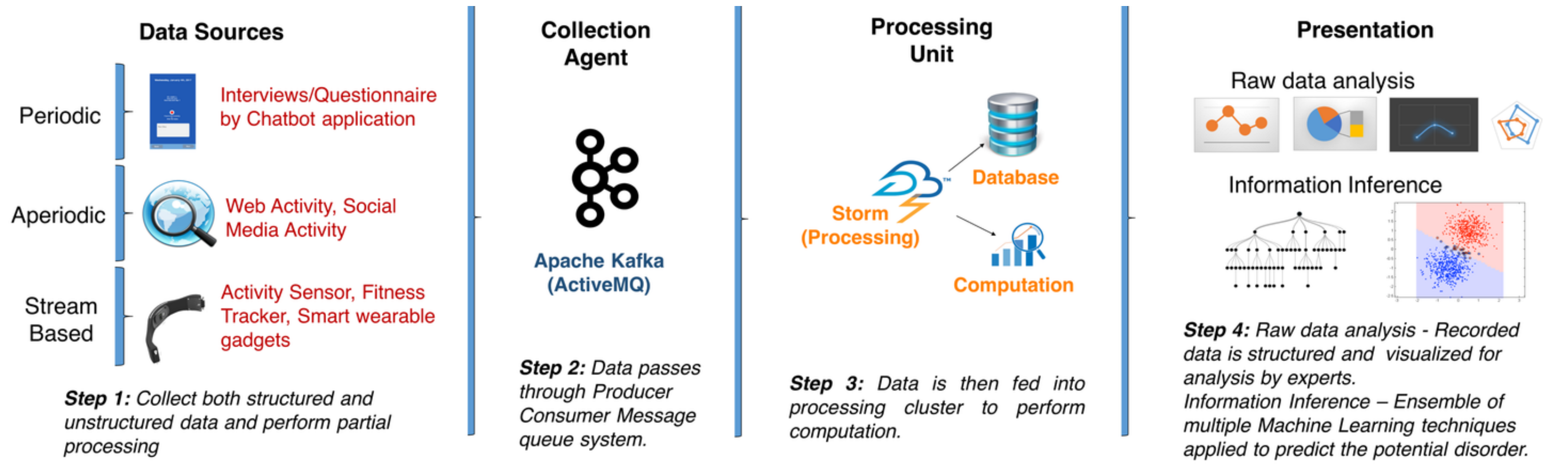

Figure 3: Methodological framework for symptom diagnosis from personal data sources

Sidebar 2: Categories of Data Sources

Periodic Questionnaires by a chat-bot (see in Figure 4) are used to regularly record subjective experiences of a person as speech or text. Many existing virtual assistant applications can also be utilized.
Aperiodic These are dependent upon the amount of time that a user may want to spend on it. Some of the rich examples are web and social media activity.
Stream based These include activity sensors, fitness trackers, and smart wearable gadgets. These are specialised devices to track vital signs of their user in real-time, like heart-rate, sleep cycle, body movements and composition.

Data Sources

Today, both structured and unstructured data has become pivotal in uncovering patterns for better insights on disease/disorder diagnosis. In order to understand day-to-day thoughts, emotions, behaviors and expressions, we have broadly identified three categories of data sources (see Figure 3 Step 1 and Sidebar 2).

Data Collection

Data is cleaned and processed partially on the local devices like mobiles or local servers, and then collected to be sent to centralised cloud servers (see Figure 3 Step 2). In order to ensure scalability and security of the model, we propose a subscription based approach for adding and managing provenance. To channel the data, we use a producer-consumer message queue system, Apache Kafka. It has a capacity to handle around 100,000 requests per second. This is managed by Apache Zookeeper to ensure load balance and fault tolerance.

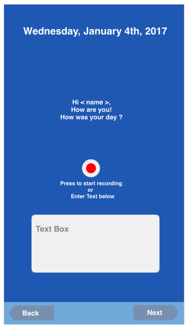

Figure 4: Prototype for Chatbot, a mobile application for recording emotions and experiences via Interviews/Questionnaire.

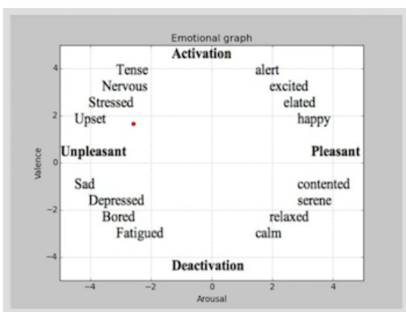

Figure 5: Russell circumplex model. Plot generated for the following test data: *"I am afraid of what others will think of me. I made a horrible mistake. I should never had trusted him."*

Storage and Processing

In the previous section, we discussed about edge level processing and passing the data into message queue. This data is fed into processing cluster in private authenticated cloud storage (see in Figure 3 Step 3). We developed the cluster on top of Apache Storm as it provides linear scalability and is self-maintained by Apache Zookeeper.

Learning and Analysis

Once we model the data, it is used to learn and analyse about patterns. We generate two kinds of reports, firstly, raw data analysis and then, information inferences (see Figure **??** Step 4).

Raw data analysis. The data recorded from a variety of sources is learned and visualised. The experts may study and understand certain patterns to predict prognosis.

Information Inference. The sampled data about the user can indicate several symptoms specific to psychiatric disorders. Data about a particular symptom that has been collected from a variety of sources compensates for some missing values and enhances the confidence level of overall prediction. Several machine and deep learning techniques are applied to the data and then used for Ensemble Learning to aid prediction of potential psychiatric disorder based upon symptoms.

Since a basic understanding through emotion and disposition analysis is required, we have worked upon a proof-of-concept based upon Russell's Circumplex model. We utilized the Affective Norms for English Words (ANEW) dataset available for popular words with values for valence and arousal for males and females separately, to train a simple mood classifier as in [6]. For a given a speech or text input, we can visualise the emotional state of the user on a plot. A test case for emotion classification and visualization (see Figure 5).

CONCLUSION

We propose to make healthcare "knowledge rich" by harnessing the data available around us and applying ensemble learning for computational psychiatry to assist diagnosis and prognosis. The key contributions of our work:

- Identification of data sources from day-to-day life to assist evidence-driven symptomatic diagnosis of psychiatric disorders
- Design of methodological framework for processing the collected data.

Sidebar 3: Advantages

User Control and Freedom Subscription-based model to decide which data sources to allow for diagnostic assessment.

Visibility of Recorded Symptoms Maintain digital health history, visualise data patterns and show it to doctors in case of clinical assessment and, lawyers in case of medical evidence requirement.

Aesthetic and Minimalist Design Symptoms recorded in current natural setting, through speech input and background processes in most cases.

Consistency and Feedback Nuanced 24x7 multi-scale time series analysis and subtle feedback through short diagnostic questions.

Sidebar 4: Disadvantages

Erroneous Recordings Security breaches on social media and erroneous wearable devices can add noise to the recorded data. Sometimes, web activity may not be indicative of the user's state (for example, certain web activity could be for research purposes).

Acceptability It is important on how the psychiatric workforce explores the acceptability of such a system and its results.

Accessibility Contrary to the assumption of regular personal use of smart phones, Internet search, social media or wearable gadgets, many people in developing nations are without these amenities. Some degree of assistance can be provided to them through short targeted diagnostic questions on SMS service.

Discussion

The proposed model targets the data sources which the users are already sharing with on-line advertisers and e-commerce businesses. The design of the system focusses on how users can be enabled to record their own health symptoms and at their discretion.

With more smart devices being developed and connected to Internet-of-Things, personal informatics is changing very rapidly. But people often abandon self-tracking tools [4] and design of such data collection tools needs to consider the psychology of the users very carefully. Specialised devices would perhaps be designed and prescribed by doctors, especially when they need to track certain symptoms in large number of patients while in natural routine.[1] In cases of False Positive inferences, it needs to be carefully examined by an expert. There is a need for a diagnostic system that comprises of both, tools and psychiatric expertise, to utilize this data effectively.

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