Data source analysis in mood disorder research

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***Abstract*— Mood disorders have been a relevant topic for the last few years. Nowadays, there are projects in the mental health area which are supported by technological devices that improve the efficiency of treatments by effortlessly allowing the gathering of biological and psychological indicators from patients. One of the goals of this document is to describe the most common methods for collecting most of those indicators and to study which of them can be applied to the Bip4Cast project. The purpose of this article is to analyze the sources of information that have been used successfully in the study of emotional disorders as well as alternative sources of information from the monitoring of movement and sounds in the patient's environment. This article shows the results of the analysis of traditional information sources. The results show a lack of precision in the data on fundamental variables such as sleep quality and motor activity. Therefore, the study demonstrates the need to include new sources of information to increase the quality of the data before applying crisis prediction algorithms. The need to monitor the sleep and movement of patients in order to achieve a sufficient quality in the source data from the evolutionary analysis of patients is concluded.**

Keywords—bipolar disorder; mood disorder; data gathering; machine learning; data analysis.

I. Introduction

The quality of treatments in mood disorders has acquired a high attention for researchers in the mental health field. However, despite current efforts, there is still plenty of room for improvement. Many practicians agree that knowing how patients react to treatments in advance and predicting when their mood could vary significantly are two of the most important issues to solve in order to ensure the quality of new treatments.

The proposal of the Bip4Cast project is to keep using the current monitoring of personal sessions between patients and psychiatrists, but also to add new data sources and their analysis to improve the prediction of Bipolar Disorder crises in patients. The main idea is to get advantage of the new developments in data gathering, data cleaning, and Machine Learning to monitor a set of patients and make a new approach with these data. The patients are encouraged to follow certain methods for gathering psychological and biological indicators during a particular period of time. The goal is to analyze the data gathered in order to find some common patterns that could trigger a crisis. For the process of pattern detection, some Machine Learning tools and mathematical models are being used.

The goal of this document is to cover a discussion about some methods for gathering indicators and the feasibility of their usage in this project. Apart from this introduction, this document includes the following sections: section 2 presents the state of the art related research in mood changes and patient monitoring. In section 3, several methods for gathering psychological and biological parameters are described. Section 4 covers the preliminary analytics on the Bip4Cast data sets and, finally, section 5 includes the conclusions.

II. State of the Art

Several studies about Bipolar Disorder state that a relationship exists between the different behaviors of the patients before the occurrence of a crisis [1-2]. For example, during a manic or a depressive crisis, some of these studies agree that sleeping rates are very important indicators. Vocal features as well as the rate of speech are other important indicators and there are some studies stating that the pitch is lower in a depressed state [3]. Also, parameters like the time of exposure to dark or sunny places and the physical activity are considered.

In [4], the author introduces a mobile health system using several sensors for mood detection. In [5], the author presents a research that includes Machine Learning models in a mobile application in order to estimate the mood in depressive patients. However, no objective psychological or psychiatric markers are considered due to the recording of the data being done manually by patients. Furthermore, there is an interesting study which describes the use of electroencephalography for the gathering of brain signals. It also uses non-linear features like Higuchi's Fractal Dimension and Sample Entropy to feed different Machine Learning methods [6]. In [7], a mobile application is presented for supporting the treatments of patients with Bipolar Disorder. Its key is to compare objective and subjective data. It records objective data using some features given by mobile phones like accelerometers and phone call rates. This information is used for predicting trends in the mood of the patients. However, the focus of this application is to record subjective data using a self-reporting approach.

At the present time, there are some projects within the scope of mental health which have similar approaches and try to obtain certain markers from which a common pattern can be inferred to help with the treatments. One of these projects is PSYCHE [8], whose main idea is for the patients to use a special garment made of a proper material, of which the main goal is to collect parameters from the patient in his/her daily life. The outcomes of PSYCHE are positive. However, patients said that the main inconvenient was to use the same clothes all the time, which implicates a high discomfort for the patient and therefore its non-use. Another really interesting project is MONARCA [9]. It emphasizes the use of mobile phones for the electronical monitoring of patients. The number of parameters that can be obtained through the use of a mobile phone is really high, but nevertheless, none of them are physiological parameters. Furthermore, after 3 years of activity with this application, an analysis of some non-functional requirements for the treatment of patients with Bipolar Disorder concluded that, for new developments, some details have to be taken into consideration in order to improve the ease of use, e.g.: ensuring that the patients have a data plan for their 3G connection, the need for teaching the clinicians how to operate the system, and the overheating of the smart phone from the use of an application that requires both GPS and Bluetooth.

Since few years ago, Body Sensor Networks (BSN) have made an appearance, which are a branch of wireless sensor networks (WSNs) that conform one of the core technologies of IoT developments in the healthcare system [10]. Its purpose is to provide an integrated hardware and software platform which facilitates the future development of pervasive monitoring systems. BSN allow the monitoring of patients by using a collection of tiny-powered and lightweight wireless sensor nodes. These nodes are placed on the skin and sometimes integrated with different garments, so that the patient's health-related data can be collected and transferred to the healthcare staff in real time. However, the development of this new technology in healthcare applications without considering security makes patient privacy vulnerable. For this reason, several research projects are currently being carried out to try to cover this vulnerability [11].

III. Data Source Analysis

All the research that is currently being conducted suggests a wide variety of indicators for taking mood disorder treatments into account. The indicators themselves and the way in which they are collected are strongly related. In this section, several data sources for gathering those indicators are described. Depending on the indicator they gather or the type of device, they are classified into 6 groups as shown below.

1. Smart wristband/smart band. These devices include a set of sensors which measure daily activity by means of accelerometers. They create variables such as an activity tracker (resting, moving or sleeping), a pedometer (steps taken and distance traveled), the calories burned, a sleep monitor (awake, slight and deep sleeping), the heart rate and the blood oxygen level. The most relevant variable measured from this type of device is the sleep indicator. Almost all researchers agree that sleep quality is the best indicator in Bipolar Disorder treatments. The CHOICE [12] study states that lower levels of depression are correlated with improvements in insomnia treatments, and on the other hand, high levels of mania are correlated with less need for sleep. Furthermore, a pilot randomized controlled trial demonstrated that sleep disturbance appears to be an important pathway contributing to Bipolar Disorder [13]. These data can easily be gathered from popular apps. Fig. 1 (a) shows one of the monitors used in the Bip4Cast project.

Fig. 1. Two sleep monitors in Bip4Cast (a- Garmin Vivofit3; b- Sleep Cycle for iPhone)

2. Medical bands. They allow measuring more parameters because they usually include more hardware and better features like atmospheric pressure (barometer), GPS location and magnetometer. There is some research which links episodes to disturbances in circadian rhythms and lifestyle regularity. Those indicators can be collected through these devices using the activity tracker or gyroscope. Furthermore, this research suggests that methods for tracking behavior, nutrition, blood pressure and lipid profile as well as physical/social activity and sleep-awake routines may improve treatments. In the Bip4Cast project we are using GENEActif v.1.2 for a total of 25 patients, (see [14] for more details about their use in Bip4Cast).

3. Mobile Sensors. In this group, any other kind of sensors that can be worn by the user on any other part of the body is included, e.g. for wearing on the leg, ActivPAL is a kind of device used to investigate the correlation between physical behaviors and chronic disease [15]. For using as a necklace, LeafUrban is an option (there are some versions for wearing on the wrist or attached to the clothes). It is a device designed for women and what it makes different from other devices is the tracking of the menstrual cycle, the fertility and the breathing [16]. For wearing on the head, ELF Emmit is a headband that helps the user improve the state of both mind and body by using pulsed electromagnetic stimulation (PEMS) [17]. Relevant variables include skin and breath changes, electrocardiogram and respirogram data, stress level and menstrual cycle among others.

4. Sleep Activity Recording Devices. In this group, any device specialized in recording sounds and activities during sleep is included. There are hundreds of mobile applications that record sounds during sleep. One of the main objectives is to detect snoring, for which four of the most popular applications at the moment are SleepGenius, SleepCycle (see Fig. 1 (b)), SleepBot and SleepTime. However, there are other kinds of devices with different non-invasive designs, e.g. devices attached to the mattress which can track sounds as well as heart rate, breathing, movement, etc. The reason for using these methods is to improve sleeping conditions. Almost all of these methods have one parameter in common: "breathing", which allows the detection of snoring. Habitual snoring is a prevalent condition that is not only a marker for Obstructive Sleep Apnea (OSA) but can also lead to vascular risks [18]. Some researchers have found a relationship between OSA and Major Depressive Disorder/Bipolar Disorder.

5. Forms and Questionnaires. This group contains any method which uses a questionnaire or a form for the self-reporting of mood. In current literature, these methods were designed by psychiatrists and are presented as scales. There are several scales for detecting the risk of a euphoria episode outbreak: Altman Self-Rating Mania Scale (ASRM) [19], the Clinician-Administered Rating Scale for Mania (CARS-M), the Internal State Scale (ISS), the Self-Report Manic Inventory (SRMI), etc. For depression episodes, there are several scales, like the Patient Health Questionnaire (PHQ-9) [20]. All of them consist in questionnaires which can be performed by patients. This presents the opportunity of developing digital forms based on these patients in order to facilitate their use.

Scales for detecting the risk of euphoria or mania episodes, like the Young Mania Rating Scale (YMRS) and the Bech-Rafaelsen Mania Scale (MAS), or the Hamilton Depression Rating Scale (HDRS), which detects the risk of depression, are not included because they are performed by the clinician (however, for the scope of this project, these scales are included in normal monitoring sessions). All of these questionnaires collect variables from which it is possible to measure the presence and severity of mania, depression, affective, psychological and somatic symptoms. Fig. 2 shows the interface of an application developed for collecting these data. All the details about this work are in [21].

6. Mobile Apps / Time Consumption. This group includes mobile applications that support BPD treatments and/or record smart phone use. For the aim of this project, these mobile applications were classified into two subclasses: the first one, named Bipolar Disorder Apps (BPDA) in this document, includes any applications that have been developed for supporting the treatment itself, and the second one, named Time Consumption Apps (TCA) in this document, includes any application that is able to measure the time spent using a specific mobile application.

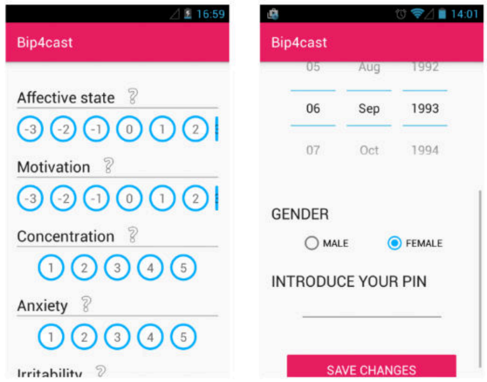

Fig. 2. First version of the app for collecting daily personal data

7. Conventional methods. Finally, patients are also being assessed periodically through interviews. This evaluation is done by psychiatrists in medical centers. For the patient, this does not imply any kind of alteration in the current treatment. However, the procedure will need the psychiatrist to send the collected data from those sessions to the data server. It is important to mention that in this phase, the Young Mania Rating Scale (YMRS) and the Hamilton Depression Rating Scale (HRDS) are included for detecting mania or depression episodes.

Also, psychiatrists can take advantage of these interviews for downloading the data recorded from wristbands and medical bands in order to later send them to a dedicated server (just in case these devices are not able to send the recorded data automatically).

IV. THE BIP4CAST PROJECT

Patients with Bipolar Disorder are characterized by a behavior which is difficult to predict. There is great deal of information which can be retrieved from biological, physiological and physical signals in order to detect episodes. Knowing which variables are correlated and which features or parameters are important is essential to build a model that will successfully predict the target of a study. The aim of this study is to investigate which features have the highest importance in health. In order to achieve this, Machine Learning algorithms and techniques are used for feature ranking.

The data used for this project is anonymized patient data gathered by psychiatrists at Clínica Nuestra Señora de la Paz in Madrid. All the data were available in an Excel file with different sheets. Even though 25 patients are already wearing a medical band (GENEActif 1.2) and we have developed an application for gathering their daily activity, for this study most of the data have been gathered in a supervised manner during medical appointments with four different patients that suffer from Bipolar Disorder. The goal for the future is that these data are both recorded by the psychiatrists in appointments and with the help of mobile applications. This way, the patients can actively participate in their own diagnosis. The data consist of 4 data sets: Episodes, which represents different episode periods in the patients (depression/mania) from a total of four patients; YMRS data set, which contains Young Mania Rating Scale [22] data (to assess mania symptoms) from a total of 48 days; HDRS data set, which contains Hamilton Depression Rating Scale [23] data (for depression), also from a total of 48 days; Interview data set, which contains 728 registers about physical and psychological items, the latter including variables like anxiety, irritability or concentration problems, and the former including more objective data, as could be the number of cigarettes smoked by the patient or the time in which the patient woke up or went to bed. The last data set used in the study is Interventions. It includes data about all the medical interventions that different doctors have had with the patients, in a total of 92 registers. For the gathering of data included in the Interview data set, a mobile application [21] has been developed, which patients can use daily to store quantitative data (number of cigarettes, menstruation, etc.) and qualitative data (feeling of stress, anxiety, etc.). In the project, we have also included studies with data from a medical bracelet (GENEActif 2.1 for 25 patients) and an application for recording night sounds. The data collected by these last two exercises will be included in subsequent studies.

The programming language used in this project is Python 2.7, which has a lot of libraries that make data cleaning and visualization less complicated, as well as applying Machine Learning algorithms. The environment used is Jupyter Notebook [24]. Scikit-learn [25] is the Machine Learning library of choice for this project because it includes preprocessing and cross-validation tools as well as all the known baseline Machine Learning algorithms. This project is shared in a public GitHub repository, which can be found at [26].

A. Data Cleaning

The first step of the project consisted in the data cleaning which included the gathering of the data that we would be working with. In order to gather the data, we exported each sheet, from the Excel file that was given to us by the hospital, to csv format. The initial Excel file was divided into five different sheets: Episodes, YMRS, HDRS, Interview Data Set (IDS) and Interventions. In order to export them to a format readable by Pandas [27], we saved each sheet as CSV UTF-8 in Microsoft Excel. Some other improvement was done in relation to data cleaning: filling the empty values, converting them from Float to Integer and data type revision.

B. Exploratory Data Analysis

After the data cleaning, we performed an Exploratory Data Analysis, in order to visualize how the data behaved. We used histograms, heatmaps and scatterplots in this part. For instance, the YMRS data set correlation heatmap showed that aggressiveness and verbal expression were correlated. This could mean that if the patient talks a lot (excessive speech rate), this behavior would probably be accompanied by excessive energy or hyperactivity (Disruptive-Aggressive Behavior). The scattterplot matrix from the YMRS data showed that hyperactivity and irritability have a similar distribution as well as a correlation between verbal expression and euphoria. The HDRS data set analysis showed a similar distribution between suicide and precocious insomnia (difficulty of sleep early in the night). The HDRS data set correlation heatmap showed a high correlation between depressed mood and work: the less a patient is willing to work or do other activities, the more depressed he or she will probably feel. At this stage of the research, the best data set regarding both size and accuracy was the Interview Data Set (IDS). During its analysis, we found a clear linear relationship between the variables mood and motivation. The Intervention data set presented a lack of correlation between the level of relief in a patient and the GAF (Global Assessment of Functioning). A good summary of all these results can be read at [26].

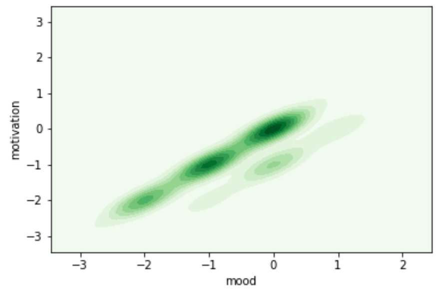

Fig. 3. 2D kernel density plot of *mood* and *motivation* in Interview data set

C. Data Combination

The goal of this phase was to find data set combinations that had enough data for the algorithms to process so that we could later see which data sets returned the highest accuracy. In order to get the combinations right, we defined a function that obtained the date of each entry and compared it with the different episodes of depression and mania in the Episode data set, which was the target of the prediction. For the entries or rows that were not recorded in the Episode data set, we assumed that the patient was in a euthymic state. This way, we got three possible states that a patient could be in: Depression (D), Mania (M) and Euthymic (N). For instance, with the HDRS and Episode combination we could see that when the patients had a depression episode, the value of depressed mood was much higher, almost always between 2 and 3, which meant that they either spontaneously reported feeling depressed or they communicated feeling depressed in a non-verbal way, judging by the rating items from the Hamilton Depression Rating Scale (HDRS). We could also see that when the patients were in a depression state (because of the predominance of green points on higher values of the work axis, where green represented patients in a state of depression), they started feeling loss of interest in activities they usually performed or there was a decrease in the time spent on work and other activities, which made perfect sense according to this rating scale.

D. Application of the Algorithms

The data sets on which we tested the algorithms were: YMRS (Young Mania Rating Scale data), HDRS (Hamilton Depression Rating Scale data), Interviews (interview data, IDS), Interventions (intervention data), YMRS-HDRS (combination of the YMRS and HDRS data) and Interviews-Interventions (combination of the Interview and Intervention data). Fig.4 shows the diagram of the process followed during this study.

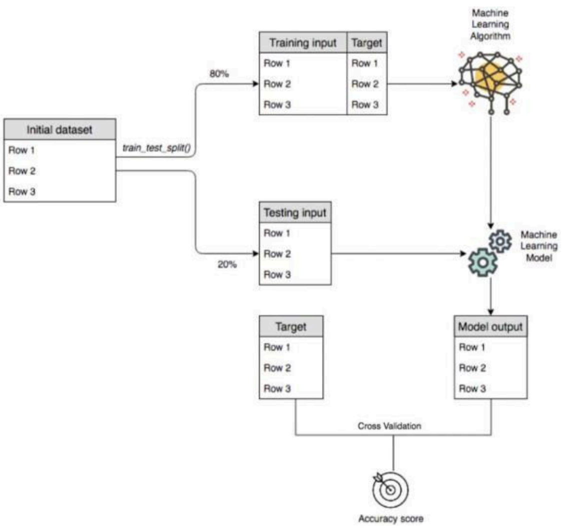

Fig. 4. Diagram of the Machine Learning algorithm application process

The algorithms that we used for this part were: Decision Tree [27], Random Forest [28], Support Vector Machines [29] and Logistic Regression [30]. The reason why these algorithms have been chosen for this project is explained in [26], in the section belonging to each algorithm.

The fact that these algorithms have been applied in this project does not mean that they are the best option for the classification of Bipolar Disorder states, but rather that they are the most suitable ones given the amount of data and the number of features used for the project. In future studies that make use of this project, if the data sets are larger it could be interesting to apply other algorithms too, like the Naïve Bayes [31] algorithm or any kind of Boosting algorithm [32], as to see how they perform on this particular classification problem.

Before applying each algorithm, as is necessary for every classification problem, the original data needed to be split into training and testing sets. Later, the training data would be used to train the prediction models and the testing data would be used to compare the output of the model with the real targets by cross-validation, a technique presented first by M. Stone in 1974 [33], that is used widely in Machine Learning for algorithm performance comparison.

The testing set is used for obtaining the accuracy of the model, as mentioned above, which is done by comparing the output obtained from the testing input and the real output of the testing set. In order to divide the original data sets into training and testing sets, we used the train_test_split() function from the scikit-learn library [25], where the test size represents the percentage of the data that is used for the testing set. After the algorithms were applied, the cross_val_score() function, which is also included in the scikit-learn library, was called in order to evaluate the score by k-fold cross-validation [33].

The best way to compare the accuracies obtained with the different algorithms on all the data sets was to make an algorithm performance matrix, which is shown in Table 1. This matrix showed that, in average, the data set that returned the best prediction accuracy (69%) with the algorithms was the Interview data set, as seen on the right column. The algorithm that performed the best, also in average (62%), was the Logistic Regression algorithm, as seen on the column farthest down.

Even though the algorithm that had the best accuracy average was the Logistic Regression, we stated that the Random Forest algorithm made the most accurate predictions in the sense that they were very reasonable given the behavior of the patients, which we tested with randomized data. These predictions made possible the implementation of a small program with the Random Forest classifier that we obtained, and which can be seen in [26].

TABLE I. ACCURACIES WITH DIFFERENT ALGORITHMS

Algorithms/Datasets	Decision Tree	Random Forest	SVM	Logistic Regression	Average
YMRS	36%	38%	38%	76%	47%
HDRS	78%	55%	36%	62%	58%
Interviews	70%	72%	68%	67%	69%
Interventions	44%	65%	57%	51%	54%
YMRS-HDRS	63%	63%	70%	33%	57%
Interviews-Interventions	67%	17%	42%	83%	52%
Average	60%	52%	52%	62%	

V. Conclusions and Future Work

Having a deep understanding of the data is essential in any Machine Learning project focused on a branch of medical science like psychiatry, where knowing which behaviors are normal and abnormal in the patients can help us create much more precise prediction models. The amount of data used and the nature of the data source are very important factors because with a larger suitable amount of data we will be able to get prediction accuracies with a much higher level of confidence. In the same way that understanding the data is important, having a deep perception of the theory behind each algorithm used, as well as their many implementations, is crucial in order to get the models to perform in the best possible way.

In this project, several groups of data collected in a supervised way have been analyzed and a set of Machine Learning algorithms has been applied. The results allow us to make decisions about the new sources of relevant information to be incorporated in consequent studies. It is concluded that the data from sleep and daily activity, measured both by movement and sounds, are relevant for improving the prediction of a crisis in patients with Bipolar Disorder. Therefore, a future project that includes group 1 bracelets instead of the current medical wristbands is proposed, because the latter are too expensive and invasive, and the development of a new mobile application that, in addition to the daily data, includes sensitization data and sounds. Future work will also analyze the EEG data collected during supervised monitoring for the purpose of performing a comparative analysis. The implementation with Jupyter will also allow us to perform the same studies on larger databases when the number of patients in the experiment is higher.

The most immediate use of the results obtained in this project would be to train the same algorithms used but with larger amounts of data, in order to see if they perform in a similar way. Gathering objective data from devices like phones or wristbands is something that can be accomplished quite easily according to the work already done in this sense. The goal of this task would be to compare the performance of different algorithms on the objective data gathered from these devices with the performance results obtained on the subjective data used in this project.

As for other more indirect applications of the results obtained during this project, the implementation of a drug recommending system for patients with Bipolar Disorder could be made by predicting the states in which the patients are during a certain period of time. These predictions could be stored in a database which also contains the medicine that these patients have been prescribed with during the same period of time, thus providing the possibility of seeing how each patient reacts to the different types of drugs used.

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