mDB: Monitoring Dysfunctional Behaviors for Patients with Bipolar Disorder

Kushan Choksi, Sanjay Nagaraj, Ryan Thielke, and Shan Lin*

***Abstract*—Bipolar Disorder is a common mental illness affecting millions of people worldwide. It is most commonly presented as periods of depressive lows and manic highs, both of which can be extremely uncomfortable and distressing for the individual affected. Existing bipolar patient monitoring relies on subjective self-reports, which are inaccurate and biased. Moreover, many symptoms are not easily recognized or are ignored by the patient, resulting in a loss of information and misleading reports. To achieve reliable daily monitoring of dysfunctional behaviors, we propose a system mDB that uses a mobile phone to monitor a variety of symptomatic activities, in the hopes of improving care and quality of life for these individuals.**

I. Introduction

It is estimated that 7 million people in the United States suffer from bipolar disorder according to National Institute of Health [1]. Bipolar Affected Disorder (BPAD) typically presents itself as two distinct periods that cycle over time. These include depression and mania. Depression is described as a persistent low mood, sadness, or feelings of emptiness or hopelessness. It may be accompanied by a range of external symptoms including changes in sleep, loss of interest, agitation, restlessness, and social isolation to name a few. Mania, while also intrusive and disruptive, is on the opposite end of the spectrum, and is characterized by elevated mood. It can cause increases in energy levels leading to a decreased need for sleep, increased rate of speech, pacing, recklessness, and impulsiveness[1].

While mania can be distressing, it is the depression part that is most concerning, as this can be extremely painful for the individual, and brings along with it an increased risk of suicide. Additionally, patients with BPAD have a significantly higher risk of suicide over other mental disorders [2]. Often, mania is followed by a deep phase of depression, as the body can no longer sustain the high energy levels present in mania.

Treatment plans for patients with BPAD primarily rely on patient therapist/doctor communication , which is sometimes insufficient in effectively managing illness. Firstly, the patient may not be able to recognize some of the symptoms in themselves, or may ignore them. This is especially true during manic episodes, where patients may be extremely resistant to accepting they are still ill since they may feel healthy. They may cease to take prescribed medication, and end up spiraling worse, often requiring hospitalization. Whereas during period of depression, patients may intentionally avoid talking about certain aspects during appointments, being resistant to accepting help.

Given the fact that current technological aids for patients are rather limited, patient monitoring usually relies on the patient's subjective and voluntary self-report. Certain apps exist to log mood on a day-by-day basis, in an attempt to predict when the next mood swing will happen [3]. But these swings may not be perfectly cyclic, and the impact of such system is minimal since it does not incorporate any physical manifestations of the illness. Wearable systems, such as MONARCA [4] and PSYCHE [5], employ wearable sensors to gathered data from patients affected by mood disorders and predict pre-manic episode warnings. However, wearable sensors are not available for most patients in practice. Also, this system usually employs fixed baseline values for various predictions, which may or may not hold true for all patients.

We propose a mobile phone based system mDB that can continuously collect dysfunctional physiological and activity information about a patient, to better gain insight into the affect on an individual, so that the proper intervention and treatment steps can be taken. mDB creates quantifiable reports for better doctor-patient communication that includes periods of restlessness, sleeplessness and visualisation of activity level trends and sentiment. It also computes personalized baseline for recognition based on historical data collected from smartphone sensors. Mobile phone based monitoring and graphical reports of symptoms lead to more efficient treatment and diagnosis of BPAD [6]. mDB is deployed with 3 patients for 30 days to test its effectiveness, experimental results show that mDB detected valuable symptoms of patients in a reliable and timely manner.

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II. METHODOLOGY

An end-to-end architectural block diagram of mDB is given in Fig.1. mDB collects data from sensors in a patient's mobile and wearable devices, which includes motion data, location, transportation mode, acoustic data, and text data. These data-sets are analyzed in real time on cloud to identify dysfunctional behaviors of the patient. The machine learning based analysis includes feature extraction, level categorisation, feature to symptom transformation, and report generation. This report gives the doctor a detailed analysis on the features which would help them perform just-in-time intervention with a patient. Our technical design deals with data acquisition and storage, feature analysis and visualisation followed by a detailed graphical report generation to reduce communication information loss between a patient and his doctor, which in turn can vouch for more efficient treatment as hinted by literature.

This work apprehends most of the behavioral symptoms in terms of matrices and tangible values using sensor data accumulated by any general smart phone. It also includes detailed information on a variety of external and behavioral habits, described below. For example, if a patient is sleeping less than usual, or outside of the general population baseline, it is not the system's intent to classify this behavior as "manic". Instead, it show up as abnormal on the report, at which point the doctors inquire about this behavior with the patient. So the goal here is to highlight any anomaly which differentiate the report parameters from the baseline extracted from the database. The report summarize the symptoms of BPAD as functions of sleep pattern, activity level, text sentiment analysis and driving quality of the user as explained in the later sections.

Firstly, proposed methodology deals with data acquisition and database management for feature extraction. Secondly, it is necessary to extract baselines for the key areas previously discussed from the historical database. This would include both baseline data for the general population, as well as rolling baseline for the patient. From here, an anomaly detection algorithm is applied to determine deviations from the norm. These are highlighted on the doctor's report, and used as talking points during therapy sessions. It is noted that the anomaly detection is aimed to help doctor understand patient behavior, it does not include detection for illness prediction. However, level categorisation of feature can certainly give a clear indication of improvement/deterioration of BPAD symptom and would help in easy quantification of severity of the same.

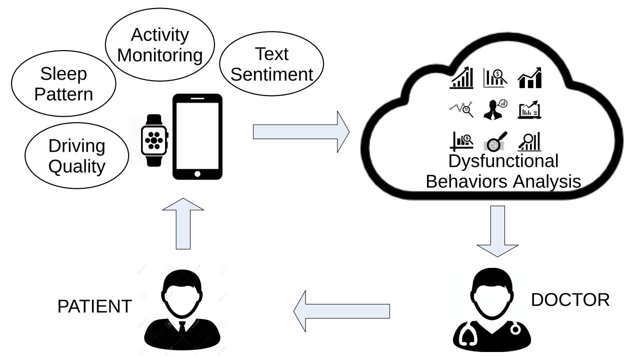

Fig. 1: mDB Architecture

III. DESIGN AND EVALUATION

A. Data acquisition

mDB is implemented on Android and Firebase cloud platform. Data was gathered from 3 users over a span of 30 days as part of a class project, which is allowed according to the Standard Operating Procedures at Stony Brook University.

Data collected span across GPS Data, Acceleration Data, Speed Data and Text Data using APIs for the Accelerometer and GPS Modules. The sampling frequency of the accelerometer acquisition was 100 Hz, however it was down sampled based on application as discussed in the later section. The current GPS location was updated when the location changed, rather than during discrete time intervals. Data collection was restricted keeping in mind privacy of user and sensor installed in very basic smart phone devices.

Sleep Pattern: Data was collected by placing the mobile phone in sleep mode, on the bed next to the three users for 30 days. Sleep quality was assessed by using the acceleration peaks induced by movements of sleep.

Activity Level: Activity level of the person was measured by monitoring a combination of time spent at a place and the number of steps taken by the person during a day. With the help of GPS we collected the time each user spent per day at the places designated as Home, Work and Recreational Centre(Gym). The accelerometer based step counter gave an approximation of the number of steps the person travelled.

Text Sentiment Analysis: Sentiment Analysis was carried out by analyzing the texts sent out by a person along with analysis of their social media posts. This was subject to privacy permissions granted by the user.

Driving Quality: Driving Quality was measured by recording the acceleration and speed data while driving cars. The phone was placed in the docking station and the readings recorded were stored on cloud.

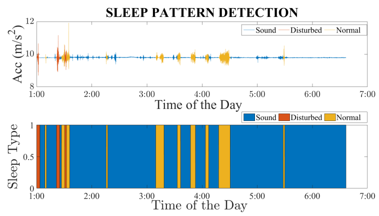

Fig. 2: Sleep level detection : Disturbed, Normal and Sound Sleep

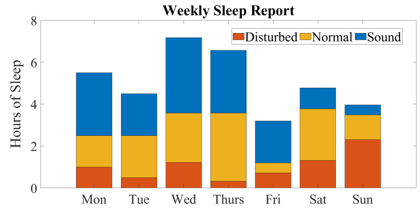

Fig. 3: Weekly sleep analysis for patient with mental disorder.

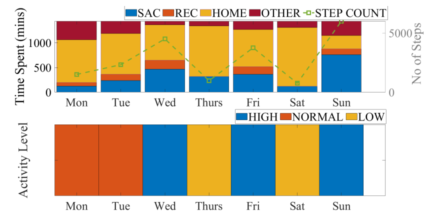

Fig. 4: Location and activity detection

B. Selection of feature for analyzing patient disorder

Features have been selected in such a way that it may be very useful and highly correlated to the symptom mentioned in motivation section. The feature selection for mental disorder symptom analysis are as listed below:

Sleep Pattern: Biomarkers of depressive episodes include heightened fragmentation of rapid eye movement (REM) sleep, reduced REM latency, increased REM density, and a greater percentage of awakenings, while biomarkers of manic episodes include reduced REM latency, greater percentage of stage I sleep [7]. The quality of sleep was hence quantified/categorised into sound, disturbed and normal sleep based on these biomarkers. This feature was devised using sleep mode data and acceleration data set. This has a direct correlation to health of a patient suffering with BPAD [8].

Activity Level: Activity levels have proven to have a mixed effect on patients having BPAD. Based on the type of BPAD (Type I or Type II) a person is suffering from the doctor might need to monitor the activity of the person accordingly to determine level of activity a person must indulge in.[9]. In order to help the doctors monitor the activity levels of a person we have given a graphical representation of the users activity data. This feature was devised using GPS data, step counter implementation data and location priority. Where, location data was further categorized into Home, Work, Gym and others. Furthermore, the others data is analysed to check if user goes to restricted areas like for example casino's, Bars which show signs of addiction to gambling or alcoholism in a person. Step counter and location analysis together are used to graphically depict the activity level.

Driving Quality: Quality or nature of indicates the kind of mood the person is in and also indicates intention to harm others[10]. Hence, this feature was devised using acceleration data and speed data [11], which were further categorised into hard braking, hard acceleration and normal zone. This data is used to derive driving level labels i.e, Rash and normal driving.

Text Sentiment Analysis: Based on observations made by researchers a person suffering from BPAD exhibits suicidal risks[10]. One of the prominent ways of understanding a person's mood is based on analysing his text messages or social media posts. Thereby a real person's text data was used for analysing the sentiment and generating a report.

C. Anomaly or severity level categorisation for the features

It is imperative to understand behavior of the user with a certain degree of detail to relate it with mental disorder symbol. It is also equally important to see if there are and unusual improvement or deterioration in user behavior in a specific feature related to specific symptom. Hence, this paper is focused on highlighting the state of features and abnormalities observed in various features as discussed in the following subsections.

Sleep level detection: This application generates sleep quality reports based on total sleeping hours and quality of sleep. The idea is to categorise sleep data per day into three categories as sound, normal and disturbed. Data pre-processing was managed using Savitzky-Golay digital filter to eradicate noisy signals for proper peak based sleep detection [12]. Furthermore, proposed model uses frequency and amplitude of peak and peak impact as features for sleep detection. Peak impact is used to ensure that sleep detection considers only significant peaks using unsupervised algorithm [13]. It shall be noted that the methodology avoided magnitude of peak as a feature to ensure that sleep detection is accurate irrespective of placement of smart phone. The analysis obtained can be observed using Fig. 2. The red markers indicates disturbed sleep, the yellow marker indicate normal sleep and blue marker indicate sound sleep. Frequency of red and yellow marks suggest sleeplessness symptoms of chronic disorder according to a doctor patient interview. Chronic disorder is common in patients with anxiety, depression, BPAD, and attention deficit hyperactivity disorder (ADHD) [14]. Here it is evident that the proposed methodology can effectively categorize sleep based on frequency and magnitude of perturbation. However, the treatment team

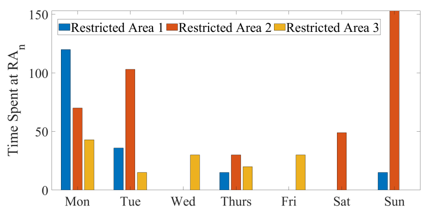

Fig. 5: Weekly report on time spent(in minutes) at restricted areas

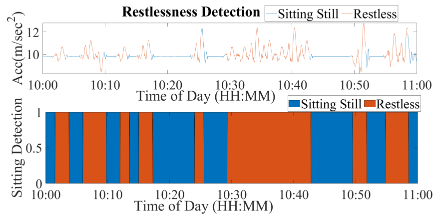

Fig. 6: Restlessness detection

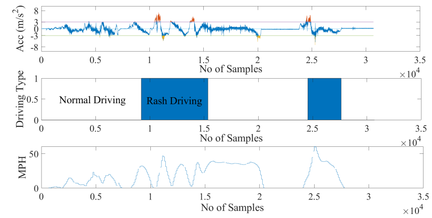

Fig. 7: Driving Analysis

would be keen at observing weekly or monthly report of patient, a representative report collected from one of our patients is shown in Fig. 3. It shall be noted that report less insomniac episodes suggested by patient suffering through BPAD leave ambiguity in treatment [14]. Such reports can easily quantification sleeplessness and lack of sound sleep in patient.

Activity levels: Mental health has close association with patient's activity level and routine. The proposed methodology takes that argument into consideration and analyse the time spent at various location using the GPS data set along side the step counter. Here the location were divided into home, work, recreational and other, where other is further analyzed to check if user is spending his/her time at restricted area associated by the treatment team as shown in Fig. 5. According to a patient suffering from mental BPAD restricted areas suggested are bars, gambling clubs, mourning ceremonies, etc but not limited to the same. Recent findings from descriptive and social epidemiology suggest different restricted zones for patient with various levels and types of mental disorder [15].Our proposed methodology analysis the location and step count data to derive activity labels for a day as shown in Fig. 4. High activity: $>$ 4000 steps or spends more than 60 minutes at Gym, Normal Activity: $<$ 4000 steps spends at least 30 minutes in gym, Low activity: $<$ 2000 steps or spends no time at Gym. This thresholds as specific to US adults as suggested in [16]. The activity levels were assigned by help of a classification algorithm [17].

$$J_{th} = norm(th_1) + norm(th_2) \tag{1}$$

The algorithm uses eq 1 to derive a soft joint threshold from threshold for time spent at GYM and steps per day which were decided empirically. From Fig. 8 we can see that our algorithm classifies a person who spends more time in the Gym or travels more than on foot in a particular day is classified to have higher activity levels, whereas a person who sits at home or work without much movement is predicted to have low activity levels. This color based report of the The monthly report of patient can be given using a pie chart that may help the treatment team to understand if there is any paradigm shift in the patient behavior in Fig. 8.

Quality of Driving: The driving behavior in general have huge correlation with the mental state of a person [18]. Manic episodes may cause reckless, aggressive driving behaviors [19]. The driving analysis uses acceleration data and the sleep mode data collected using Android studio. The driving analysis was accomplished based on hard acceleration and hard deceleration as shown in the Fig. 7. The red peaks indicate sudden harsh acceleration and yellow peaks indicate sudden braking/retardation. A peak is categorised as harsh acceleration based on the magnitude of the peak/time with respect to the normalised acceleration of the period of time for which the data. A higher number of peaks on a regular basis show the doctor that the person is having episodes of mood swings. The proposed methodology uses a time window based analysis to identify a driving behavior into rash or normal driving based on the frequency of harsh acceleration and deceleration. The patient is required to toggle driving button to ON mode prior to driving.

Restlessness: It is non trivial to analyse if a user is restless or not due to ambiguity between perturbation due to noise, sleep and restlessness are very similar. Hence the proposed methodology devises a restlessness detection algorithm based on acceleration data, sleep mode and location data. The algorithm detects restlessness only when the user has sleep mode turned off and is not spending time at recreational center. Moreover, restless is defined based on magnitude and frequency of perturbation using unsupervised clustering similar to sleep pattern recognition as shown in Fig.6.

Sentiment analysis of user text messages: This paper includes the sentiment polarity based on Textblob as documented in [20]. TextBlob inherently uses Bayes classifier for text sentiment analysis. The Bayesian analysis helps the algorithm to derive text polarity and subjectivity. Polarity in sentiment analysis refers to identifying sentiment orientation in written or spoken language. Other types of

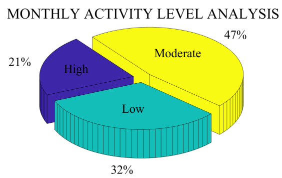

Fig. 8: Monthly Activity Analysis

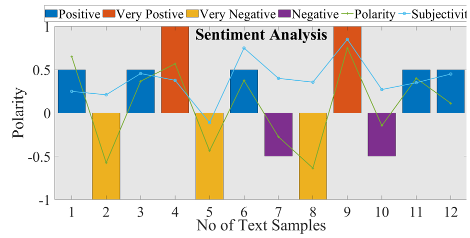

Fig. 9: Sentiment analysis for a day

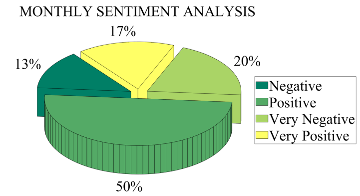

Fig. 10: Monthly sentiment analysis

sentiment analysis include fine-grained sentiment analysis which provides more precision in the level of polarity (e.g. very positive, positive, neutral, negative, and very negative) as adopted in the proposed methodology. Whereas, Subjectivity is when text is an explanatory article which must be analysed in context. The text analysis for a single of the user can be observed in Fig. 9. Moreover, the monthly analysis of sentiment analysis is shown in Fig. 10.

Battery Usage The app battery drainage was analysed on a 3700 mAh lithium ion battery. The app consumes an average 2.5% per hour and 11.6% per hour when running in the background and in the activity monitoring mode respectively. Battery consumption could be further improved by modifying sensor acquisition methods.

IV. Conclusion

The paper was focused on reducing the loss of information that is obligatory during vocal interaction between a patient and the doctor, by recording and analyzing patient behavior. Such continuous monitoring creates a near loss-less informative environment between the patient and the doctor, leading to better treatments. The contribution of the paper lies in continuous symptom monitoring, symptomatic feature selection, and anomaly detection complimented with a report generation for a patient and doctor usage.

Acknowledgment

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