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DIAGNOSIS OF PSYCHIATRIC DISORDERS USING EEG SIGNAL AND MACHINE LEARNING

Mrs. Zeenat Sheikh
M.Tech , Student, Electronics and Communication Engg.
Anjuman College of Engineering And Technology
Nagpur, India
zeenat.neha19@gmail.com

Dr. Muzaffar Khan
Assistant Professor , Electronics and Communication Engg.
Anjuman College of Engineering And Technology
Nagpur, India
muzaffarkhanacet@gmail.com

***Abstract*— This paper explores the use of machine learning in medical diagnosis by an automated diagnosis procedure based on machine learning methodology using electroencephalograph (EEG) data is proposed for diagnosis of psychiatric illness. EEG signal is analyzed in time and frequency domain to extract relevant feature from 32 channel EEG signal. The dimensionality of extracted feature is reduced using feature selection techniques. A variety of classification algorithm is used to classify the class label to achieve high classification. The proposed automated diagnosis system is designed to differentiate various psychiatric conditions, often specific symptoms can appear in more than one diagnostic category, and diagnostic criteria can overlap to the point where confident differentiation is often impossible and adversely affects recovery of the patient. Even the psychiatric expert can have difficulty distinguishing certain psychiatric conditions. The proposed study, demonstrate the use of machine learning methodologies for psychiatric diagnosis with high accuracy to be used in clinical environment.**

Keywords—Machine learning, medical diagnosis, Electroencephalogram, psychiatric, feature selection, classification.

I. INTRODUCTION

Early diagnosis of mental disorders is crucial for successful treatment. However, despite well-established clinical guidelines, making an accurate diagnosis can be challenging and often complex [1]. Generally, these guidelines involve a clinical interview carried out by psychiatrists where two different tests are usually employed, the Diagnostic and Statistical Manual of Mental Disorders (DSM) of the American Psychiatric Association [2]. In this regard, the expertise of the clinical staff that perform these tests and interviews is decisive, as it is a subjective process, where depending on the previous experience of clinical staff and understanding of the results obtained the correct diagnosis can be successful or no. The use of electroencephalograms (EEGs) combined with machine learning or deep learning has become a helpful tool that permits to classify EEG signal characteristics depending on mental states and illness [3-6].

EEG is a signal pattern that is obtained by amplifying and recording the spontaneous biological potential of the brain on the scalp. This potential has been shown to reflect the macroscopic activity of the brain surface and is typically acquired using noninvasive electrodes applied onto the scalp. These electrodes capture the inherent and periodic electrical impulses generated by clusters of brain cells [7]. EEG is used in the diagnosis and prognosis of mental disorders because it provides brain biomarkers. However, only highly trained doctors can interpret EEG signals due to its complexity.

Therefore, an early and accurate diagnostic of mental disorders could improve the quality of life of patients. EEG is performed by using a noninvasive device that captures the electrical brain activity produced by its upper layers. It consists of an array of electrodes which are placed over the scalp of the patient. EEG signal is complex, nonlinear and non-stationary which makes it very tedious to interpret visually and highly difficult to extract the significant features from them. The resting frontal EEG alpha asymmetry is reliably assessed in clinically depressed patients; thus, it serves as a trait marker of risk for depression and other emotion-related psychopathology. The importance of EEG in psychiatric diseases is increasingly being recognized as it has the potential for diagnosis and to guide treatment. The Psychiatric EEG Evaluation Registry (PEER) is a clinical phenotypic database comprising data correlating EEGs and medication treatment outcomes for various mental health diagnoses [8]. Patients with psychiatric disorders may have abnormal EEG findings, such as epileptic activity or slow wave activity, which can be a non-specific sign of brain disease. The prevalence of EEG abnormalities in patients with mental illness is significantly elevated. It ranges from 20% to 70% higher when compared to healthy controls [9]. This study explores early diagnosis of mental disorders using EEG signal and machine learning techniques as a diagnostic tool for psychiatric disorders.

II. LITERATURE REVIEW

[10]. **Wu, C.-T.; Huang, H.-C.; Huang, S.; Chen, I.-M.; Liao, S.-C.; Chen, C.-K.; Lin, C.; Lee, S.-H.; Chen, M.-H.; Tsai, C.-F.; et al. Resting-State EEG Signal for Major Depressive Disorder Detection: A Systematic Validation on a Large and Diverse Dataset. Biosensors 2021, 11, 499. https://doi.org/10.3390/bios11120499:** The study by Wu, C.-T et al. conducted a study using resting-state EEG data from 400 participants across four medical centers to evaluate the classification performance of four common EEG features: band power (BP), coherence, Higuchi’s fractal dimension, and Katz’s fractal dimension. They employed a sequential backward selection (SBS) method to identify the optimal feature subset. To address the significant data variability arising from the large dataset and multi-site EEG recordings, the researchers introduced a conformal kernel (CK) transformation to enhance the performance of support vector

machine (SVM) classification of major depressive disorder (MDD) versus healthy controls (HC). The findings revealed that (1) coherence features constituted 98% of the optimal feature subset; (2) the CK-SVM model outperformed other classifiers, including K-nearest neighbors (K-NN), linear discriminant analysis (LDA), and SVM; and (3) the combination of the optimal feature subset and CK-SVM achieved a high five-fold cross-validation accuracy of 91.07% on the training set (140 MDD and 140 HC) and 84.16% on the independent test set (60 MDD and 60 HC). These results indicate that coherence-based connectivity is a more reliable feature for achieving high and generalizable MDD detection performance in real-world clinical settings.

[12]. **Redwan, S.M., Uddin, M.P., Ulhaq, A. et al. Power spectral density-based resting-state EEG classification of first-episode psychosis. Sci Rep 14, 15154 (2024).** https://doi.org/10.1038/s41598-024-66110-0 **:** The study by Redwan, S.M., Uddin, M.P., Ulhaq, A., et al. (2024) explores the use of power spectral density (PSD) based resting-state electroencephalography (EEG) for classifying first-episode psychosis (FEP). This research contributes to the growing body of literature that investigates objective, neurophysiological markers for early detection and diagnosis of psychiatric disorders. The authors leverage the spectral characteristics of brain activity during a resting state, which is a common and relatively easy-to-acquire EEG paradigm, to identify distinct patterns in individuals experiencing their first episode of psychosis. This approach is significant as it aims to provide a non-invasive and potentially more objective diagnostic tool compared to traditional clinical assessments, which can be subjective and time-consuming. The study's focus on FEP is particularly important, given that early intervention in psychosis has been shown to improve long-term outcomes. By analyzing the power distribution across different frequency bands in the EEG signal, the researchers aim to develop a robust classification model that can differentiate FEP patients from healthy controls, thereby offering a promising avenue for supporting clinical decision-making and facilitating timely intervention.

[9]. Singh M, Muhmmad A, Jahangiri FR. Electroencephalography (EEG) in Psychiatry: A Review. J of Neurophysiological Monitoring 2023; 1(1): 44-50. doi:10.5281/ zenodo.1020798.: The review by Singh, Muhammad, and Jahangiri (2023) in the Journal of Neurophysiological Monitoring comprehensively examines the utility of Electroencephalography (EEG) in the field of psychiatry. The authors emphasize the inherent link between psychiatry and neuroscience, highlighting that many prevalent mental disorders, such as depression and generalized anxiety, are associated with structural and functional changes in brain regions. They position EEG as a valuable, non-invasive, efficient, and relatively inexpensive neuroimaging technique for measuring brain electrical activity. While traditionally recognized as a diagnostic tool for epilepsy, the review underscores the growing research interest in EEG's role in diagnosing other psychiatric and neuropsychiatric disorders. The article notes that patients with mental illnesses frequently exhibit abnormal EEG findings, including epileptic activity or slow wave activity, with the prevalence of such abnormalities significantly elevated (20% to 70% higher) compared to healthy controls. Ultimately, this review delves into the scope of using EEG for diagnosing and understanding mental disorders, acknowledges its limitations, and explores the future potential of EEG as a diagnostic tool in psychiatric practice.Cao and Huang present a method for thyroid nodule detection in ultrasound images using kernel Principal Component Analysis (PCA) and SVM. They first apply kernel PCA to reduce the dimensionality of the ultrasound images and then use SVM for classification. Experimental results demonstrate the effectiveness of the proposed method in accurately detecting thyroid nodules, achieving high sensitivity and specificity. This study highlights the potential of kernel PCA and SVM for improving the performance of thyroid nodule detection systems in medical imaging.

A.

III. METHODOLOGY

The research methodology for diagnosing psychiatric disorders using EEG signals and machine learning typically involves several core steps.

- First, **data acquisition** is paramount, involving the recording of resting-state or task-based EEG from both patient groups (diagnosed with specific psychiatric disorders) and healthy controls, alongside relevant clinical and demographic data.

- Next, **rigorous preprocessing** is crucial to remove noise and artifacts inherent in EEG signals (e.g., eye blinks, muscle activity) using techniques like filtering and independent component analysis. Following this, **feature extraction** transforms the raw EEG data into meaningful numerical representations, commonly including power spectral density (PSD) in various frequency bands, connectivity measures (e.g., coherence, phase lag index), and non-linear dynamics. These features are then often subjected to **feature selection or dimensionality reduction** to optimize the dataset for the machine learning model and prevent overfitting.

- Finally, **machine learning models** (ranging from traditional classifiers like SVMs and Random Forests to deep learning architectures like CNNs and LSTMs) are trained and validated using cross-validation to classify psychiatric disorders, with performance evaluated using metrics such as accuracy, sensitivity, and specificity, aiming to establish objective diagnostic markers.

Figure 3.1 depicts Proposed model for diagnosis of mental disorders which can work offline mode, also provides the additional feature such as to provide a pre-trained classifier on a database. The classifier trained on a larger database is suitable to generalize the performance of the classifier.

Flow Chart :

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Classifier	Accuracy	Precision	Recall	F1 score	Avg per class accuracy
KNN	0.8351	0.8358	0.8351	0.8268	0.8351
SVM	0.6617	0.6712	0.6617	0.6567	0.6617
RF	0.9257	0.9266	0.9257	0.9250	0.9257

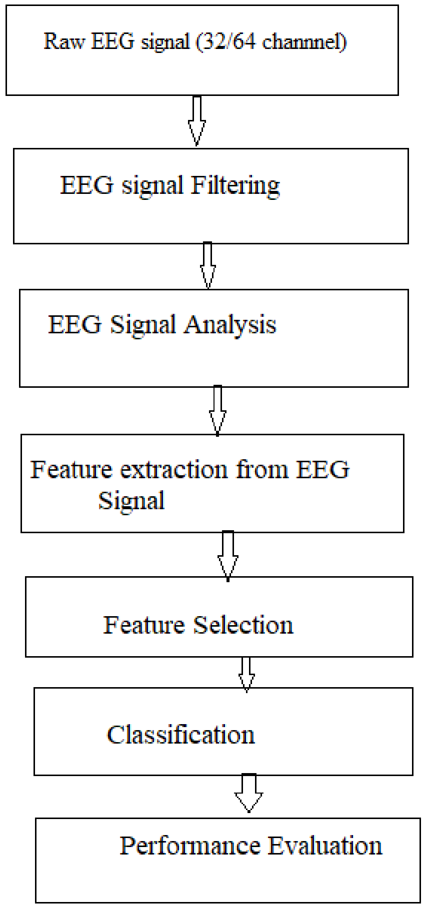

Fig 3.1 : flow chart of Diagnosis of Psychiatric Disorders

S. No	Mental Disorder	No of Subject
1	Mood disorder	266
2	Addictive disorder	186
3	Trauma and stress related disorder	128
4	Schizophrenia	117
5	Obsessive compulsive disorder	46
6	Healthy control	95

Table 3.1: depict type main mental disorder and number of subjects

IV. RESULT

From Table 4.1 The accuracy achieved in terms of mean F1 score by KNN, SVM and Random Forest classifier were 0.8268, 0.6567 and 0.9250. While highest average per class accuracy achieved by KNN, SVM and Random Forest classifier were 0.8351, 0.6617 and 0.9257 using all feature combination using 10-fold cross-validation, which partitions the original sample into 10 disjointed subsets, using nine of those subsets in the training process. Demographic parameter such as age, sex, years of education and IQ level were included with PSD+ FC feature.

Table 4.1 Result of classification for k=10-fold validation for classification of mental disorder

Figure 4.1 depict F1 score, Precision, Recall and accuracy of KNN, SVM and Random Forest over different fold during 10-fold cross validation. While Figure 4.2 depict average of F1 score, precision, recall and accuracy of KNN, SVM and Random Forest for 10-fold cross validation.

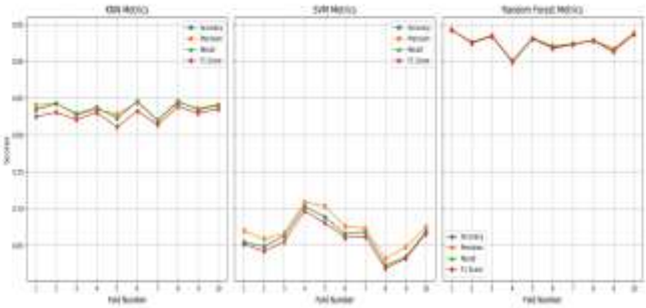

Figure 4.1 depict F1 score for different number of folds

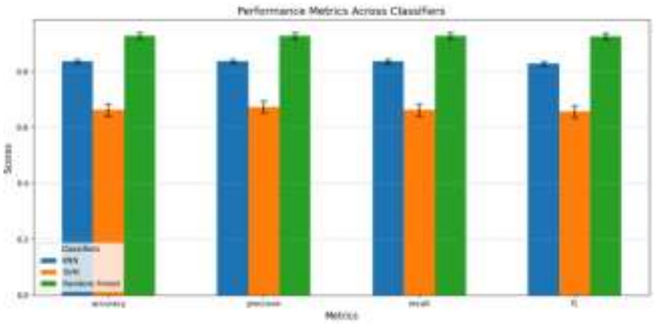

Figure 4.2 depict performance metric in terms mean accuracy, precision, recall and F1 score

The highest overall accuracy in term of F1 score, precision, recall and accuracy Random Forest. The classification strategy one vs all category. The SVM which good for binary classification had shown lowest accuracy among all classifier. Random Forest though achieved highest overall accuracy is computationally expensive when it comes to train classifier over large database.

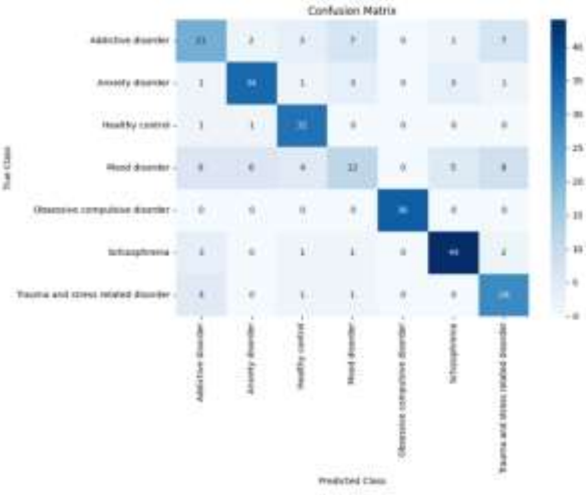

Figure 4.3 depict confusion matrix of CNN classifier

4.2 Result obtained from CNN

In case of convolutional neural network structure used depicted Table 3.1, The data pre-processed with PSD and FC generated 1140 features. PCA with 99% variance was applied to the data, and thus 223 principal components were extracted. CNN classifier achieved highest accuracy for obsessive compulsive disorder with F1 score of 1. The class imbalance is evident for the multiclass of the main. Disorder variable. We have used techniques such as dropout, batch normalization, and early stopping were applied to avoid overfitting.

Table 4.2 depict: Confusion matrix of CNN

Disorder	Precision	Recall	F1 score	support
Addictive disorder	0.5833	0.5122	0.5455	41
Anxiety disorder	0.7907	0.7907	0.7907	43
Healthy control	0.7619	0.9412	0.8421	34
Mood disorder	0.5000	0.2927	0.3692	41
Obsessive compulsive disorder	1.0000	1.0000	1.0000	36
Schizophrenia	0.8302	0.8627	0.846251	41
Trauma and stress related disorder	0.6087	0.8235	0.7000	43
Average accuracy	0.7393280			

V. CONCLUSION

In conclusion, we found that an ML approach using EEG could predict major psychiatric disorders with differing degrees of accuracy according to diagnosis. Each disorder classification model demonstrated different characteristics of EEG features. EEG ML is a promising approach for the classification of psychiatric disorders and has the potential to augment evidence-based clinical decisions and provide objectively measurable biomarkers. It would be advantageous to provide the automated diagnostic tools in future medical healthcare. The current study has several limitations. First, the effects of medication, comorbidity, and severity of disorder were not controlled. Our current study offers the following clinical insights: higher severity disorders increase the accuracy of the ML discrimination.

The convergence of EEG signal analysis and machine learning techniques holds immense promise for revolutionizing the diagnosis of psychiatric disorders. As highlighted by numerous studies, this interdisciplinary approach leverages the high temporal resolution and non-invasiveness of EEG to capture subtle neurophysiological biomarkers often indicative of mental health conditions. By applying various machine learning algorithms, from traditional methods like Support Vector Machines (SVMs) and Random Forests to advanced deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), researchers are demonstrating impressive accuracy in classifying and even predicting the onset of disorders like depression, anxiety, and schizophrenia. While traditional machine learning models often require meticulous feature engineering, deep learning excels at automatically extracting complex patterns from raw EEG data, albeit with greater computational demands and a need for larger datasets. Despite ongoing challenges related to data quality, standardization, and the inherent complexity of psychiatric disorders, the growing body of research consistently points towards EEG and machine learning as a powerful combination for developing objective, efficient, and potentially personalized diagnostic tools, thereby significantly advancing early intervention and treatment strategies in mental healthcare.

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