RESEARCH PAPER

Hybrid CNN-LSTM-SVM Model to Detect MDD from EEG Signals

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ABSTRACT
According to World health organization 5.7 % of adult suffer from depression around the world and these people die 10 to 20 year earlier then general population. Stressful environment or personal factors may be major cause of depression. The diagnosis of depression exclusively depends on interaction between doctor and patient as there is no direct lab test available to detect depression. Electroencephalograms (EEG) are non-invasive and has potential to capture brain behaviour in form of signals. In our study an attempt was made to distinguish between Major Depressive Disorder (MDD) patients and healthy control. The EEG data used in this work is publicly available dataset, consisting of 19 channel recordings from both 34 MDD patients and 30 healthy subjects under controlled conditions. EEG recording with closed eyes was used in this experiment. EEG signals have a specific range for healthy person but it altered in MDD patient. On these EEG recording, time domain and frequency domain features were extracted. Random Forest, XGBoost, Stacking Ensemble, EEGNet, CNN-LSTM and proposed CNN-LSTM-SVM were applied. Highest subject level accuracy was attained by proposed method 96.43 % followed by CNN-LSTM (90%). Other performance parameters like F1-score (0.96), Sensitivity (0.96), Specificity (0.97), AUC-ROC (0.98), kappa value (0.93) which showed proposed model CNN-LSTM-SVM overperformed other models. Our system is designed as a decision-support tool for MDD assessment.
Keywords: *Electroencephalograms, Major Depressive disorder, frequency band, EEGnet, SVM, Power Spectral Density (PSD), Random Forest, Support Vector Machine (SVM).XGboost, Convolutional Neural network (CNN), Long short term memory (LSTM), EEGNet*
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1. INTRODUCTION:

Feeling sad or experiencing a low mood is a common aspect of human life and is generally not considered a clinical concern when it is transient. However, when such feeling persists over a extended period of at least two months or more, they may indicate the presence of Clinical Depression or Major Depressive Disorder (MDD), one of the most prevalent forms of depression. A person suffering from depression experience perpetual and incessant sadness, social and physical anhedonia along with difficulty in handling day to day life activities such as sleeping, working or eating. It is a type of illness that can affect anyone— regardless of age, race, income, culture or education. Research suggests that genetic, biological, environmental, and psychological factors play an important role in depression. According to World Health Organization (WHO) reports, approximately 332 billion of world population has been diagnosed with depression which includes 5.7% adults and 5.9% senior citizens. Among adults, 4,6 % men and 6,9 % women suffer from Depression [1].

MDD is characterised by persistent low mood, decreased interest in pleasurable activities, feeling of guilt or useless, lack of energy, poor concentration sleep disturbance and suicidal thoughts [2]. Semi-structured interviews between patients and healthcare professionals are a common component of conventional approaches for diagnosing and tracking depression. Following the guidelines outlined in the Beck Depression Inventory (BDI) and Diagnostic and Statistical Manual for Mental Disorders-V (DSM-V), the questionnaire sessions are performed [3].

Electroencephalography (EEG) signals is a non-invasive method in which electrodes are placed on scalp to capture

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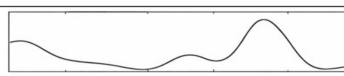
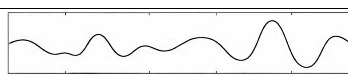
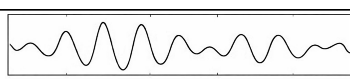
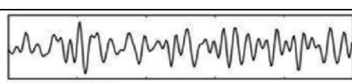
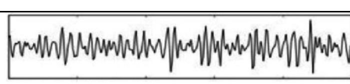
electrical activity of brain. EEG signals are measured in microvolts and are characterized by varying frequency which acts as biomarkers for various brain conditions. MDD causes degradation in brain performance leading to modification of electrical activity in brain. Thus, analysing EEG signals of a person can help in diagnosing clinical Depression. Moreover, EEG is a cost-effective technique with widespread availability. The time scale of EEG is in milli-seconds which is also same as that of neural activity thus giving better temporal resolution.[4] EGG signals are captured from Frontal and temporal lobe of brain, detect depression as Frontal lobe is responsible for maintaining control, plan, and monitor our behaviour. While frontal lobe control emotion. Frequency pattern of our brain changes with change in state of our brain and this change is studied to detect depression.[5]

EEG signal can be extracted into machine understandable format using python MNE library. This extracted signal can be pre-processed and given to machine learning algorithms for classifying depressed patient and healthy control. Machine learning (ML) and deep learning (DL) algorithms have demonstrated significant potential in identifying complex patterns within data. Following adequate training on representative datasets, these algorithms can effectively learn discriminative features associated with MDD patient with certain level of accuracy.

The main objective of this study is to develop a hybrid ML-DL framework for the detection of MDD using EEG signals. Traditional ML and DL models often exhibits limitation in capturing the complex spatial and temporal characteristics inherent in EEG data. To address these limitations a hybrid model integrating Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks and Support Vetor Classifiers (SVCs) is proposed. EEG signals are primarily characterized by two fundamental attributes: amplitude and frequency. Different regions of the brain generate distinct frequency bands as shown in Table 1. In individuals with MDD, alteration in the amplitude and rhythmic activity of these brain waves are observed. Such abnormalities can be analyzed using advanced computational techniques to facilitate the identification of depression disorders. In this study, frequency domain features like power spectral density (PSD) measures, were extracted from EEG and are utilized to train and evaluate the models. The proposed framework seeks to improve the accuracy and robustness of depression detection by leveraging the complementary strengths of spatial feature extraction, temporal sequence modelling, and efficient classification. The findings of this study may contribute to the development of reliable computer-aided diagnostic systems for early identification of MDD.

Table 1: EEG Frequency band and their Characteristics[6].

Frequency Band	**Graph**	**Frequency Range (Hz)**	**Characteristics & Relevance**
Delta (δ)		0.5 - 4	In healthy person it is observed during deep sleep but in depressed person it was observed during awake state. Also Delta power during sleep was found to be lower in depression than in healthy controls
Theta (θ)		4 - 7	Observed during light sleep, drowsiness, meditation; linked with relaxation. In depressed person. Patient with depression show reduced theta waves.
Alpha (α)		8 - 12	Observed during relaxed wakefulness with eyes closed while in depressed person it is fluctuated due to increased power in specific brain regions, indicating a state of lower attention or disengagement
Beta (β)		13 - 30	Observed during active thinking, focus, alertness and anxiety but in depressed person there is reduced beta activity, which may correlate with cognitive slowing, decreased concentration, and overall mental fatigue.
Gamma (γ)		30 - 80 (or 100)	In healthy person it shows sensory processing, perception, memory binding. Compared to normal persons, patients with depression exhibited a considerably higher gamma rhythm power

2. RELATED WORK:

N Ahire (2025) used EEG signals from 34 Depression patients and 30 healthy control and extracted different statistical features which was used to train 1D-CNN, SVM and Logistic Regression for classification and observed that signal collected while subjects performing task gave maximum accuracy compared to Eyes Closed (EC) and Eyes Open (EO).Accuracy achieved was 90.21%, 89.3% and 88.4% by 1DCNN, SVM and Logistic Regression respectively [7].

K Padmaleela et al. (2024) proposed Discrete wavelet technique (DWT) for the sub-band signal decomposition and extract the multidimensional suite of geometrical, statistical and physiological features and then deploy a genetic algorithm to identify the most informative features for depression recognition. Use of Genetic algorithm has demonstrated an increased accuracy of 3% to 5%. Among various Machine learning model used SVM achieved highest accuracy of 91.73% and F1 Score of 91.45% [8].

N Sharma et al. (2024) utilized Deep wavelet scattering network (DWSN) to extract features from EEG signal and then it used Medium Neural Network (MNN) to attained 99.95% accuracy with 0.99 kappa value while Wide Neural Network (WNN) attained 99.3% accuracy with 0.987 kappa value [9].

M Ying et al. (2024) suggested an EEG based transformer model (EDT) in which attention mechanism was used to capture spatial and temporal features while CNN was used to classify subject as healthy and depressed person the model achieved accuracy of 92.25 %, having F1 score of 0.93 and kappa score of 0.85 [10].

Xia et al. (2023) developed an end-to-end DL architecture based on EEG signals to classify MDD patients with the healthy control. The architecture automatically map latent spatial connectivity relationships across EEG channels utilizing a multi-head self-attention mechanism, a parallel two-branch CNN module the extract deep features and resulting into the classification through a fully connected layer. Utilizing a leave one subject out cross validation strategy, the network attained a full frequency band accuracy of 91.06% but the model was trained only on 1 public dataset. Spatial and temporal information from EEG was not integrated, which would have increased the model performance further [11].

Ksibi et al. (2023) aimed at developing a model using MODMA dataset to identify EEG signals and recognize depression pattern. This paper has classified MDD into 6 types as Trauma, Mood disorder, Obsessive-compulsive disorders, Addictive disorder, Schizophrenia and Anxiety disorder. CNN-LSTM algorithm attain accuracy of 97% over Random Forest and XGboost but dataset didn't have sufficient negative sample and severity of depression is not measured [12].

Dev et al. (2022) focused on exploring biomarkers for depression and systematically reviewed 52 research articles using the PRISMA-P protocol. They have concluded that Neural Connectivity Analysis and Brain Topological Mapping hold significant promise for identifying depression biomarkers. It is also observed that EEG signals of the frontal and parietal-occipital cortex of the right hemisphere has proven highly discriminative in separating depressed and healthy brains. CNN and SVM are the best classification algorithms for depression detection using EEG, but authors have suggested using data argumentation technique to overcome the problem of small dataset [13]

Song et al. (2022) proposed a framework having features of CNN and LSTM based on transfer learning and concluded that LSDD-EEG algorithm gives better accuracy over traditional ML algorithms and CNN for all frequency band, but author also suggested that proper preprocessing techniques are required to enhance accuracy of the model [14]

Sarkar et al. (2022) presented multiple computational framework for tracking EEG based depression by evaluating four deep learning architectures (MLP, CNN, RNN, RNN with LSTM) against two Supervised Machine Learning Techniques (SVM and LR). It is observed that among deep learning model, RNN acquired the highest performance with the accuracy of 97.50% in Training Set and 96.50% in the Testing set followed by RNN with LSTM model where 40% data is in the Testing Set. Both Supervised Machine Learning Models namely SVM and LR have outperformed with 100.00% and 97.25 % accuracies in Training Phase and Testing Phase respectively [15].

3. DATASET AND PARTICIPANT:

This study used publicly available dataset obtained from figshare.com [16], comprising 64 EEG recordings in European File Format (edf). The dataset comprised EEG recording from 64 participants, including 34 MDD patients and 30 healthy control subjects. All EEG recordings were acquired at Hospital University Sains Malayasia (HUSM), Malayasia. EEG were recorded from all 64 subjects under the eyes closed condition, which is considered more effective for detecting depression compared to the eyes open condition. All 34 MDD (17 males and 17 females) patients were in age group of 28 to 52. Diagnostic and Statistics Manual-IV (DSM-IV) technique were used in identification of MDD patients. To eliminate the potential influence of medication on EEG signals, all MDD patients discontinued antidepression medicines two-week prior to EEG recording. The second group of 30 healthy control (21 Males and 9 Females) belonged to age group of 23 to 53 years. Psychiatric conditions of all healthy participant were examined prior and all of them were found fit for the experiment. [17]

4. EEG DATA ACQUISITION PREPROCESSING AND FEATURE EXTRACTION:

4.1 EEG Data Acquisition

EEG recording from all 64 subjects in closed eyes state was collected using 19 channel EEG montage which has electrodes fitted according to International 10-20 System. Each EEG signal was recorded for 5 minutes and sampled at (f_s=256 Hz). As shown in Fig,1 EEG recording was captured from Frontal lobe (Fp1, Fp2, F7, F8, F3, F4 and

Fz); Parietal lobe (Pz, P3 and P4); Occipital lobe (O1 and O2); central lobe (C3, Cz and C4) and temporal lobe (T3, T5, T4 and T6)

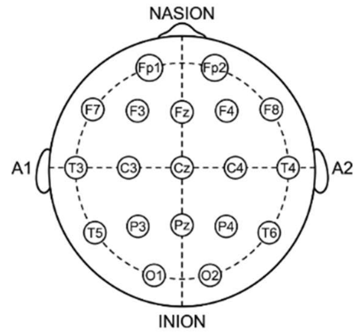


Fig. 1 19 channel EEG Montage

4.2 EEG Data Preprocessing consisted of below steps:

Step 1: Removal of artifacts: When EEG recording is conducted eyes blink, muscle movements and heartbeat adds noise to EEG data. These noises have high frequency so bandpass filter of 0.5 Hz to 45 Hz was used in this experiment to remove these noises.

Step 2: Independent Component Analysis (IDA): IDA was performed to separate out artifacts which has frequently been in range 0.5 Hz to 45 Hz, as bandpass filter failed to remove these artifacts due to overlapping frequency range. IDA successfully separated eye blinks and other artefacts presents in EEG data while recording.

Step 3: Segmentation/Epochs: Analysing complete EEG signals altogether is not possible so we divide EEG signals into segments or epochs of 5 sec overlapped with 1 sec. These segments were grouped together, and label were assigned to them as we wanted to classify subjects and not epochs. Label "0" was assigned to segments belongs to healthy subjects and label 1 was assigned to segments belonged to MDD subject.

Step 4: NumPy Dataset formation: The previous step generated 3 NumPy arrays named as X_DataEpochs with dimension 4308 x 19, Y_LabelsEpochs with dimension 4308 x 1 and Group_Epochs with dimension 64 x 1. X_DataEpochs array contains the segmented EEG data represented in microvolts while Y_LabelsEpochs stores the corresponding class label for all segments. Group_Epochs array contains the subject identifiers facilitating the mapping of EEG segments and their associated labels to the respective subjects for group-based analysis and validation.

4.3 Features Extraction from Processed EEG Signal: Time Domain features and Frequency Domain Features were applied to epoched EEG data (sampled at 250 Hz) to capture neurophysiological markers relevant to MDD as below.

4.3.1 Time Domain Features: Features like mean, standard deviation, skewness, kurtosis, peak to peak amplitude and root mean square (rms) were extracted to capture amplitude distribution and signal morphology.

4.3.2 Frequency Domain Features: Power Spectral Density (PSD) was used to extract spectral power power using Welch method across five frequency band: delta δ ((0.5–4 Hz), theta θ (4–8 Hz), alpha α (8–12 Hz), beta β (12–30 Hz), and gamma (30–45 Hz). And mean band power is computed per channel for each band. These frequency band were used to calculate clinical relevance ratio as shown in Table 2.

Table 2: Derived Clinical Relevance Ratio for MDD[18]

Ratio	Clinical Relevance
θ / α	Frontal theta elevation in depression
α / β	Cortical hypoactivation
δ / θ	Slow-wave dominance
(δ+θ) / (α+β)	Slow-to-fast power ratio
α / Σ(all bands)	Relative alpha power

Also, Spectral Entropy is calculated over normalized welch PSD per channel to resolve problem of irregularity of power spectrum and Pearson corelation coefficient is calculated across all channels pair to calculate Inter Channel corelation this helped to encode functional connectivity pattern across the scalp

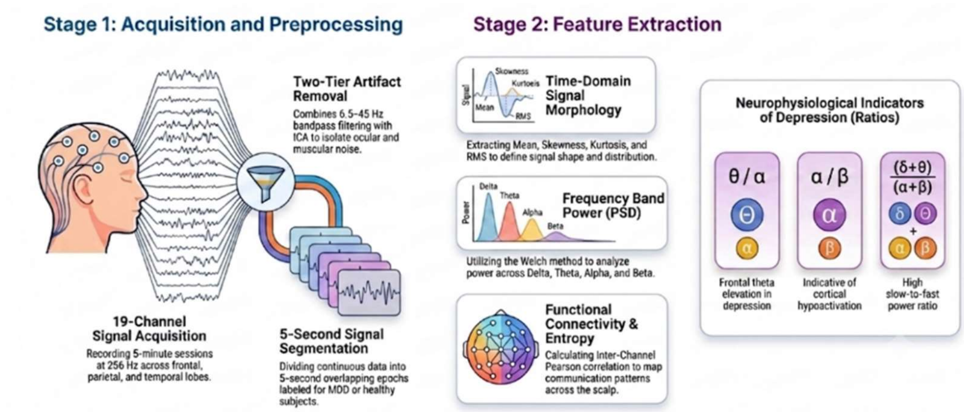


Fig 2: EEG Processing Pipeline for MDD classification

5. MACHINE LEARNING METHODOLOGY AND PERFORMANCE EVALUATION:

5.1 Machine Learning and Deep Learning Models

Time and Frequency domain features extracted from above pipeline consist of 4308*610 dimension. 10-fold cross validation technique was applied on all below mentioned models to reduce overfitting. Also, epoch level and subject level accuracy both were calculated by all models to handle problem of Data-leakage, class imbalance, noise and to relate model performance over epochs and subjects.

a. **Random Forest**: It is bagging approach based ensemble machine learning technique consisting of multiple decision tree classifier running in parallel capable of handling high dimensional, mixed type data such as EEG signals, It performs very well on small to medium size data which is very common in psychiatric research due to privacy and cost constrains, Its ability to handle noisy, imbalanced and non-normally distributed data make it suitable for MDD classification[19].

b. **XGBoost:** It is boosting approach ensemble machine learning technique consisting of multiple decision trees running sequential in which initial decision trees are called as base learners and later on used decision trees are called as advanced learners. In XG boost each classifier are trained on misclassified data of previous classifier this reduces overall chances of misclassification which is very important in healthcare domain. It has build-in Regularization (L1 and L2) to avoid any kind of overfitting. Its capability to handle missing data, suitable for small to medium size dataset, ability to capture non-linear relationship make its suitable for MDD classification. [20]

c. **Stacking Ensemble**: This technique gives us flexibility to use customized classifier which was not possible in Random Forest and XGBoost ensemble technique. It gave us the flexibility to use heterogeneous machine learning models in parallel and serious to achieve low bias and low variance along with providing benefits of ensemble learning as shown in below figure.

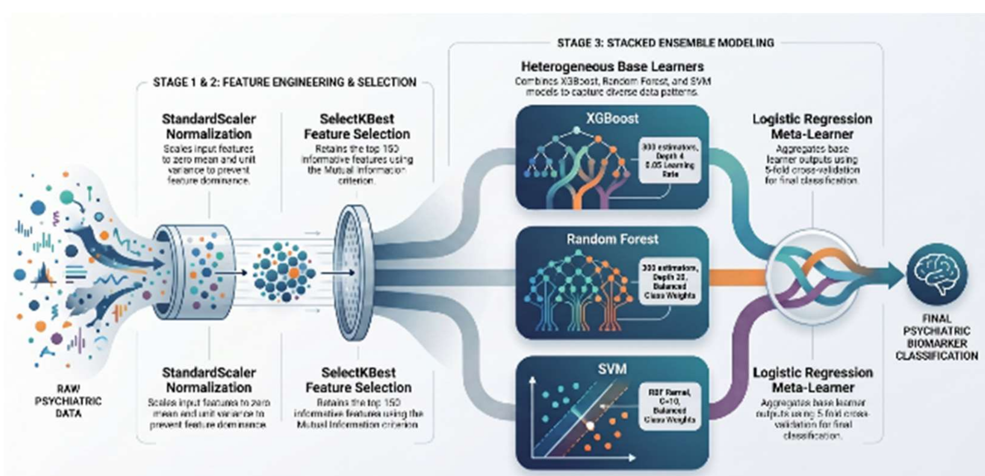


Figure 3: Stacking Ensemble Architecture

d. **EEG-Net:** EEG Net is compact CNN designed classification of EEG signals used in Brain Computer Interface (BCI).It architecture consist of temporal convolutional layers to learn frequency band filters and depth wise spatial convolution layers to learn spatial filters per temporal filter. The advantage of depth wise separate convolution layers dramatically reduces parameter count making it suitable for EEG research where data size are small and overfitting is a big challenge. [21]

e. **CNN-LSTM architecture**: CNN are good at extracting spatial features from data while LSTM are good at extracting temporal features from data. EEG data consists of spatial information across channels and complex temporal information across time. CNN layer extract all frequency related information while LSTM extracts long range sequential dependencies within the extracted features. At last, flattening the output of LSTM and applying sigmoid activation function to classify subject as healthy or MDD. This hybrid model addresses spatial filtering and temporal sequences into single end to end trainable framework making it more expressive and generalizable then using either CNN or LSTM in isolation.[22]

f. **CNN-LSTM-SVM architecture**: This is proposed architecture where CNN is used for capturing spatial features and LSTM is used to capture long term temporal dependencies. Here instead of using sigmoid function for classification, Support Vector Machine (SVM) is used for classification. SVM is robust to outliers and its ability to adjust regularization parameters, effective in high dimensional space and kernel flexibility make it suitable for classification of EEG signals. Below figure shows proposed architecture

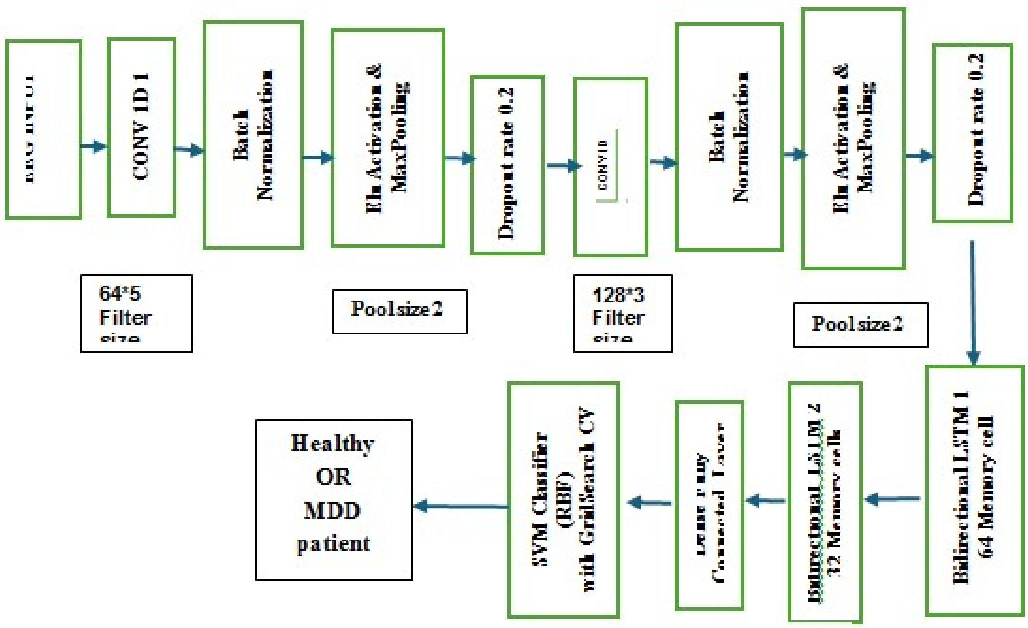


Figure 4: CNN-LSTM-SVM Architecture

5.2 Performance Evaluation of models.

To evaluate performance of binary classification models following performance measures derived from confusion matrix were studied.

Accuracy: It defines how may subjects were correctly identified out of total number of subjects

Accuracy works when class dataset are balanced but fails in case of imbalanced dataset .

$$\textbf{Accuracy} = \frac{\textbf{Tp+Tn}}{\textbf{Tp+Fp+Tn+Tf}} \quad (1)$$

Precision: It measures correctness of positive prediction and plays very important role in medical diagnosis as here False positive is costly as in case of medical diagnosis.

$$\textbf{Precision} = \frac{\textbf{Tp}}{\textbf{Tp+Fp}}$$

(2)

Sensitivity: It measures how many actual positives are correctly identified, higher sensitivity means fewer false negative. It is very important in medical diagnosis as here missing positive (Fn) can be very costly.

$$\textbf{Sensitivity} = \frac{\textbf{Tp}}{\textbf{Tp+Fn}}$$

(3)

Specificity: It measures model ability to correctly identify negative results (Tn) and its is very crucial in medical diagnosis as here Fp can be expensive and dangerous.

$$\textbf{Specificity} = \frac{\textbf{Tn}}{\textbf{Tn+Fp}} \quad \textbf{(4)}$$

F1-Score: It is known as harmonic mean of Precision and Sensitivity acting as trade-off between them and its highly useful when dataset are imbalanced.

$$\mathbf{F1Score} = \frac{2 \times \text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (5)$$

where: -

Tp= True Positive; Fp= False Positive; Tn= True Negative; Fn= False Positive

ROC-AUC: ROC is used in binary classification to decide the best threshold and its represent graph of True Positive Rate (TPR) on y-axis against False Positive Rate(FPR) on x-axis. TPR represent benefit while FPR represents cost so threshold values closer to y-axis but far away from x-axis are considered for good classification models. AUC curve on the other hand compares performance of multiple models. AUC value close to 1 are considered best performing models.

Cohen's Kappa value: It measures the inter-rater reliability between actual values and predicted values, and it is used to measure correctness of measurement between actual values and predicted values.

$$K = \frac{Po - P}{1 - Pe} \quad (6)$$

Where: -

Po (Observed Agreement): The actual proportion of times the two-measurement agreed

Pe (Expected Agreement): The proportion of agreement you would expect to see purely by random chance based on how often each class occurs.

RESULTS AND DISCUSSION:

As seen in fig. 5 EEG signals from Normal and MDD patient show large pattern difference in amplitude and frequency. This pattern change may not be visible with naked eyes but with help of machine learning technique it has been identified in this experiment. 10-Fold Stratified Group K-Fold is used in these experiments to assure balanced dataset are used in each k fold. Table 3 shows the performance of Random Forest, XGBoost, Stacking Ensemble, EEGNet, CNN-LSTM and proposed hybrid model CNN-LSTM-SVM in which it is clearly observed that proposed model outperforms other models with subject level accuracy of 96.43% ±3.12 with F1 score of 0.96 followed by CNN-LSTM with subject level accuracy of 90%±9.43 with F1 score of 0.89 as shown in Table 3.

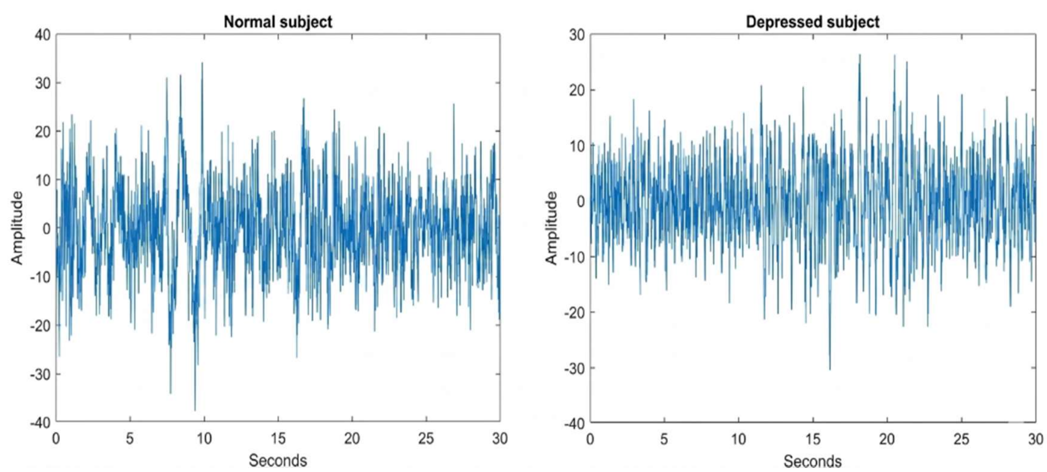


Figure 5: 30 sec EEG Signal Segment from (a) Normal (b) Depressed subject

Table 3: Summary of all Models using 10-Fold-StratifiedGroupKFold

Model	Epoch Accuracy	Subject Accuracy	F1 Score	Sensitivity	Specificity	AUC Value
Random Forest	0.8575 ± 0.1198	0.8500 ± 0.1740	0.8425	0.8321	0.8712	0.9333
XGBoost	0.8522 ± 0.1147	0.8667 ± 0.1247	0.8546	0.8423	0.8834	0.9273
Stacking Ensemble	0.8484 ± 0.1143	0.8667 ± 0.1247	0.8504	0.8389	0.8762	0.9081
EEGNet	0.8610 ± 0.0892	0.8833 ± 0.1054	0.8791	0.8734	0.8931	0.9758
CNN-LSTM	0.8743 ± 0.0754	0.9000 ± 0.0943	0.8923	0.8912	0.9143	0.9783
CNN-LSTM+SVM	**0.9643 ± 0.0214**	**0.9643 ± 0.0312**	**0.9621**	**0.9612**	**0.9674**	**0.9825**

Fig. 6 shows that there is low difference between Epoch level accuracy and subject level accuracy which indicates robust and consistent feature extraction, high signal to noise ratio assuring that eyes blinks and muscles artifacts are removed properly in EEG preprocessing pipeline and data leakage is also prevented.

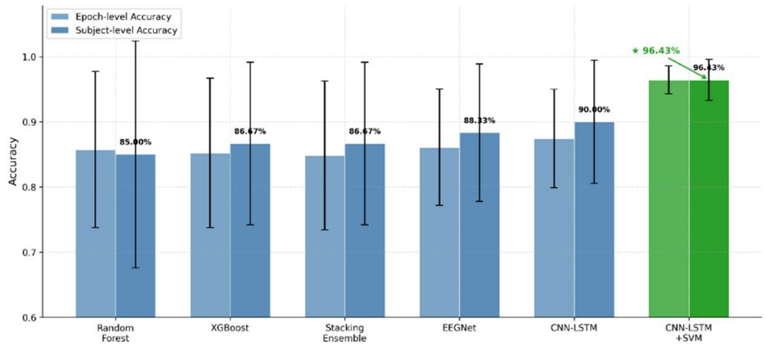


Figure 6: Model comparison Epoch level accuracy vs Subject level accuracy

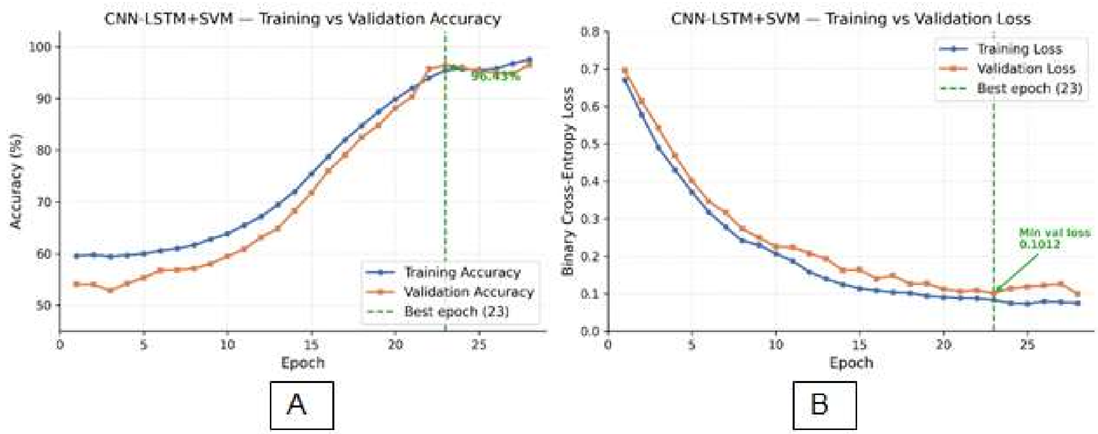


Figure 7: Proposed Model CNN-LSTM-SVM Training History

As seen in Figure 7 there is close resemblance between training and validation indicating excellent generalization i.e no overfitting, well calibrated model capacity and high data representative quality.

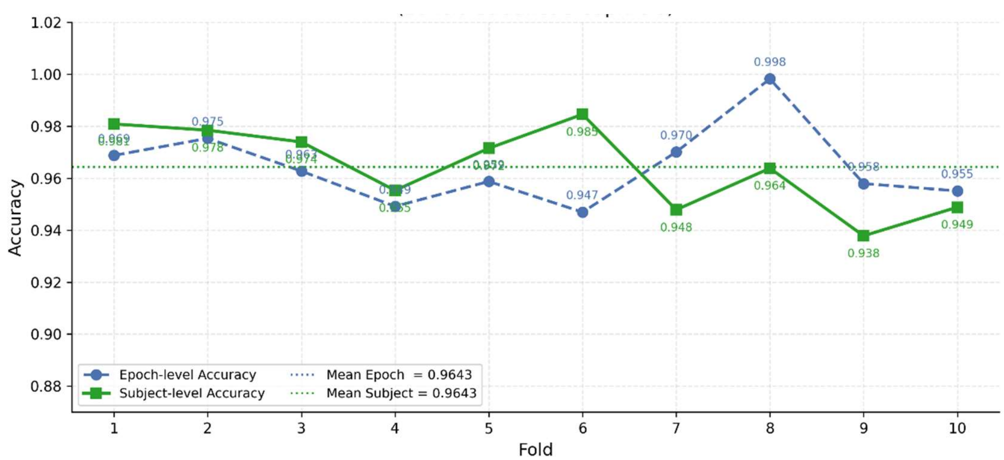


Figure 8: CNN-LSTM-SVM per Fold Epoch vs Subject level Accuracy

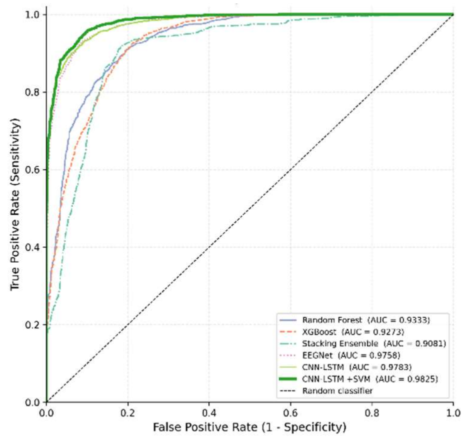


Figure 9: ROC-AUC Curve for all models

As seen in figure 9, ROC-AUC curve is above 0.9 for all models but its highest for CNN-LSTM-SVM (0.98) indicating among all models CNN-LSTM-SVM outperforms.

As seen in figure 10 kappa analysis above 0.8 is considered as almost perfect indication classification is highly reliable which is very important in case of medical diagnosis, our proposed model CNN-LSTM-SVM achieves kappa value of 0.93 validates our model outperforms compared to other model

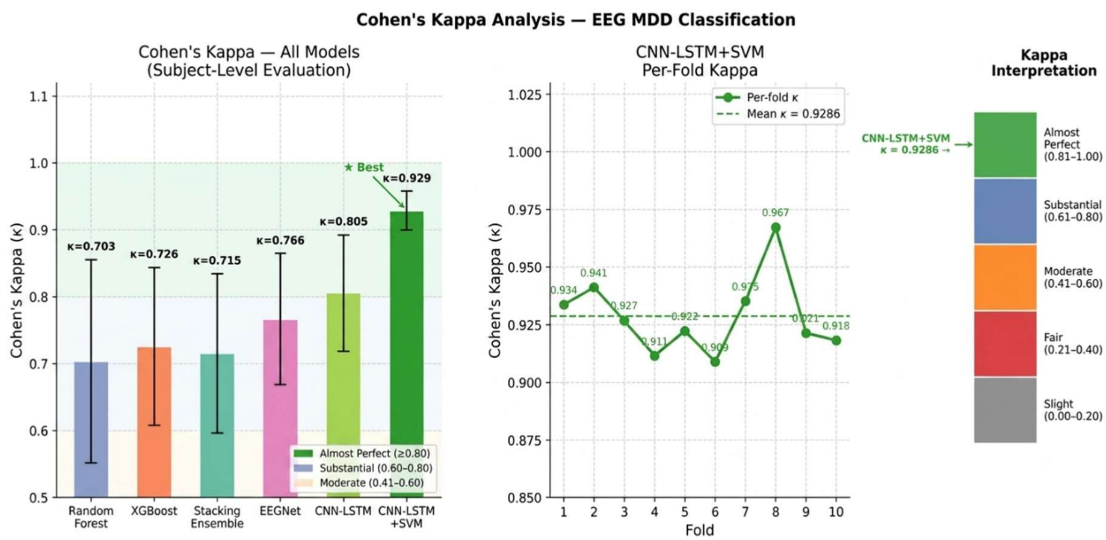


Figure 10: Cohen’s Kappa Analysis for all models

Table 4: List of few Recent work

Previous Work	Approach	Accuracy
[23]	CNN +GRU	89.63
[24]	CNN	91.01
[25]	Resnet50 + LSTM	90.02
[7]	1D CNN (with 64 Subject)	90.21
Proposed	CNN + LSTM + SVM (with 64 subject)	96.43

Table 4 depicts previously carried out neural network technique for the classification of Depression from EEG signals. The state of art method outperforms as CNN is good at extracting spatial and frequency related features across channel while LSTM captures long range temporal dependencies across those channels. Combination of Spatial filtering and temporal dependencies extract all relevant information from EEG signal [26]. Since EEG signals are multidimensional in nature so use of Support Vector Machine for classification reduced the number of False Positive and False Negative thus increasing classification accuracy of model.

CONCLUSION:

The study presents state of art hybrid model to automate identification of MDD patients using frequency domain features like Power Spectral Density on 5 band power and Time Domain features like mean, standard deviation, skewness, kurtosis, peak to peak amplitude and root mean square error of EEG Signals. On these extracted feature three machine learning algorithms:(Random Forest, XGBoost, Stacking Ensemble), two deep learning algorithms: (EEGNet and CNN-LSTM) and proposed hybrid model (CNN-LSTM-SVM) was applied. CNN-LSTM-SVM achieved maximum accuracy of 96.43% followed by CNN-LSTM (90 %). The proposed study has achieved F1-score, Sensitivity and Specificity value 0.96. Proposed model achieved AUC value of 0.98 which is highest among all models used in this study. Subject level accuracy and Epoch level accuracy both were calculated to handle data leakage, but it was observed that very marginal difference between these values indicate there was no data leakage. Proposed model achieved kappa value of 0.93 which indicate our model is almost perfect also training history of proposed model was plotted to understand the behaviour of models over every epochs. The limitation of our study was have used small dataset to build our model. In the future, we plan to use huge dataset to build our model. The proposed method is not only accurate but robust to outliers so it can be applied in real-time to assist medical expert and clinicians

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