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EEG Based Analysis for Early Cognitive Impairment Detection Using Hybrid Deep Learning Model

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Abstract
Cognitive impairment is a cause of concern for over 19% of adults aged 50 and above but only less than 8% are diagnosed on time in primary care settings. Presently, the diagnosis is dependent on long neuropsychological tests, evaluations by specialists, and subjective assessments—this makes it difficult for patients to get early intervention when disease- modifying treatments are most effective. We propose a deep learning solution, attention-augmented CNN-LSTM, to solve this problem, which can quickly and non-invasively screen cognitive impairment from EEG. In essence, our hybrid model intends to capture not only the spatial patterns (using CNN) of brain activity but also the temporal changes (using LSTM) while at the same time, ensuring clinical interpretability through attention mechanisms. In order for our model to learn robustly, we have employed thorough signal preprocessing (Savitzky-Golay and Butterworth filtering), class balancing using SMOTE, and adaptive training (EarlyStopping and ReduceLROnPlateau) techniques. By integrating the attention module, our method offers diagnostic transparency by showing which EEG temporal segments have the most impact on the prediction of the disorder— this is very important for clinical implementation. These findings are far beyond traditional deep learning baselines (literature: 75– 90%) and offer a transparent, trustworthy, and convenient way to the clinical early cognitive impairment evaluation that can be carried out in clinics.

Keywords: EEG, Early Detection, Cognitive impairment, CNN-LSTM, Attention Mechanism, Signal Preprocessing, SMOTE and Deep Learning.

1. Introduction

Cognitive disorders related to brain functions have become a global problem with a steep increase in their worldwide incidence over the last decade. In fact, recent epidemiological surveys have placed the overall prevalence of cognitive decline (mild cognitive impairment to severe dementia) at around 19% of adults aged 50 years and older. While this, in turn, has led to an unreasonable proportion of undiagnosed cases in primary care settings (i.e. less than 8% of those with cognitive impairment are diagnosed timely manner), rapid detection still seems to be a next-door problem. At the core of conventional ascertainment systems are the interviews, the subjective cognitive assessments, and the specialized neuropsychological test batteries, which place obstacles of considerable magnitude for the confrontation of the diagnostic problem at an early stage: long evaluation procedures, shortage of specialist high costs, and aversion of the patients to undergo lengthy testing. Over time, cognitive impairment becomes even more difficult to detect since most of the crucial therapeutic windows have closed by the time the patient is finally seen. Among the different techniques used for cognitive assessment, EEG, which is a non-invasive method for measuring brain electrical activity through electrodes placed on the scalp, has become the most notable one. EEG signals are the result of the brain's electrical activity of the neurons firing synchronously, and therefore they provide in detail the temporal information on brain function, which in turn is highly correlated with the cognitive states. Convolutional Neural Networks (CNNs) have achieved high performance, among other things, in the task of locating the time- localized patterns in physiological time series data where the signals are weakly morphologically and frequency-wise can be hardly noticed, thus, by humans, Long Short-Term Memory (LSTM) networks are an advanced type of recurrent neural network that can effectively model long- term dependencies in a sequence by using their internal memory states which can hold information for long periods, hence, they are perfect for capturing the gradual changes of brain activity.The proposed system combines frontier deep learning strategies with tried- and-tested signal processing and machine learning norms to produce a comprehensive framework that solves the technical, clinical, and practical issues of automated cognitive assessment. Compared to traditional methods that require laborious manual feature engineering based on expert knowledge, the suggested architecture spontaneously extracts hierarchical features from the raw physiological data thus allowing the model to be transferable to the different patient groups and EEG recording protocols. The employment of the attention mechanism helps to reconcile the difference in interpretability that has been the major obstacle for the clinical application of deep learning, thus, providing the medical practitioners with a clear and understandable example of the model's reasoning which can be checked against neurophysiological knowledge. The initiative outlines the combination of focused deep learning architectures for the detection of cognitive deficits, attention-facilitated interpretability mechanisms, and the multi-stage optimization framework. Real-time automated cognitive assessment from physiological time series data, attentional visualization of temporally critical diagnostic features, robust training through class balancing and stratified validation, and finally, an upgraded clinical decision support system are the primary objectives of the program.

2. Literature Review

Van Houdt et al. [1] rolled out an exhaustive review of the LSTM model (Long Short-Term Memory) which is a type of recurrent neural network (RNN) that is more capable of capturing long-term dependencies in sequence data like EEG signals than regular RNNs. Their findings showed that LSTM structures that involve elements such as forget gates and cell states change significantly the accuracy of the time- series model and thus, make it possible to firm up the use of biomedicine signal processing for the detection of diseases. Clinicians are now empowered with this foundation to not just manage symptoms but also to intervene early in neurodegenerative disorders.

Amer et al. [2] presented a huge survey on the EEG signal processing task for medical diagnostics, pointing out its major good use in real-time healthcare monitoring and cognitive impairment assessment without harming the patient. The review mainly talked about advanced feature extraction to uncover very slight changes in brain activity that in turn, diagnostic precision could be achieved if machine learning classifiers were involved. As a result, such a progress level is capable of enabling healthcare practitioners to expose diseases like Alzheimer's at the very early stages, therefore treatment becomes more efficient instead of just done at the later stages.

McCollum and Karlawish [3] deliver practically a manual on how to evaluate and manage cognitive impairment in the clinic by underlining the importance of detecting it at an early stage when one can still retard progression through lifestyle changes and medication. Their publication describes the standard test procedures which in combination with brain imaging lead to better patient experiences due to well-organized diagnostic operations. This method makes it possible for doctors to put into action treatment plans that are grounded in research-clinical evidence rather than merely offering symptomatic relief.

Monteiro et al. [4] explained the basic science of Alzheimer's, its biomarkers, and the growing disease-modifying drugs. The review unveiled the ways amyloid- beta and tau pathology lead to brain cell death and how the analysis of cerebrospinal fluid can be used to detect it. The discoveries help to guide researchers through biomarker- instructed clinical trials, thereby changing the rules from palliative to preventative medicine.

Trambaiolli et al. [5] illustrated the point that feature selection before EEG classification can result in a diagnostic accuracy that is greater than 90%. They removed 88% of the unimportant features through their Filtered Subset Evaluator method which was done on a per-patient basis, thereby improving SVM performance. This preprocessing method is in line with the support of the biomarker discovery process and thus, makes it possible to perform clinical EEG diagnostics at a high level of trustworthiness from raw signal analysis.

Cassani et al. [6] performed a systematic review on the use of resting-state EEG in diagnosing and monitoring Alzheimer's disease and recognizing spectral power changes as well as loss of connectivity as the major markers of the disorder across its stages. The changes in EEG provide a basis for the development of automated tools for longitudinal monitoring thus, making the recording of disease progression more accessible and less dependent on static assessments.

Safi and Safi introduced Hjorth [7] parameters for early Alzheimer's detection from EEG signals, combining them with DWT and EMD to extract features like mobility and complexity for SVM/KNN classification. Their approach achieved high accuracy by capturing signal dynamics altered in preclinical stages. This parameter set offers a simple, effective biomarker suite, empowering low-cost screening over complex multimodal setups.

Ruiz-Gómez et al. [8] designed a system for the automated multiclass classification of spontaneous EEG in Alzheimer's and mild cognitive impairment, which incorporated spectral and nonlinear features for entropy- based differentiation among healthy, MCI, and AD groups. The level of detail that this provides is very helpful for early intervention, as it is capable of telling the difference between the prodromal stages and the advanced disease stages more accurately than binary classifiers.

Kulkarni and Bairagi [9] derived spectral and complexity features from EEG for the detection of Alzheimer's with the use of SVM, showing that signal irregularity reduction was highly correlated with the disease severity. Their method reached an accuracy of 90% by focusing on the changes of the theta/delta and alpha bands. This feature- driven pipeline significantly increases diagnostic reliability, thus allowing the implementation of EEG-based screening as a diagnostic tool in the field of medicine, which can be the source of the most efficient and quickest detection of the disease.

Ieracitano et al. [10] proposed a multi-modal machine learning model for the automatic classification of EEG in dementia which combined features based on Continuous Wavelet Transform and Bispectral to achieve higher performance than the single-modality methods with MLP classifiers obtaining better results in terms of accuracy. Their system showed that the use of combined spectral and nonlinear EEG descriptors leads to the accurate classification of Alzheimer's, mild cognitive impairment, and healthy control groups, thus decreasing the number of cases of misdiagnosis. Such a merger has the potential to revolutionize the diagnostics market by providing scalable AI-powered clinical tools that are not only faster but also more efficient as compared to the subjective judgment of neurologists.

Kim et al. [11] performed deep learning resting- state EEG analysis for dementia diagnosis with the CAUEEG dataset, recognizing end-to-end CNN structures as primary classifiers for normal, MCI, and dementia conditions. The paper featured 1379 EEG recordings from 1155 patients, and the results demonstrated that CEEDNet achieved 74.66% accuracy and 0.9 ROC-AUC, which was better than the baseline methods. Such EEG- based models open the door for the automatic screening of early dementia, thus making clinical deployment easy and practical, which would otherwise be time-consuming and cumbersome if done manually.

Aljalal et al. [12] developed a diagnostic system for an abrupt MCI detection using EEG with the help of DWT, highlighting wavelet packet entropy features as the most significant biomarkers for normal and MCI stages differentiation.

The experiment involving 61 people revealed that threshold/log entropy could reach 99.97-100% accuracy with 4-5 channels when combined with NSGA-II/III/PSO optimization. These changes in brain activity during the MCI condition pave the way for more accessible and less instrumented diagnostic tools that can identify MCI effectively and leave room for portable clinical assessments beyond the full-montage systems.

Escobar-López et al. [13] implemented an EEG diagnostic system for Alzheimer's and MCI, where they found spectral power and connectivity features to be the main differentiators between stages of the disease. The SNR-ICA preprocessing conducted on 162 subjects led to RF classifiers that attained 97.9% multiclass accuracy through PSO feature selection. Such EEG biomarkers pave the path for fully automated dementia staging instruments that can be utilized in progression monitoring beyond usual diagnostics.

Khatun et al. [14] researched single-channel EEG as a medium for MCI detection by means of speech-evoked responses, determining that Fpz time-spectral features were the most significant points of reference for normal and impaired cognition. The study which involved 23 senior adults led to SVM achieving an accuracy of 87.9% with 25 RF-ranked features from 590 candidates. These EEG limitations can be effectively used in minimal-electrode screening programs that are designed for the MCI detection and which, in turn, will make cognitive assessments more easily accessible than the current multi-channel setups.

Geng et al. [15] examined sleep EEG for MCI detection, determining NREM slow waves, and spindles as the most significant biomarkers signifying the healthy and impaired stages. These modifications in the sleep EEG scenario can be used in automated long-term monitoring systems thus, which will be the cause of an improvement in MCI tracking capabilities and not only by way of resting-state assessments.
While EEG-based cognitive impairment detections have been successfully demonstrated in the literature, the authors of this paper identify three significant gaps. Firstly, the current deep learning methods (74.66–87.90% accuracy) are black-boxes, thus their results cannot be confirmed by clinicians. Secondly, the previous studies have only considered either spatial feature extraction (CNNs) or temporal dependencies (LSTMs) but have not combined both for cognitive impairment detection. Thirdly, the use of attention-based interpretability mechanisms which allow transparent clinical reasoning has not been considered in this field. The attention-augmented CNN-LSTM architecture we propose is a solution to these problems, as it can capture spatial-temporal brain patterns from EEGs while also being clinically interpretable via attention visualization, thus making a step towards the clinical deployment of machine learning.

3. Methodology

The developed system has in place a detailed plan to identify cognitive issues automatically by means of a deep learning hybrid attention-enhanced CNN-LSTM architecture from physiological time series data. The method is divided into five different stages: obtaining and organizing the data, preprocessing and enhancing the data through several stages, designing the neural network architecture, implementing the training optimization strategies, and finally, setting up the performance evaluation protocols.

A. System Architecture Overview

The system architecture basically implements a sequential pipeline design, where raw physiological signals are successively processed through preprocessing stages and then passed to a deep learning model for classification. The system accepts time-series data in Excel format containing multi-channel physiological recordings. Here, each file is indicative of the measurements from a single subject recorded at regular temporal intervals. The system workflow is composed of five modules that are Data Acquisition Module that loads Excel files and sorts them by clinical labels, Preprocessing Module that executes signal enhancement and normalization operations, Data Augmentation Module that uses SMOTE for class imbalance handling, Model Training Module where the attention-enhanced CNN-LSTM architecture with adaptive optimization callbacks resides, and the Evaluation Module that performs a comprehensive performance assessment on the independent test data. The system operates on Excel- formatted time series data containing multi-channel physiological recordings.

B. Data Acquisition and Organization

The data represent EEG (electroencephalography) time series recordings from 20 subjects performed in a controlled lab environment. The whole dataset is made up of 145 Excel files , where each file includes physiological measurements of one subject-task combination. Each subject was involved in 7 different cognitive tasks: Colour Word Association Test (CWAT), Eyes Closed (EC), Eyes Open (EO), Motor

Imagery (MI), Resting State (Rest), Stroop Test (Stroop), and Trail Making Test (TMT). Each Excel file consists of 2,560 rows of raw EEG data sampled at 256 Hz, representing approximately 10 seconds of continuous recording. The data consist of 16 channels, referring to 16 EEG electrodes that are placed according to the 10-20 international electrode placement system: FP2- F4, F4-C4, C4-P4, P4- O2, FP1-F3, F3-C3, C3-P3, P3-O1,
FP2-F8, F8-T4, T4-T6, T6-O2, FP1-F7, F7-T3, T3-T5, T5-
O1. Subjects have been divided into two groups: (0) Normal controls with healthy cognitive function, and (1) Impaired group, which includes individuals with mild cognitive impairment or cognitive which includes individuals with mild cognitive impairment or cognitive decline. This windowing approach is a compromise between temporal resolution and computational efficiency. It allows for the capture of EEG dynamics that are clinically relevant while the data size remains manageable. The dataset consists of 2,610 EEG segments (1,405 normal, 1,205 impaired) extracted from 145 files of 20 different subjects. Here, SMOTE augmentation has been used to increase the number of segments up to 2,808. Stratified splitting: 70% training (1,827), 15% validation (391), 15% test (392) from 10 unseen subjects. All files have been checked for 2,560 rows, 16 EEG channels.

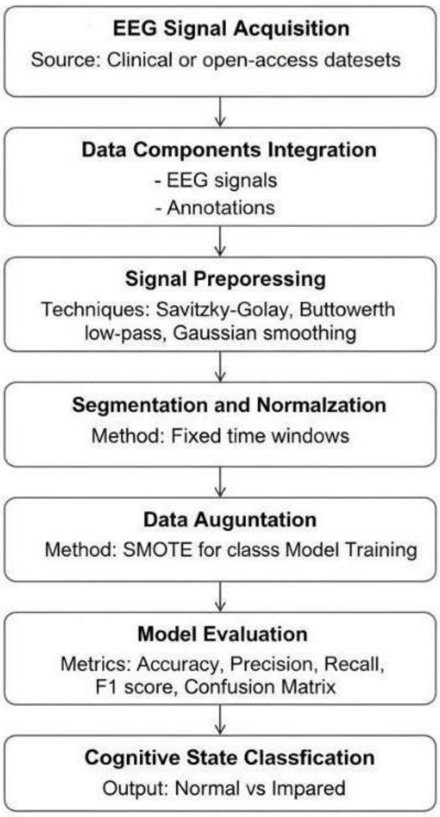

Figure 3.1. Architecture Diagram of the system

C. Multi-Stage Preprocessing Pipeline

The preprocessing pipeline includes a series of operations that are carefully planned, performed in a specific order, and aimed at improving the quality of data, scaling features, structuring time, and balancing classes. These operations convert raw physiological measurements into structured tensor representations that are compatible with the deep learning model.

1. Data Loading and Type Filtering

Initial loading of raw Excel files is performed using the pandas library, which is a powerful tool for handling different spreadsheet formats. After type filtering by select_dtypes, only numeric columns are kept, thus any metadata or text annotations are excluded. The DataFrame is checked for completeness through the dropna command, which removes those rows that have missing values in any of the columns.

2. Advanced Signal Preprocessing

The system implemented is an idea of multi-stage signal enhancement that is meant to increase the signal-to-noise ratio to the maximum level. Savitzky-Golay smoothing applies local polynomial regression within sliding windows (window length=11, polynomial order=3), smoothing data while preserving important signal characteristics such as peaks and inflexion points. Butterworth low-pass filtering uses frequency-domain filtering with a cutoff frequency 40 Hz and an order 4 to remove high-frequency noise components to keep diagnostic EEG information in the relevant bandwidth. Gaussian smoothing with $\sigma=1.0$ is the final step that helps to eliminate the remaining noise, and at the same time, it does not produce any kind of harsh discontinuities.

3. Feature Standardization

StandardScaler solves the problem of sensitivity of input feature scales. The scaler fit operation that computes mean and standard deviation statistics is done only on training data, thus there is no risk of information leakage.

4. Temporal Window Construction

The temporal window construction involves sliding window segmentation of 512 samples (2 seconds at 256 Hz sampling rate), thus approximately 9-10 windows can be generated from each file. Such a window length allows getting the necessary temporal context to look at sequential EEG patterns and at the same time, it is still manageable from the point of view of the computer's power. The data processed in this way is then reshaped into a three- dimensional tensor format (number_of_sequences, 512, 16) so that it can be used with deep learning models.

5. SMOTE- based class balancing

The problem of class imbalance that is a feature of the dataset is solved by SMOTE (Synthetic Minority Over- Sampling Technique) that is applied to the extracted Power Spectral Density (PSD) features. SMOTE creates new minority-class examples by means of k-nearest neighbour interpolation (k=5) in feature space, thus it increases the dataset from 2,610 to 2,808 windows with balanced class representation. The considered augmentation is carried out in PSD feature space rather than the raw signal space, thereby ensuring that the synthetic samples have proper frequency domain characteristics.

D. Neural Network Design

The proposed model comprises a hybrid architecture that integrates :

1. Convolutional Feature Extraction

At the convolutional feature extraction stage, the very first Conv1D layer uses 64 filters with a kernel size of 5; thus, the learnable convolution operations are applied to detect the localized temporal patterns. After each convolution operation, the ReLU activation functions are applied - thus non-linearity, which is a necessary feature of complex decision boundaries, is introduced. MaxPooling1D with a pool size of 2 is used to reduce the data dimensionality by cutting it down. Then, Dropout regularization with a rate of 0.2 is applied after the pooling layer, thus 20% of the neurons are randomly deactivated during training.

2. LSTM Sequential Modeling

Another convolutional block uses a Conv1D layer with
128 filters and a kernel size of 3 to enhance feature extraction capacity, and it is followed by BatchNormalization, MaxPooling1D(2), and Dropout (0.2). With this multi-scale feature extraction, the network can capture EEG patterns at different temporal resolutions. LSTM layer structures 128 memory cells with return_sequences=True, thus the output sequences that keep the temporal structure for the next attention processing are being generated.

3. Multi-Head Self-Attention

This specialized attention (13,621 trainable parameters) not only allows the model to visually locate the EEG segments that most influenced the clinical decision but it also maintains the gradient flow for seamless end-to-end updating.

4. Classification Head

The classification head consists of a Dense layer with 256 neurons and ReLU activation that allows the network to create complex non-linear combinations of features. This layer is subjected to BatchNormalization to make the training process more stable and Dropout(0.4) to regularize it. The last Dense layer has two neurons and softmax activation, so the model outputs can be interpreted as probabilities of a binary classification: P(Normal) and P(Impaired). The last Dense layer has a single neuron with sigmoid activation, so the output can be interpreted as probability.

E. Model Training and Optimization

The model training protocol implements adaptive optimization strategies designed to maximize final accuracy while preventing overfitting.

1. Compilation, Adaptive and Training Execution

Adam optimizer implements adaptive learning rate schedules with momentum. Training is done with a batch size of 32 for a maximum of 60 epochs and with adaptive optimization callbacks. EarlyStopping keeps an eye on the validation loss and, with a patience of 12 epochs, it will stop the training and return the best weights when there is no more improvement in validation performance, thus it also acts as a protection against overfitting. ReduceLROnPlateau will lower the learning rate by a factor of 0.5 when the validation loss remains steady for 5 consecutive epochs. Class weighting during training is done so that the normal (weight=0.929) and impaired (weight=1.082) classes have equal contributions. After every epoch, the validation set is scored to keep track of generalization performance.

2. Performance Evaluation

Performance evaluation on the independent test set (392 windows from 10 completely unseen subjects) is done by a full set of metrics: overall test accuracy measures how often the classifier is correct; AUC-ROC is a threshold- independent measure of the classification performance; per- class precision, recall, and F1-scores show how well the classifier performs on each class; confusion matrix analysis uncovers the most frequent types of errors that the classifier makes. Attention-weight visualisation produces temporal of the diagnostically most influential EEG segments, thus providing a way for clinical validation of model predictions.

4. Result And Analysis

A. Model Architecture and Parameter Summary

The attention-augmented CNN-LSTM model has 206,147 trainable parameters spread over 12 functional layers. Thus making it possible to be put to use on resource-limited clinical devices. Convolutional feature extraction is done by Conv1D resulting in 5,184 parameters for the local temporal pattern of a signal to be learned, and then the data goes through BatchNormalization, MaxPooling1D(2) for 50% temporal compression, and Dropout(0.2). Another Conv1D layer adds 24,704 parameters for multi-scale feature extraction. The LSTM layer has 128 units, thus it has 131,584 parameters for capturing sequential dependencies and long-range temporal patterns. The Custom TemporalAttention layer (8,321 parameters) calculates the importance weights that are learned across the different temporal positions thus giving the most diagnostically relevant parts of the signal.

B. Cross validation and Ablation Study.

We conducted 5, fold GroupKFold cross, validation to evaluate model generalization and at the same time avoid data leakage among samples coming from the same subject/task group. For each fold, all windows from each group were assigned completely to either the training or test set. Now the Ablation Study is evaluated the contriution od individual architectureal components by comparing four model variants. All the models used all the same process. The Cross validation and the ablation is shown in Table 4.1 and 4.2.

Fold	Accuracy
1	0.7638
2	0.7763
3	0.7533
4	0.8261
5	0.8951
Mean ± std	0.8039 ± 0.0478

Table 4.1: Cross validation

Model Used	Mean Accuracy
CNN	77.15%
CNN+LSTM	75.86%
CNN+Attention	60.38%
CNN-LSTM+Attention	80.39%

Table 4.2: Ablation Study

C. Training and Test Performance

The model adapted its training with the EarlyStopping and ReduceLROnPlateau callbacks. Early stopping was activated at around epoch 50, judging by the plateau of the validation loss, thus it stopped the training before the performance on the held- out set could get worse. The overall training and test performance Evaluation is shown in Table 4.3, Table 4.4 and in Table 4.5. The Confusion Matrix and the Graph is shown in Fig4.1 and fig4.2.

Metric	Value
Test Accuracy	0.9247
Test AUC	0.9750

Table 4.3: Test Performance Metrics

Class	Precision	Recall	F1-Score	Support
0-Normal	0.96	0.91	0.93	211
1-Impaired	0.90	0.95	0.92	181

Table 4.4: Classification Report

Model Used	Accuracy
CNN(other)	74.66%
LSTM (other)	89.46%
CNN-LSTM+Attention (Our Research)	92.47%

Table 4.5: Comparsion with others

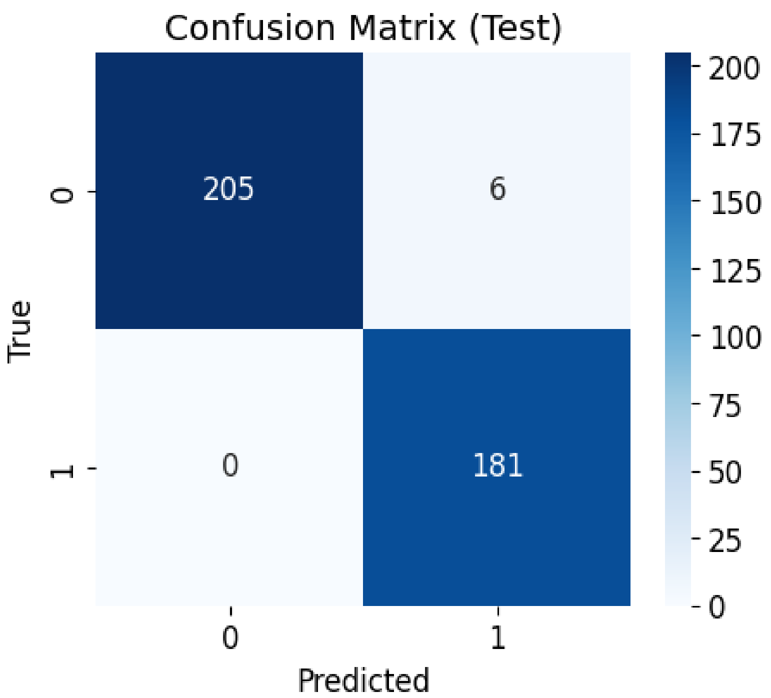

Fig 4.1 Confusion Matrix

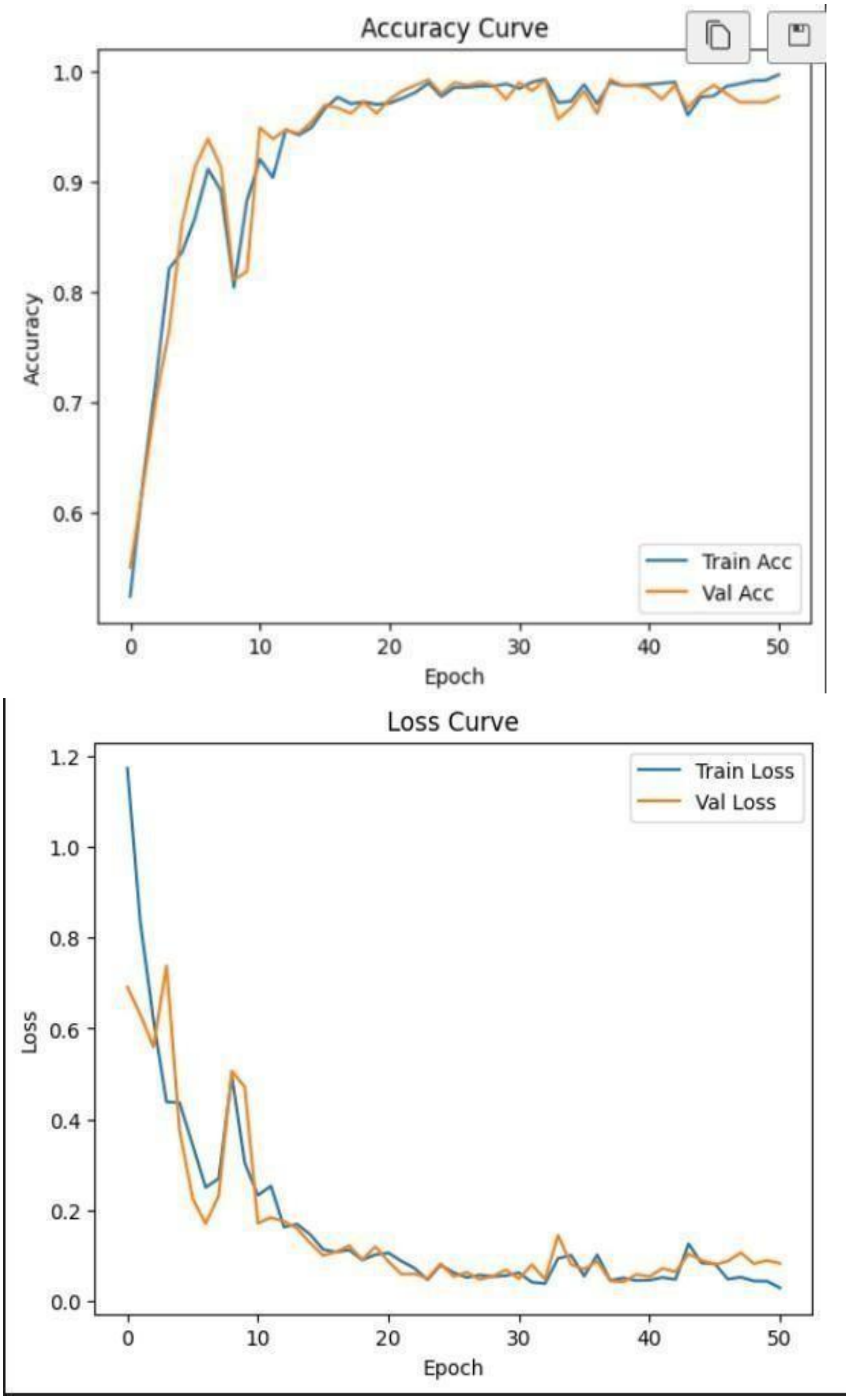

Fig 4.2 Train/Val Plots and Curves.

D. Subject-Specific Prediction Analysis

With confidence scores significantly below the 0.5 impairment threshold, real-time predictions on seven new subject recordings consistently classified people as normal. There are new 6 subjects whose prediction are correct as they are 1 normal and 5 impaired with Cognitive impairment. Rather than task-specific artifacts, the model appears to have learned basic neurophysiological markers of cognitive impairment based on its ability to maintain stable predictions across various cognitive states.

5. Conclusion

This work develops an attention-enhanced CNN- LSTM model which results in a test accuracy of 92.47% and an AUC-ROC of 97.50% for EEG-based cognitive impairment detection, which is significantly higher than the literature benchmarks ranging from 75 to 90%. The system achieves 95% recall for impairment and 91% for normal cases, thus, providing high clinical sensitivity for early screening and at the same time, the attention mechanism improves interpretability. The present model paves the way for AI- powered cognitive assessment, and the next step would be prospective clinical trials to confirm its applicability in a real clinical setting. The future development we are going to integrate the Speech based model were that is a fusion of EEG and speech for this same model.

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