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Contribution of Scalp Regions to Machine Learning-Based Classification of Dementia Utilizing Resting-State qEEG Signals

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Purpose: This study aims to investigate using eyes-open (EO) and eyes-closed (EC) resting-state EEG data to diagnose cognitive impairment using machine learning methods, enhancing timely intervention and cost-effectiveness in dementia research.

Participants and Methods: A total of 890 participants aged 40–90 were included in the study, comprising 269 healthy controls (HC), 356 individuals with mild cognitive impairment (MCI), and 265 with Alzheimer's disease (AD) from a cohort study. Resting-state EEG (rEEG) signals were recorded and transformed into relative power spectral density (PSD) data for analysis. The processed PSD data, representing 19 scalp regions, were then input into a Random Forest (RF) machine learning classifier to identify distinctive EEG patterns across the groups. Statistical comparisons between the groups were conducted using one-way ANOVA, applied to the relative PSD features extracted from the EEG data, to assess significant differences in EEG activity across the diagnostic categories.

Results: The study found that rEEG-based categorization effectively differentiates between cognitively impaired individuals and healthy individuals. The EO rEEG achieved the highest performance metrics across various models. For HC vs MCI (combined hemisphere), the accuracy, sensitivity, specificity, and AUC were 92%, 99%, 83%, and 96%, respectively. For HC vs AD (parietal, temporal, occipital), these metrics were 95%, 96%, 94%, and 99%. The HC vs CASE (MCI + AD) (combined hemisphere) results were 90%, 99%, 73%, and 92%. The metrics for HC vs MCI vs AD (frontal, parietal, temporal) were 89%, 88%, 94%, and 96%.

Conclusion: The study demonstrates that EO rEEG can effectively distinguish between cognitive impairment and healthy states, leading to early diagnosis, cost-effective treatment, and better clinical outcomes for dementia patients. EO and EC rEEG models trained with relative PSD, particularly from parietal, temporal, occipital, and central scalp regions, can significantly assist clinicians in practice.

Keywords: electroencephalography, eyes-open, eyes-close, quantitative, machine learning, Alzheimer's disease, mild cognitive impairment, power spectrum density

Introduction

Electroencephalography (EEG) is currently utilized as a biomarker for the early diagnosis and detection of Alzheimer's disease (AD) and other forms of dementia through quantitative EEG (qEEG) analysis.[1–3] Resting-state EEG (rEEG), recorded in eyes-open (EO) and eyes-closed (EC) conditions, allows for the assessment of brain activity when subjects are awake but not engaged in specific tasks.[4] AD is the most common cause of dementia, characterized by progressive memory loss and cognitive impairment, predominantly affecting individuals over 65 years of age.[5] The pathological hallmarks of AD include the accumulation of amyloid β (Aβ) peptides forming senile plaques and neurofibrillary tangles composed of hyperphosphorylated tau proteins.[6–8] These pathological changes lead to neuronal loss and synaptic dysfunction, particularly in the hippocampus and cortical regions critical for cognitive function.[6,7]

Such neurodegenerative processes disrupt normal neuronal communication and cortical network oscillations, which are reflected in EEG recordings as alterations in power spectral density (PSD) across different frequency bands.[9,10] Specifically, AD is associated with slowing EEG rhythms, characterized by decreased power in higher frequency bands (alpha and beta) and increased power in lower frequency bands (delta and theta).[11,12] Mild cognitive impairment (MCI),

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considered a transitional stage between normal aging and dementia, also exhibits EEG changes, although to a lesser extent than AD.[10] Researchers aim to identify biomarkers for early detection and differentiation between healthy controls (HC), MCI, and AD populations by analyzing these EEG alterations, particularly in PSD. Given the expected doubling of dementia prevalence in the next 20 years due to increased life expectancy,[9,13] early detection methods like EEG analysis are important.

The diagnosis of dementia and MCI is made easy by neuroimaging technique.[14] Although widely used for diagnosis, advanced techniques like magnetic resonance imaging (MRI) and positron emission tomography (PET) have several limitations, including radiation risks, high cost, prolonged processing times, and immobility.[15] However, the EEG method will likely be essential for meeting these needs.[16]

The qEEG method of analyzing EEG data involves numerical analysis of the EEG signals.[17] A standard qEEG marker is frequency domain analysis, achieved through Fast Fourier Transform (FFT) spectral analysis and time analysis.[18,19] This approach has been identified as a promising indicator of disease state in dementia patients.[20] The FFT-based spectral analysis calculates the average amplitude and power of EEG oscillations across different frequency bands over a set recording period.[21]

Previous studies utilizing qEEG features to differentiate cognitive impairment from healthy participant groups have primarily focused on EC rEEG recordings.[7,22,23] It has been shown that, during EC rEEG, dementia patients display a decrease in higher frequency bands, specifically alpha and beta, and an increase in lower frequency bands like delta and theta within the EEG spectrum compared to healthy participants.[4,24] The EO rEEG is less commonly utilized in dementia research because, during EO conditions, the alpha peak does not exhibit as significant a decrease in dementia patients compared to healthy individuals, making it less informative using traditional analysis methods.[25,26]

While qEEG can detect AD, its limitations include low anatomical specificity and suboptimal diagnostic performance when used in isolation.[27] To enhance diagnostic accuracy, our study explores the application of machine learning algorithms in analyzing qEEG data. Recent advancements have demonstrated that machine learning can significantly improve EEG-based AD classification by leveraging sophisticated architectures and optimized feature selection. For example, Kachare et al[28] applied an LCADNet, a lightweight convolutional neural network (CNN) for the AD detection model, streamlines the detection process by extracting disease-specific EEG features and achieved an impressive accuracy of 98.5%, making it highly effective for AD classification tasks. Similarly, a STEADYNet algorithm was designed on spatiotemporal analysis to multichannel EEG data, optimizing AD, MCI, and frontal temporal dementia (FTD) with classification accuracy to as high as 99.65% while maintaining reduced inference times suitable for real-time applications.[29]

Additionally, the integration of metaheuristic algorithms with time-frequency feature selection has further optimized classification, with methods achieving binary classification accuracy up to 99.72%.[30] Random Forest (RF) classifiers and similar techniques have also been instrumental in predicting progression from MCI to AD by identifying complex patterns within EEG data, often undetectable by conventional statistical approaches.[31,32] Collectively, these machine learning applications address the limitations of qEEG, positioning it as a valuable tool for advancing the early detection and diagnosis of AD.

Studies have predominantly focused on utilizing features from EC rEEG in combination with machine learning for the early diagnosis of MCI and other forms of dementia.[23,33] Simfukwe et al[33] demonstrated that machine learning algorithms applied to EC rEEG features could distinguish between MCI and AD patients with significant accuracy. However, a research gap exists concerning using EO rEEG data with machine learning techniques.

In this study, we investigate the hypothesis that including EO and EC rEEG data provides a valuable source of statistically significant qEEG features for machine learning classification. We aim to determine if EO-relative PSD data can be utilized to classify dementia with machine learning and which EEG channels are more substantial in predicting cognitive impairment.

Methods

Demographics of the Participants

The EEG signals of 890 subjects, including healthy controls (HC, n=269), individuals with MCI (n=356), and those with AD (n=265), were analyzed. The average ages of these groups were 64.54±9.03, 73.95±7.77, and 76.94±8.03, respectively (mean ± standard deviation, here and throughout) (Figure 1). The dataset was collected following approval from the Chung-Ang University Hospital Institutional Review Board (IRB No. C2012049) under ethics committee approval (Number 1792–012-

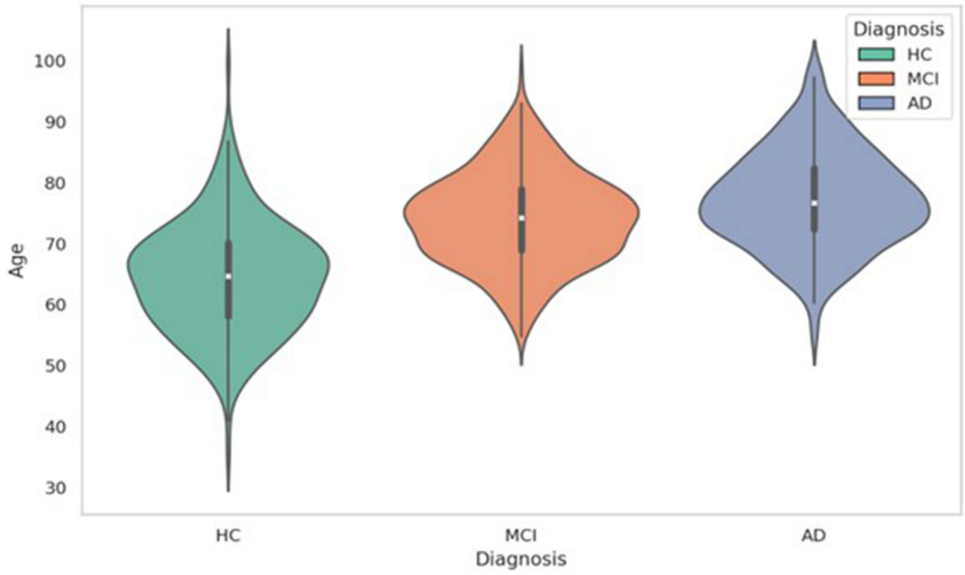

Figure 1 Demographics of age in different diagnosis groups.
Note: Data are shown as mean ± standard deviation.
Abbreviations: HC, healthy controls; MCI, Mild cognitive impairment; AD, Alzheimer's disease.

300). This cohort study was conducted at the hospital to assess the prevalence of cognitive impairments and the associated risk factors among the elderly following the Declaration of Helsinki. Written informed consent was obtained from all participants.

Participants with evidence of brain disease, psychosis, epilepsy, or stroke on MRI that was considered to cause cognitive impairment, as well as those with a history of drug addiction within the past 10 years, were excluded.

The selection criteria of the HC group were suitable for the 28 normal elderly criteria of Christensen et al,[34] and had a Korean Mini-Mental State Examination (K-MMSE) score of −1 SD (Standard Deviation) or higher, Korean-Instrumental Activities of Daily Living (K-IADL) was set to 0.42 or less, and Korean Dementia Screening Questionnaire (KDSQ) was set to 6 points or less.[35,36] The criteria for MCI subjects were complaining of memory impairment, but less than −1 SD in the reference mean value considering age and education in all cognitive function areas Seoul Neuropsychological Screening Battery (SNSB), and non-dementia state as a result of diagnostic and statistical manual of mental disorder, 4th edition (DSM-IV) by the American Psychiatric Association.[37–40]

The diagnostic criteria for AD subjects included clinical recognition of a progressive memory decline, a reduction in the patient's ability to perform activities of daily living, personality changes, and objective verbal memory assessment using the SNSB.[41] SNSB is a test developed in Korea that comprehensively evaluates cognitive abilities, encompassing memory, attention, language, associated processes, and visuospatial function (Supplementary Table 1). A neurologist performed all diagnoses based on neuropsychological examination and criteria.[41] The subjects' EEG data were pre-processed to remove artifacts using the EEGlab tool in the MATLAB environment.

The EEG signals were collected using Comet AS40 amplifier EEG hardware (GRASS; Telefactor, USA) and gold-cup EEG electrodes. The electrodes were placed according to the international 10–20 system, resulting in 19 electrodes positioned at Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2, with the earlobes serving as reference points (Supplementary Figure 1). During the EEG recording sessions, the skin impedance of the electrodes was maintained consistently below 5kΩ. The EEG signals were digitally recorded and stored on magnetic disks. Before recording, the signals underwent digital filtering. Bandpass filtering, a crucial step in EEG signal processing, was used to isolate the desired frequency range while attenuating frequencies outside this range. Our study selected a 0.5 to 70 hz range to retain relevant EEG frequencies and eliminate unwanted noise.

During the EEG recording, participants were instructed to keep their eyes open or closed. Sampling was done at a frequency of 200 hz, with 10 recordings taken for both EO and EC conditions, each lasting 30 seconds, resulting in approximately 3 minutes of data. For the analysis, 45 epochs of four seconds each were selected. The recorded data for both

EO and EC rEEG were converted using the connected ear reference and saved in text format without artifact removal. Participants were instructed to stay relaxed and still in a quiet room, avoiding movements such as swallowing or blinking.

The raw EEG signals were processed using the EEGlab toolbox version 2022 within the MATLAB software environment version R2021a (https://sccn.ucsd.edu/eeglab). The preprocessing involved standard procedures such as amplification, signal filtering, artifact removal, and independent component analysis (ICA). These preprocessing steps were carried out according to a general block diagram, as shown in Figure 2, ensuring that the EEG signals used for extracting relative power spectrum density (PSD) analysis were free from artifacts.

Relative PSD and Feature Selection

The relative PSD at the sensor level was calculated using the Welch method within the Brainstorm toolbox (https://neuroimage.usc.edu/brainstorm/) in the MATLAB environment. This analysis was conducted across specific frequency bands: delta (2–4 hz), theta (5–7 hz), alpha (8–12 hz), beta (15–29 hz), and gamma (30–70 hz). The relative power was determined by averaging the power of the FFT coefficients over overlapping windows.

After segmenting the EEG signals, the resulting segments were processed through a feature extraction module to reduce data size while preserving critical discriminatory information necessary for classification. This process enhances the classifier's effectiveness by ensuring the extracted features are rich in discriminatory details. Features were extracted from EEG data across 19 channels, as detailed in Table 1. These features were used in various combinations during classifier training and were categorized into frontal (F), occipital (O), central (C), temporal (T), and parietal (P) regions.

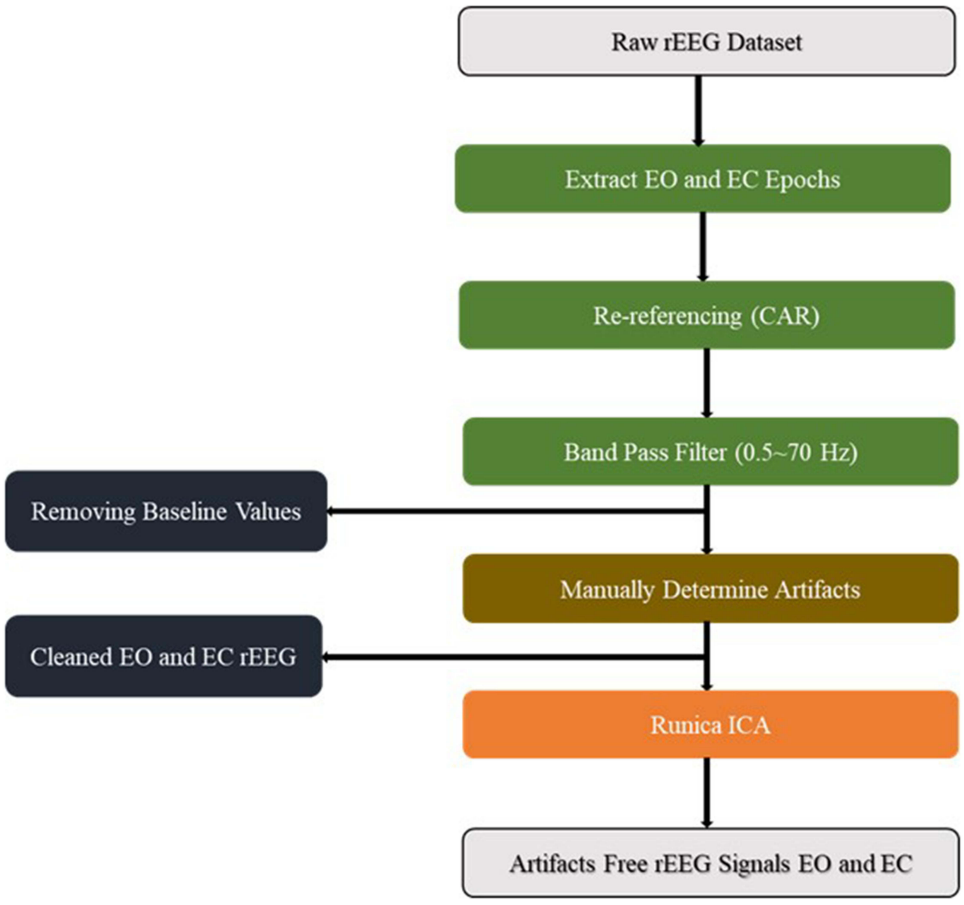

Figure 2 A schematic representation of the preprocessing steps and artifact removal applied to EEG signals.
Abbreviations: rEEG, resting state electroencephalography; EO, eyes-open rEEG; EC, eyes-close rEEG; CAR, common average reference; ASR, Artifact reconstruction; ICA, independent component Analysis.

Table 1 Brain Areas and Associated Channels

Scalp Regions	Combined Channels
Frontal	Fz, FP1, FP2, F3, F4, F7, F8
Occipital	O1, O2
Central	Cz, C3, C4
Temporal	T3, T4, T5, T6
Parietal	Pz, P3, P4
Right-hemisphere	FP2, F4, F8, C4, T4, P4, T6, O2
Left-hemisphere	C3, T3, FP1, F3, F7, P3, T5, O1
Combined hemisphere	Right-hemisphere + Left-hemisphere

Abbreviations: F, frontal; O, occipital; C, central; T, temporal, P, parietal.

Statistical Analysis and Model Training

Statistical analyses were performed using a one-way ANOVA test in the Python programming language (https://www.python.org/), utilizing the Pycharm integrated development environment (IDE) from JetBrains (https://www.jetbrains.com/pycharm/). The "f_oneway" function from the Scipy library (https://docs.scipy.org/doc/scipy/index.html) was applied to compare the relative PSD between the HC, MCI, and AD groups. A significance threshold of $p < 0.05$ was used to determine statistical significance.

The initial model training step involved organizing, preprocessing, and cleaning the EEG dataset, which comprised PSD features as outlined in Table 1, using the Pandas library in Python within the JupyterLab environment (https://www.anaconda.com/). This process included addressing missing values, normalizing feature ranges, and removing outliers to ensure the dataset's quality before proceeding with model training.

In the second step, the subjects were categorized into different classes for training: HC vs MCI, HC vs AD, HC vs CASE (MCI + AD), and HC vs MCI vs AD. We developed four distinct models to predict these classifications among subjects using the Random Forest (RF) classifier. The RF algorithm is a widely used supervised classification technique that constructs multiple decision trees (DTs) from random subsets of the dataset, following the bagging principle.[42]

The third step involved splitting the dataset and training the machine learning models using the RF algorithm in the scikit-learn library (https://scikit-learn.org/stable/index.html). The data was imported and formatted from a ".xlsx" file containing features from each EEG channel, as described in Table 1. The `train_test_split` function from scikit-learn was used to randomly divide the data into training and test datasets, with 70% allocated for training and 30% for testing.

Results

A total of 16,910 relative PSDs from each EEG channel, corresponding to 890 subjects, were divided into two datasets: training and testing. Each subject contributed 19 relative PSDs from each EEG channel. The first model was trained using 11,875 relative PSDs from 269 hC and 356 subjects with MCI in the training and testing dataset. The second model's training and testing dataset comprised 10,146 relative PSDs from 269 hC and 265 subjects with AD. The third model utilized a training and testing dataset containing 16,910 relative PSDs from 269 hC and 621 CASE subjects (combining MCI and AD). The last model involved a three-way classification of HC, MCI, and AD, including all datasets. The distribution of the datasets for EO and EC rEEG was equal before model training (Table 2).

The RF machine learning algorithm (link to the algorithm) was developed in Python using scikit-learn on Google Colab (https://colab.google/) with a GPU system featuring 24 GB of RAM. Models for HC vs MCI, HC vs AD, HC vs CASE (MCI + AD), and HC vs MCI vs AD for both EO and EC rEEG were evaluated using various metrics: accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the curve (AUC). The best results were achieved with "n_estimators = 100".

Table 2 Demographics of Subjects and Relative PSD Dataset Included in This Study and Their Classification in Training and Testing Dataset

Classification	HC vs MCI		HC vs AD		HC vs CASE		HC vs MCI vs AD	
Model	EO	EC	EO	EC	EO	EC	EO	EC
No. of Subjects	625 (11,875)		534 (10,146)		890 (16,910)			
Training Dataset	438 (8322)		374 (7106)		623 (11,837)			
Testing Dataset	187 (3553)		160 (3040)		267 (5073)			

Abbreviations: HC, healthy control; MCI, mild cognitive impairment; AD, Alzheimer's disease; EO, eyes-open; EC, eyes-closed; rPSD, relative power spectrum density.

The evaluation performance of the RF classifier for different classification tasks based on various rEEG combined channels is summarized in Table 3. For the HC vs MCI model using the combined hemispheres, the classifier achieved 92% accuracy, 99% sensitivity, 83% specificity, 88% PPV, 98% NPV, and 96% AUC for EO. For EC, it achieved 83% accuracy, 89% sensitivity, 75% specificity, 81% PPV, 85% NPV, and 93% AUC. These results indicate effective differentiation between healthy controls and MCI subjects under both conditions, with the best performance in EO.

In the HC vs AD task, the combined Parietal, Temporal, and Occipital scalp regions demonstrated 95% accuracy, 96% sensitivity, 94% specificity, 94% PPV, 96% NPV, and 99% AUC for EO. For EC, the Central region achieved 89% accuracy, 88% sensitivity, 89% specificity, 88% PPV, 89% NPV, and 96% AUC. Focusing on specific scalp regions, the Parietal, Temporal, and Occipital regions model showed high performance for EO, while the Central region model achieved notable performance for EC.

For HC vs CASE (MCI + AD), the combined hemispheres model achieved 90% accuracy, 99% sensitivity, 73% specificity, 89% PPV, 96% NPV, and 92% AUC for EO. For EC, it achieved 86% accuracy, 98% sensitivity, 59% specificity, 84% PPV, 92% NPV, and 93% AUC based on the Frontal, Temporal, Central, and Occipital combination, with the best performance in EO.

In the three-way classification of HC vs MCI vs AD, the combined Frontal, Parietal, and Temporal regions model achieved 89% accuracy, 88% sensitivity, 94% specificity, 91% PPV, 95% NPV, and 96% AUC for EO. EC achieved 79% accuracy, 75% sensitivity, 88% specificity, 75% PPV, 87% NPV, and 91% AUC with the Frontal, Temporal, Central, and Occipital regions. The combined regions model demonstrated consistent performance across these metrics, with the highest performance in EO.

Table 3 Performance Metrics for EO and EC rEEG Classification Models in Differentiating Cognitive States

Classification	Scalp Regions (Model)	Acc	Sens	Spec	PPV	NPV	AUC
HC vs MCI	Combined Hemispheres (EO)	92%	99%	83%	88%	98%	96%
	Combined Hemispheres (EC)	83%	89%	75%	81%	85%	93%
HC vs AD	Parietal, Temporal, Occipital (EO)	95%	96%	94%	94%	96%	99%
	Central (EC)	89%	88%	89%	88%	89%	96%
HC vs CASE	Combined Hemisphere (EO)	90%	99%	73%	89%	96%	92%
	Frontal, Temporal, Central, Occipital (EC)	86%	98%	59%	84%	92%	93%
HC vs MCI vs AD	Frontal, Parietal, Temporal (EO)	89%	88%	94%	91%	95%	96%
	Frontal, Temporal, Central, Occipital (EC)	79%	75%	88%	75%	87%	91%

Abbreviations: EO, eyes-open; EC, eyes-closed; Acc, accuracy; Sens, sensitivity; Spec, specificity; PPV, positive predictive value; NPV, negative predictive value; AUC, area under the curve; HC, healthy controls; MCI, mild cognitive impairment; AD, Alzheimer's disease; CASE, MCI + AD.

Confusion matrices were plotted to illustrate the classification performance of the models based on the test dataset. The HC vs CASE (MCI + AD) EO model demonstrated strong performance, accurately identifying 156 cognitively impaired subjects as true positives, with 20 false positives, 53 true negatives, and 2 false negatives. This performance was superior to the other models (Figure 3a–d).

Discussion

In this paper, we trained a machine learning classifier RF with relative PSD of EO and EC of rEEG to predict cognitive impairment among 890 subjects. Although various neuroimaging techniques, such as MRI and PET, can diagnose dementia by offering quantitative data on brain abnormalities, qEEG presents a non-invasive and cost-effective alternative for early detection and disease monitoring.[43] Furthermore, EEG analysis through qEEG is essential for the early detection of dementia and for evaluating the severity of the condition.[44,45] Research has demonstrated the potential of using qEEG to detect early-stage dementia, highlighting how changes in EEG signals are linked to the onset and progression of the disease.[46,47] This study analyzed the relative PSD from rEEG of HC, individuals with MCI, and those with AD for EO and EC, which were used in machine learning algorithms. The averages of the 19 EEG channels in the delta, theta, alpha, beta, and gamma frequency bands were analyzed for EO and EC rEEG of different scalp regions with topographic mapping (Figures 4 and 5).

Figure 4 and 5a and b show significant differences in mean power across frequency bands (delta, theta, alpha, beta, gamma) for different scalp regions (frontal, occipital, central, temporal, parietal, left hemisphere, right hemisphere, and combined hemispheres) EO and EC EEG recordings among HC, individuals with MCI, and AD patients.

In the Figure 4a EO condition, AD patients exhibit higher mean power in the delta and theta bands and reduced alpha power, particularly in the temporal and parietal regions, consistent with findings of increased low-frequency power and impaired cognitive processing in AD.[48] In contrast, Figure 4b EC, AD patients similarly show elevated delta and theta power and reduced alpha power, especially in the temporal, parietal, and right hemisphere regions, aligning with evidence of disrupted neural activity in dementia.[23] EC data generally show more precise differentiation between groups, likely due to reduced artifacts.

Figure 5a and b further illustrates these findings with topographic maps demonstrating the distribution of EEG power across frequency bands in both EO and EC conditions. In Figure 5a, the EO topographic maps reveal that AD patients exhibit distinct patterns of increased low-frequency power in the delta and theta bands across various scalp regions, particularly in the frontal and temporal areas. This pattern suggests heightened cognitive load or disrupted neural connectivity in AD, which may contribute to cognitive deficits observed in these patients.[49]

Conversely, the maps for the alpha band indicate a notable decrease in power in AD patients, especially in the temporal and parietal regions. This reduction in alpha activity is significant, as alpha waves are typically associated with relaxed wakefulness, suggesting that AD patients may exhibit less neural efficiency during cognitive tasks compared to HC and individuals with MCI.[50] In Figure 5b, the topographic maps reinforce observations from the EO condition, showing enhanced differentiation between groups in delta and theta power in the temporal and parietal regions, where AD patients again display marked increases. This consistent pattern underscores the potential of topographic mapping to identify neurophysiological changes in AD.

Numerous studies have assessed the sensitivity and specificity of classification algorithms for clinical diagnosis and early detection of dementia using EO and EC rEEG.[23,25] This study aimed to develop machine learning models to detect MCI and AD among subjects using the relative PSD from 19 EEG channels, which were grouped into different scalp regions as features in the dataset (Table 1). This approach can assist clinicians in the early diagnosis of cognitive impairment and in classifying its severity. The second model, trained to differentiate between HC and AD subjects using relative PSD from EO EEG signals of the Parietal, Temporal, Occipital, and Central scalp regions, showed the best performance. The scalp regions are critically involved in various cognitive functions and are commonly impaired in AD.[51] Specifically, the Parietal and Occipital lobes are essential for sensory information processing and visual perception, while the Temporal lobe is crucial for memory and auditory processing. The Central brain region integrates sensory input and motor functions.[52]

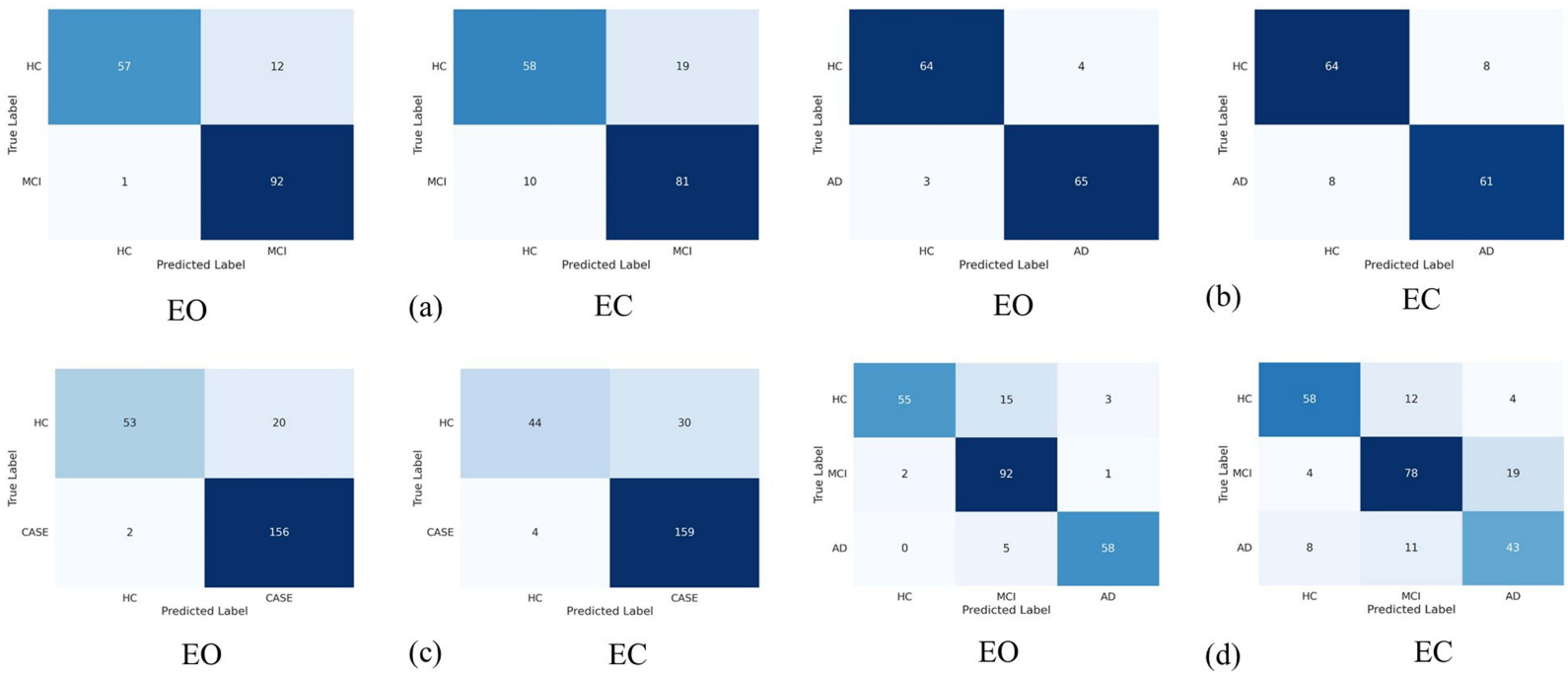

Figure 3 (**a–d**). The confusion matrices of the four predictors HC vs MCI, HC vs AD, HC vs CASE, and HC vs MCI vs AD for EO vs EC.
Note: The confusion matrices were obtained from the test dataset on each model classification performance.

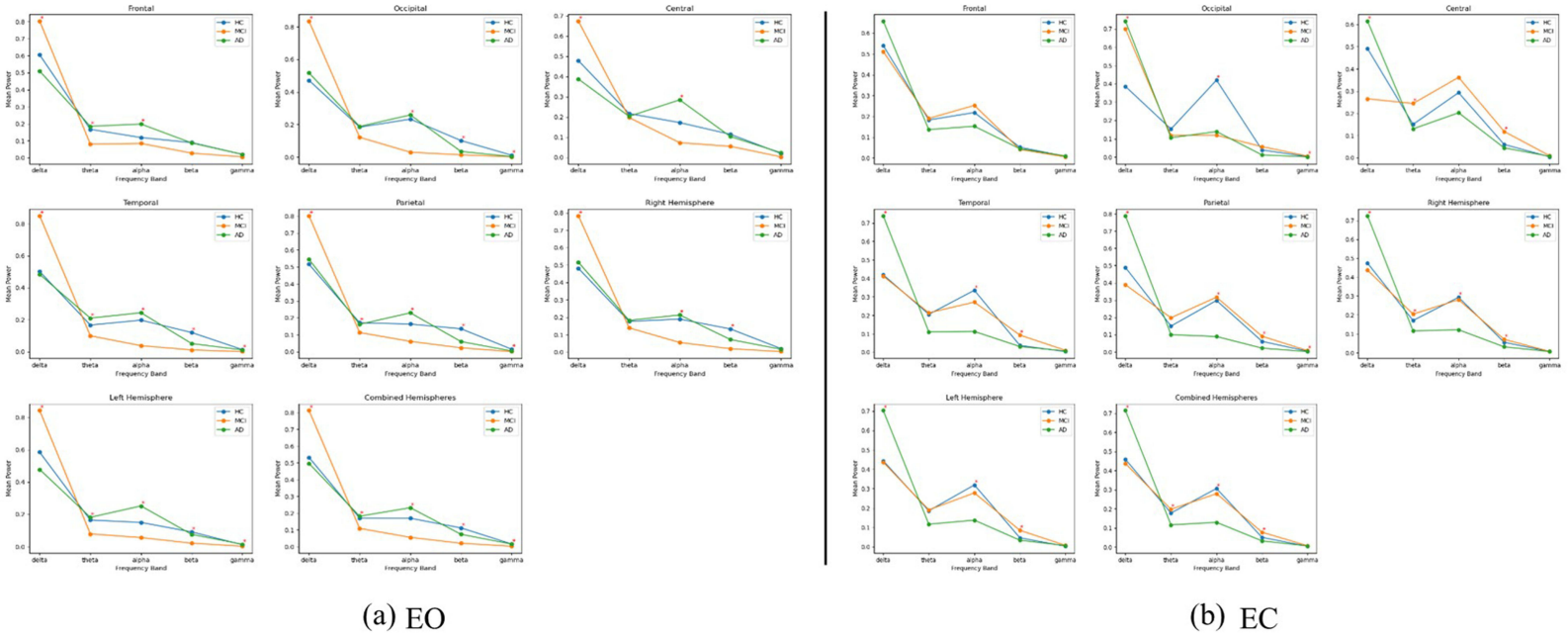

Figure 4 (**a** and **b**). The average EO PSD of 19 EEG channels in the (a) delta, (b) theta, (c) alpha, (d) beta, and (e) gamma frequency band for HC, MCI, and AD groups in different scalp regions for EO vs EC.
Note: *Shows the significant difference $p < 0.05$.
Abbreviations: PSD, power spectrum density; EEG, electroencephalography; MCI, mild cognitive impairment; AD, Alzheimer's disease; HC, healthy controls; EO, eyes-open; EC, eyes-closed.

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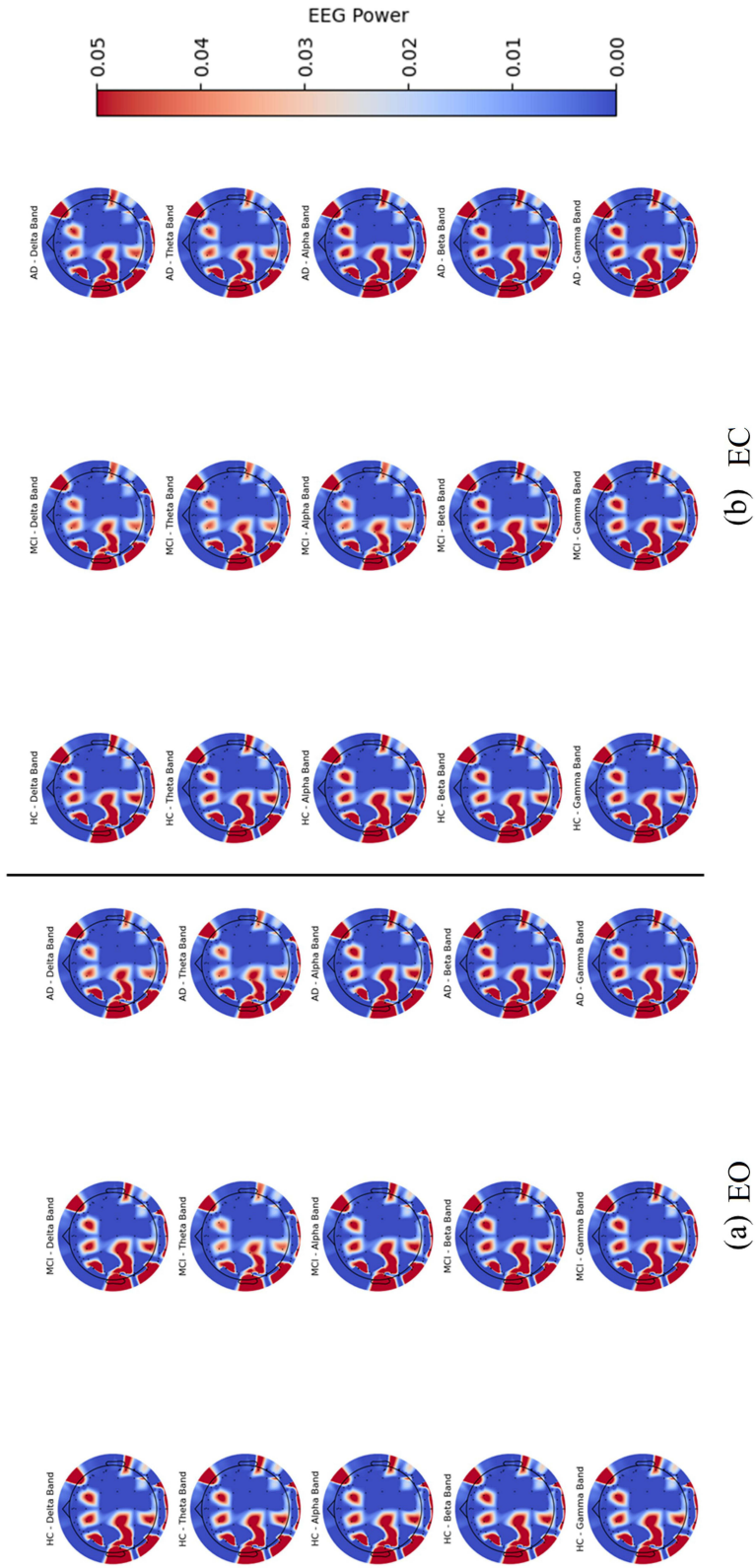

Figure 5 (**a** and **b**): Topographic maps of EEG PSD in the EO and EC conditions across frequency Bands for HC, MCI, and AD Groups: (a) Delta, (b) Theta, (c) Alpha, (d) Beta, (e) Gamma.
Abbreviations: PSD, power spectrum density; EEG, electroencephalography; MCI, mild cognitive impairment; AD, Alzheimer's disease; HC, healthy controls; EO, eyes-open; EC, eyes-closed.

The model achieved a high accuracy of 95% in classifying AD subjects. Sensitivity was 96%, indicating its ability to correctly identify AD patients, while specificity was 94%, reflecting its accuracy in identifying healthy individuals. The PPV and NPV were 94% and 96%, respectively. The AUC was 99%, underscoring the model's excellent overall performance. All models trained with EO rEEG channels outperformed those trained with EC rEEG. This improved performance with EO data is due to the increased cognitive and sensory processing with EO, capturing more diverse brain activity related to visual and attentional processing.[53] The study by Jennings et al[25] utilized both EO and EC resting state EEG in distinguishing different types of dementia based on machine learning classification algorithms. It showed that EO rEEG could be useful in the early diagnosis of cognitive impairment. These showed that the EO rEEG could be utilized to classify cognitive impairment, and our analysis with machine learning for all models supported their observations. Our findings suggest that EO qEEG data is an underutilized resource for diagnosing and classifying dementia. Since EO EEG data is often collected alongside standard EC data, it can be easily used to improve differentiation between MCI and AD in clinical settings.

Several techniques using qEEG have been applied for the early diagnosis of MCI and AD. Kim and Kim[54] developed a model to differentiate between MCI and HC using machine learning, incorporating features based on the relative PSD of various EEG frequency bands. While their model achieved 75% accuracy in the binary classification of HC vs MCI, our study demonstrates improved performance, suggesting that our approach may better capture the distinctions between these groups. This comparison highlights how advancements in feature selection and model design in our study have resulted in more accurate classification, building on the foundation of previous work and addressing some of the limitations of earlier models.

In comparison to the study by Fan et al,[55] multiscale entropy (MSE), a complexity metric, was used to convert EEG signal components into numerical values, which were then input into linear regression machine learning models. Their approach, which utilized an unbalanced dataset of 15 hC and 108 AD cases and calculated 46,471 features, achieved a maximum accuracy of 82%. While their results demonstrate the potential of MSE for EEG analysis, the use of an unbalanced dataset raises concerns about potential bias in the model's performance. In contrast, our study, which employed PSD features with a more balanced dataset, resulted in improved classification accuracy, suggesting that the combination of balanced data and alternative feature extraction methods may provide a more robust and generalizable model for distinguishing between HC and AD patients.

Durongbhan et al[56] proposed a supervised classification framework that utilized EO EEG signals to differentiate between normal controls and participants with AD dementia. This framework included topographic visualization, feature extraction, K-nearest neighbor classification, data augmentation, and quantitative evaluation. Using the K-nearest neighbor algorithm, the framework achieved a 99% classification accuracy on short (4-second) EO EEG epochs for detecting AD among participants. Fisco et al[57] also applied various tree-based supervised algorithms using EC qEEG features derived from time-frequency analysis based on discrete Fourier and Wavelet transforms. The study analyzed 109 samples categorized into HC, MCI, and AD classes. The discrete Fourier feature extraction yielded accuracies of 71.2% for HC vs MCI, 72% for HC vs AD, and 80.2% for MCI vs AD. In contrast to the current study, the proposed RF algorithm for supervised learning was evaluated using relative PSD from both EO and EC EEG recordings across 19 channels for each subject, resulting in better performance.

The EO and EC methods have proven highly effective in distinguishing dementia groups.[7,21] Previous EC data research has compared derived and relative PSD measures, revealing significant differences between AD and other dementias.[21,44] Consequently, exploring EO-derived relative PSD measures could further improve inter-group classification methods. More research studies utilizing EO data may be needed due to the need for highly trained technical staff to identify and clean EEG signals. EC EEG is easier to preprocess than EO, as EC segments inherently have fewer ocular movement artifacts and no blink artifacts.[58]

This study demonstrated the contribution of different scalp regions using EEG channels from EO and EC conditions. It used an RF machine learning algorithm trained with relative PSD features from 19 EEG channels. The findings revealed that EEG channels from the parietal, temporal, occipital, and central scalp regions are important in dementia research.

Previous studies have highlighted the importance of these regions. EEG channels from the parietal region (Pz, P3, P4) are associated with spatial awareness and navigation, often impaired in dementia.[59] Temporal region channels (T3, T4, T5, T6) are critical for memory processing, with dysfunction as a hallmark of AD.[60] Occipital region channels (O1, O2),

primarily responsible for visual processing, show altered EEG patterns in dementia, indicating widespread neural network disruptions.[61] Central region channels (Cz, C3, C4) reflect broader impacts on sensorimotor areas, which are significantly affected in dementia.[62]

Although the study acknowledges the effectiveness of conventional classifiers, it is important to address certain limitations of EEG as a tool in clinical practice. While the classification results in the study were promising, EEG has inherent limitations, including its relatively low spatial resolution compared to imaging techniques like MRI, and its susceptibility to artifacts from muscle movement and external noise. These factors could affect the precision of the study's findings, particularly in more complex classification tasks. To address these limitations in future research, integrating EEG with other neuroimaging methods, employing advanced artifact removal techniques, and leveraging multi-modal data with deep learning models could enhance the accuracy and clinical relevance of EEG in understanding neurodegenerative diseases.

Conclusion

This study highlights the effectiveness of using EO and EC rEEG data combined with machine learning methods to diagnose cognitive impairment. The RF classifier, applied to relative PSD data from rEEG signals, successfully identified unique EEG patterns across scalp regions, enabling accurate differentiation between cognitively impaired individuals and healthy controls. The EO rEEG achieved the highest performance metrics, demonstrating its potential in clinical settings.

The findings indicate that rEEG-based categorization is a powerful tool for early diagnosis and intervention in dementia, offering a cost-effective and timely approach to treatment. Using EO and EC rEEG models trained with relative PSD data can enhance clinical practice by providing clinicians with reliable methods to distinguish between cognitive impairment and healthy states. EEG channels from the parietal, temporal, occipital, and central scalp regions were shown to be particularly important in dementia research. Overall, this approach promises improved clinical outcomes and better management of dementia through early and accurate diagnosis.

Abbreviations

EEG, Electroencephalogram; HC, Healthy control; Mild Cognitive Impairment (MCI); AD, Alzheimer's disease; Aβ, Amyloid beta; p-tau, Phospho-tau; t-tau, Total-tau; CSF, Cerebrospinal fluid; MRI, Magnetic resonance imaging; PET, Positron emission tomography; PSD, power spectrum density; ANOVA, analysis of variance; MATLAB, Matrix laboratory; FFT, Fast Fourier Transform; qEEG, Quantitative electroencephalogram; EO, Eyes-open; EC, Eyes-closed; K-MMSE, Korean Mini-Mental State Examination; SD, Standard deviation; SNSB, Seoul Neuropsychological Screening Battery; ICA, Independent component analysis; ASR, Artifact subspace reconstruction.

Ethics Approval and Consent to Participate

The study was conducted by the Declaration of Helsinki and approved by the Institutional Review Board of the Chung-Ang University Hospital (IRB No. C2012049). The IRB of Chung-Ang University Hospital waived informed consent since this study was retrospective and blinding the data's personal information was performed. All methods were carried out following relevant guidelines and regulations.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis, and interpretation, or all these areas; took part in drafting, revising, or critically reviewing the article; gave the final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors declare that they have no competing interests in this work.

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