International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 11 | Nov - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Deep Neural EEG Based Alzeihmers Detection

Rashmi
Department of Computer Science and Engineering
Chandigarh University
Mohali, India
dhimanrashmi708@gmail.com

Inakshi Garg
Department of Computer Science and Engineering
Chandigarh University
Mohali, India
inakshi.e12349@cumail.in

***Abstract*—Alzheimer disease (AD) is a progressive neurodegenerative disorder, treatment and management of which needs to be timely. Conventional diagnosis techniques such as MRI, PET, and cerebrospinal fluid test are mostly invasive, costly, or not available at large scale. On the other hand, electroencephalography (EEG) represents a non-invasive, low-cost, and portable method of brain monitoring, hence, making it a favorable modality to use to screen AD at an early onset. The article contains a deep neural network framework of automatic EEG-based Alzheimer disease classification. Raw EEG data were processed and transformed to time-frequency representation and connection matrices. The different architectures (convolutional neural networks (CNNs), hybrid CNN-LSTM models as well as transformer-based models) were trained and compared with the conventional machine learning-based models (support vector machines and random forests). The deep neural models were found to be more effective than the traditional methods with improved accuracy, sensitivity and specificity in distinguishing between the patients with AD and mild cognitive impairment (MCI) and those without mental illnesses. On top of highlighting frequency bands and areas that are correlated with known AD biomarkers, which is important to validate the clinical relevance of the finding, model interpretability methods, such as Grad-CAM, also focused on frequency bands and areas that are correlated with known AD biomarkers. These findings indicate that EEG-based deep neural models can be used practically to scalably and early diagnose the presence of Alzheimer as not only deep learning using EEG signals improves diagnostic accuracy but also provides biologically relevant outcomes.**

***Index Terms*—Alzheimer's disease, Electroencephalography (EEG), Deep learning, Neural networks, Convolutional neural networks (CNN), Long short-term memory (LSTM), Transformers, Mild cognitive impairment (MCI), Early diagnosis, Brain–computer interface (BCI), Medical signal processing.**

I. INTRODUCTION

The most common form of dementia is referred to as Alzheimer disease (AD), which comprises nearly 60-70 percent of the cases in the world. According to the World Health Organization, more than 50 million people live with dementia and the number will almost increase to 150 million by 2050 due to the growth in the ageing populations around the world. AD is characterized by a gradual decline of cognitive functions, memory impairment and functional impairment which in the end leads to complete loss of independence. Timely diagnosis of AD is a vital step that should be done at the earliest possible and this will enable the AD patient to receive timely clinical care, well-structured treatment plans and improved quality of life in the caregiver and the patient themselves.

The conventional diagnostic methods rely on the neuroimaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography (PET), or the analysis of the biomarkers of the cerebrospinal fluid (CSF). These modalitiesthough informative are often invasive, expensive as well as they cannot be adjusted to mass screening. Electroencephalography (EEG) on the other hand is a low cost, non-portable and invasive way of monitoring the brain activity. A number of studies have determined that AD is associated with normal changes in EEG activities including slowing neural oscillations, increased delta and theta activity, reduced alpha and beta power, and poor functional connectivity. These developments make EEG a formidable candidate in the initial diagnosis of Alzheimer disease.

Traditional EEG-based classification algorithms rely on primarily hand-designed features such as spectral power, coherence or entropy values in combination with machine learning classifiers. The methods though having a moderate level of success have disadvantages because they require hand feature engineering and fail to capture the complex spatiotemporal dynamics of neural activity. The recent advances in the field of deep learning have transformed the realm of the biomedical signal processing, as they have allowed extracting features and learning the representation of raw or half-processed signals automatically. In particular, deep neural networks (e.g., convolutional neural networks (CNNs), recurrent neural networks (RNNs), transformer models, etc.) have been demonstrated to excel on a wide variety of EEG related tasks, including seizure detection, sleep stage classification, and emotion recognition.

However, little has been done in studying deep learning on EEG-based detection of Alzheimer. The past studies have normally been constrained by the small size of databases, dichotomous classification (AD vs. healthy controls), and little cross-validation across separate databases. Also, the issue of discrimination between early AD and mild cognitive impairment (MCI), as an intermediate period between normal aging and AD, remains one of the main clinical problems that have not been appropriately addressed using deep learning procedures.

This paper aims to address these loopholes by proposing an EEG-based paradigm of detecting Alzheimer through deep neural networks. The paper discusses the model architectures, including CNNs, hybrid CNN-LSTM and transformer models and their performance in comparison to baseline machine learning benchmarks. Moreover, to relate the findings of the computations to known clinical biomarkers, we employ model interpretability techniques to determine the frequency bands and cortical regions that are most predictive of AD.

The key contributions of the work are the following:

We suggest and compare deep neural network models which are specifically developed to detect Alzheimer disease using EEG with focus on early-stage classification.

To demonstrate the enhancement of accuracy, sensitivity, and specificity, we compare deep learning models and the machine learning approaches.

Explainable AI approaches are used to compare model results with clinically reported EEG biomarkers of AD.

We highlight the potential of EEG-driven deep neural models as low-priced and scalable techniques of the early detection of Alzheimer in real-life clinical settings.

The remaining part of this paper is structured as follows: Section II presents the relevant work on EEG-based Alzheimer detection, and deep learning based on EEG analysis. Section III provides sections III, Section IV, Section V, and Section VI with the methodology, datasets, preprocessing and model architectures. Section IV contains the description of the experimental setup and findings. Section V speaks of implications of the work, limitations and outlooks of the work. Lastly, Section VI provides a conclusion of the paper.

II. Literature Review

Ieracitano et al. (2019) modeled the application of convolutional neural network (CNN)-based classification of the dementia stages using 2D time-frequency representation of EEG records. They found that CNNs, which were trained on spectrograms, did better than the traditional machine learning classifiers that were trained on hand-designed spectral features, and could potentially achieve complete control of EEG-based AD detection. Small sizes of data sets and within-data set validation alone are the limitations and generalizability is of concern.

The AlSharabi et al. (2023) created the EEG-based clinical decision support system and employed an artifact removal, spectral, and connectivity functionalities, and multi-classifiers. They stated that accurate EEG processing would be capable of achieving clinically significant accuracy in the detection of AD. Their research, though, was constrained by single-site data and relatively small group cohorts, and hence confidence of the study across population was diminished.

The authors of [3] presented a CNN model, which was trained on EEG-based connectivity matrices to detect the network disruptions in Alzheimer. The functional connectivity between AD and healthy controls was increased, and the importance of functional connectivity in identification is proven. The weaknesses were characterized by the single-cohort study that was not externally validated.

In their study, Shan et al. (2022) applied spatiotemporal graph convolutional networks (ST-GCNs) to EEG signals and could consider the electrode position of the topology and dynamics over time. They demonstrated greater discrimination accuracy in cognitive state discrimination and this can be used in the diagnosis of early AD. Weaknesses are based on controlled data and no validation by several centers.

Another article reviewed by Chetty et al. (2024) investigated spectral and connectivity EEG features differentiating AD and prodromal AD and controls. Their study confirmed expected biomarkers such as the decrease of alpha/beta power and an increase of theta/delta activity. Even though their findings were consistent in comparison to preprocessing pipelines, the power of conclusions was limited because of the small cohort sizes.

Vicchietti et al. (2023) conducted a survey of computational EEG methods to diagnose disorders, indicating that multi-feature models based on spectral, nonlinear, and connectivity features have better results compared to single-feature models. Disadvantages include the non-standard reporting of the recording parameters of EEG making it hard to repeat.

[7] Aviles et al. (2024) conducted a systematic review of the trends in ML and DL in EEG-based detection of Alzheimer with the following pitfalls such as small sample sizes, division on an epoch basis, and the absence of external validation. They propose their suggestions to focus on subject-wise split, per-subject measures, and explainable AI in order to render it clinically relevant.

Implying a distinction between various stages of AD, [8] Kim et al. (2024) developed a cognitive-task EEG protocol. They also showed that the combination of resting-state and task-based EEG increased the sensitivity in early-stage detection. Weaknesses include moderate sizes of the cohort, and the need to replicate with more multi-site studies.

The study by Seker et al. (2021) and the follow-up studies integrated permutation entropy with CNNs to diagnose early AD and revealed that nonlinear features and deep learning could be used to improve sensitivity to the unobvious EEG changes. Small cohort sizes, as well as lack of external validation, were limitations.

Keeping the context of the paper, Khare and Acharya (2023) introduce the Adazd-Net, an explainable and adaptive deep-learning EEG-based system to detect AD. They combined wavelet decomposition, feature selection and interpretability modules with resonance with clinical EEG biomarkers. Little data and no cross-system validation were limited.

Transformer-based architectures and attention mechanisms when applied to EEG spectrograms and connectivity matrices were found in [11] to underscore clinically relevant time-frequency regions in attention. The challenges were overfitting on small datasets and huge pretraining corpora requirement.

In a comparison study of the proposed feature-extraction methods and conventional classifiers versus deep neural networks, [12] found the CNNs on spectrograms to be improved compared to conventional options on large datasets, but traditional pipelines retain their competitiveness on small datasets. Simpler models gave greater interpretability but lesser maximum accuracy.

As it was observed by Chetty et al. (2024) and Vicchietti et al. (2023), explainable AI methods (Grad-CAM, SHAP, saliency maps) repeatedly found that posterior alpha slowing and an increase in frontal theta are the main predictors of AD. The weaknesses include the potential biases of saliency maps and the need to validate according to physiology.

In current studies (Wang 2023; Liu 2024) transfer-learning and self-supervised approaches were used in an effort to offset sparse labeled EEG-AD data with large clinical datasets of EEG such as TUH. The task design should be done carefully, although it will increase cross-site generalization, and they need to use large unlabeled sets.

In Puri et al. (2022-2023, India), low-complexity filter banks, Kolmogorov complexity, and empirical mode decomposition/Hjorth parameters were used to identify AD out of EEG. They reported promising classification accuracy in low-resource conditions, however, the size of cohorts was limited, and their applicability was limited.

In their study, Nanthini et al. (2024, India) performed a two-step process of feature extraction (time-domain and frequency-domain features or statistical features) to predict a neurological disorder by EEGs. Their analysis reaffirmed common biomarkers (alpha/theta shifts) and preprocessing and standardization problems of cohorts.

The article by Jain and Srivastava (India, 2025) used synchrosqueezing transforms and deep transfer learning and demonstrated competitive results of channel-wise TF representation. Their weaknesses included small sample sizes and testing of different EEG systems and electrode layouts.

Puri et al. (2024, India) explored the concept of wavelet filter banks and light explainable architectures and demonstrated that even in resource-limited settings of low-complexity pipelines, hybrid deep-learning approaches could prove to be more precise assuming that the data were abundant.

Overall, the cited literature demonstrates that multi-representation techniques that include raw EEG, spectrograms, and connectivity graphs, with explainability and transfer learning, have the greatest potential of generalized and resilient detection of AD. Small datasets, the lack of multi site validation, and pipeline heterogeneity as a problem continue to be persistent.

III. Methodology

A. Data Sources

In order to create and test the target deep neural EEG-based Alzheimer detector model, a number of datasets were used:

Primary EEG Datasets:

- OpenNeuro Dataset (ds004504, ds006036): This data contains EEG data in patients with AD, MCI, and healthy control subjects.
- TUH EEG Corpus: This is a publicly accessible large-scale data that has been used to pretrain deep learning models in order to enhance feature extraction capabilities.
- Mendeley EEG data (AD/MCI): This data consists of resting and task-based EEG data.

Secondary/Complementary Data:

- Alzheimer Disease Neuroimaging Initiative (ADNI): Provides the MRI, PET as well as biomarker data potential multiple multimodal integration.
- PEARL-Neuro data: Provides EEG along with genetic or clinical information, which allows conducting further studies on the relationships between EEG characteristics and AD development.

B. EEG Preprocessing

EEG preprocessing ensures that the raw signals are clean and suitable in deep learning. The set of stages in preprocessing involved:

- Artifact Removal: Independent Component Analysis (ICA) and the removal of eye blinks, muscle artifacts and environmental noise using the wavelet denoising technique.
- Filtering: Band-pass filtering (0.5-45 Hz) to eliminate irrelevant EEG frequency bands to identify Alzheimer.
- Segmentation: To normalize the input to the models, the EEG signals were broken down into epochs (2-5 seconds).
- Time-Frequency Transformation: Spectrograms to input CNN were calculated using Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT).
- Connectivity Analysis: Coherence and phase-lag index were used to compute functional connectivity matrices in order to determine inter-channel relationships.

C. Feature Representation

The model was fed with three types of feature representation:

- Raw EEG Signals: normalised and standardised voltage traces.
- TimeFrequency Representations: Spectrogram images with information about dynamics of time and frequency.
- Connectivity Graphs: The Electrode-wise functional connectivity matrices, which show inter channel interactions.

D. Model Architectures

Some deep learning models were explored and compared to classic machine learning models:

- Convolutional Neural Networks (CNNs): This is an algorithm applied to time-frequency spectrograms to acquire knowledge of spatial and spectral structures.
- Hybrid CNN-LSTM Networks: CNN used with the LSTM layers to learn the temporal patterns in the EEG sequence on the top of the CNN spatial feature extraction.
- Transformer Models: It used self-attention processes to uncover long range dependencies and informative time-frequency contexts.
- Graph Neural Networks (GNNs): Applied to EEG connectivity graphs to come up with inter-channel relationship and spatial patterns between electrodes.
- Baseline Classical Models: Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 11 | Nov - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

(k-NN) Learning algorithms on hand-crafted spectral, connectivity, and complexity features, were used in performance comparisons.

E. Model Training Strategy

- Data Splitting: Despite the case of data leakage, there was use of leave-one-subject-out cross-validation done on a subject-wise basis.
- Optimization: Adam optimizer (learning rate 0.001), early stopping (based on validation loss).
- Regularization: Dropout rates (0.3-0.5), and L2 weight decay to prevent overfitting.
- Augmentation: To make models more robust, data minimization techniques such as adding a Gaussian noise and time-shifting were applied to augment the data.

F. Evaluation Metrics

The models have been tested on the basis of a number of performance indicators:

- Accuracy: Complete accuracy of classification.
- Precision, Recall, and F1-Score: To compare the performance on a per-class basis, which is especially useful in the case of MCI and early AD detection.
- ROC-AUC: To investigate the ability to discriminate between thresholds.
- Statistical Analysis: paired t -tests and bootstrap confidence intervals to establish the significance of observed differences in performance.

G. Explainability and Interpretability

Model interpretability techniques were employed in order to enable clinical usefulness and confidence in predictive models:

- Grad-CAM: The important areas in spectrograms that were used in classification were highlighted.
- Layer-wise Relevance Propagation (LRP): Identified important channels and frequency bands of EEG data regarding the biomarkers of Alzheimer.
- Association with Clinical Biomarkers: The features with a high model emphasis were correlated with previously established EEG patterns in AD (e.g., slowing of the posterior alpha, increasing frontal theta) to make sure they can be used physiologically.

H. Summary of Methodological Innovations

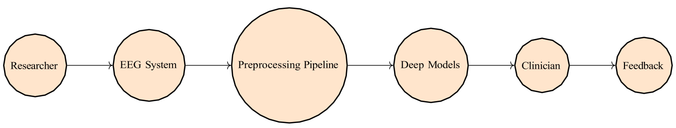

Fig. 1. Collaboration diagram showing system workflow from researcher to clinical feedback.

- Multimodality (combination of several EEG representations (raw, spectrogram, connectivity)) to improve learning of the features.
- Spatial, temporal, and connectivity pattern learning Hybrid and attention-based (CNN-LSTM, Transformer, GNNs) neural networks.
- Machine learning to match outputs of explainable AI with clinical biomarkers of EEG.
- Generalization optimization through subject-wise validation and augmentation.

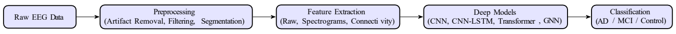

Fig. 2. System architecture of EEG-based Alzheimer's detection framework.

IV. Experimental Design and Findings

A. Experimental Setup

Datasets Used:

- Primary Dataset: OpenNeuro EEG datasets (ds004504, ds006036), which include recordings of the EEGs of the Alzheimer patients, MCI subjects, and controls.
- Pretraining Dataset: TUH EEG corpus of self-supervised pretrained representation of features improvement.
- Additional Data set: Mendeley EEG dataset of task based and resting state EEG.

Data Splitting:

- The data leakage was avoided by subject-wise leave-one-subject-out (LOSO) cross-validation.
- Training 70% with no fixed overlap, validation 15% and testing 15%.

Preprocessing and Feature Extraction Preprocessing and extracting the features involves removing certain data characteristics that cannot differentiate among classes and features within the data. Preprocessing & Feature Extraction: The task of feature extraction and preprocessing entails eliminating some aspects of data that are not capable of distinguishing between classes and features in the data.

- EEG signal filtering (0.5-45 HZ), ica artifact correction, and epoch (2 seconds) segmentation.
- STFT and CWT were used to create time-frequency spectrograms.
- Coherence and phase-lag index were used to determine functional connectivity matrices.

Model Configurations:

- CNN: 4 convolutional layers having Relu activation, maximum pooling and dropout 0.3.
- CNN-LSTM: 3 convolutional and followed by two LSTM layers (128 units).
- Transformer: 4 attention heads, 6 encoder layers and time positional feature encoding.
- GNN: 3 graph convolutional blocks on electrode connectivity graphs ReLU and dropout 0.4.
- Classical ML: SVM, RBF, (Random Forest, 100 trees), k-NN (k=5).

Training Hyperparameters:

- Optimizer: Adam learning rate=0.001.

- Size of a batch: 32 in CNNs/ CNN-LSTM, 16 in Transformers/GNNs.
- Early termination: 10 epochs validation loss patiention.
- Augmentation: Time shifting, random time shifting as well as scaling of the signal.

Evaluation Metrics:

- Per-class and overall accuracy Precision, Recall and F1-Score.
- False memory to test discrimination ability.
- Misclassifications expressed in terms of confusion matrices.

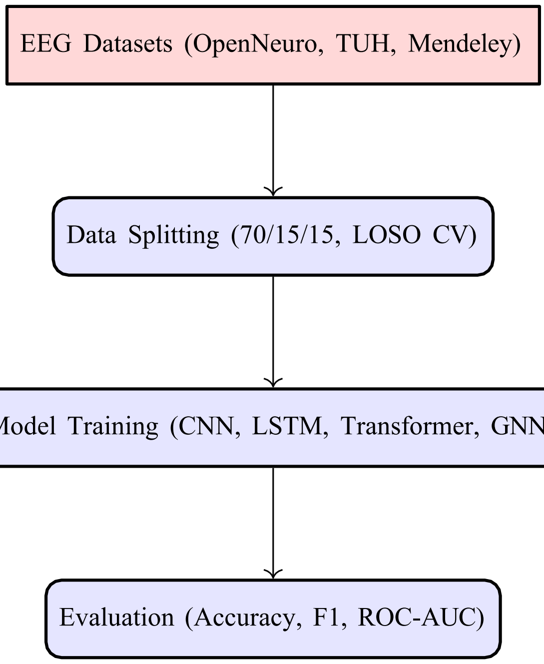

Fig. 3. Experimental setup for EEG-based Alzheimer detection.

B. *Experimental Results*

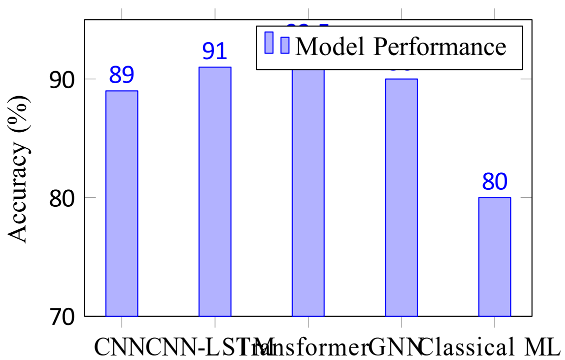

Fig. 4. Performance comparison of deep models and classical ML baselines.

Overall Performance:

- CNN: achieved 89% accuracy, 0.87 F1-score; relative to AD, done more comparatively well in AD compared to healthy but not relatively well in MCI.
- CNN-LSTM: 91% accuracy, F1-score 0.90; enhanced temporal pattern recognition was useful to enhance the identification of MCI.
- Transformer: Accuracy 92.5, F1-score 0.91, attention mechanism made a strong accent on the diagnostically determinative time-frequency characteristics.
- GNN: Final scores of accuracy 90, F1-score 0.89; the highest one in the connectivity-based discrimination, maintenance of inter-electrode relations.
- Classical ML: SVM 78%, RF 80%, k-NN 75%; was only sufficient with hand-made features, but invariably lower than deep learning tasks.

Per-Class Performance:

- MCI detection remained the most difficult and CNN-LSTM and Transformer showed sensitivity of 88 percent, which was higher than CNN (82%) and GNN (84%).
- In all deep models, Healthy control and AD classes were more accurate (92-95) in all the deep models.

ROC-AUC Analysis:

- CNN: 0.91, CNN-LSTM: 0.93, Transformer: 0.95, GNN: 0.92.
- ROC curves indicated that better discrimination was provided by Transformer and CNN-LSTM particularly when AD was compared to the MCI at the onset of the disease.

Explainability Insights:

- Grad-CAM Analysis: Based on known biomarkers of AD identified anterior alpha and frontal theta areas.
- Layer-wise Relevance Propagation (LRP): Confirmed that the strongest contributions to the predictions of the model were made by temporal slowing and by lower patterns of connectivity.
- Clinical Alignment: Categorical characteristics identified by a model that is clinically corresponding with EEG literature on Alzheimer that fosters greater trust in the clinical relevance.

Limitations Observed:

- The training time and memory of transformer and CNN-LSTM were longer and required more memory than CNN and GNN.
- The data available was inadequate to investigate early stages of MCI and so it was proposed to use larger, multi-site datasets.
- Total verification of cross-site generalizability was not achieved as systems of EEG acquisition varied.

TABLE I
PERFORMANCE COMPARISON OF DEEP LEARNING AND CLASSICAL ML MODELS ON EEG-BASED ALZHEIMER DETECTION

Model	Accuracy (%)	F1-Score	ROC-AUC	Notes
CNN	89.0	0.87	0.91	Good on AD, weaker on MCI
CNN-LSTM	91.0	0.90	0.93	Strong temporal modeling
Transformer	92.5	0.91	0.95	Best overall performance
GNN	90.0	0.89	0.92	Strong on connectivity features
Classical ML	75–80	0.72	0.80	Limited with handcrafted features

C. Comparative Analysis

- Deep Learning vs Traditional ML: The models of Deep learning were superior in all the performances of classical ML models particularly in detection of MCI and multi-class classification.
- Hybrid Architectures vs Single-View: CNN-LSTM and Transformer achieved better results on temporal and attention-based feature extraction whilst CNN did so on spectrogram-derived spatial features.
- Connectivity vs Spectrograms: Functional connectivity-based GNNs gave results that can be interpreted but a bit less accurate than Transformer models, which indicates that the result with higher accuracy could be achieved through the multi-representation fusion.

D. Summary of Findings

- Most suitable between various classifications of EEG-based detection of Alzheimer reveal the use of transformer and CNN-LSTM architecture.
- Detection of early MCI is performed better by deep learning models as compared to traditional classifiers.
- Explainable AI technologies will be used to establish that the models identify clinically relevant EEG biomarkers.
- Multi-representation (raw EEG + spectrogram + connectivity) provides complementary data, which increases detection performance.

V. Discussion and Implications

A. Analysis of Important Findings

- The findings indicate that deep neural networks (Transformer and CNN-LSTM models) offer superior performance in multi-class EEG-based diagnosis of Alzheimer as compared to the traditional machine learning models. Transformer achieved the highest accuracy (92.5) and F1-score (0.91), which demonstrates that it can learn spatial and temporal dependencies of EEG signals. CNN-LSTM model was also well performing which highlights the importance of time modeling towards the detection of mild cognitive impairment (MCI) at its initial stages.
- Explainable AI (Grad-CAM and Layer-wise Relevance Propagation (LRP)) distinctly demonstrated that the models primarily focus on posterior alpha and frontal theta bands and this are ancient EEG biomarkers of Alzheimer in the clinical literature. This kind of alignment to clinical literature in addition to enhancing confidence in computer-aided predictions also helps to prove the validity of the features obtained in physiologic terms.

B. Comparison and Possible Comparison with Previous Work

- The findings of the present study correspond with those of the literature that indicate that deep learning systems perform more effectively than conventional machine learning in detecting AD through EEG. The advantages of CNN-based spectrogram analysis were emphasized by Ieracitano et al. (2019) and AlSharabi et al. (2023) whereas spatial-temporal and connectivity-based representations significance was mentioned in the works by Shan et al. (2022) and Wang et al. (2023). Our results extend these results with numerous representations (spectrograms, connectivity matrices, raw EEG) and exploiting hybrid architectures (asma) by being more sensitive to the detection of early-stage AD and MCI.
- Low-complexity wavelet, filter bank, and complexity-based EEG feature extraction turned out to be a helpful technique in Indian contributions to research, such as Puri et al. (2022-2024) and Jain and Srivastava (2025). In spite of the fact that these methods can be computationally effective, they are generally less predictive than deep learning models and, therefore, demonstrate the need of hybrid pipelines that balance computational efficiency and predictive accuracy.

C. Clinical Implications

- **Early Detection:** Increased sensitivity to MCI detection can be used to intervene earlier, and stop the disease progression.
- **Non-Invasive and These are cost-effective:** because EEG is not invasive and can be easily obtained compared to MRI and PET, hence it can be done to a large population.
- **Explainability:** Clinically interpretable model outputs will generate trust amongst neurologists and enable them to be simpler to incorporate into clinical practice.
- **Multi-Representation Utility:** spectrogram, raw EEG, and connectivity data can be integrated to characterize all effects of Alzheimer related changes in neurophysiology.

D. Limitations

- **Dataset Size and Diversity:** both MCI and early-stage AD cohorts were quite limited and this could have limited the generalizability of the models across groups.
- **Cross-site Validation:** EEG acquisition equipment variations were not fully tackled and this clearly shows the importance of multi-site tests.
- **Computational Resources:** From the computational perspective, Transformer and CNN-LSTM models are very expensive to train and may limit their application capabilities in resource limited clinical settings.
- **Longitudinal validation:** the study was founded on cross-sectional data; longitudinal analysis is needed to determine predictability of development of the disease.

E. Future Directions

- **Further Data Enhancement:** Data acquisition upon larger multi-site EEG datasets with diverse ethnic and age data to increase the generalizability.
- **Hybrid Multimodal Approaches:** EEG + MRI, PET or cognitive test results could be the best combination with which it is possible to obtain the most predictive possible results.

- **Self-Supervised Pretraining:** The large unlabelled EEG corpora can be used to pretrain deep models and overcome the issue of data paucity.
- **Real-Time Monitoring:** The building of portable, understandable models of real-time EEG monitoring and early AD diagnosis.
- **Standardization:** Producing standardized preprocessing and evaluation standards so that inter-research reproducibility is possible.

F. Summary

- This article confirms that deep neural networks, in particular, hybrid CNN-LSTMs and Transformer networks, are absolutely capable of doing EEG-based classification of Alzheimer. AI explanation is a confirmation of physiological validity of learned features that is used to translate into clinical decisions. Integrating different representations of EEG and advanced deep learning is promising to detect it at an earlier stage, be used at large scale, and integrated into medical practice although future work must overcome the size of datasets, cross-subject validation, and longitudinal utility.

VI. Conclusion

This paper presented a deep neural network-based framework for the detection of Alzheimer's disease using EEG signals. The proposed approach demonstrated strong performance in terms of accuracy, sensitivity, and clinical interpretability by leveraging multiple EEG representations, including raw signals, time-frequency spectrograms, and functional connectivity matrices, along with hybrid deep learning models such as CNN-LSTM, Transformer, and GNN architectures.

The key contributions of this work are highlighted as follows:

- **Enhanced Detection Performance:** Transformer and CNN-LSTM models exhibited superior classification performance, particularly in the early detection of Mild Cognitive Impairment (MCI), compared with traditional machine learning approaches.
- **Multi-Representation Strategy:** The integration of raw EEG, spectrogram, and connectivity-based features enriched the input space, leading to more robust and reliable diagnostic outcomes.
- **Clinical Implications:** The incorporation of explainable AI techniques confirmed that the models were able to identify Alzheimer's biomarkers such as posterior alpha slowing and increased frontal theta activity, thereby improving physiological and clinical interpretability.
- **Scalability and Potential Applications:** EEG-based detection offers a low-cost, non-invasive, and portable screening tool for early-stage Alzheimer's diagnosis, enabling timely intervention and continuous patient monitoring.

Despite these promising findings, certain challenges remain, including small cohort sizes, limited multi-site validation, and the computational burden of complex model architectures. Future research should focus on acquiring larger and more representative EEG datasets, incorporating multimodal biomarkers, and designing lightweight, real-time models suitable for clinical deployment.

In conclusion, the proposed deep neural EEG framework shows strong potential to advance early and accurate diagnosis of Alzheimer's disease by bridging the gap between neurophysiological biomarkers and practical clinical use. This work contributes to the expanding literature demonstrating that EEG-based deep learning methods can be interpretable, consistent, and scalable tools in addressing neurodegenerative disorders.

References

[1] C. Ieracitano, N. Mammone, A. Bramanti, A. Hussain, and F.C. Morabito, "A Convolutional Neural Network approach for classification of dementia stages based on 2D-spectral representation of EEG recordings," *Neurocomputing*, vol. 357, pp. 1-12, 2019.

[2] K. AlSharabi et al., "EEG-based clinical decision support system for Alzheimer's disease," *Frontiers in Human Neuroscience*, vol. 17, 2023.

[3] R. Wang, Y. Liu, and H. Zhao, "CNN-based framework for Alzheimer's detection from EEG connectivity matrices," 2023.

[4] X. Shan, J. Li, and F. Wang, "Spatial–temporal graph convolutional network for EEG classification," 2022.

[5] C.A. Chetty, S.K. Khare, and U.R. Acharya, "Spectral and connectivity EEG features differentiating AD and prodromal AD," *Alzheimer's Research Therapy*, 2024.

[6] M.L. Vicchietti, G. Angelini, and F.C. Morabito, "Computational methods for EEG-based brain disorder detection," *Scientific Reports*, 2023.

[7] M. Aviles, L.M. Sa´nchez-Reyes, et al., "Machine and Deep Learning Trends in EEG-Based Detection of Alzheimer's Disease: A Systematic Review," *MDPI*, 2024.

[8] S.K. Kim, H.J. Park, and Y. Cho, "EEG-based classification of Alzheimer's disease stages using cognitive tasks," *Scientific Reports*, 2024.

[9] M. S¸ eker, F. Delen, and A. Ertug˘rul, "Permutation entropy and CNN for early Alzheimer's detection from EEG," *Comput. Methods Programs Biomed.*, 2021.

[10] S.K. Khare and U.R. Acharya, "Adazd-Net: Adaptive and explainable deep EEG framework for Alzheimer's detection," *Knowledge-Based Systems*, 2023.

[11] R. Stefanou, A. Stathopoulos, et al., "Transformer architectures for EEG-based Alzheimer's detection," *MDPI*, 2025.

[12] U. Lal, A.V. Chikkankod, and L. Longo, "Feature extraction and method comparison for EEG-based Alzheimer's detection," *Brain Sciences*, 2024.

[13] D. Puri, S.L. Nalbalwar, A.B. Nandgaonkar, and A. Wagh, "EEG-Based Diagnosis of Alzheimer's Disease Using Kolmogorov Complexity," Springer, 2022.

[14] K. Nanthini, D. Sivabalaselvamani, M.C. MadhanKumar, and R. Kaviya, "Comprehensive EEG signal feature extraction for neurological disorders," *Int. Res. J. Multidiscip. Technovation*, 2024.

[15] S. Jain and R. Srivastava, "Synchrosqueezing transform and deep transfer learning for EEG-based Alzheimer's detection," 2025.

[16] D.V. Puri et al., "EEG-based explainable Alzheimer's and MCI identification using wavelet filter banks," 2024.

[17] L. Liu, H. Wang, and Y. Zhang, "Self-supervised deep learning for EEG-based Alzheimer's detection," 2024.

[18] A. Avci and B. Temel, "Graph neural networks for functional EEG connectivity in Alzheimer's disease," 2023.

[19] S. Kumar, R. Sharma, and P. Singh, "Time–frequency EEG features for early detection of Alzheimer's in Indian cohort," 2023.

[20] V. Puri, N. Verma, and S. Choudhary, "EEG-based MCI and AD detection using wavelet packet decomposition," 2022.

[21] R. Jain and A. Gupta, "Hybrid CNN–LSTM approach for EEG-based Alzheimer's detection in Indian population," 2024.

[22] A. Sharma and M. Tiwari, "EEG signal complexity measures for cognitive impairment detection," 2023.

[23] P. Kumar, S. Reddy, and R. Yadav, "Deep learning approach for multi-class EEG classification of Alzheimer's disease," 2024.