European Journal of Computer Science and Information Technology, 14(5),1-19, 2026
Print ISSN: 2054-0957 (Print)
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Enhanced EEG Architectural Framework Signal for Health Care Depression Detection Management using Residue Number System

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doi: https://doi.org/10.37745/ejcsit.2013/vol14n5119 Published July 04, 2026

Citation: Oyinlola O.A., Olatunbosun L.O., Akinyemi O.S., Babatunde R.S., Gbolagade K.A. (2026) Enhanced EEG Architectural Framework Signal for Health Care Depression Detection Management using Residue Number System, *European Journal of Computer Science and Information Technology*, 14(5),1-19

Abstract; *Accurate depression detection is essential for timely intervention and treatment, current models leverage the rich spatial and temporal information embedded in EEG signals captured from the subjects. However, EEG signals are dynamic and needs large feature space. This oversight has significant implications for mental health diagnostics and patient outcomes, underscoring the importance of developing more effective computational models. Current deep learning models for depression detection using EEG signals have some limitations and these include the mutual exclusiveness of the temporal and spatial convolutions making it unable to rely solely on single feature extraction methods for effectively capturing of the patio-temporal characteristics of EEG data. Also, the EEG signals are highly dense and contain multiple channels, capturing such variations over multiple channels and over time is a challenge. Further, previous research failed to consider the multiple channel relationships of EEG signals at different times collectively. For the purpose of effective accuracy and precision, This study embraced the potential capability of Residue Number System (RNS) model for accuracy, sensitivity, and specificity to enhanced EEG based depression detection speed and accuracy network using Graph Convolutional Gated Recurrent Unit develop depression detection model that leverages the aforementioned limitations and methodological components for improved diagnostic accuracy The model achieves the accuracy came out to be 92.25%, the F1-score was 0.9266 and the sensitivity was 0.9483.*

Keywords: electroencephalogram (EEG) signals, residue number system (rns) model brain waves, notch filtering,

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INTRODUCTION

The discovery of electrical currents in the brain goes back to 1875 when British doctor Richard Caton who placed two electrodes on the scalp of a participant and thus captured brain activity in the form of electrical signals (Sanei & Chambers, 2013). In 1924, German neurologist Hans Berger interpreted these electrical activities and proposed the name "electroencephalogram" for the first time to introduce the signals in the human brain (Hamidreza et al., 2023) Major Depressive Disorder (MDD) is a known mental health problem that is categorized by symptoms like anxiety and insomnia. These symptoms usually result to self-difficulties which is a common global phenomenon as seen in COVID-19 pandemic. The diagnosis of the depressed person typically involves interviews and psychiatric scales like Psychiatric Questionnaire 9 (PHQ-9) and Beck depression Inventory (BDI) (Gijzen et. al., 2021). Also, detecting variations in brain activity of individuals with depression is a form of non-invasive technique where the abnormal behavior of neurotransmitters affects neural communication.

Researchers have evaluated the fluctuation of brain patterns using EEG (electroencephalogram) as clinical indicators for cognitive disorders, ischemic strokes, and other central nervous system diseases (Johnson et al., 2020). Also, this depression negatively downsize the neural activity of the brain of a patient (Khadidos et al., 2023). However, conducting specialized physician interviews is a time-consuming and labor-intensive process, while rating scale assessments are vulnerable to deception. On the other hand, EEG is not only non-invasive but promotes low data collection costs, providing high temporal resolution of brain activity (Johnson et al., 2020). However, there are some challenges regarding raw EEG signals: 1) EEG signals exhibit nonlinear dynamics and non-stationary behavior over time and are different for each participant, and 2) EEG recordings involve multiple channels and high sampling rates, resulting in large feature spaces (Khadidos et al., 2023). Thus, extracting informative features from raw EEG signals is challenging and as a result, there is a pressing need for a more objective and efficient diagnostic approach for depression. However, recent research has successfully employed two primary methodologies to detect depression using the signals collected from the EEG.

LITERATURE REVIEW

Electroencephalography (EEG) is a clinical screening technique that measures the electrical activity generated by brain neurons on the scalp as illustrated in figure 2.1. It is a powerful tool in 10 clinical neuro physiology as it can capture and reflect both normal and abnormal brain activity (Hamidreza *et a*l., 2023). A brain-computer interface (BCI) is a system that interprets signals collected from brain waves and responds accordingly. This system requires training of both the computer and the user. For example, users may learn to move a cup of water on a screen by imagining the movement of their left or right hand. During this process, specific brain waves are generated, enabling the computer to learn to understand and recognize user commands (Hamidreza *et al.*, 2023)

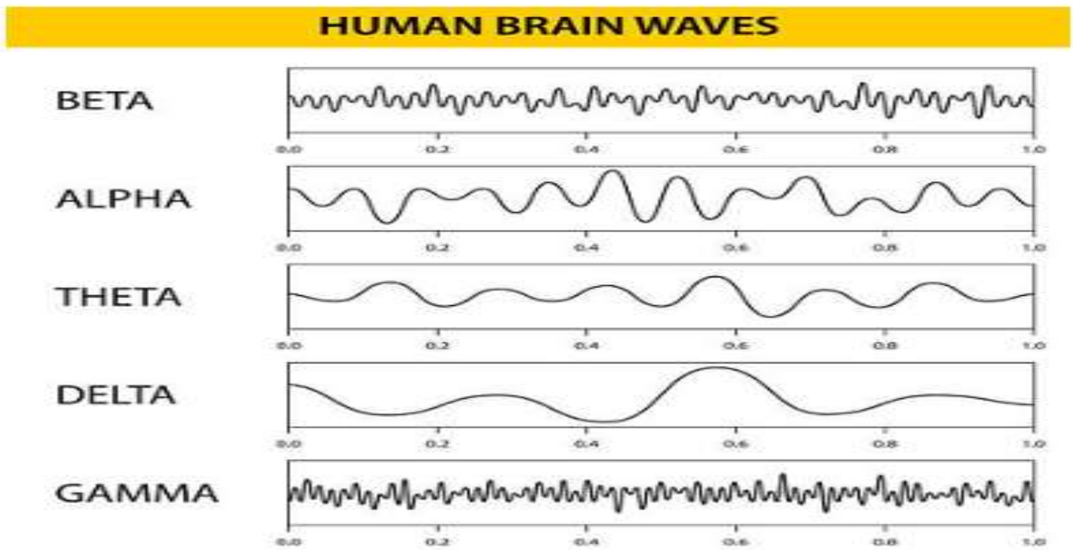

Figure .1: EEG Brain waves Architecture (Hamidreza *et al*., 2023)

The Brain Waves Neurological Disorders (ND) can be identified by visual examination of EEG signals. Well trained clinicians are very experienced with the general appearance of brain activity patterns in the EEG signals. The amplitudes and frequency of such signals alter when a person's state changes, such as awake and sleep. The features of the signal patterns also vary with age. EEG signals are made up of frequency bands ranging from low to high frequencies (0-60 Hz). Various brain activities and conditions can be determined using the extracted frequency patterns from collected oscillations (Hamidreza *et al.*, 2023). They are listed as follows: Delta waves (below 4 Hz) are correlated to deep sleep. They have a high amplitude, low frequency pattern. Theta waves (4–8 Hz) are common in old memories and dreaming states, it will also occur when subjects are experiencing anxious states, traumatic brain injury and epilepsy. The alpha band (8–13 Hz) usually represents relaxed and calm states. The amplitude of alpha waves is in the range of 10 to 50 mV. Beta (13-30Hz) waves have higher frequency but lower amplitude. It can happen when the subject is alert, aroused and focused. The gamma band (30-50 Hz) represents cognitive functions like creativity, perception and problem solving (Oyinlola *et al*., 2025).

The Recording of EEG **by** the International Federation of Electroencephalography and Clinical Neurophysiology came up with a standardisation for electrode placement termed the 10-20 electrode placement system in 1958 (Jasper, 1958). The electrode locations in EEG recordings are labelled based on the neighbouring brain areas: F (frontal), C (central), T (temporal), P (parietal/posterior), and O (occipital). Each letter is followed by odd numbers to indicate electrode positions on the left hemisphere and even numbers for those on the right (Hamidreza ***et al.,*** 2023) EEG signals are typically displayed as a two-dimensional matrix of real values that describe task-relevant brain potentials. The two dimensions represent the spatial and temporal properties of the EEG data. Spatial resolution refers to the placement of electrodes on the scalp, while temporal resolution refers to the sampling rate or the number of data points collected per second. The number of electrodes can range from 1 to 256, and sampling rates commonly range between 128 and 1000 Hz (Altaheri ***et al.*** 2023)

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Significant of the Study

This study is significant because it addresses the growing need for an accurate and objective method of detecting depression using EEG signals. Traditional diagnostic approaches largely depend on clinical interviews, subjective assessments, and self-reported symptoms, all of which may be influenced by personal bias, limited insight, or stigma. By developing a more reliable EEG-based depression detection model, this research contributes to the advancement of objective neurophysiological markers that can support

MATERIALS AND METHOD

Like most quantitative research this study commenced with data collection and data preprocessing. To do this, clean raw EEG data obtained from the source are used whereby noise and artifacts are eliminated through filtering, normalization among others. Based on spatial relationships between channels, a correlation matrix is derived and a fused spatial-temporal graph for data representation is included. The deep learning model is then proposed based on which the feature extraction with CNN layers in the spatial domain, and the LSTM layers in the temporal domain are involved, and the GNNs for learning both spatial-temporal features. The model is tested using cross-validation on a dataset of EEG signal and is capable of good performance. The model effectiveness can be evaluated by using the performance metrics consisting of accuracy, sensitivity, specificity, and F1-score. Finally, the results are compared to existing state-of-the-art approaches to highlight the improvements offered by this research.

Data Collection

The input to the system is an EEG dataset (EEG: Depression Rest Dataset) specifically collected for analyzing depression-related patterns. This dataset contains raw EEG signals that need further processing for feature extraction and classification. The EEG data was recorded using the 128-channel Amps 300 amplifier (Electrical Geodesics Inc., OR, USA) at a sampling frequency of 1000 Hz. The EEG data acquisition was conducted during the resting. Structural MRI data for the same participants were acquired at the University of Oklahoma Health Science Center (OUHSC) MRI facility using a GE MR750 scanner. The scans were obtained with GE's BRAVO sequence, with a field of view (FOV) of 240 mm and 180 axial slices per slab.

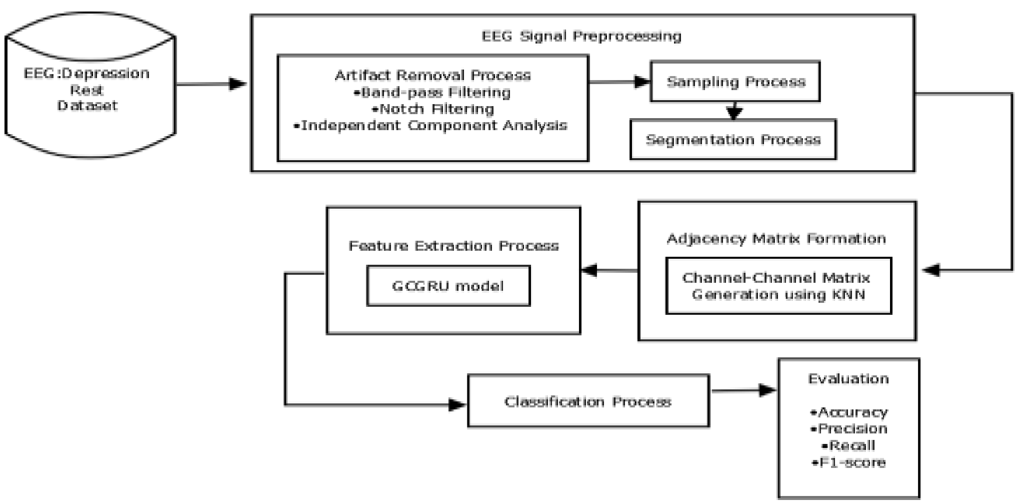
Preprocessing in EEGLAB: After the data acquisition, a band-pass filter (0.5–100 Hz) and a notch filter (58–62 Hz) were applied to remove noise. Noisy channels and artifacts (e.g., from eye blinks, muscle movements, or heartbeats) were identified and removed. Bad channels were replaced using interpolation, and the data was re-referenced to the average of all electrodes. The data was then sampled down to 250 Hz to reduce file size while keeping enough detail. No data segments were removed to ensure the continuity needed for later analysis.

EEG S
gnal Preprocessing

Artifact Removal Process: This step clear out any sorts of, for instance; eye blinks or muscle movements which are sometimes displayed as artifacts by employing certain methods like; band-pass filtering, notch filtering, and Independent Component Analysis (ICA).

Sampling Process: They enhance the signals or reduce the rate of the signals to a common sampling rate for all data.

Segmentation Process: The idea of continuous EEG is that signals are obtained continuously during EEG recording and therefore, the continuous signals can be segmented into smaller segments or time windows in order to help analysis and processing.



The EEG Architectural Framework for Depression Detection

Figure 2. Overall System Architecture of the Designed model

The Steps involved in the overall architecture of the proposed model has been explained and it is elucidated below:

Feature Extraction Process: The preprocessed EEG segments are next inputted into a GCGRU (Graph Convolutional Gated Recurrent Unit) model which extracts temporal spatial and frequency features from the given signals. This model integrates graph-based structures with temporal dynamics for enhanced feature extraction.

Adjacency Matrix Formation: Channel-Channel Matrix Generation using (KNN)**.** The between-channel relationship is represented using a graph-based adjacency matrix. The efficiency of the classification process depends on the applied indicators which include accuracy, precision, recalls and F1-score.

Classification Process: The extracted features from the GCGRU model are passed to a softmax classifier that categorizes the input EEG data as indicating depression or not, based on learned patterns.

Evaluation: The performance of the classification process is assessed using metrics such as accuracy, precision, recall, and F1-score. These metrics provide insights into the system's effectiveness and reliability in detecting depression.

EEG Recording Setup

The dataset used in this study involves EEG signals from 42 subjects: 21 participants diagnosed with mental disorders and 21 healthy controls. From this cohort of participants we have twenty participants categorized as Healthy Controls (HC), signifying they present no signs or history of Major Depressive Disorder (MDD). The other 22 participants are patients diagnosed with MDD, so the resulting dataset can be used to compare neural activity in healthy people and individuals with the disease. Every subject provided two runs of EEG recording which were under similar environment, which were named run-01 and run-02.

These sessions were designed to record stable field activity patterns. However, in the present study, only the data collected from the run-02 is assigned as the experimental data since the recordings selected are clear and noise free. The data from run-02 demonstrated significantly less noise and fewer disturbances compared to run-01, ensuring a more reliable foundation for subsequent preprocessing and analysis.

The EEG data was stored in two standard file formats commonly used in neuroscience research: **`.set` files and `.fdt` files** The format of both these files are text files which contain XML formatted specification. The `.set` files are used as a kind of labels, which consist of basic information about the EEG signals, including the sampling frequency, names, and order of the EEG channels, time length of signals, and signal type or experimental notes. This metadata puts the data in perspective so as to enable correct interpretation of the EEG data. On the other hand, the actual EEG signals are kept in the `.fdt` files because storing time-series data in forms such as bitmap consumes a lot of space, therefore the signals are in binary forms to allow efficient storage of the channels.

The results more understandable for the analysis, the raw EEG signals were extracted from these files using the MNE – is a special library for the electrophysiological data analysis which works in Python language. From this library, the compilation of the `.set` and `.fdt` file formats was facilitated making the data more analytical friendly. These raw EEG data were then, transformed into CSV (Comma-Separated Values) files for analysis. In these CSV files, a column is one of the 16 EEG channels (Fp1, Fp2, F3, and so on) and a row holds the signal values collected in different time instances which denote the dynamic neural activity during EEG session. This transformation not only simplifies data handling but also facilitates further preprocessing and feature extraction processes necessary for the study's objective of identifying neural patterns associated with depression

Band-pass Filtering:
This is another important method used in processing of EEG signals that is serving as a tool in extraction of essential frequency bands of the raw EEG signals. EEG is comprised of brain wave activities, which occur in a number of frequency bands that relate to a variety of mental processes and mood. They said that band-pass filtering enables the picking of specific frequency bands of interest and rejection of noise and artifacts outside these bands. This process means that it has possibilities of having only the particular frequency that might be of importance in the given analysis. In EEG analysis, the typical frequency bands of interest are:

1. **Delta (0.5–4 Hz)**: Associated with deep sleep.
2. **Theta (4–8 Hz)**: Linked to relaxation and drowsiness.
3. **Alpha (8–12 Hz)**: Common during wakeful relaxation, particularly with eyes closed.
4. **Beta (12–30 Hz)**: Associated with active thinking and problem-solving.
5. **Gamma (30–100 Hz)**: Linked to higher cognitive processing and sensory integration.

The **band-pass filter** allows signals to pass through only those frequencies within a defined range while attenuating frequencies outside of this range. Arithmetically, the filtering process can be calculated as follows:

$$y(t) = \int_{-\infty}^{\infty} x(\tau) \cdot h(t-\tau)d\tau \tag{1}$$

Where:

- x(t) is the original signal,
- h(t) is the impulse response of the band-pass filter,
- y(t) is the filtered output signal.

For practical purposes, the cutoff frequencies of the filter are set with regards to the band of interest (here 0.5–100 Hz for general signal analysis of EEG). By applying the filter, signals that fall outside the target frequency range are suppressed

Equation for Frequency Response

The transfer function $H(f)$ of a band-pass filter is typically defined as in equation (2):

$$\mathrm{H(f)} = \frac{1}{1+j\left(\frac{f-f_c}{B}\right)} \tag{2}$$

Where:

- f_c is the center frequency,
- B is the bandwidth, and
- j is the imaginary unit.

Band-pass filtering is essential for focusing on the frequencies that correspond to neural activity relevant to the depression detection while minimizing interference from noise sources or irrelevant frequencies.

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Notch Filtering:

Another important method in the EEG signal preprocessing that is notch filtering; it is aimed to eliminate the narrow-band interference mainly the power-line noise at the specific frequency. This type of noise originates from the electrical grid at the standard frequency of 50 Hz or 60 Hz depending on region and is very destructive to EEG signals if not well addressed. Notch filtering is a process of filtering out a particular frequency together with all those that are related to it by an integer multiplication factor and passing all the other frequencies intact. This is achieved by applying a filter with a very narrow bandwidth centered at the interference frequency. Mathematically, a notch filter is a type of band-stop filter, and its transfer function $H(f)$ is given by:

$$H(f) = \frac{f^2 + B^2}{f^2 + (f - f_0)^2} \tag{3}$$

Where:

- f_0 is the frequency to be attenuated (typically the power-line frequency, 50 Hz or 60 Hz),
- B is the bandwidth of the filter,
- f is the frequency of the signal.

This filter cuts down the power-line noise in the vicinity of f0 more or less effectively eradicating the interference but not the brain wave signals. An example is the 60 Hz notch filter that is commonly used in those areas that are served by 60 Hz power-line frequency. A typical preprocessing of EEG data involves notch filtering because the obtained data contains interference signals. It is particularly important in environments where electrical noise is prevalent, such as in clinical or laboratory settings.

Independent Component Analysis (ICA)

ICA is one of the robust computational techniques used in this study to decompose the EEG signal into the set of independent components. It allows to state the decomposition of artifacts like eye movements, muscular activity, or cardiac signal's origin in particular sources. Some of these components can then be selectively removed or attenuated by the researchers allowing only the true signal originating from the neurons of interest to be recorded. The consequence is a sample of EEG signal less interfered by the non-brain activity that makes the process of obtaining more accurate and credible information possible. The ICA model assumes that the observed EEG signals X are a linear mixture of statistically independent sources S, given by:

$$X = A.S \tag{3.1}$$

Where:
X is the observed signal matrix (n×t), with n channels (electrodes) and t time points.

- S is the source signal matrix (n×t), representing independent components.
- A is the mixing matrix (n×n), which combines the source signals linearly.

Primary aim of ICA is to find an estimator for S and A that makes elements in S as much as possible independent. This is achieved by finding a de-mixing matrix W, such that:

$$S = W.X \tag{3.2}$$

Here:

$$W=A^{-1}, \tag{3.3}$$

the inverse of the mixing matrix, transforms the observed signals X into the independent components S.

For EEG preprocessing, ICA is used in order to factorize the neural signals from artifacts. Components corresponding to artifacts for instances: eye blinks, movements of the muscles are recognized and excluded, and the cleaned signal returns:

$$X_{cleaned} = A \cdot S_{cleaned} \tag{3.4}$$

Where other techniques such as $S_{cleaned}$ fail in identifying artifact-related components. This process helps in improving the quality of the signal and also ensures that the features extracted are very appropriate for the neural activity. When using these two techniques simultaneously or sequentially, the quality of the EEG data is improved. Cleaner data not only facilitates better feature extraction but also supports more accurate classification and analysis in downstream tasks, such as diagnosing medical conditions or assessing cognitive states.

Sampling Process in EEG Signal Processing

This process of sampling is a critical feature for pre-processing EEG data to ensure that the signals are both representative and characterized by manageable noise levels and artifacts. In the research article, down sampling is used in an attempt to convert the high frequency of the sampling rate on the EEG recordings to a standard low frequency rate. Described change is necessary to enhance the aspects regarding the data flow processing but maintaining all the relevant characteristics of signals.

This entails lowering the numeric value of samples gathered in a second by picking every N^{th} sample from the original signal. The factor N is called the down sampling factor, and can be calculated as:

$$N = \frac{f_{original}}{f_{target}} \tag{4}$$

Here:

- $f_{original}$ is the original sampling frequency (1000 Hz),
- f_{target} is the desired sampling frequency (500 Hz),
- N is the downsampling factor.

Low pass filters are first used before conducting the downsampling action on the signal. The first filtering step is a common place to apply this since failure to do this would result in aliasing due to the reduced sampling rate distorting some of the high frequency components. The low-pass filter removes frequency components above the Nyquist frequency, which is half the target sampling rate, ensuring that the resampled signal accurately represents the original data within the desired frequency range and the equation used to calculate this frequency is given below:

$$f_{Nyquist} = \frac{f_{target}}{2} \tag{4.1}$$

Such filtering is required before the down sampling to eliminate aliasing which is a condition where high frequency signals are sampled and passed as low frequency signals. The low-pass filter smooth the signal by suppressing components above $f_{Nyquist}$ ensuring that the downsampled signal accurately represents the original within the target frequency range. In this case, the gains from the sampling process, especially in a process of down sampling, are numerous. First, it ensures uniformity across datasets, making it possible to compare EEG signals from different participants under consistent conditions. Second, since down sampling helps to reduce the data size, the computational load is greatly reduced and the patterns of neural activity contained within the EEG signals can be analyzed accurately and without manipulation. The resulting downsampled signal, $x_{resampled}[n]$ is expressed as:

$$x_{resampled}[n] = x[n \cdot N] \tag{4.2}$$

Where as:

- x[n] is the original discrete signal,
- N is the down sampling factor,
- n denotes the index of the data points which are resampled.

In this work, the sampling process is again involved and in particular down sampling is key in providing a standard EEG signal that can go through the next phases as segmentation, feature extraction and classification. By focusing on the most relevant aspects of the signal and eliminating redundant data points, the process ensures the reliability and efficiency of the analysis.

Algorithm for feature extraction process

Input: electrodes.tsv, k, threshold (thr), S
Output: $A_S \in \mathbb{R}^{16\times 16}$
1. For S in $1:42$:
2. Initiate electrode coordinates matrix $C = \{C_1 \dots C_{16}\} \in \mathbb{R}^{16\times 3}$
3. For C in $1:16$:
   a. For each dimension d in C in $1:3$:
   b. $D(i,j) = sqrt(sum((C_{i[d]} - C_{j[d]})^2$ #Compute pairwise distance Euclidean distance between all pairs of channels $i,j \in [1,16]$
   c. Compute $I[i] = argsort(D(i,:))[:k+1]$ #Get k nearest neighbours of
   d. the channel i
   e. For each neighbour in $I[i]$:
   i. If $D(i,j) < thr$:
   ii. Assign $A_S[i,j] = D(i,j)$
   iii. Normalise A_S # to get 0 and 1 values of edges
   iv. End
   f. End
4. End
5. End
End

Classification process
The classification process utilizes a unified brain network to model spatial and temporal patterns in EEG data for depression detection. By structuring EEG signals into graphs with channels as nodes and inter-channel relationships as edges, the method captures complex brain dynamics. The GCGRU model integrates graph convolution and temporal analysis to extract spatio-temporal features, while attention-based pooling highlights critical EEG channels. These refined features are used to classify individuals as either healthy controls or having major depressive disorder, providing a robust framework for understanding neural activity differences.

Spatio-Temporal Analysis Using GCGRU
The classification process begins with extracting spatio-temporal features from the unified brain network using the GCGRU model. The unified brain network $G_{st} = (C, As, Tensor)$ is constructed for each subject, where C represents EEG channels (nodes), A_S denotes the adjacency matrix, and the tensor captures the time-dependent channel features. This representation effectively encodes spatial and temporal information, enabling a robust foundation for feature extraction.

Spatial features are initially derived from the adjacency matrix and the tensor data through graph convolution layers. The residual-based graph convolution operation generates feature maps for each time step t as:

$$F_{X_{st}} = cat(f_1(X_{st}), f_2(X_{st})) \tag{5}$$

where $f_1(X_{st})$ and $f_2(X_{st})$ are the outputs from two graph convolution layers. These features, $F_{X_{st}}$, describe the inter-channel spatial relationships within the EEG data. To model temporal variations, the extracted spatial features $F_{X_{st}}$ are fed into the GCGRU cell, which integrates graph convolution operations within the update mechanism of the GRU. The GCGRU cell calculates the temporal hidden state h_t as:

$$h_t = GRU(F_{X_{st}}) \tag{5.1}$$

This mechanism captures the temporal correlations in EEG data across brain regions, ensuring that the network accounts for the evolution of signals over time.

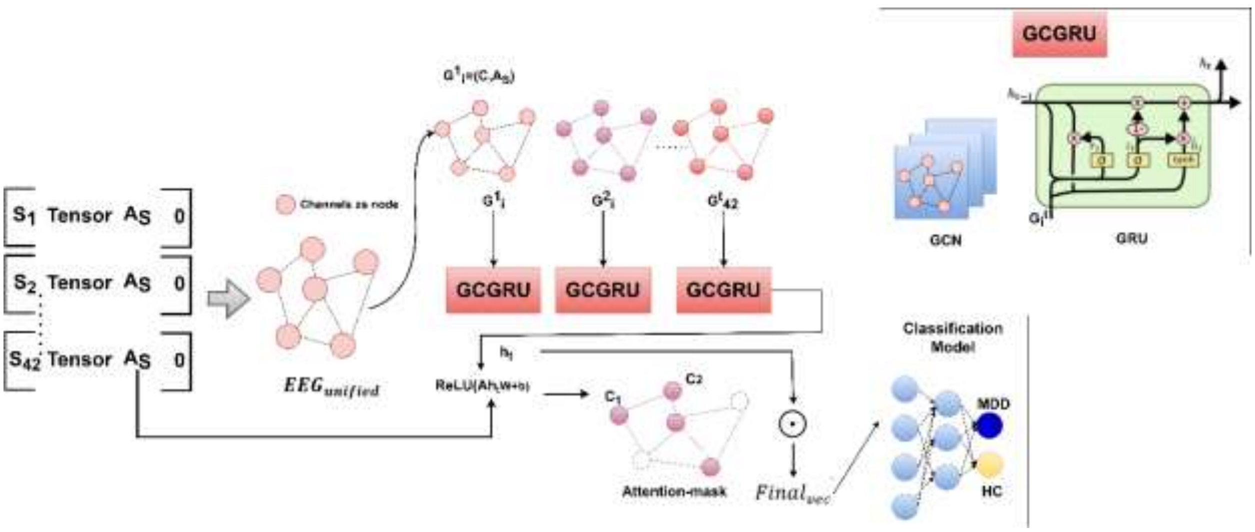

Figure 3.: Framework for Depression Detection using the GCGRU Model

The above given figure 3. outlining the depression classification using EEG data including constructing unified brain networks, extracting Spatio-temporal features and Classification. The workflow is detailed as follows:

Input Representation: Unified brain networks are constructed using preprocessed EEG data obtained from 42 subjects, S1, S2 …S42. Both of them are described by an adjacency matrix AS, which determines the connections between the channels within the network; tensors that capture the temporal dynamics of EEG signals; and the channels considered as nodes of the given graph. This unified representation, referred to as EEG unified, forms the foundation for subsequent graph-based feature extraction.

Unified Brain Network Construction:
The unified brain network is obtained by integrating the subject-wise adjacency matrices and features collectively into one framework. This allows the modeling of spatial relationships between EEG channels (nodes) and the temporal evolution of signals over time.

Feature Extraction Using GCGRU:
The unified brain network is processed through multiple layers of Graph Convolutional Gate Recurrent Units. Each GCGRU layer combines the capabilities of Graph Convolutional Networks and Gate Recurrent Units:

- **GCN** is used to model spatial dependencies, extracting features based on the adjacency structure of the graph.
- **GRU** captures temporal correlations across time steps, retaining essential information about the evolution of EEG signals. These layers operate sequentially on the brain networks (G1, G2, ..., G42) to generate intermediate hidden states (h_t), encapsulating spatio-temporal relationships.

Attention Mechanism: The output from the GCGRU layers undergoes an attention pooling mechanism. This step identifies the most critical EEG channels and time steps by assigning weights to nodes (channels) based on their importance. An attention mask is applied to refine the features, focusing on key regions of the brain that contribute most to depression classification.

Feature Aggregation and Max-Pooling: The attention-pooled features are subjected to max-pooling to extract the top indices (C1, C2) of the most significant activations. This operation reduces the feature dimensionality while retaining the most informative elements of the representation.

Final Vector Representation: The refined feature vector ($Finalvec$) combines the critical spatio-temporal and attention-weighted information, serving as the input to the classification model.

Classification: The final feature vector is feed into a fully connected layer, where softmax is applied to output likelihood of a subject belonging to either the MDD or more likely the HC category. The classes obtained from the classification process are the depression probability of each subject.

It is clear from this figure 3.3, it is dealing with the pipeline from raw EEG data to depression prediction, focusing on the fusion of spatial and temporal aspects through GCGRU and attention mechanisms. It showcases how the model leverages graph-based learning to capture the intricate relationships in EEG data for precise classification.

Attention-Based Pooling and Classification
The next step is to use attention to select dominant EEG channels in predicting BCI mapping, comparing them to spatial-temporal features as nodes. The attention scores for each node are computed as:

$$S_c^{node} = ReLU\left(A_s h_t W_{pool} + b_{pool}\right) \qquad (5.2)$$

where W_{pool} and b_{pool} are the pooling weights and biases, and $A_s h_t$ is the final activations of the GCGRU model. Max-pooling is applied to select the indices of the highest activations, given by:

$$Top_{indx} = argmax(S_c^{node}) \qquad (5.3)$$

Using the selected indices, the final feature vector is computed through attention masking as:

$$Finalvec = \sum_{n=1}^{Top_{indx}} mask_{Top_{indx}} h_t \quad (5.4)$$

The vector $Finalvec$ forms the basis for the critical features for the classification of depression. This vector is passed through a fully connected layer to compute the depression probability using the softmax function:

$$P(y|X) = softmax\left(W_f Finalvec + b_f\right) \quad (5.5)$$

where W_f and b_f are weight and bias of the classification layer. The softmax function outputs the probability distribution over the classes (MDD and HC).

This classification framework ensures the model effectively identifies key spatial and temporal EEG patterns, enabling accurate depression prediction. The performance of this process is evaluated using accuracy metrics and optimized through fine-tuning techniques.

Algorithm 3.2: Algorithm of the entire proposed framework

Input: Subjects S
Output: MDD, NC labels (depression classification).

1. For each subject ID in $S = 42$:
   a. Load and store the electrode file containing 16-channel information.
   b. For channels (C) in $1:16$: # spatio-temporal EEG data preprocessing
      i. Algorithm 1 is initiated
      ii. End
   c. Construct the adjacency matrix A_s using KNN method
   d. If 0<BDI<17, then #Extracting the labels of the subject based on BDI scores.
   e. Set Label $L_S = 0$ # HC
   f. Else
   g. Label $L_S = 1$# MDD
   h. End
   i. Initialize a Unified brain network # spatio-temporal feature fusion
   j. Append the Unified brain network to $empty\_list$.
2. End For
3. For i in $EEG_{unified}$:
   a. Considering the nodes as Channels in C and Edge features as the unified brain network
   b. For epochs in $1:50$:
      i. Train the model $GCGRU(S_i, A_{S_i}, T_{seg_j,C,f,t}, y_i)$#GCGRU model
      ii. Generate the Spatio-temporal feature embedding h_t
4. End
5. Apply max-pooling to h_t and $A_{s,t}$ # embeddings from the last GRU at t # t varies for each subject
6. Generate the scores of nodes (channels) Sc_{node}.
7. Sort and generate the indices of top channels with high scores (Top_{indx}).
8. Generate the final vector representations as $Final_{vec} = mask(Top_{indx}) \odot h_t$
9. Classification using the embeddings.

The algorithm describes the process for classifying subjects into MDD and HC using spatio-temporal EEG data and a GC-GRU model. The method integrates spatio-temporal preprocessing, adjacency matrix construction, and feature embeddings into a unified framework for robust depression classification. For each subject S, the electrode file containing 16-channel spatial information is loaded. Spatio-temporal preprocessing of EEG data is initiated using Algorithm 1 to prepare the signals for feature extraction. An adjacency matrix A_s is constructed for the subject using the KNN method, which captures spatial relationships among the EEG channels. Based on the subject's Beck Depression Inventory (BDI) scores, labels are assigned: Label = 0 for healthy controls (BDI scores between 0 and 17) and Label = 1 for MDD (BDI scores ≥ 17). Next, a Unified Brain Network is initialized, combining spatial and temporal features into a single framework. The network is appended to a list, which accumulates such representations for all subjects. For each subject's unified network, EEG channels are treated as nodes, and their relationships are encoded as edges. Using a GC-GRU model, spatio-temporal embeddings h_t are generated over 50 training epochs, with the model incorporating both graph-based spatial dependencies A_s and temporal sequences $Tseg$. Max-pooling is applied to the final embeddings h_t and adjacency matrix A_s,t to summarize critical features at each time step t . $Snode$ values are then calculated for each node, to produce scores for the relative importance of the channels. The channels which are ranked are identified using the indices $Topindx$ and by masking the weights with $Topindx$, a final vector representation called $Finalvec$ is generated. This vector then passes to a classifier to decide on the subject type, that is either MDD or HC. This framework effectively combines spatial, temporal, and neural connectivity patterns to achieve accurate depression classification.

Models Evaluation

The following parameters will be needed for the implementation of the depression detection in the EEG signals using graphical deep learning as illustrated in **Table 5.1**. The experiment will be carry out on google colab pro for the analysis of feature extraction and classification model for the depression detection. This section will presents a comparative analysis of the model's performance against the existing methods after simulations and it will showcase the effectiveness of the GCGRU model

Table 5.1: Experimental Setup of Collab

Parameter	**Value**
GPU	Nvidia Tesla T4
GPU VRAM	15 GB
RAM	51 GB
Optimal Hidden Dimension	64
Subjects	42
EEG Segments	490 (232 MDD, 248 HC)
Batch Size (GCGRU)	40 EEG clips
Epochs (GCGRU)	100
Dropout Probability	0.7
Loss Function (GCGRU)	Binary Cross-Entropy with Logits

Performance Evaluation Metrics

In the context of the designed GCGRU model for detecting depression using EEG signals, performance evaluation metrics will be used to determine the designed model's classification accuracy, stability, and consistency. The specific measures like Accuracy, Precision, Recall, F1-score and the RoC Curve will be used to measure the probability of diagnosing individuals with MDD against Healthy Controls. The metrics to be considered for evaluations are explained below:

(i.) **Accuracy:** This represent an index of the general performance of the GCGRU model on differentiating the MDD and HC EEG signals. It will measure the ratio of correctly classified segments to the total number of EEG segments.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

(ii.) **Precision:** This will measure the efficacy of GCGRU model in accurately classifying MDD instances with minimum inclusion of HC instances. It is particularly important to minimize false alarms in depression detection. The formula is:

$$Precision = \frac{TP}{TP + FP}$$

(iii.) **Recall:** It is also referred to as Sensitivity or True Positive Rate; Recall will calculates the ratio of the actual MDD segments detected by the model. It focuses on minimizing the number of undetected MDD cases.

$$Recall = \frac{TP}{TP + FN}$$

(iv.) **F1-Score:** This will consider both Precision and Recall rates when evaluating the GCGRU model for depression detection in detail. It is especially useful for imbalanced datasets, as it penalizes extreme disparities between Precision and Recall. The formula is:

$$F1 - Score = 2x \frac{Precision \times Recall}{Precision + Recall}$$

(v.) Receiver Operating Characteristic **(RoC)** Curve: The RoC Curve will be used to analyze the trade-off between the GCGRU model's sensitivity (Recall) and specificity across different classification thresholds. The RoC will enable us to plots the True Positive Rate (TPR) against the False Positive Rate (FPR) and to visualize the model's discriminative ability. The False Positive Rate (FPR) is calculated as:

$$FPR = \frac{FP}{FP + TN}$$

The Area Under the Curve (AUC) summarizes the RoC Curve into a single value, with higher AUC values indicating superior model performance in distinguishing MDD from HC. For depression detection, the AUC close to 1 demonstrates the model's robustness and reliability.

(i.) **Where the performance monitors such as TP, TN, FP and FN can be explained as below:**
(ii.) **True Positive (TP):** A **True Positive** refers to a situation where the model correctly identifies an EEG segment as belonging to the MDD class.
(iii.) **True Negative (TN): A True Negative** occurs when the model correctly classifies an EEG segment as belonging to the HC class.
(iv.) **False Positive (FP):** A **False Positive** happens when the model incorrectly predicts an EEG segment as MDD, even though it truly belongs to the HC class.
(v.) **False Negative (FN):** A **False Negative** occurs when the model incorrectly predicts an EEG segment as HC, even though it truly belongs to the MDD class.

Model Testing
To enhance scalability and clinical applicability after the implementation of the models, the five metrics will be used to determine the flexibility of the model, the efficient, and low-in computational load on google colab environment.

Summery, Conclusion and Research Gaps Identified

Limitations of Existing Combined CNN–LSTM Models
Although CNN–LSTM hybrid models consistently outperform single-model architectures, their effectiveness is heavily dependent on the quality of input data, which varies considerably across studies. Furthermore, CNN-based EEG models—including CNN, 1D-CNN, and 2D-CNN remain limited in their ability to fully represent the complexity of EEG signals, particularly when it comes to capturing long-range temporal dependencies and spatial relationships. These limitations highlight the need for improved modeling strategies that can better integrate both temporal and spatial EEG characteristics.

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