Personalized Mental Health Care: A Survey on EEG-Based Depression Detection System

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***Abstract*—Depression broadly affects emotional and cognitive well-being, greatly increases healthcare burdens, and constitutes a worldwide public health issue. Several standard diagnostic techniques, such as clinical interviews in addition to self-reported questionnaires, often do not have objective biomarkers, therefore a variety of misdiagnoses can occur. Electroencephalography (EEG) shows promise for detecting depression by capturing neural activity in real-time and identifying brain connectivity patterns associated with mood disorders. However, classifying depression using EEG presents multiple challenges since real-time applications require large feature extraction and involve large computational requirements. This systematic review focuses on new improvements in EEG-based depression detection using machine learning and deep learning models, examining 32 studies published from 2018 to 2024. The reviewed studies explore a range of feature extraction methods, including time-domain, frequency-domain, and nonlinear features, along with advanced techniques like Continuous Wavelet Transform (CWT) and Empirical Mode Decomposition (EMD). Deep learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), as well as Graph Convolutional Networks (GCNs) have all demonstrated large improvements regarding classification accuracy. Based on the findings, hybrid models that combine different feature sets and classification methods seem to work well. Despite all these improvements, many challenges, including dataset variability, demographic biases, and computational complexity remain. For helping clinical applications, research must diligently create easier-to-read models, develop exceptionally portable EEG systems, and substantially improve real-time capabilities. EEG-based depression detection could be part of standard healthcare if these limits are fixed, and this could lead to more custom and quick treatments.**

Keywords—EEG, depression detection, machine learning, deep learning, feature extraction, real-time monitoring, neural biomarkers

I. INTRODUCTION

Depression has emerged as an important public health concern and is known as one of the main causes of disability, affecting millions of people around the world. Its major effect extends beyond harming people, considerably disrupting their cognitive and emotional states and simultaneously increasing healthcare costs and diminishing general quality of life [26]. For effective treatment and management of depression's multidimensional nature and complexity, accurate and timely diagnosis is important.

Clinical interviews and self-reported questionnaires, traditional ways to diagnose depression, often rely on personal opinions that may be inconsistent and biased. These typical methods often do not have the objective biomarkers needed to accurately diagnose and check if treatments are working, possibly causing wrong diagnoses and poor care.

Electroencephalography (EEG) has become an increasingly useful tool. It allows for a more objective detection of depression over extended periods. EEG (electroencephalography) captures brain activity in real-time, revealing the neural mechanisms associated with mood disorders. This technique can illustrate brain connectivity and functional dynamics, helping us to identify patterns indicative of depression.

EEG-based approaches have limited potential. They face several challenges. Because feature extraction techniques often depend on many handcrafted features and these may not fully encapsulate all complexities of EEG signals, their applicability across all diverse populations is limited. Current models have difficulty analysing the temporal dependencies in EEG data as well as the spatial dependencies, thereby limiting classification performance [2][14][22]. Using advanced deep learning models in real-time in clinics is hard because it requires a lot of computing power.

Recent improvements in machine learning and signal processing techniques have shown the potential to improve the accuracy of EEG-based depression classification. Several innovations are being explored to improve feature extraction as well as classification outcomes. Hybrid deep learning models integrating Convolutional Neural Networks (CNNs) with Long Short-Term Memory networks (LSTMs), Graph Convolutional Networks (GCNs) along with attention mechanisms are many examples.

Many studies provide new frameworks for fixing the problems with current practices. Examples include techniques such as Self-Attention Graph Pooling, which improves EEG graphs as well as retains key information for improved sorting, along with Microstate Analysis, created to detect shifting EEG patterns related to depression [25]. Methods of Multiview Feature Extraction are also in development for the thorough analysis of the temporal, spectral and time-frequency characteristics of EEG signals.

More research is needed to prove these new methods work in the future, using bigger datasets and different groups of people. For depression detection, the primary aim is to develop EEG-based systems that are highly reliable, objective and clinically applicable. These systems can help with early response and create personalized treatment plans for each person, which significantly improves patients' health and quality of life.

II. MOTIVATION

The growing mental health crisis, particularly the underdiagnoses and under treatment of depression, has significant personal and societal impacts. Electroencephalography (EEG) offers a non-invasive, cost-effective method to measure brain activity, providing valuable insights into mental health conditions. With advancements in artificial intelligence (AI), including machine learning and deep learning, automated and accurate analysis of complex EEG patterns is now possible. This technology enables real-time monitoring of mental health, allowing for the early detection of depression and timely interventions. Such systems not only reduce the burden on healthcare providers but also improve patient outcomes and contribute to broader mental health awareness.

III. SYSTEMATIC REVIEW

To demonstrate the consequences of our research, we reviewed 32 research articles published in the past 7 years (2018-2024) from the IEEE database. In our analysis, we detailed the methods used for signal pre-processing, feature extraction and selection, supervised classification models, as well as their corresponding accuracy.

A. Eligibility Criteria

The eligibility criteria encompass two main aspects: study design and time frame, which involves the selection of studies, and reporting criteria, which pertains to the chosen years and languages. For our systematic review, we included only articles published in English within the last 7 years.

B. Search String Strategy

Before submitting research articles to databases, authors typically provide keywords to help others locate their work more easily. A well-constructed search strategy adheres to predefined limits and preferred terms. In addition to using keywords, one can also search for articles by selected words in the title or abstract. Our search strings utilized Boolean operators to refine our search. The common Boolean operators used are:

- AND (must be included)

- OR (may or may not be included)

The following search strings were used:

-(“Depression”) AND ((“EEG”) OR (“Electroencephalography”)) AND (“IEEE”)

-(“Depression”) AND ((“EEG”) OR (“Electroencephalography”)) AND (“IEEE”) AND ((“Deep Learning”) OR (“Machine Learning”))

- (“MODMA”) AND (“IEEE”)

IV. RESULTS AND ANALYSIS

A. Participants and Data Collection

The studies reviewed include a diverse range of participants, frequently involving 20 to 100 people, along with patients diagnosed with Major Depressive Disorder (MDD) in addition to healthy controls for comparison. Inclusion criteria are set using firm clinical tests and participants are carefully matched for demographic variables such as age and gender. Selection of the right groups of people often involves tools like the Beck Depression Inventory II [30]. EEG data is often recorded using multiple configurations, with 3, 32, 64, or 128 electrodes placed according to the 10-20 international system [18]. Resting states are when data are collected. For a thorough assessment of neural responses, all participants either keep their eyes fully open or completely closed and all participants engage in specific tasks like viewing emotionally charged stimuli [30]. Each recording session will last approximately 4 to 30 minutes for each participant to greatly minimize participant fatigue while still gathering sufficient data for analysis [10][13][14][15][16][25][31].

B. EEG Signal Preprocessing

Noise removal in EEG signal processing importantly uses key techniques to greatly improve data quality. For band pass filtering, Butterworth or Chebyshev filters are regularly used to exclusively retain frequencies applicable to the analysis, normally from 0.5 to 70 Hz and a notch filter thoroughly eliminates all 50 Hz power line interference [3][5][9][10][12][15][17], considerably improving the recorded signals. ICA is used to locate and remove artifacts related to eye movements, muscle activity and other external non-neural signals. EEG segments are manually inspected in some studies. This thoroughly guarantees complete data integrity and quality, complementing all automated methods. EEG data is segmented into periods [13][14][32]. These periods are generally of a 5 to 10 second duration following the removal of noise as well as artifacts. Overlapping segments are used in some studies to better catch temporal dynamics, which improves feature extraction for later analysis.

C. Feature Extraction

In the analysis of EEG signals, key insights into the related neural activity are gained through the careful extraction of various features. Time-domain features are calculated to show baseline characteristics and statistical metrics, such as mean, variance, skewness and kurtosis [9][17]. Frequency-domain features are also obtained by deriving power spectral density (PSD) [9]. Techniques like Fast Fourier Transform (FFT) allow the analysis of different frequency bands, including delta, theta, alpha, beta and gamma [8][27]. One key metric is peak power. Key metrics are mean frequency as well as band power ratios. Fig. 1 shows the placement of electrodes in a 16-channel EEG headset, which is commonly used in most papers.

The implementation of specific advanced Empirical Mode Decomposition (EMD) techniques improved classification accuracy by exactly 6.71% in comparison to typical feature extraction methods[4][26]. This improvement shows the importance of consistently using advanced techniques for better detection of key EEG features. Our analysis showed that delta and theta frequency bands differentiated people with depression and alpha and beta bands also improved classification performance [3][6][16][31]. This differentiation stresses how useful specific frequency analysis is for EEG-based diagnostics.

The Approximate Entropy, Sample Entropy and Renyi entropy nonlinear features are extracted to assess the degree of complexity and irregularity of the EEG signals [1][4][16][23][28][30]. To create time-frequency views of the EEG data, advanced techniques like Continuous Wavelet Transform (CWT) [19] along with Short-Time Fourier Transform (STFT) [1][10] are applied, which considerably aids in catching rapid changes in frequency components as well as provides an importantly more detailed perspective of brain activity that evolves.

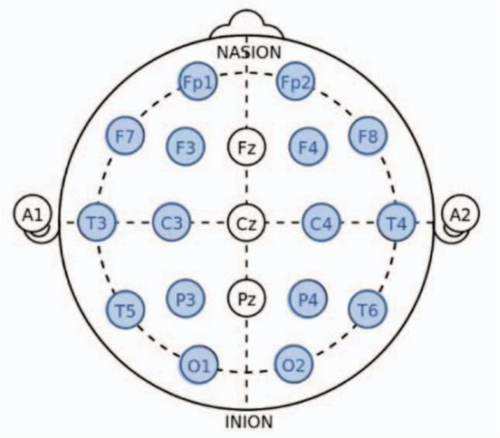

Fig. 1. Distribution of 16-Channel Brain Electrodes.

D. Feature Selection

Dimensionality reduction techniques are often needed to refine the feature space well in EEG signal analysis. Principal Component Analysis (PCA) [2][23] is employed to retain the most informative variables for classification. These approaches streamline data by curtailing all data to only its most salient components, thereby improving the efficacy of all ensuing analyses.

People frequently use feature importance methods, such as Information Gain, ReliefF and Recursive Feature Elimination (RFE), to find and rank the features that matter most for sorting tasks [16]. Researchers can use these methods to make their models better at predicting things and they can use less computing power on big datasets.

E. Classification Models

In the area of machine learning approaches for EEG signal analysis, Support Vector Machines (SVM), Random Forests (RF), Decision Trees (C4.5) and k-Nearest Neighbors (KNN) are common classifiers frequently used across many studies. Many researchers frequently explore both ensemble methods and hybrid models. These integrate multiple classifiers. This improves predictive accuracy, giving greater robustness in detecting depression patterns. Alongside customary machine learning techniques, deep learning approaches, particularly Convolutional Neural Networks (CNNs) recognized for their capacity to extract spatial features from time-frequency maps, have achieved common popularity. To catch particular temporal dependencies within the EEG data, Long Short-Term Memory (LSTM) networks are commonly employed, carefully allowing consideration of time-series dynamics. To improve how well time-series classification tasks work, some studies suggest using CNN along with LSTM architectures, using the good qualities of both for finding depression more accurately [2][10][12][22][23][27][29].

F. Validation and Evaluation

Strong model evaluation in EEG signal analysis is thoroughly accomplished via particular techniques, such as k-fold cross-validation and leave-one-subject-out strategies, substantially helping guarantee the thorough generalizability and complete reliability of the results. Evaluation metrics are used for assessing how well the model works. These metrics include accuracy, sensitivity, specificity, F1-score, as well as Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These metrics offer a detailed view of how well the models classify data. Confusion matrices visualize classification performance across every class, like healthy as well as depressed people, thus offering a representation of the model's strengths along with weaknesses in distinguishing between conditions. Validating findings is important with this thorough evaluation framework. The effectiveness of depression detection methods based on EEG signals improves to a certain degree as well.

The reviewed studies used strong validation methodologies, specifically K-Fold and Leave-One-Out cross-validation techniques [15][23]. The findings are more reliable because the majority achieved statistical importance ($p < 0.01$). Based on the Friedman Test, the model improvements were important, showing the proposed methods worked better than the standard baseline approaches [4][23][24][25][26][27][28][29].

G. Demographic Factors and Functional Connectivity

Incorporating age and gender, specific demographic variables, into the models improved classification accuracy by a definite range of 3-6% [18]. This finding certainly supports using personalized approaches to detect depression with EEGs. It clearly creates specific diagnostic approaches that carefully account for all individual differences. Patients suffering from depression, according to the study, had more synchronization in the left frontal, temporal and parietal lobes, but less synchronization in the right frontal lobe [31]. Changes in how functional connections are patterned suggest some neural networks are affected, which changes how we understand the neurophysiological origins of depression [13][16][31].

H. Combined Features

The integration of remarkably diverse feature types, including functional connectivity and multiple frequency bands led to a peak classification accuracy [13][16]. This all-embracing approach to feature selection shows that multi-faceted analyses are important for strengthening how a model operates and for improving how durable its forecasts are.

I. Additional Considerations

To address disparities in dataset representation, different techniques, like class weighting and Weighted Focal Binary Hinge Loss are actively employed to handle class imbalance effectively, especially when depressed subjects are importantly underrepresented [19][32]. These strategies seek to improve the ability of machine learning models to accurately detect depression. All models are trained on a balanced dataset. Many recent studies are investigating the practicality of immediate depression detection using online EEG processing and classification. This points out many possible practical uses both in clinics and for keeping track of oneself. Integrating advanced EEG analytics into everyday practices offers the promise of real-time capabilities, supporting timely interventions in addition to increasing patient care.

J. Overall Findings

The results strongly affirm that EEG signals are effective tools for detecting most depression cases. Models across a spectrum also show accuracy gains and fewer misclassifications. To further this progress, we recommend exploring several multimodal approaches that integrate EEG with other modalities, along with adopting advanced machine learning techniques (e.g., deep learning and attention mechanisms), like speech analysis. These strategies are important for building better detection skills and a more detailed sense of depression.

V. DISCUSSION

The improvements in methodologies for detecting depression through EEG signals represent an important improvement at the confluence of neuroscience and machine learning[26]. As summarized in the TABLE 1, deep learning techniques have been incorporated and this key development has greatly elevated classification accuracy, with some reporting performance metrics exceeding 90% and reaching 100% in specific scenarios. Machine learning algorithms can find many detailed patterns in EEG data. These patterns closely relate to multiple depressive symptoms. Integrating EEG data with methods like speech analysis and behavioral measures may improve detection abilities and provide a fuller view of what causes depression.

The trained models are now much stronger because the advanced preprocessing techniques and automated feature extraction have greatly reduced the need for manual processes[14][19].

Integrating multiple EEG features, like frequency band analysis along with functional connectivity measures, both improves our comprehension of the neurophysiological mechanisms underlying depression, as well as points out the possibility of creating objective biomarkers[21]. These biomarkers could be important additions to regular diagnostic methods. They let you measure depression in a more exact and countable way.

Despite these promising improvements, our review also finds some limitations that need our attention. Because many investigations often use small sample sizes, it's important to ask if the findings are generalizable. For example, studies using mainly college students may not accurately represent the variety of people affected by depression. Future research should use larger, more varied datasets to confirm these findings in other groups of people and to make sure the findings apply more widely.

The sensitivity of EEG signals to many external aspects like ecological noise and artifacts creates definite challenges for data reliability. Feature extraction consistency may be hurt by inconsistent signal quality, possibly making classification results unreliable. This points out the need for preprocessing methods that sufficiently reduce these influences as well as adequately improve the results' reliability and the developed models' integrity.

These studies have several advanced models. They introduce large computational complexity. Because many deep learning methods require a lot of processing power and resources, using them in clinical settings can be hard. These models descriptively show state-of-the-art performance. More efficient algorithms are needed to achieve similar accuracy with substantially reduced computational demands. This would greatly ease common adoption and thoroughly promote the integration of these techniques into routine clinical practice.

All in all, these large improvements in EEG signal analysis for depression detection offer particularly important opportunities for improving diagnostic accuracy and further deepening the comprehension of the condition's key neurophysiological underpinnings[21]. Deep learning achieved many promising results. Multimodal approaches supplemented these results, which were certainly outstanding. To make these methods more widely applicable, it is important to address the current limitations, which are small sample sizes, sensitivity to external factors and high computational costs. Once we get past these problems, we can create objective biomarkers that give us useful information to improve treatment and patient care for depression.

TABLE 1. Review of EEG-Based Algorithms for Brain Signal Analysis for Depression

References	Algorithm	Best frequency band	No. of electrodes	Brain areas	Data collection	Data preprocessing	Sampling frequency rate	Accuracy
[1]	MV-SDGC-RAFFNet	-	128 (MODMA), 19 (HUSM)	Prefrontal (FPZ and FP2), Frontal(F2)	MODMA (Lanzhou University), HUSM (Malaysia)	Baseline removal, detrend, low-pass filter (0–64 Hz)	250 Hz (MODMA), 256 Hz (HUSM)	95.53%(MODMA), 99.19% (HUSM)
[2]	Att-1D-CNN-BiLSTM	-	16 + 1 reference electrode (CZ) + 1 grounding electrode (GND)	Fp1, Fp2, F7, F8, F3, Fz, F4, T3, C3, Cz, C4, T4, P3, Pz, P4, T5, T6, O1, O2	MODMA & Self-acquisition Dataset	Baseline removal, bandpass filter (0.5–50 Hz), ICA for artifact removal	250 Hz (MODMA)	96.65% (MODMA)
[3]	End-to-End Deep Learning Model	Delta (0.5 - 4 Hz), Beta (13 - 30 Hz), Gamma (30 - 70 Hz)	19	Fp1, Fp2, F7, F8, F3, Fz, F4, T3, C3, Cz, C4, T4, P3, Pz, P4, T5, T6, O1, O2	Public EEG dataset (30 MDD patients, 28 healthy controls)	Notch filter (50 Hz noise removal), band-pass filtering (0.1 - 70 Hz), re-referencing, Z-score transformation	256 Hz	91.06% (full-band), 98.45% (10-fold CV)
[4]	Improved Empirical Mode Decomposition (EMD) feature extraction and SVM classification	Gamma (30 - 70 Hz), Beta (13 - 30 Hz)	3	Prefrontal lobe (Fp1, Fpz, Fp2)	EEG data from Beijing Anding Hospital, Capital Medical University and The Third People's Hospital of Tianshui City	High-pass filter (1 Hz), low-pass filter (40 Hz), Discrete Wavelet Transform, Kalman filtering	250 Hz	88.07%
[5]	Customized Inception Time Deep Learning Model	-	19	Fp1, Fp2, Fz, F3, F4, F7, F8, T3, T4, T5, T6, P3, P4, Pz, O1, O2, C3, C4, Cz	Public EEG dataset (34 MDD patients, 30 healthy controls)	Band-pass filtering (0.1-70 Hz), Notch filter (50 Hz), Artifact Subspace Reconstruction (ASR)	256 Hz	91.67%(full channel),87.5%(reduced channel)
[6]	Multi-Channel Frequency Network (MUCHf-Net)	Delta, Theta, Alpha	16	Prefrontal & Parietal Lobes	EEG from 300 individuals (DP: 100, SCZ: 100, Normal: 100) + Public dataset (30 individuals)	Band-pass filter (0.3–45 Hz), ICA for artifact removal, Welch method for frequency spectra	128 Hz (hospital data), 250 Hz (public dataset	87.71% (Triple classification),
[7]	Brain Functional Network (EEG-based)	Theta (4-8 Hz), Alpha2 (10-13 Hz)	64	left central (LC), left temporal (LT), left frontal (LF), left parietal-occipital (LPO), and right temporal (RT) regions	24 MDD patients & 24 healthy controls (Lanzhou University Second Hospital, China)	Band-pass filtering (0.5-50 Hz), EOG noise removal, Power Spectrum & Phase Lag Index (PLI) calculations	250 Hz	93.31%
[8]	DNN (Deep Neural Network)	Alpha (8-13 Hz), Theta (4-7 Hz)	8	Frontal lobe (Fp1, Fp2), Occipital lobe (O1, O2)	50 subjects (43 valid) – College and graduate students aged 18-27	Fast Fourier Transform(FFT) and Discrete Wavelet Transform(DWT) for feature extraction, noise filtering, statistical feature extraction (mean, min, max, SD)	300 Hz	100% (FFT+DNN), 93%+ (DWT+DNN)
[9]	Combinatorial convolutional and temporal convolutional neural network (CNN-TCN)	-	64	Whole Scalp	EEG signals of 119 individuals (eyes-open & eyes-closed states)	Notch filter (50Hz), Bandpass filter (0.2Hz–50Hz), Butterworth filter (order=5, 1Hz–50Hz), Independent Component Analysis (ICA)	500 Hz	MSE: 5.64±1.6 (eyes-open), 9.53±2.94 (eyes-closed); MAE: 1.73±0.27 (eyes-open), 2.32±0.35 (eyes-closed)

References	Algorithm	Best frequency band	No. of electrodes	Brain areas	Data collection	Data preprocessing	Sampling frequency rate	Accuracy
[10]	STFT+CNN-LSTM (DepCap)	-	19	Fp1, Fp2, F3, F4, F7, F8, Fz, T3, T4, T5, T6, P3, P4, Pz, O1, O2, C3, C4, Cz	64 subjects (34 MDD patients, 30 healthy)	Band-pass filtering (0.5-70 Hz), Notch filter (50 Hz), ICA for artifact removal, STFT for feature extraction	-	99.9%
[11]	DepL-GCN	-	128(MODMA), 64(PRED+CT)	-	MODMA and PRED+CT	Differential Entropy (DE) features extracted, adjacency matrix created based on correlation	250 Hz (MODMA), 500 Hz (PRED+CT)	75.47% (MODMA), 77.97% (PRED+CT)
[12]	Hybrid of LSTM and Spiking Neural Networks (SNN)	-	62	Frontal and prefrontal cortex regions	PRED+CT(72 females and 49 males)	Downsampling, Baseline removal, 50 Hz notch filter, Bandpass (0.2-50 Hz), Butterworth filter, ICA	500 Hz	-
[13]	SGFGCN (Specific-General Functional Graph Convolutional Network)	-	105 (from 128, after preprocessing)	Frontal lobe, Posterior parietal lobe, Occipital lobe	MODMA dataset, 24 MDD patients, 29 HCs, 5-minute resting-state EEG	0.1-45 Hz bandpass filter, ICA artifact removal, averaging reference method	250 Hz	97.20%
[14]	DeprNet (Deep Convolutional Neural Network)	-	19	Fp1, Fp2, F3, F4, F7, F8, Fz, T3, T4, T5, T6, P3, P4, Pz, O1, O2, C3, C4, Cz	Resting-state EEG recording for 9 minutes per subject, covering 33 subjects (18 normal, 15 depressed	High-pass filter (0.1 Hz), low-pass filter (100 Hz), notch filter (50 Hz), Independent Component Analysis (ICA) to remove artifacts	256 Hz	91.4%
[15]	FFNN (Fuzzy Function Neural Network)	-	19	-	EEG signals from 60 depressed subjects (30 males, 30 females, avg. 32.4 years) recorded at Atieh Psychiatry Centre, Tehran, Iran, under resting state with closed eyes	High-pass Butterworth filter (0.5 Hz), low-pass filter (45 Hz), notch filter (50 Hz), ICA for artifact removal, segmentation into 6-sec windows, PCA with Gaussian kernel	256 Hz	90% (best accuracy with all features combined)
[16]	C4.5, Best-First Decision Tree (BFDT), Logistic Regression (LR)	Alpha, Beta	90 (after preprocessing)	Frontal, Parietal-Occipital, Temporal	24 MDD patients, 29 NC; 5-minute resting-state EEG	Filtering (1-40 Hz), Artifact Removal (EOG, EMG), Channel Interpolation, Re-referencing, Epoch Selection	250 Hz	Up to 84.18% (alpha, PLI), 82.81% (beta, All Features)
[17]	Decision Tree (J48), K-nearest neighbors (KNN), Multilayer perceptron (MLP), and Best-First (BF) Tree	-	3	Fp1, Fpz, and Fp2	MODMA Dataset (55 subjects: 26 depressed, 29 healthy)	Noise removal using average referencing and notch filter, segmentation with 10s overlapping windows	250 Hz	Decision tree outperformed with the accuracy of 95.76%
[18]	1-D CNN with Demographic Attention	Beta (13-25 Hz))	3	Prefrontal (Fp1, Fpz, Fp2)	170 subjects (81 depressed, 89 normal), 90s resting-state EEG with closed eyes	High-pass (1 Hz) & low-pass (40 Hz) filtering, Wavelet transform & Kalman filtering for EOG removal, 4s non-overlapping sliding windows	250 Hz	75.29%
[19]	Time-Frequency Convolutional Networks (TFCN)	-	128	-	MODMA dataset, 24 depressed and 29 healthy participants	EEG data preprocessing conducted in MATLAB using the EEGLAB toolbox	250 Hz	100%

References	Algorithm	Best frequency band	No. of electrodes	Brain areas	Data collection	Data preprocessing	Sampling frequency rate	Accuracy
[20]	ResNet-101	-	3	Prefrontal lobe (Fp1, Fpz, Fp2)	MODMA dataset (55 participants: 26 MDD patients, 29 healthy controls), 90s recording in a quiet room	Discrete Fourier Transform (DFT), Directed Graph Representation	50 Hz	91.03%
[21]	Support Vector Machine (SVM)	Gamma (30–80 Hz)	59	Frontal, Central, Temporal, Parietal, Occipital	Face-in-the-crowd task with 16 depression patients and 14 healthy controls	Band-pass filtering (0.05–100 Hz), artifact removal, segmentation (-200 ms to 1000 ms)	1000 Hz	84% (Positive Stimuli), 85.7% (Negative Stimuli)
[22]	GCN-based model (1DCNN+LSTM +GCN)	-	128	Frontal, Central, Occipital	MODMA dataset (resting-state EEG from 24 depressed and 29 healthy subjects)	Bandpass filter (1-40 Hz), CAR re-referencing, ICA-based artifact removal	250 Hz	76.5%
[23]	Among various algorithms, CNN produced the highest accuracy	Alpha	19	Frontal, Parietal, Temporal, Occipital	EEG recordings, 19-channel EEG device	ICA, Bandpass filtering (1-40 Hz)	256 Hz	99.31%
[24]	Adaptive Graph Topology Generation (AGTG) module, a Graph Convolutional Gated Recurrent Unit (GCGRU) module, and a Graph Topology-based Max-Pooling (GTMP) module	Gamma	16	Parietal lobe at P3, Frontal lobe at Fp1, and Temporal lobe at T4	Resting-state EEG from University of New Mexico & Third People's Hospital of Jian City, China	Bandpass filtering (0.5Hz - 100Hz), Notch filtering (50Hz/60Hz), Resampling (200Hz), Artifact removal (FASTER algorithm)	500Hz (downsampled to 200Hz)	77.78% (Public dataset), 95.61% (Own dataset)
[25]	SGP-SL (Self-attention Graph Pooling with Soft Label)	-	128 for high-density EEG, 3 for simplified EEG	-	MODMA dataset, recorded under resting-state condition	EEG signals segmented into 2-second sub-subjects, augmentation applied	250 Hz	84.91%
[26]	Regularization Parameter-Based Improved Intrinsic Feature Extraction Method via Empirical Mode Decomposition (EMD)	1 Hz-40 Hz	64-channel, 128-channel, and 3-channel	Prefrontal lobe (Fp1, Fpz, Fp2) and signals from frontal lobe and bilateral temporal region	MODMA and 64-channel Brain Products (BP) electrode cap, 128-channel HydroCel Geodesic Sensor Net, and 3-channel wearable EEG devic	EEGLAB toolbox. Signals were downsampled to 250 Hz, filtered between 1-40 Hz, and cleaned of artifacts using ICA and Kalman filtering.	1000 Hz(64-channel EEG downsampled to 250 Hz), 250 Hz (128-channel and 3-channel)	87.50%(64-channel) , 88.50% (MODMA), 84.85% (3-channel resting-state), 77.68% (3-channel auditory stimulus-evoked signals)
[27]	Combination of Vision Transformer, pre-trained CNN networks (ResNet, DenseNet, EfficientNet), and 1D-CNN with LSTM for feature extraction from EEG and speech signals	0.5 Hz to 28 Hz, covering frequency bands Alpha, Beta1, Beta2, Beta3, Theta, and Delta	-	-	MODMA dataset, which includes EEG and speech data collected from 52 subjects (both clinically depressed and normal control	Spatial filtering to reduce variations, short-time Fourier Transform (STFT) for spectrogram extraction, and transformation into mel spectrograms	-	99.12%-left hemisphere and 97.66%-right hemisphere. CNN-based frameworks achieved 85.62% for mild depression detection

References	Algorithm	Best frequency band	No. of electrodes	Brain areas	Data collection	Data preprocessing	Sampling frequency rate	Accuracy
[28]	DIL-MDD (Data-Free Domain Incremental Learning for Major Depressive Disorder Detection) framework, which includes Adaptive Class-tailored Threshold Learning (ACTL) and Data-Free Domain Alignment (DFDA)	-	-	-	Multiple datasets including DAIC-WOZ, CMDC, and MODMA. It includes audio, textual, and neuroimaging data	Feature extraction using openSMILE for audio data and BERT/Chinese-BERT for text-based features	-	Accuracy ranges from 61.54% to 82.29% depending on the dataset and the experimental setup
[29]	MS²-GNN (Modal-Shared Modal-Specific Graph Neural Network)	-	The MODMA dataset includes 128-channel EEG signals	-	DAIC-WOZ dataset: Includes audio, video, and text collected from 189 subjects. MODMA dataset: Contains 128-channel EEG and audio signals from 37 subjects	LSTM, graph-based transformations, reconstruction networks	-	Accuracy of 89.13 with DAIC-WOZ and 86.49 with MODMA
[30]	Linear SVM	The alpha band led to the best classification performance in the Neu_block, while the gamma band was best in the Emo_block	16	Electrodes were placed covering frontal, central, temporal, parietal, and occipital regions	Collected using a 128-channel HCGS, amplified by an EGI system, and recorded with Net Station software. The EyeLink 1000 Desktop Eye Tracker was used to collect EM data	EEG data were filtered (1–40 Hz), cleaned of artifacts using FastICA, and normalized using z-score normalization	250Hz	83.42% using the Linear SVM
[31]	Binary linear support vector machine (SVM) classifier with leave-one-out cross-validation.	1-40 Hz	128-channel HydroCel Geodesic Sensor Net	Left frontal, temporal, and parietal lobes, and the right occipital lobe	Resting-state EEG data were recorded for 5 minutes with eyes closed	Filtered using a Hamming windowed Sinc FIR filter, artifact removal was performed, and data were re-referenced using the REST method	250 Hz	Accuracy of 92.73% with an area under the curve (AUC) of 0.98
[32]	Linear Graph Convolution Network (LGCN) integrated with Weighted Focal Binary Hinge (WFBH) loss and a Transformer model for classification	Beta and low gamma (25–140Hz)	19	Frontal, temporal, parietal, occipital, and central brain regions	Hospital Universiti Sains Malaysia (HUSM) 64 participants (34 with MDD and 30 healthy)	Filtered using a Butterworth bandpass filter (0.5 Hz - 70 Hz) and a 50 Hz notch filter for noise removal. Independent Component Analysis (ICA) to remove artifacts like eye blinks and muscle movements	4-second epochs (1024 samples each), suggesting a 256 Hz sampling frequency	99.92% accuracy, 99.90% sensitivity, 99.95% specificity, and 99.97% precision

This gives a better comprehension of how depression works. As the field progresses, we support focusing on real-time monitoring. It also needs to be scalable for clinical use. Classification performance greatly increases with feature extraction technique improvements. SVD-improved EMD and Time-Frequency Convolutional Networks are two substantially important examples.

Models can make personalized mental health assessments better by using several demographic variables[18]. These assessments can result in customized therapeutic treatments.

Effective AI tools in clinics are needed to detect depression in its early stages, research indicates.

Expanding the breadth of all datasets helps to fully grasp AI methods. These steps will greatly improve the efficacy of EEG-based depression detection systems while also providing more thorough and accessible mental health care solutions. Through energetic innovation and strong cross-disciplinary collaboration, we can truly advance the field. Research understandings are translatable into clinical applications that are important for all people affected by depression.

VI. CONCLUSION

In summary, advances in artificial intelligence and multimodal data are enhancing the potential of EEG-based methods for detecting depression. AGTG + GCGRU + GTMP, SGP-SL and other new frameworks show that adaptive graph learning and self-attention mechanisms are important, as these frameworks are very accurate in classifying depression [24][25]. Hybrid deep learning CNN-LSTM models are quite effective when processing EEG signals, a truly important improvement in diagnostics [3][10][23][27].

Changed functional connectivity is shown by the findings to be an important neural marker for depression [7][13][16][31].

VII. FUTURE ENHANCEMENT

Future research should focus on thoroughly improving the utilization of EEG signals for depression detection. Several compact, portable EEG systems developed for real-time monitoring will further ease routine assessment of patients' mental health, offering data useful for clinicians and patients alike [17]. To guarantee ultimate robustness across depression severity levels, the model validation will be considerably improved via the expansion of the EEG datasets collection to include populations that are greatly larger and more diverse. Artificial intelligence models should be more interpretable. This would be an improvement. By enabling healthcare professionals to understand as well as rely on the decision- making processes of these systems, trust is encouraged. Complete optimization of hardware as well as software is necessary for real-time applications, in order to make EEG- based depression detection tools practical for all everyday uses. When machine learning models are personalized, diagnoses and treatments may improve since interventions can be better suited to each patient. Lastly, exploring advanced analytical techniques, such as attention mechanisms and deep learning architectures, will likely improve the reliability and performance of EEG analyses in detecting depression [5]. By focusing on these enhancements, future research can significantly advance the field, ultimately leading to better patient outcomes and more effective treatment options.

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