

EEG-Based Depression Detection

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Abstract—This study is based on improving diagnosis of depression by analyzing electroencephalography (EEG) signals. These signals can provide useful information but are often complicated to interpret. We compare two methods for classifying these signals using the 128 channel MODMA dataset, which includes data from individuals with Major Depressive Disorder (MDD) and healthy controls (HC). We initially processed the data through techniques such as band-pass filtering, Common Average Referencing (CAR), and Independent Component Analysis (ICA). Then, we applied two approaches: traditional Machine Learning models (XGBoost, Random Forest, Logistic Regression) on extracted statistical and spectral features, versus a hybrid 1D CNN and BiLSTM architecture for automated temporal feature learning. The hybrid deep learning model outperformed the traditional methods and baseline models, with an accuracy of 96.2% and a balanced F1 score of 0.95. Beyond accuracy, the hybrid model demonstrated stronger capability in capturing non-linear and non-stationary EEG dynamics enabling more reliable early depression screening using EEG signals. It can be now stated that advanced neural models can set a new standard in mental health diagnostics.

Index Terms—EEG, Depression Detection, MODMA, Machine Learning, Deep Learning, CNN, BiLSTM, Signal Processing, ICA, CAR.

I. INTRODUCTION

Depression is a significant condition, but diagnosing it often depends on patient reports and clinical interviews. Therefore better data-driven methods are required for diagnosing depression. One effective technology for this demand is electroencephalography (EEG). EEG provides high temporal resolution, allowing researchers to study the brain activities and connections associated to Major Depressive Disorder (MDD).

Many traditional methods for detecting depression with EEG use manually extracted features, such as power spectral density and entropy, analyzed with machine learning models. While these methods have some success, they struggle with EEG's complex nature, which include changing conditions like artifacts, eye and muscle movements and noise that can decrease the accuracy. New advancements in deep learning can help to diagnose the depression without manually extracting the features. Hybrid models combine Convolutional Neural Networks (CNNs) to analyze spatial data with Long Short Term Memory (LSTM) networks to study data over time.

This study provides a comparison of these two methodologies for depression classification using the 128-channel MODMA dataset. We compare the effectiveness of a hybrid CNN-LSTM architecture with traditional ML models. Our approach includes a consistent preprocessing pipeline that features band-pass filtering, notch-filtering and Independent

Component Analysis (ICA). By developing a framework that captures complex, non-linear neural relationships, this work contributes to a more reliable system for depression detection, supporting early diagnosis and personalized mental healthcare.

Section II discusses associated works on this topic. Section III gives an overview of the dataset, data preprocessing and feature extraction. Section IV explains the methodology and the experimental setup. Section V contains the results of our models. Section VI is the discussion of the results, while the Section VII provides the conclusion and future work.

Fig 1 depicts the approach used in this study for depression detection using EEG signals.

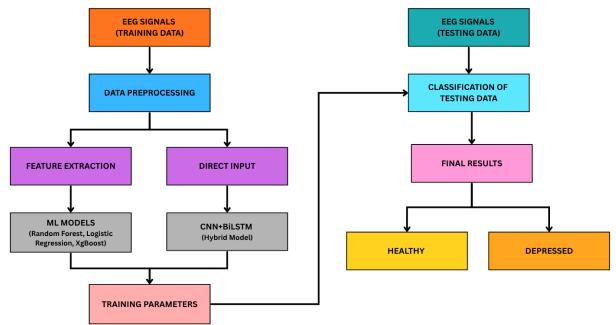


Fig. 1: Overall workflow of the proposed EEG-based depression detection framework, illustrating data preprocessing, feature extraction for ML models, and direct temporal feature learning for the CNN–BiLSTM hybrid model leading to final classification.

II. LITERATURE REVIEW

Recent research extensively explores both machine learning (ML) and deep learning (DL) for EEG-based depression detection. DL models show a vast range of outcomes; for example, Li et al. [13] developed a resting-state CNN achieving 66.40% accuracy, while more advanced architectures like the EEG Mind Transformer by Liu et al. [14] show high accuracy by automatically learning hierarchical features. However, traditional ML approaches remain highly competitive. Khan et al. [11] achieved 96.36% accuracy on the MODMA dataset with a Best First Tree, and Sarkar et al. [3] reported 97.85% accuracy using SVM, depending on robust feature engineering like Power Spectral Density (PSD).

A significant research gap still exists in spite of these differing findings: there aren't any straightforward, equitable comparisons between ML and DL techniques that use the same

dataset and standardized preprocessing and validation for both. The present study fills this gap by evaluating a hybrid CNN and BiLSTM model on the MODMA dataset against baseline classifiers (Logistic Regression, Random Forest, XGBoost), using a consistent preprocessing pipeline to guarantee a reliable performance comparison.

III. DATASET

This study is done on Multi Modal Open Dataset for Mental Disorder Analysis (MODMA), contains EEG recordings from both 128 electrode and 3 electrode devices of healthy participants having age 16–56, categorized as Major Depressive Disorder (MDD) or Healthy Control (HC). This study focuses on the 128 channel resting state EEG data, collected when participants are relaxed with closed eyes. Total no of participants were 53 , out of which 20 participants were identified with Major Depressive Disorder (MDD) and 9 as Healthy Controls (HC).

A. Data Preprocessing

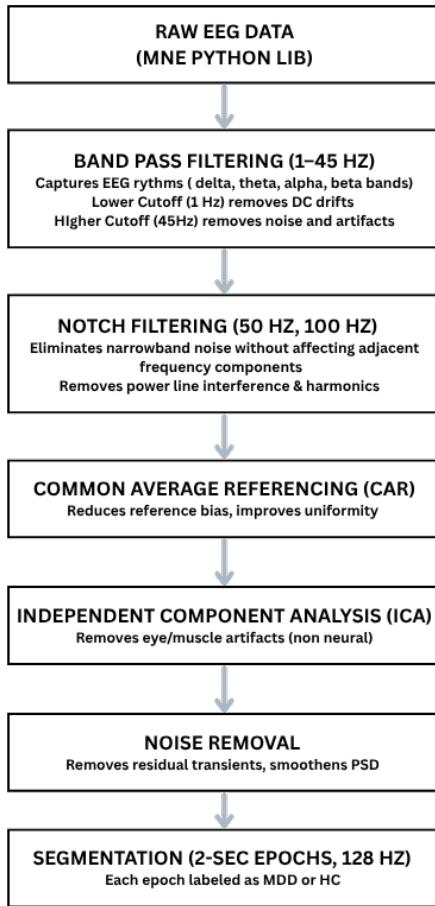


Fig. 2: EEG Data Preprocessing Pipeline.

The raw EEG signals are preprocessed using MNE Python library through an end to end pipeline. Processing is done to remove the noise, ocular and muscular artifacts , retain the

clean signals. The cleaned signals are divided into 2-second epochs (128 Hz sampling rate), each epoch labeled as either Major Depressive Disorder (MDD) or Healthy Control (HC).

Fig 2 shows the end-to-end EEG Data Preprocessing Pipeline.

B. Feature Extraction & Visualization

All EEG recordings were segmented into continuous 2-second segments, or epochs. Each epoch contained EEG data from multiple channels, and both time domain and frequency domain features were extracted from each channel to summarize the signals numerically for machine learning models. All extracted features from every EEG channel were combined into a single feature vector for each epoch.

Fig 4 depicts the average EEG Power across frequency bands.

1) *Time-Domain Features*: Time-domain features tells us the statistical properties of the signals like mean, standard deviation, minimum, maximum, skewness, and kurtosis.

Table I illustrates the extracted time-domain features.

Fig 3 shows the Time-Domain Feature Distributions Across EEG Channels.

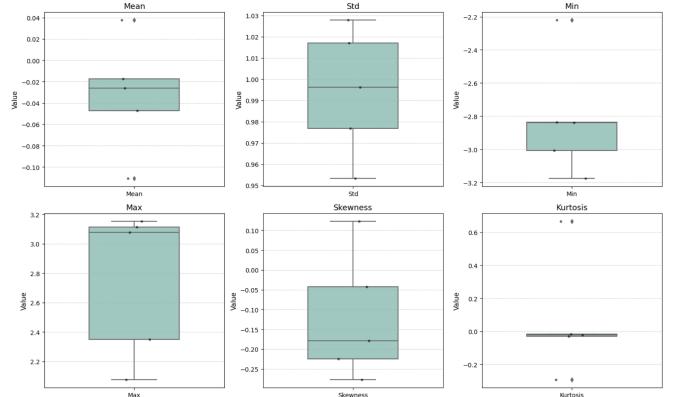


Fig. 3: Time-Domain Feature Distributions Across EEG Channels

TABLE I: Sample of Extracted Time Domain Features

Channel	Mean	Std	Min	Max	Skewness	Kurtosis
Ch1	0.0008	0.9741	-2.6197	3.8527	0.3036	0.5084
Ch2	0.0080	0.9820	-3.2413	3.0789	0.0803	0.0062
Ch3	-0.0448	1.0097	-2.6969	2.6324	0.0743	-0.0561
Ch4	0.1535	0.9336	-2.4239	2.5269	0.0495	-0.2377
Ch5	0.0808	1.0247	-2.8963	2.5797	-0.0436	-0.1160

TABLE II: Sample of Extracted Frequency Domain Features

Channel	Delta	Theta	Alpha	Beta	Gamma
Ch1	0.00889	0.008709	0.008613	0.015058	0.013865
Ch2	0.017357	0.013491	0.024791	0.014951	0.013169
Ch3	0.014690	0.012114	0.014181	0.020477	0.014962
Ch4	0.021977	0.009993	0.010043	0.016333	0.015275
Ch5	0.020112	0.018040	0.021754	0.010413	0.024786

2) *Frequency-Domain Features*: Frequency-domain features were extracted using the Welch Power Spectral Density (PSD) method, which estimates how the signal's power is distributed across frequencies. The average power was calculated for frequency bands: Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–45 Hz) for each channel.

Table II illustrates the extracted frequency-domain features.

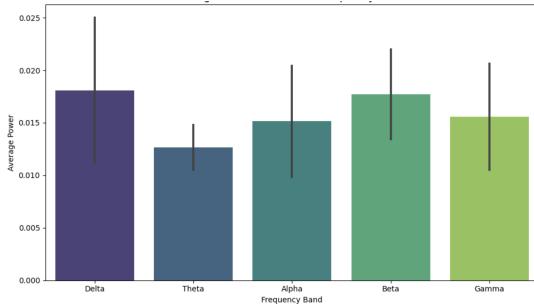


Fig. 4: Average EEG power across frequency bands

Note: This feature extraction step was performed only for traditional machine learning models (Random Forest, XGBoost, and Logistic Regression) and was not used for the deep learning model.

This design choice was intentional. The deep CNN-BiLSTM model learns discriminative temporal-spatial characteristics directly from raw EEG signals, whereas traditional ML models require manually created statistical time-domain and frequency-domain features for classification. To determine whether hybrid feature fusion enhances performance, future research could examine concatenating derived spectral features with deep embeddings.

IV. METHODOLOGY

A. Machine Learning Models

Three machine learning models were implemented, Logistic Regression, Random Forest, and XGBoost.

Logistic Regression (LR): Used as a baseline classifier, can handle overfitting and imbalance.

Random Forest (RF): An ensemble of multiple decision trees trained on random subsets of features and data samples.

XGBoost (XGB): A boosting algorithm that builds models sequentially to correct errors.

Fig 5 depicts the logistic regression implementation.

Fig 6 shows the random forest classification implementation.

Fig 7 depicts the XGBoost algorithm implementation.

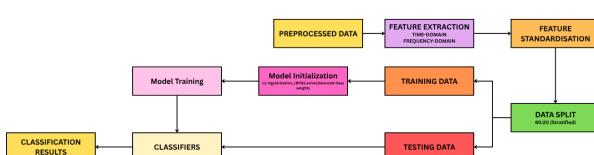


Fig. 5: Overall Workflow of Logistic Regression Algorithm

TABLE III: Model Parameters for Machine Learning Models

Parameter	LR	RF	XGB
Solver / Trees	LBFGS	200	150
Regularization	L2	—	L1=0.5, L2=2.0
Class Weight	Balanced	—	—
Max Iterations	1000	None	3
Learning Rate	—	—	0.15
Train-Test Split	80:20	80:20	80:20
Random State	42	42	42

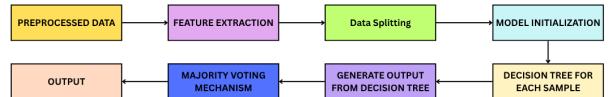


Fig. 6: Overall Workflow of Random Forest Approach

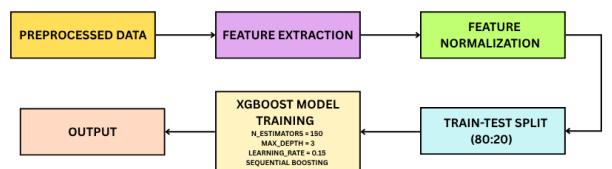


Fig. 7: Overall Workflow of XGBoost Approach

B. CNN-BiLSTM Hybrid Model

We created a hybrid sequential architecture to capture the spatiotemporal characteristics of multichannel EEG. The input is initially changed from (channels, timepoints) to (timepoints, channels). Features are extracted from spatial data using 1D CNN layers. Patterns and connections between electrodes are identified by them, while also reducing noise. These CNN layers create feature maps, which are sent as input to the LSTM (BiLSTM) layer. It is bidirectional in nature which captures data in both directions and understands changes over time.

In order to achieve the binary classification between depressed and healthy participants, this combined feature set is input into fully connected layers and a final sigmoid classifier. Between the CNN layers, regularization techniques and dropout layers are used to prevent overfitting.

Fig 8 depicts the CNN-BiLSTM Model architecture.

Table V highlights the parameters and the complete architecture of the CNN-BiLSTM hybrid model.

TABLE IV: Model Hyperparameters for training and optimization

Hyperparameter	Property
Epochs	50
Batch Size	64
Learning Rate	0.001
Optimizer	Adam
Loss Function	Binary Cross-Entropy

TABLE V: CNN-BiLSTM Model Parameters

Layer	Properties
Input Layer	Shape = (128 channels, 256 timepoints) → Permuted to (256, 128)
Conv1D Layer 1	Filters = 32, Kernel Size = 3, Activation = ReLU
Batch Normalization	Stabilizes learning
MaxPooling1D Layer 1	Pool Size = 2
Dropout Layer	Dropout rate = 0.3
Conv1D Layer 2	Filters = 64, Kernel Size = 3, Activation = ReLU
Batch Normalization	Further stabilizes learning
MaxPooling1D Layer 2	Pool Size = 2
Dropout Layer	Dropout rate = 0.3
BiLSTM Layer	Units = 64, Dropout = 0.3
Dense Layer	64 neurons, Activation = ReLU
Dropout Layer	Dropout rate = 0.4
Output Layer	1 neuron, Activation = Sigmoid

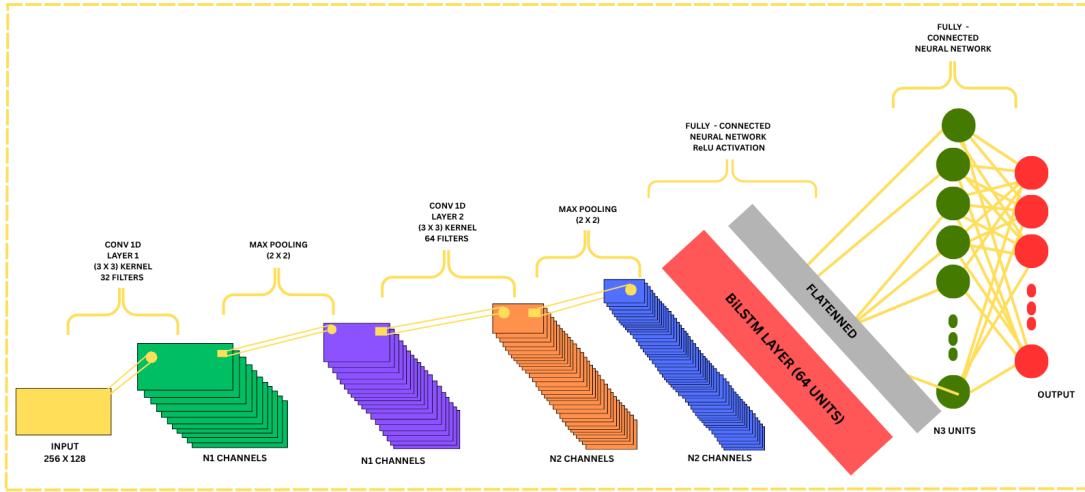


Fig. 8: Architecture of CNN-BiLSTM Hybrid Model

C. Evaluation of Training Model

Model performance was evaluated using Accuracy, Precision, Recall, F1-Score, ROC-AUC.

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

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

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

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

ROC-AUC represents the model's ability to differentiate MDD from HC (AUC = 1: perfect, AUC = 0.5: random).

V. RESULTS

A. Machine Learning Models

Logistic Regression achieved an epoch-level accuracy of 87.7% with AUC ≈ 0.90 but a slightly lower recall for the MDD class (0.83).

Random Forest achieved an epoch-level accuracy of 92.7% with AUC near 0.95, achieving strong generalization.

XGBoost achieved the highest epoch-level accuracy of 94.8%, among all other evaluated machine learning models.

Table VI gives the classification report comparison between ML models and the CNN-BiLSTM Hybrid Model.

Fig 9 shows the comparison of ROC curves of the three ML models.

B. CNN-BiLSTM Hybrid Model

The CNN–BiLSTM hybrid model achieved an spectacular overall accuracy of 96.2%. For HC (Category 0), it recorded a precision of 0.96, recall of 0.97, and F1-score of 0.97, indicating impressive detection consistency. For MDD(Category 1), it achieved a precision of 0.96, recall of 0.95, and F1-score of 0.96. These results indicate that this model can effectively identify both the classes.

Fig 10 shows the ROC Curve for CNN-BiLSTM Model.

VI. DISCUSSION

As shown in our comparison, there was a clear performance hierarchy. The hybrid CNN-BiLSTM model achieved the highest accuracy of 96.2%, exceeding the top-performing traditional XGBoost model's 94.8% and Random Forest's 92.7%.

TABLE VI: Classification Report Comparison Across Models

Model	Class	Precision	Recall	F1-Score	Accuracy	Support
Logistic Regression	0 (Healthy Control)	0.87	0.91	0.89	0.877	209
	1 (MDD)	0.89	0.83	0.86		172
	Macro Avg	0.88	0.87	0.87		
Random Forest	0 (Healthy Control)	0.91	0.96	0.93	0.927	209
	1 (MDD)	0.95	0.88	0.92		172
	Macro Avg	0.93	0.92	0.93		
XGBoost	0 (Healthy Control)	0.94	0.97	0.95	0.948	209
	1 (MDD)	0.96	0.92	0.94		172
	Macro Avg	0.95	0.95	0.95		
CNN-BiLSTM	0 (Healthy Control)	0.96	0.97	0.97	0.962	1657
	1 (MDD)	0.96	0.95	0.96		1358
	Macro Avg	0.96	0.96	0.95		

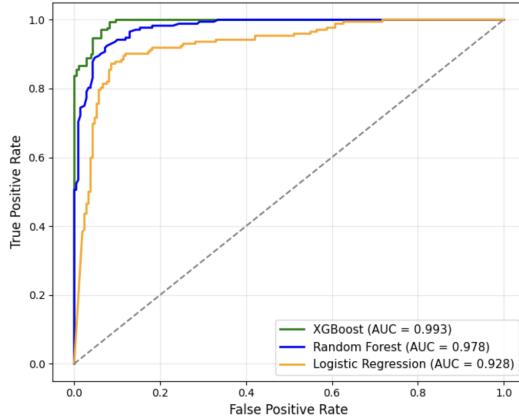


Fig. 9: Comparison of ROC Curves of the three traditional Machine Learning Models

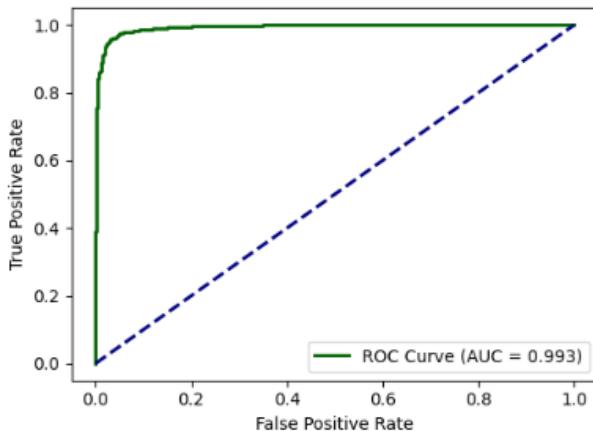


Fig. 10: ROC Curve for CNN-BiLSTM Model

The hybrid model also outperformed the baseline models made by other researchers in terms of accuracy and f1 score. Beyond accuracy, the hybrid model demonstrated stronger capability in capturing non-linear and non-stationary EEG dynamics, enabling more reliable mental health assessment.

Even with these promising outcomes, the deep learning

model remains a "black box", making it challenging to determine which EEG channels or frequency bands are most important for classification. In contrast, ensemble models like XGBoost, though slightly less accurate, offer better interpretability through feature importance rankings. Future research will visualize channel-level and spectral importance using explainability techniques like SHAP and Grad-CAM to enhance interpretability and show which EEG channels or frequency bands provide greater contributions toward classifying depression. Furthermore, future studies should focus on (i) cross-subject generalization with more diverse and larger EEG datasets to improve robustness, and (ii) multi-modal data fusion by combining EEG with behavioral or auditory cues for a comprehensive evaluation of mental health.

VII. CONCLUSION

This study was done on EEG based MODMA dataset to detect depression using traditional machine learning models (XGBoost, Logistic Regression, Random Forest) and a hybrid deep learning CNN-BiLSTM model. The CNN-BiLSTM achieved the highest accuracy of 96.2% by effectively capturing complex spatial and temporal patterns. XGBoost and Random Forest achieved 94.8% and 92.7% accuracy, while Logistic Regression achieved 87.7%. Traditional ML models were faster and simpler, but the hybrid deep learning model proved to be better in understanding complex data patterns. However, the limited dataset of 53 participants posed challenges for generalization. Future work, as discussed earlier, will focus on enhancing interpretability and cross-subject robustness. Overall, this research establishes a strong baseline for data-driven mental health diagnostics, moving toward reliable and clinically applicable depression detection systems.

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