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Review of Machine Learning based Depressive Disorder Using EEG Signal

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***Abstract*— Depressive disorder is a serious and widespread mental health issue affecting millions worldwide. Traditional diagnostic approaches primarily rely on subjective assessments, which can often lead to delayed or inaccurate diagnoses. Recently, the application of machine learning (ML) techniques on electroencephalogram (EEG) signals has emerged as a promising approach to objectively detect and classify depressive disorders. EEG signals capture the brain's electrical activity, offering a non-invasive, cost-effective, and real-time method for mental health evaluation. This review aims to provide a comprehensive overview of the current advancements in machine learning-based methods for depressive disorder detection using EEG signals. It discusses the types of EEG features extracted, the preprocessing techniques employed, various ML algorithms implemented, and the performance metrics achieved.**

***Keywords*—EEG, ML, Depression, Electrical activity, Brain.**

I. Introduction

Depression, clinically known as major depressive disorder (MDD), is one of the leading causes of disability worldwide. It affects individuals across all ages, cultures, and socio-economic backgrounds, severely impacting their personal, social, and occupational functioning. Early and accurate detection of depression is crucial for initiating effective treatment and improving patient outcomes. However, conventional diagnostic procedures, such as clinical interviews and psychological questionnaires, are largely subjective and often influenced by patients' self-reporting and clinicians' interpretations. These methods may not always capture the underlying neurological changes associated with depressive states.

In recent years, there has been a growing interest in leveraging objective biomarkers to support the diagnosis of depression. Among various neuroimaging techniques, electroencephalography (EEG) stands out due to its non-invasive nature, high temporal resolution, portability, and relatively low cost. EEG records the brain's electrical activity and provides valuable insights into neural patterns and functional abnormalities that are often linked to depressive disorders. Subtle alterations in brainwave patterns, such as changes in alpha, beta, theta, and delta rhythms, can serve as indicators of depression.

The rise of machine learning (ML) techniques has further propelled the potential of EEG-based depression detection. Machine learning algorithms are capable of automatically learning complex patterns and distinguishing depressive individuals from healthy controls based on EEG features. Various ML models, including support vector machines (SVM), k-nearest neighbors (KNN), decision trees (DT), random forests (RF), artificial neural networks (ANN), and deep learning architectures, have been employed to enhance diagnostic accuracy and reduce human dependency.

The process generally involves multiple stages: EEG signal acquisition, preprocessing to remove noise and artifacts, feature extraction and selection, model training, and validation. Preprocessing methods like Independent Component Analysis (ICA), filtering, and artifact rejection are critical to ensuring the quality of EEG data. Feature extraction techniques, including time-domain analysis, frequency-domain analysis, and time-frequency transforms like wavelet decomposition, help in highlighting relevant characteristics for classification.

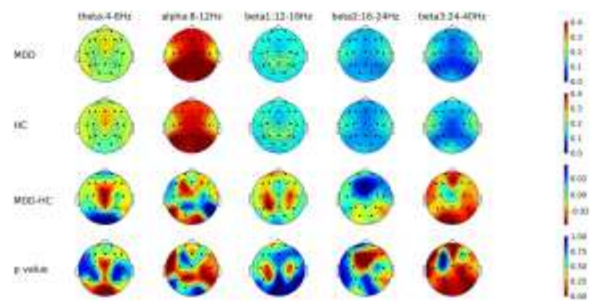

Figure 1: EEG signals waves

Despite significant progress, several challenges remain. Variability in EEG signal characteristics among individuals, differences in data collection protocols, small sample sizes, and the interpretability of machine learning models are major concerns. Moreover, clinical translation demands robust, generalizable models that perform consistently across diverse populations.

This review systematically explores the intersection of EEG-based signal processing and machine learning methodologies for depressive disorder detection.

It critically analyzes existing literature, categorizing studies based on the ML models used, types of EEG features extracted, preprocessing pipelines adopted, and evaluation metrics reported. Furthermore, it discusses limitations in current approaches and identifies opportunities for future research, such as the incorporation of deep learning, multimodal data fusion, real-time monitoring systems, and personalized mental health interventions. By consolidating the existing knowledge and highlighting ongoing challenges, this review aims to guide researchers, clinicians, and engineers in developing more effective and accessible diagnostic tools for depression.

II. LITERATURE SURVEY

Kowli and Padole [1] proposed a multifeature fusion approach using EEG signals to detect Major Depressive Disorder (MDD). Their method integrates temporal, spectral, and spatial features to enhance detection accuracy and reduce reliance on single-feature analysis. Experimental results demonstrated improved performance compared to conventional EEG-based models. The study highlights the importance of combining multiple signal characteristics for reliable depression assessment. This work establishes a foundation for automated EEG-based diagnostic tools in mental health.

Habib et al. [2] introduced MDDBranchNet, a deep learning model for detecting MDD from ECG signals. The hierarchical network structure allows extraction of complex temporal features automatically, eliminating the need for manual preprocessing. The model showed high classification accuracy in distinguishing depressed and non-depressed subjects. The approach demonstrates the effectiveness of ECG signals for mental health monitoring and the potential of deep learning in biomedical applications.

Ahmed, Khan, and Hussain [3] applied a wavelet entropy-based feature extraction method for EEG depression detection. By analyzing the complexity and irregularity of EEG signals, the method captures subtle changes associated with depressive states. Classification based on these features outperformed traditional feature-based approaches. The study highlights the computational efficiency of wavelet techniques and their suitability for large-scale EEG analysis. It provides a robust framework for early depression screening.

Seal et al. [4] developed DeprNet, a deep convolutional neural network framework designed to detect depression using EEG. The model extracts hierarchical features capturing both spatial and temporal EEG patterns, reducing the need for extensive manual feature engineering. Evaluation on benchmark datasets confirmed its high accuracy and robustness. The work contributes to the advancement of automated, deep learning-based mental health diagnostics.

Sun and colleagues [5] combined functional brain network analysis with traditional EEG biomarkers for depression recognition. By integrating connectivity measures with conventional EEG features, the model achieved superior performance compared to single-feature approaches. The study emphasizes the importance of network-level information in understanding depressive patterns. Results indicate enhanced interpretability and reliability in EEG-based depression detection, paving the way for improved clinical applications.

Zheng, Zhu, and Lu [6] focused on identifying stable EEG patterns over time for emotion recognition. Their approach emphasizes longitudinal analysis to extract consistent temporal features, improving the robustness of affective state detection. The method allows the model to handle variability in EEG signals across sessions. Experimental validation showed reliable recognition of emotional states over extended periods. This study provides valuable insights for designing emotion recognition systems based on temporal EEG patterns.

Fang et al. [7] developed a real-time EEG-based emotion recognition system using edge AI and a CNN-based System-on-Chip design. The architecture enables on-device processing for low-latency predictions while maintaining high accuracy. Their experiments confirmed effective recognition of multiple emotional states in real time. This research demonstrates the feasibility of integrating AI-powered emotion detection directly into wearable and IoT devices. The system bridges practical EEG monitoring with advanced deep learning techniques.

Bota et al. [8] reviewed machine learning approaches for emotion recognition using physiological signals. The study highlighted existing methodologies, challenges, and future directions, focusing on data variability, sensor limitations, and model generalization. Multimodal integration was identified as crucial for improving accuracy. The review provides a comprehensive perspective on the current landscape and identifies key areas for future research in physiological-based emotion detection.

Wang, Chi, Yuan, and Geng [9] proposed an emotion recognition approach based on the Cloud Model theory. The method translates uncertain and imprecise physiological data into recognizable emotional states, enabling real-time detection with reduced computational demands. Experiments validated its effectiveness and scalability for distributed systems.

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This approach demonstrates the potential of cloud-based models in large-scale emotion monitoring and IoT applications.

Khalil et al. [10] reviewed deep learning techniques for speech emotion recognition, analyzing CNNs, RNNs, and hybrid approaches. The review addressed challenges such as speech variability, background noise, and real-time processing constraints. Deep learning was shown to capture both temporal and spectral features efficiently, improving recognition accuracy. The study provides a roadmap for future research in speech-based emotion recognition and highlights the integration of AI for practical emotion detection systems.

Table 1:
Summary of preceding methods on MDD using EEG [2]

Author, Year	Subjects	Used Method	Accuracy(%)
Bairy et al. [21], 2016	15 Control, 15 Depressed	DWT+SVMRBF	88.92
Mumtaz et al. [22], 2017	30 Control, 33 Depressed	Power features+SVM	98.4
Bairy et al. [23], 2017	15 Control, 15 Depressed	Spectra features+Bagged tree	94.30
Liao et al. [24], 2017	20 Control, 20 Depressed	Kernel eigen filter bank+SVM	81.23
Acharya et al. [25], 2018	15 Control, 15 Depressed	CNN	93.54
Ay et al. [26], 2019	15 Control, 15 Depressed	CNN-LSTM	97.66
Li et al. [27], 2019	27 Control, 24 Depressed	ConvNet	85.62
Wan et al. [28], 2020	12 Control, 23 Depressed	HybridEEGNet	79.08
Sharma et al. [29], 2021	24 Control, 21 Depressed	CNN-LSTM	99.10
Sharma et al. [30], 2021	30 Control, 34 Depressed	Non-linear features+SVMRBF	98.9
Chao et al. [31], 2021	14 Control, 16 Depressed	Spatial pattern	84
Loh et al. [32], 2022	30 Control, 34 Depressed	CNN	99.58
Present work, 2022	30 Control, 34 Depressed	STFT+CNN-LSTM	99.58

Nemati et al. [11] proposed a hybrid latent space data fusion method for multimodal emotion recognition. Their approach integrates features from multiple modalities such as EEG, facial expressions, and speech signals to improve recognition accuracy. By mapping different modalities into a shared latent space, the model captures complementary information effectively. Experiments demonstrated enhanced performance compared to unimodal approaches. This study highlights the importance of multimodal fusion in robust emotion detection systems.

Zhang, Jolfaei, and Alazab [12] developed a face emotion recognition method using convolutional neural networks combined with image edge computing. The system enables efficient on-device processing, reducing latency for real-time applications. Their method effectively extracts spatial features from facial images to detect emotions with high accuracy. Results show that edge AI can enable practical deployment in IoT and mobile platforms. This approach bridges deep learning and distributed computing for emotion recognition.

Ferreira et al. [13] introduced physiologically inspired deep neural networks for emotion recognition. The model integrates biological signals, such as heart rate and EEG, to capture affective states. This design allows learning of intrinsic patterns reflecting emotional responses. Experiments confirmed that combining physiological data with deep learning improves recognition accuracy. The study demonstrates the potential of bio-inspired approaches for reliable emotion detection.

Yang, Wu, Zheng, and Lu [14] presented an EEG-based emotion recognition framework using a hierarchical network with subnetwork nodes. The model captures both local and global patterns in EEG signals to classify emotional states accurately. Subnetwork nodes allow fine-grained feature extraction from different brain regions. Evaluation shows improved performance over traditional EEG analysis methods. This hierarchical approach emphasizes the role of structural network modeling in EEG-based emotion recognition.

Zhang, Zhang, Huang, Gao, and Tian [15] proposed a hybrid deep model for audio–visual emotion recognition. By combining audio features with visual cues, the system captures multimodal affective information effectively. The hybrid approach leverages convolutional and recurrent networks for feature learning. Experiments demonstrated significant accuracy improvements over single-modal methods. This work highlights the advantages of integrating audio and visual modalities for emotion recognition.

Zhao et al. [16] investigated emotion analysis for personality inference using EEG signals. Their method links EEG-derived emotional features to personality traits through machine learning models. The study emphasizes understanding individual differences in emotional responses. Results indicate accurate inference of personality characteristics from neural activity patterns. This research provides insights into affective computing and personalized emotion recognition.

Table 2:
Performance comparison [2]

Parameters	VGG16	AlexNet	Inception	ResNet50	CNN	CNN-LSTM	CNN-GRU
Accuracy(%)	96.22	94.98	97.00	97.32	99.10	99.9	99.84
Sensitivity(%)	95.00	92.89	98.1	97.93	98.73	100	100
Specificity(%)	96.98	94.90	97.32	98.50	99.36	99.81	99.57
Precision(%)	94.69	95.10	96.55	96.79	98.98	99.47	99.23

Kim, Kim, Kim, and Lee [17] developed a framework for recognizing image-based emotions using deep neural networks. The model extracts high-level semantic features from images to classify emotional content.

Experimental results show high accuracy across multiple emotion categories. The study demonstrates the effectiveness of deep learning for image emotion recognition. It contributes to building intelligent systems capable of understanding visual affective cues.

Xu, Fu, Jiang, Li, and Sigal [18] explored heterogeneous knowledge transfer in video emotion recognition, attribution, and summarization. Their model transfers learned representations across datasets to improve performance on unseen videos. The approach combines deep learning with transfer learning techniques for scalable emotion analysis. Results show enhanced generalization and robustness in emotion recognition tasks. This study highlights the benefits of leveraging cross-domain knowledge for video-based affective computing.

Liu et al. [19] proposed a facial expression-based emotion recognition system for human-robot interaction. The model captures dynamic facial cues to enable responsive robot behavior. Experiments demonstrated improved interaction quality and accuracy in real-time scenarios. This research bridges emotion recognition with practical robotics applications. It emphasizes the importance of adaptive affective systems in human-robot collaboration.

Tzirakis, Trigeorgis, Nicolaou, Schuller, and Zafeiriou [20] developed an end-to-end multimodal emotion recognition framework using deep neural networks. Their model processes audio, visual, and textual signals simultaneously for unified prediction. End-to-end training allows the network to learn optimal features automatically. Results show superior performance compared to traditional fusion approaches. This work demonstrates the effectiveness of deep multimodal integration for accurate emotion detection.

III. CHALLENGES

1. *EEG Signal Variability:* One of the primary challenges in depressive disorder detection using EEG signals is the inherent variability in EEG data across individuals. Factors such as age, gender, genetic background, medication intake, lifestyle habits, and even current mood states can significantly alter brain wave patterns. This variability makes it extremely difficult to develop machine learning models that can generalize well across diverse populations without suffering performance degradation.
2. *Small and Imbalanced Datasets:* The availability of large, labeled EEG datasets for depressive disorder detection is very limited. Collecting EEG data from patients with depression is time-consuming, expensive, and ethically sensitive. As a result, most studies rely on small datasets, often with class imbalance where the number of depressed and non-depressed samples is unequal. This scarcity hampers model training, increases the risk of overfitting, and reduces the reliability of the machine learning predictions.
3. *Artifact Contamination:* EEG signals are highly prone to contamination from various artifacts such as eye blinks, muscle movements (electromyography noise), head movements, and environmental electromagnetic interference. These artifacts can distort the true neural signals and introduce misleading patterns into the data. If artifacts are not effectively detected and removed during preprocessing, machine learning models may learn to associate noise patterns with depression, leading to incorrect predictions.
4. *Complex Feature Extraction and Selection:* Extracting relevant features from EEG signals is complex because depressive disorder indicators may not be obvious or localized but instead be hidden within subtle temporal (time-domain), spectral (frequency-domain), or spatial (electrode connectivity) characteristics. Advanced signal processing techniques are needed to uncover these hidden patterns, and poor feature selection can significantly impact model performance.
5. *Lack of Interpretability:* While deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have shown high accuracy, they often act as "black boxes" with minimal transparency about how decisions are made. In clinical contexts, this lack of interpretability raises concerns, as healthcare professionals need to understand and trust the outputs before using them for diagnosis or treatment planning.
6. *Standardization Issues:* There is a notable lack of standardization in EEG data acquisition across studies. Differences in electrode placements, sampling frequencies, recording protocols, and experimental conditions make it hard to replicate results or benchmark algorithms against each other. This inconsistency limits the development of universally accepted machine learning models for depression detection.

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7. *High Computational and Hardware Requirements:* Many modern machine learning algorithms, especially deep learning approaches, require significant computational power, large memory, and high-end GPUs for model training and inference. Additionally, high-quality EEG equipment is needed for accurate recordings. These requirements make the deployment of such models in resource-constrained environments (such as small clinics or rural healthcare centers) difficult.
8. *Clinical Integration and Regulatory Approval:* Even if a machine learning model performs well in research settings, integrating it into clinical practice is not straightforward. It requires rigorous clinical trials, validation across diverse populations, compliance with healthcare regulations (such as FDA or CE approval), and ensuring the model is user-friendly for clinicians. Overcoming these hurdles is essential to transition from experimental research to practical healthcare tools.

IV. Proposed Plan

The proposed plan is as followings-

1. *Comprehensive Data Collection:* Gather a diverse EEG dataset covering various age groups, genders, and depression severity levels to minimize bias and improve model generalization.
2. *Advanced Preprocessing Techniques:* Apply sophisticated preprocessing methods such as Independent Component Analysis (ICA), wavelet denoising, and artifact rejection algorithms to remove noise and ensure clean EEG signals for analysis.
3. *Robust Feature Extraction:* Extract a wide range of features including time-domain, frequency-domain (e.g., power spectral density), and connectivity features (e.g., coherence and phase locking value) to capture meaningful patterns associated with depressive disorders.
4. *Feature Selection and Dimensionality Reduction:* Use feature selection techniques like Recursive Feature Elimination (RFE) and dimensionality reduction methods such as Principal Component Analysis (PCA) or t-SNE to identify the most relevant features and reduce model complexity.
5. *Hybrid Machine Learning and Deep Learning Models:* Implement hybrid models combining traditional machine learning (e.g., SVM, Random Forest) with deep learning architectures (e.g., CNN-LSTM) to leverage both feature engineering and automatic feature learning.
6. *Model Interpretability Enhancement:* Integrate explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) values or LIME (Local Interpretable Model-agnostic Explanations) to make model decisions more transparent and trustworthy for clinicians.
7. *Cross-Validation and External Validation:* Apply rigorous k-fold cross-validation and test the models on external datasets to ensure that performance metrics are reliable and not overly optimistic.
8. *Clinical Collaboration and Trials:* Partner with hospitals and mental health centers to conduct clinical trials, validate the models in real-world settings, and gather feedback for continuous improvement.

V. Conclusion

The use of machine learning techniques for depressive disorder detection using EEG signals offers promising prospects but still faces several technical, ethical, and clinical challenges. Variability in EEG signals, small datasets, and lack of interpretability pose significant obstacles that must be addressed systematically. This review highlights a proposed plan focusing on comprehensive data preprocessing, robust feature extraction, hybrid model development, and ethical considerations to overcome these hurdles. By combining technological innovation with clinical collaboration and real-world validation, future research can pave the way for reliable, interpretable, and accessible EEG-based diagnostic systems, ultimately supporting better mental health care delivery.

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