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EEG-based Bipolar Disorder Deduction using Machine Learning

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***Abstract*— This review aims to critically assess the different approaches of employing EEG signals and machine learning algorithms for the diagnosis of bipolar disorder. Data acquisition is done by EEG, while signal preprocessing, feature extraction and feature selection, and classification are done by machine learning algorithms. The performance of different machine learning approaches in classifying bipolar disorder was evaluated by reviewing 40 studies published between2018 and2022. More specifically, it analysed the most promising classifiers, namely Support Vector Machine, Random Forest, Logistic Regression, and Naive Bayes, in the successful classification of bipolar disorder with an accuracy ranging from 64.80% to 93%. The study methodology involved the acquisition of EEG signals by the OPENBCI software and implementation in Python. Anticipated results are expected to show statistically significant large amplitude differences in EEG signals across healthy controls and bipolar disorder patients during mania or depression phase, especially in the delta and theta frequency bands. The objective of the study is to develop an early diagnosis of bipolar disorder with EEG using a non-invasive approach.**

***Keywords*— EEG signals, bipolar disorder, machine learning, signal processing, classification algorithms, feature extraction, brain activity analysis.**

I. INTRODUCTION

So far, humans have placed much protection over their brains, adding osseous tissue and cerebrospinal fluid around the brain, thereby creating the most complex organ that controls all mental and physiological behavior. It consists of billions of neurons, which work very closely together by accepting and giving electrical impulses. With disconnections in nerve cells along some routes, it can lead to abnormal processing of information, as what happens in the case of behavioral and mood change and cognition alteration [1].

Mental illnesses are among the contemporary challenges of the health sector. In 2017, the World Health Organization (WHO) estimated that 970 million people were suffering from various forms of mental illness at that time.

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Bipolar disorder is marked by recurrent episodes of moods during which there are extreme variations in mood; the episodes alternate between depressive and manic ones. The depressive phase is characterized by an almost constant feeling of sadness, while the manic episode is characterized by euphoria and increased irritability, activity, and energy levels. Stressful life events, brain chemistry imbalances, genetic predisposition, medications, substance abuse, and childhood trauma may contribute to bipolarity in an individual [2].

Machine learning, a branch of artificial intelligence, has enabled machines to find patterns in data and make decisions with almost no human input at all. When applied for analyzing bipolar disorder, it made use of the knowledge created through the existing data by supplementing the analysis with machine learning algorithms into a novel patient identification, classification, and prediction system. The paper is a review of the bipolar disorder classification endeavors that have utilized machine learning as derived from the analyses of 10 different research articles from 2018 to 2022. This non-invasive technique measures the electrical activity of billions of neurons as they fire in concert with chemical and electrical signals. Irregularly shaped waveforms, produced by this concert of firing neurons, are recorded on the EEG, mirroring the architecture of brain activity beneath it.

Mental disorders occupy some of the most high-prevalent and high-disability groups of diseases in the world [1]. Bipolar disorder entails severe mood swings, episodes of mania, and depressive states that cause patients much suffering. Any delays in treatment add to patient stress and risk increasing the chances of cardiac complications, brain stroke, and worse outcomes altogether. Estimates of the WHO's Global Burden of Disease show that prevalent bipolar disorder increased from 38.53 million in 2017 to 39.55 million by 2019. The increasing population affected in Malaysia rose from 109,239 in 2017 to 112,509 in 2019.

Bipolar disorder is often misdiagnosed early on in cases where symptoms are instead thought to be ADHD or ODD among children; in other words, patients have often been labeled as merely depressed, which inhibits productive treatment and leads to complications.

The main goal of this project is to develop an EEG and machine-learning-based diagnostic tool for improved classification of bipolar disorder to allow early diagnosis and better patient resolution. Some issues to be researched are: How are EEG signals captured from the body and further processed? What would be the most suitable algorithms for processing bipolar disorder-related datasets? What importance does EEG signals play in the detection and classification of bipolar disorder? The main research objectives can be found in these points: To collect EEG data with OPENBCI software based on their initialization procedures. Apply machine learning methods to bipolar disorder datasets. To diagnose and classify bipolar disorder using EEG signals coupled with machine learning techniques. Recognizing the progressive nature of bipolar disorder, the early intervention becomes obligatory. Clinical and medical research explore the characterization, modeling, and diagnostic assessment of mental disorders. Neuroimaging techniques, like electroencephalography (EEG), measure the brain's state and functioning fluctuations in response to mental stress. The present project employs software developed by OPENBCI for EEG signal conduction. OPENBCI provides a great amount of flexibility, an inexpensive bio-sensing microcontroller platform capable of sampling very high-quality EEG signals. In the optimal context of diagnosing bipolar disorder, we will study machine learning algorithms such as Support Vector Machine (SVM), Logistic Regression (LR), Naive Bayes (NB), and K-Nearest Neighbor (KNN). The proposed machine-learning algorithm will be implemented and simulated using the Python software. Bipolar disorder classification is attempted in this research using EEG data along with computerized machine learning systems. This work will help in the early detection of problems, thus aiding medical practitioners and researchers. Thus, understanding the machine learning applications in the detection of neurological disorders helps bring these diagnostic abilities into play and better outcomes for such patients.

II. Literature Review

Deriving its name from Latin Cervus "deer," this organ seems to have the shape of a deer. The brain is greatly involved in every function, from thinking and remembering through feeling, moving, breathing, regulating temperature, and even eating. About 60% of a 3-pound adult brain is fat, and probably 40% comprises water, carbohydrates, proteins, and electrolytes. The brain contains vast networks of nerves, blood vessels, neurons, and glial cells that carry electrical and chemical signals throughout the body [3]. Functional anatomy shows that the human brain has four large divisions. Embracing the highest number of functional activities is the frontal lobe which continually engages in activities such as emotional-cognitive processing, mood-regulating activities like the production of speech, the assessment of behavioral performance, motivation, strategizing, decision-making, and planning [2]. Located at the center of the brain, the parietal lobe essentially houses the awareness of spatial relationships that are important for object identification and the interpretation of sensations such as pain and touch. The last of the lobes in the human brain is the occipital lobe, whose main function is to house the primary visual cortex. The temporal lobes are found on each side of the spinal cord. The cognitive activities that occur here include auditory processing, emotional regulation, the sense of smell, understanding languages, learning, and creating visual, verbal, and auditory memories [2].

A. Effects of Bipolar Disorder on Brain Structure

The prefrontal cortex, amygdala, and hippocampus are three critical brain structures affected in bipolar disorder. The prefrontal cortex serves as the primary processing power of the human brain while the amygdala is responsible for emotional processing and the hippocampus operates in the posterior region of the temporal lobe. The hippocampus is responsible for the storage of memories and regulation of cortisol levels. High levels of cortisol in patients with bipolar disorder contribute to inhibited neuronal differentiation and retraction of hippocampal neurons, thus contributing to memory impairments. The prefrontal regions undergo a decrease in volume as a response to elevated cortisol levels. The amygdala wolfing around in emotional control becomes hyperplastic and hyperactive conjointly to hypomania and manic episodes related to elevated levels of cortisol. The hypertrophic and hyperactive amygdala, with some irregulating on the other brain areas, induces sleeplessness and behavioral disorders. Research from the USC Stevens Neuroimaging Institute through the ENIGMA (Enhancing Neuro Imaging Genetics Through Meta-Analysis) project confirmed that patients with bipolar disorder showed much less gray matter in distinct regions of the brain.

The evaluation of abnormality of brain electrical activity or brain wave activity as seen in an electroencephalogram (EEG) occurs through placing electrodes-small metal discs with tiny wires-onto the scalp. Electrical charges from brain cells are amplified and displayed as graphs, thus making the activity of the neurons themselves visible on the computer screen. EEGs are widely used in evaluating several brain disorders, from rapidly spiking waves to seize seizure events to diagnosing Alzheimer's disease, sleep disorders, brain tumors, and herpes encephalitis.[5] Furthermore, it can look at blood flow to the brain within the operation and correlate that to the patterns of electrical activity in the brain.

B. EEG Frequency Bands

The electroencephalograph uses frequency-as-in-number-of-recurrent-waves-per-second-in-its-receiving-data-signals to detect the frequency-division bands belonging to raw EEG. Five frequency bands typical for describing raw EEG:

Delta (0-4 Hz): The lowest frequency essentially representative of deep sleep, being associated with some pathological processes, with delta waves appearing in most developmental stages, the slowest moving with the greatest amplitude accessing the mind unconsciously.

Theta (4-8 Hz): Typically slow waves, considered the ideal storage for feelings, thoughts, and experience - related to intuition, creativity, daydreaming, and spiritual consciousness: big theta waves usually characterize periods of meditation, prayer, and spiritual awareness, signifying the crossing of wakefulness into sleep.

Alpha (8-12 Hz): Alpha waves enhance creative thinking, mental coordination, and stress reduction. With his maximum frequency around ten hertz, alpha waves medialize rational and intuitive functions of the brain. It mostly occurs and becomes dominant after the age of thirteen, and has its sources in white matter, but has its most dominant location from occipital areas and frontal cortices.

Beta (13-30 Hz): "Although beta waves normally appear symmetrically prominent in the frontal regions and are decreased or absent in areas of cortical damage, they are fast waves indicating desynchronized active cortex within the subject." This pattern depicts someone who is alert, uneasy, eyes opened, referred to as normal activity in EEG findings.

Gamma (>30 Hz): The 30 to 44 Hz frequency range present in every brain territory. When processing simultaneous multi-source data, the 40 Hz activity aggregates key task regions. Well-managed 40 Hz activity pairs with good memory while a deficient 40 Hz activity underpins learning difficulties.

C. Machine Learning

Basically, machine learning (ML) sits as a subsection of artificial intelligence, with ML being concerned with the ability of computers to analyze and extrapolate data patterns and build models with very little intervention on the part of a human. This conception allows for three main types of machine learning models:

Supervised: The aim in supervised learning is to teach algorithms to categorize or predict the data correctly with the help of labeled training datasets. As new data come in, the model weights will be adjusted till optimal fitting occurs. This is practically executed using cross-validation to ensure that the model generalizes well (and hence does not suffer from either bias or variance). These include Support Vector Machines (SVM), neural networks, Naive Bayes and other varieties, Logistic Regression, Random Forests, and linear regression [6].

Unsupervised: Algorithms under this framework allow machine learning to evaluate and group unlabeled datasets, discovering unseen patterns without human supervision. Applications include similarity vs. dissimilarity detection, customer segmentation, image, and pattern recognition, and exploration data analysis. Commonly used dimensionality reduction methods are Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) [6].

Semi-supervised: This learning combines supervised and unsupervised to borrow some features and classifications from a small, labeled data set to train on a large-scale unlabeled dataset. The efficacy of this learning approach can be seen when there is not sufficient labeled data available to train a supervised algorithm or when the costs of labeling are too high.

D. Related Research and Comparative Analysis

In-depth investigations have been conducted in applying machine learning to the diagnosis of bipolar disorder. H. Rubin-Falcone et al. [6] classified bipolar disorder as opposed to major depressive disorder with Support Vector Machine trained on morphometry data with 75.0% accuracy and 73.1% sensitivity. A. R. Eugene et al. [7] went on to predict lithium treatment responsiveness using gender-specific gene expression biomarkers respectively with Decision Tree and Random Forest approaches with a reported 96% sensitivity for male responders and 92% for female responders.

G. O. Belizario et al. [8] effectively forecast patient Predominant Polarity using Random Forest algorithms inside R, achieving 64.80% correct predictions. H. Salem et al. [9] studied borderline personality characteristics and the prediction of readmission by Support Vector Machine classifiers with Python 2.7, obtaining 86% accuracy.

R. Achalia et al. [10] studied various approaches that integrate imaging from multiple sources using Support Vector Machines to reach a classification of healthy controls versus patients with bipolar disorder with an accuracy of 87.60%. H. Li et al. [11] developed SVM-based models to distinguish bipolar patients using gather and functional magnetic imaging from resonance, attaining 87% success rate in recognition.

L. de S. Rotenberg et al. [12] analyzed Multiple Machine Learning techniques, namely Random Forest, Support Vector Machines, Naive Bayes, Multilayer Perceptron, and Logistic Regression, yielding 72.0% positive classification accuracy and 77.3% negative classification accuracy with Random Forest.

H. O. Sonkurt et al. [13] used modified Polyhedral Conic Function classifiers in Python 3.7 to distinguish healthy subjects from bipolar disorder patients with 78% accuracy. R. Dou et al. [14] investigated juvenile bipolar disorder classification using six classifiers including Logistic Regression, Support Vector Machine, Naive Bayes, and K-Nearest Neighbor, with Logistic Regression yielding a maximum of 84.19% accuracy.

K. G. Hospital research [15] using automated machine learning with Ridge Logistic Regression models achieved 93% AUC for positive bipolar classifications, representing the highest accuracy among reviewed studies.

III. Research Methodology

The term "research methodology" comprises guidelines or procedures that govern the study process regarding the resources and goals of the study and the effective means of providing solutions to the research questions. The methodology explains that the selected methods and techniques used are best suitable for achieving research goals and objectives, as well as justifying the design choices made. Explicitly defined methodology is one of the very relevant foundations upon which scientific research is grounded and furthers the cause of consistency and reproducibility of work, which can actually be checked by other researchers. The data acquisition is defined as working with EEG recordings from some physical phenomenon, putting those in a form that can be further analyzed and processed with a computer. Of course, the actual EEG signals at this early stage of development will be coexistent with some noise and artifacts, and here comes the step for preprocessing, where clean EEG signals are stripped off these foreign inputs. The feature extraction is the creation of smaller, more manageable classes from raw data, while feature selection is the process of reducing the number of input variables to only those that are regarded as important. The prediction tasks will be, in the end, carried out by classification in machine-learning models. In consideration of ethical and health concerns, it was decided to use non-invasive EEG signaling in the clinical analysis of bipolar disorder. An electroencephalogram device measures electrical brain activity through electrodes placed on the subject's head, thus non-invasively detecting brainwave patterns. The study proposed EEG electrodes were placed on the forehead to detect brain electrical activity and record it. The amplified and digitized signals were transferred to OPENBCI software for processing and storage. EEG signals result largely from voltage difference across pairs of electrodes on the scalp. The EEG test channel tests activity between two electrodes. The four-channel EEG system used here sampled the signal.

A. EEG Dataset Collection

About two subjects participating in this research study were one who has normal states and another who has bipolar disorder; both of them are 19 years old. The EEG machine was used to collect signals from each participant. The EEG sampling system chosen for this study was the OPENBCI board, one which is inexpensive and versatile in its application. EEG data collected through an OPENBCI board gets transmitted via Bluetooth to an OPENBCI program and processed further analysis and preprocessing, with the signals being stored on that software.

B. Preprocessing

Preprocessing refers to the operations that are applied to the data before the analysis and interpretation of the same. These procedures are extremely crucial for neuroimaging data, including EEG. EEGs picked up at the scalp are contaminated by both brain activity and non-brain electrical activity. Preprocessing removes such noise, so one can better understand the underlying neural signals. EEG signal preprocessing removes undesirable noise and prepares the data for further processing, which is fundamental in brain-computer interface applications.

C. Descriptive Statistic Analysis and Noise Removal

The early preprocessing phase has received preliminary work during the semi-automated signal preparation. Early preprocessing of interfering noise must include user head motions contaminating EEG signals. Such processes would pave the way for further processing for feature extraction and classification. Data segments contaminated by noise are removed completely, followed by restoration based upon relationships with other remaining signals. Notch filtering at 60 Hz is applied to the EEG data to eliminate noise.

D. Filtering

Filtering out high-frequency and very low-frequency sounds together with line noise at 50-60 Hz. Undoubtedly, the application of digital filters on raw EEG recordings will assist in interpreting contaminated EEG signals. The three major types of filters include low-pass, high-pass, and bandpass. Low-pass filters allow frequencies lower than a given cutoff to pass and attenuate those frequencies above the cutoff level. High-pass filters allow signals above a certain cutoff frequency to pass while reducing intensities below that frequency. Noise is filtered by bandpass filters that consist of a combination of both low-pass and high-pass filters that stop signals outside of their frequency ranges.

E. Feature Extraction

Before PCA provides the correct summary of the original data distribution, it can analyze which combinations of the input feature sets yield maximum variances while at the same time minimizing reconstruction error [16]. Feature extraction helps improve accuracy of learned models by extracting properties from input data, while improper assignment of features to the most essential classification signal means the classifier will not perform well [17]. Unnecessary data are deleted to reduce dimensionality, thereby speeding up training and inference [18]. Principal Component Analysis (PCA) must, therefore, be considered the best feature extraction method.

F. Feature Selection

Feature selection reduces model input variables by extracting useful information while discarding irrelevant or noisy information [19-23]. Automatic feature selection for machine learning models according to problem types is developed. Important characteristics are retained with the possible removal of features or the addition of new ones [24]. Intrinsic, wrapper method, and filter method are the three broad families of feature selection algorithms [25].

G. Classification

Classification is simply a machine learning approach with one or more factors that predict incoming data and likely classifications to be formed about it in different formats, whether structured or unstructured [26]. The Random Forest application for machine learning averages the outputs from several decision trees applied to various sections of a dataset, thus enhancing the overall accuracy.

IV. Results

This section addresses anticipated study outcomes. EEG signals, once sampled, undergo preprocessing. Feature extraction, feature selection, and classification processes will be implemented in subsequent research phases.

Simply an apparatus engaged during noise removal-depending mainly on the straight operation, it is the fixed response and, is the compatible with embedded microprocessors. It records signals mainly in the power spectrum from 1 Hz to 30 Hz. Low frequency sources of noise include scalp perspiration, head movements, and slowly drifting electrode cables into EEG signals. High frequency noise includes electromagnetic interference and muscle contractions, especially in those found in the face and neck area. In standard EEG processing, low-pass filters were applied for a frequency range greater than 50 Hz and high filter passage was below 1 Hz in restoring much slow frequencies. The spectral analyses of EEG signals reveal significant variance between healthy individuals and those suffering from bipolar disorder. Spectral analysis of preprocessed EEG recordings from healthy people shows uniform amplitude distribution across the frequency bands, with energy concentrated in the alpha and beta frequency ranges.

Analysis of channels shows consistent signal properties before and after preprocessing, meaning that noise has been effectively removed without loss of a great deal of signals. Spectral analysis performed on subjects with bipolar disorder presents stark differences in amplitude distribution as compared to healthy controls. The analyses report that significant differences exist between pre-processed and post-processed EEG signals; the most pronounced differences were seen in delta and theta frequency bands. If the amplitude is enhanced in certain frequency bands, these changes act in an abnormal way with respect to the activity of the brain or the levels of neurotransmitters during manic or depressive episodes. Figure 1 displays the Mild Average Person Brain Waves and Figure 2. displays Bipolar Disorder Person Brain Waves.

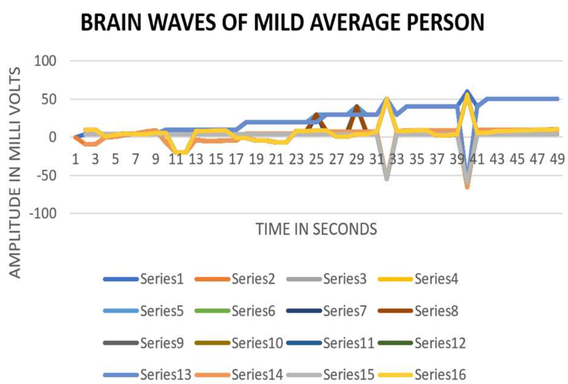

Figure 1. Mild Average Person Brain Waves

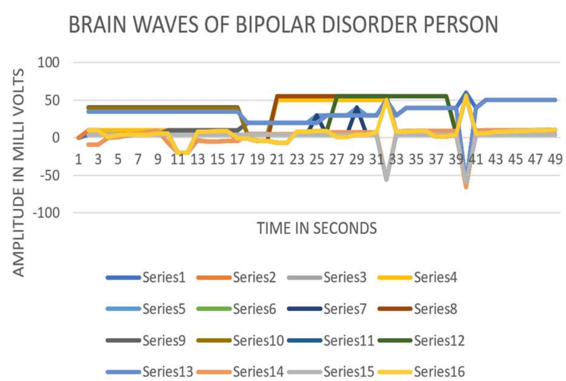

Figure 2. Bipolar Disorder Person Brain Waves

Such amplitude differences between EEG readings in healthy and bipolar persons confirm the existence of a neurological difference among those patients. Bipolar patients may display higher amplitude in selected EEG frequency bands, though most consistently in delta or theta range during mania or depression. Such increased amplitudes appear implicated by altered neurotransmitter levels that affect brain activity levels. During mania, there may be increased brain activity in certain regions, thus leading to higher amplitude of EEG signals in some frequency bands. Whereas this change finds application for detection and classification of bipolar disorder.

V. Conclusions

As is evident from this analysis, the validity of using artificial intelligence when classifying bipolar disorder with EEG signals can be easily assessed. Studies of 10 papers published between 2018 and 2022-I.e., 2018 through 2022-have shown that classifications from machine learning methods yielded accuracies between 64.80 and 93%, with the highest performance expected from the most sophisticated SVM and AutoML methods. It could be said that the popular machine learning algorithms for classification of bipolar disorder include Support Vector Machines, Random Forests, and Logistic Regression.

EEG signals are acquired non-invasively, preprocessed adequately, subjected to feature extraction, and subsequently classified using machine learning. It is hypothetically a promising form of diagnosis. The Electrophysiological amplitude differences between healthy and bipolar patients constitute an objective measure as a biomarker that can be automated for detection. Such methods would enhance early diagnosis of bipolar disorder for significantly better outcomes and improved patient treatment efficacy. The other future directions would focus on increasing the size of the dataset to embrace varying patient populations, real-time classification systems, and clinical implementation of these systems, as well as investigating hybrid machine-learning approaches that may combine several algorithms. Whereas multimodal neuroimaging with EEG data integration is still underway, there is great promise for improving the performance of classifications. Analysis of occurrence patterns in time and deep learning mechanisms should be explored to give indication on how disease develops and prediction on therapeutic response.

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