Bipolar Disorder: Early Prediction and Risk Analysis using Machine Learning

Nisha Agnihotri[1*], Sanjeev Kumar Prasad[2]

School of Computing Science and Engineering, Galgotias University, Greater Noida, UP
School of Computing Science and Engineering, Galgotias University, Greater Noida, UP
nisha.agnihotri_phd20@galgotiasuniversity.edu.in , sanjeevkps2002@gmail.com

ABSTRACT

These days' mental illness is a prime cause of functional and social issues in our day to day life. Neuroscience revels that our brain is the root cause of mental stress, anxiety and Depression. The mood and chronic levels in our brain results in various physiological disorders Like Bipolar disorder(BD). Bipolar Disorder is a mood disorder which has different stages from manic episodes to severe depression. Clinical and Research data shows that delay in treatment results in high level of stress and mood swing episodes with worse discourse like cardiac arrest, brain stroke, heart attack and depression. This paper aims at identifies the mental level by studying feature selection, classification and cross validation. Therefore, this paper proposes the Machine Learning(ML) based framework that identifies the bipolar disorder in early stage and the proposed framework help in making a computer - based predicting and diagnosis tool mental and stress detection. Further, this paper analyses the different transformation like depression to Mania, from depression to BD, from BD to hypomania and to identify pre-bipolar depression. The machine learning algorithms like Support Vector Machine(SVM), Logistic Regression(LR), Naïve Bayes(NB) and K-Nearest Neighbor(K-NN) for analysing the risk factors and accuracy to get output. Different Machine Learning Models are used to analyse the risk factors and accuracy in detection of mental stage. The Precision, accuracy, F1 score and recall value analysis are deducted on dataset to predict the required result.

Keywords: *Machine Learning, Bipolar Disorder, Python, Mood Disorder, Depression.*

1. INTRODUCTION

Bipolar disorder is the most dangerous and life threatening disorder in the field of psychiatry. Many work is being done in the field of Medical Science, but when we look in the field of Psychiatry, there is still many miles to go. In this paper they focus on risk analysis factors for prediction and early signs of illness to achieve this goal (Subhani et al., 2017). Bipolar disorder has a progressive nature which needs an early intervention strategy. There are many proposed models to identify the mental conditions of an individual. Such systems are based on Machine Learning Algorithms which works on Test and Train data. To obtain the critical response for mental stress neuroimaging modals such as electroencephalography (EEG) is used to record the state and functional variations in the brain (Mateo-Sotos et al., 2020). An assessment of stress has extracted several physiological features and employed ML classification Models. A methodology to predict quantitative differences between stress and control condition as well as different levels of stress. The dataset taken into consideration have different features and attributes related to mental state of patients using various means. Analysing various models of researchers this was analysed that if symptoms are studied and analysed in time with physician's consultancy and guidance then the patients can be given proper guidance and treatment. The severe mental condition like brain storm, anxiety, Depression and bipolar disorder can be taken care in advance so that they cannot reach a maximum Level (O'Donovan et al., 2020).

All around the world large number of peoples are suffering from severe Bipolar and Depressive Disorders. The classification, characterization, modelling and diagnostic analysis of these Mental disorders are of prime importance in Clinical and medical Research. The selective features are applied to some ML classifier models like Support Vector Machine(SVM), Logistic Regression(LR), Naïve Bayes(NB) and K-Nearest Neighbor(K-NN). A computer based mental arithmetic test was employed to test stress of both stressed and controlled persons (Subhani et al., 2017).

1.1 Identifying Risk factors of Bipolar Disorder onset and Course

Identifying risk factors at early stages are an important key for treatment and need less interventions (Vieta et al., 2018). Episodes of depression with psychotic symptoms and an early onset gives result to predict conversion to Bipolar disorder. The combined interaction between prodromal symptoms and risk factors may lead to Bipolar Disorder. Still the real mechanism of this remains unknown. There are three types of Risk factors affecting bipolar disorder peoples as shown in Figure 1., they are Environmental Risk Factors, Biological Risk factors and Prodromal Symptoms.

1.1.1 Environmental Risk factors

There are various risk factors related to environment have been proposed for ipolar disorder. These factors include stressful life events like sexual abuse, antidepressant use or substance misuse such as alcohol or cocaine misuse (Vieta et al., 2018).

1.1.2 Biological Risk Factors

Biological risk factors include family history of people suffering from bipolar disorder or other neurodevelopment factors like child development delay (Vieta et al., 2018). The details of family history are one of the major risk factors for bipolar disorder, whereas sexual abuse has been consistently related to a worse illness course (Vieta et al., 2018).

1.1.3 Prodromal Symptoms

Symptoms of this bipolar disorder can be heterogeneous i.e. this has mixed features of anxiety, depressive symptoms, mood lability, psychosis or subjective sleep problems as predictors of dimensional factors of bipolar disorder. The most important and robust predictive factor is the presence of hypomanic subthreshold symptoms. These symptoms of bipolar disorder can be heterogeneous (Vieta et al., 2018). Dimensional factors predictive of bipolar disorder include anxiety and depressive symptoms, mood lability, and psychosis or subjective sleep problems, but the most robust predictive factor is the presence of subthreshold (hypo)manic symptoms.

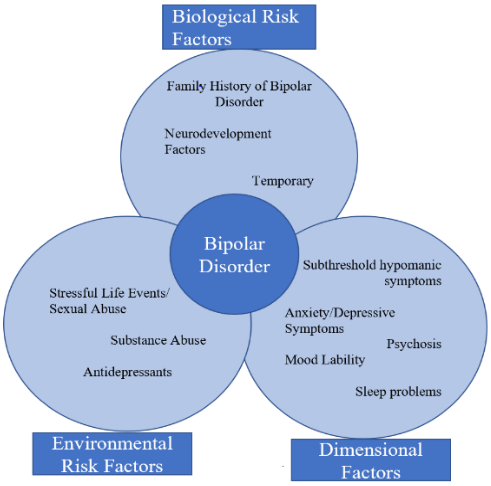

Figure 1. Risk factors affecting bipolar disorder patients

1.2 Depression preceding diagnosis of bipolar disorder

Initially we have gone through the identification of clinical characteristics of patients having depressive episodes who subsequently develop episodes of Mania and Hypomania (O'Donovan et al., 2020). These depressive episodes are transforming from stage to stage in the following manner. This transformation can be done in following ways: -

1.2.1 Onset polarity and interval from Initial depression to Initial Mania:

These patients have depressive episodes that transform into mania. Their family data suggest the polarity at onset is possibly a heritable trait and may identify separate categories or subtypes of genetic bipolar disorder. This transformation is quite familiar in depressive peoples (O'Donovan et al., 2020).

1.2.2 Conversion from major depression to BD:

Major depression is a very serious and mental illness which can be treated in time and handled at ease (O'Donovan et al., 2020). A set of observations are related to longitudinal cohort of people suffering from major depression. If they are observed for sufficient times, then many of them will convert from depression to BD-I and BD-II. Factors related to Risk for Conversion from Depression to bipolar disorder are: -

- Family history and details of bipolar disorder.
- Early onset polarities.
- Typical feature related to disorder.
- Psych motive retardation.
- Functional impairment.
- Mixed features.
- Initial hypomanic symptoms

1.2.3 Bipolar Depression in absence of hypomania:

Many studies show that not all bipolar depression patients develop some mania episodes (O'Donovan et al., 2020). Their family history is an important factor indicating different types of depression. Clinical features are summarised to identify pre-bipolar depression. The clinical features show a transformation precedes a confirmed diagnosis of BD and Unipolar Depression (O'Donovan et al., 2020). They have to identify whether a patient having depression have symptoms of bipolar depression, if yes, then what will be the after effects or outcomes of clinical management. Assessment of Family history of bipolar disorder patients is very important at an early stage. This shows the environmental and biological factors relating and affecting to genetic disorder (O'Donovan et al., 2020). Assessment of course of illness like the course of medication, long illness, bed reddens and other factors are also assessed for analysis. Clinicians are facing difficulty to assess early onset and recurrent episodic depression as well as seasonality and hormonal status, the changes in the course of illness with time and attention is paid to past and prospective course in a methodical manner (O'Donovan et al., 2020). This is very important where there is a family history of bipolar disorder or an early onset. The mixed symptoms of analysis and assessment which interprets in depressive and bipolar episodes are the best challenge for the clinicians when we look for guidance from the literature having broad and narrow interpretations of mixed symptoms (O'Donovan et al., 2020). Pragmatic management of possible and probable pre-bipolar depression is also studied. This is largely accepted that bipolar and Unipolar depression are treated differently, there is an overlap of minority of bipolar –I and some bipolar-II depressions that may be distinct in response to antidepressants (Agnihotri et al.,2022). Some specific treatments for depression with family history of bipolar disorder. There can be no recommendations specifically for bipolar disorder group at this time as all the data is extrapolation. Clinicians should be experienced and have good knowledge of Unipolar, bipolar, child and adolescent, youth guidelines. There are mixed guidelines for bipolar states and are applicable where they can fit and change according to treatment response (Agnihotri et al.,2022).

1.3 Related Study

The review gives a comprehensive literature and study on Depression, bipolar disorder and ML techniques for the prediction and analysis of Risk factors in Bipolar Disorder. the literature aiming to reduce the prevalence of anxiety disorders through effective early prediction, in a way to improve the health and life of such patients in reducing health care delay and medical cost.

Few studies show that researchers attempted to find out patients suffering from Bipolar Disorder. A study proposed a ML framework involved in feature selection, EEG feature Extraction, classification and tenfold cross validation by reducing 94.6% accuracy for two-Level identification of stress and 83.4 % accuracy for multiple level identification (Subhani et al., 2017). The characterization of early stages of BD, early recognition and treatment are critical in preventing unfavourable outcomes (Rios et al., 2015). In another study, it was predicted that a hypomania related symptoms from patterns of whole-brain results in activation in two independent samples. It works on early identification of individual’s level bipolar disorder risk in young adults (De Oliveira et al., 2015). One of the paper discussed that the output that CNN MDRP with random forest has high accuracy than other algorithms in bipolar disease prediction. This paper shows the changes in Grey matter and white Matter of the different data groups individuals (Sujatha et al., 2021). The implementations of early intervention strategies may help to change the outcome of the illness and evert potentially irreversible harm to patients with BD (Vieta et al., 2018). Another study focuses on depression that precedes an onset of manifest BD as early stage BD (O’Donovan et al., 2020). A research paper proposed an Extreme gradient boosting (XGB) Machine Learning method involving an EEG signal is proposed. A standard 10-fold cross validation process with 94% high prediction accuracy, precision>0.94 and high recall >0.94. XGB system trained with clinical data may serve as a new tool to assist in the diagnosis of patients with BD (Mateo-Sotos et al., 2020). Flask web framework was used to handle HTTP requests of the predictions. HTML page was created to display the predictions (Geetha et al., 2020). Another researcher studies a ML DT algorithm about structured and unstructured data for portioning of data. It reaches a94.8% quicker speed to produce report consist of possibilities of occurrence of disease (Chen, M et al., 2017). Applying various ML models on patient’s data also helped in creating a prediction model of various symptoms (Leal J, 2018). In another study, a prediction model was developed to detect depression and anxiety in aged patients by studying there clinical and demographic features using ML algorithms (Sau et al., 2018).

A team of researchers has classified the depressive and manic states of patients by using smartphone integrated sensors technology (Grünerbl et al., 2018). A study investigated the highest feature of importance in health to be monitored using ML techniques for ranking symptoms of Bipolar Disorder (Doryab et al., 2018). For understanding patient's health, a model was prepared of mood charting for patient monitoring and gave day to day analysis and understanding of patient health (Bauer et al., 2018). A study correlated mental health symptoms gathered from smartphones and draw a conclusion that the daily records of physical and social activities should be recorded for a certain interval of time (Faurholt-Jepsen et al., 2018). AD model was designed which predicted depressing state from real time tweets (Kumar et al., 2019). Another study suggested a methodology to evaluate ML techniques suggested a methodology to minimize human interference of data collection and labelling (Liu, D et al.,2021). A literature search for the prediction of anxiety disorders was presented in one of the studies using ML algorithm to support care of patients and their early predictions (Muhammad et al.,2020). ML model for a high quality solutions of brain disorder using online tools like Facebook, twitter, etc. was keenly studied and results were obtained for the same [(Islam et al.,2018)]. Another team of researchers focused on various conditions of mental health and application of ML on psychology and mental health disorder (Shatte et al.,2019). The finding of neuro-imaging technologies in clinical assessment of children using qualitative estimation of psychopathology provided a better understanding of imaging technologies (Lee et al.,2019). Ml model on electronic dataset record to reduce health risk by providing valuable prediction information gave insights on electronic imaging technologies which can be further studied using ML (Martinez et al.,2018). Another study reflected an Ml model to demonstrate a wide range of diagnosis treatment research support and clinical supervision on mental health patients (Gupta et al.,2020).

Lockdown can save lives and is considered most effective in the present pandemic situation. Students have adapted well to the stay at home restrictions and are hopeful that life will soon be normal. Students have experienced major teaching-learning disruption and their prime concerns at this moment include the uncertain schedule of forth coming examinations, admission to the next higher level courses, and summer internships (Mehta et al.,2020). How the lockdown time save lives and is the only possible way to deal with pandemic? Students learn how to manage their studies and other activities with online platforms like online Teaching Learning, Webinars, Internships and many more. This all is possible with hope that one day everything will be normal. Studying different parameters which effects in the prediction of depression by collecting dataset using questionnaire, social media post, verbal communication and face to face interaction (Mehta et al.,2020). Another study presented the algorithms which are commonly used their properties and performances always play the role of a guide in selecting the right and appropriate model for the diagnosis. ML help as a platform or bridge between the patient's embarrassment about revealing their problems and psychiatrists' critical shortfall about the therapy (Sarala et al.,2019). There has been a study related to a text analytical tool having a sensor and camera for self-testing scales in smart devices for detecting anxiety and depression (Shrestha et al.,2019). Applying Ml model stress pattern of working and stressed adults and to find the factors which determine the stress level gave better understanding on stress levels (Kiranashree et al.,2021). Using advance AI technologies and ML models, a personalized system that work on emotional support for a particular person facing mental illness (Vikhrov et al.,2021). An algorithm has been proposed also to classify and examine mental health disorder and its type (Kouris et al.,2005).

The proposed work is the comparison of the performance of different machine Learning algorithms on the dataset. For this the dataset is divided into two groups- training and test dataset. ML techniques are applied separately to conclude the best possible model for diagnosing Bipolar disorder. The final conclusion is drawn from the precision, recall, accuracy values and F1 score of all the algorithms, i.e. Random Forest, SVM, LR, KNN for both BD and controlled patients. We studied another objective where we found out Bipolar disorder groups scored comparatively different from other groups, through emotional valence stimuli. The result shows Linear Regression is best for prediction of disorder where as SVM, KNN and Random Forest works fine with few outliers.

2. Materials and Methods

Records of people suffering from bipolar disorder and several healthy peoples which was downloaded and visually recorded to identify and extract meaningful data and information from complex datasets by predicting day to day analysis of patient (Vuppalapati et al., 2020). Each participant has gone through both stress and control conditions, performed on separate days having gap of one week and this is to reduce the effect of Learning on the performance. Also half of them undergone stress condition which are followed by control condition, other half undergoes these conditions in an opposite manner. Both the conditions have their own rest time in the start and a habituation phase and a recovery phase to the participants. The time to solve the Test during stress was less as compared to response time during practice session (Subhani et al., 2017). The mental stress condition and control condition are having habituation, Rest, recovery time accordingly as shown in Figure 2(a) and 2(b).

Mental Stress Condition

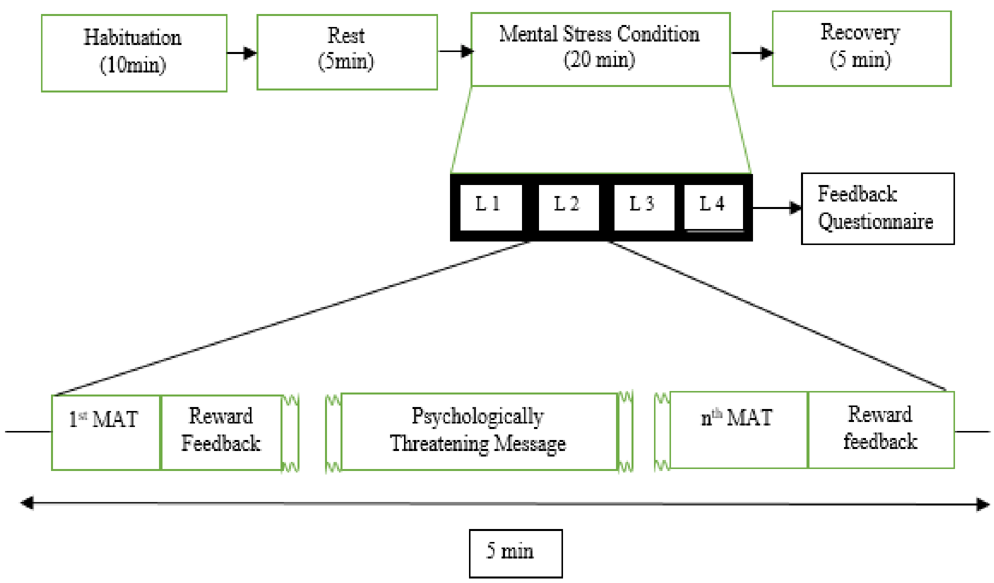

Figure 2(a). Phases of Mental stress condition of participants

Control Condition

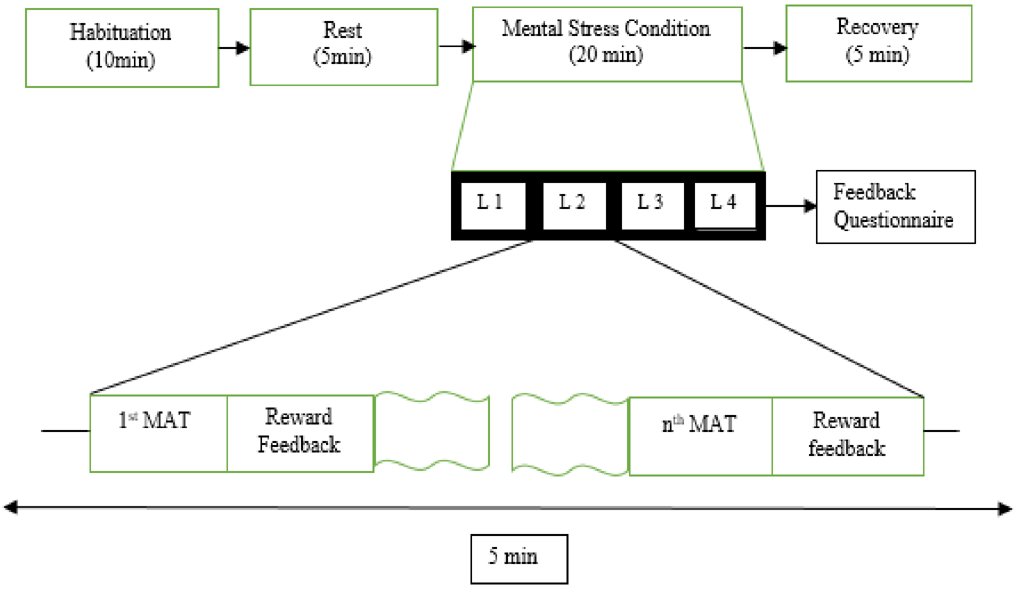

Figure 2(b). Phases of Control condition of participants.

The methodology involves four steps, Data acquisition, Pre-processing of data, Feature Extraction and Classification of models as shown in Figure 3., in which patient's readings of Bipolar Disorder I and II and Unipolar Disorder were examined with the help of MiniPons and were compared with healthy individuals who were not suffering from any mental disorder. Pre-processing patient's data helped us to study complex state of suffering patients through nonverbal channels and with this we were able to eliminate the interference. Through each channel we examined different features based on emotional valence of patient's stimuli. After pre-processing data and building database ML algorithms were studied on bipolar patients.

2.1 Data Acquisition and Pre-Processing

The dataset taken in consideration is from the data source -Theory of mind in remitted bipolar disorder of Participants. Bipolar disorder dataset taken oon the basis of questionnaires and surveys asked to the patients collected through MiniPons, which was based on Interpersonal accuracy in recognition of dynamic nonverbal signals. MiniPons help us to accurately test the meaning of nonverbal cues. By grouping the data of stimuli in a 2x2 design we combined affective valence and dominance. The categories depicted Video channels of three different types and two different types of audio channels. The computer application representing stimuli helped to administered the data and responses were recorded. In recording the response, individuals were asked to select the subject from the two different possible options (Espinós et al., 2020). Dataset taken in consideration has been divided on the following factors:

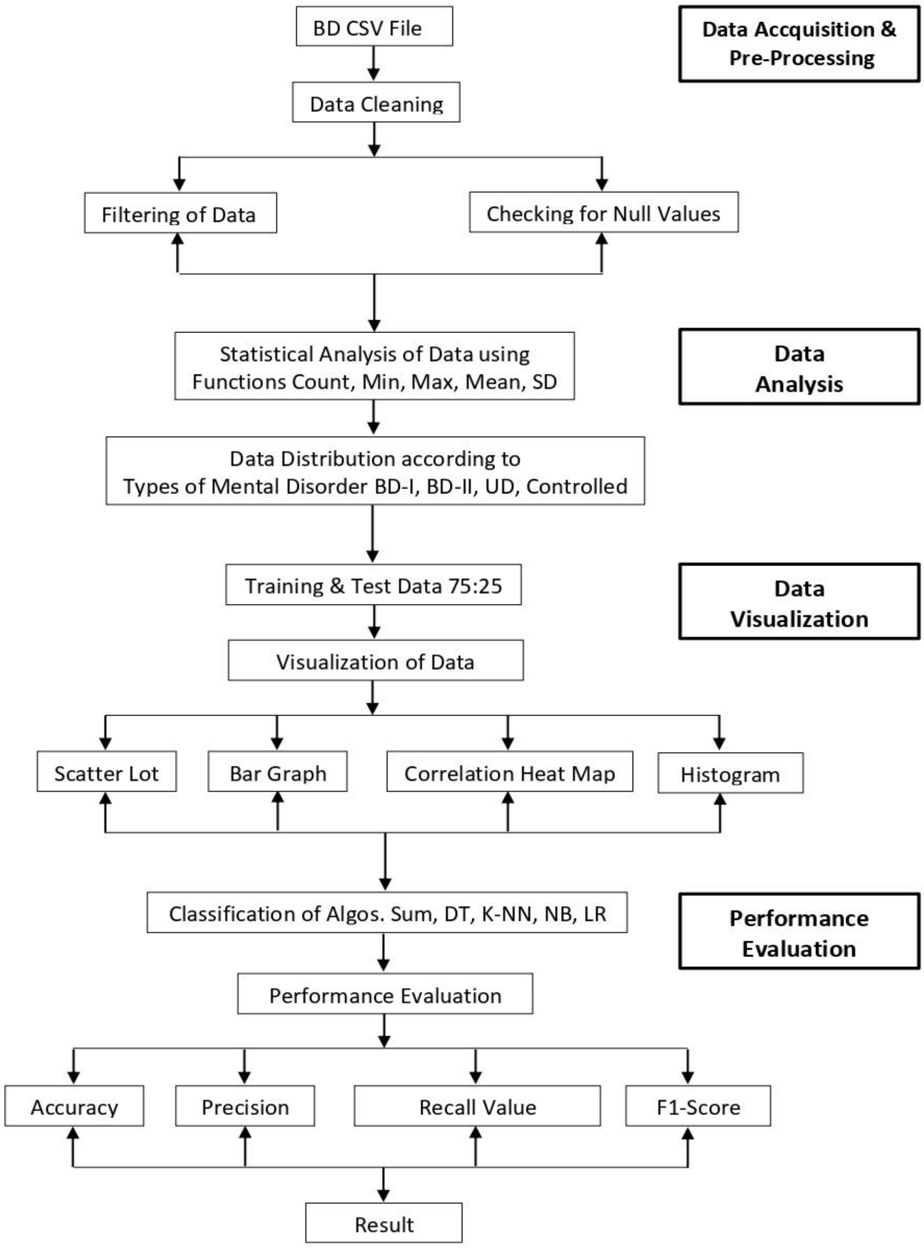

Figure 3. Proposed Machine Learning Framework for identifies

- Group: Bipolar, Control, Depressive.
- Type: BD-I, BD-II, Control, Depressive.
- Right_Answer: Number of right answer to the MiniPons assessment.
- Assessment scales- Audio_prosody, Combined_Channel, Face_video, Body_video, Positive_valence, Negative_valence, Dominant, Submissive.

Collection of raw data from patient's history for both healthy and depressive persons. Many Apps are also developed to gather patient's data (Vuppalapati et al., 2020). The data collected from data acquisition phase is processed in an understandable format. This is required to study various symptoms and behaviours of patient. This is done by following methods:

2.1.1 Data Cleaning:

This is done to remove irrelevant or unwanted data in patient's prescription which is of no use in diagnose is filtered (Agnihotri et al.,2022).

2.1.2 Data Transformation

The raw data collected is transformed into an understandable dataset for implementation (Agnihotri et al.,2022).

2.1.3 Checking for Null values

Data is checked whether it has any null or missing fields. In this study as in Table 1, we have (Islam et al.,2018)7 people who participated out of which 119 were diagnosed with BD (F= 56, M=63). Out of 119, 70 were diagnosed with BD I (F=30, M=40, Mean age=44.50, SD=11.50) and 49 out of 119 were diagnosed with BD II (F=23, M=(Islam et al.,2018), Mean age= 49.90, SD =11.50). For Comparing the data 39 euthymic patients were diagnosed with UD (F=33, M=6, Mean age=62.90, SD=9.71) and 119 healthy patients (F=65, M=54, Mean age=46.10, SD=10.80). The Occurrence of depression was found to be twice in women as compared to men in UD. As UD usually occurs usually 10 years later as compared to BD, the age of UD patients were higher as of BD patients (Espinós et al., 2020). There are no null values in the dataset.

Table 1 Comparing UD and BD patients according to the clinical conditions.

	Bipolar Disorder I (n=70)	Bipolar Disorder II (n=49)	Uni-Polar Disorder (n=39)	Control Patients (n=119)
Male [n(%)]	40(57.10%)	(Islam et al.,2018)(53.10%)	6(15.40%)	65(54.60%)
Female [n(%)]	30(42.90%)	23(46.90%)	33(84.60%)	54(45.40%)
Age	44.5≤age≤56.5	49.90≤age≤60.50	62.90≤age≤71.71	46.10≤age≤55.71
Onset age	20.23≤age≤24.13	(Islam et al.,2018).50≤age≤35.80	33.47≤age≤41.9	

2.2 Data Analysis

Data analysis is an explanatory approach to analyse datasets to summarize their main characteristics. The critical process of performing preliminary investigations of the data to discover different behaviours to test their hypothesis and to monitor assumptions with the help of descriptive statistics and graphical representations i.e. with statistical and visual methods

2.2.1 Training Data

Machine learning model is generally divided into training and test dataset. Training Dataset helps to create the model which can be trained to perform following Machine learning algorithms.

2.2.2 Test Data

Test data evaluate the dataset on the performance bases. For the dataset analysis, we have divided the dataset on a ratio of 75:25. Since the dataset has 277 observations, 207 observations fall into the training dataset and 70 observations under test dataset to perform the analysis.

2.3 Data Visualization

Visualizing data is one of the most important aspect while applying machine learning models. It can be done through various methods such as histograms, scatter plots, bar graphs, heat correlation matrix, etc. It gives a detailed study of the dataset on all the parameters mentioned.

Scatter density Plots: To understand the distribution of values in the dataset, scatter and density plot is used which proves to be useful in analyzing the characteristics of data and also help us to understand the behavior of the dataset to a certain extent. In Figure 4, we have understood the behavior of 11 different attributes by relating them with the type of disorder.

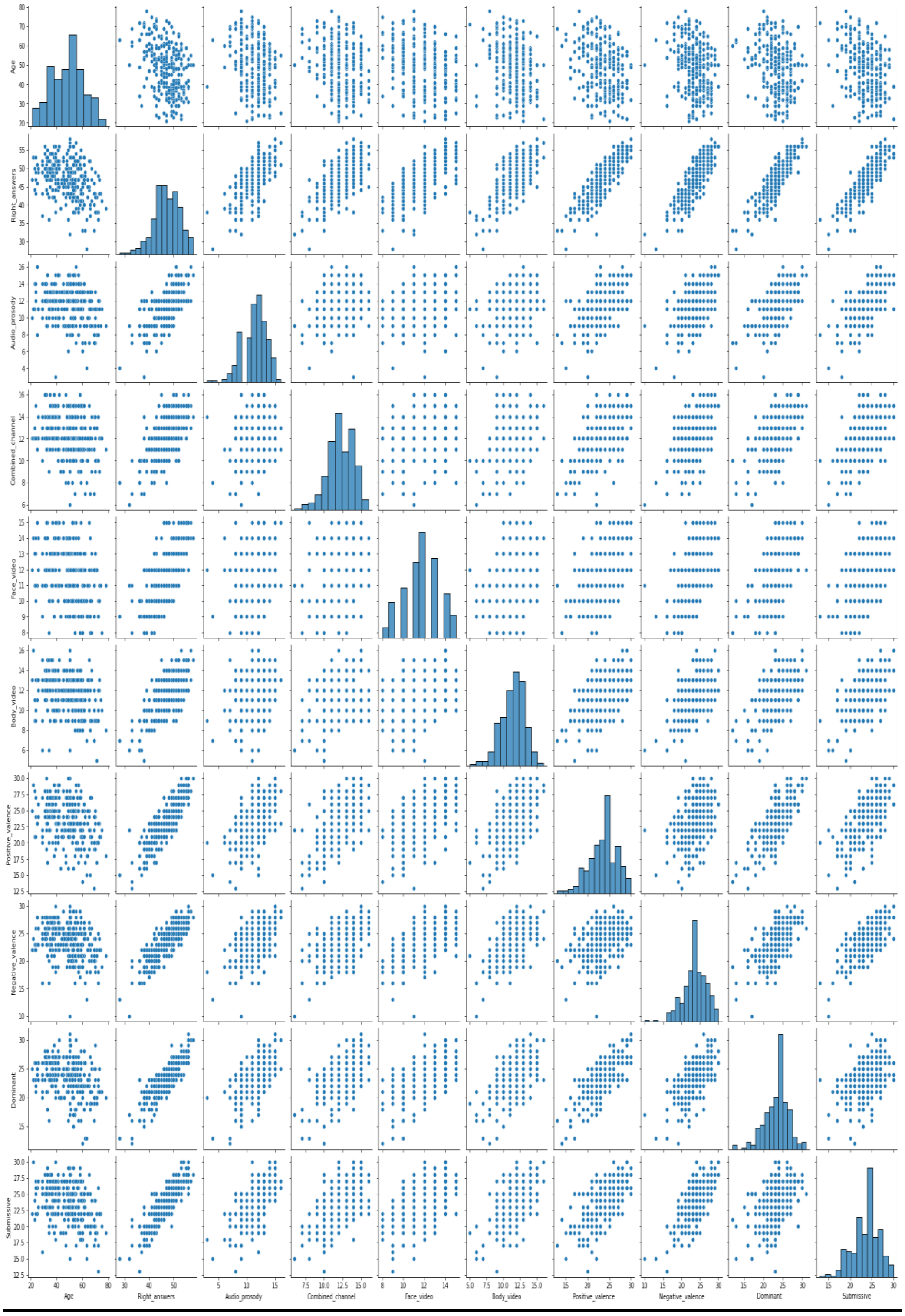

Figure 4. Data visualization through Scatter and Density Plot

2.4 Classification of Algorithms

The Python language was applied to the Machine learning algorithms using Python 3.6. as shown in Fig.4. This predicted the people suffering from bipolar disorder, according to the level of severity. The database has been divided

into two sets namely training set and test set on ratio basis 75:25, respectively. The operating principles of each machine learning algorithm are described in the following sections.

2.4.1 Logistic Regression (LR)

This model is two-fold regression model which is commonly known as Logit model and in which variable dependency is a phase. It mainly covers the binary dependence issues of ‘0’ and ‘1’ by representing pass/fail, win/loss, life / death or healthy/illness. Circumstances in which variables depend on more than two outcome categories can be analyzed in bulk deflation, or, if multiple phases are ordered, in systematic retrieval. LR gives two-fold outcomes (Sun et al.,2019).

2.4.2 Decision Tree(DT)

Decision Tree Model Construct a decision Made model which predicted an authenticated values of attributes in the data. Decision fork in tree structures until a prestige decision is taken for a given dataset. Decision trees are modelled on data for grouping and regression methods. DT are often expeditors and precise (Saylan et al.,2016).

2.4.3 Support Vector Machine(SVM)

SVM is a machine learning ML algorithm that works for segmentation and classification functions but is widely used in classification. This model has been used late in many programs because with its ability to differentiate and present quality, it separates data sequentially into two different categories (also known as hyperplanes), having a maximum distance between the two categories. It is a presentation of examples such as points in space, mapped so that the examples of the different categories are separated by a clear gap as wide as possible. New models were then drawn in that space and it was predicted that they would be in the category depending on which side of the gap they fell into (Rahman et al.,2020).

2.4.4 K- nearest neighbor algorithm(K-NN)

k-nearest neighborhood algorithm (k-NN) is used for classification and regression between the model and is one of the easiest machine learning algorithm. The input contains the closest examples of training in the feature space and the output depends on whether k -NN is used for classification or regression. In the k-NN classification, an item is divided by a majority vote of its neighbors, the object is given the most common category among its closest neighbors (k total, usually small). If k = 1, then the object is simply assigned to the category of the nearest neighbor. In k-NN regression, the output is a structural value of an object. This value is the average of the nearest k values.

2.4.5 Artificial Neural Networks(ANN)

Artificial Neural Networks structure enables the designs to process information in the same way as our biological brains, by being inspired by how our nervous system works. This makes them useful tools to solve problems such as facial recognition, which our blood brain can easily do.

In an ANN, firstly, the input from the input layer is fed up to each node in the hidden layer and after that it is fed to each node in the output layer. As there can be a number of nodes per layer and also several hidden layers are also present we need to be careful while passing before they finally reach the output layer. Selecting the right number of nodes and layers is important later on when using a neural network to run a given problem.

2.4.6 Naïve Bayes(NB)

Naive Bayes is a simple process used for the construction of classifiers models that provide class labels in problematic situations, represented as veneer of value elements, where class labels are taken from a limited set. It is not a single algorithm to train such dividers, but a family of algorithms based on the same principle: all Bayes dividers assume that the value of a particular element is more independent than any other factor, given the flexibility of the class.

2.5. Performance Evaluation Metrics

Once the algorithms are applied, it is important to validate and undergo performance evaluation to finally conclude which model is the best. Performance evaluation is done by calculating accuracy, precision, recall and F1 score for each algorithm and the algorithm with highest value fits the best (Mateo-Sotos et al., 2020).

For performance evaluations, there can be four types of outcomes for the test data i.e. true positives, true negatives, false positives, false negatives.

2.5.1 Accuracy

Accuracy is calculated by considering the percentage of correct predictions made out of all the predictions for the test data.

$$\text{Accuracy} = \frac{\text{Number of correct predictions in test data}}{\text{No of predictions in test data}}$$

2.5.2 Precision

Precision value identifies the number of relevant data points from the test data. It indicates the number of true positive predictions made out of the sum of true and false positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives+False Positives}}$$

2.5.3 Recall

Recall value give the percentage of correctly identified true positives. It is calculated by considering no of true positives divided by sum of true positives and false negatives.

$$\text{Recall} = \frac{True\ Positives}{True\ Positives + False\ Negativs}$$

2.5.4 F1 Score

F1 score value is calculated when precision and recall value are combined together in a single metric by harmonic mean.

2.5.5 Area Under ROC(AUROC)

Area under ROC helps to distinguish between the classes. Higher value of AUCROC shows better classification between positive and negative classes (Mateo-Sotos et al., 2020).

2.5.6 Matthews Correlation Coefficient(MCC)

For measuring the quality of binary and multiclass class classification MCC value is calculated (Mateo-Sotos et al., 2020). The MCC values gives the difference between the values that has been predicted with the actual values.

2.5.7 Cohen's Kappa

For assessing the level of agreement between two raters that rate the same thing while making predictions, Cohen's kappa vales are calculated (Mateo-Sotos et al., 2020). The necessary assumption for the raters is that two raters each must rate at least one trial from each sample taken in consideration.

3. Results

In this section, we have discussed about the results obtained through the MiniPons records, for the classification of bipolar disorder. We have compared various machine learning algorithms on various aspects and drawn conclusion about which is the best suited model. The different attributes in the dataset have been studied through classifying them as training and test data. According to the results obtained, it shows that linear regression model is the best suited method to classify different features.

We have studied all the models by calculating the balanced accuracy, recall, precision and F1 score of all the models for the patients suffering from bipolar disorder, unipolar disorder and controlled patients, such as Linear regression, Support Vector Machines, K-nearest neighbors and Random Forest.

Through our analysis in Table 2. SVM and KNN models resulted with lower classification values as compared to other methods with around 84% and Random forest resulted moderate classification values around 89% whereas Linear regression had the best outcome with accuracy up to 97% for the MiniPons records.

Table 2. Table representing Precision, Accuracy, Recall and F1 Score calculated through mean and standard deviation of these models for the proposed machine learning algorithm.

Methods	Precision	Accuracy	Recall	F1-Score
SVM	83,54±0.76	84,49±0.81	83,98±0.36	84,65±0.48
K-NN	84,65±0.43	84,09±0.28	84,76±0.56	83,45±0.39
Random Forest	88,35±0.45	88,98±0.34	87,99±0.(Islam et al.,2018)	88,89±0.87
Logistic Regression	97,37±0.46	97,65±0.34	97,(Islam et al.,2018)±0.65	97,67±87

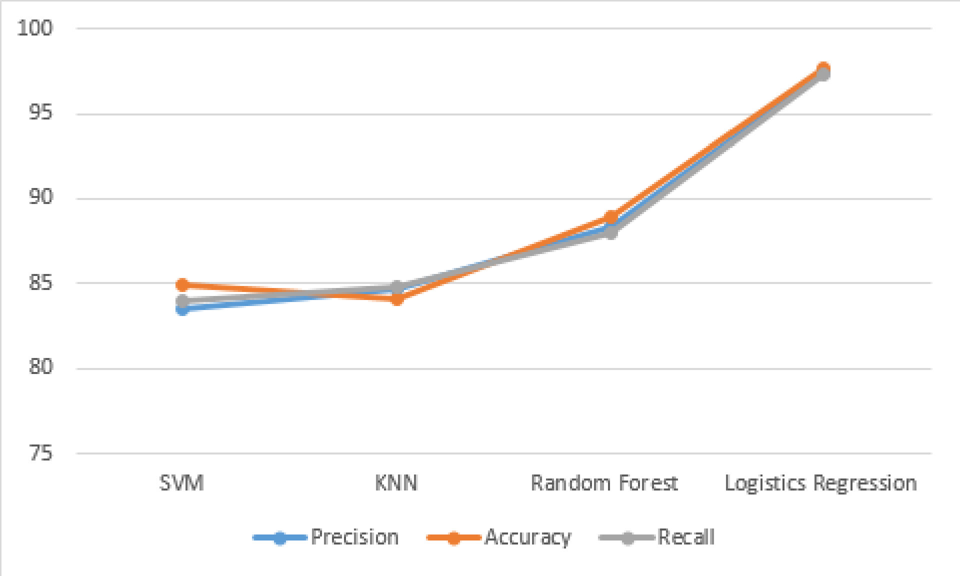

Figure 5. Graphical Representation of Precision, Accuracy and Recall for all the models.

Even for the Precision, Recall and F1 scores values, Linear Regression model gave the best result as compared to the other models ranging around 97 % for the MinPons records of patients suffering from Bipolar Disorder.

For better understanding and analyses, the dataset was studied through various other parameters as well such as

AUROC, MCC and Cohen’s kappa Method to verify whether Linear regression model is the best suited model or not in Table 3. These methods analyses
the better functioning of all the models while classifying them into two different classes.

Table 3. The AUROC, MCC and Cohen's Kappa Method calculation through mean and standard deviation method for all the models.

Methods	Precision	Accuracy	Recall	F1-Score
SVM	83,54±0.76	84,49±0.81	83,98±0.36	84,65±0.48
K-NN	84,65±0.43	84,09±0.28	84,76±0.56	83,45±0.39
Random Forest	88,35±0.45	88,98±0.34	87,99±0.26	88,89±0.87
Logistic Regression	97,37±0.46	97,65±0.34	97,26±0.65	97,67±87

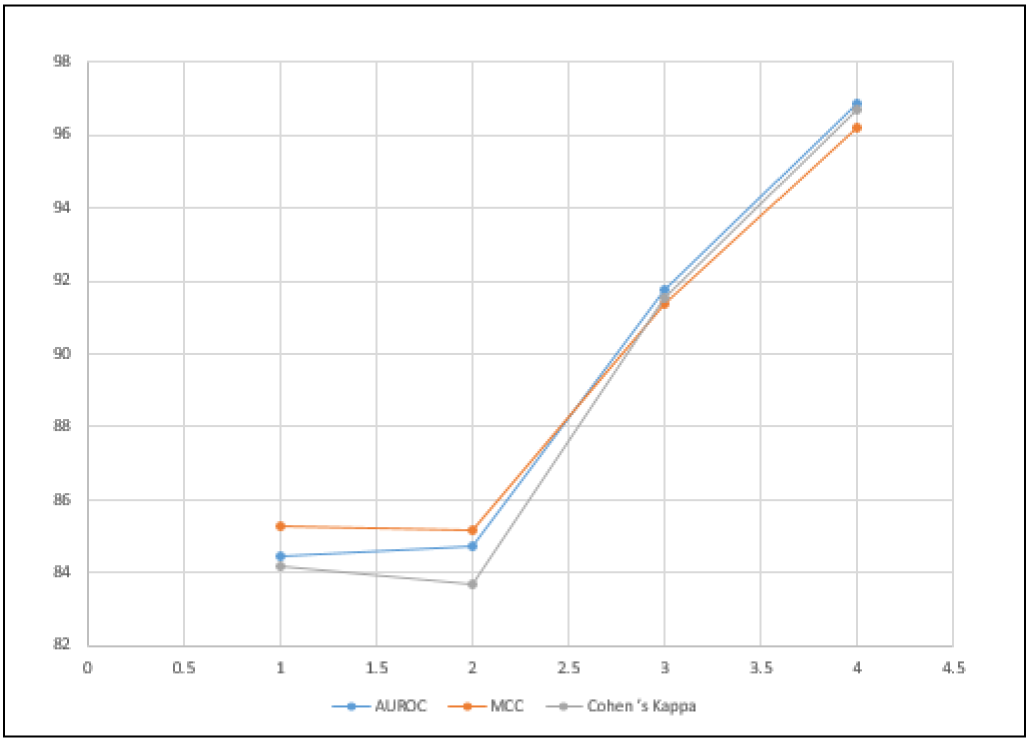

Figure 6. Graphical Representation of AUROC, MCC and Cohen's Kappa method for all the models

After analyzing our models through these parameters, we obtained the values for all our Machine Learning models and it is said that Matthews correlation coefficient prediction is the most accurate of all as in this we can obtain higher value only if we obtain higher prediction results in the confusion matrix for all the four categories i.e. true and false positives, and true and false negatives.

In the MCC method, we can see that linear regression model is providing a value closer to 1 that is around 96% whereas random forest depicted moderate value around 91% and again, SVM and KNN models gave the lowest result around 85%.

In Figure 5, we have undergone a graphical analysis of our result by comparing Linear regression models with the other models on the basis of precision, recall and accuracy values.

In Figure 6, we have analyzed the values of Linear regression models with the other models on the basis of MCC, Cohen's Kappa method and AUROC.

Through the results we can conclude that Linear regression modes has attained higher values for the classification of Bipolar disorder values. These results can help all the medical clinicians in their practice to predict early risk of bipolar disorder.

4. Discussion

Predicting Bipolar Disorder or any other mental disorder is a very challenging task as their diagnosis in itself is very difficult. But this selected model can help the clinicians for better study and understanding about patient's health. Our selected model Linear Regression has shown the best accuracy for distinguishing between patients suffering from bipolar disorder and controlled patients through MiniPons data with a maximum accuracy around 97 % as compared to other models. The comparison of the Linear regression model with the other models such as SVM, KNN and Random Forest proved us that linear regression model can perform well with even higher dimensions of data even through avoiding any sort of over training.

The proposed systems will help to give a deep insight to the clinicians and technicians for future related studies and proves to be a reliable tool for automatic analysis in the diagnosis of bipolar disorder. In the future work further research can be done to implement deep learning modals to study each and every activities and day to day changes in patients. This includes face recognition and different feature selection algorithms.

5. Conclusions

Through our study we have finally concluded that the proposed Linear Regression model which we have considered to understand that the behavior of patients suffering from Bipolar Disorder and controlled patients fits the best in the applied algorithm. For this, we compared the Linear Regression model with the Other models that is SVM, KNN and Random forest and clearly the selected model Linear Regression provided the highest values of precision, recall and accuracy as compared to others. This makes the model feasible for other automatic analysis for the diagnosis of Bipolar Disorder and will play a vital role in the decision making process for the clinicians and technicians in this field.

Acknowledgments

We are grateful to the patient representatives for providing feedback to the study design and focus group questions to conduct our study and analysis for diagnosing bipolar disorder patients and provide them the best aid.

Data Availability Statement

All relevant data are available within the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

REFERENCES

[1] Subhani, A. R.; Mumtaz, W.; Saad, M. N. B. M.; Kamel, N.; Malik, A. S. Machine Learning Framework for the Detection of Mental Stress at Multiple Levels. *IEEE Access* **2017**, *5*, 13545–13556. https://doi.org/10.1109/access.2017.2723622.

[2] Rios, A. C.; Noto, M. N.; Rizzo, L. B.; Mansur, R.; Martins, F. E., Jr; Grassi-Oliveira, R.; Correll, C. U.; Brietzke, E. Early Stages of Bipolar Disorder: Characterization and Strategies for Early Intervention. *Rev. Bras. Psiquiatr.* **2015**, *37* (4), 343–349. https://doi.org/10.1590/1516-4446-2014-1620.

[3] de Oliveira, L.; Portugal, L. C. L.; Pereira, M.; Chase, H. W.; Bertocci, M.; Stiffler, R.; Greenberg, T.; Bebko, G.; Lockovich, J.; Aslam, H.; Mourao-Miranda, J.; Phillips, M. L. Predicting Bipolar Disorder Risk Factors in Distressed Young Adults from Patterns of Brain Activation to Reward: A Machine Learning Approach. *Biol. Psychiatry Cogn. Neurosci. Neuroimaging* **2019**, *4* (8), 726–733. https://doi.org/10.1016/j.bpsc.2019.04.005.

[4] Sujatha, R.; Tejesh, K.; Krithi, H.; Shri, H. R. *Detection of Bipolar Disorder Using Machine Learning with MRI*; 2021.

[5] Vieta, E.; Salagre, E.; Grande, I.; Carvalho, A. F.; Fernandes, B. S.; Berk, M.; Birmaher, B.; Tohen, M.; Suppes, T. Early Intervention in Bipolar Disorder. *Am. J. Psychiatry* **2018**, *175* (5), 411–426. https://doi.org/10.1176/appi.ajp.2017.17090972.

[6] O'Donovan, C.; Alda, M. Depression Preceding Diagnosis of Bipolar Disorder. *Front. Psychiatry* **2020**, *11*, 500. https://doi.org/10.3389/fpsyt.2020.00500.

[7] Geetha, G.; Dr, K. Prediction of Diabetics Using Machine Learning. *International Journal of Recent Technology and Engineering (IJRTE)* **2020**, No. 5.

[8] Mateo-Sotos, J.; Torres, A. M.; Santos, J. L.; Quevedo, O.; Basar, C. A Machine Learning-Based Method to Identify Bipolar Disorder Patients. *Circuits Systems Signal Process.* **2022**, *41* (4), 2244–2265. https://doi.org/10.1007/s00034-021-01889-1.

[9] Alonso, J. F.; Romero, S.; Ballester, M. R.; Antonijoan, R. M.; Mañanas, M. A. Stress Assessment Based on EEG Univariate Features and Functional Connectivity Measures. *Physiol. Meas.* **2015**, *36* (7), 1351–1365. https://doi.org/10.1088/0967-3334/36/7/1351.

[10] Espinós, U.; Fernández-Abascal, E. G.; Ovejero, M. Theory of Mind in Remitted Bipolar Disorder: Interpersonal Accuracy in Recognition of Dynamic Nonverbal Signals. *PLoS One* **2019**, *14* (9), e0222112. https://doi.org/10.1371/journal.pone.0222112.

[11] Thieme, A.; Belgrave, D.; Doherty, G. Machine Learning in Mental Health: A Systematic Review of the HCI Literature to Support the Development of Effective and Implementable ML Systems. *ACM Trans. Comput. Hum. Interact.* **2020**, *27* (5), 1–53. https://doi.org/10.1145/3398069.

[12] Beaufort, I. N.; De Weert-Van Oene, G. H.; Buwalda, V. A. J.; de Leeuw, J. R. J.; Goudriaan, A. E. The Depression, Anxiety and Stress Scale (DASS-21) as a Screener for Depression in Substance Use Disorder Inpatients: A Pilot Study. *Eur. Addict. Res.* **2017**,

23 (5), 260–268. https://doi.org/10.1159/000485182.

[13] Vuppalapati, C.; Khan, M. S.; Raghu, N.; Veluru, P.; Khursheed, S. A System to Detect Mental Stress Using Machine Learning and Mobile Development. In *2018 International Conference on Machine Learning and Cybernetics (ICMLC)*; IEEE, 2018.

[14] Priya, A.; Garg, S.; Tigga, N. P. Predicting Anxiety, Depression and Stress in Modern Life Using Machine Learning Algorithms. *Procedia Comput. Sci.* **2020**, *167*, 1258–1267. https://doi.org/10.1016/j.procs.2020.03.442.

[15] Chen, M.; Hao, Y.; Hwang, K.; Wang, L.; Wang, L. Disease Prediction by Machine Learning over Big Data from Healthcare Communities. *IEEE Access* **2017**, *5*, 8869–8879. https://doi.org/10.1109/access.2017.2694446.

[16] Leal, J. *Application of Machine Learning Algorithms for Bipolar Disorder Crisis Prediction*; ApplicationOM, 2018.

[17] Sau, A.; Bhakta, I. Predicting Anxiety and Depression in Elderly Patients Using Machine Learning Technology. *Healthc. Technol. Lett.* **2017**, *4* (6), 238–243. https://doi.org/10.1049/htl.2016.0096.

[18] Kumarasinghe, K.; Kasabov, N.; Taylor, D. Deep Learning and Deep Knowledge Representation in Spiking Neural Networks for Brain-Computer Interfaces. *Neural Netw.* **2020**, *121*, 169–185. https://doi.org/10.1016/j.neunet.2019.08.029.

[19] Doryab, A.; Frost, M.; Faurholt-Jepsen, M.; Kessing, L. V.; Bardram, J. E. Impact Factor Analysis: Combining Prediction with Parameter Ranking to Reveal the Impact of Behavior on Health Outcome. *Pers. Ubiquitous Comput.* **2015**, *19* (2), 355–365. https://doi.org/10.1007/s00779-014-0826-8.

[20] Grünerbl, A.; Muaremi, A.; Osmani, V.; Bahle, G.; Ohler, S.; Tröster, G.; Mayora, O.; Haring, C.; Lukowicz, P. Smartphone-Based Recognition of States and State Changes in Bipolar Disorder Patients. *IEEE J. Biomed. Health Inform.* **2015**, *19* (1), 140–148. https://doi.org/10.1109/JBHI.2014.2343154.

[21] Faurholt-Jepsen, M.; Bauer, M.; Kessing, L. V. Smartphone-Based Objective Monitoring in Bipolar Disorder: Status and Considerations. *Int. J. Bipolar Disord.* **2018**, *6* (1), 6. https://doi.org/10.1186/s40345-017-0110-8.

[22] Bauer, M.; Grof, P.; Rasgon, N.; Glenn, T.; Alda, M.; Priebe, S.; Ricken, R.; Whybrow, P. Mood Charting and Technology: New Approach to Monitoring Patients with Mood Disorders. *Curr. Psychiatry Rev.* **2006**, *2* (4), 423–429. https://doi.org/10.2174/157340006778699747.

[23] Kumar, A.; Sharma, A.; Arora, A. Anxious Depression Prediction in Real-Time Social Data. *SSRN Electron. J.* **2019**. https://doi.org/10.2139/ssrn.3383359.

[24] Liu, D.; Feng, X. L.; Ahmed, F.; Shahid, M.; Guo, J. Detecting and Measuring Depression on Social Media Using a Machine Learning Approach: Systematic Review (Preprint). *JMIR Preprints*, 2021. https://doi.org/10.2196/preprints.27244.

[25] Muhammad, A.; Ashjan, B.; Ghufran, M.; Taghreed, S.; Nada, A.; Nada, A.; Maryam, A. Classification of Anxiety Disorders Using Machine Learning Methods: A Literature Review. *Insights Biomed Res* **2020**, *4* (1). https://doi.org/10.36959/584/455.

[26] Islam, M. R.; Kabir, M. A.; Ahmed, A.; Kamal, A. R. M.; Wang, H.; Ulhaq, A. Depression Detection from Social Network Data Using Machine Learning Techniques. *Health Inf. Sci. Syst.* **2018**, *6* (1), 8. https://doi.org/10.1007/s13755-018-0046-0.

[27] Shatte, A. B. R.; Hutchinson, D. M.; Teague, S. J. Machine Learning in Mental Health: A Scoping Review of Methods and Applications. *Psychol. Med.* **2019**, *49* (9), 1426–1448. https://doi.org/10.1017/S0033291719000151.

[28] Portugal, L. C. L.; Schrouff, J.; Stiffler, R.; Bertocci, M.; Bebko, G.; Chase, H.; Lockovitch, J.; Aslam, H.; Graur, S.; Greenberg, T.; Pereira, M.; Oliveira, L.; Phillips, M.; Mourão-Miranda, J. Predicting Anxiety from Wholebrain Activity Patterns to Emotional Faces in Young Adults: A Machine Learning Approach. *NeuroImage Clin.* **2019**, *23* (101813), 101813. https://doi.org/10.1016/j.nicl.2019.101813.

[29] Martínez, A.; Benítez, R.; Estrada, H.; Hernández, Y. Predictive Model for Detection of Depression Based on Uncertainty Analysis Methods. *Proc. (MPDI)* **2018**, *2* (19), 551. https://doi.org/10.3390/proceedings2190551.

[30] Santosh, A.; Shinde, M.; Raja Rajeswari, P. Intelligent Health Risk Prediction Systems Using Machine Learning: A Review. *International Journal of Engineering & Technology* **2018**, *7* (3).

[31] Librenza-Garcia, D.; Kotzian, B. J.; Yang, J.; Mwangi, B.; Cao, B.; Pereira Lima, L. N.; Bermudez, M. B.; Boeira, M. V.; Kapczinski, F.; Passos, I. C. The Impact of Machine Learning Techniques in the Study of Bipolar Disorder: A Systematic Review. *Neurosci. Biobehav. Rev.* **2017**, *80*, 538–554. https://doi.org/10.1016/j.neubiorev.2017.07.004.

[32] Lee, H.-J. Addendum to the Acknowledgements: Mood Prediction of Patients with Mood Disorder by Machine Learning Using Passive Digital Phenotypes Based on Circadian Rhythm: A Prospective Observational Cohort Study (Preprint). *JMIR Preprints*, 2019. https://doi.org/10.2196/preprints.15966.

[33] Sun, Q.; Yue, Q.; Zhu, F.; Shu, K. The Identification Research of Bipolar Disorder Based on CNN. *J. Phys. Conf. Ser.* **2019**, *1168*, 032125. https://doi.org/10.1088/1742-6596/1168/3/032125.

[34] Saylan, C.; Yilancioglu, K. Classification of Schizophrenia and Bipolar Disorder by Using Machine Learning Algorithms. *J. Neurobehav. Sci.* **2016**, *3* (3), 92. https://doi.org/10.5455/jnbs.1471026038.

[35] Rahman, R. A.; Omar, K.; Mohd Noah, S. A.; Danuri, M. S. N. M.; Al-Garadi, M. A. Application of Machine Learning Methods in Mental Health Detection: A Systematic Review. *IEEE Access* **2020**, *8*, 183952–183964. https://doi.org/10.1109/access.2020.3029154.

[36] Mehta, M.; Julaiti, J.; Griffin, P.; Kumara, S. Early Stage Machine Learning-Based

Prediction of US County Vulnerability to the COVID-19 Pandemic: Machine Learning Approach. *JMIR Public Health Surveill.* **2020**, *6* (3), e19446. https://doi.org/10.2196/19446.

[37] Gupta, M.; Vaikole, S. Recognition of Human Mental Stress Using Machine Learning Paradigms. *SSRN Electron. J.* **2020**. https://doi.org/10.2139/ssrn.3571754.

[38] Priya, A.; Garg, S.; Tigga, N. P. Predicting Anxiety, Depression and Stress in Modern Life Using Machine Learning Algorithms. Procedia Comput. Sci. 2020, 167, 1258–1267. https://doi.org/10.1016/j.procs.2020.03.442.

[39] Goli, H.; Aparna, C. Performance Research on Different Machine Learning Algorithms for Detection of Sleepy Spindles from EEG Signals. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* **2019**, *8* (9S2), 203–208.

[40] Saral, B.; Priya. Screen Time Addiction and Psychological Metric Analysis among Teens Using Machine Learning Techniques. *J. Adv. Res. Dyn. Control Syst.* **2019**, *11* (10-SPECIAL), 119–124. https://doi.org/10.5373/jardcs/v11sp10/20192782.

[41] Shrestha, A.; Dang, J.; Nakajima, K.; Wang, X. *Image Processing-Based Real-Time Displacement Monitoring Methods Using Smart Devices. Structural Control and Health Monitoring*; 2019.

[42] Kiranashree, B.; Ambika, V.; Radhika, A. Analysis on Machine Learning Techniques for Stress Detection among Employees. *Asian Journal of Computer Science and Technology* **2021**, *10* (1), 35–37.

[43] Vikhrov, I.; Ashirbaev, S. *Covid-19 Monitoring and Tracking System Using Information Technologies and Artificial Intelligence. Health Problems of Civilization*; 2021.

[44] Kouris, I. N.; Makris, C. H.; Tsakalidis, A. K. Using Information Retrieval Techniques for Supporting Data Mining. *Data Knowl. Eng.* **2005**, *52* (3), 353–383. https://doi.org/10.1016/j.datak.2004.07.004.

[45] Gitlin, M.; Malhi, G. S. The Existential Crisis of Bipolar II Disorder. *Int. J. Bipolar Disord.* **2020**, *8* (1), 5. https://doi.org/10.1186/s40345-019-0175-7.

[46] Chien, I.; Enrique, A.; Palacios, J.; Regan, T.; Keegan, D.; Carter, D.; Tschiatschek, S.; Nori, A.; Thieme, A.; Richards, D.; Doherty, G.; Belgrave, D. A Machine Learning Approach to Understanding Patterns of Engagement with Internet-Delivered Mental Health Interventions. *JAMA Netw. Open* **2020**, *3* (7), e2010791. https://doi.org/10.1001/jamanetworkopen.2020.10791.

[47] Mateo-Sotos, J.; Torres, A.; Santos, J.; Quevedo, O.; Basar, C. *A Machine Learning-Based Method to Identify Bipolar Disorder Patients. Circuits, Systems, and Signal Processing*; 2021.

[48] Vinodh. Perspective Analysis of Dyslexia Detection among Children's Using Paradigms of Machine Learning and Artificial Intelligence. *J. Adv. Res. Dyn. Control Syst.* **2020**, *12* (7), 582–589. https://doi.org/10.5373/jardcs/v12i7/20202041.

[49] Agnihotri, N.; Prasad, S. K. Review on Machine Learning Techniques to Predict Bipolar Disorder. *Turk. J. Comput. Math. Educ. (TURCOMAT)* **2022**, *13* (2), 195–206.

[50] Agnihotri, N.; Prasad, S. K. Predicting the Symptoms of Bipolar Disorder in Patients Using Machine Learning. In *2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART)*; IEEE, 2021; pp 697–702.

.