Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 32s (2025)
https://www.jneonatalsurg.com

Advanced Time Series Analysis of EEG Signals for Major Depressive Disorder Detection through an Attention Augmented Residual Convolutional Neural Network

Anjan Kumar B S[1], Dr. H N Suresh[2], Dr. Ranjitha S[3]

[1]Research Scholar, Department of Electronics and Instrumentation, Bangalore Institute of Technology, Bengaluru – 560004,
Email ID: anjan.cmp@gmail.com
[2]Professor, Department of Electronics and Communication, AMC Engineering College, Bengaluru-560083,
Email ID: drsuresh.narayanagowda@amceducation.in
[3]Software Engineer, Bengaluru,
Email ID: ranjithaneha@gmail.com

Cite this paper as: Anjan Kumar B S, Dr. H N Suresh, Dr. Ranjitha S, (2025) Advanced Time Series Analysis of EEG Signals for Major Depressive Disorder Detection through an Attention Augmented Residual Convolutional Neural Network. *Journal of Neonatal Surgery*, 14 (32s), 1731-1740.

ABSTRACT

The Major Depressive Disorder (MDD) has been regarded as a serious and prevalent illness that affects functional frailty, but its precise symptoms are unknown. Manually detecting MDD is therefore a difficult and individualised task. Electroencephalography signals have demonstrated promise in supporting diagnosis; nevertheless, more development is needed to increase precision, clinical usefulness, and effectiveness. In this paper, Advanced Time Series Analysis of EEG Signals for Major Depressive Disorder Detection through an Attention Augmented Residual Convolutional Neural Network (TSA-EEGS-MDDD-AARCNN)is proposed. Initially, the signals are collected from EEG Psychiatric Disorders Dataset. Then, the input signals are fed into preprocessing stage. In pre-processing, Regularized Bias-Aware Ensemble Kalman Filter (RBAEKF) is used to remove the noise and artifacts in electroencephalography signal. After that, the pre-processed data are given into Attention Augmented Residual Convolutional Neural Network (AARCNN) for Major Depressive Disorder Detection as normal and Major Depressive Disorder. After that a channel-selection strategy, consisting of three steps, is applied to eliminate redundant channels utilizing Lotus Effect Optimization Approach (LEOA).Then effectiveness of the proposed approach is compared with other existing approaches. The proposed technique attains 16.28%, 30.78% and 25.29% higher accuracy and 19.45%, 20.22% and 22.28% higher precision comparing with existing techniques such as an automated detection of most depressive diseases with electroencephalography signals: a time series categorization utilizing DL (AD-MDD-EEGS-DL), Decision Support Scheme For Most Depression Detection Utilizing Spectrogram and CNN with electroencephalography signals (DSS-MDD-CNN-EEGS) and End-To-End DL Method for Electroencephalography - derived major depressive disorder categorization (ETE-DL-EEG-MDDC) respectively.

Keywords: *Attention Augmented Residual Convolutional Neural Network, EEG Psychiatric Disorders Dataset, Regularized bias-aware ensemble Kalman filter, Lotus Effect Optimization Algorithm, Major Depressive Disorder.*

1. INTRODUCTION

The quality of life is significantly impacted by mental health issues from childhood through teenage years and adulthood [1]. Mental illnesses account for 30–40% of continual sick leave with cost about 3% of GDP, making them one of the main causes of disability worldwide, but particularly in western nations. Unipolar depression, commonly referred to as MDD, is one of the major common mental health circumstances [2]. Because suicide is more likely in those with depression, it ranks ninth in terms of both disability and death [3].In order to diagnose depression, psychiatrists typically analyse patients' questionnaires or ask about their symptoms, thoughts, feelings, and behaviour patterns. A popular technique for recording the electrophysiological dynamics of the brain caused by neural activity in real time is the electroencephalogram (EEG), which enables the examination of cognition, brain function or malfunction, and possible indicators of mental illnesses [4]. Several sensors, or electrodes, are positioned on various parts of the scalp in a conventional EEG. It has been shown to be useful in diagnosing diseases related to the nervous system, cognitive psychology, and psychophysiology [5].

The existing detection process in Major Depressive Disorder (MDD) is often time-consuming, costly, and may not always identify the most informative symptoms for each patient. Traditional methods may be inefficient and invasive, posing challenges to timely and accurate detections. Also the detection of MDD remains a significant challenge due to the limitations of existing diagnostic methods, which are often subjective and reliant on clinical interviews or self-reported questionnaires. These drawbacks in the existing method inspire us to implement this study.

The novelty of the proposed TSA-EEGS-MDDD-AARCNN approach lies in its combination of several innovative techniques for exploiting EEG signals to detect MDD. In order to effectively eliminate noise and artefacts from the raw EEG signals and guarantee the quality of the data for further analysis, this method integrates an RBAEKF in a unique way. The technique then makes use of an AARCNN, which improves MDD detection by utilising residual connections to increase learning efficiency and attention mechanisms for selective focus on significant features. After that, the LEOA is used to ensure that only the most informative channels are used for MDD identification, a three-step channel-selection is also added to find and remove duplicated channels.

The important contributions of this are abridged below:

- The Advanced Time Series Analysis of EEG Signals for Major Depressive Disorder Detection through an Attention Augmented Residual Convolutional Neural Network (TSA-EEGS-MDDD-AARCNN) is proposed in this segment.
- Developing a Regularized bias-aware ensemble Kalman filter method for removing the noise and artifacts in EEGPsychiatric Disorders signal.
- The Attention Augmented Residual Convolutional Neural Network method including of various numbers of dropout layers, convolutional layers, max-pooling layers and activation functions it detecting the Major Depressive Disorder Detection as normal and Major Depressive Disorder.
- Then Lotus Effect Optimization Algorithmis used as channel-selection approach, which includes three channel-selection processes, is performed to leave out redundant channels.
- The proposed TSA-EEGS-MDDD-AARCNN approach is likened with existing techniques like AD-MDD-EEGS-DL, DSS-MDD-CNN-EEGS, and ETE-DL-EEG-MDDC respectively.

The paper arranges itself as bellow: Section 2 covers the literature survey, Section 3 discusses the proposed section, Section 4 presents the result and discussion, and Section 5 proves the conclusion of the paper.

2. LITERATURE SURVEY

Several research works presented in the literatures were based on Major Depressive Disorder Detection utilizing deep learning; few of them were reviewed here,

In 2022, Rafiei, A., et.al, [6] have presented an automated detection of MDD with electroencephalography signals: a time series categorization utilizing DL. It presents the automatic detection of major depressive disorder utilizing deep neural network framework and EEG data was the main emphasis. First, a customized inception time model was used to identify MDD patients using raw 19-channel EEG signals. After that, redundant channels were eliminated using a channel-selection approach that consisted of three steps. It provided higher accuracy and lower precision.

In 2022, Loh, H.W., et.al, [7] have suggested a decision support scheme for MDD utilizing spectrogram with CNN and electroencephalography signals. It presents a Convolutional neural networks (CNN) and spectrogram images served as the basis for the unique DL model. In order to create spectrogram images of both healthy people and MDD patients, the electroencephalography signals were first exposed to the Short-Time Fourier Transform (STFT). Following that, the Convolutional neural networks approach was fed these spectrogram images in order to automatically identify MDD patients and healthy participants. It provided high precision and low recall.

In 2023, Xia, M., et.al, [8] have presented an end-to-end DL approach for EEG-based MDD categorization. In this suggested paper, an end-to-end integrated Deep Learning approach was presented to categorize major depressive disorder patients with healthy controls using resting-state ECG data. After using a multi-head self-attention method to automatically learn the possible connectivity relations between electroencephalography channels, the model used a parallel two-branch Convolutional neural networks module to extract higher-level features before a fully connected layer completed the classification.It provided high recall and lower accuracy.

In 2023, Khadidos, A.O., et.al, [9] have suggested a computer aided detection of Major Depressive Disorder utilizing EEG signals. The suggested paper has taken into consideration two datasets: the public and private datasets. Depression affects Detrended Fluctuation Analysis as well. Therefore, the model can serve as a useful tool for depression diagnosis. The study demonstrates that depression impacts of the brains temporal region because it detected MDD with a high degree of accuracy utilizing only temporal channel electroencephalography data and the identical set of variables and classifiers in each the private as well as public datasets. It provided high precision and low recall.

In 2023, Bashir, N., et.al, [10] have suggested a ML framework for detection of MDD utilizing non-invasive electroencephalography signals. The suggested paper used a variety of ML approaches as well as one DL strategy to present an electroencephalography–derived screening of Major depressive disorder. Prior research on electroencephalography-derived Major depressive disorder decoding had mostly focused on a small number of characteristics. In addition to more thorough feature-based electroencephalography analysis, thorough comparisons of various methodologies were required. It provided higher accuracy and lower precision.

3. PROPOSED METHODOLOGY

Major Depressive Disorder (MDD) is a frequent mental health circumstance that has become widespread globally and is associated with abnormalities in the brain's anatomical and functional connections. Effective treatment for MDD requires early diagnosis, which is both essential and challenging. The block diagram of proposed TSA-EEGS-MDDD-AARCNN is shown in figure1,

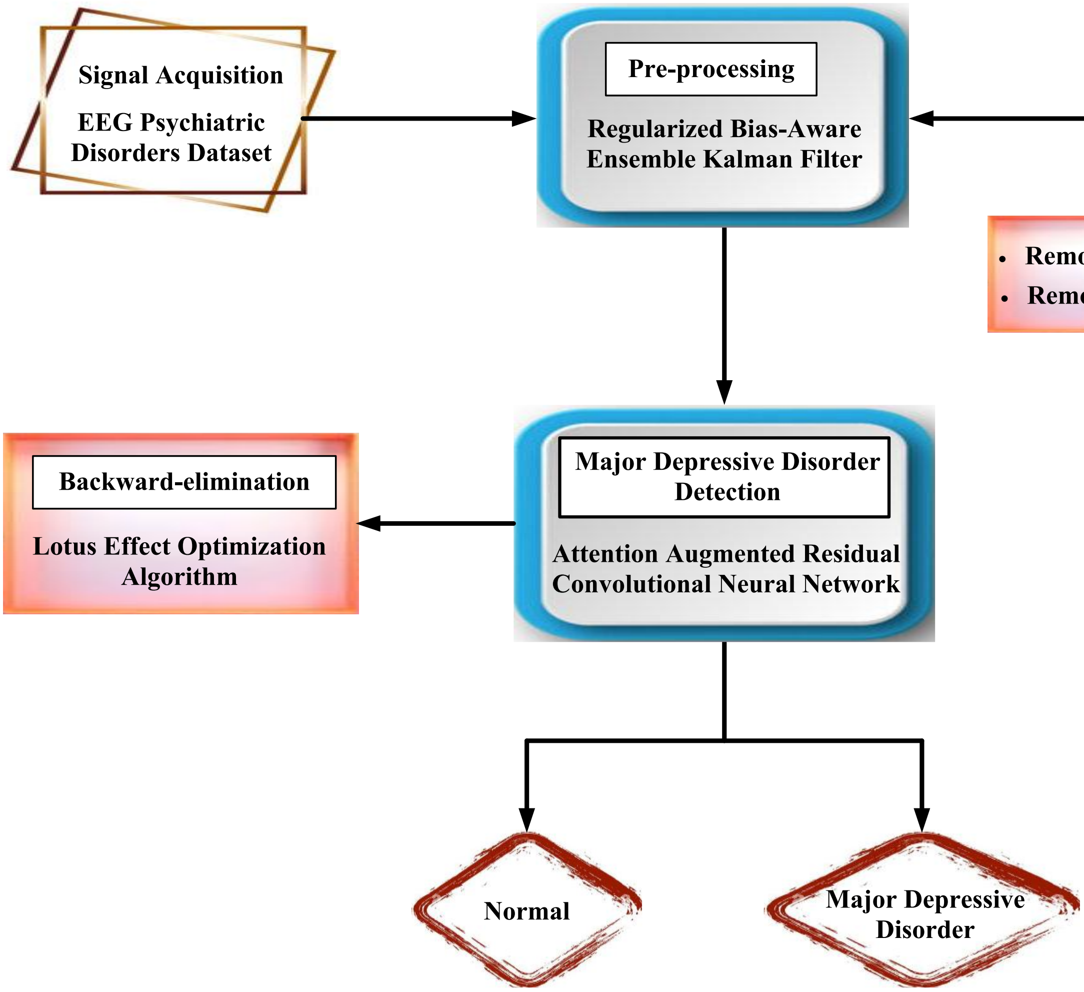

Figure 1: Block Diagram of the Proposed TSA-EEGS-MDDD-AARCNN System

3.1 Signal Acquisition

The input signals are collected from EEG Psychiatric Disorders Dataset [11]. A psychiatric disorder is a mental illness that significantly alters your thoughts, feelings, and/or behaviour, increasing the risk of distress, mortality, or loss of freedom. EEG recordings from people with a range of mental disorder, including MDD, schizophrenia, anxiety, and bipolar disorder, are commonly included in the EEG Psychiatric Disorders Dataset. Both raw and preprocessed EEG signals obtained from several electrodes positioned on the scalp in accordance with accepted electrode placement schemes, such as the 10-20 or 10-10 system, are frequently included in these datasets. Different states, such as resting (eyes open or closed) or performing particular cognitive or affective tasks, may be used to record the data.

3.2 Pre-processing using Regularized Bias-Aware Ensemble Kalman Filter (RBAEKF)

The Pre-processing utilizing Regularized Bias-Aware Ensemble Kalman Filter [12] is discussed in this part. The aim of RBAEKF is to remove the noise and artifacts in EEG signal that needs to be eliminated. By using an ensemble approach and regularization, it stabilizes estimation and improves reliability. The RBAEKF ensures that the alignment can allow the relationship between physiological responses and mental states to be well established. The filter becomes reliable as well as effective in a variety of situations due to its regularisation, which also helps to increase convergence rates. It eliminated the unnecessary data and transformed the source codes into relevant values calculated as given in equation (1),

$$L(\psi_l)=\left\|\psi_l-\psi_l^h\right\|^2_{E_{\psi\psi}^{h-1}}+\left\|a_l-f_l\right\|^2_{E_{ff}^{-1}}+\gamma\left\|d_l\right\|^2_{E_{dd}^{-1}}\text{'}\ for\ l=0,....,o-1 \tag{1}$$

Here, $\|\cdot\|^2_{E^{-1}}$ represent the operator, a represents the data size, f denotes the noisy signal data, E^{-1} represent the semi-positive matrix, γ denotes the hyper parameter, ψ_l denotes the variable parameter and l denotes the ensemble number. If, for every ensemble member, an analysis value minimizes the regularized bias conscious cost function. The alignment allows for the obvious establishment of the relationship between physiological responses and cognitive processes. Throughout the data gathering process, maintaining data integrity and making sure all signals are calibrated and operating as intended are essential as given in equation (2),

$$d_l^c \approx d_l^h + L^h O\left(\psi_l^c-\psi_l^h\right) \tag{2}$$

Here, d_l^h represent the intended variable, L^h represent the wavelength of signal, O represents the sampling rate, and l denotes the ensemble number. It is also essential to prepare the gathered data for analysis. It is significant that the minimization issue becomes quadratic as a result of linearization as given in equation (3),

$$\psi_l^c=\psi_l^h+M\left[\left(\mathrm{I}+L^h\right)\left(f_l-a_l^h\right)-\gamma E_{ff}E_{dd}^{-1}L^h d_l^h\right] \tag{3}$$

Here, M denotes the linearization value, I signifies the bandwidth value, and γ denotes the hyper parameter. By using RBAEKF, remove the noise and artifacts from the input data. After that, the pre-processed EEG signal data is given into detection process. The preprocessed data is given into detection phase.

3.3 Major Depressive Disorder Detection using Attention Augmented Residual Convolutional Neural Network

In this section, the Major Depressive Disorder Detection using Attention Augmented Residual Convolutional Neural Network (AARCNN) [13] is discussed. The AARCNN is used to detect Major Depressive Disorder as normal and Major Depressive Disorder. Residual learning promotes greater generalization by maintaining important features across layers, which enhances accuracy and resilience, especially when dealing with noisy data. Then the feature fusion layers combine features from various layers to capture complex data patterns and relationships. The Classification Layer, entirely correlated layers and a softmax activation function, produces the last event categorization results, determining whether thedisorder. The convolutional layer to detection is calculated as given in equation (4),

$$K_0=Conv(p_d) \tag{4}$$

Where, K_0 denotes the time series, $Conv$ is the convolutional layer, p_d is the detected events. It has been demonstrated that AARCNNcan function well with multidimensional time-series data of varying lengths. The AARCNN can automatically extract pertinent patterns from both short and large time series to this module, which contains filters of various lengths. Then the weight matrix of detection is calculated in equation (5),

$$\hat{\varpi}^{k_{g,m}}=soft\max_{2d}(\varpi^{k_{g,m}}) \tag{5}$$

Where, $\hat{\varpi}^{k_{g,m}}$ denotes the analysing the weight matrix, $soft\max_{2d}$ applying Softmax function to a matrix of detection. Then calculate the detection output value as given in equation (6),

$$\varpi_{w.s}^{k_{g,m}}=\left(\frac{1}{\sqrt{S_D}}\right)(D_{g,m}\cdot H_{g,m}+D_{g,m}\cdot k_{n-k}^D+D_{g,m}\cdot m_{n-k}^D) \tag{6}$$

Where, $\varpi_{w.s}^{k_{g,m}}$ denotes the detection of output value, S_D is the detection of signal value, $D_{g,m}$ represents the MDD classes, $H_{g,m}$ is the input feature of spatial size, k_{n-k}^D is the learnt positional encodings for relative height, m_{n-k}^D is the number of frame locations encodings for relative height. Finally, theAARCNN for the Major Depressive Disorder Detection has been done. Major Depressive Disorderis detected normal and Major Depressive Disorder.

3.4 EEG Channel Selection

After developing anAARCNN model that is both reliable and effective in classifying people with 19 channels, the goal is to investigate the potential for classification using fewer channels.They are useful for identifying correlated, duplicate, and redundant information and are rather quick and cheap to compute.Multicollinearity, particularly when a mixture of features may improve the entire performance of the method, is not detectable by these methods. As explained in the sections that follow, it has used three complementing feature selection procedures to identify the major successful channels.

3.4.1 Mean Absolute Difference (MAD)

At the initial stage of feature selection, it computed the Mean absolute difference for every channel of every participant'selectroencephalography signals. This technique calculates the absolute difference between a channel's data and the mean value as given in equation (7),

$$MAD_j = \frac{1}{o}\sum_{k=1}^{o}\left|Y_{jk} - \overline{Y}_j\right| \tag{7}$$

Where, Y_{jk} represents the k^{th} signal value of the j^{th} channel, $\overline{Y}_j$ represents mean value of j^{th} channel, and o represents the amount of signal values. The absence of the square in the former is the primary difference between the variance threshold measures and the MAD. A channel may be more effective and have greater discriminatory power if its MAD is higher. Because there is no significant variation in the channels' means absolute difference values, determining which channel to exclude from the classification task is challenging. However, the mean absolute difference data will be compared with the results of the next test to identify the very important channels set.

3.4.2 Correlation Coefficient

Finding the correlation coefficients for different channels was the second step. An algorithm based on correlation measures the link between features by predicting one from the other if they are correlated. To put it another way, the correlation coefficient shows how one attribute changes in connection to another. The more similar two qualities are to one another, the higher the correlation between them. Given the likelihood that the second channel won't receive new data, the learning model may only require one of them if the channels are uncorrelated with one another. The correlation coefficients are calculated as given in equation (8),

$$\beta_{yz} = \frac{Cov(y,z)}{\delta_y\ \delta_z} \tag{8}$$

Where, β_{yz} denotes the connection coefficient from y and z channels, δ_y denotes the standard deviation (SD) of channel y , δ_z implies SD of channel z . The threshold for eliminating one of the two correlated channels in order to investigate correlated channels has been established at a correlation coefficient of 0.75. Initially, channels that are linked to three or more channels are not included. After that, the Mean absolute difference measure finds this of the two channels should be removed if their correlation coefficients are equal to or greater than 0.75.

3.4.3 Backward-Elimination using Lotus Effect Optimization Algorithm

In this section, Backward-elimination using Lotus effect optimization algorithm (LEOA) [14] is discussed. The lotus leaf's super-hydrophobic and self-cleaning properties are indicated by its effect.The pollen of the same plant is used for fertilisation in the non-biological procedure known as self-pollination. The wind and water release are two elements that aid in the pollination of these flowering plants. In order to identify the ten most influential channels and achieve the goal of a proper categorization with the fewest count of channels, it has used the backward removal procedure. In contrast to the first two steps, which employ univariate statistics to evaluate the intrinsic qualities of the channels, this approach investigates every conceivable subset of channels and evaluates their presentation by training and testing the classifier on that subset.

3.4.1 Stepwise Procedure of LEOA

The step by step process is described to eliminate the redundant channels. The optimal solution is promoted using LEOA approach.

Step 1: Initialization

The population in LEOA has to be initialized by generating a collection of random solutions. It can use the following matrix to indicate that each Lotus Effect Optimization Procedure is given equation (9),

$$D = \begin{bmatrix} D_1^1 & D_1^2 & \dots & \dots & D_1^b \\ D_2^1 & D_2^2 & \dots & \dots & D_2^b \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ D_n^1 & D_n^2 & \dots & \dots & D_n^b \end{bmatrix} \quad (9)$$

Where, the goal is to minimize to function, the step mass should be chosen so that it minimizes the function worth at the new idea and n represent count of paths, b is the execution paths.

Step 2: Random Generation

The input parameters generated at arbitrary solution from the initialization. Optimal fitness values were selected based on obvious hyper parameter situation.

Step 3: Fitness Function

A arbitrary solution is created using initialized evaluations. This is derived in equation (10),

$$Fitness\ \ Function = e\lim inating\ \ redundant\, channel \quad (10)$$

Step 4: Exploration Phase

Dragonflies carry out global pollination that is the same as the proposed algorithm's exploratory phase in the LEOA. The dragonfly algorithm takes into account two ideas of food and enemy in addition to three fundamental characteristics of insect swarms: separation, alignment, and cohesiveness. The accuracy of the models after training is then compared. Consequently, each subset has undergone channel selection and classification, and the one with the lowest lost function has been chosen as given in equation (11),

$$T_a^s = \sum_{b=1}^{Z} Y_a^s - Y_b^s \quad (11)$$

Where T_a^s denotes the current position, $\sum_{b=1}^{Z}$ represents the amount of entities in the neighborhood, Y_a^s is the current being's spot with directory in completion repetition, Y_b^s is position of separate neighborhood in growth iteration.

Step 5: Exploitation Phase

The exploitation phase is local pollination, or self-fertilization. A coefficient specifies the scope of each blossom's increasing area around the finest-discovered flower in this type of auto gamy. By eliminating one channel at a time, this algorithm tests every possible channel combination using a greedy search strategy. To identify the most inefficient channel, each subset initially consists of 11 of the 12 channels. After eliminating one channel, it proceeded to remove the remaining ten out of eleven channels(12),

$$Y_a^{s+1} = Y_a^s + Q(e^*) \quad (12)$$

Where, Y_a^{s+1} denotes the current number of iterations, Y indicates the growth area, Q is the exploitation movement, e^* signifies the found pollen position among all growth iterations.

Step 6: Termination Condition

The redundant channels were eliminated with the aid of LEOA, repeat step 3 iteratively till fulfil halting criteria $D = D + 1$. Then, LEOA method effectively did the backward elimination of the approach.

4. RESULT AND DISCUSSION

In this part, the simulation outcomes of the indicated procedures are discussed. Python is employed to execute the proposed model on the Windows operating system. The models were trained with 8 GB of Random Access Memory and an Intel® Core (TM) i5 CPU. This study focused on a 64-bit Windows-OS. The obtained outcome of the proposed TSA-EEGS-MDDD-AARCNN approach is analyzed with the existing techniques like AD-MDD-EEGS-DL [6], DSS-MDD-CNN-EEGS [7], and ETE-DL-EEG-MDDC [8] respectively.

4.1 Performance measures

Accuracy, Precision, and recall performance measures are employed to define the performance of proposed method.

- True Positive (TP) : Number of positive major depressive disorder detection correctly detected as positive.
- True Negative (TN) : Number of positive major depressive disorder detection correctly detected as negative.
- False Positive (FP) : Number of negative major depressive disorder detection incorrectly detected as positive.
- False Negative (FN) : Number of negative major depressive disorder detection incorrectly detected as negative.

4.1.1 Accuracy

The Accuracy is a measure employed to assess a detection system's performance in correctly identifying instances within a given dataset, categorized as design the user experience. Then the calculation of Accuracy is given in equation (13),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{13}$$

4.1.2 Precision

Precision calculates the system's capability to recognize positive cases correctly out of all predicted positive cases, which is determined by equation (14),

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{14}$$

4.1.4 Recall

Recall is measured by separating overall amount of elements in positive class by number of true positives. It’s determined by equation (15),

$$recall = \frac{TP}{(TP + FN)} \tag{15}$$

4.2 Performance Analysis

Figure 2-4 depicts stimulation results of TSA-EEGS-MDDD-AARCNN proposed method. Then, the proposed IoT-ID-MSGWCN-EUN approach is compared to existing techniques like AD-MDD-EEGS-DL, DSS-MDD-CNN-EEGS, and ETE-DL-EEG-MDDC respectively.

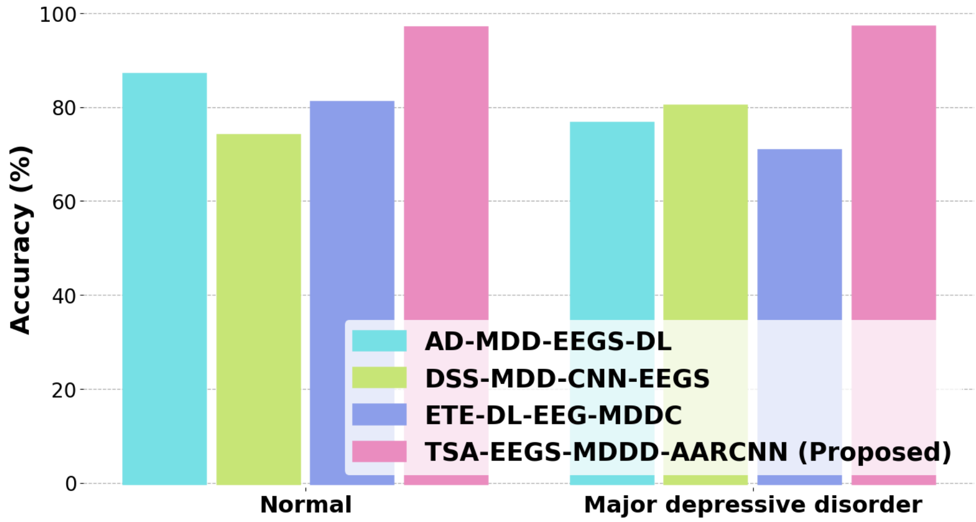

Figure 2: Analysis of accuracy performance

Figure 2 portrays the analysis of accuracy performance. By using a Residual Convolutional Neural Network (ResNet), which successfully captures both short- and long-term properties in the EEG data while avoiding problems like vanishing gradients because of its residual learning mechanism, the model takes use of these temporal correlations. Here, TSA-EEGS-MDDD-AARCNN attains 16.28%, 30.78% and 25.29% higher accuracy at normal; and 23.63%, 21.05%, 19.54% higher accuracy at major depressive disorder when comparing to the existing as AD-MDD-EEGS-DL, DSS-MDD-CNN-EEGS, and ETE-DL-EEG-MDDCrespectively.

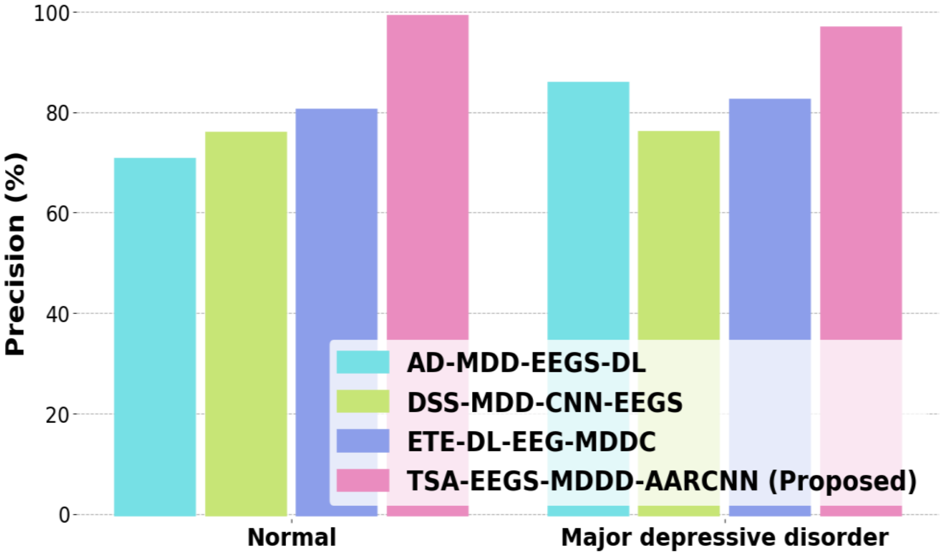

Figure 3: Analysis of precision performance

Figure 3 portrays the analysis of precision performance. The proposed model may focus on the frequency bands and time intervals that are most suggestive of MDD by using an optimized AARCNN, which increases the precision of its predictions. Here, TSA-EEGS-MDDD-AARCNN attains 19.45%, 20.22% and 22.28% higher precision at normal; and 15.28%, 26.27%, and 20.14% higher precision at major depressive disorder when comparing to the existing AD-MDD-EEGS-DL, DSS-MDD-CNN-EEGS, and ETE-DL-EEG-MDDCrespectively.

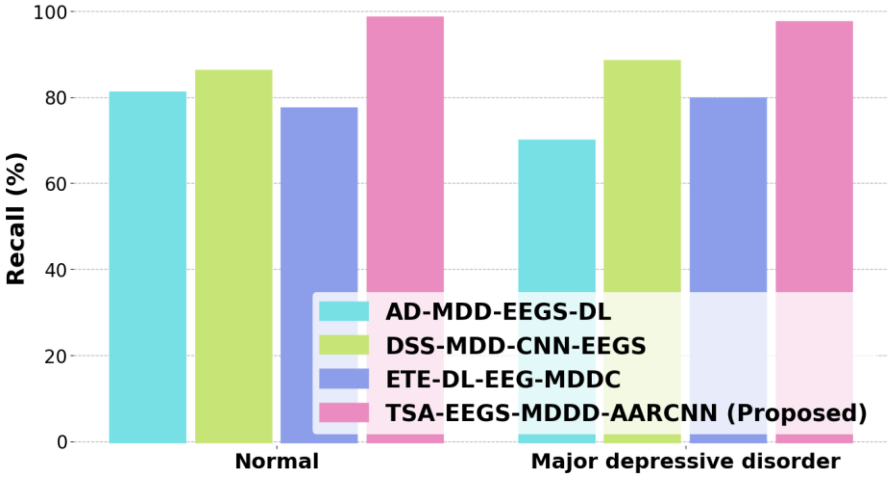

Figure 4: Analysis of Recall performance

Figure 4 displays the analysis of recall performance. Using AARCNN enhances the proposed model's recall to various MDD manifestations by enabling it to learn deeper, more complex characteristics from the EEG signals. This further adds to good recall. Here, TSA-EEGS-MDDD-AARCNN attains 28.96%, 33.21% and 23.89% higher recall at normal; and 18.65%, 23.54%, and 19.89% higher recall at major depressive disorderwhen comparing to the existing as AD-MDD-EEGS-DL, DSS-MDD-CNN-EEGS, and ETE-DL-EEG-MDDC respectively.

4.3 Discussion

In this work, TSA-EEGS-MDDD-AARCNN model for major depressive disorder detection is discussed. In the proposed TSA-EEGS-MDDD-AARCNN method is collected the input signal data from EEG dataset.More precisely, the proposedTSA-EEGS-MDDD-AARCNN model significantly reduces the sources needed to run the method because they do not demand for specific algorithms or techniques to organize data for the categorization process. According to the proposed method, using AARCNNtechniques for major depressive disorder detection improves accuracy and recall. The empirical evaluation of proposed TSA-EEGS-MDDD-AARCNN method is highlighted through a range of evaluation metrics, including Accuracy, Precision, and recall. Here, presenting 99.18% accuracy; 98.37% precision; and 98.5% recall achieved by the proposed technique. It shows that the proposed TSA-EEGS-MDDD-AARCNN method is better than existing models for major depressive disorder detection.

5. CONCLUSION

The proposed TSA-EEGS-MDDD-AARCNN method focusses on major depressive disorder detection using the AARCNNtechnique. The major depressive disorder using AARCNNand the weight parameters of AARCNN optimized using LEOA. The effectiveness of AARCNN for dealing with time series data was demonstrated by using a customised InceptionTime model. The proposed TSA-EEGS-MDDD-AARCNN method is executed in python. The efficiency of the proposed TSA-EEGS-MDDD-AARCNN method approach contains 28.96%, 33.21% and 23.89% higher recall when analyzed to the existing methods such as AD-MDD-EEGS-DL, DSS-MDD-CNN-EEGS, and ETE-DL-EEG-MDDCrespectively.The model can have limited generalisation capabilities and be less robust across various populations if the dataset is not sufficiently representative. Future research could improve scalability and privacy across distributed datasets by incorporating hybrid deep learning. Furthermore, adding explainability frameworks and expanding the model to include several data may enhance the model's robustness, detection transparency, and uptake in various detection settings.

REFERENCES

[1] Cui, W., Sun, M., Dong, Q., Guo, Y., Liao, X.F. and Li, Y., 2023. A multiview sparse dynamic graph convolution-based region-attention feature fusion network for major depressive disorder detection.IEEE Transactions on Computational Social Systems.

[2] Zhang, B., Wei, D., Yan, G., Li, X., Su, Y. and Cai, H., 2023. Spatial–temporal eeg fusion based on neural network for major depressive disorder detection. Interdisciplinary Sciences: Computational Life Sciences, 15(4), pp.542-559.

[3] Price, G.D., Heinz, M.V., Collins, A.C. and Jacobson, N.C., 2024. Detecting major depressive disorder presence using passively-collected wearable movement data in a nationally-representative sample.Psychiatry research, 332, p.115693.

[4] Sharma, G., Joshi, A.M., Gupta, R. and Cenkeramaddi, L.R., 2023. DepCap: a smart healthcare framework for EEG based depression detection using time-frequency response and deep neural network. IEEE Access, 11, pp.52327-52338.

[5] Ravan, M., Noroozi, A., Sanchez, M.M., Borden, L., Alam, N., Flor-Henry, P. and Hasey, G., 2023. Discriminating between bipolar and major depressive disorder using a machine learning approach and resting-state EEG data.Clinical Neurophysiology, 146, pp.30-39.

[6] Rafiei, A., Zahedifar, R., Sitaula, C. and Marzbanrad, F., 2022. Automated detection of major depressive disorder with EEG signals: a time series classification using deep learning. IEEE Access, 10, pp.73804-73817.

[7] Loh, H.W., Ooi, C.P., Aydemir, E., Tuncer, T., Dogan, S. and Acharya, U.R., 2022. Decision support system for major depression detection using spectrogram and convolution neural network with EEG signals. Expert Systems, 39(3), p.e12773.

[8] Xia, M., Zhang, Y., Wu, Y. and Wang, X., 2023. An end-to-end deep learning model for EEG-based major depressive disorder classification.IEEE Access, 11, pp.41337-41347.

[9] Khadidos, A.O., Alyoubi, K.H., Mahato, S., Khadidos, A.O. and Mohanty, S.N., 2023. Computer aided detection of major depressive disorder (MDD) using electroencephalogram signals. IEEE Access, 11, pp.41133-41141.

[10] Bashir, N., Narejo, S., Naz, B., Ismail, F., Anjum, M.R., Butt, A., Anwar, S. and Prasad, R., 2023. A machine learning framework for Major depressive disorder (MDD) detection using non-invasive EEG signals. Wireless Personal Communications, pp.1-23.

[11] https://www.kaggle.com/datasets/shashwatwork/eeg-psychiatric-disorders-dataset

[12] Nóvoa, A., Racca, A. and Magri, L., 2024. Inferring unknown unknowns: regularized bias-aware ensemble

Kalman filter. Computer Methods in Applied Mechanics and Engineering, 418, p.116502.

[13] Zhang, B., Sifaou, H. and Li, G.Y., 2023. Csi-fingerprinting indoor localization via attention-augmented residual convolutional neural network.IEEE Transactions on Wireless Communications, 22(8), pp.5583-5597.

[14] Dalirinia, E., Jalali, M., Yaghoobi, M. and Tabatabaee, H., 2024. Lotus effect optimization algorithm (LEA): a lotus nature-inspired algorithm for engineering design optimization. The Journal of Supercomputing, 80(1), pp.761-799.