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BIPOLAR DISORDER CLASSIFICATION USING MACHINE LEARNING

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Abstract
Bipolar illness presents a significant diagnostic challenge due to its clinical variability and comorbidity with other diseases. Our research addresses these issues by developing a machine learning system aimed at enhancing diagnostic accuracy in clinical settings. We assessed many algorithms, such as J48, Random Forest, SMO, Naive Bayes, Logistic Re- gression, Simple Logistic, and the deep learning model Multilayer Perceptron (MLP), us- ing feature selection and stacking methodologies. With 90.00% accuracy for Naive Bayes and 91.67% accuracy for Stacking, we discovered notable improvements. These results underscore the significance of state-of-the-art machine learning methods for improving the classification of bipolar disorder and delivering more precise diagnostic and treatment tools.

INTRODUCTION

1.1 Introduction

This chapter examines the classification of bipolar disorder(BD) with a particular focus on feature selection using sophisticated computational techniques such as artificial neu-ral networks (ANNs), stacking, and machine learning algorithms.Description of problem, goals,along with an important domain, a research challenge and thesis motivation .

Bipolar Disorder

Globally, 2% of the population has BD, and an additional 2% has sub-threshold forms of the illness.(Librenza-Garcia et al., 2017) Bipolar disorder is among the top 10 causes of disability-adjusted life years in youth, according to the World Health Organization. Patients with bipolar illness had completed suicide rates of 4.9% for women and 7.8% for men, and their life expectancy was determined to be 9 years lower. While there are a number of therapies available to prevent and manage mood episodes, their effectiveness is often limited, and around 60% of patients relapse into depression or mania within the first two years of starting medication. (Librenza-Garcia et al., 2017).

It often begins during emotional states triggered by interruptions in cognition they can vary greatly, from extreme frenzy and excitement to profound sadness.(Jan et al., 2021)An epidemiological survey indicates that the incidence is increasing annually at a rapid pace. A direct link has been shown between BD and a higher risk of premature mortality. Bipolar illness patients frequently have life expectancies that are 9 to 17 years shorter than those of healthy people, which results in difficult living conditions.

Moreover, other studies con- ducted in other countries, like Denmark and the United Kingdom, assert that throughout the previous several decades, this mortality difference has been gradually widening. Although the majority of BD mortality cases are caused by diabetes and cardiovascular problems, other reasons include unintentional disasters.

(Sonkurt et al., 2021) Reports state that before the condition manifests, approximately 75% of individuals with bipolar disorder go through a depressive period. As a result, ac- cording to current diagnostic criteria, there is a ten-year lag between the start of the earliest symptoms and the accurate diagnosis. The clinical heterogeneity of bipolar disease may make getting the correct diagnosis difficult. Over one-third of patients had to wait more than ten years for an official diagnosis, and over 70% of bipolar patients had a false posi- tive. The high disability burden, low diagnostic accuracy, and diagnostic delay of bipolar disorder highlight the criticality of making an accurate and timely diagnosis.

(de Siqueira Rotenberg et al., 2021) Healthcare institutions are utilizing more digital technology and combining clinical practice to efficiently target individualized treatment. By streamlining repetitive operations like note-taking and data scanning, machine learning (ML) in conjunction with current clinical procedures may benefit physicians by freeing up time for more in-person interactions with patients. We thus want to contribute to therapeutic thought leadership with our exploratory study, provide a new paradigm for more attentive

and comprehensive listening, and shed light on BD recurrence patterns.

Major mood fluctuations associated with bipolar disease, including manic and depres- sive episodes, can cause a variety of issues with day-to-day functioning. Elevated mood, more energy, less need for sleep, and impulsive conduct are characteristics of manic episodes, while extended sadness, low energy, hopelessness, and disinterest in activities are charac- teristics of depression. These fluctuations have a significant impact on both personal and professional lives.

As time passes ,we become increasingly aware of the fact that we cannot precisely identify the reason for the disease and that it has a significant impact on everyone's life.

Types of Bipolar Disorder

Bipolar disorder comes in three different forms. In all three groups, there are discernible differences in energy, mood, and degree of activity. These feelings range from extremely "down," melancholy, apathetic, or hopeless periods (referred to as depressive episodes or cyclothymic disorder) to extremely "up," happy, excited, or vivacious behavior (referred to as manic episodes or Bipolar I). Manic episodes that are less severe are referred to as(hypomanic episodes or bipolar type II).

Bipolar I disorder

Bipolar I illness patients have severe, debilitating depressions and manic episodes. Bipolar I disorder is detected in 0.6% of people,determined by a World Health Organi- zation survey. The peak onset of bipolar I illness occurs in the third decade of life, often beginning in late adolescence or early adulthood (ages 20).(M.D., 2021).

Bipolar II disorder

Individuals diagnosed with bipolar II illness experience fully developed periods of hy- pomania and depression. Despite frequently experiencing moderate mixed moods, some individuals never experience full-blown mania.According to estimations from the World Health Organization, 0.4 people will have bipolar II disorder in their lives. (M.D., 2021).

cyclothymic disorder

People who have cyclothymic disorder frequently endure brief episodes of hypomania and depression mixed with sporadic periods of steady mood. The patient does not, by def- inition, experience fully developed manic or severe depression episodes. These people ef- fectively alternate between moderate melancholy and mild euphoria practically nonstop.An estimate of between 0.4% and 2.4% has been found in recent investigations on community populations. (M.D.,

2021).
The diagnosis of bipolar disorder (BD) is difficult as there are inconsistent biomarkers and a wide range of symptoms. Patients who seek therapy for depression frequently have BD misdiagnosed as major depressive disorder (MDD) 69% of the time. Merely 20% of individuals with BD receive a diagnosis during the first year of pursuing therapy. The dif- ficulty in diagnosing patients could be brought on by patients' uneasiness with disclosure and the ignorance of medical personnel. Patients with bipolar disorder also seek medical assistance when they are sad as opposed to manic. Diagnoses of borderline personality disorder (BPD) are complicated by co-occurring conditions such as attention-deficit hyper- activity disorder (ADHD), alcohol use disorder, and borderline personality disorder(Liu et al., 2021).

(Ceccarelli & Mahmoud, 2022) study offers a unique multimodal framework that com- bines textual, audio, and video modalities for the detection of mental disorders from videos. It incorporates temporal information and models the dynamic development of characteris- tics using recurrent neural network topologies. The framework shows superior performance on two datasets of mental diseases compared with state-of-the-art methods, underscoring the need of accounting for the temporal evolution of each modality for accurate identifica-tion.

(Ceccarelli & Mahmoud, 2022) A research made available a collection of sensor data from individuals with depression, which included motor activity recordings from unipo- lar and bipolar patients as well as healthy controls. In two trials, the model's accuracy was 0.991; UMAP dimensionality reduction and neural networks produced the best results. Ac-cording to the study, evaluating how medical professionals rate depressed symptoms may aid in our comprehension of the connection between depression and motor activity. The research emphasizes the potential of wearable sensors to assess mental health conditions.

(Mateo-Sotos et al., 2022) Using EEG data from Virgen de la Luz Hospital, a research suggests utilizing extreme gradient boosting (XGB) machine learning technique to diag- nose bipolar illness. The approach works better than four other supervised machine learn- ing algorithms: support vector machines, decision trees, Gaussian Naive Bayes, and k- nearest neighbors. With its superior prediction accuracy of 94%, high precision, and good recall, the XGB technique is a strong contender for the right diagnosis. The clinical data- trained XGB system may offer a novel diagnostic tool for bipolar illness.

In order to achieve the highest accuracy, this study uses a variety of features from a dataset to classify depression, Bipolar I and II, and normal conditions. We obtained an impressive 91% accuracy by using artificial neural networks (ANN), stacking techniques, and machine learning algorithms. To improve the classification performance, the research focuses on careful feature selection. The study substantially advances the field of psychi- atric diagnosis and treatment by demonstrating the efficacy of sophisticated computational methods in accurately diagnosing and differentiating between various mental health condi- tions through rigorous model training and validation.

1.2 Background of the study

Globally, Bipolar Disorder (BD) affects around 2-3% of the population and is a chronic mental condition. by recurring bouts of mania or hypomania and depression. .Despite advances in understanding its neurobiological underpinnings, BD remains challenging to diagnose accurately due to its heterogeneous presentation and overlapping symptoms with other mood disorders. ML techniques off a promising approach to improve the classifi- cation and subtyping of BD by leveraging diverse data sources and extracting meaningful patterns from complex datasets(Merikangas et al., 2011).

(Arbabshirani et al., 2017)Using ML algorithms on structural and functional MRI data, it has been possible to distinguish BD patients from healthy controls and find neuroimaging biomarkers predictive of diagnostic status. Neuroimaging studies have yielded important insights into the neuroanatomical and functional alterations associated with BD.

Clinical data has demonstrated the potential for ML approaches to be applied in order to automate diagnostic decision-making and predict treatment response based on symptom profiles and longitudinal trajectories. Clinical assessments, such as symptom severity rat- ings and diagnostic interviews, are critical to the diagnosis and management of BD.(Cao et al., 2018).

Genetic studies have implicated numerous susceptibility genes and molecular pathways in the etiology of BD. ML models integrating genetic data, such as single nucleotide poly- morphisms (SNPs) and gene expression profiles, have been developed to identify genetic risk factors and stratify patients into biologically meaningful subgroups(W. Wang et al., 2017).

Psychiatric conditions are complicated, encompassing a wide range of neurobiologi- cal factors and symptoms. To comprehend their intricacies, researchers are increasingly turning to multivariate pattern categorization techniques, especially supervised machine learning approaches. These approaches do, however, come with special difficulties and trade-offs. (Nielsen et al., 2020).This study focuses on functional connectivity with mag- netic resonance imaging and attempts to offer best practices for assessing machine learning applications in mental diseases. Classifications must be clinically relevant, free of con- founding factors, and evaluated for generalizability and performance in order to have trans-lational use.

(Antosik-Wó jcíń ska et al., 2020) systematic review explores smartphone-based systems for monitoring and detecting phase changes in bipolar disorder (BD). The study found that objective data collected from smartphones, including phone calls and usage data, can accurately predict mood status. However, there is no clear evidence of the superiority of machine learning approaches. The review concludes that smartphone-based monitoring could significantly improve BD management.

Despite the growing body of literature on ML-based BD classification, several chal- lenges remain, including data heterogeneity, small sample sizes, and model interpretabil- ity. Future research efforts should focus on addressing these limitations through large-scale collaborative initiatives, incorporating multimodal data fusion techniques, and enhancing the clinical utility of ML mdels through interpretable decision support systems(Varoquauxet al., 2017).

(de Siqueira Rotenberg et al., 2021)Four popular machine learning algorithms did rather well in the prediction test: Random Forests, Support Vector Machines, Na¨ıve Bayes, and Multilayer Perceptrons. This research employed ML approaches to predict depressive re- lapses in bipolar disorder (BD). The three primary mood symptoms seen during relapse visits were interest, depression, and vigor. The paper makes the case that using machine learning models in BD research may be a workable way to aid in medical judgment and stop relapses in the future.

In summary, ML techniques have considerable promise for enhancing the classification and understanding of bipolar disease across several domains, including neuroimaging, clin- ical assessment, and genetics. The application of big data analytics and multidisciplinary teamwork in artificial intelligence (AI)-based solutions can boost the precision of diagnosis and provide more customized treatment choices for individuals with BD.

1.3 Problem statement

The severe and protracted mental disease known as bipolar disorder makes it extremely dif-ficult for a person to operate in social, professional, and personal spheres. The primary tools used in the conventional diagnosis of bipolar illness are clinical interviews, self-reported questionnaires, and the clinician's experience. Because bipolar disorder symptoms often mimic those of other mental health diseases, such as major depressive disorder and bor- derline personality disorder, this may lead to a delayed or incorrect diagnosis.(Phillips & Kupfer, 2013). An inaccurate or delayed diagnosis may result in poor therapy, worsening the patient's disease and boosting the chance of comorbidity such as suicide. (Grande et al.,2016).

The development of ML techniques presents a viable solution to these diagnostic issues by enabling the study of complex and large-scale datasets to find subtle patterns and pre- dictive traits associated with bipolar disorder. ML techniques, particularly artificial neural networks (ANNs) and stacking methods, have showed potential in increasing the accuracy and timeliness of psychiatric diagnoses(Dwyer et al., 2018).

Effective feature selection, on the other hand, is a key stage in the modeling process be- cause it not only improves model performance by minimizing dimensionality and overfit- ting, but it also simplifies model interpretation by emphasizing the most relevant predictors of bipolar illness. Nonetheless, the success of these models depends heavily on the quality of the input characteristics. (Guyon & Elisseeff, 2003).

This research aims to develop a robust and scalable machine learning framework that can be implemented in clinical settings to support clinicians in making more accurate and
timely diagnoses of bipolar disorder. The study will investigate and evaluate various ma- chine learning and deep learning approaches for the classification of bipolar disorder, with a focus on feature selection techniques.

The study will compare different algorithms, such as support vector machines, random forests etc, identifying the most effective ways for accurate and early diagnosis. . Addition- ally, the integration of stacking methods—which combine multiple classifiers to improve predictive performance—will be examined to determine their efficaciousness in enhancingdiagnostic accuracy.

1.4 Research Question

To achieve the goals of this study, the following research questions on the diagnosis of bipolar disorder developed .

RQ1: How may feature selection methods improve machine learning models' inter- pretability and accuracy when it comes to classifying bipolar disorder?

RQ2: What is the stacking ensemble algorithm methods improving the classification accuracy of bipolar disorder compared to individual machine learning models?

RQ3: How does the integration of feature selection and stacking methodologies help in the creation of more durable and trustworthy bipolar illness diagnostic tool compared to standalone machine learning approaches?

1.5 Research Objective

More efficiency in differentiating between persons with bipolar disorder and healthy ones is our aim.In order to determine which classifier has the highest accuracy, we apply various classifier to a specific dataset.

The study's long term goal is to identify bipolar disorder using machine learning, ANN's, and stacking. Finding new classifier that employed both more accurate and less expensive is one of the study objective and provide patients with information as quickly aspossible.

In order to predict bipolar disorder patients with classification techniques as discussed above, the specific objectives of this study is follows:

Main Objective of this research:

RO1: To identify and evaluate the most informative features associated with bipolar disorder using feature selection methods.

RO2: To investigate the effectiveness of stacking multiple machine learning models, including classifiers such as Naive Bayes, Random Forests, and SMO etc in improving the accuracy and generalization of bipolar disorder classification.

RO3: To develop a comprehensive framework that integrates feature selection tech- niques and stacking algorithms to construct an optimized machine learning model capable of accurately classifying individuals with bipolar disorder, thereby providing a valuable diagnostic tool for clinicians and researchers.

The finding of this study will help clinical practitioners improve their practices and methods for classifying BD patients.

1.6 Research Scope

This study primary goal is to enhance currently available ML methods to accurately diag- nose BD. It also aim to determine which feature set essential for prediction using a dataset with multiple feature sets and to determine how accurate bipolar disorder can be identified.

The goal of the research is to categorize Bipolar I

and II, depression, and normal states by creating and assessing sophisticated machine learning models, such as those utilizing artificial neural networks (ANNs) and stacking approaches. The investigation starts with the careful gathering of a broad dataset that includes pertinent clinical, demographic, and other variables.
In order to improve model performance and lower computational complexity, the em- phasis switches to feature selection, which involves selecting important attributes. To cre- ate reliable classification models, ANNs, stacking techniques, and conventional algorithms like decision trees and support vector machines are used.
using all feature subsets and the top seven features chosen using the Ranker feature selection approach, this study's accuracy was 91.67% we use a dataset of 120 patients and classify the BD and healthy patients utilising the software called Waikato Environment for Knowledge Analysis(WEKA).
With the fewest possible features, we were able to attain the highest accuracy in this investigation. The computation time for predicting Bipolar disorder decreased by using the fewset feature feasible, which is beneficial for clinical practitioners.
To guarantee accuracy, precision, recall, and F1-score, these models go through ex- tensive training and cross-validation. After a comparative study determines which mode performs best, it is implemented and evaluated in a real-world setting.

1.7 Research Significance

The advancement of artificial intelligence approaches will benefit greatly from this re- search.The success that ML has achieved in numerous field ,the conclusion of enhanced accuracy, and the optimization of outcome have all improved over time as a result of new breakthroughs in this field.
Given all of these consideration, we have decided to focus our thesis on exploiting dataset to predict bipolar disorder. We also aim to determine which feature set is essen- tial and useful for enhancing the accuracy for predicting bipolar disorder. A supervised machine learning feature selection classification method is utilised to distinguish between patients with normal and BD. It is crucial in determining the BD patients who have an 80% chances of receiving a bipolar disorder. These method can potentially marginally change results and have a higher accuracy in bipolar disorder prediction.
The choice of the database for classifying is one of this research's most significant contribution, the selection of feature subset, the implementation of various classifier, the selection of the most effective feature by using feature selection method, and the results for bipolar disorder prediction with greater accuracy by comparing previous work using the same database.

1.8 Thesis Organization

Introduction, Literature Review, Research Methods, Findings and Discussion, and Conclu- sion are the five chapters that makeup this research thesis.
Chapter 1: "Introduction " chapter presents introduction of the research, background study, problem statement, research questions, research objective, significance and scope ofthe research.
Chapter 2 : The "Literature Review" chapter presents related background theory on bipolar disorder classification and summary of all research paper for bipolar disorder clas-sification.
Chapter 3: The " Methodology" chapter provide a detailed view of different steps used in proposed framework.
Chapter 4: The "Result and Discussion "present the outcome derived from the experi- ments performed. Each investigation redeemed in accordance with the objective. Derived result also given in this chapter.
Chapter 5: The "Conclusion" this chapter examines the key findings of the study, its limitation, and possible future research direction.

LITERATURE REVIEW

2.1 Introduction

The complex mental illness known as bipolar disorder, which is characterized by extreme mood swings from manic highs to depressive lows, may be challenging to identify and treat. (Tomasik et al., 2021).Conventional diagnostic techniques depend on self-reported experiences and clinician interviews, which may be laborious and subjective. A viable substitute method for classifying bipolar illness is machine learning (ML), which has the potential to increase early intervention, speed, and accuracy.

Numerous investigations have looked into the application of ML for the classification of bipolar illness, with encouraging outcomes. . Research by (Tomasik et al., 2021) uti- lized an ML algorithm trained on data from online mental health questionnaires and blood biomarkers. This approach yielded an Area Under the Receiver Operating Characteristic Curve (AUROC) of 0.92, demonstrating high accuracy in differentiating bipolar disorder from major depressive disorder. Similarly, studies using neuroimaging data, such as elec- troencephalogram (EEG) or magnetic resonance imaging (MRI), have shown encouraging
results. (Campos-Ugaz et al., 2023) provides a review of such studies, highlighting the potential of EEG-based ML models for achieving over 90.

These findings suggest that ML has the potential to revolutionize bipolar disorder clas- sification. However, it is crucial to acknowledge the limitations of current research. Data quality and availability are critical factors, and studies often rely on relatively small datasets (Campos-Ugaz et al., 2023). Additionally, the generalizability of ML models across differ- ent populations and clinical settings requires further investigation.

Despite these limitations, the potential benefits of ML for bipolar disorder classification are undeniable. By leveraging large datasets and sophisticated algorithms, ML can provide objective and efficient tools to support clinicians in diagnosis and treatment planning. This can ultimately lead to improved patient outcomes and a better understanding of bipolar disorder itself.

By Analysing the most recent machine learning diagnostic for bipolar disorder the con- tribution categorized into Machine Learning(ML)in section 2.3,Bipolar Disorder (BD) in section 2.4,Classification in section 2.5.Hence,this chapter present an overview of the litere- ture review or releated work the methods that already used for Bipolar disorder classifica-tion.

2.2 Role Of Machine Learning in Mental Health

ML is a rapidly developing and revolutionary field in mental health care that holds enor- mous potential for enhancing the precision of diagnoses, customizing treatment regimens, facilitating early intervention, and offering real-time monitoring and feedback. This section
offers a thorough analysis of the body of research, covering the approaches, uses, and re- sults of machine learning in the field of mental health as well as the difficulties and potential paths forward for this emerging field.

Improving the accuracy of diagnoses is one of the main uses of ML in mental health. Conventional approaches to diagnosing mental health disorders frequently depend on pa- tient self-reports of symptoms and judgments from clinicians, both of which can be erro- neous and subjective. On the other hand, ML algorithms are capable of examining big and intricate datasets to find patterns that could point to certain mental health issues. (Duan et al., 2020) demonstrated the efficacy of ML models in accurately classifying bipolar disor- der by analyzing patient data that included demographic, clinical, and genetic information. These models significantly outperformed traditional diagnostic methods, reducing the rate of misdiagnosis and improving patient outcomes.

Moreover, ML has been applied to the diagnosis of other mental health conditions such as depression and anxiety. For instance (Cho et al., 2018) utilized ML algorithms to ana- lyze electronic health records and predict the onset of depression with high accuracy. The study highlighted that ML models could identify subtle patterns in patient data that are often missed by clinicians, thus providing a more reliable diagnostic tool. ML is also revo- lutionizing the way mental health treatments are personalized. By analyzing data from past treatments and outcomes, ML algorithms can predict which treatment strategies are likely to be most effective for individual patients. (Martin et al., 2019)

conducted a comprehen- sive review of ML applications in mental health, highlighting several studies where ML was used to tailor treatments for conditions such as depression and anxiety. These person- alized approaches not only improve treatment efficacy but also reduce the risk of adverse
effects and enhance patient adherence to treatment protocols.

(Kessler et al., 2016) used ML to develop personalized treatment recommendations for patients with depression. The study employed data from randomized controlled trials to train ML models that could predict patient responses to different antidepressant medi- cations. The results showed that ML-based treatment recommendations significantly im- proved treatment outcomes compared to standard care.

Another significant contribution of ML to mental health care is in the realm of predictive analytics. By analyzing patterns in data over time, ML algorithms can predict the onset or recurrence of mental health conditions, enabling early intervention. (Faurholt-Jepsen et al., 2017) used ML to analyze data from smartphone sensors and self-reported mood assessments to predict mood episodes in patients with bipolar disorder. The model was able to predict mood episodes with high accuracy, allowing for timely interventions that could potentially prevent full-blown episodes.

Similarly, (Barnett et al., 2018) created an ML model to forecast the suicide risk in people with mental health issues. The model outperformed conventional risk assessment instruments in its ability to identify high-risk people by evaluating data from electronic health records. When these people are identified early on, immediate measures that may save lives can be made.

The use of wearable devices and mobile applications has opened new avenues for real-time monitoring of mental health conditions. ML algorithms can process data from these devices to provide continuous feedback on a patient's mental health status. (Mohr et al., 2017) developed an ML-based system that monitored speech patterns, physical activity, and social interactions through a smartphone app to detect signs of depression and anxiety in real-time. The system provided immediate feedback to patients and clinicians, facilitating prompt adjustments to treatment plans.

In another study,(R. Wang et al., 2014) used wearable sensors to monitor physiological signals such as heart rate and skin conductance in patients with anxiety disorders. ML algorithms analyzed the data to detect anxiety episodes and provided real-time alerts to patients, enabling them to implement coping strategies and prevent escalation.

By enabling early intervention, personalizing treatment plans, increasing diagnostic accuracy, and offering real-time monitoring and feedback, Machine learning in the field of mental health has the potential to completely transform it. ML is expected to become more and more important in improving mental health outcomes and care as the field develops.

2.3 Machine Learning

ML is a technique that builds training models and reliably classifies fresh data using em- pirical data. Its advantages in diagnosing and predicting future disease progression are significant, particularly in individual-level analysis. (Gao et al., 2018)The most impor- tant benefit is that these research attempt to create computational tools that may be used to apply individual-level analysis to major depressive disorder (MDD) and differentiate it from controls or mood disorder subgroups. They also incorporate imaging measures into therapeutic treatment.

Because bipolar illness patients have a wide range of clinical characteristics, machine learning approaches can offer important insights in areas like diagnosis, individualized therapy, and prognostic direction.(Librenza-Garcia et al., 2017) investigates the application of machine learning methods to the prediction of bipolar disorder diagnosis and clinical outcomes. 51 research from January 2017 were included in the 757 abstracts that the authors retrieved. To differentiate bipolar disorder diagnosis from other mental diseases or healthy controls, the majority employed various layers of biological evidence.

Individual level classification is really made feasible by machine learning approaches. Many studies have examined the classification accuracy of machine learning-based neu- roimaging investigations during the past 20 years, with a focus on diagnosis and treatment response (Kim & Na, 2018).

Precision medicine is a medical strategy that aims to improve treatment quality and accessibility by focusing on each patient's unique processes. Using methods like machine learning, it examines clinical data and electronic health records to build analytical models for clinical decision-making(de Siqueira Rotenberg et al., 2021).

(Yasin et al., 2021) Deep learning is a well-liked field of study that provides precise predictions for the categorization of depression in electroencephalogram (EEG) signals. Deep learning extracts complex characteristics from massive amounts of data by using numerous layers, in contrast to typical machine learning.

(Sonkurt et al., 2021)The use of machine learning is increasingly being explored due to its great sensitivity and specificity. Machine learning algorithms have successfully distin- guished between bipolar illness and healthy controls with good accuracy.

Table 1.1 Previous work of machine learning

Author(s)	**Objective**	**Research Method**	**Key Findings**
(Gao et al.,2018)	To develop Machine learning-based translational biomarkers could improve understanding of mood disorders, despite the challenge of confirming early depressive episodes	Classification Methods	In particular, this work uses data from magnetic res- onance imaging to diagnose mood disorders and look into treatment results. It also explores machine learn- ing techniques for brain imaging categorization and predictions in depression. In an effort to inform in- dividualized therapeutic therapy, it addresses obsta- cles, potential restrictions, and future possibilities in the development of MDD biomarkers.
(Librenza-Garcia et al.,2017)	To conduct a literature study on the use of machine learning methods to the evaluation of bipolar illness pa tients .	Review Method	The majority of research employed many layers of biological data to differentiate bipolar disorder diag- noses from other mental diseases or healthy controls, according to a review of the literature on machine learning approaches in bipolar disorder evaluation. To produce clinical phenotypes that are more trustwor- thy, unsupervised machine learning was employed. The study came to the conclusion that machine learn- ing may offer helpful information on prognostic pre- diction, customized therapy, and diagnostics.

(Kim, Yong-Ku et al.,2018)	This study assesses the suitabil- ity of machine learning classifi- cation methods that detect and differentiate between mood disorders using brainMRI data in order to improve patient outcomes and decision-making.	Review Method	Mood disorders leading to socioeconomic burdens are linked to neural substrates including the thalamus, ventral striatum, hippocampus, amygdala, prefrontal cortex, and corpus callosum. However, it is unclear what their clinical importance is. Machine learning- capable brain MRIs have the potential to identify indi- viduals uniquely; nevertheless, considerations such as cost-effectiveness and comorbidities must be made.
Author(s)	**Objective**	**Research Method**	**Key Findings**
(de Siqueira Rotenberg et al.,2021)	To enhance patient outcomes and early intervention techniques, to forecast depressive relapses in bipolar disorder patients.	Classification Method	Four machine learning methods were used in this investigation on a cohort of 800 patients using the STEP-BD dataset. This illustrated how medical decision-making about therapy and preventing future relapses might benefit from the use of machine learning-based precision medicine models.
(Yasin, Sana and Hussain et al.,2021)	Evaluates the usefulness of neural network-based methods for diagnosing major depressive disorder and bipolar disorder using elec- troencephalogram (EEG) data, with special attention to reliability, accuracy, and clinical relevance.	Review Method	Focusing on Major Depressive Disorder (MDD) and Bipolar Disorder (BD), the study highlights the need of phenotypic characterization using biomarkers such as EEG data. The paper discusses EEG-based tech- niques, public databases, and biomarkers for the diagnosis of different diseases. In conclusion, suggestions are provided for improving model depend- ability in psychiatric and deterministic computational intelligence-based systems.
(Sonkurt et al.,2021)	To improve the precision of the bipolar illness diagnosis by creating and assessing a machine learning model that uses information from cognitive assessments.	Classification Method	This study uses a unique machine-learning method in conjunction with a broader neuropsychological examination to reliably distinguish bipolar disorder patients from healthy controls. Six CANTAB exams were used to evaluate the study's participants. To categorize participants, the Polyhedral Conic Functions technique was employed.

2.4 Bipolar Disorder

Bipolar disorder (BD) is a severe, chronic illness that significantly affects psychosocial functioning and quality of life. It is also the second most common mental illness in terms of the days on which youth are unable to finish their assignments; out of every 100,000 individuals in the general population,5.2 are estimated to have BD annually Risk factors for borderline personality disorder (BD) include criminal behavior, impulsivity, ADHD,
generalized anxiety disorders and separation anxiety, early-onset panic episodes and panic disorder, and generalized anxiety disorders. Risk variables included in risk calculators include family history, age of onset in the family, psychosocial functioning, mood and anxiety symptoms, and mood ladders(de Pablo et al., 2023).

The combined suicide rate among people with bipolar illness (BD) is around 164 per 100,000 person-years, and the lifetime incidence of suicide attempts can reach 34%. Com- pared to the general population, BD patients have a suicide risk that is around 20–30 times higher. A significant independent risk factor for another attempt at suicide is a history of previous suicide attempts, which may indicate the degree of intent to die. Those who tried suicide were more likely to self-harm again the next year; 1.6% of them died by suicide in the first 12 months, and 3.9% died by suicide in the first 5 years. (Tian et al., 2023).

(Zhu et al., 2023) International classifications such as DSM-IV and ICD-10 are used to evaluate patient symptoms in order to diagnose BD and MDD. Based on these initial characteristics, doctors create differential diagnoses and choose additional criteria such as imaging scans, blood tests, physical examinations, and medical histories. The current categorization systems need several symptoms in an attempt to increase diagnosis accuracy; however, biomarker profiling methodologies may be able to do so in mental healthcare.

(Sankar et al., 2023) This is the first research to predict individual-level elevated and sad mood symptomatology in BD using a machine learning technique. The researchers hypothesized that individual differences in the severity of symptoms associated with depression in a left dlPFC system and individual differences in the severity of symptoms associated with elevated mood in a right vPFC system would be predicted by changes in whole-brain, intra- and interhemispheric functional connectivity.

(Tripathi et al., 2023) The research improved the ability to anticipate the reaction of lithium patients and developed an algorithm for bipolar disease diagnosis by utilizing elec- trophysiological recordings. Improved classification schemes utilizing information theory boost accuracy for patients responding to lithium medication (LR patients) from 81% to 99% and for BD patients from 60% to 74%.

Using neuroimaging data, machine learning (ML) can aid in the diagnosis of BD. (Nunes et al., 2020)research used machine learning (ML) to analyze magnetic resonance imaging (MRI) data from 2167 control subjects and 853 BD members of the ENIGMA consortium. Accuracy ranged from 45.23% to 81.07% in the results, with aggregate subject-level analyses producing the best accuracy.

Table 2.2 Previous work of Bipolar Disorder

Author(s)	Objective	Research Method	Key Findings
(de pablo et al.,2023)	To assess previous research and pinpoint predictive indicators for correctly differentiating between bipolar illness I and II in high-risk people, hence enhancing early de- tection and intervention techniques	Review Methods	A thorough analysis of 13 trials including 678 individ- uals at clinically high risk (CHR-BD) for bipolar disorder revealed that those who satisfied the BD-NOS criteria had the highest likelihood of acquiring BD- I/II. According to the study, BD-I and BD-II devel- oped at various rates, and after two years, the likeli- hood of having BD I/II ranged from 7.1% to 23.4 %.
(Tian, Shui and Zhu et al.,2023)	To create and validate machine learning models that predict suici- dality in bipolar disorder patients by analyzing brain activity variability.	Prediction Method	Through the identification of clinically discernible aberrations in the rhythms of instinctual brain activity, this work has the potential to further our understanding of the neuroscience of suicidal conduct.
(Sankaret al.,2023)	To identify brain functional con- nectome patterns that can predict mood symptoms in individuals with bipolar disorder, enhancing diag- nostic accuracy and personalized treatment approaches.	Prediction Method	Finding brain functional connectomes predictive of depressive and hypertensive mood symptomatology in bipolar disorder (BD) patients is the aim of the research, which use the machine learning approach known as Connectome based Predictive Modeling (CPM).
(zhu et al.,2023)	To use the machine learning tech- nique called as Connectome-based Predictive Modeling (CPM) to dis- cover brain functional connectomes predictive of depressed and hy- perbolic mood symptomatology in people with bipolar disorder (BD).	Classification Method	With the goal of reducing the number of patients misdiagnosed with major depressive disorder (MDD) and bipolar disorder (BD), the research developed an electronic medical record based diagnosis system based on machine learning. The algorithm simulates human clinical reasoning to try and make forecasts comprehensible by measuring and visualizing features.
Author(s)	Objective	Research Method	Key Findings

(Tripathi et al.,2023)	To enhance the prediction of lithium response in patients with bipolar illness in order to improve individualized treatment outcomes and precision medicine methods.	Prediction Method	The study aimed to improve the prediction of a patient's response to lithium (Li), a mood stabilizer, and develop a diagnostic algorithm for bipolar disorder. Electrophysiological recordings were performed on dentate gyrus granule neurons from nine subjects. The results showed that information theory features improved classification schemes, allowing for better differentiation between BD patients and control individuals.
(Nunes et al.,2020)	To develop predictive models for identifying distinct bipolar disorder subtypes.	Classification Method	In an ENIGMA collaboration investigation, ML was used to MRI data from 853 BD and 2167 control subjects. The results indicated that the accuracy ranged from 45.23 percent to 81.07 percent, with the best accuracy coming from aggregate subject-level analysis. Age and anticonvulsant treatment were linked to higher likelihood of accurate categorization.

2.4.1 Bipolar Disorder Classification Through clinical,demographic and expert Diagnose

(Reinares et al., 2013)According to the American Psychiatric Association (APA), 1994, bipolar disorder (BD) is a complex and chronic mental illness marked by recurring bouts of depression and mania. The course of a disease might vary greatly depending on how endpoints are defined. Functional objectives are concerned with psychosocial, residential, and vocational function; clinical endpoints are concerned with syndromal or symptomatic remission.

The Restoration of patients quality of life is the ultimate objective of treatment consequently, functional endpoints are now prioritized since they are the most important to patients and should be the center of care planning.

(Struyf et al., 2008) The data set on gene expression in schizophrenia and bipolar illness from the Stanley Neuropathology Consortium was examined. Six categorization techniques fared better than the rest, according to the study, including support vector machines (SVMs). SVMs were shown to have a high rate of success in differentiating between normal control and bipolar disorder and schizophrenia, and their classification performance increased with the inclusion of clinical and demographic data. Nevertheless, the study also discovered that some factors, including drug and alcohol abuse, may alter gene expression and make it more difficult to pinpoint the genes that are directly linked to the illnesses.

In a study of (Passos et al., 2016)Machine learning algorithms were trained using 144 patients, clinical, and demographic data to identify individuals who have attempted suicide. The relevance vector machine (RVM) method yielded a 72% accuracy rate. Notable pre- dictors were a history of psychosis, cocaine dependency, depressive hospitalizations in the past, and PTSD comorbidity.

(Perlis et al., 2006) The study looked for clinical traits that would set bipolar individuals apart from unipolar depression in people experiencing major depressive episodes. Data from non-psychotic outpatients were obtained from three extensive multicenter clinical studies carried out in the United States. An earlier age at beginning, a larger number of preceding depressive episodes, the Montgomery-Å sberg Depression Rating Scale, the Hamilton Anxiety Rating Scale, and eight particular symptom items were shown to be associated with bipolar depression. Individuals with unipolar depression were more likely to exhibit sad behavior, intellectual, somatic, respiratory, genitourinary, and melancholic symptoms, whereas bipolar patients were more likely to feel worries.

Table 2.3 Previous work of Bipolar Disorder Classification Through clinical,demographic and expert Diagnose

Author(s)	Objective	Research Method	Key Findings
(Reinares et al 2013	To better individualized treatment plans and long-term prognosis by developing a clinical staging system for bipolar illness and classifying patients into subgroups according to functional results.	The diagnosis was confirmed through the use of the Structured Clinical Interview.	Based on two underlying dimensions—one for dis- ease severity and another for cognitive function our results offer the first staging categorization of BD that has been objectively derived. This method may be improved by including more dimensions and evaluating the emergent classes' potential predictive utility and repeatability. Creating a disease staging system for BD will enable more homogenous patient groups to be chosen for study and enable patients to get individualized therapy planning.
(Struyf, Jan and Dobrin et al.,2008)	To develop an integrated model of schizophrenia and bipolar illness that incorporates gene expression, clinical, and demographic data to enhance the precision of diagnosis and enable individualized treatment plans.	case study	With the inclusion of demographic and clinical data, the article shows that Support Vector Ma- chines (SVMs) can effectively differentiate between schizophrenia and bipolar illness from normal con- trol. Statistical power is still decreased when factors like drug and alcohol usage are taken into account.
(Passos et al .,2016	To enhance early diagnosis and in- tervention techniques by identifying a clinical indicator of suicidality in people with mood disorders.	A machine learning-based pilot research.	The model estimates suicide risk in mood disorder patients using demographic and clinical variables, guiding interventions selection and future research.

(Perlis et al.,2006)	To compare the clinical characteristics of major depressive disorder and bipolar depression in exten- sive multicenter studies in order to improve differential diagnosis and treatment approaches.	Research compared 477 bipolar disorder-diagnosed subjects with major depressive disorder	The study emphasized the need for more suitable therapy selection in individuals having severe depressive episodes by comparing data from three US clinical trials to uncover clinical markers that potentially distinguish bipolar from unipolar depression.

2.5 Classification

There are different methodologies and numerous procedures that can used for bipolar dis- order classification .Here we can discuss some methods to diagnose bipolar disorder.

2.5.1 Different methods to diagnose Bipolar Disorder

(Belizario et al., 2019)The study determined the predominant polarity (PP) in 148 patients with bipolar disease by utilizing clinical data and machine learning. With an AUC ROC of 74.72%, the algorithm classified patients as having manic or depressive PP using the Random-Forest technique. Clinical variables that were significant were age at onset of first depressive episode, number of hospitalizations, BD Type II, manic start, delusions, psychotic symptoms, and tobacco use. Significant factors included concurrent conditions including anxiety, alcoholism, eating problems, and drug misuse, as well as family history and hallucinations. This approach shows that it is possible to accurately classify bipolar disease by integrating clinical data with machine learning.

The use of ML in the diagnosis of mental illnesses like as bipolar disorder (BD) has grown in favor. Neuroimaging and electrophysiological studies reveal structural and func- tional abnormalities in the brain between BD patients and healthy persons, indicating neu- rological alterations associated with the condition. Clinical prediction tools may be devel- oped via machine learning algorithms, which generate predictions and extract knowledge. Currently, ML is used in MRI and EEG studies to differentiate BD from healthy people and other mental illnesses, which may help determine the kind and severity of therapy.(Campos- Ugaz et al., 2023).

Using MRI images, (Huang et al., 2024) This study differentiates major depressive disorder (MDD) from bipolar disorder (BD) using structural connectome analysis and ma- chine learning techniques. Each patient group has distinct nodal changes: those with MDD show anomalies in the default mode network and left thalamus, while those with BD show particular differences in prefrontal regions. ML algorithms are able to distinguish between BD and MDD with an amazing accuracy rate of 90.3%, suggesting that ML has the poten- tial to be used for accurate mental condition diagnosis.

The goal of the genetic research was to find diagnostic genes linked to metabolic syn- drome and bipolar disorder. (Shen et al., 2023) study used the Limma software to identify differentially expressed genes (DEGs) based on a validation dataset from the Gene Expres- sion Omnibus. A protein-protein interaction network was built using ML methods, finding
2,289 DEGs related with bipolar illness and 691 module genes connected to metabolic syndrome. Notably, five candidate genes (AP1G2, C1orf54, DMAC2L, RABEPK, and ZFAND5) revealed as having high diagnostic potential for these diseases.

(Nova, 2023) study uses machine learning to classify mental diseases based on text data from social media subreddits. The dataset contains 10,000 rows from the 'BPD', 'bipolar', 'depression', and 'anxiety' subreddits. Data was cleaned using text preprocessing techniques, which included eliminating URLs, punctuation, and stopwords. Three models were evaluated:

multinomial Naive Bayes, multi-layer perceptron, and lightGBM. The results showed an accuracy of 0.706 for Multinomial Naive Bayes and 0.68 for Multi-layer Perceptron, with LightGBM doing better in classification.

So, (G. Wang et al., 2024) study uses structural MRI (sMRI) and functional MRI (fMRI) data to develop a novel multimodal diagnostic model for bipolar illness. The spatiotemporal pyramid structure extracts fMRI features, whereas the Patch Pyramid Feature Extraction Module extracts sMRI features. The suggested approach achieves the state of the art by outperforming others in balanced accuracy, according to extensive trials.

Table 2.4 Previous work of Different methods to diagnose Bipolar Disorder

Author(s)	Objective	Research Method	Key Findings
(Belizario et al.,2019)	To precisely ascertain a patient's probability score (PP) while investigating correlations between PP and clinical and demographic factors, excluding the quantity and polarity of previous episodes.	Classification Method	The study utilized machine learning algorithms to accurately classify patients with Bipolar Disorder's pre- dominant polarity, achieving an AUC ROC of 74.72 percent , identifying associated variables such as age, hospitalizations, and comorbid anxiety disorders.
(Huang et al.,2024)	To distinguish between Major Depressive Disorder (MDD) and Bipo- lar Disorder (BD) by developing accurate neuroimaging biomarkers using structural connectome analysis and machine learning algorithms.	Classification Method	The study uses machine learning algorithms and structural connectome analysis to discriminate between Major Depressive Disorder (MDD) and Bipolar Disorder (BD). Similarities between MRI scans and their startling 90.3% accuracy rate point to the possi- bility of using them to diagnose mental diseases.
(Shen, Jing and Feng et al.,2023)	To identify the metabolic syndrome associated bipolar affective disorder useful diagnostic candidate genes.	deep bioinfor- matics analysis and machine learning com- bined	With validation data and machine learning ap- proaches, the study finds diagnostic candidate genes for bipolar illness with metabolic syndrome. There is diagnostic significance for five potential genes (AP1G2, C1orf54, DMAC2L, RABEPK, and ZFAND5).
(Nova, Kannane., 2023)	To develop machine learning methods for automatically classifying mental disorders using textual data from social media.	Classification Method	The study uses machine learning models to classify mental disorders from social media subreddits. Three models were used: Multinomial Naive Bayes, Multi-layer Perceptron, and LightGBM. The Multinomial Naive Bayes model achieved 0.706 accuracy, while the Multi-layer Perceptron model achieved 0.68.
Author(s)	Objective	Research Method	Key Findings

(Wang, Guoxin and Shi et al ., 2024)	To create and test a new bi- pyramid multimodal fusion technique to in- crease the precision and depend- ability of bipolar disease diagnosis.	A Two-Pyramid Multimodal Fusion Method for Bipolar Disorder Identification.	Using sMRI and fMRI data, this work suggests a unique multimodal diagnostic paradigm for bipolar illness. Spatiotemporal pyramid structure is used to extract fMRI features, whereas Patch Pyramid Feature Extraction Module is used to obtain sMRI features. Numerous tests demonstrate that the suggested approach achieves the state of the art by outperforming others in balanced accuracy.

2.6 Summary

The literature review of recent work done in the problem domain provided in this chapter . Additionally,this chapter discusses the detail of recent work that make use of ML and DL techniques.This study objective is to forecast bipolar disorder using machine learning techniques or classification method . During the current trials , ML algorithms such as Naive Bayes , Logistic ,Simple logistic,SMO,j48,Random forest used to classify bipolar disor- der and apply Artificial neural network (Multilayer perceptron) and stacking to improve classification accuracy.The research methodology and recommended model for identifying bipolar disorder in the following chapter (Chapter 3).Additionally,it include each stage in the categorization of bipolar disorder using ML algorithms ,including data gathering ,fea ture extraction and selection.

METHODOLOGY

3.1 Introduction

This section covers the research methodology, which covers the strategies and tactics used to meet goals and respond to research questions. a systematic process and methodical technique to conduct experiments and create a shared foundation.Section 3.2 discusses the supervised learning approach; Section 3.3 discusses data collection; Section 3.4 dis- cusses feature selection and ranking; Section 3.5 discusses classification strategies; and Section 3.6 discusses the classification algorithm.The procedures in the suggested frame- work, which were implemented to the selected data during this analytical study activity, are depicted graphically in figure 3.1.Section 3.9 provides a summary of this chapter's con-tents.

3.2 Supervised Learning Approach

Models are created using ”training data” using a collection of algorithms referred to as the supervised machine learning (ML) approach.by creating a connection between the model's inputs and outputs.Both the input and the outputs should be included in the training data. In essence, supervised learning is the process of teaching or training a computer with labeled input.Thus, the right reaction has been assigned to certain data.Following that, a fresh set of examples (data) are fed into the machine, allowing the supervised training process to analyze the training sets (data) and generate the desired output from classified data.You can use supervised learning approaches to finish tasks that need regression and classification.

3.3 Data Collection

The dataset used in this work to classify bipolar disorder was obtained from the Kaggle ma- chine learning repository(kaggle ˙ dataset). 120 psychology patients with 17 key symptoms for major depressive disorder(Bipolar Type-2), manic bipolar disorder(Bipolar Type-1), de- pressive bipolar disorder(Depression), and normal individuals make up the dataset.

The 17 key symptoms that psychiatrists use to diagnose the diseases listed are included in the dataset. The behavioral symptoms are measured using a Comma Separated Value (CSV) format and include the following: Overthinking, Aggressive Response, Optimism, Sexual Activity, Concentration, Try-Explaning, Nervous Breakdown, Sadness, Exhaus- tion, Euphoria, Sleep Disorder, Mood Swings, Suicidal Thoughts, Anorexia, Anxiety, Try- Explaining, Nervous Breakdown, and Ignore and Move on.

The people in the Normal group use their therapy time for enriching their living skills, receiving specialized counseling, and personal growth. These people are not the same as those with Major Depressive Disorder or Bipolar Disorder, even if they could also have mild mental health issues.

3.3.1 Dataset Features

The research used a carefully collected dataset, "Dataset-Mental-Disorders.csv," which is available for download and is intended to encompass an extensive range of mental health conditions and the associated symptoms.

Four group of patients distinguished: Bipolar Type-1, Bipolar Type-2 ,Depression and normal, are included in the dataset,28 patients with Bipolar Type-1,31 patients with Bipolar Type-2 ,31 patients with depression,and 30 patients with normal.

This dataset includes a variety of features, such as Sadness, Exhaustness, Euphoric, Sleep disorder, Mood swings, Suicidal thoughts, Anorexia, Anxiety, Try-explaining, Ner- vous breakdown, Ignore, Move-on, Admitting mistakes, Overthinking, Aggressive re- sponse, Optimism, Sexual activity, and Concentration.

It is made up of a significant number of distinct instances, each carefully established with a diagnosis made by mental health specialists. In order to replicate the complexity of mental health diagnoses in the real world, the dataset's diversity and depth are essential. This creates a solid basis for the deployment and assessment of machine learning models.

Table 2.1 The search source in Table 3.1 represent the electronic database, search item, with search keywords. The main keyword used to perform the experimental study were Machine learning, Bipolar Disorder Prediction ,clinical data, Classification.

Search space	Description
Electronic databases	ACM Digital library,IEEE Xplore,Google Scholar, SpringerLink, ScienceDirect,ISI Web of Knowledge
Searched Item	Journal,Workshop and conference papers
Language	English
Searched keyword	Machine learning ,Bipolar disorder ,classification,Clinical data.

3.4 Feature Selection

The choice of features is increasingly important in ML research .The feature selection ap- proach's goal is to choose a select few important features from a huge dataset that contains many different features sets .The most common selection of feature subsets techniques are wrapper and filter .The algorithm for machine learning is not necessary for the filter ap- proach to work .To find the features, it makes use of mutual and statistical information.

We used feature selection in our study on bipolar disorder classification to improve our machine learning models' interpretability and performance. In particular, we used the Ranker method in combination with the GainRatioAttributeEval algorithm.

By calculating the gain ratio relative to the class, the GainRatioAttributeEval algorithm, a sophisticated feature selection technique, assesses an attribute's value. An attribute's relevance is evaluated using a gain ratio, which is a generalization of information gain that considers both the amount of information an attribute provides about the class and its intrinsic information. This reduces a common issue with traditional information gain: the bias towards attributes having a large number of disparate values.

GainRatioAttributeEval played a key role in selecting the most illuminating clinical and demographic characteristics from a potentially huge and complicated dataset in the context of classifying bipolar disorder. These characteristics include a range of clinical symptoms, demographic data, and professional diagnoses that are essential for precise categorization. GainRatioAttributeEval and the Ranker approach together allowed us to methodically find and choose the most important criteria for the classification of bipolar disorder. This enhanced our machine learning models' precision and effectiveness while also offering more precise insights into the main causes of the illness, enabling more accurate diagnosis and comprehension.

3.5 Feature Ranking

We used the Ranker approach to choose and prioritize the most important attributes in our dataset for bipolar disorder categorization. This strategy proved critical to improving the performance and interpretability of our machine learning models.

We chose the top eight attributes by rating them in order of significance: mood swings, suicidal thoughts, sadness, Euphoric, optimisim, sexual activity, and aggressive response utilising the waikato Environment for Knowledge Analysis (WEKA) software's 10-fold cross validation test mode and the best initial filter approach using Gain Ratio Attribute Eval

Selecting the features is essential because they depend on correctness.if the character- istics not properly chosen, accuracy will deteriorate and the desired outcomes would not be obtained. To increase its accuracy, the ranker algorithm technique used.

This method not only increased the accuracy of the categorization but also offered deeper insights into the main variables linked to bipolar disease, enabling improved moni- toring, diagnosis, and treatment planning.

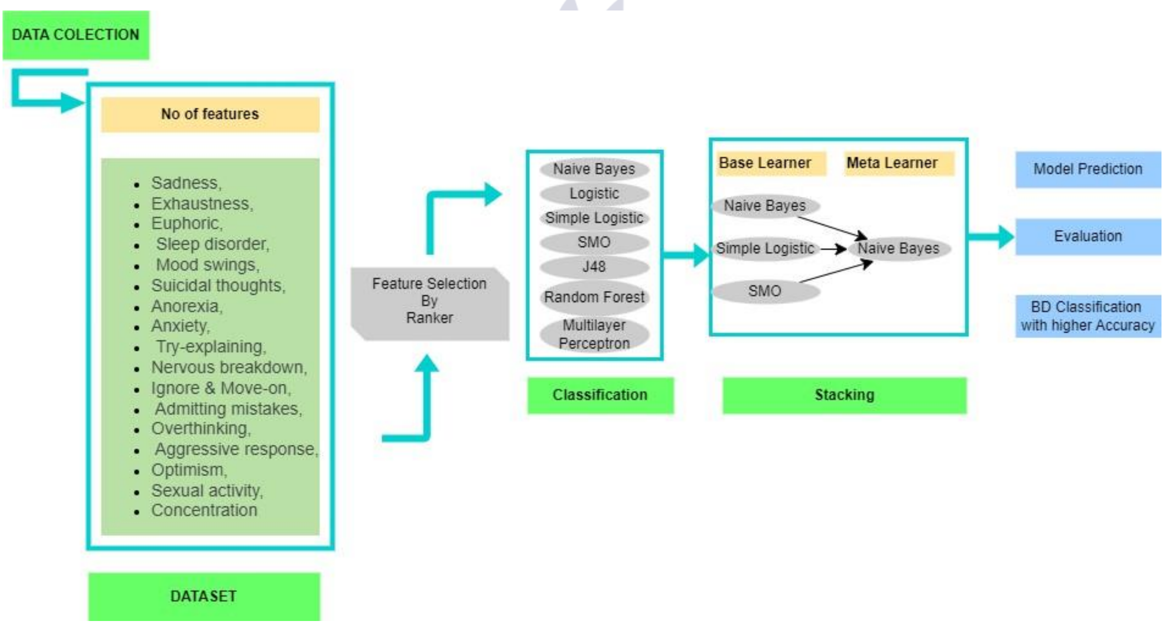

Figure 3.1 A Block diagram

3.6 Classification Methods

The goal of classification in machine learning is to apply predetermined labels to new samples based on their attributes. It is a supervised learning method. The primary objective is to develop a model that accurately divides unknown data into discrete groups. This study evaluates the predictive power of several categorization approaches for bipolar illness based on a collection of characteristics.

A classifier is an algorithm that makes use of the training dataset to learn and categories every new data point. In contrast, a classification model uses a mapping function to determine the class label for the testing data using information from the training dataset. A feature-linked dataset that makes it easier to build precise prediction models .

using WEKA software, seven separate classifier given traits to differentiate between normal individual and BD sufferers. With 10-fold cross-validation test mode, these characteristics given to the Naive Bayes ,Logistic, Simple Logistic,SMO,J48,Random Forest, Multilaye perceptron models. We compare the various characteristics and classifier using the overall accuracy.

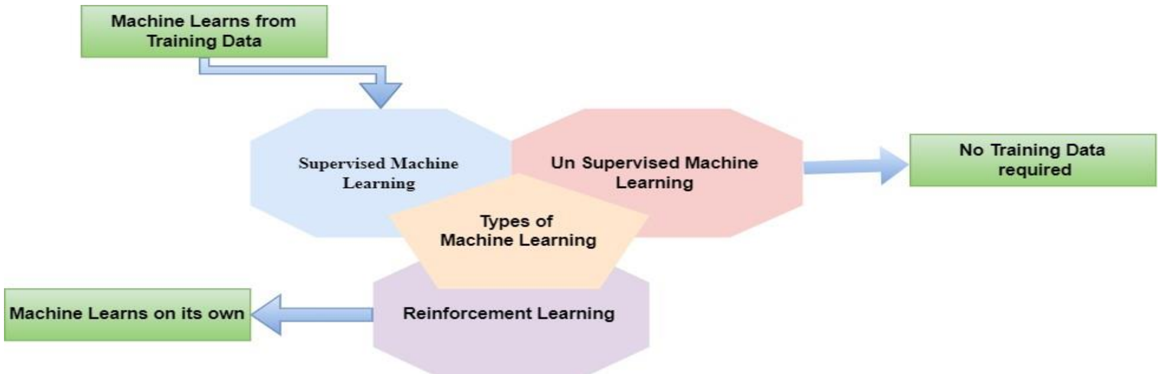

Figure 3.2Types of Machine Learning

3.7 Classification Algorithms

Features given into the Naive Bayes, Logistic, Simple Logistic,SMO,J48,Random Forest, Multilayer perceptron using 10-fold Cross Validation test mode .Comparing different characteristics
and classifier done using the overall accuracy.

3.7.1 Naive Bayes

The probabilistic classifier Naive Bayes uses the Bayes Theorem under the strict presump- tion of feature independence. The method performs effectively in a variety of real-world applications, including text categorization, despite this "naive" assumption. Because Naive Bayes determines the class with the highest probability after calculating the likelihood of each class using the input attributes, it is computationally efficient. with most cases, it's a suitable option with dimensionally complicated inputs. The method's ability to pick up new skills fast from a minimal quantity of training data makes it popular for tasks like spam filtering and document classification. (Mitchell, 1997).

The classifier must then be trained on the processed data, and its performance must be assessed using metrics such as accuracy, precision, recall, and F1-score. Naive Bayes' main advantages are its scalability and efficiency, especially when working with huge datasets. However, its feature independence assumption does not always hold true in intricate real- world circumstances. However, its simplicity and stability make it a useful tool for investi- gating and putting into practice classification schemes in mental health diagnosis.

3.7.2 Logistic

A logistic function is used in the logistic regression linear binary classification model to forecast the probability of a binary result, or one of two potential classes. The logistic function is helpful for calculating probabilities since it transforms all real-valued numbers into the range [0, 1]. In order to maximize the probability of the data, the coefficients of the input characteristics are assessed using logistic regression. When there is a roughly linear connection between the input characteristics and the target variable, this technique works well. Although the main use of

logistic regression is in binary classification, one-vs- rest and other techniques may be utilized to apply logistic regression to multiclass issues. (Mitchell, 1997).
To classify bipolar disorder, logistic regression involves preprocessing the data to han- dle missing values and normalize features, selecting relevant clinical and demographic vari- ables, training the model on a subset of the data, and evaluating its performance using met-rics such as accuracy, precision, recall, F1-score, and AUC-ROC. Despite its simplicity and ease of implementation, logistic regression presupposes a linear relationship between char- acteristics and log probabilities of outcome, which may fail to capture the data's complex-ity. However, its clarity and usefulness in a variety of circumstances make it an important tool for developing diagnostic models for bipolar disease.

3.7.3 Simple Logistic

Simple Logistic is a type of logistic regression that seeks to reduce model complexity by limiting the number of parameters. This is quite successful when overfitting is an issue, especially for smaller datasets or ones with a large number of features. Simple Logistic, by using fewer parameters, can be more computationally efficient and generalize better to previously unknown data sets. The approach strikes a balance between model simplic- ity and prediction accuracy, yielding more dependable projections in real-world scenar-ios(Mitchell, 1997).
Building the decision tree and improving the logistic regression parameters at each leaf trains the model. Metrics including accuracy, precision, recall, and F1-score are evaluated as part of performance evaluation. The hybrid technique of Simple Logistic offers a useful tool for diagnosing bipolar disorder based on complex and varied data features by balancing the interpretability of logistic regression with the capacity to handle non-linear patterns.

3.7.4 SMO

Support vector machines (SVMs), which are helpful for classification tasks, can be trained using Sequential Minimal Optimization (SMO). Finding the hyperplane in the feature space that best divides the classes is how support vector machines (SVMs) operate. It may require a lot of processing power to solve the quadratic programming problem used in the training method. SMO simplifies the process by dividing it into smaller subproblems that can be solved analytically. This makes SMO incredibly efficient and scalable, allowing SVMs to be employed with large datasets. SMO is particularly beneficial when the dataset has a large number of features(Mitchell, 1997).
SMO allows the model to identify complex patterns and relationships in the data, which in turn creates a solid framework for more accurately and consistently diagnosing bipolar disorder.

3.7.5 J48

J48 uses the C4.5 algorithm for decision tree learning. Decision trees are a popular classifi-cation method that divides the dataset recursively depending on the values of input features, forming a tree structure with each leaf representing a class label. J48 outperforms its pre- decessor, ID3, by handling both categorical and continuous data and pruning the tree to avoid overfitting. The technique uses information gain to choose the best characteristic to split the data at each node, resulting in a model that is simple to understand and apply. J48 decision trees are especially useful for problems with non-linear correlations between input attributes and destination variables(Mitchell, 1997).
This methodology yields easily comprehensible and analyzed results that are clear and interpretable, offering important insights into the variables that influence the diagnosis of bipolar disorder. When creating predicting frameworks for mental health disorders, J48 is a useful tool because of its capacity to manage intricate relationships and generate a model that is both understandable and efficient.

3.7.6 Random Forest

Using many decision trees and combining their predictions, Random Forest is an ensemble learning technique that increases accuracy and durability. Each tree in the forest is trained using a distinct subset of the training data and features in order to reduce variance and prevent overfitting. The final prediction is often determined by averaging the predictions of all the trees in the case of regression assignments, or by a majority vote in the case of classification jobs. Random Forest is quite useful for many classification problems when dealing with large datasets with plenty of variables(Mitchell, 1997).

The Random Forest algorithm is a potent tool for enhancing diagnostic accuracy and creating efficient classification frameworks for bipolar disorder because of its resilience to noise and variability in the data as well as its ability to offer feature importance scores.

3.7.7 MLP

A multilayer perceptron (MLP) is a neural network that is intentionally constructed from multiple layers of neurons. Three layers make up its composition: an input layer, an output layer, and one or more hidden layers. Throughout training, a weight is assigned to every connection that a neuron in one layer has with every other neuron in the layer below it. Given their ability to represent intricate non-linear correlations between the target variable and the input attributes, machine learning models (MLPs) find extensive use in fields such as speech recognition and photo identification. Multilayer perceptrons (MLPs) are fre- quently trained via backpropagation, which lowers the error between predicted and actualoutputs.

Artificial neural networks (ANNs) are a useful tool for constructing advanced diagnos- tic models for bipolar disorder because of their high classification accuracy and capacity to handle huge and complicated datasets. These models provide insights that are not readily available with simpler techniques.

3.8 Stacking

The final prediction is made by training a meta-model using the outputs of these foundation learners. Stacking is an ensemble learning strategy that involves training many models, sometimes known as base learners, on the same dataset. The theory behind stacking is that it may frequently outperform any single model by combining the advantages of several models to provide higher predicted performance. This approach is particularly helpful for difficult classification problems when no single model can fully capture the characteristicsof the data(Mitchell, 1997).

This method enables a more thorough examination of the clinical and demographic information, which may result in a more accurate and trustworthy diagnosis of bipolar illness.

3.9 Evaluation Metrics

Evaluation metrics must be included in any classification algorithm that used to evaluate performance. Each categorization framework's development must include it as a crucial component. It displays the outcome's accuracy percentage, classifier performance, dataset affects, and various methods and conditions that we used for the trials. Confusion matrix is a crucial part of performance metrics that show the results of any assessment and used to assess the classifier's performance.

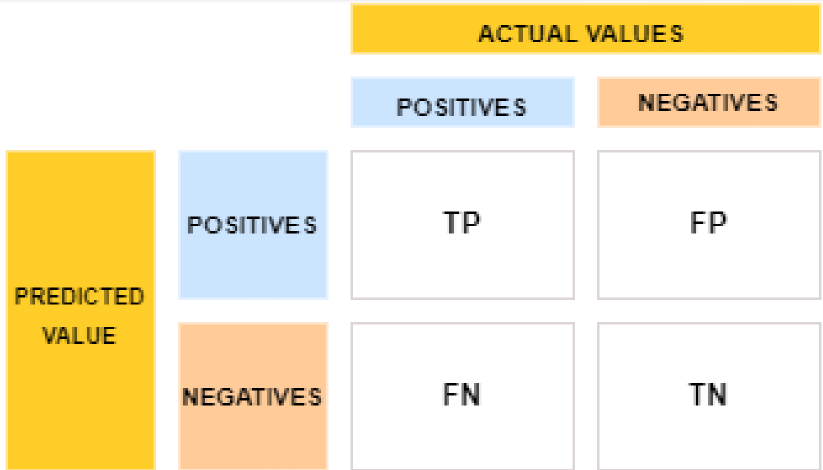

Figure 3.3Confusion Matrix

3.9.1 Confusion Matrix

The confusion matrix is one of the simplest ways to assess the model's accuracy and cor- rectness. It is helpful for classification tasks when the output separated into two or more class categories. Despite the fact that the confusion matrix alone is not a performance in-
dicator, most performance measures constructed entirely on the confusion matrix and its corresponding statistics .The following statements are linked to the confusion matrix.

True Positives(TP): The model predicted yes (they have the disease), and they do havethe disease.

True Negatives(TN): The model predicted No,b ut they do not have the disease.

False Positives(FP): The model predicted No but they actually have the disease Known as Type 1 error.

False Negatives(FN): The model predicted No,b ut they actually do have the disease Known as Type 2 error.

3.9.2 Accuracy

The percentage of accurate diagnosis results Known as accuracy.A percentage of the sam- ples that are correctly categorised.

Accuracy=TP+TN/TP+TN+FP+FN

3.9.3 Precision

Precision is the total number of accurate results that our machine learning model has pro-duced.

precision=TP/TP+FN

3.9.4 Recall

Amount of positive results that our ML model return is its recall. Recall is measurable by

Recall=TP/TP+FN

3.9.5 F1-score

The F1 score's harmonic representation of precision and recall. The weighted sum of pre- cision and recall used to determine it. The optimal and optimal values for F1 are 1 and 0. you may determine the F1 score via

F1=2X(precision x recall)/(precision + recall)

3.10 Summary

We describe our primary research technique in this chapter.We outlined the specific proce- dures and associated methods of our classification system for Bipolar disorder. We outline the many framework steps, including dataset aggregation, feature choice, feature rank- ing, classification and evaluation methods.The list of classifier used in classification ap- proach provided in this section.This chapter has a presentation on the feature selection method.Using the suggested approach ,extensive testing done on this dataset.We described each of the seven machine learning-based classifier that employed during the classification process.Finally , talked about how our research study evaluated.

Results and Discussion

4.1 Introduction

This section of the dissertation provides an

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explanation of the findings from the experiments carried out using the methodology discussed in the previous section. In order to classify bipolar disorder, this thesis mainly employed feature selection strategies in combination with several machine learning and deep learning models. Our objective was to improve the categorization of bipolar disorder in terms of both speed and accuracy.

4.2 Dataset

The chapter describes the results of an experimental research done on a specific dataset which was obtained from Kaggle, had 120 instances and 18 attributes that are important for categorizing bipolar disorder. Along with additional symptoms and behavioral indica- tors, these traits include ”Depression,” ”Exhaustion,” ”Euphoria,” ”Sleep Disorder,” ”Mood Swings,” and ”Suicidal Thoughts.” Additional traits such as ”Anorexia,” ”Anxiety,” ”Ner- vous Breakdown,” and ”Overthinking” provide additional insight into the diverse ways that bipolar disorder presents itself. ”Try-explaining,” ”Ignore and Move-On,” ”Admitting Mistakes,” ”Aggressive Response,” and ”Optimism” are a few instances of behavioral re-sponses that symbolize the different coping mechanisms people can employ.The dataset is completed by other important variables like ”Sexual Activity” and ”Concentration,” which guarantee a comprehensive perspective of each case. This large-scale dataset makes it eas- ier to conduct a detailed study, which in turn allows for the creation of advanced machine learning models that accurately classify bipolar disease.

Sadness	Euphoric	Exhausted	Sleep dissor	Mood Swing	Suicidal tho	Anorxia	Authority Re	Try-Explana	Aggressive I	Ignore & Mc	Nervous Bre	Admit Mista	Overthinkin	Sexual Activ	Concentrati	Optimisim	Expert Diagnose
Usually	Seldom	Sometimes	Sometimes	YES	YES	NO	NO	YES	NO	NO	YES	YES	YES	3 From 10	3 From 10	4 From 10	Bipolar Type-2
Usually	Seldom	Usually	Sometimes	NO	YES	NO	NO	NO	NO	NO	NO	NO	NO	4 From 10	2 From 10	5 From 10	Depression
Sometimes	Most-Often	Sometimes	Sometimes	YES	NO	NO	NO	YES	YES	NO	YES	YES	NO	6 From 10	5 From 10	7 From 10	Bipolar Type-1
Usually	Seldom	Usually	Most-Often	YES	YES	YES	NO	YES	NO	NO	NO	NO	NO	3 From 10	2 From 10	2 From 10	Bipolar Type-2
Usually	Usually	Sometimes	Sometimes	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	5 From 10	5 From 10	6 From 10	Normal
Usually	Sometimes	Sometimes	Most-Often	NO	YES	YES	YES	NO	NO	NO	NO	YES	NO	3 From 10	5 From 10	5 From 10	Depression
Seldom	Usually	Seldom	Sometimes	YES	YES	YES	NO	YES	YES	NO	YES	YES	YES	7 From 10	2 From 10	9 From 10	Bipolar Type-1
Usually	Sometimes	Sometimes	Sometimes	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES	5 From 10	5 From 10	5 From 10	Normal
Most-Often	Seldom	Most-Often	Usually	YES	YES	YES	NO	YES	YES	NO	YES	NO	NO	8 From 10	2 From 10	3 From 10	Bipolar Type-2
Usually	Seldom	Most-Often	Sometimes	NO	NO	NO	NO	YES	NO	NO	YES	YES	YES	3 From 10	4 From 10	2 From 10	Depression
Seldom	Sometimes	Seldom	Seldom	NO	NO	NO	YES	NO	NO	NO	NO	YES	NO	5 From 10	7 From 10	8 From 10	Normal
Seldom	Sometimes	Sometimes	Usually	YES	YES	YES	NO	YES	YES	NO	YES	NO	YES	8 From 10	4 From 10	9 From 10	Bipolar Type-1
Most-Often	Sometimes	Most-Often	Usually	YES	YES	YES	NO	YES	YES	NO	YES	NO	YES	9 From 10	2 From 10	4 From 10	Bipolar Type-2
Usually	Usually	Sometimes	Sometimes	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO	5 From 10	7 From 10	5 From 10	Normal
Usually	Seldom	Most-Often	Usually	NO	YES	NO	NO	YES	NO	YES	YES	YES	YES	5 From 10	4 From 10	2 From 10	Depression
Sometimes	Sometimes	Sometimes	Sometimes	YES	NO	YES	NO	YES	YES	NO	NO	NO	YES	6 From 10	4 From 10	6 From 10	Bipolar Type-1
Sometimes	Usually	Sometimes	Sometimes	NO	NO	NO	NO	YES	NO	NO	NO	YES	NO	5 From 10	4 From 10	6 From 10	Normal
Usually	Sometimes	Most-Often	Sometimes	YES	NO	NO	NO	YES	YES	NO	YES	NO	YES	6 From 10	2 From 10	3 From 10	Bipolar Type-1
Most-Often	Seldom	Most-Often	Most-Often	NO	NO	NO	NO	YES	NO	YES	YES	YES	YES	3 From 10	4 From 10	1 From 10	Depression
Sometimes	Usually	Usually	Sometimes	NO	NO	NO	YES	YES	YES	NO	NO	YES	YES	4 From 10	4 From 10	6 From 10	Normal
Sometimes	Sometimes	Sometimes	Usually	YES	NO	NO	YES	YES	YES	NO	YES	YES	YES	6 From 10	2 From 10	3 From 10	Bipolar Type-2
Usually	Sometimes	Sometimes	Sometimes	YES	YES	YES	NO	YES	YES	NO	NO	NO	YES	6 From 10	4 From 10	6 From 10	Bipolar Type-1
Sometimes	Sometimes	Sometimes	Usually	NO	NO	YES	YES	YES	NO	NO	NO	NO	YES	3 From 10	7 From 10	6 From 10	Normal

Figure 4.1Bipolar Disorder Data Set Obtained from Kaggle.

The Experimental Results in Section4.2 provide the foundation for the discussion in this chapter.Compare result in section 4.3 the Discussion in 4.4 this chapter is summarised in Section 4.5.

4.3 Experimental Results

Detail and findings of experimental study presented in this chapter . As previously men- tioned, we have used a data set with various features.Using the WEKA software's Classi- fication method, we applied the feature selection technique to a specific dataset using the ”Ranker” method and we were able to identify the seven best features that are crucial for identifying Bipolar disorder in individual.

The goal of this study is to determine which features have the highest accuracy for predicting Bipolar disorder . we examined the efficacy of different machine learning ap- proaches and a deep learning model on the classification of bipolar disorder. The algorithms included J48, Random Forest, SMO, Naive Bayes, Logistic Regression, Simple Logistic, and Multilayer Perceptron (MLP), an artificial neural network model.

We compared the accuracy and computing time of each model before and after applying feature selection techniques.Purpose of experimental investigation was to generate some insights about the problem.The seven best features were;Mood

Swings, Suicidal Thoughts, Sadness, Euphoria, Optimism, Sexual Activity, and Expert Diagnosis. They give the best accuracy of 91.67% with the help of stacking method. The other classifier gives the 90.83% by MLP,90% by Naive Bayes,78.33% by Logistic ,90.83% by Simple Logistic,90.83% by SMO,80%by J48,82.50% by Random Forest in 10 fold cross-validation results.

4.3.1 Experimental Results on Machine learning ,Deep learning ,and Stacking model's with All Attributes

We Conducted independent experiments on six machine learning classifier's included Naive Baye's,Logistic,Simple Logistic,SMO,J48,Random Forest and one deep learning model called ANN's Multilayer Perceptron(MLP) than apply stacking by using All Attributes .

The experimental results on different classifier's are as follows:

1:Naive Bayes

The Naive Bayes classifier achieved an accuracy of 87.5%, with 105 correctly classi- fied instances out of 120, and a Kappa statistic of 0.8333. Its performance metric includes a mean absolute error of 0.8333, a root mean squared error of 0.2076, and a ROC Area of 0.983.The confusion matrix showed 29 Bipolar Type-2 correctly identified and 2 in- correctly misclassified, 27 Depression correctly identified and 4 instances misclassified, 23 Bipolar Type-1 correctly identified and 5 instances misclassified, 26 Normal correctly identified and 4 instances misclassified.

Table 3.1 Confusion Matrix Table.

a	b	c	d	classified as
29	0	2	0	a = Bipolar Type-2
0	27	2	2	b = Depression
1	0	23	4	c = Bipolar Type-1
0	2	2	26	d = Normal

Table 4.2 Naive Bayes Detailed Accuracy with All Attributes.

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.935	0.011	0.967	0.935	0.951	0.934	0.996	0.989	Bipolar Type-2
0.871	0.022	0.931	0.871	0.9	0.868	0.983	0.963	Depression
0.821	0.065	0.793	0.821	0.807	0.747	0.972	0.908	Bipolar Type-1
0.867	0.067	0.813	0.867	0.839	0.783	0.979	0.948	Normal
Weighted Avg. 0.875	0.041	0.878	0.875	0.876	0.836	0.983	0.953	

2: Logistic

The Logistic classifier achieved an accuracy of 70.83%, with 85 correctly classified instances out of 120, and a Kappa statistic of 0.611. Its performance metric includes a mean absolute error of 0.1423, a root mean squared error of 0.3695, and a ROC Area of 0.915 .The confusion matrix showed 25 Bipolar Type-2 correctly identified and 6 incorrectly misclassified, 21 Depression correctly identified and 10 instances misclassified, 18 Bipolar Type-1 correctly identified and 10 instances misclassified, 21 Normal correctly identified and 9 instances misclassified.

Table 4.3 Confusion Matrix Table

a	b	c	d	classified as
25	1	5	0	a = Bipolar Type-2
5	21	1	4	b = Depression
6	2	18	2	c = Bipolar Type-1

1	2	6	21	d = Normal

Table 4.4 Logistic Detailed Accuracy with All Attributes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.806	0.135	0.676	0.806	0.735	0.637	0.912	0.774	Bipolar Type-2
0.677	0.056	0.808	0.677	0.737	0.66	0.928	0.865	Depression
0.643	0.13	0.6	0.643	0.621	0.501	0.883	0.715	Bipolar Type-1
0.7	0.067	0.778	0.7	0.737	0.657	0.934	0.827	Normal
Weighted Avg. 0.708	0.096	0.718	0.708	0.709	0.616	0.915	0.797	

3: Simple Logistic

The Simple Logistic classifier achieved an accuracy of 89.27%, with 107 correctly clas- sified instances out of 120, and a Kappa statistic of 0.611. Its performance metric includes a mean absolute error of 0.1423, a root mean squared error of 0.3695, and a ROC Area of 0.915 .The confusion matrix showed 25 Bipolar Type-2 correctly identified and 6 in- correctly misclassified, 21 Depression correctly identified and 10 instances misclassified, 18 Bipolar Type-1 correctly identified and 10 instances misclassified, 21 Normal correctly identified and 9 instances misclassified.

Table 4.5 Confusion Matrix Table.

a	b	c	d	classified as
28	0	3	0	a = Bipolar Type-2
0	30	1	0	b = Depression
2	0	24	2	c = Bipolar Type-1
0	2	3	25	d = Normal

Table 4.6 Simple Logistic Detailed Accuracy with All Attributes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.903	0.022	0.933	0.903	0.918	0.89	0.988	0.97	Bipolar Type-2
0.968	0.022	0.938	0.968	0.952	0.936	0.995	0.986	Depression
0.857	0.076	0.774	0.857	0.814	0.755	0.962	0.895	Bipolar Type-1
0.833	0.022	0.926	0.833	0.877	0.841	0.981	0.947	Normal
Weighted Avg. 0.892	0.035	0.895	0.892	0.892	0.858	0.982	0.951	

4: SMO

The SMO classifier achieved an accuracy of 82.5%, with 99 correctly classified in- stances out of 120, and a Kappa statistic of 0.7664. Its performance metric includes a mean absolute error of 0.2681, a root mean squared error of 0.3375, and a ROC Area of 0.935 .The confusion matrix showed 29 Bipolar Type-2 correctly identified and 2 incorrectly misclassified, 26 Depression correctly identified and 5 instances misclassified, 20 Bipolar Type-1 correctly identified and 8 instances misclassified, 24 Normal correctly identified and 6 instances misclassified.

Table 4.7 Confusion Matrix Table

a	b	c	d	classified as
29	0	2	0	a = Bipolar Type-2
1	26	0	4	b = Depression
5	0	20	3	c = Bipolar Type-1

1	1	4	24	d = Normal

Table 4.8 SMO Detailed Accuracy with All Attributes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.935	0.079	0.806	0.935	0.866	0.818	0.944	0.792	Bipolar Type-2
0.839	0.011	0.963	0.839	0.897	0.867	0.959	0.888	Depression
0.714	0.065	0.769	0.714	0.741	0.666	0.901	0.669	Bipolar Type-1
0.8	0.078	0.774	0.8	0.787	0.714	0.932	0.731	Normal
Weighted Avg. 0.825	0.058	0.83	0.825	0.825	0.77	0.935	0.773	

5: J48

The J48 classifier achieved an accuracy of 81.67%, with 98 correctly classified in- stances out of 120, and a Kappa statistic of 0.7555. Its performance metric includes a mean absolute error of 0.1269, a root mean squared error of 0.2991, and a ROC Area of 0.889 .The confusion matrix showed 25 Bipolar Type-2 correctly identified and 6 in- correctly misclassified, 27 Depression correctly identified and 4 instances misclassified, 22 Bipolar Type-1 correctly identified and 6 instances misclassified, 24 Normal correctly identified and 6 instances misclassified.

Table 4.9 Confusion Matrix Table

a	b	c	d	classified as
25	0	6	0	a = Bipolar Type-2
0	27	0	4	b = Depression
3	1	22	2	c = Bipolar Type-1
0	5	1	24	d = Normal

Table 4.10 J48 Detailed Accuracy with All Attributes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.806	0.034	0.893	0.806	0.847	0.8	0.901	0.797	Bipolar Type-2
0.871	0.067	0.818	0.871	0.844	0.788	0.906	0.78	Depression
0.786	0.076	0.759	0.786	0.772	0.701	0.853	0.618	Bipolar Type-1
0.8	0.067	0.8	0.8	0.8	0.733	0.892	0.673	Normal
Weighted Avg. 0.817	0.061	0.819	0.817	0.817	0.757	0.889	0.72	

6: Random Forest

The Random Forest classifier achieved an accuracy of 85.83%, with 103 correctly clas- sified instances out of 120, and a Kappa statistic of 0.811 . Its performance metric includes a mean absolute error of 0.2212, a root mean squared error of 0.2859, and a ROC Area of 0.974 .The confusion matrix showed 30 Bipolar Type-2 correctly identified and 1 in- correctly misclassified, 26 Depression correctly identified and 5 instances misclassified, 22 Bipolar Type-1 correctly identified and 6 instances misclassified, 25 Normal correctly identified and 5 instances misclassified.

Table 4.11 Confusion Matrix Table

a	b	c	d	classified as
30	0	1	0	a = Bipolar Type-2
1	26	1	3	b = Depression
3	0	22	3	c = Bipolar Type-1
0	2	3	25	d = Normal

Table 4.12 Random Forrest Detailed Accuracy with All Attributes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.968	0.045	0.882	0.968	0.923	0.896	0.995	0.988	Bipolar Type-2
0.839	0.022	0.929	0.839	0.881	0.845	0.974	0.939	Depression
0.786	0.054	0.815	0.786	0.8	0.741	0.959	0.892	Bipolar Type-1
0.833	0.067	0.806	0.833	0.82	0.758	0.968	0.887	Normal
Weighted Avg. 0.858	0.047	0.86	0.858	0.858	0.812	0.974	0.928	

7: MLP

The MLP classifier achieved an accuracy of 90.83%, with 109 correctly classified in- stances out of 120, and a Kappa statistic of 0.8776. Its performance metric includes a mean absolute error of 0.0661, a root mean squared error of 0.1947, and a ROC Area of 0.985. The confusion matrix showed 30 Bipolar Type-2 correctly identified and 1 incorrectly misclassified, 30 Depression correctly identified and 1 instances misclassified, 23 Bipolar Type-1 correctly identified and 5 instances misclassified, 26 Normal correctly identified and 4 instances misclassified.

Table 4.13 Confusion Matrix Table

a	b	c	d	classified as
30	0	1	0	a = Bipolar Type-2
1	30	0	0	b = Depression
4	0	23	1	c = Bipolar Type-1
1	1	2	26	d = Normal

Table 4.14 ANN's (Multilayer Perceptron) Detailed Accuracy with All Attributes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.968	0.067	0.833	0.968	0.896	0.86	0.993	0.982	Bipolar Type-2
0.968	0.011	0.968	0.968	0.968	0.957	0.992	0.976	Depression
0.821	0.033	0.885	0.821	0.852	0.81	0.973	0.934	Bipolar Type-1
0.867	0.011	0.963	0.867	0.912	0.887	0.979	0.939	Normal
Weighted Avg. 0.908	0.031	0.912	0.908	0.908	0.88	0.985	0.958	

8: Stacking

The Stacking classifier achieved an accuracy of 89.17%, with 107 correctly classified instances out of 120, and a Kappa statistic of 0.8555 . Its performance metric includes a mean absolute error of 0.0812, a root mean squared error of 0.2066, and a ROC Area of 0.961 .The confusion matrix showed 29 Bipolar Type-2 correctly identified and 2 in- correctly misclassified, 29 Depression correctly identified and 2 instances misclassified, 24 Bipolar Type-1 correctly identified and 4 instances misclassified, 25 Normal correctly identified and 5 instances misclassified.

Table 4.15 Confusion Matric Table

a	b	c	d	classified as
29	0	2	0	a = Bipolar Type-2
0	29	1	1	b = Depression
1	1	24	2	c = Bipolar Type-1
0	2	3	25	d = Normal

Table 4.16..Stacking Detailed Accuracy with All Attributes

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.935	0.011	0.967	0.935	0.951	0.934	0.974	0.965	Bipolar Type-2
0.935	0.034	0.906	0.935	0.921	0.893	0.992	0.975	Depression
0.857	0.065	0.8	0.857	0.828	0.774	0.932	0.836	Bipolar Type-1
0.833	0.033	0.893	0.833	0.862	0.819	0.941	0.862	Normal
Weighted Avg. 0.892	0.035	0.894	0.892	0.892	0.857	0.961	0.912	

Summary of diffrent classifiers

The performance characteristics and execution times of many machine learning algo- rithms that were used to complete a classification task are compiled in the table below. The algorithm name, accuracy, and execution time are some of the metrics. The outcomes illustrate the compromises made by each strategy between computation efficiency and ac-curacy.

Table 4.17 Summary of different classifiers accuracies and ccomputational time with all attributes

Sr #	Classifier	Correctly/ classified	Computational Time
1	Naive Bayes	87.50%	0 Seconds
2	Logistic	70.83%	0.25 seconds
3	Simple Logistic	89.17%	0.03 seconds
4	SMO	82.50%	0.04 seconds
5	J48	81.67%	0 seconds
6	Random Forest	85.83%	0.04 seconds
7	MLP	90.83%	0.84 seconds
8	Stacking	89.17%	0.35 seconds

In Table 4.17 presented all the accuracy and computational time utilising all features when six machine learning classifier, one deep learning classifier and stacking used in a 10-fold cross validation.

4.3.2 Experimental Results on Machine learning, Deep learning, and Stacking model's with feature selection.

Experimental results were obtained by identifying bipolar disorder utilizing deep learning, stacking models, and machine learning, with a Ranker feature selection technique. Mood swings, suicidal thoughts, depression, euphoria, optimism, sexual activity, and expert diag- nosis were selected as the seven essential traits. By giving priority to the most informative features, the Ranker method significantly enhanced the performance and computational time of the model.

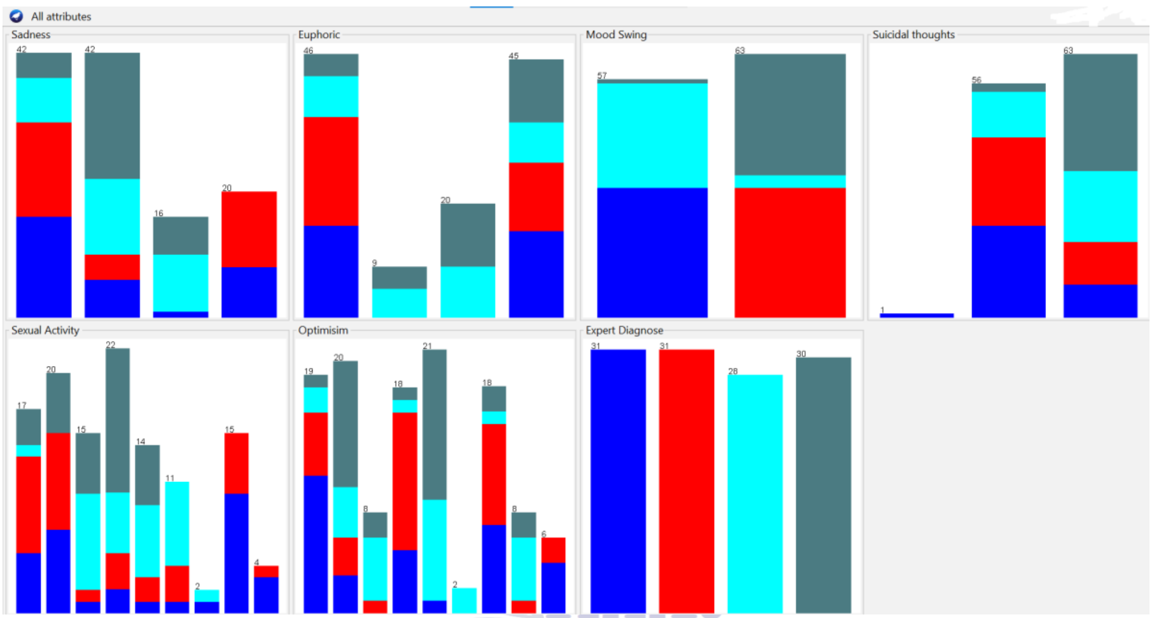

Figure 4.2Graphically representation of feature selection by Ranker method

The experimental results on different classifiers with feature selection are as follows:

1: Naive Bayes

The Naive Bayes classifier achieved an accuracy of 90%, with 108 correctly classified instances out of 120, and a Kappa statistic of 0.8666 . Its performance metric includes a mean absolute error of 0.0964, a root mean squared error of 0.1979, and a ROC Area of 0.985 .The confusion matrix showed 29 Bipolar Type-2 correctly identified and 2 in- correctly misclassified, 29 Depression correctly identified and 2 instances misclassified, 24 Bipolar Type-1 correctly identified and 4 instances misclassified, 26 Normal correctly identified and 4 instances misclassified.

Table 4.18 Confusion Matrix Table

a	b	c	d	classified as
29	0	2	0	a = Bipolar Type-2
0	29	1	1	b = Depression
1	0	24	3	c = Bipolar Type-1
0	2	2	26	d = Normal

Table 4.19 Naive Baye's Detailed Accuracy with best seven features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class

0.935	0.011	0.967	0.935	0.951	0.934	0.995	0.989	Bipolar Type-2
0.935	0.022	0.935	0.935	0.935	0.913	0.994	0.983	Depression
0.857	0.054	0.828	0.857	0.842	0.793	0.975	0.934	Bipolar Type-1
0.867	0.044	0.867	0.867	0.867	0.822	0.976	0.926	Normal
Weighted Avg. 0.9	0.033	0.901	0.9	0.9	0.868	0.985	0.959	

2: Logistic
The Logistic classifier achieved an accuracy of 78.33%, with 94 correctly classified instances out of 120, and a Kappa statistic of 0.711 . Its performance metric includes a mean absolute error of 0.1082, a root mean squared error of 0.325 , and a ROC Area of 0.932 .The confusion matrix showed 25 Bipolar Type-2 correctly identified and 5 incorrectly misclassified, 26 Depression correctly identified and 5 instances misclassified, 20 Bipolar Type-1 correctly identified and 8 instances misclassified, 23 Normal correctly identified and 7 instances misclassified.

Table 4.20 Confusion Matrix Table

a	b	c	d	classified as
25	1	4	1	a = Bipolar Type-2
0	26	2	3	b = Depression
4	0	20	4	c = Bipolar Type-1
2	3	2	23	d = Normal

Table 4.2 1 Logistic Detailed Accuracy with best seven features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.806	0.067	0.806	0.806	0.806	0.739	0.939	0.823	Bipolar Type-2
0.839	0.045	0.867	0.839	0.852	0.802	0.97	0.9	Depression
0.714	0.087	0.714	0.714	0.714	0.627	0.9	0.782	Bipolar Type-1
0.767	0.089	0.742	0.767	0.754	0.67	0.915	0.755	Normal
Weighted Avg. 0.783	0.072	0.784	0.783	0.784	0.712	0.932	0.817	

3: Simple Logistic
The Simple Logistic classifier achieved an accuracy of 90.83%, with 109 correctly clas-sified instances out of 120, and a Kappa statistic of 0.8777. Its performance metric includes a mean absolute error of 0.0837, a root mean squared error of 0.1994, and a ROC Area of 0.976 .The confusion matrix showed 29 Bipolar Type-2 correctly identified and 2 in- correctly misclassified, 30 Depression correctly identified and 1 instances misclassified, 24 Bipolar Type-1 correctly identified and 4 instances misclassified, 26 Normal correctly identified and 4 instances misclassified.

Table 4.22 Confusion Matrix Table

a	b	c	d	classified as
29	0	2	0	a = Bipolar Type-2
0	30	0	1	b = Depression
1	1	24	2	c = Bipolar Type-1
0	2	2	26	d = Normal

Table 4.23 Simple Logistic Detail accuracy with best seven features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.935	0.011	0.967	0.935	0.951	0.934	0.996	0.991	Bipolar Type-2
0.968	0.034	0.909	0.968	0.937	0.916	0.994	0.988	Depression
0.857	0.043	0.857	0.857	0.857	0.814	0.946	0.86	Bipolar Type-1
0.867	0.033	0.897	0.867	0.881	0.843	0.962	0.872	Normal
Weighted Avg. 0.908	0.03	0.909	0.908	0.908	0.878	0.976	0.93	

4: SMO

The SMO classifier achieved an accuracy of 90.83%, with 109 correctly classified in- stances out of 120, and a Kappa statistic of 0.8777. Its performance metric includes a mean absolute error of 0.2597, a root mean squared error of 0.3263, and a ROC Area of 0.964 .The confusion matrix showed 30 Bipolar Type-2 correctly identified and 1 incorrectly misclassified, 30 Depression correctly identified and 1 instances misclassified, 25 Bipolar Type-1 correctly identified and 3 instances misclassified, 24 Normal correctly identified and 6 instances misclassified.

Table 4.24 Confusion Matrix Table

a	b	c	d	classified as
30	0	1	0	a = Bipolar Type-2
0	30	0	1	b = Depression
0	0	25	3	c = Bipolar Type-1
0	3	3	24	d = Normal

Table 4.25 SMO Detailed Accuracy with best seven features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.968	0	1	0.968	0.984	0.978	0.988	0.967	Bipolar Type-2
0.968	0.034	0.909	0.968	0.937	0.916	0.986	0.929	Depression
0.893	0.043	0.862	0.893	0.877	0.839	0.938	0.806	Bipolar Type-1
0.8	0.044	0.857	0.8	0.828	0.774	0.941	0.786	Normal
Weighted Avg. 0.908	0.03	0.909	0.908	0.908	0.878	0.964	0.874	

5: J48

The J48 classifier achieved an accuracy of 80%, with 96 correctly classified instances out of 120, and a Kappa statistic of 0.7333. Its performance metric includes a mean abso- lute error of 0.1431, a root mean squared error of 0.3009, and a ROC Area of 0.891 .The confusion matrix showed 25 Bipolar Type-2 correctly identified and 6 incorrectly misclas- sified, 27 Depression correctly identified and 4 instances misclassified, 21 Bipolar Type-1 correctly identified and 7 instances misclassified, 23 Normal correctly identified and 7 in-stances misclassified.

Table 4.26 Confusion Matrix Table

a	b	c	d	classified as
25	0	6	0	a = Bipolar Type-2
0	27	0	4	b = Depression
4	0	21	3	c = Bipolar Type-1
0	5	2	23	d = Normal

Table 4.27 J48 Detailed Accuracy with seven best features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.806	0.045	0.862	0.806	0.833	0.779	0.899	0.795	Bipolar Type-2
0.871	0.056	0.844	0.871	0.857	0.806	0.939	0.87	Depression
0.75	0.087	0.724	0.75	0.737	0.655	0.856	0.594	Bipolar Type-1
0.767	0.078	0.767	0.767	0.767	0.689	0.866	0.594	Normal
Weighted Avg. 0.8	0.066	0.801	0.8	0.8	0.735	0.891	0.717	

6: Random Forest

The Random Forest classifier achieved an accuracy of 82.5%, with 99 correctly classi- fied instances out of 120, and a Kappa statistic of 0.7667. Its performance metric includes a mean absolute error of 0.1691, a root mean squared error of 0.2558, and a ROC Area of 0.970 .The confusion matrix showed 26 Bipolar Type-2 correctly identified and 5 in- correctly misclassified, 26 Depression correctly identified and 5 instances misclassified, 22 Bipolar Type-1 correctly identified and 6 instances misclassified, 25 Normal correctly identified and 5 instances misclassified.

Table 4.28 Confusion Matrix Table

a	b	c	d	classified as
26	0	5	0	a = Bipolar Type-2
0	26	0	5	b = Depression
3	0	22	3	c = Bipolar Type-1
0	3	2	25	d = Normal

Table 4.29 Random Forest Detailed Accuracy with best seven features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.839	0.034	0.897	0.839	0.867	0.823	0.989	0.972	Bipolar Type-2
0.839	0.034	0.897	0.839	0.867	0.823	0.98	0.952	Depression
0.786	0.076	0.759	0.786	0.772	0.701	0.959	0.9	Bipolar Type-1
0.833	0.089	0.758	0.833	0.794	0.722	0.949	0.87	Normal
Weighted Avg. 0.825	0.057	0.83	0.825	0.826	0.769	0.97	0.924	

7: MLP

The MLP classifier achieved an accuracy of 90.83%, with 109 correctly classified in- stances out of 120, and a Kappa statistic of 0.8777. Its performance metric includes a mean absolute error of 0.0612, a root mean squared error of 0.2077, and a ROC Area of 0.976 .The confusion matrix showed 29 Bipolar Type-2 correctly identified and 2 incorrectly misclassified, 30 Depression correctly identified and 1 instances misclassified, 24 Bipolar Type-1 correctly identified and 4 instances misclassified, 26 Normal correctly identified and 4 instances misclassified.

Table 4.30 Confusion Matrix Table

a	b	c	d	classified as
29	0	2	0	a = Bipolar Type-2
0	30	0	1	b = Depression

2	0	24	2	c = Bipolar Type-1
0	1	3	26	d = Normal

Table 4.31 Multilayer Perceptron Detailed Accuracy with best seven features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.935	0.022	0.935	0.935	0.935	0.913	0.987	0.976	Bipolar Type-2
0.968	0.011	0.968	0.968	0.968	0.957	0.996	0.992	Depression
0.857	0.054	0.828	0.857	0.842	0.793	0.95	0.867	Bipolar Type-1
0.867	0.033	0.897	0.867	0.881	0.843	0.969	0.912	Normal
Weighted Avg. 0.908	0.03	0.909	0.908	0.908	0.879	0.976	0.939	

8: Stacking

The Stacking classifier achieved an accuracy of 91.67%, with 110 correctly classified instances out of 120, and a Kappa statistic of 0.8889. Its performance metric includes a mean absolute error of 0.0851, a root mean squared error of 0.2024, and a ROC Area of 0.968 .The confusion matrix showed 29 Bipolar Type-2 correctly identified and 2 in- correctly misclassified, 30 Depression correctly identified and 1 instances misclassified, 24 Bipolar Type-1 correctly identified and 4 instances misclassified, 26 Normal correctly identified and 4 instances misclassified.

Table 4.32 Confusion Matrix Table

a	b	c	d	classified as
29	0	2	0	a = Bipolar Type-2
0	30	0	1	b = Depression
0	0	25	3	c = Bipolar Type-1
0	2	2	26	d = Normal

Table 4.33 Stacking Detailed Accuracy with best seven features

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.935	0	1	0.935	0.967	0.957	0.991	0.972	Bipolar Type-2
0.968	0.022	0.938	0.968	0.952	0.936	0.982	0.922	Depression
0.893	0.043	0.862	0.893	0.877	0.839	0.946	0.805	Bipolar Type-1
0.867	0.044	0.867	0.867	0.867	0.822	0.936	0.804	Normal
Weighted Avg. 0.917	0.027	0.918	0.917	0.917	0.89	0.964	0.878	

Summary of different classifiers

The following table aggregates the performance metrics and execution times of multiple machine learning algorithms used on a categorization task. The metrics include the name of the algorithm, the accuracy percentage, and the execution time. The outcomes illustrate how each method's accuracy and computing efficiency are traded off.

Table 4.34 Summary of different classifiers accuracies and computational time with best seven features

Sr #	Classifier	Correctly/ classified	Computational Time
1	Naive Bayes	90.00%	0 Seconds
2	Logistic	78.33%	0.06 seconds

3	Simple Logistic	90.83%	0.01 seconds
4	SMO	90.83%	0.02 seconds
5	J48	79.17%	0.1 seconds
6	Random Forest	85.00%	0.01 seconds
7	MLP	90.83%	0.26 seconds
8	Stacking	91.67%	0.3 seconds

4.4 Compare Results

This section looks at how well multiple machine learning models, one deep learning model, and one stacking model classify bipolar disorder in terms of accuracy and computation time. The analysis covers two scenarios: one that makes use of all features, and the other that makes use of a selected selection of features (mood swings, suicidal thoughts, sadness, euphoria, optimism, sexual activity, and expert diagnosis).

Results with All Features

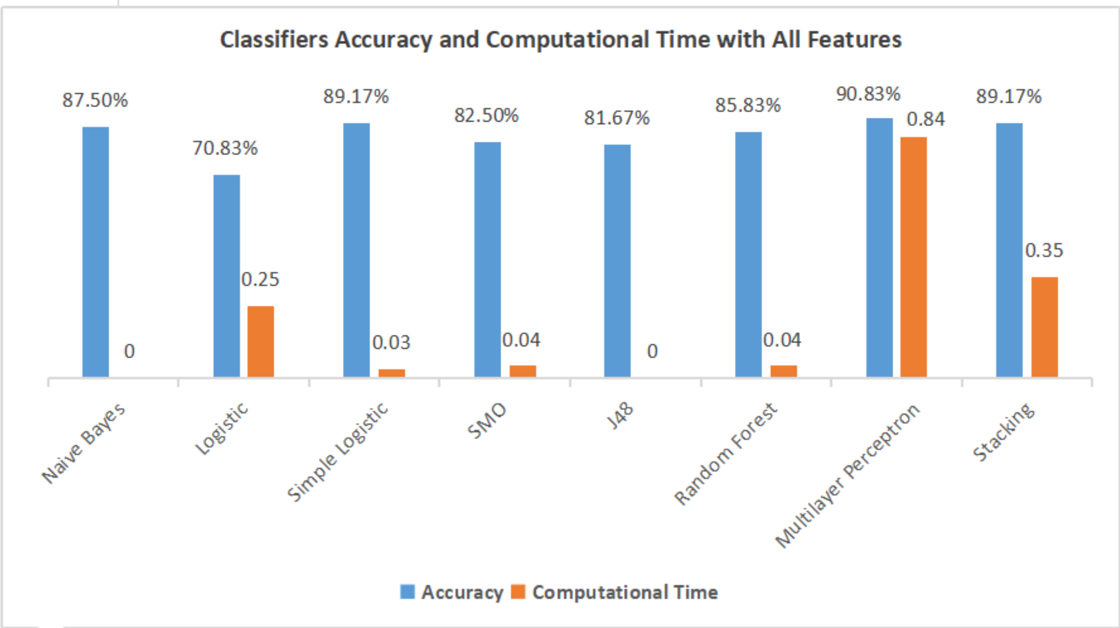

Figure 4.3Graphically representation of different classifiers accuracies and computationaltime by using all features

Figure 4.3 displays the accuracy and computation times of six machine learning models, one stacking model that utilizes all of the features, and one deep learning model (ANN multilayer perceptron):

- **Naive Bayes:** 87.50% accuracy was obtained in 0 seconds of computational time.
- **Logistic:** 70.83%accuracy was obtained in 0.25 seconds of computational time.
- **Simple Logistic:** 89.17%accuracy was obtained in 0.25 seconds of computationaltime.
- **SMO:**82.50%accuracy was obtained in 0.04 seconds of computational time.
- **J48:** 81.67%accuracy was obtained in 0 seconds of computational time
- **Random Forest:** 85.83%accuracy was obtained in 0.04 seconds of computationaltime.
- **MLP:** 90.83%accuracy was obtained in 0.84 seconds of computational time.
- **Stacking:** 89.17%accuracy was obtained in 0.35 seconds of computational time.

Results with Feature Selection

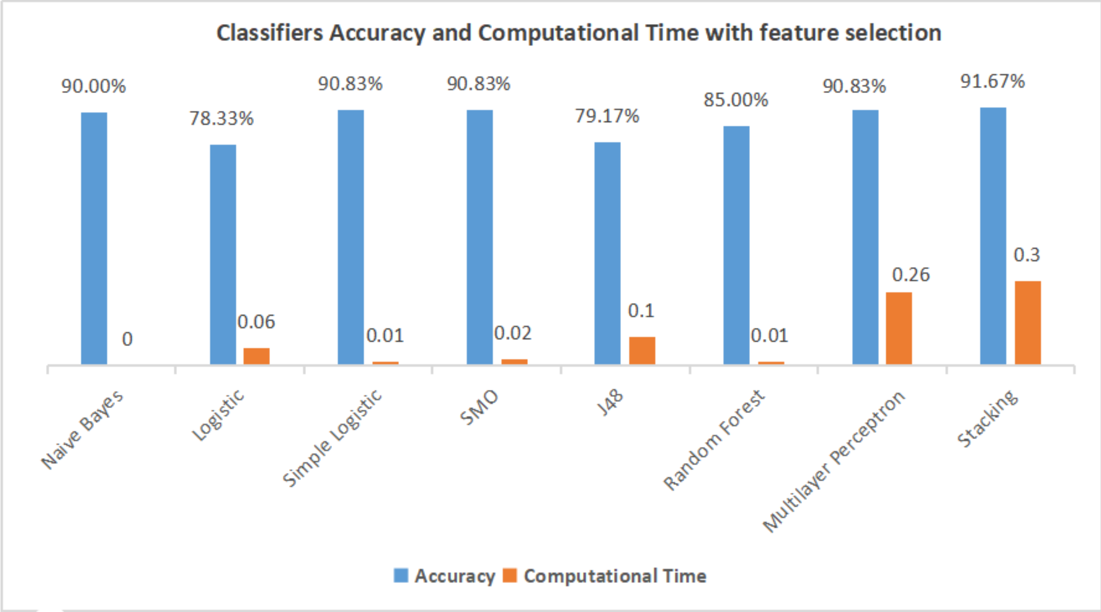

Figure 4.4Graphically representation of different classifiers accuracies and computationaltime by using feature selection

Figure 4.4 illustrates how the models performed better and required less computing time when feature selection was applied, focusing on the seven key features.

- **Naive Bayes:** The accuracy increased to 90.00% while the computational time stayed at 0 seconds.
- **Logistic:** computation time was reduced to 0.06 seconds while accuracy increasedto 78.33
- **Simple Logistic:** Computational time was reduced to 0.01 seconds while accuracy increased to 90.83
- **SMO:** Computational time was reduced to 0.02 seconds while accuracy increased to90.83
- **J48:** The computational time increased to 0.1 seconds, and accuracy reduced marginally to 79.17%.
- **Random Forest:** The computational reduced to 0.01 seconds, and accuracy reduced marginally to 85.00%.
- **MLP:** Computational time was reduced to 0.26 seconds while accuracy remained at 90.83%.
- **MLP:** Computational time was reduced to 0.3 seconds while accuracy increased to 91.67%.

4.5 Disscusion

The comparative analysis demonstrates that feature selection enhances model performance and reduces calculation times. The stacking model and the deep learning model (ANN multilayer perceptron) had the best accuracy. Combining predictions from various meth- ods, the stacking model yielded the best overall results, with a computational time of 0.3 seconds and an accuracy of 91.67%. This improvement highlights how important it is to select relevant attributes for an accurate and useful bipolar disorder classification. The full comparison in Figures 4.3 and 4.4 highlights these findings, providing a clear illustration of the impact of feature selection on model performance.

4.6 Summary

The chapter discusses an experimental study on a Kaggle dataset containing 120 instances and 18 attributes for categorizing bipolar disorder. The dataset includes symptoms and behavioral indicators like depression, exhaustion, euphoria, sleep disorder, mood swings, suicidal thoughts, anorexia, anxiety, nervous breakdown, and overthinking. The study com- pares the performance of machine learning models, a deep learning model, and a stacking model in classifying bipolar disorder. The selected features included mood swings, suici- dal thoughts, sadness, euphoria, optimism, sexual activity, and expert diagnosis. The ANN multilayer perceptron consistently outperformed other models in accuracy. The stacking model also showed significant improvement, emphasizing the importance of selecting relevant features in machine learning and deep learning applications for bipolar disorder classification.

Conclusions and Recommendations

5.1 Conclusions

The study we conducted on bipolar disorder classification outperforms earlier studies by using six machine learning algorithms (Naive Bayes, Logistic, Simple Logistic, SMO, J48, and Random Forest) and one deep learning method (MLP). In contrast to previous research that did not use feature selection and stacking, we used these strategies to improve model performance. Our results reveal that Naive Bayes attained an accuracy of 90.00%, which is much higher than the previously reported 83.3%. Similarly, Simple Logistic and SMO models achieved 90.83% accuracy, whereas Stacking achieved the maximum accuracy of91.67%, matching the best previous findings while improving robustness and reliability. These developments highlight the importance of feature selection and stacking in enhanc- ing the prediction capability of models, providing a more accurate and efficient approach to bipolar disorder classification.

5.2 Limitation

The dataset quantity and quality are significant limitations of this study, which may have limited the models' accuracy and generalizability. The restricted dataset may not prop- erly capture the range of bipolar disease presentations, thus impacting the effectiveness of machine learning, deep learning, and stacking models.

5.2 Future Work

Future work should concentrate on expanding the dataset to cover a wider spectrum of bipo- lar illness presentations and improve model accuracy and generalizability. Experimentingwith more complex algorithms, such as hybrid and ensemble techniques, and incorporating a larger range of features could help enhance classification performance.

Bibliography

Antosik-Wójcińska, A. Z., Dominiak, M., Chojnacka, M., Kaczmarek-Majer, K., Opara,
K. R., Radziszewska, W., Olwert, A., & Święcicki, Ł. (2020). Smartphone as a monitoring tool for bipolar disorder: A systematic review including data analy- sis, machine learning algorithms and predictive modelling. *International journal of medical informatics*, *138*, 104131.

Arbabshirani, M. R., Plis, S., Sui, J., & Calhoun, V. D. (2017). Single subject prediction of brain disorders in neuroimaging: Promises and pitfalls. *Neuroimage*, *145*, 137–165. Barnett, I., Torous, J., Staples, P., Sandoval, L., Keshavan, M., & Onnela, J.-P. (2018). Re-lapse prediction in schizophrenia through digital phenotyping: A pilot study. *Neu-ropsychopharmacology*, *43*(8), 1660–1666.

Belizario, G. O., Junior, R. G. B., Salvini, R., Lafer, B., & da Silva Dias, R. (2019). Pre- dominant polarity classification and associated clinical variables in bipolar disorder: A machine learning approach. *Journal of affective disorders*, *245*, 279–282.

Campos-Ugaz, W. A., Garay, J. P. P., Rivera-Lozada, O., Diaz, M. A. A., Fuster-Guillén, D., & Arana, A. A. T. (2023). An overview of bipolar disorder diagnosis using ma- chine learning approaches: Clinical opportunities and challenges. *Iranian Journal of Psychiatry*, *18*(2), 237.

Cao, B., Luo, Q., Fu, Y., Du, L., Qiu, T., Yang, X., Chen, X., Chen, Q., Soares, J. C., Cho,

R. Y., et al. (2018). Predicting individual responses to the electroconvulsive therapy with hippocampal subfield volumes in major depression disorder. *Scientific reports*,8(1), 5434.

Ceccarelli, F., & Mahmoud, M. (2022). Multimodal temporal machine learning for bipolar disorder and depression recognition. *Pattern Analysis and Applications*, *25*(3), 493– 504.

Cho, H., Yen, P.-Y., Dowding, D., Merrill, J. A., & Schnall, R. (2018). A multi-level us- ability evaluation of mobile health applications: A case study. *Journal of biomedical informatics*, *86*, 79–89.

de Pablo, G. S., Cabras, A., Pereira, J., Santos, H. C., de Diego, H., Catalan, A., González-Pinto, A., Birmaher, B., Correll, C. U., & Fusar-Poli, P. (2023). Predicting bipolar disorder i/ii in individuals at clinical high-risk: Results from a systematic review. *Journal of affective disorders*, *325*, 778–786.

de Siqueira Rotenberg, L., Borges-Junior, R. G., Lafer, B., Salvini, R., & da Silva Dias,

R. (2021). Exploring machine learning to predict depressive relapses of bipolar disorder patients. *Journal of Affective Disorders*, *295*, 681–687.

Duan, L., Shao, X., Wang, Y., Huang, Y., Miao, J., Yang, X., & Zhu, G. (2020). An in- vestigation of mental health status of children and adolescents in china during the outbreak of covid-19. *Journal of affective disorders*, *275*, 112–118.

Dwyer, D. B., Falkai, P., & Koutsouleris, N. (2018). Machine learning approaches for clin- ical psychology and psychiatry. *Annual review of clinical psychology*, *14*(1), 91– 118.

Faurholt-Jepsen, M., Frost, M., Martiny, K., Tuxen, N., Rosenberg, N., Busk, J., Winther, O., Bardram, J. E., & Kessing, L. V. (2017). Reducing the rate and duration of re-admissions among patients with unipolar disorder and bipolar disorder using smartphone-based monitoring and treatment–the radmis trials: Study protocol for two randomized controlled trials. *Trials*, *18*, 1–13.

Gao, S., Calhoun, V. D., & Sui, J. (2018). Machine learning in major depression: From classification to treatment outcome prediction. *CNS neuroscience & therapeutics*, *24*(11), 1037–1052.

Grande, I., Berk, M., Birmaher, B., & Vieta, E. (2016). Bipolar disorder. *The Lancet*, *387*(10027), 1561–1572.

Guyon, I., & Elisseeff, A. (2003). An introduction to variable and feature selection. *Journal of machine learning research*, *3*(Mar), 1157–1182.

Huang, Y., Zhang, J., He, K., Mo, X., Yu, R., Min, J., Zhu, T., Ma, Y., He, X., Lv, F.,

et al. (2024). Innovative neuroimaging biomarker distinction of major depressive disorder and bipolar disorder through structural connectome analysis and machine learning models. *Diagnostics*, *14*(4), 389.

Jan, Z., Ai-Ansari, N., Mousa, O., Abd-Alrazaq, A., Ahmed, A., Alam, T., & Househ,

M. (2021). The role of machine learning in diagnosing bipolar disorder: Scoping review. *Journal of medical Internet research*, *23*(11), e29749.

Kessler, R. C., van Loo, H. M., Wardenaar, K. J., Bossarte, R. M., Brenner, L. A., Cai, T., Ebert, D. D., Hwang, I., Li, J., de Jonge, P., et al. (2016). Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports. *Molecular psychiatry*, *21*(10), 1366–1371.

Kim, Y.-K., & Na, K.-S. (2018). Application of machine learning classification for struc- tural brain mri in mood disorders: Critical review from a clinical perspective. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *80*, 71–80.

Librenza-Garcia, D., Kotzian, B. J., Yang, J., Mwangi, B., Cao, B., Lima, L. N. P., Bermudez,

M. B., Boeira, M. V., Kapczinski, F., & Passos, I. C. (2017). The impact of machine learning techniques in the study of bipolar disorder: A systematic review. *Neuro- science & Biobehavioral Reviews*, *80*, 538–554.

Liu, Y. S., Chokka, S., Cao, B., & Chokka, P. R. (2021). Screening for bipolar disorder in a tertiary mental health centre using earlydetect: A machine learning-based pilot study. *Journal of Affective Disorders Reports*, *6*, 100215.

Martin, S., Colle, R., El Asmar, K., Rigal, A., Vievard, A., Feve, B., Becquemont, L., Ver- stuyft, C., & Corruble, E. (2019). Homa-ir increase after antidepressant treatment in depressed patients with the met allele of the val66met bdnf genetic polymorphism. *Psychological Medicine*, *49*(14), 2364–2369.

Mateo-Sotos, J., Torres, A., Santos, J., Quevedo, O., & Basar, C. (2022). A machine learning- based method to identify bipolar disorder patients. *Circuits, Systems, and Signal Processing*, *41*(4), 2244–2265.

M.D., F. M. M. (2021). *What are the different types of bipolar disorder?* [Accessed: 2024-08-06]. https://www.psychologytoday.com/us/ blog/bipolar-101/202104/what-are- the-different-types-bipolar-disorder

Merikangas, K. R., Jin, R., He, J.-P., Kessler, R. C., Lee, S., Sampson, N. A., Viana, M. C., Andrade, L. H., Hu, C., Karam, E. G., et al. (2011). Prevalence and correlates of bipolar spectrum disorder in the world mental health survey initiative. *Archives of general psychiatry*, *68*(3), 241–251.

Mitchell, T. (1997). *Machine learning*. McGraw-Hill. https://books.google.com.pk/books?id=EoYBngEACAAJ

Mohr, D. C., Zhang, M., & Schueller, S. M. (2017). Personal sensing: Understanding men- tal health using ubiquitous sensors and machine learning. *Annual review of clinicalpsychology*, *13*(1), 23–47.

Nielsen, A. N., Barch, D. M., Petersen, S. E., Schlaggar, B. L., & Greene, D. J. (2020). Machine learning with neuroimaging: Evaluating its applications in psychiatry. *Bi- ological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *5*(8), 791–798.

Nova, K. (2023). Machine learning approaches for automated mental disorder classification based on social media textual data. *Contemporary Issues in Behavioral and SocialSciences*, *7*(1), 70–83.

Nunes, A., Schnack, H. G., Ching, C. R., Agartz, I., Akudjedu, T. N., Alda, M., Alnæs, D., Alonso-Lana, S., Bauer, J., Baune, B. T., et al. (2020). Using structural mri to identify bipolar disorders–13 site machine learning study in 3020 individuals from the enigma bipolar disorders working group. *Molecular psychiatry*, *25*(9), 2130–2143.

Passos, I. C., Mwangi, B., Cao, B., Hamilton, J. E., Wu, M.-J., Zhang, X. Y., Zunta-Soares, G. B., Quevedo, J., Kauer-Sant'Anna, M., Kapczinski, F., et al. (2016). Identifying a clinical signature of suicidality among patients with mood disorders: A pilot study using a machine learning approach. *Journal of affective disorders*, *193*, 109–116.

Perlis, R. H., Brown, E., Baker, R. W., & Nierenberg, A. A. (2006). Clinical features of bipolar depression versus major depressive disorder in large multicenter trials. *American Journal of Psychiatry*, *163*(2), 225–231.

Phillips, M. L., & Kupfer, D. J. (2013). Bipolar disorder diagnosis: Challenges and future directions. *The Lancet*, *381*(9878), 1663–1671.

Reinares, M., Papachristou, E., Harvey, P., Bonnín, C. M., Sánchez-Moreno, J., Torrent, C., Ayuso-Mateos, J. L., Ploubidis, G. B., Vieta, E., & Frangou, S. (2013). Towards a clinical staging for bipolar disorder: Defining patient subtypes based on functional outcome. *Journal of affective disorders*, *144*(1-2), 65–71.

Sankar, A., Shen, X., Colic, L., Goldman, D. A., Villa, L. M., Kim, J. A., Pittman, B., Scheinost, D., Constable, R. T., & Blumberg, H. P. (2023). Predicting depressed and elevated mood symptomatology in bipolar disorder using brain functional con- nectomes. *Psychological Medicine*, *53*(14), 6656–6665.

Shen, J., Feng, Y., Lu, M., He, J., & Yang, H. (2023). Identification of the role of immune-related genes in the diagnosis of bipolar disorder with metabolic syndrome through machine learning and comprehensive bioinformatics analysis. *Frontiers in Psychi-atry*, *14*, 1187360.

Sonkurt, H. O., Altınöz, A. E., Çimen, E., Köşger, F., & Öztürk, G. (2021). The role of cognitive functions in the diagnosis of bipolar disorder: A machine learning model. *International Journal of Medical Informatics*, *145*, 104311.

Struyf, J., Dobrin, S., & Page, D. (2008). Combining gene expression, demographic and clinical data in modeling disease: A case study of bipolar disorder and schizophre- nia. *Bmc Genomics*, *9*, 1–22.

Tian, S., Zhu, R., Chen, Z., Wang, H., Chattun, M. R., Zhang, S., Shao, J., Wang, X., Yao, Z., & Lu, Q. (2023). Prediction of suicidality in bipolar disorder using variability of intrinsic brain activity and machine learning. *Human brain mapping*, *44*(7), 2767–2777.

Tomasik, J., Han, S. Y. S., Barton-Owen, G., Mirea, D.-M., Martin-Key, N. A., Rustogi, N., Lago, S. G., Olmert, T., Cooper, J. D., Ozcan, S., et al. (2021). A machine learning algorithm to differentiate bipolar disorder from major depressive disorder using an online mental health questionnaire and blood biomarker data. *Translational psychi-atry*, *11*(1), 41.

Tripathi, U., Mizrahi, L., Alda, M., Falkovich, G., & Stern, S. (2023). Information theory characteristics improve the prediction of lithium response in bipolar disorder pa- tients using a support vector machine classifier. *Bipolar Disorders*, *25*(2), 110–127.

Varoquaux, G., Raamana, P. R., Engemann, D. A., Hoyos-Idrobo, A., Schwartz, Y., & Thirion, B. (2017). Assessing and tuning brain decoders: Cross-validation, caveats, and guidelines. *NeuroImage*, *145*, 166–179.

Wang, G., Shi, S., An, S., Fan, F., Ge, W., Wang, Q., Yu, F., & Wang, Z. (2024). A bipyramid multimodal fusion method for the diagnosis of bipolar disorders. *ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Pro- cessing (ICASSP)*, 1746–1750. https : / / doi . org / 10 . 1109 / ICASSP48485 . 2024 .10446012

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., & Campbell, A. T. (2014). Studentlife: Assessing mental health, academic perfor- mance and behavioral trends of college students using smartphones. *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous com-puting*, 3–14.

Wang, W., Huang, S., Hou, W., Liu, Y., Fan, Q., He, A., Wen, Y., Hao, J., Guo, X., & Zhang,

F. (2017). Integrative analysis of gwas, eqtls and meqtls data suggests that multiple gene sets are associated with bone mineral density. *Bone & Joint Research*, 6(10), 572–576.

Yasin, S., Hussain, S. A., Aslan, S., Raza, I., Muzammel, M., & Othmani, A. (2021). Eeg based major depressive disorder and bipolar disorder detection using neural net- works: A review. *Computer Methods and Programs in Biomedicine*, *202*, 106007.

Zhu, T., Liu, X., Wang, J., Kou, R., Hu, Y., Yuan, M., Yuan, C., Luo, L., & Zhang, W. (2023). Explainable machine-learning algorithms to differentiate bipolar disorder from major depressive disorder using self-reported symptoms, vital signs, and blood- based markers. *Computer Methods and Programs in Biomedicine*, *240*, 107723.