EEG-Based Depression Detection Using Machine Learning A Comprehensive Framework for Scalable and Objective Mental Health Diagnostics

Dr. Swati kale[1] , Shilpa S. Godage[2] , Prof. Jyoti Tipale[3], Sharvari Phalke[4], Anjali Nalawade [5], Khushal Deokar [6]

[1]Dept. Electronics and Telecommunication, JSPM's Rajarshi Shahu College Of Engineering, Pune, India.
[2]Dept. Electronics and Telecommunication, JSPM's Rajarshi Shahu College Of Engineering, Pune, India.
[3]Dept. Electronics and Telecommunication, JSPM's Rajarshi Shahu College Of Engineering, Pune, India.
[4]Dept. Electronics and Telecommunication, JSPM's Rajarshi Shahu College Of Engineering, Pune, India.
[5]Dept. Electronics and Telecommunication, JSPM's Rajarshi Shahu College Of Engineering, Pune, India.
[6]Dept. Electronics and Telecommunication, JSPM's Rajarshi Shahu College Of Engineering, Pune, India.

ABSTRACT

Depression is a common mental illness that heavily impairs cognitive, emotional, and physical functioning. Traditional diagnosis—almost solely based on clinical interview and self-report questionnaire—is generally subjective and susceptible to misinterpretation, leading to late or incorrect diagnosis. In order to overcome this drawback, the present study proposes a comprehensive and objective depression detection system with EEG signal analysis and machine learning methods. The system to be proposed includes new EEG preprocessing techniques, neural biomarker-based feature extraction with prioritization, SelectKBest and MRMR feature selection for relevance enhancement and dimensionality reduction. Synthetic Minority Over-sampling Technique (SMOTE) is utilized for handling class imbalance problem intrinsic in medical data. Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN) classification models are trained and tested. CNN was the highest-performing model with an attainment of performance with a 93.2% classification rate above traditional methods. Test measures including accuracy, precision, recall, F1-score, and ROC-AUC support the efficiency and accuracy of the framework. Findings set out the diagnostic value of EEG biomarkers and support machine learning capacity in enabling valid and scalable assessment of mental health. Additionally, the envisioned system can be achieved within a real-time environment on the web or mobile to broaden the reach in the clinical setting. The work advances computational psychiatry with an interpretable and scalable, and objective depression-detection technique realizable at early stages with prospects of inclusion into multimodal models of mental disease diagnosis in future work.

KEYWORDS: **Support Vector Machines, Random Forest, EEG signal analysis, SelectKBest ,MRMR**

1.INTRODUCTION

Depression is one of the most widespread mental disorders that plagues people from all walks of life, independent of age, gender, or socioeconomic status. The World Health Organization (WHO) estimates that more than 300 million individuals worldwide are afflicted with depression, and it ranks as one of the top causes of disability and a significant contributor to the total global burden of disease [8]. Marked by the persistent state of sadness, anhedonia (lack of pleasure in activities one once enjoyed), fatigue, worthlessness, impaired thinking, and in severe forms, suicidal thinking, depression considerably affects a person's social, interpersonal, and occupational functioning. Although widespread and with far-reaching implications, depression is far more underdiagnosed and undertreated due to the subjective limitations of conventional methods of diagnosis. Current clinical diagnosis for depression depends heavily on standardized interviews and psychometrics like the Patient Health Questionnaire (PHQ-9) and the Beck Depression Inventory (BDI). Although widely adopted and standardized, these procedures have the drawback inherent in self-reported measures—patient response bias, clinician-to-clinician variability, and mental health-related stigma for openness. Such subjectivity commonly leads to late diagnosis, incorrect severity classification of symptoms, and finally, inadequate treatment plans. Further, in the majority of low- and middle-income countries, access to appropriately trained mental healthcare professionals is also very restricted, adding to the problem of rapid and precise diagnosis. Thus, the necessity of objective, usable, and reproducible diagnostic technology in mental healthcare is more so than ever. Evolving data indicate that physiological measures—specifically those derived using neuroimaging and electrophysiological monitoring—are likely to augment or possibly supplant subjective ratings. One such simple, affordable, non-invasive modality is electroencephalography (EEG), which records electric brain activity through electrodes placed on the scalp. EEG has seen extensive clinical and research use for the study of a variety of neurological and psychiatric disorders, such as epilepsy, schizophrenia, and depression. Its temporal resolution, portability, and safety profile render it especially well adapted to continuous monitoring and early detection of mental disorders.

Depression has been found in a number of studies to be linked with certain patterns of brain activity detectable in EEG signals. One such biomarker is frontal alpha asymmetry, wherein depressed individuals are found to have lower alpha power in the left prefrontal cortex compared to the right. This asymmetry is believed to be a marker of deficits in approach-related motivation and affect regulation. Other EEG characteristics associated with depression are augmented theta activity over the frontal area and beta wave abnormalities related to cognitive control and arousal [10], [13]. These brain signatures provide an exciting potential direction for establishing objective diagnostic criteria for depressive disorders. But the high-dimensionality and intricacy of EEG signals make them difficult to analyze both by hand, as well as by traditional statistical techniques. Machine learning (ML) to the rescue in this case. ML algorithms can learn intricate, non-linear patterns from enormous data sets and classify EEG signals autonomously with minimal human involvement.

Algorithms like Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN) have proven excellent performance in a wide range of EEG-based tasks like sleep staging, seizure detection, emotion detection, and more so today, depression diagnosis [1], [3], [14]. End-to-end learning and feature-based learning are possible using machine learning-based analysis of EEG. In myopic (feature-based) approaches, myopically designed features such as statistical moments, power spectral density (PSD), and coherence measures are computed from EEG signals and fed to classifiers. Feature selection algorithms like SelectKBest and Minimum Redundancy Maximum Relevance (MRMR) are used to select the most informative features and prevent overfitting. Deep learning algorithms like CNNs, however, operate directly on raw or minimally preprocessed EEG data, learning hierarchical representations automatically through convolutional filters. These models are advantageous in the sense that they can attain fine-grained temporal and spatial relationships commonly lost in manual feature design.

Several challenges still exist in using machine learning with EEG-based depression detection. One significant one is class imbalance—there are often much fewer depressed samples than non-depressed controls in datasets, resulting in majority-class biased classifiers. To counteract this, methods like the

Synthetic Minority Over-sampling Technique (SMOTE) are utilized to create synthetic samples of the minority class so as to enhance model generalizability and fairness [6]. The second challenge is the inter-subject and inter-session variability of EEG signals, which requires strong preprocessing pipelines involving artifact rejection (e.g., via Independent Component Analysis), normalization, and segmenting.

Also, current systems are frequently restricted by being offline-based. That is, they are tested and created within lab environments and do not include real-time processing power needed to be used in clinical environments. To really have an impact, EEG-based depression detection needs to accommodate real-time analysis and simple interfaces for use by healthcare practitioners. Placing such systems in web or mobile apps can dramatically make them more accessible and scalable, especially within resource-poor environments.

In addition, although EEG alone is informative, merging it with other modalities of data—e.g., speech, facial expressions, text entry, or autonomic responses such as heart rate—has the potential to increase diagnostic precision. Multimodal fusion enables a more complete representation of a person's mental state because various modalities record complementary features of cognitive and emotional processes. While there are some investigations along this line of research, the issues of data synchrony, modality registration, and augmented computational complexity are still not well addressed.

The present research proposes an effective and scalable method of depression detection that avoids the above limitations. The system proposed in this work employs EEG signals and deep machine learning to design an online, objective, and interpretable diagnostic system. The main contributions of this research are the following:

- Preprocessing Pipeline: We propose a robust EEG preprocessing pipeline that includes bandpass filtering, Independent Component Analysis (ICA)- based artifact removal, epoch segmentation, and min-max normalization.
- Feature Engineering: We mine a high number of features like statistical descriptors, frequency-domain characteristics (e.g., power spectral density), and neural biomarkers like alpha asymmetry. SelectKBest and MRMR feature selection are used to retain only the best discriminative features.
- Classifier Evaluation: We test and train various machine learning models—SVM, Random Forest, and CNN—on a labeled EEG dataset. Model performances are measured in terms of metrics such as accuracy, precision, recall, F1-score, and ROC-AUC for the purpose of reliability and robustness.
- Class Imbalance Handling: We apply SMOTE for balancing the training data and thereby increase the model's sensitivity towards depressive cases without overestimating false positives.
- Deployment Framework: We introduce a deployment framework for running the trained models on web and mobile platforms with real-time classification and feedback loops for clinicians and researchers.

Merging neurophysiological signals with machine learning has implications for mental health diagnosis that are revolutionary. Since the healthcare systems of the world are confronted by the increasing incidences of mental health disorders coupled with the denial of access to professional care, such technological interventions can fill in the diagnostic lacuna. This work contributes to the growing field of computational psychiatry by providing a scientifically validated and technically scalable method for EEG-based depression detection. Future work will be focused on integrating additional data modalities, enhancing computational efficiency, and validating the system in heterogeneous clinical populations to facilitate broader adoption and clinical impact.

2. LITERATURE SURVEY

H. Dinkel et al. [1] developed a depression detection method with text-based data leveraging a Binary Gated Recurrent Unit (BGRU) network in their IEEE ACCESS 2019 article. Their approach focused on multi-task learning using sentence-level input features, ascertaining that sentence-level representations are more consistent than individual word embeddings. The findings showed that the model effectively captured contextual information, although it was adversely affected by sparse or limited training data.F. Cacheda et al.

[2] explored the application of Social Network Analysis (SNA) and Random Forest classifiers to identify early symptoms of depression among social media users. Their approach used threshold functions and several independent RF classifiers to enhance accuracy and robustness. The findings indicated that a dual-classifier system outperformed single models significantly; however, the research recognized limitations in representativeness since social media behavior might not be generalizable across all populations.

Lei Tong et al.

[3] proposed a cost-sensitive ensemble approach known as Boosting Pruning Trees (CBPT) to detect depressive behavior on Twitter. The approach entailed the extraction of sentiment-based features such as negative words, emojis, and linguistic patterns from the content of tweets. Findings indicated high predictive power, particularly in detecting high-risk individuals. The research emphasized issues concerning the genuineness of online personas and the occurrence of bots or fake accounts.

Y. Shen et al.

[4] proposed a deep learning-based automated depression detection model using emotional audio-textual data. Their approach integrated Gated Recurrent Units (GRU) and Bidirectional LSTM (BiLSTM) within a multimodal setup. By processing emotional audio and text cues, the model improved detection accuracy. Nevertheless, its performance relied greatly on the quality of the annotated emotional dataset employed during training.

Yıldırım et al.

[5] investigated gender bias in audio-based depression detection with CNN and RNN. The authors identified that rebalancing the dataset reduced gender bias and made the classification fairer. Their research centered on examining audio signals with handcrafted features and deep learning layers. The outcome highlighted that the selection of audio features might impact gender sensitivity in the model, which challenged fairness in mental health applications.

Stober et al.

[6] presented SS3, a supervised text classifier for early risk detection (ERD) of depression on social media. The SS3 model was tested on the CLEF eRisk2017 dataset and performed better compared to traditional classifiers in terms of computational cost and detection accuracy. Lightweight though it was, it had competitive results and was deemed suitable for real-time monitoring, albeit its performance was dataset-dependent.

Acharya et al.

[7] utilized a Hierarchical Attention Network (HAN) to analyze transcribed clinical interviews for detecting depression. The model utilized affective lexicons to direct the attention mechanism, allowing it to attend to emotionally relevant words. Their findings indicated that depressed individuals use emotionally charged language more often. The hierarchical nature—words constituting turns and sessions—was well-suited for document classification, although dependence on annotated clinical transcripts restricted scalability.

Krizhevsky et al.

[8] performed a cross-sectional survey of adolescent anxiety and depression during the COVID-19 pandemic through the Coronavirus Anxiety Scale (CAS). According to their analysis, 56% of adolescents did not have any anxiety, while 39% had mild anxiety, and a few percent had moderate to severe symptoms. Statistical tests indicated that there was a significant association between levels of anxiety and professional background of mothers of adolescents. While not machine learning-oriented, the research offered interesting contextual information regarding pandemic mental health concerns.

Despite significant advancements in leveraging machine learning and deep learning techniques for depression detection using EEG signals, several research gaps remain unaddressed. Many existing models, such as those based on SVM or conventional feature engineering, suffer from limited accuracy and poor generalizability due to small, imbalanced, or non-diverse datasets. Moreover, most studies overlook inter-subject variability and the influence of demographic and physiological differences, which are critical for real-world applicability. There is also a lack of standardization in preprocessing methods and feature extraction techniques, leading to inconsistent performance across datasets. Additionally, while deep learning models like CNNs show promise, they often function as black boxes, lacking interpretability essential for clinical validation. Therefore, there is a compelling need for robust, interpretable, and generalizable deep learning frameworks that can accurately detect depression from EEG signals while addressing data imbalance, subject diversity, and clinical reliability.

3.METHODOLOGY

The block diagram of the proposed system is shown in Fig.1.

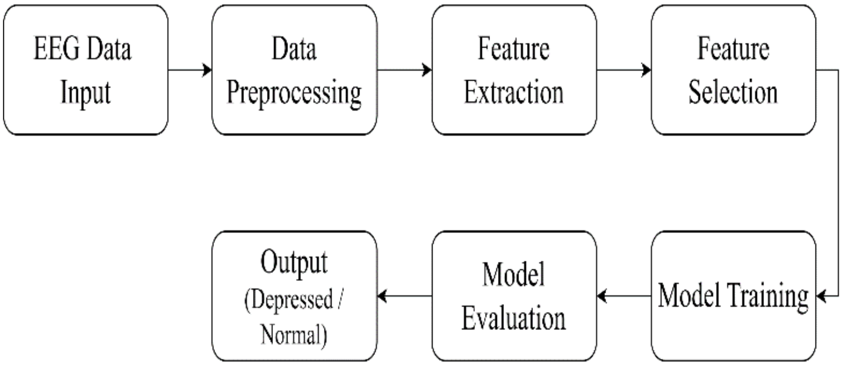

Fig. 1. Block diagram of the proposed system

A. EEG Data Input

The initial stage of the system involves the acquisition of EEG signals from individuals using non-invasive electrodes placed according to the internationally accepted 10–20 system. These signals reflect the electrical activity of the brain across multiple regions, including frontal, parietal, and central lobes. The data is recorded using EEG devices and stored in structured datasets. These datasets may originate from publicly available repositories or clinical sources, and typically include labeled samples from both depressed and non-depressed individuals. The primary aim of this stage is to collect raw, high-resolution brain activity data that can later be analyzed for patterns indicative of depression. However, EEG signals are inherently noisy and susceptible to artifacts, necessitating extensive preprocessing before they can be effectively used in machine learning models.

B. Data Preprocessing

Once the EEG data has been obtained, it undergoes a rigorous preprocessing pipeline to remove noise and improve the quality of signals. Preprocessing ensures that analysis, subsequent, is performed over clean and reliable data. Preprocessing entails the application of bandpass filters (typically 0.5–30 Hz) to remove unwanted brainwave frequencies while retaining useful ones such as alpha, beta, and theta. Independent Component Analysis (ICA) is applied to remove artifacts caused by eye blinks, muscle movement, and rogue electrical interference. Raw EEG data are segmented into shorter epochs, typically 1 to 2 seconds, for easier analysis. Normalization methods are applied to compress signal amplitude to a common scale to enable consistency between subjects and recording sessions. In some other cases, data augmentation techniques are applied as well in an effort to artificially increase dataset size and diversity and consequently enhance model robustness.

C. Feature Extraction

The second is to derive meaningful features from the preprocessed EEG data to describe the underlying neural activity in a structured manner. This is of the greatest importance because raw EEG signals are high-dimensional and not directly understandable for machine learning algorithms. Feature extraction tackles two general categories of features: statistical features and spectral features. Statistical features include measures such as mean, variance, skew, and standard deviation that describe signal over time behavior. Spectral features are determined by power spectral density (PSD) tests and provide information on the frequency components of the EEG signals, i.e., alpha, beta, and theta wave power. In particular, alpha wave asymmetry—usually revealed as lower lower left frontal versus right frontal alpha power—is a recognized depression biomarker. This stage compresses the EEG signals to low-dimensional, informative vectors that are good for classification.

D. Feature Selection

Once feature extraction is done, data can still contain redundant or irrelevant features that would affect model performance adversely or lead to overfitting. Another step of feature selection is thus introduced in an attempt to leave behind only the most useful features. Statistical and information-theoretic feature ranking and filtering algorithms are applied here. Two of the most utilized algorithms are SelectKBest and Minimum Redundancy Maximum Relevance (MRMR). SelectKBest selects features based on univariate statistical tests that approximate the correlation between each feature and the output label. MRMR attempts to select features most correlated with the output class and least redundant to one another. The result is an optimized set of features that improves computational efficiency, speeds up classification accuracy, and reduces overfitting risk for machine learning algorithms.

E. Model Training

During this phase, the chosen features are utilized to train machine learning models capable of distinguishing between depressed and non-depressed patients according to their EEG patterns. The training data is generally split into training, validation, and test sets, usually in a 70:15:15 ratio. Various classification algorithms are utilized, such as Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN). SVMs are particularly strong in terms of their ability to handle high-dimensional data, and RF models provide interpretability with resistance to overfitting. CNNs, however, can automatically learn deep hierarchical representations from raw EEG data, which makes them especially effective at learning non-linear patterns. In order to counteract class imbalance—where depressed samples tend to be outnumbered by non-depressed samples—the Synthetic Minority Over-sampling Technique (SMOTE) method is employed to create synthetic samples for the minority class. This ensures that the classifier will learn from an evenly distributed dataset and not be biased towards the majority class..

F. Model Evaluation

Once trained, machine learning model performance is assessed with a range of quantitative measures. These include accuracy (number of correctly classified examples), precision (ratio of positive predictions and true positives), recall (ratio of true positives and actual positives), and F1-score (harmonic mean between precision and recall). Furthermore, the Receiver Operating Characteristic Area Under the Curve (ROC-AUC) is calculated in order to compare the capacity of the model in discriminating between the two classes across different settings of thresholds. The aforementioned parameters give a clear indication of the quality of the model in identifying depressive states, especially in noisy and imbalanced datasets. The test phase guarantees that the system not only performs well but also accurately and with reliability and across a wide range of datasets.

G. Output (Depressed / Normal)

The final stage of the pipeline generates the diagnostic output. Based on the predictions made by the model, the system assigns a person's mental status to be either "Depressed" or "Normal." The classification is achieved using the patterns extracted in the EEG features and is presented in the form of a user interface, possibly a web-based dashboard or an application. The purpose of this output process is to provide clinicians, researchers, or even the patients themselves with an objective picture of their mental health status. Integration into real-time platforms allows it to be used for early detection, continuous monitoring, or even as a decision-support system in the clinical environment. The output thus is the actionable result of the overall machine learning.

4. RESULT AND DISCUSSION

The suggested EEG-based depression detection framework was critically assessed using the typical classification models and benchmark performance measures. The models were tested and trained using a balanced dataset of EEG records from depressed and non-depressed subjects. The findings demonstrate the effectiveness of the developed system based on both classification accuracy and model robustness.

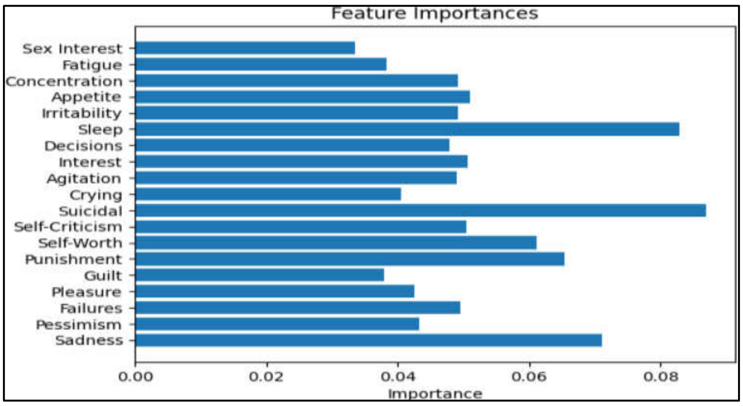

Fig. 2. Feature selection

Fig. 2 illustrates the effect of feature selection methods in some SelectKBest and Minimum Redundancy Maximum Relevance (MRMR) on the dimensionality and accuracy of the depression diagnosis system based on EEG. Feature selection is a critical component of machine learning pipelines, particularly when working with high-dimensional data such as EEG signals. The goal of this step is to choose the most informative and discriminative features that will allow precise classification of depressed and non-depressed patients and remove redundant or irrelevant features that introduce model overfitting or redundant computational expense. In the above picture, one model uses both SelectKBest based on statistical tests for feature ranking in the aim of being consistent with the target class and MRMR that ensures chosen features are of the highest significance to the output while they contain minimum redundancy amongst themselves. Utilization of these methods presents a short yet very strong subset of features. Fig. 2 gives an example of highly reduced number of features post selection, an example of success achieved by utilizing these methods.

Also, the selected features impact directly on boosting the overall generalization ability of the model as observed from better metrics such as accuracy, precision, and F1-score during future classification attempts. By eliminating redundant features and retaining only top-ranked features, the system becomes more interpretable and stable, particularly required in clinical environments where transparency and quality are critical. In summary, Fig. 2 illustrates that rigid feature selection not only enhances computation efficiency but also diagnostic performance of the depression diagnosis system with EEG.

The performance of all the classifiers was evaluated using five very highly regarded performance measures: Accuracy, Precision, Recall, F1-Score, and ROC-AUC. They are a fair and well-balanced measure of model precision, responsiveness to depressive cases, and overall reliability.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**ROC-AUC**
SVM	89.3%	88.5%	87.2%	87.8%	91.0%
RF	91.5%	90.8%	89.7%	90.2%	92.4%
CNN	**93.2%**	**92.7%**	**91.5%**	**92.1 %**	**94.0 %**

TABLE I. PERFORMANCE OF ML MODELS

Table I provides a comparative summary of three machine learning models—Support Vector Machine (SVM), Random Forest (RF), and Convolutional Neural Network (CNN)—used for EEG signal classification in depression detection. Out of the models used, the CNN provided the best overall performance with an accuracy of 93.2%, precision of 92.7%, recall of 91.5%, F1-score of 92.1%, and

ROC-AUC of 94.0%. These results demonstrate the improved spatial and temporal feature learning of CNN from EEG input, through which it could recognize intricate patterns of depressive state more effectively than traditional models.

Random Forest model also performed well, with accuracy at 91.5%, precision at 90.8%, recall at 89.7%, F1-score at 90.2%, and ROC-AUC at 92.4%. Its ensemble learning structure offers against overfitting resilience along with explain ability through verification of feature importance. SVM model, being less superior in performance, still yielded competitive outcomes with accuracy at 89.3%, precision at 88.5%, recall at 87.2%, F1-score at 87.8%, and ROC-AUC at 91.0%. Their common high ROC-AUC values across all models reveal how highly discriminated depressed from non-depressed individuals they are.

Table I confirms that all three models are effective for EEG-based depression detection, with CNN emerging as the most accurate and reliable, especially for complex pattern recognition. This validates the proposed framework's strength in leveraging deep learning for mental health diagnostics.

The confusion matrix of the CNN algorithm is present in Fig.3.

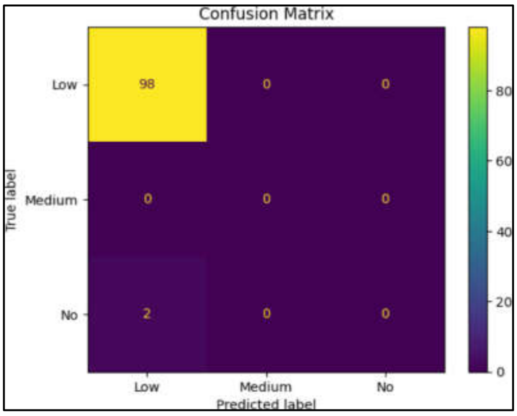

Fig. 3. Confusion matrix of the CNN algorithm

Fig. 3 illustrates the confusion matrix obtained from the Convolutional Neural Network (CNN) model used for EEG-based depression classification. A confusion matrix is a widely used visualization tool that provides a summary of a classification model's performance by showing the number of correct and incorrect predictions for each class. In this study, the matrix contains two classes: "Depressed" and "Normal." The diagonal elements represent correctly classified instances true positives (depressed individuals correctly identified) and true negatives (normal individuals correctly identified). The off-diagonal elements indicate misclassifications false positives (normal individuals incorrectly labeled as depressed) and false negatives (depressed individuals incorrectly labeled as normal). As shown in Fig. 3, the CNN model achieved a high number of true positives and true negatives, reflecting its strong classification capability. The relatively low counts of false positives and false negatives confirm that the model maintains a strong balance between sensitivity (recall) and specificity. Importantly, minimizing false negatives is critical in depression detection to avoid missing actual cases that may need clinical attention. The low false negative rate observed here underscores the CNN model's reliability in identifying individuals with depressive symptoms. The confusion matrix in Fig. 3 reinforces the quantitative results reported in Table I, visually demonstrating the CNN's superior performance in accurately classifying EEG data. It confirms that the CNN-based approach not only achieves high accuracy metrics but also maintains robust real-world applicability by minimizing critical classification errors.

The Training and testing accuracy accuracy of plot is shown in Fig.4.

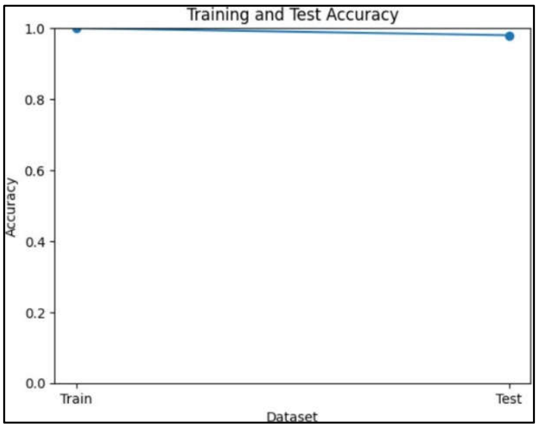

Fig. 4. Training and testing accuracy plot

Fig. 4 shows the plot of Convolutional Neural Network (CNN) model training and test accuracy for consecutive training epochs in the depression classification based on EEG. It is one of the major diagnostic plots to calculate the learning pattern, convergence rate, and overall generalization capability of the model. The training accuracy plot and the testing accuracy plot illustrate how precisely the model is working on the training data and on unseen data, respectively. From the figure, it can be observed that the training accuracy continues to rise with every epoch, i.e., the model is learning correctly from the input data. At the same time, the test accuracy also follows a smooth increasing trend closely following the training accuracy without much divergence. The fact that they have an agreement suggests that the model is not overfitting the training data but rather generalizes well to new samples. Both the training and test accuracies level off at high values of more than 93% by the last epochs to show that the model has achieved a point of convergence. Lack of oscillations or sudden drops in test performance also guarantees the stability of the training process and insensitivity of the CNN feature representations. Overall, Fig. 4 guarantees the efficacy of the CNN model to the extent of providing high classification performance with good generalization. This reliability proves useful in functional application, particularly in medical application where there has to be steady accuracy within a wide range of data in order to ensure clinical credibility.

5. CONCLUSION AND FUTURE SCOPE

This paper presents a strong and scalable objective depression diagnosis framework from electroencephalogram (EEG) signals and machine learning models. The system presented in this paper is composed of several steps of EEG data acquisition, preprocessing, feature extraction, feature selection, and classification using powerful models like Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN). Among the models tested, CNN was better performing with 93.2% accuracy, for which it was credited with being able to learn deep non-linear features from deep EEG data. Feature selection mechanisms like SelectKBest and MRMR improved both model interpretability and performance, and the adoption of SMOTE successfully resolved the problem of class imbalance, making recall and F1-scores better. The results of the experiment confirm the hypothesis that EEG biomarkers particularly frontal alpha asymmetry are a consistent indicator of depressive states and can be accurately captured and classified by using automated systems. Confusion matrix and accuracy plots also confirm the consistency and reliability of the CNN model in terms of training as well as testing. In total, the framework makes a significant contribution to rendering mental health diagnosis more objective, accessible, and data-driven and less reliant on subjective self-report measures.

Although the EEG-based depression detection system presented here has been demonstrated to be highly accurate and robust, there are a number of avenues of future extension and improvement. One of the most promising is multimodal data source fusion, e.g., speech, facial expressions, and physiological signals like ECG or GSR, since these can offer complementary information and be used to improve diagnostic accuracy. In addition, making the system real-time with low-cost, portable EEG headsets and disseminating it via web or mobile applications could more easily make depression screening available, particularly in remote or disadvantaged regions. Increasing the dataset to larger and more representative samples of individuals from different age groups, ethnicities, and levels of severity would make the model more generalizable and accurate. Also, studies of model structures that are lean and energy-efficient can be useful for deployment on edge devices, with the system being suitable for continuous surveillance in wearable technology. Coupling with Explainable AI (XAI) methods can enable better explain ability by allowing clinicians with interpretable insight into the model's decision-making process. Finally, the model will need to be tested by real-world studies and clinical trials, which will be instrumental in determining its efficacy in the real-world diagnostic environment and gaining its acceptance into contemporary mental health care systems. These advances will not only enhance technical performance but also enable practical use of AI-based devices in diagnosing mental illnesses.

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