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Clinical Application of Machine Learning Methods in Psychiatric Disorders

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Abstract: Psychiatric disorders, especially bipolar affective disorder, present a significant burden on national and global healthcare systems, warranting advanced clinical management methods. Machine learning (ML) has emerged as a reliable tool to advance diagnosis, treatment, and monitoring. This paper compiles insights from literature to confirm the applicability of ML models in the clinical setting.

The findings indicate that ML can predict psychiatric disorder symptoms from speech and imaging data with up to 89% accuracy. Furthermore, individual responses to treatment and remission cases can be forecasted with accuracies exceeding 80%. ML can also predict prevailing symptoms after treatment with up to 91.26% accuracy.

Keywords: Psychiatric disorders, bipolar affective disorder, machine learning, diagnosis, prognosis, treatment

I. INTRODUCTION

The prevalence of psychiatric disorders has proliferated in recent years, increasing the demand for effective diagnosis methods and treatments. According to the World Health Organization (WHO) [1], there has been a 13% global rise in mental health disorders. This problem is significant regardless of demographics.

For example, 20% of the world's adolescents and children have a psychiatric disorder, while about 14% of adults aged above 60 are affected [1] [2].

The high incidence of psychiatric disorders and the associated health risks are mainly due to the difficulty of early diagnosis and treatment, which is associated with patients' heterogeneity and the complexity of neuronal degeneration. Machine learning (ML), a subset of artificial intelligence (AI), has emerged as a potential tool to help address these issues. ML models can directly predict psychiatric disorders and determine appropriate clinical interventions, helping deliver patient-specific treatment.

II. MACHINE LEARNING APPLICATIONS IN MANAGING PSYCHIATRIC DISORDERS

ML can be mainly applied to diagnose mental health issues and recommend patient-specific treatments and interventions. The underlying feature extraction, classification, and selection methods can learn features from various sources, such as neuroimaging brain data, and respond to data variations and individual patient differences.

These provisions enhance the accuracy, performance, and reliability of disease-specific diagnostic methods. Furthermore, ML algorithms can combine clinical diagnosis and pre-trained data on treating psychiatric disorders to prescribe clinical interventions with the highest possibility of achieving positive health outcomes. This section describes ML and summarizes recent proposals regarding diagnosing and treating psychiatric disorders.

A. Machine Learning

ML is an AI domain that allows computer algorithms to learn patterns in data without explicit programming. Supervised and unsupervised learning are among the most commonly used ML approaches [3]. Supervised learning predicts outcomes using labeled data input, while unsupervised learning features no explicit guidelines or measurements.

Ensemble learning can also be used to enhance model performance or minimize the probability of selecting poor-performance models [3]. Deep learning (DL) and neural networks have become increasingly prominent types of ML because of their ability to solve multiple problems, such as natural language processing, speech recognition, and image processing [3] [4]. For example, the said methods can predict negative symptoms of schizophrenia from speech signals and bipolar disorder (BD) from magnetic resonance imaging (MRI) and computed tomography scans [5]. The most preferred algorithms in the medical context include support vector machines (SVMs), random forests (RFs), and gradient boosting (GB) [5].

B. Assessing Psychiatric Disorder Symptoms

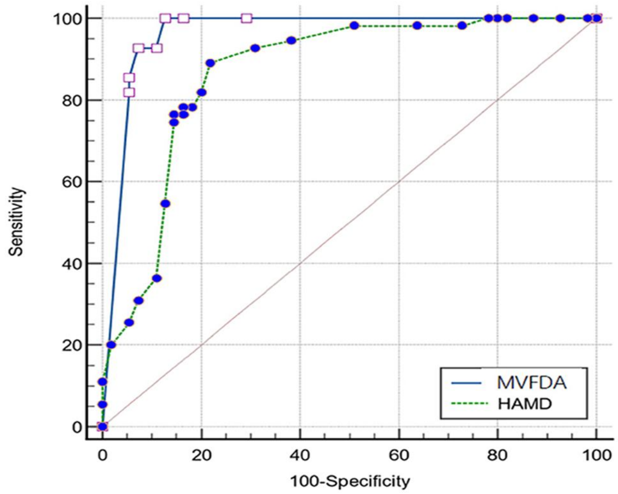

Fig. 1: The superiority of the MVFDA over the conventional HAMD-25 [7]

Researchers have presented extensive evidence indicating the efficacy of ML models for predicting psychiatric disorders from verbal cues. Li et al. [6] use DL-based natural language processing (NLP) methods to analyze depressive symptoms during clinical interviews. This approach attains an F1 score of 0.719 when categorizing the four-level depression severity and 0.890 when assessing the presence of depressive symptoms [6]. Similarly, Luo et al. propose using ML to predict psychiatric disorders from speech [7]. The authors use the multidimensional speech feature diagnosis and evaluation system (MVFDA) that amalgamates DL and multidimensional speech features for diagnosing depressive disorder in adolescents and children. As illustrated in Fig 1., this ML approach outperforms the 24-item Hamilton Rating Scale for Depression (HAMD-24), with a 90.91% specificity and 92.73% sensitivity [7]. These reports indicate that ML models can be trained to detect psychiatric disorder symptoms from patients' regular speech, accelerating the diagnosis process and accuracy.

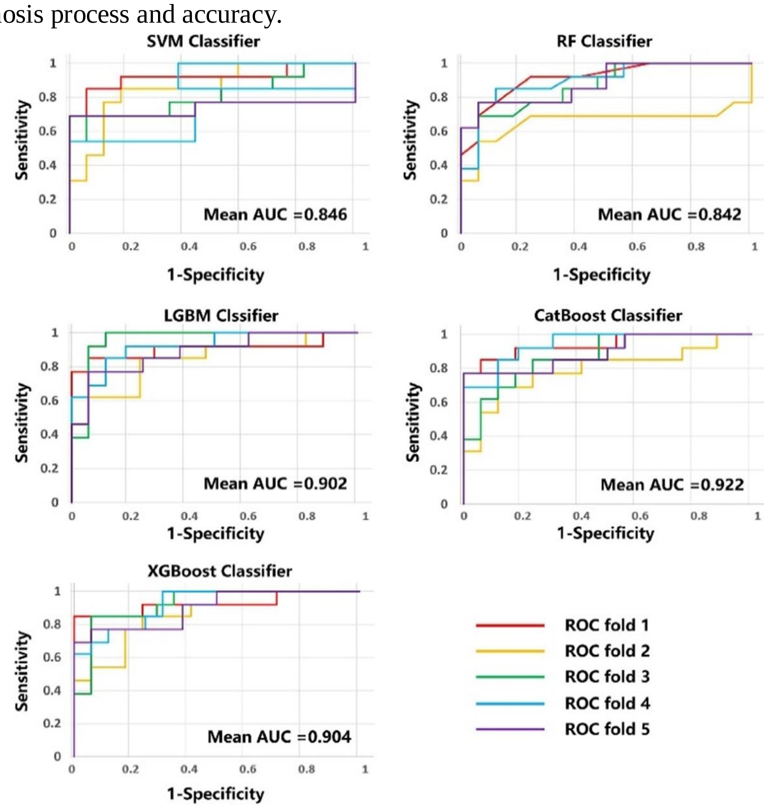

Fig. 2: Comparative AUC and ROC values for SVM, RF, LGBM, XGBoost, and CatBoost classifiers [10]

Similarly, ML models can rapidly predict psychiatric disorders from imaging data. Venkatapathy et al. [8] propose graph theory-based graph convolution networks and a resting-state functional MRI data analysis to diagnose depression. This approach achieves 0.24% down-sampling accuracy and 71.18% up-sampling accuracy for detecting patients with major depressive symptoms [8]. Similarly, Cao et al. [9] use DL on structural magnetic resonance imaging (sMRI) to predict depression symptom phenotypes in late-life depression. The ML approach accurately predicts the regions of interest in the orbital frontal cortex and anterior cingulate, indicating the potential for rapid diagnosis. Furthermore, ML can be used to predict the adverse health outcomes of prevailing psychiatric disorders among patients. For example, Yu et al.'s [10] ML technique, based on multimodal MRI radiomics, predicts the risk of stroke among psychiatric disorder patients with a 0.788 F1 score, 0.902 specificity, 0.739 sensitivity, and 0.831 accuracy. Fig. 2 indicates the comparative AUC and ROC values for the main classifiers in Yu et al.'s study. These findings further demonstrate the potential of ML to revolutionize the use of medical imaging for diagnosing mental health problems.

ML also provides a feasible platform to differentiate psychiatric disorders, a crucial role considering there are over 200 types of known mental health disorders. Su et al. [11] illustrate the use of ML to distinguish major depressive disorder from bipolar depression.

The study leverages lymphocyte subpopulation-based features to predict the maladies with an accuracy exceeding 90% [11]. The samples for the clinical trials are obtained from peripheral blood, which is less invasive, reinforcing the validity of the proposed method. Similarly, Gong et al. [12] use XGBoost, an ML prediction model, to improve classification ability. The technique successfully differentiates major depressive disorder from bipolar disorder with a 0.849 accuracy [12]. Furthermore, the model distinguishes major depressive disorder from bipolar disorder with depressive episodes with a 0.899 accuracy [12]. Differentiating the maladies, including bipolar disorder, depressive episodes, major depressive disorder, and schizophrenia, facilitates accurate and responsive treatment.

C. Prognosis and Treatment of Psychiatric Disorders

ML can also be applied to predict individual responses to psychiatric disorder treatments. Squarcina et al. [13] investigate the feasibility of different DL models for predicting depression treatment response. Their findings indicate that the ML approach achieves accuracies of about 80%, outperforming conventional regression methods [13]. Wallert et al. [14] also recommend using ML and multimodal data to predict remission among depression patients after internet-delivered psychotherapy. The researcher's RF model predicts remission with an average accuracy of 0.656 [14]. Grzena et al. [15] find similar results for using ML and multimodal data for predicting treatment response for late-life depression, which affects adults aged 60 and above. The authors report that the SWM-radial bias function and RF outperform conventional clinical methods, with a cross-validated AUC of 0.80 and 0.83, respectively [15]. The treatment outcome predictions can be leveraged to inform personalized treatment and promote positive patient outcomes.

Furthermore, ML can be combined with additional devices, such as wearable sensors and mobile phones, to detect changes in patients' health that indicate new or reoccurring psychiatric disorders. For example, Chalmers et al. [16] illustrate the positive results of using ML and smart meter data to detect variations in sleep behavior, a common indicator of depression and Alzheimer's disease. The authors use the VPC neural network classifier, achieving a 95.96% accuracy, with 0.975 specificity and 0.943 sensitivity [16]. Wearable sensors measuring variables like temperature, galvanic skin response, and heart rate can also be used to predict stress among patients.

Salafi and Kah use SVM and K-means clustering to predict stress levels from wearable sensor data with 91.26% accuracy [17]. These findings indicate that care practitioners can use devices and sensors on patients to monitor health outcomes and promptly detect remissions or mental health complications.

D. Clinical Applications of ML to Bipolar Affective Disorder

The previous sections indicate the general suitability of ML for diagnosing psychiatric disorders and predicting treatment and health outcomes. These benefits are retained for the clinical management of bipolar affective disorder, commonly reported in literature as just bipolar disorder (BD).

Specifically, ML models can be used to rapidly diagnose BD, helping differentiate it from other psychiatric disorders and determining appropriate treatment. Furthermore, ML systems can predict treatment outcomes and disease progression, allowing care practitioners to deploy more aggressive, patient-specific interventions. High accuracies are attained across all these applications, as indicated in the studies reviewed hereafter.

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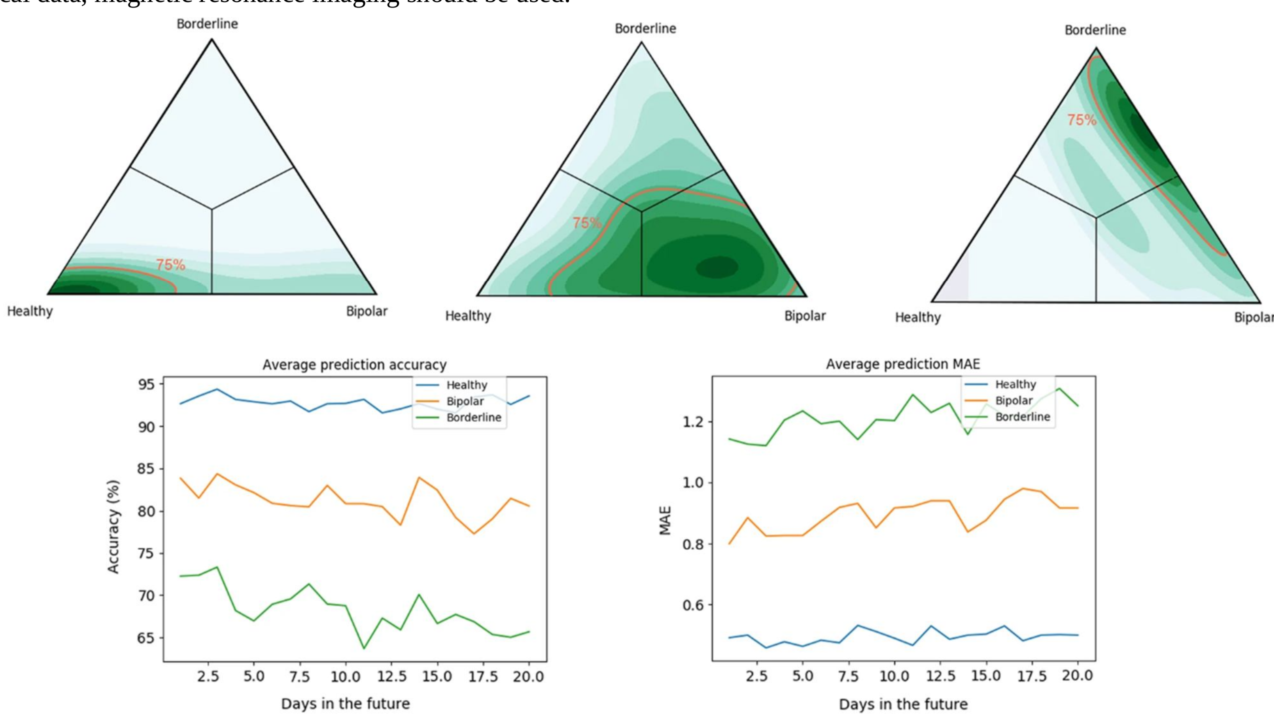
1) Diagnosing BD

Jan et al. [18] review the role of ML in diagnosing BD. They report that about 60% of BD patients are misdiagnosed and treated for depression, increasing the associated risks of morbidity and mortality. Thus, the authors investigate reports in literature, using a systematic review to determine if ML can help improve the diagnosis accuracy and ensure appropriate treatment. The study finds multiple candidate models for this application, including DL-based models, clustering algorithms, natural language processing, model-based clustering, regression models, and classification systems. Regardless of the model type, magnetic resonance imaging is preferred to classify BD patients. Furthermore, the accuracy range is 64% to 98% [18]. These findings indicate the reliability of ML to rapidly and accurately predict BD symptoms.

Besides directly diagnosing BD, ML can be used to differentiate the said malady from other common psychiatric disorders with similar symptoms. This role is particularly beneficial for distinguishing BD from borderline personality disorder (BPD). Both conditions have overlapping behaviours and symptoms, including deliberate self-harm, suicidality, and dysphoric mood states [19]. Bayes et al. illustrate the ability of ML to differentiate BD and BPD cases accurately [19]. The authors apply an ML approach to 82 patients meeting the Diagnostic and Statistical Manual (DSM) criteria for BD and BPD. The diagnosis is based on sequential data collected using smartphone mood ratings. The model classifies BP and BPD with 84.1%-87.8% and 50%-57.7% accuracy, respectively [19]. The accuracy in differentiating between the two disorders is 73.1% to 73.9% [19]. The accuracies exceed the classification accuracy attained using DSM criteria.

Arribas et al. [20] present a signature-based ML model for differentiating BD from BPD. The authors use the daily mood ratings of 130 patients with BD and BPD, collected using a bespoke smartphone app over a year. Consequently, a signature-based learning technique captures the changing interrelationships between different mood elements, helping classify patients' diagnoses and predict the consequent mood. As illustrated in Fig. 3, The ML approach classifies patients into appropriate diagnostic groups with 75% accuracy (healthy, bipolar, and borderline), while conventional methods only achieve 54% accuracy. In particular, the learning model predicts BD with 82-90% accuracy and BPD with 70-78% accuracy. These results indicate the possibility of improving BD diagnosis baselines. For example, the model in [20] improves the BD prediction accuracy reported by [19] by up to 2.2%. Moreover, the studies by [19] and [20] indicate that mood ratings are the ideal type of historical data when diagnosing BD. Without such historical data, magnetic resonance imaging should be used.



a Healthy participants, **b** Bipolar participants and **c** Borderline participants. Bottom: Decay in accuracy (left) and MAE (right) of the mood predictions for the three clinical groups, when the prediction horizon is increased

Fig. 3: The diagnosis classification and multiperiod mood prediction by Arribas et al.'s model [20]

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2) Treatment and Prognosis of BD

ML can be used to select appropriate treatment for BD. According to Passos et al. [21], this approach can guide personalized medicine to help reduce the reliance on group-based methods. In this case, ML is developed into user-friendly calculators that can be incorporated into the clinical workflow of electronic health records. A calculator fundamentally predicts patient responses to specific interventions, and care practitioners can opt for alternative therapies in case of negative predictions [21. Researchers suggest that such calculators are feasible for predicting BD patients' multimorbidity profile and other nuances [21]. Fleck et al. [22] support this premise by presenting the LITHium Intelligent Agent, a linguistic ML system for predicting BD patients' responses to lithium treatment. The model achieves near-perfect classification accuracy, predicting post-treatment malady alleviation at eight weeks with 88% training accuracy and 80% validation accuracy [22]. The ML system also outperforms conventional deterministic comparison methods. Therefore, ML can help reduce the morbidity and mortality associated with delayed or inaccurate treatment.

ML also offers a platform to predict individual responses to BD treatment and potential future medical complications. de Siqueira et al. [23] document the use of ML to predict depressive relapses among BD patients. They implement multiplayer perceptron, Naïve Bayes, RFs, and SWMs on a dataset comprising data from 507 relapse and 293 no-relapse patients. As illustrated in Fig. 4, all three algorithms reasonably predict depressive relapse, with F-measures ranging between 61% and 80% [23]. The RF approach achieves the highest prediction accuracy (74% for the no-relapse group and 68% for the relapse group) [23]. Salem et al. [24] also report the feasibility of ML in predicting rapid readmission of BD patients. The authors find that their ML model can identify the main predictors for the risk of 30-day readmission with 77% specificity and 83% sensitivity [24]. Fig. 5 illustrates the comparative sensitivity and specificity performance, with a ROC curve representing the receiver operating characteristic curve. These findings demonstrate that ML enables personalized medicine by helping care practitioners predict and avert adverse treatment and health outcomes.

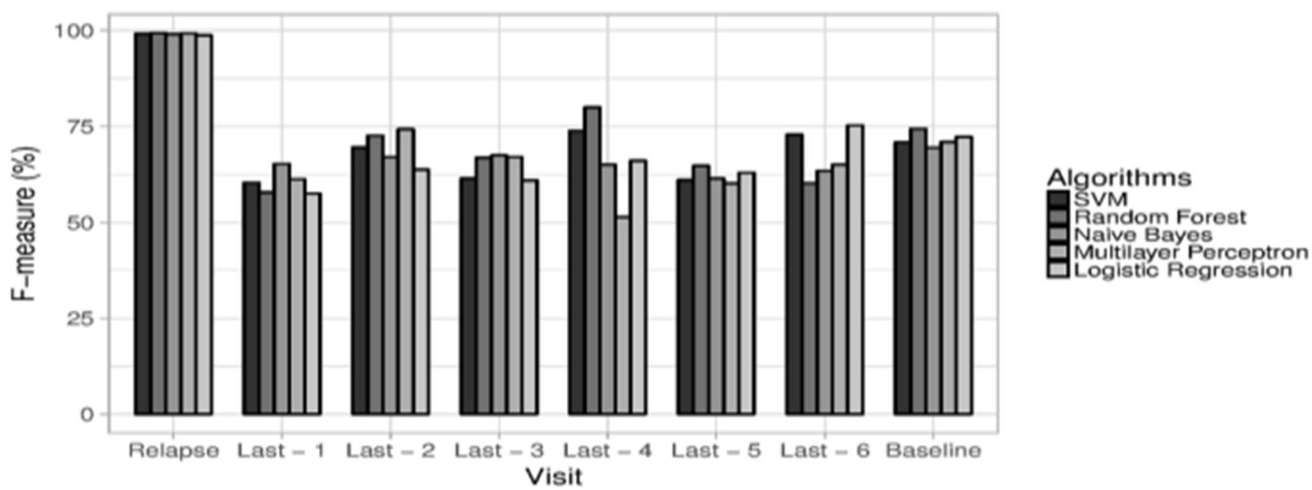

Fig. 4: Comparative F-measure by visit in [23]

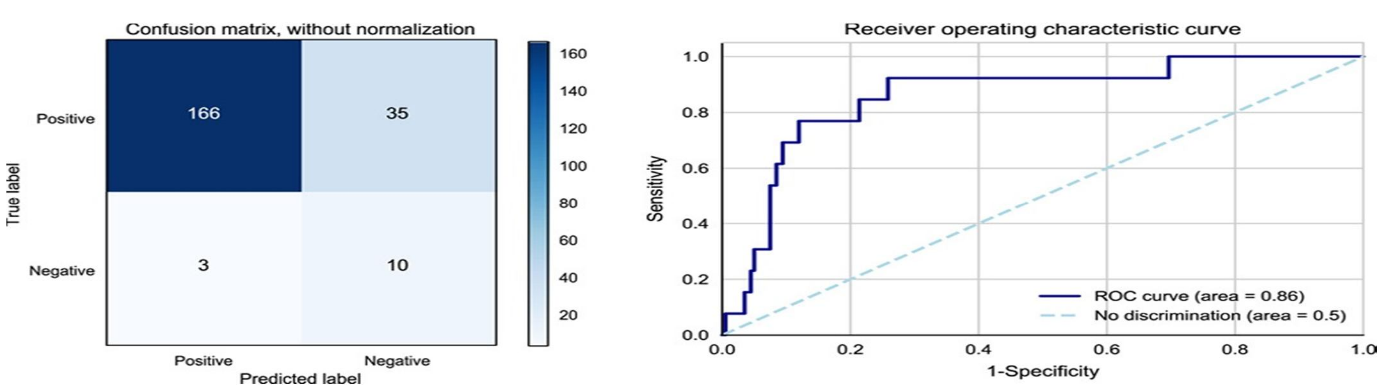

Fig. 5: The ML model performance in [24]

III. CONCLUSION

Psychiatric disorders, particularly BD, present a significant national and global burden, necessitating elaborate diagnosis, treatment, and patient monitoring interventions. ML has emerged as a feasible platform for improved clinical management of the disorders in recent years. For example, ML models can predict symptoms from speech and imaging data with up to 89% accuracy. Furthermore, ML can be used to differentiate between psychiatric disorders, with accuracies exceeding 90%. This role is particularly crucial due to the large number of mental health issues and the high misdiagnosis risk. Under prognosis and treatment, ML can be used to predict individual responses to treatment and remission cases, with accuracies exceeding 80%. ML models can also be used to analyze data from sensors and wearable devices to monitor patient's health outcomes and promptly detect psychiatric complications. Based on reports in literature, ML outperforms conventional clinical methods in all the mentioned application areas, indicating the potential to revolutionize the diagnosis, treatment, and management of BD. However, pertinent issues, such as system security and patients' privacy, should be resolved before ML methods are used on a large scale.

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