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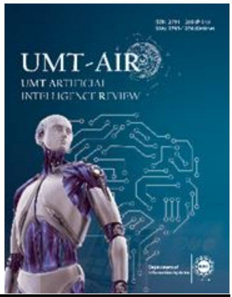

Title:	**EEG-Based Depression Detection using Time-frequency Representation and Transfer Learning Techniques on MODMA Dataset**
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EEG-Based Depression Detection using Time-frequency Representation and Transfer Learning Techniques on MODMA Dataset

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ABSTRACT According to the World Health Organization (WHO), millions of people are affected by mental health issues, and depression is increasing rapidly. Present methods for depression detection include surveys, clinical interviews, and questionnaires that are very time-consuming and often not accurate. Many people do not express their feelings in interviews with doctors, or sometimes provide incorrect information. So, these techniques are not fully reliable. Using Electroencephalography (EEG) signals, the current study diagnosed depression in a better way since these signals record the brain activity directly. If the EEG shows some disturbance or unusual patterns in the brain activity, this means that the person is disturbed and facing depression. The MODMA dataset is a multimodal dataset that is widely used and medically tested for EEG signals. Many Machine Learning Algorithms (MLA's), feature extraction techniques, and Deep Learning (DL) approaches have been applied to EEG for depression detection. However, the EEG signal is a 1-D signal that changes with respect to time, so it is sometimes used to detect depression. To solve this issue, researchers converted the EEG from a 1-D to a 2-D signal using time-frequency representation with transfer learning techniques. CNN-based pretrained models used for depression detection performed well on image data. Many studies showed that the combination of transfer learning with time-frequency representation is very effective and improves accuracy. This study primarily discussed transfer learning and time-frequency representation techniques for EEG-based depression detection. Finally, this technique would be used for other neurological disorders in the future.

INDEXED TERMS electroencephalography, major depressive disorder, MODMA, transfer learning

I. INTRODUCTION

Depression is a common mental disorder. According to the World Health Organization (WHO), millions of people are affected by this condition. Mental health problems are increasing day by day [1–4]. Furthermore, these problems disturb many people's daily life activities [5]. Poor mental health also affects physical health because when someone is not mentally strong, their physical health would not be good. Currently-diagnosed methods used for depression detection are subjective and often do not provide accurate results. Many researchers rely on surveys, interviews, and questionnaires but these are not reliable resources for depression detection. Sometimes patients do not express their feelings clearly, or they hide their emotions, which makes detection incorrect. In other cases, people do not fill surveys properly,

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do not read the questions appropriately, or randomly choose answers, leading towards incorrect results. These methods are very time-consuming and not always effective. Depression is also hard to diagnose because many individuals avoid sharing their feelings with others. Moreover, they express strong emotions on the outside, while their mental health is negatively affected. Proper diagnosis and treatment of depression is quite important [6], [7]. Lack of proper attention to depression treatment may cause long-term neurological disorders [8]. According to recent researches in Machine Learning (ML) and Deep Learning (DL), EEG-based detection methods provide more objective information [9].

Electroencephalography (EEG) is used to record the brain's electrical activity. The EEG electrode cap is simply placed on the scalp, and it records the brain activity. As compared to MRI or CT scans, an EEG is very affordable. Moreover, EEG is a very reliable method for detecting mental health conditions as compared to survey methods. Different parts of the brain communicate with each other, and the EEG shows the brain activity using alpha, beta, and theta waves. If a person is depressed, their brain waves change, especially on the left side of the brain which, in turn, changes the brain activity. In previous years, many ML and DL approaches have been used for depression detection. Using ML classifiers, such as Logistic Regression (LR), SVM, and KNN, with feature extraction and selection techniques, depression patterns can be easily detected in EEG signals [10]. There are some problems with these methods, and they also have limited accuracy. To overcome these limitations, many researchers use DL algorithms without feature extraction techniques. They use Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Graph Neural Networks (GNNs), and Convolutional Neural Networks (CNNs) in combination with many hybrid models and get very good performance in classifying depression [11].

EEG signal is a 1-D time series signal, and it changes over time. So, it continuously changes, and here a problem arises: signals cannot be captured accurately because it changes again and again. Therefore, to overcome this problem, the study used a 2-D time- frequency representation CNN. For instance, a 1-D time series signal was converted into a time-frequency representation (short-term Fourier transform, continuous wavelet transform, Q-transform, T-transform, discrete Fourier transform) by changing it into images and then applying certain transfer learning techniques. Transfer learning techniques with pretrained CNN models have a strong performance. This review mainly focused on EEG-based depression detection using time-frequency representation and transfer learning approaches. Moreover, the study also discussed some previous approaches. Recent research shows that these approaches provide promising results in capturing the EEG signals and classifying depression.

Audio-based datasets are generally less reliable than EEG datasets, such as the 128-electrode resting-state EEG dataset and the 3-electrode EEG dataset. This study focused on a 128-electrode resting-state EEG experiment and analyzed the performance of ML and DL approaches using this dataset [12]. EEG is a technique used to record the brain's electrical activity and to identify signal patterns associated with different mental health conditions. EEG recordings are commonly obtained during a resting state, in which a person is awake, relaxed, and not engaged in any specific task. Under resting-state conditions, EEG signals exhibit clearer and more stable wave patterns.

Different brain regions are associated with physiological states related to emotions. These regions are represented by specific EEG electrode locations. For instance, lower left frontal electrodes including FP1, FP2, F3, F4, and FZ are linked to depression-related activity, particularly in the alpha and theta frequency bands. Electrodes T3 and T4 are also associated with mental disorder patterns and are primarily related to theta and alpha activity. Additionally, parietal and occipital electrodes, including P3, P4, O1, and O2, are involved in cognitive processing and are associated with alpha and beta frequency bands. Figure 1 illustrates the brain regions used for depression detection.

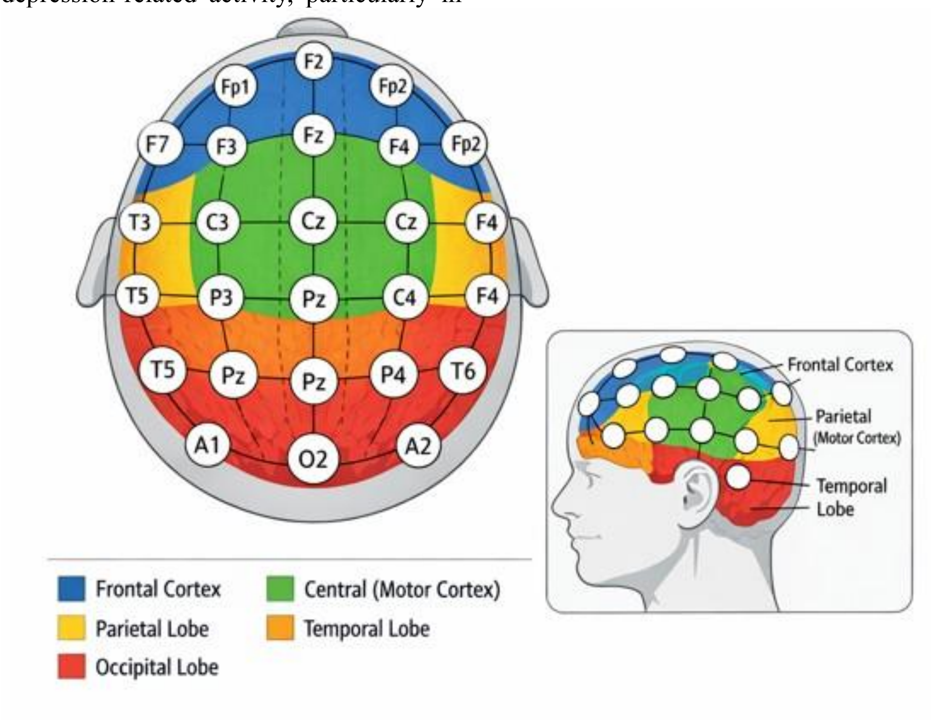

FIGURE 1. Different Brain Regions used in Detection

EEG frequency bands play a crucial role in understanding and detecting depression-related patterns. Different frequency bands, including alpha, beta, theta, delta, and gamma, are associated with mental disorders and exhibit abnormal activity in the brain. Research indicates that alpha and theta waves are particularly effective in capturing depression-related patterns [13]. Alpha waves are associated with relaxation, while theta waves are linked to emotional processing, deep relaxation, and creativity. The alpha frequency range is between 8 and 13 Hz, and the theta range is between 4 and 8 Hz. During resting or relaxed states, these waves are more prominent and can reveal patterns associated with depression. Delta waves, which range from 0.5 to 4 Hz, are primarily related to sleeping patterns. Beta waves, ranging from 12 to 35 Hz, are associated with active attention and concentration. Gamma waves, with frequencies between 30 and 45 Hz, are related to higher-level cognitive processing. Disturbances in these frequency bands reflect abnormal brain activity and can be used to identify mental health conditions.

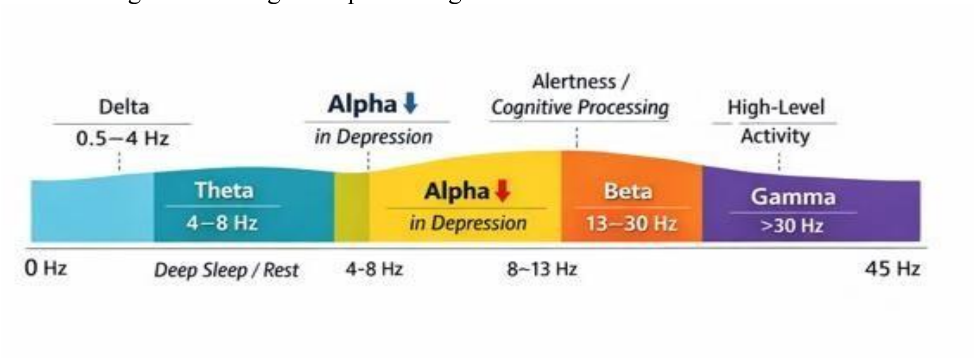

FIGURE 2. Different frequency bands representation

II. LITERATURE REVIEW

In recent years, with the rapid development of cognitive research technologies, EEG recordings of brain activity have been widely used to investigate brain behavior in various mental health disorders. In many developing countries, there is a shortage of qualified physicians for mental health treatment, and public awareness of mental health issues remains limited. Consequently, automated and objective diagnostic methods have gained increasing attention. [14] conducted a resting-state EEG study using the MODMA dataset for depression detection. They applied several feature extraction techniques, including linear, nonlinear, and functional connectivity features, as well as Phase Lag Index (PLI), to preprocess raw EEG signals before inputting them into ML and DL models. Four classifiers—LR, Decision Tree (DT), Naïve Bayes (NB), and K-Nearest Neighbors (KNNs)—were evaluated in combination with feature selection methods. By combining these features with LR and the ReliefF feature selection technique, classification accuracy was achieved. [15] proposed a depression detection approach using resting-state EEG signals recorded from only three electrodes (Fp1, Fpz, and Fp2). Instead of using 128 channels, the authors focused on reducing system complexity by developing a patient-friendly and low-cost solution. The approach concentrated on prefrontal channels, which are strongly associated with emotional processing. Band-pass filtering was applied during preprocessing to remove noise, followed by extraction of both linear and nonlinear features. For classification, Support Vector Machines (SVMs) and KNNs were used. The KNN model achieved an accuracy of 72.25%

using features, such as correlation dimension, Rényi entropy, C0, and maximum value. While, SVM achieved an accuracy of 71.42%. These results suggest that combining linear and nonlinear features can yield meaningful performance. However, limitations remain due to the small sample size and moderate classification accuracy. [16] employed various feature extraction techniques, including nonlinear dynamical analysis and wavelet power spectrum extraction, and used the extracted features as input to an

SVM classifier. Their approach achieved high classification accuracy for depression detection. Proposed DL frameworks using one-dimensional CNN and LSTM networks, achieving accuracies of 98.32% and 95.97%, respectively, for unipolar depression classification using EEG data. [12] implemented multiple ML classifiers, including KNN, SVM, DTs, and Artificial Neural Networks (ANNs), and found that KNN achieved the highest accuracy. [17] introduced a CNN-based approach in which features learned through DL were used as input to an SVM classifier. These features were converted into image representations corresponding to EEG cap layouts for both original and transformed features. Other studies employed feature extraction methods, such as discrete cosine transform and discrete wavelet transform, combined with classifiers including SVM, KNN, ANN, and NB, to detect depression patterns from EEG datasets [18]. Song et al. [19] proposed an EEG transformer model combined with LSTM networks for depression classification and achieved promising results. Since EEG signals vary rapidly over time, several studies have introduced methods to convert one-dimensional EEG signals into two-dimensional time–frequency representations to improve classification performance. Some studies directly applied CNN models without transfer learning or pretrained networks by converting EEG signals into Short-time Fourier Transform (STFT) spectrograms and feeding them into deep CNN architectures, achieving satisfactory accuracy [20]. Time frequency transformation methods, such as STFT and Continuous Wavelet Transform (CWT) convert one-dimensional EEG signals into two-dimensional representations that capture both spectral and temporal information [21]. This enables CNNs to effectively identify brain activity patterns.

Previously, EEG-based depression detection faced challenges due to limited dataset sizes and an increased risk of overfitting. Applying ML and DL models directly to one-dimensional EEG signals often fails to capture transient brain activity patterns that appear and disappear over time, leading to reduced detection performance [22].

To address these issues, various feature extraction and selection techniques have been used during EEG preprocessing. This study investigated how combining time–frequency representations with transfer learning techniques improves the classification of depressed and non-depressed individuals.

TABLE I

SUMMARY OF EXISTING STUDIES

References	Study Focus	Dataset	Methodologies	Strengths	Limitations
[14]	Resting-state EEG-based depression detection	128-channel MODMA Dataset	Linear, non-linear, functional connectivity PLI feature extraction, and ML classifier (LR, DT, NB, and KNN)	Feature extraction with LR and ReliefF achieved 82.31% accuracy	Accuracy is still normal and needs a larger dataset, and also improves the method for classification.

References	Study Focus	Dataset	Methodologies	Strengths	Limitations
[15]	Resting state 3 electrodes (Fp1, Fp2, Fpz)	3-Electrodes MODMA Dataset	Feature extraction, both linear and non-linear used	SVM achieved 71.42% accuracy, and KNN achieved 72.25% accuracy	Low sample size and classification improved with better methods
[16]	Feature selection for depression classification	MODMA Dataset	Non-linear dynamical features and SVM used for classification	Wavelet power spectrum extract and feed features as the input to SVM classifier, get good accuracy	Classification improves with other techniques
Mumtaz & Qayyum [23]	DL-based depression detection	MODMA Dataset	1D CNN and LSTM achieved higher accuracy	With the combination of hybrid models get good accuracy	An EEG signal is a non-stationary signal. It changes over time and requires a technique to capture accurate patterns.
[12]	Comparison of different ML classifiers	EEG Dataset	KNN, SVM, DT, and ANN from these KNNs achieved higher accuracy	Different classifiers' accuracy checked.	Also, limited accuracy requires the use of advanced methods
Song et al. [19]	EGG transformer model with LSTMs	MODMA Dataset	Different hybrid model combinations	High performance	Accuracy must be improved
[24]	Transfer learning with CNN	MODMA Dataset	Used ReliefF + KNN classifier and pretrained restnet18 model	Uses features with transfer learning and applied to EEG data.	Used restnet18, it must be improved with other techniques.
Jia et al. [25]	Multimodal EEG + audio	MODMA Dataset	STFT EEG spectrogram and	Higher accuracy achieved, and	It improves accuracy but other methods

References	Study Focus	Dataset	Methodologies	Strengths	Limitations
			DenseNet121 transfer learning	multimodal data improves detection	are needed.
[26]	Time-frequency and spatial topology	MODMA Dataset	Time-frequency representation and Graph Convolutional Network (GCN)	Strong accuracy because spatial topology combines with time-frequency representation	Time-representation also gives accuracy with other combinations
Qiu et al. [27]	Graph network with time-frequency representation	MODMA Dataset	Graph Neural Network (GNN)	High accuracy	Heavy computation
Zhao et al. [28]	Time-frequency with SSL	MODMA Dataset	Time-frequency fusion model with self-supervised	Improves representation accuracy	Needs more validation

III. METHOD

A. MODMA DATASET

MODMA is a multimodal dataset designed for mental disorder analysis. It includes a 128-channel EEG dataset, an audio dataset, and a 3-Electrode EEG dataset. The dataset contains EEG and audio recordings from clinically diagnosed patients with depression as well as matched healthy control subjects. All participants were carefully diagnosed and selected by professional psychiatrists in hospital settings.

1) FULL BRAIN 128-ELECTRODES

In this experiment, EEG recordings were obtained under two conditions: resting state and dot-probe task. During resting-state recordings, participants remained in a state of relaxation with their eyes closed and without any movement. The participants were awake. When the mind is relaxed, EEG recordings exhibit clearer and more stable brain activity patterns. Therefore, depression-related patterns can be more effectively detected in the resting state.

During the dot-probe task, images were presented to the participants and categorized into four emotional groups: fear, sadness, happiness, and neutral. Participants were instructed to observe the image and respond when a dot appeared. If the dot appeared on the left side of the screen, the participant pressed the key “1”, and if it appeared on the right side, the participant pressed the key “4”. Participants completed a practice session before the experiment to become familiar with the task. This task was designed to evaluate attentional responses, as individuals with depression often exhibit delayed reaction times. A total of 52 participants were included in this experiment, and their demographic and clinical characteristics are reported in Table II.

TABLE II

128-CHANNEL PARTICIPANTS LIST

Participants	Category	Gender (M/F)	Age
24	Depressed	13 males & 11 females	16-56 years
29	Healthy	20 males & 9 females	18-55 years

2) 3-ELECTRODES EEG EXPERIMENT

The 3-Electrode EEG recordings were obtained exclusively under resting-state conditions. The prefrontal lobe is strongly associated with emotional processing and mental disorders. During the resting state, EEG signals were recorded from three prefrontal electrodes (Fp1, Fpz, and Fp2). A total of 55 participants were included in this dataset, and their demographic and clinical characteristics are reported in Table III.

TABLE III

3-CHANNEL PARTICIPANTS' LIST

Participants	Category	Gender (M/F)	Age
26	Depressed	15 males & 11 females	16-56 years
29	Healthy	19 males & 10 females	18-55 years

3) AUDIO EXPERIMENT

For the audio experiment, participants completed three fixed tasks: interviews, reading, and picture description. Text materials were presented on a computer, and participants were instructed to complete each task. During the interviews, 18 questions with positive, neutral, and negative content were asked. In the reading task, participants read a short story entitled *"The North Wind and the Sun."* For the picture description task, three different types of images were presented, and participants were asked to describe them. A total of 52 participants took part in the experiment, and their demographic and clinical characteristics are reported in Table IV.

TABLE IV

AUDIO DATASET PARTICIPANTS' LIST

Participants	Category	Gender (M/F)	Age
23	Depressed	16 males and 7 females	16-56 years
29	Healthy	20 males and 9 females	18-55 years

B. PREPROCESSING

The MODMA dataset contains 128-channel EEG recordings obtained in a complete resting state, ideally without eye blinks, muscle movements, or hand movements. In practice, however, small movements, such as eye blinking or muscle activity occur, and the EEG may also capture electrical noise from the environment. To ensure that the signals are suitable for depression classification or other analyses, preprocessing is applied to convert raw, noisy EEG recordings into clean, reliable signals. Preprocessing is therefore a critical step for enhancing signal quality and enabling accurate classification. The preprocessing steps used in this study included filtering, artifact removal, segmentation, normalization, and channel selection.

1) FILTERING

EEG recordings capture all electrical activity in the resting state, including minor movements. To remove frequency components that are not related to brain activity, filtering is applied. Noise can arise from hand movements, muscle contractions, body movements, or other physiological activities, such as sweating, which may interfere with the true brain signals. Several types of filters are commonly used to address these issues. High-pass filters remove low-frequency noise, for instance, signals below 0.5 Hz. On the other hand, low-pass filters eliminate high-frequency noise, such as signals above 45 Hz. Bandpass filters, which combine high-pass and low-pass filtering, retain signals within a specified range, typically 0.5–50 Hz for depression detection. The Butterworth filter is often applied with a low cutoff of 1 Hz and a high cutoff of 50 Hz to achieve smooth signal retention. Notch filters are used to remove power line noise, which is 50 Hz in Pakistan but may vary in other countries. Overall, filtering effectively reduces noise and preserves the brain's electrical activity for subsequent analysis.

2) ARTIFACT REMOVAL

Although EEG signals originate from brain activity, they are often contaminated by artifacts, such as eye blinks, cardiac activity (ECG), muscle activity (EMG), and head movements. These artifacts overlap with the EEG frequency range, making filtering alone insufficient to remove them. Common techniques for artifact removal include Independent Component Analysis (ICA) and manual artifact rejection. ICA separates EEG signals into independent components, identifies components associated with artifacts, removes them, and reconstructs a clean EEG signal, thereby preserving the underlying brain activity. Manual artifact rejection involves visually inspecting the EEG and removing noisy segments, which is typically applied to small datasets with pronounced artifacts but is time-consuming and subjective. Overall, artifact removal is essential for improving the reliability of extracted features by eliminating non-neural signals and enhancing the quality of EEG data for further analysis.

3) SEGMENTATION

Segmentation divides continuous EEG recordings into smaller time windows. Since EEG signals are non-stationary and brain activity changes over time, ML models require fixed-length inputs. For instance, a 2-second window with 50% overlap creates multiple EEG segments from a single recording. Two types of segmentations are commonly used: overlapping and non-overlapping.

Overlapping windows produce smoother transitions and more data, and are preferred in most studies. Segmentation complements filtering by providing appropriate-sized input for feature extraction and classification.

4) NORMALIZATION

Next, there is a technique called normalization. In normalization, there are different channels that have different amplitudes and different times. Normalizations confuse ML models. Common normalization methods are used: min-max normalization, in which data is scaled between 0 and 1, and z-score normalization, in which the mean is 0, and the standard deviation is 1. The Z-score is commonly used in many research studies. This study used normalization to improve the model's performance.

5) CHANNEL SELECTION

Not all EEG channels provide equally informative signals for depression detection. Channel selection techniques focus on the most relevant electrodes, often in the frontal or prefrontal regions (e.g., FP1, FP2, FP3, FP4). Selecting appropriate channels helps reduce noise and improves the accuracy of classification models.

FIGURE 3. General EEG preprocessing pipeline

In summary, EEG signals contain various types of noises. Preprocessing, including filtering, artifact removal, segmentation, normalization, and channel selection, enhances signal quality and plays a crucial role in improving model performance. Figure 2 illustrates the preprocessing workflow, showing how raw EEG signals are converted into clean EEG signals for subsequent analysis.

C. TIME-FREQUENCY REPRESENTATION

The STFT produces an output image known as a spectrogram, which resembles a heatmap. It divides a long EEG signal into small time windows, allowing the visualization of frequency components over time. Since EEG signals are non-stationary and change continuously, STFT enables observation of both short- and long-term frequency patterns. In a spectrogram, the x-axis represents time, the y-axis represents frequency, and the color indicates signal strength or power. Similarly, the CWT generates an output called a scalogram. Wavelets, which are localized in time and frequency, capture patterns that vary over time. In a scalogram, the x-axis represents time, the y-axis represents scale or frequency, and the color represents the energy or power of the EEG signal.

To leverage these time–frequency representations for

classification, researchers often construct small CNNs with two to three convolutional layers, followed by a max-pooling layer and a dense SoftMax layer. These networks, although simple, often achieve better accuracy than traditional ML classifiers. Since EEG signals are non-stationary, one-dimensional inputs alone may fail to capture relevant temporal patterns [29]. Therefore, EEG signals are converted into two-dimensional time–frequency representations, such as STFT, CWT, discrete Fourier transform, Q-transform, or T-transform, which are suitable for CNN-based analysis.

Pre-trained CNN models, such as VGG and ResNet, can be employed by loading the model, optionally freezing early layers, and replacing the final classification layer [30]. Fine-tuning involves training the new layer or slightly adjusting deeper layers, allowing the network to adapt to EEG-specific patterns while minimizing overfitting.

D. MACHINE LEARNING (ML) APPROACHES

On the 128-electrode resting-state EEG dataset, researchers applied various ML classifiers for depression detection. During preprocessing, feature extraction and selection techniques were employed to convert raw EEG signals into numeric features that classifiers can effectively interpret. Feature extraction offers several advantages. It reduces the high dimensionality of raw EEG signals, compresses the data, and highlights meaningful depression-related patterns. Linear features capture changes in power and energy within brain signals, nonlinear features reflect the complexity of neural activity, and connectivity features represent communication between different brain regions.

By transforming raw EEG signals into numeric representations, classifiers can more accurately identify depression patterns. Despite feature extraction, some irrelevant or noisy features may remain, and feature selection methods, such as ReliefF are used to retain the most informative features. After feature selection, classifiers including LR, SVM, KNNs, and RF are trained on linear, nonlinear, and functional connectivity features.

Different combinations of these features are evaluated to determine the optimal configuration. The highest classification accuracy, 82.31%, was achieved using functional connectivity features derived from PLI combined with ReliefF feature selection and LR.

E. DEEP LEARNING (DL) APPROACHES

1) RECURRENT NEURAL NETWORKS (RNNS)

Recurrent Neural Networks (RNNs) are a type of neural networks designed to handle sequential and temporal data. Unlike traditional feedforward networks, RNNs contain loops that enable the network to retain information from previous time steps, making them suitable for EEG time-series analysis. By providing input sequences of EEG signals, RNNs can output classifications of depressed or non-depressed states. However, RNNs face challenges, such as vanishing or exploding gradients, which limit their ability to capture long-term dependencies due to restricted memory.

LSTM networks address these limitations and, when combined with CNNs, have been shown to achieve higher accuracy in detecting depression patterns [31, 32]. The Gated Recurrent Unit (GRU) is a simplified variant of LSTM that merges the input and forget gates into a single update, reducing computational complexity while maintaining strong performance. Research indicates that GRUs can achieve comparable accuracy to LSTMs with faster training times. Given that, depression may influence the temporal evolution of brain signals. These sequential models are particularly effective for analyzing EEG data in depression classification tasks.

2) GRAPH NEURAL NETWORK (GNN)

GNNs are a type of neural network designed to operate on graph-structured data, learning representations for nodes, edges, or entire graphs that can be used for classification tasks. GCNs, a specific type of GNN, apply convolutional operations on graph nodes in a manner analogous to how CNNs process image pixels. In EEG-based depression detection, signals are first decomposed into standard frequency bands, that is, alpha, beta, theta, and delta, and time–frequency features are extracted from each band. These features serve as input for the nodes, while an adjacency matrix encodes the functional connectivity between EEG channels. By processing both node-level features and the connectivity structure, GCNs can effectively classify individuals as depressed or non-depressed. This captures spatial and functional relationships in the EEG data that traditional models may overlook.

3) CNN MODEL

CNNs have proven to be highly effective for depression detection using EEG signals. Since raw EEG signals are one-dimensional and non-stationary, they are often transformed into two-dimensional representations, such as wavelet images or time–frequency maps of specific frequency bands. Various CNN architectures are then employed to automatically extract features relevant for depression classification.

To reduce computational costs and leverage prior knowledge, transfer learning techniques are commonly applied. This allows researchers to fine-tune pretrained CNN models on EEG data rather than training the network from scratch. This approach has been shown to achieve high classification accuracy while efficiently adapting the models to the specific characteristics of EEG signals associated with depression.

A 1D CNN processes EEG signals along a single temporal dimension, applying convolutional filters to each channel to detect depression-related patterns. In studies using the 128-channel MODMA dataset, each EEG channel provides a long 1D time series. The filters slide across time to extract temporal features, such as abnormalities in alpha and beta waves or other brain activation patterns associated with depression.

One advantage of 1D CNNs is that they can directly learn from raw EEG signals without requiring feature extraction or transformation into numeric representations. While 1D CNNs can effectively capture temporal structures and achieve good classification accuracy, they are less commonly used than 2D CNNs or hybrid architectures due to the risk of overfitting, especially when channel numbers are limited. To mitigate this, researchers employ techniques, such as batch normalization, data augmentation, and dropout. Additionally, 1D CNNs are often combined with other architectures, including LSTM networks, attention mechanisms, GCNs, or transfer learning applied to 2D time–frequency representations. Although 1D CNNs offer a simple architecture and reduce preprocessing requirements, hybrid models that integrate multiple architectures generally achieve higher accuracy for depression detection from EEG data.

Pretrained CNN architectures, such as VGG, ResNet, Inception, and EfficientNet, have been trained on millions of images from ImageNet and are capable of extracting complex features from new image data using transfer learning. In EEG-based depression detection, researchers using the 128-channel MODMA dataset first select relevant channels and convert the corresponding EEG signals into two-dimensional time–frequency images. These images are then used as input for transfer learning with pretrained CNN models.

Converting EEG signals into image representations is essential because CNNs are inherently designed to process spatial patterns. Applying CNNs directly to raw 1D EEG signals without transformation may lead to suboptimal performance. Transfer learning allows the model to leverage previously learned features, fine-tune on EEG data, and achieve improved classification accuracy for depression detection.

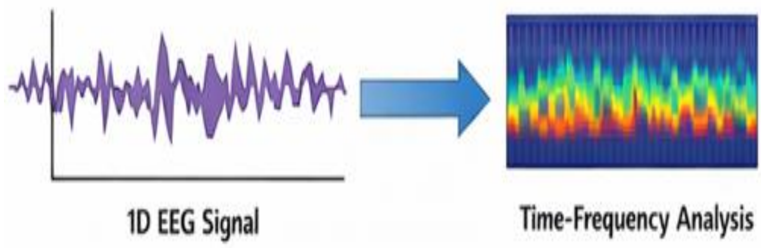

FIGURE 4. Conversion of 1D to 2D

Figure 4 shows the conversion of a 1D EEG signal into a 2D time-frequency, because EEG signals change over time, making it difficult to detect correct patterns. That is why it was converted into 2D.

4) TRANSFER LEARNING

Transfer learning is a highly effective technique for EEG-based depression detection, particularly when datasets are too small to train DL models from scratch, which can lead to overfitting and high computational costs.

In this approach, EEG signals are first preprocessed to remove noise and select relevant channels. The one-dimensional signals are then transformed into two-dimensional time–frequency representations, such as STFT or CWT images.

These images are input into pretrained CNN models, including VGG-16, VGG-19, ResNet18, ResNet50, InceptionV3, and DenseNet121. Early layers of these networks are typically frozen, while the final layers are fine-tuned on the EEG images to adapt the models to depression classification.

Pretrained CNNs have already learned to detect edges, shapes, textures, and patterns from millions of images. This allows them to extract meaningful features from complex EEG time–frequency representations with minimal additional training.

Among these architectures, VGG networks are widely used in EEG studies due to their simple design, ease of fine-tuning, and strong performance on time–frequency images. Although, they are computationally intensive due to the large number of parameters. ResNet models, in contrast, are deeper networks that use residual connections to mitigate vanishing gradients, enabling better feature learning, improved generalization, and superior performance on complex EEG images.

Transfer learning in EEG analysis can be further enhanced by integrating attention mechanisms, hybrid DL models, or multimodal EEG-fMRI datasets to improve classification accuracy and interpretability [33]. Additionally, model explainability methods, such as Grad-CAM, may help visualize which brain regions and frequency bands contribute most to the depression predictions, aiding clinical adoption.

Figure 4 illustrates the depression detection pipeline: raw EEG signals are preprocessed, converted into 2D time-frequency images, and analyzed using pretrained CNNs with transfer learning.

In traditional ML approaches, features, that is, linear, nonlinear, or connectivity-based are extracted and fed into classifiers, such as LR, SVM, KNN, or DTs to detect depression. DL approaches, including RNNs, LSTMs, and combinations with GNNs or GCNs, have also been applied, achieving high classification accuracy. However, because EEG signals are non-stationary, converting 1D signals into time–frequency images is essential before applying CNN-based transfer learning. Across multiple studies, transfer learning with pretrained CNNs consistently outperforms both traditional ML and other DL methods. This highlights its effectiveness in detecting depression from EEG data. Figure 5 summarizes the various ML, DL, and transfer learning models used in recent studies.

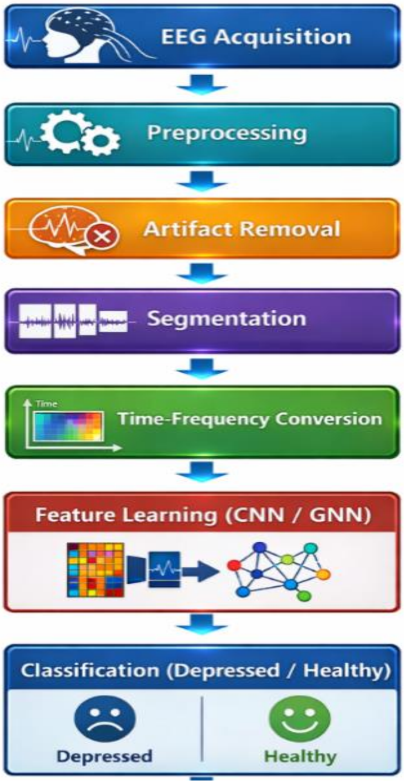

FIGURE 5. Depression detection pipeline

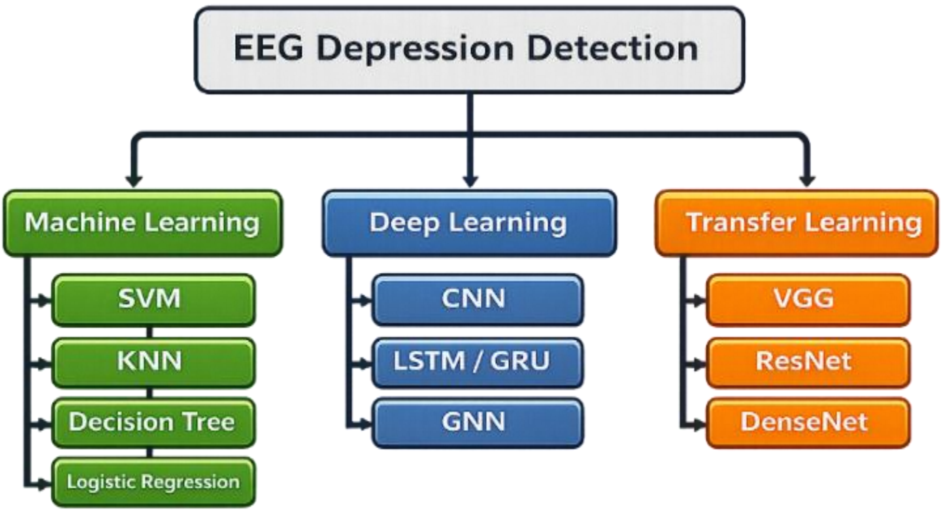

Figure 6. Different ML, DL, and transfer learning

IV. RESULTS AND DISCUSSION

Various classical ML models have been applied to the MODMA dataset to classify individuals as depressed or non-depressed. Traditional algorithms, such as KNNs, SVMs, LR, DTs, and NB achieve reasonable accuracy when utilizing linear and non-linear EEG features. Among these, SVMs and DTs tend to perform slightly better, reaching accuracies around 77%–78%, respectively. On the other hand, KNN and NB show slightly lower performance around 65%–70%, respectively. These results indicate that classical ML approaches are effective for capturing general patterns in EEG signals. However, their performance is somewhat limited when compared to more complex DL architectures.

Figure 6 illustrates the comparative accuracy of these classical ML models on the MODMA dataset. This highlights the variations in performance across different algorithms. This separate visualization allows readers to clearly understand the relative strengths of traditional models without mixing them with DL results.

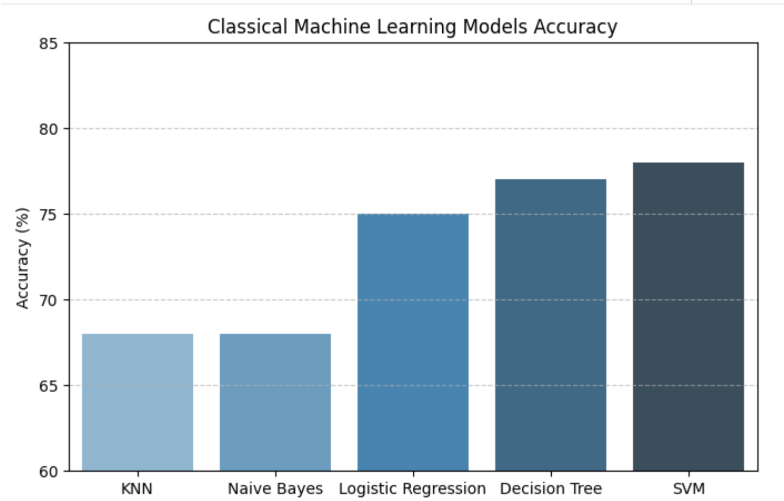

FIGURE 7. Different machine learning models' accuracy

DL approaches, particularly 1D CNNs, perform exceptionally well on the MODMA dataset, especially when combined with hybrid architectures. Standalone 1D CNNs achieve accuracies ranging from 65% to 70%. On the other hand, hybrid models, such as CNN + LSTM, which capture long-term temporal dependencies, improve performance to approximately 85%.

Incorporating attention mechanisms, which focus on the most relevant temporal segments, further increases accuracy to 85%–92%. Advanced combinations, such as CNN + GCNs achieve the highest accuracy of around 95%.

In addition, 2D CNNs using time–frequency representations and transfer learning approaches also demonstrate strong performance, achieving up to 97% accuracy without requiring multiple model combinations. These DL and hybrid methods benefit from automatically extracting relevant features from multi-channel EEG data, providing superior performance compared to classical ML approaches.

Figure 7 presents a clear comparison of DL and hybrid model performance on the MODMA dataset. This emphasizes the advantage of combining CNNs with LSTMs, attention mechanisms, or GCNs for depression detection. The figure also underscores the high potential of 2D CNNs and transfer learning for efficient classification.

Although hybrid models provide strong performance, 2D CNNs using time–frequency representations and transfer learning also achieve high accuracy without combining multiple architectures.

This comparative study analyzed the MODMA dataset using different approaches and summarized their results. The primary focus was on the 128-channel EEG dataset, though results were also considered from the 3-channel EEG dataset. This demonstrated strong performance when combined with transfer learning techniques, as illustrated in the graph 9.

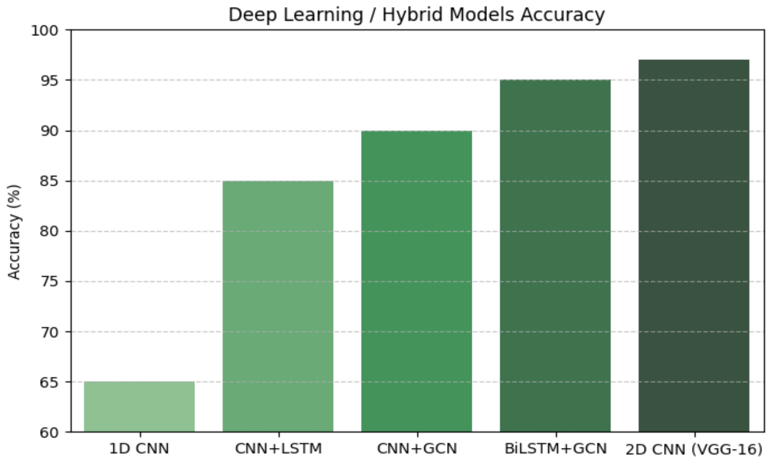

FIGURE 8. Comparison of deep learning models' accuracy

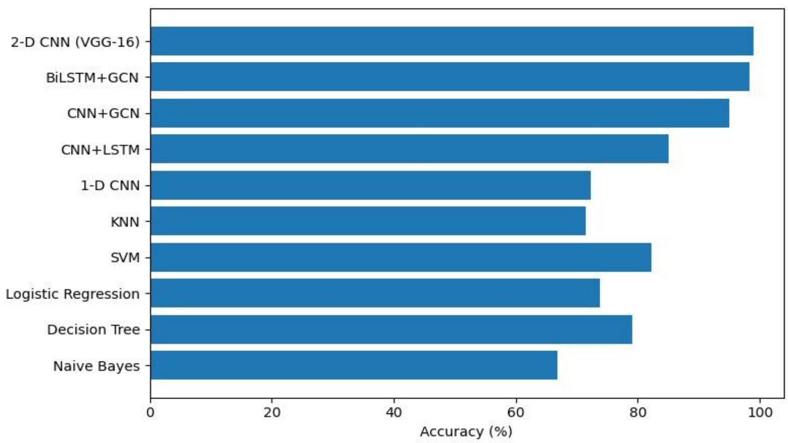

FIGURE 9. Comparison of different models' accuracy

A. CONCLUSION

This study analyzed multiple ML, DL, and transfer learning approaches for depression detection using the MODMA dataset. Furthermore, the study also compared the performance of linear and nonlinear feature extraction techniques combined with ML classifiers, including KNN, NB, DT, LR, and SVM, and reported their classification accuracies. DL approaches were also examined, such as RNNs (LSTM and GRU) and their combinations with CNNs. This helped evaluating their performance on the MODMA dataset. The analysis demonstrated that 1D CNNs and 2D CNNs applied to time–frequency representations, combined with transfer learning techniques, achieved the highest performance and represented a promising direction for future research.

Most studies rely on the limited MODMA dataset, and further research should incorporate additional datasets to enhance generalization. Although the MODMA dataset is currently the most medically validated dataset for EEG-based depression detection, it remains relatively small. This highlights the need for more comprehensive datasets. Another limitation is the inherent noise in EEG recordings; although preprocessing can reduce noise, residual artifacts may still affect feature extraction and model performance. Additionally, multimodal approaches that integrate EEG with other data modalities could improve the classification of different depression patterns. For future research, expanding datasets and applying explainable AI techniques may facilitate clinical adoption. Given the serious impact of depression on mental health, early and accurate detection is crucial to prevent long-term consequences.

Author Contribution

Rida Fatima: conceptualization, methodology, data curation, formal analysis, visualization, writing – original draft. **Amad Ud Din:** methodology, validation, writing – review & editing. **Amair Arsalan:** investigation, validation, writing – review & editing.

Conflict of Interest

The authors of the manuscript have no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability Statement

Data supporting the findings of this study will be made available by the corresponding author upon request.

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