International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# Revolutionizing the Alzheimer's Disease Stage Diagnosis through AI-Powered approach

[1]Rageshri Bakare, [2]Virendra V. Shete, [3]Ioannis Kompatsiaris, [4]Magda Tsolaki

**Submitted**: 27/11/2023 **Revised**: 07/01/2024 **Accepted**: 17/01/2024

**Abstract:** AI and machine learning are changing Alzheimer's disease diagnosis. These advancements are improving massive dataset analysis, enabling early diagnosis and personalized treatment. With the Continuous Wavelet Transform and Pearson's Correlation Coefficient, Electroencephalogram signal processing has become important. Machine learning classifiers enhance diagnostic accuracy. PCC-KNN, which prioritizes alpha frequency band, improves classification accuracy by combining pattern recognition and connection insights. EEG signal parameters of unhealthy and healthy patients are compared by extracting CWT and PCC parameters. KNN, SVM, RF and DNN are trained as classifier algorithms. Using PCC to detect brain area correlations and alpha frequency oscillations helps uncover neurological disease connection problems. Combining KNN improves pattern recognition for complex alpha dynamics. KNN-PCC in the alpha frequency band improves neurological disease categorization with 96% F1-score, 95% sensitivity, 99% specificity, and 97.9% accuracy. Cognitive deterioration is linked to alpha spectrum alterations. Alpha power and slow wave activity rise may be indicated in early AD patients.

***Keywords:*** *Alzheimer's Disease, Dementia, EEG signal processing, Artificial Intelligence, Machine learning, Deep learning*

## 1. Introduction

The domain of Alzheimer's Disease (AD) diagnosis is currently experiencing a paradigm shift as a result of the integration of Artificial Intelligence (AI) methodologies. The diagnosis of dementia involves several techniques, with artificial intelligence (AI) and machine learning (ML) being important tools in analyzing large datasets. These technologies help in early detection and personalized treatment approaches. The application of Electroencephalogram (EEG) signal processing techniques, such as the Continuous Wavelet Transform (CWT) and Pearson's Correlation Coefficient (PCC), has gained significant prominence in the area. CWT is used to extract both temporal and spectral features from EEG data, whereas PCC is used to measure the connectivity between various areas of the brain. [1][2]. It has been observed that ML classifiers like Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Deep Neural Networks (DNN) increase the precision of diagnostic procedures. The evaluation of classifier performance is made easier and provides insightful information when many indicators are used, such as confusion matrices and classification reports. The effectiveness of the PCC-KNN methodology, which combines pattern recognition techniques with connection insights, in the setting of alpha frequency bands is one remarkable conclusion. Artificial intelligence (AI) and machine learning (ML) combined with state-of-the-art electroencephalography (EEG) methods are revolutionizing Alzheimer's disease (AD) diagnosis. More precise and tailored treatment plans are becoming possible as a result of this merging of technology.[2]. A wide range of procedures are required for the diagnosis of dementia because it is a complicated neurological condition.

The effectiveness of the PCC-KNN methodology, which combines pattern recognition techniques with connection insights, in the setting of alpha frequency bands is one remarkable conclusion. The approach of diagnosing AD is generally being greatly altered by the combination of contemporary electroencephalography (EEG) techniques with AI and ML integration. The combination of these technologies is enabling more precise diagnosis and individualized treatment plans.[2]. Dementia is a complex neurological disease that must be diagnosed using a wide range of methods. Clinical assessment is the cornerstone, with doctors conducting in-depth interviews with patients and family members to collect data on their health, symptoms, and mental state. Cognitive testing, which includes instruments like the Mini-Mental State Examination (MMSE), the Montreal Cognitive Assessment (MoCA) etc, are used to gauge a person's mental activities. Neuroimaging techniques like MRI, PET, and SPECT help detect atrophy and functional abnormalities by providing information about the brain's anatomy, metabolism, and activity patterns, but they are expensive[3]. Biomarker study of CSF reveals disease-specific proteins in the fluid

[1]*Research Scholar, MIT SOES, MITADT University, Pune, India*
*Rageshri02@gmail.com*
[2]*Director, MIT SOES, MITADT University, Pune, India*
[3]*Researcher A, CERTH -ITI, Thessaloniki, Greece*
[4]*Professor of Neurology, MD, PhD, GAADRD, Thessaloniki, Greece*

around the brain is also expensive and invasive and all the countries did not approve these examinations. Genetic tests, such as APOE genotyping, and different mutations can reveal hereditary issues. Evaluations of a patient's functional abilities provide insight into how well he/she can handle every day routine activities. Nevertheless, the execution of these tests is a laborious process that requires the participation of compliant individuals and skilled healthcare professionals[4] . Electrical brain activity is recorded by EEG, revealing aberrant patterns associated with dementia. Accuracy in diagnosis is aided by clinical criteria and computerized cognitive testing [5].

The stages considered in this work consists of Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), Subjective Cognitive Decline (SCD). MCI is a cognitive state intermediate between normal age-related alterations and more severe cognitive decline, such as that observed in dementia [1]. Individuals with MCI have observable cognitive deficits, such as memory issues or difficulty with complex tasks, but these deficits do not substantially interfere with their activities of daily life. The progression of MCI varies between individuals, with some remaining stable, others improving, and others progressing to dementia or a more severe cognitive impairment in one year [6].Self-reported cognitive difficulties are indicative of SCD, even if formal cognitive examinations do not reliably reveal substantial deficiencies. Memory loss and struggle to focus are two indicators of SCD that may create worry and stress for those affected. Self-reporting and ruling out other possible reasons of cognitive symptoms, such as stress or depression, are crucial in making a diagnosis. Different causes of SCD lead to different prognoses; for example, some people have stable or enhanced cognitive performance while others continue to decline[6]. Neurodegeneration that worsens with time to AD causes cognitive, functional and behavioural decline. Memory loss, time and place confusion, and trouble solving problems are early signs that may progress to severe cognitive impairment and the inability to carry out routine tasks. The diagnosis is confirmed by a comprehensive medical examination, including cognitive testing, imaging, and a postmortem examination of the brain. Proteins in the brain become abnormal because of genetic, environmental, and behavioural factors that contribute to the illness. AD is fatal, although it may be controlled with medication and therapy to enhance quality of life[3]. AD is seen to be as a severance phenomenon of the brain. In AD patients, there is often a disruption in the synchronization of EEG activity, as seen by the diminished functional connectivity across various brain regions [7]. Moreover, EEG signal complexity may decrease in AD patients due to deterioration in cognitive function and structure [8]. Researchers have long focused on the breakdown of functional links between the cortex and hippocampus as a potential cause of cognitive failure in dementia and AD [9].

EEG signal processing is crucial for the accurate diagnosis of neurological illnesses. This facilitates early disease diagnosis, condition categorization, and dementia related pinpointing [10]. Treatment efficacy must be monitored and individualized depending on EEG patterns. EEG's ability to detect biomarkers and track the development of diseases without causing any harm to the patient makes it a cheap tool. In addition, it provides a risk-free alternate to conventional diagnostic procedures while still helping to monitor changes in brain health. EEG signal processing essentially improves the accuracy of diagnosing, treating, and managing a wide range of neurological illnesses [11]. Brain activity may be seen in the frequency ranges of an EEG. The theta band (4-8 Hz) is associated with REM sleep, creative thought, memory consolidation, and meditation, whereas the delta band (0.5-4 Hz) is associated with deep sleep and rejuvenation. Mental calmness is reflected in the predominance of the alpha band (8-13 Hz) during restful wakefulness. Cognitive processes, focused cognition, and alert wakefulness are characterized by the presence of beta waves (13-30 Hz). Finally, gamma waves (30-100+ Hz) have been associated with consciousness, perception, and advanced mental processes. Researchers and doctors utilizing EEG to study mental states, cognitive processes, and neurological illnesses need a firm grasp of these frequency ranges [10]. Researchers have long focused on the breakdown of functional links between the cortex and hippocampus as a potential cause of cognitive failure in dementia and AD.

AI and ML classifiers have the potential to drastically alter the field of dementia diagnosis due to their ability to detect hidden patterns, integrate several data sources, and enable rapid identification and personalised treatment approaches. As these technologies advance, it is expected that they will play an increasingly important role in improving the precision and efficacy of detecting neurological illnesses. AI/ML algorithms can reveal intricate patterns concealed in high-dimensional, complex data. Neurological disorders have grown in importance in data analysis.

## 2. Proposed Methodology

The flow diagram below is given for proposed methodology. Data is obtained, includes the sample EEG signal recordings of 42 AD-patients, 41 MCI-patients, 34 SCD-patients, and 33 Healthy subjects (HS). To increase the number of samples for training the AI/ML classification models, Data is segmented in slots of 4 seconds each. These samples are band separated and channel separated for parameter extraction. The parameters are extracted using CWT and PCC techniques. This large feature thus derived is used to train various classifiers. The performance measures are compared for various algorithms.

### 2.1 Dataset

The present repository has Matlab files pertaining to resting-state EEG recordings conducted on individuals diagnosed with AD, MCI, SCD, as well as a group of HS. The recordings were obtained utilizing the HD-EEG EGI GES 300 system. The study's participants were chosen from the memory and dementia clinic affiliated with the Greek Association of Alzheimer's Disease and Related Disorders (GAADRD). The people with AD satisfied the NINCDS-ADRDA (Alzheimer's Disease and Related Disorders Association) criteria for probable AD, which were set for the participants with AD. They also met the American Psychological Association's (APA) Diagnostic and Statistical Manual of Mental Disorders (DSM-V) criteria for dementia of AD. The participants in the MCI group, however, met the criteria established by Petersen, whereas the participants in the SCD group, in addition to following the instructions of the SCD-I Working Group, adhered to the recommendations made by the International Working Group-2 and the more recent National Institute on Aging-Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease.

Resting-State High-Density EEG recordings are obtained in advance from patients utilizing an EGI GES 300 equipped with 256 recording electrodes. The professionals always use the standard operating procedure. The signals were recorded in respect to a vertex reference electrode (Cz) at a sampling rate of 250 Hz, with AFz acting as the ground electrode and the electrode impedance being less than 50 k. The HD-EEG data were pre-processed (filtered, split, and replaced with faulty channels) using the software Net Station 4.3 so that any artefacts (EGI) could be identified. Originally, HD-EE was filtered using a 5th-order bandpass Butterworth IIR filter operating between 0.3 and 30 Hz. Resting-State High-Density EEG recordings are obtained in advance from patients utilizing an EGI GES 300 equipped with 256 recording electrodes. The professionals always use the standard operating procedure. 250 Hz sample rate, Signals were recorded in respect to a vertex reference electrode (Cz), with AFz serving as the ground electrode and the electrode impedance being less than 50 k. The HD-EEG data were pre-processed (filtered, split, and replaced with faulty channels) using the software Net Station 4.3 so that any artefacts (EGI) could be identified. Originally, HD-EEG data was filtered using a 5th-order bandpass Butterworth IIR filter operating between 0.3 and 30 Hz [2].

#### 2.1.1 Database creation/selection

The data of 42 AD patients, 34 SCD patients, 41 MCI patients and 33 HS is used in this analysis. The recordings obtained from these patients used is of 10 min each. Data splitting is used for generating a greater number of samples, the data splitting is used. The data of each subject is windowed into 4s sample each. Thus, a huge database is created for training the classifier models. The four common frequency bands found in EEG signals are -oscillation (1–4 Hz) namely delta, -oscillation (4–8 Hz) namely theta , -oscillation (8–13 Hz) namely alpha, and -oscillation (13–30 Hz) namely beta. The data repository includes the data for the distinct frequency ranges delta, theta, alpha, and beta; whereas gamma is not included in this file as during the pre-processing as mentioned earlier, the IIR filter used is windowed till 30 Hz. The data acquisition was done using 256 recording electrodes. The spatial resolution and accuracy of EEG data are both improving when the number of electrodes is increased. Yet the amount and handling time and complexity of the system, of EEG data grow correspondingly with the number of data streams[12]. Hence, the standard 20 channels are selected as per 10-20 channel mapping system for the analysis [13].

### 2.2 Feature Extraction

The selection and transformation of relevant information from raw data is known as feature extraction, and it plays a critical role in signal processing. It simplifies the analysis of the data, minimizes the amount of information that is stored, and highlights essential patterns while decreasing noise. The extracted features help in pattern detection, improve the overall efficiency of the model, and make the data easier to analyse. Additionally, they normalize the data for the sake of comparison and adjust to variations. In many different domains, the process of extracting features creates a condensed and useful representation of signals, which improves data analysis as well as decision-making and overall comprehension [14]. In this methodology CWT and PCC taken into account for extracting the parameters for training the classifier models.

#### 2.2.1 Continuous Wavelet Transform

EEG signal processing relies on the CWT's capacity to simultaneously capture time and frequency information. EEG signals are dynamic and non-stationary, making this significant. CWT's variable frequency resolution highlights transitory occurrences including seizures, cognitive activities, and event-related potentials (ERPs) [15] [16]. For neurological illness diagnosis using EEG signal processing, the CWT is better than the Fast Fourier Transform (FFT). Its ability to capture time and frequency information concurrently makes it unique. CWT's variable frequency resolution allows it to adapt to frequency content changes in EEG signals, which are non-stationary. Transient occurrences, localized abnormalities, and developing frequency patterns are fundamental to neurological illness analysis, and this attribute is essential. CWT also excels in revealing complicated non-linear correlations in neurological activity, unlike FFT. When analysing neurological illnesses, this is crucial. CWT's exact time-frequency representation improves ERPs extraction and analysis [16]. CWT detects seizures and modulates cognitive processes. It also improves ML model distinction between normal and pathological EEG patterns by enriching feature sets. Clinicians can see EEG data changes over time using CWT-generated time-frequency representations. CWT's focused focus, adaptability to shifting EEG dynamics, and capacity to capture subtle neurological patterns make it superior for EEG signal processing, especially in identifying neurological illnesses.

### 2.2.2 Pearson's Correlation Coefficient (PCC)

Pearson's correlation coefficient can augment EEG signal analysis for neurological illnesses. When combined with other feature extraction methods, it provides unique insights into these illnesses. Quantifying the linear relationship between EEG data from different brain regions reveals functional connectivity anomalies that often indicate neurological disorders. This is essential because it illuminates altered communication channels and brain connections linked with specific illnesses. Pearson's correlation across several EEG channels builds brain networks with synchronized activity patterns[17]. These patterns help detect disorder-specific anomalies, enhancing feature extraction insights. By studying correlations during cognitive activities, this technique reveals brain regions with common activity patterns, providing a deeper view of cognitive processes and helping identify neurological problems. Pearson's correlation can also help find patient population markers for certain illnesses by recognizing individual variations. By adding connectivity-based insights to conventional feature extraction methods, it provides a complete perspective of EEG data [16]. The PCC was thoroughly used to measure the linear correlation between two nodes x and y, and PCC was defined as in which n signified the length of variables and x and y accounted for the average of x and y, respectively. Refer Eq.(1) represents PCC between x and y. $r = \frac{\sum(x-\overline{x})(y-\overline{y})}{\sqrt{\sum(x-\bar{x})^2}\sqrt{\sum(y-\bar{y})^2}}$ .Equation (1) PCC was measured on a scale from 1 to 1, where 1 indicated a perfectly positive correlation, frequently referred to as a precisely linear connection, 0 indicated no correlation, and 1 indicated a completely negative correlation. The more tenuous the linear reliance between paired variables, greater the proximity the absolute value of PCC was to 1.

## 2.3 Classification using AI/ML algorithms

As part of the 10-fold cross-validation procedure, the dataset was partitioned into 10 roughly equal-sized sections, or "folds," for each iteration. Next, we used the data from each fold as a testing set, while the remaining folds were used for training. Nine of the 10 pieces are utilized for instruction, while the tenth is set aside for evaluation. Every value of k between 1 and 10 is processed in the same way. Because of this, each data point in the dataset is used for testing exactly once. Extensive testing was performed on a wide variety of datasets using several distinct approaches to learning. For the various classification techniques, we calculated an estimate for the misclassification error, a confusion matrix, and the accompanying receiver-operating-characteristic (ROC) by averaging the outcomes of ten 10-fold cross-validation iterations. Data mining is the most essential application of ML. Problem-solving is hindered by humanity's propensity to commit errors while interpreting data or trying to establish connections between different elements. In many cases, ML may be effectively utilized to these issues, leading to advancements in system efficiency and design. Each instance in a dataset is represented by an identical recuperation of features (continuous, categorical, or Boolean) when employing ML approaches. In supervised learning, instances have labels associated with the outputs they produce, whereas in unsupervised learning, instances are not labelled. Because supervised tasks are required in many machine learning applications, we will concentrate on the necessary approaches for achieving this labelling [16] [18] [19].

### 2.3.1 Support Vector Machine

EEG data analysis, especially for neurological conditions, might benefit from the robust and versatile SVM. [20] EEG data's numerous channels and time points provide high-dimensional feature spaces, which it can handle. Notably, SVM's capacity to handle non-linear correlations using kernel functions is crucial for identifying detailed patterns in EEG data. SVM's ability to distinguish disorder subtypes and severity levels in binary and multi-class classification tasks is also beneficial. In medical applications, where large datasets are hard to get, the algorithm's performance with minimal labelled data is important. SVM's margin maximization principle promotes generalization for the diagnostic models by limiting overfitting hazards. Clinically, SVM's unambiguous decision boundaries provide meaningful classification outcome communication to healthcare practitioners.

### 2.3.2 Random Forest

RF is another promising classifier. Decision trees trained on different data sets are its strength. This ensemble technique reduces EEG data fluctuation and noise to provide resilience. RF is experimented for classifying EEG signals from numerous channels and time points, which are high-dimensional. Its capacity to handle non-linear interactions without feature modification helps it capture complicated patterns that may indicate neurological diseases [21]. By using many trees' predictions, RF can overcome noise and artifacts in EEG signal analysis. For optimal performance, each approach requires parameter adjustment and validation. Class imbalances, tree depth, and tree quantity are crucial.

**2.3.3 K-Nearest Neighbours (KNN)**

When analysing EEG signals for the purpose of detecting neurological illnesses, the KNN method appears as a practical and successful classifier. Its versatility is demonstrated by its ability to process EEG signals and other complex data with relative ease. The complex and unique patterns that can be seen in EEG data are a good fit for KNN's instance-based learning mechanism. The ability of this algorithm to capture complex non-linear patterns within the data is crucial for identifying early warning signs of neurological illnesses. Because of its ease of use, KNN requires little in the way of hyperparameter tuning, which helps speed up the model selection procedure. Its openness in terms of decision-making helps clinical interpreters make sense of vital classification outcomes [22]. However, KNN has some drawbacks that should be considered. For example, it is sensitive to distance metrics and may have trouble dealing with high-dimensional data. Adjustments to preprocessing, feature scaling, and parameters are required to overcome these obstacles. KNN may lack the intricacy of some other algorithms, but its straightforward and intuitive approach provides valuable comprehension of EEG signal patterns, making it an appealing choice for the diagnosis of neurological disorders, especially when interpretability is of utmost concern.

**2.3.3 Deep Neural Networks**

The utilization of DNNs, within the framework of deep learning, has a consideration as a classifier. The advantages of deep learning in this situation encompass its ability to autonomously acquire nuanced patterns, process complex data kinds, and record temporal connections. DNNs have the capability to extract hierarchical features directly from raw data, hence eliminating the requirement for manual feature engineering. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are very suitable for analysing that are crucial for the diagnosis of neurological disorders [23]. Convolutional Neural Networks (CNNs) have exceptional proficiency in the analysis of neuroimaging data obtained from EEG, enabling the identification and differentiation of spatial patterns. The utilization of pre-trained models in transfer learning facilitates the process of adapting knowledge acquired from more extensive datasets [24]. Nevertheless, it is imperative to make meticulous architecture decisions, employ regularization techniques, and implement validation strategies to fully exploit the capabilities of deep learning for precise categorization of neurological illnesses using EEG data.

## 3. Experimental Results

Channel connectivity maps are a cornerstone of neuroimaging and neuroscience studies. Important information about how the brain's many regions interact with one another can be gleaned from these maps. Depending on the desired spatial and temporal resolution, they can be generated by methods like EEG, Magneto Encephalography (MEG), functional Magnetic Resonance Imaging (fMRI), or Intracranial Electrocorticography (ECoG). By examining the electrical or hemodynamic activity recorded from electrodes implanted on the scalp or directly on the brain's surface, these maps illustrate the functional connections or interactions between various brain regions. Synchronization and correlation patterns between distinct brain regions can be deduced from the data acquired by these electrodes. The brain's network organization and how it shifts in response to different tasks, stimuli, or neurological diseases can be better understood with the aid of connectivity maps. Resting-state connectivity, in which the brain's inherent networks are revealed even in the absence of a specific task, is studied with these methods. The following connectivity maps in figure numbers 2.1 through 2.4, are represented from the parameters obtained from PCC across the lobes, when the threshold 0.8 is considered to show the strong connectivity between the channels in various portions of the lobe. The diagrams represent the samples of subjects from each category. Similar connectivity graphs were observed for most of the subjects in every category. It is observed that the connectivity between various channels across the lobes has significantly decreased for the patients with neurological disorder. For the patients with AD it is considerably less connections are observed for the all the frequency groups. No strong connections are noticed in delta band at the threshold of 0.8.

The present study observed a very poor functional connectivity during the α-oscillations in the frontal, temporal, and central areas among individuals with AD. The connectivity was observed less in SCD and MCI subjects respectively too. Healthy patients have shown the most connected network across the lobe [25]. The findings of our study indicate that the functional connectivity, which quantifies the level of uncertainty in the power distribution of EEG data, reveals a decrease in electrical activity of individuals’ lobes of the brain with AD significantly. The classifiers were evaluated using the Confusion Matrix, Classification Report, and Receiver Operating Characteristic (ROC) curve. These methods revealed the classifiers' performance in EEG signal analysis for neurological condition diagnosis. The AI/ML classifier algorithms experimented in this methodology included KNN, SVM, RF and DNN. The classifier model was rigorously trained, validated and tested for many samples generated from the dataset available. The parameters used for training the models were obtained from the features extracted by CWT techniques and PCC parameters respectively. It was observed that the models trained with PCC parameters have outperformed the CWT parameters. The paper includes the results derived from models trained using PCC parameters.  A crucial categorization assessment tool known as the Confusion Matrix offered information on true positive, true negative, false positive, and false negative predictions. This matrix displayed the F1-score, recall, accuracy, and precision: critical metrics for diagnosing neurological disorders enabling an understanding of the models' ability to accurately identify distinct illnesses [19]. The evaluation procedure went beyond accuracy by using the Confusion Matrix, Classification Report, ROC curve, and AUC to evaluate the classifiers' strengths and PP limitations. This holistic approach to evaluation provided robust insights into their diagnostic accuracy, precision, recall, and discriminating capacities across the spectrum of neurological illness subtypes, strengthening the research's conclusions.

ML has emerged as a potent technique in the identification of early stages of neurological illnesses. The system possesses the ability to identify concealed patterns, amalgamate diverse data sources, and provide impartial evaluations. By employing predictive models to anticipate the evolution of diseases, extracting pertinent aspects from data, and assessing population trends, it facilitates the implementation of timely therapies and contributes to the reduction of healthcare expenditures.

The transformative impact of ML in the field of neurology lies in its ability to effectively handle real-time data, facilitate drug development, and enable remote monitoring. This potential holds significant promise for enhancing early diagnosis and increasing patient outcomes.

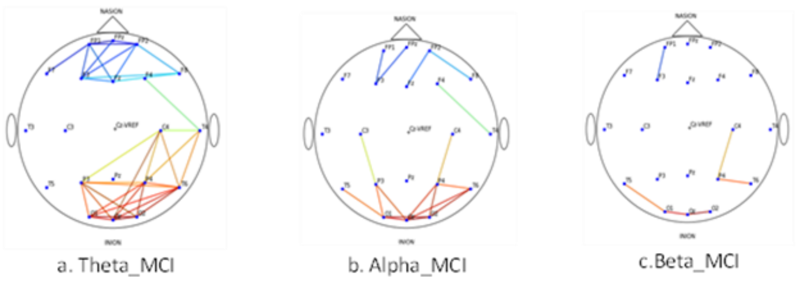



**Fig.2.2** Sample Connectivity Maps for MCI patient (a)Theta-Band (b)Alpha-Band (c)Beta-Band

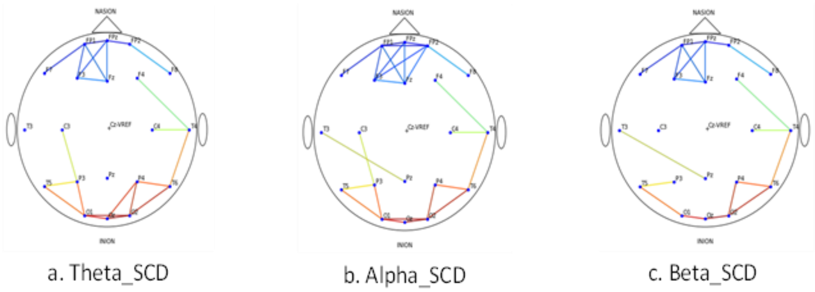



**Fig.2.3** Sample Connectivity Maps for SCD patient (a)Theta-Band (b)Alpha-Band (c)Beta-Band

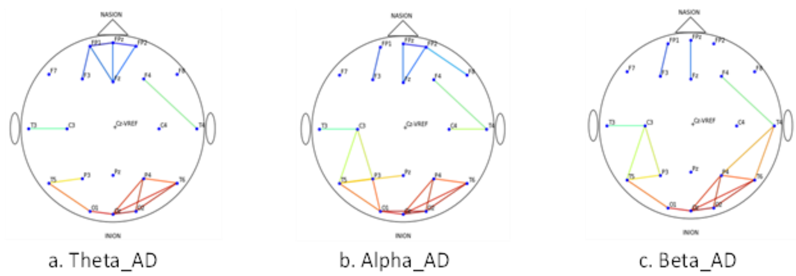



**Fig.2.4** Sample Connectivity Maps for AD patient (a).Theta-Band (b)Alpha-Band (c)Beta-Band

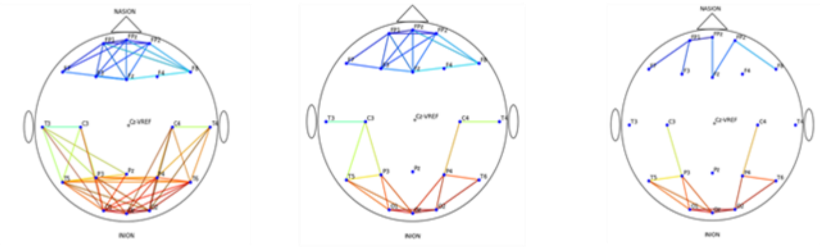



**Fig.2.1** Sample Connectivity Maps for Healthy patient (a)Theta-Band (b)Alpha-Band (c)Beta-Band

**Table 1.** Classifier Performance Evaluation for One vs Rest classes (Classification result for Beta frequency band)

| **Performance Parameters (%)** | **One vs Rest** | | | |
|---|---|---|---|---|
| | **Alpha frequency band** | | | |
| | **Classifier** | | | |
| | **KNN** | **RF** | **SVM** | **DNN** |
| **Loss** | 2% | 7% | 9% | 13% |
| **Sensitivity** | 95% | 87% | 83% | 79% |
| **Specificity** | 99% | 95% | 94% | 86% |
| **Precision** | 96% | 88% | 82% | 90% |
| **F1-score** | 96% | 88% | 82% | 87% |
| **overall Accuracy** | 97.90% | 93% | 91% | 87% |

**Table 2.** Classifier Performance Evaluation for One vs Rest classes (Classification result for Beta frequency band)

| **Performance Parameters (%)** | **One vs Rest** | | | |
|---|---|---|---|---|
| | **Beta frequency band** | | | |
| | **Classifier** | | | |
| | **KNN** | **RF** | **SVM** | **DNN** |
| **Loss** | 2% | 10% | 3% | 7% |
| **Sensitivity** | 95% | 82% | 95% | 79% |
| **Specificity** | 98% | 93% | 98% | 94% |
| **Precision** | 95% | 81% | 95% | 93% |
| **F1-score** | 95% | 81% | 94% | 93% |
| **overall Accuracy** | 97.60% | 90% | 97% | 93% |

The evaluation is improved by adding the ROC curve. The ROC curve, showing the true positive rate versus the false positive rate, showed the models' discriminating across thresholds. The AUC, a quantitative measure obtained from the ROC curve, clearly highlighted the classifiers' capacity to distinguish between classes: a vital component in neurological condition diagnosis where correct

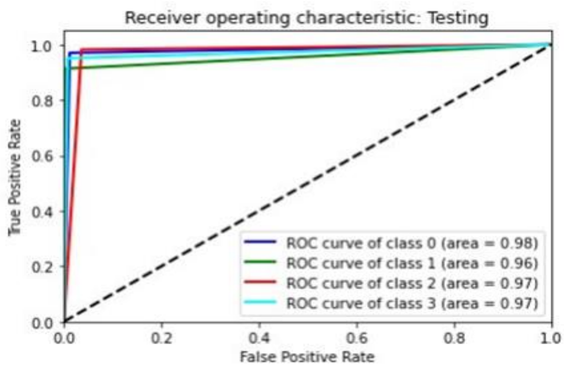
.

discrimination is crucial. The sample of best possible. In order to maximize the process of diagnosing early neurological disorders, a strategic approach could involve integrating deep learning techniques with conventional machine learning methods, thereby capitalizing on the strengths of both approaches

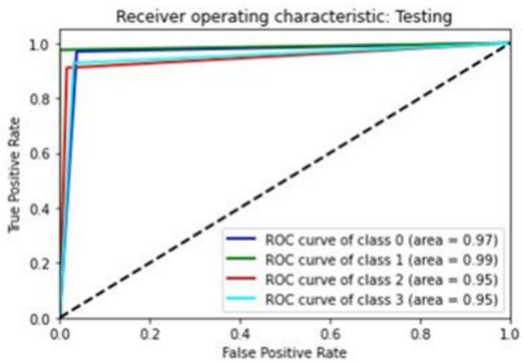
### 3.1 Discussion on result with PCC_KNN_for Alpha band

In the field of EEG signal analysis for the purpose of diagnosing neurological disorders, a significant advancement has been made through the utilization of the KNN classifier in conjunction with the PCC approach. The combination has produced noteworthy results, particularly in relation to the alpha frequency band, which is an essential element of the five unique frequency bands observed in EEG analysis. The findings of this study have considerable importance in terms of research, as they highlight the potential of utilizing an integrated strategy to greatly improve the accuracy of categorization while also providing insights into the complexities of neurological illnesses within the alpha frequency range.

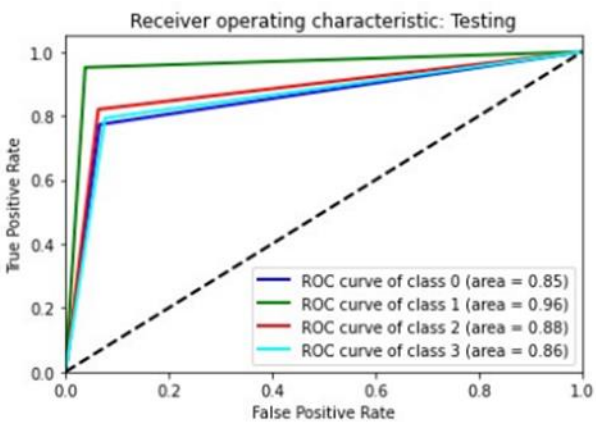
The categorization of EEG data into five distinct frequency bands is a crucial component in evaluating brain activity. The alpha frequency band, which is widely recognized for its significance in cognitive processes and brain dynamics, assumes a prominent role in this undertaking. The incorporation of the PCC technique in the study of the alpha frequency band presents a unique perspective for investigating EEG data. The ability of PCC to accurately detect and analyse linear associations among various brain regions is closely linked to the oscillation patterns of the alpha frequency. This connection has the potential to reveal minor disturbances in connectivity that are commonly observed in neurological diseases. In addition to enhancing this strategy, the incorporation of the KNN classifier in the alpha frequency leverages respective advantages of both methodologies. The ability of the KNN algorithm to accurately identify complex patterns is well-suited to the intricate nature of alpha frequency dynamics that are captured by the PCC. The combined utilization of KNN and PCC, with a specific focus on the alpha frequency band, enhances the classifier's ability to accurately distinguish between different neurological disorders based on the unique functional connectivity patterns exhibited by alpha oscillations. Table. 1 and Table. 2 indicates various performance parameters for the most sorted outputs. The tables are consolidated for Alpha frequency band and Beta frequency band. The parameters are extracted using PCC. KNN-PCC is seen to provide overall accuracy of classification of the early stages MCI, SCD, AD w.r.t to Healthy patients is 97.9%, F1-Score provided for this unbalance samples is 96%, specificity is 99%, rightly rejecting the incorrect samples and Precision observed is 96%. From a research perspective, these findings are crucial as they highlight a specialized yet powerful approach for combining the advantages of the KNN classifier and the PCC technique. The research community can get valuable insights into the underlying neurological mechanisms of illnesses by directing their attention on the alpha frequency range. This accomplishment not only improves the accuracy of classification, but also offers a distinct viewpoint for investigating the importance of alpha frequencies in neurological illnesses. This ultimately facilitates a more comprehensive understanding of the underlying mechanisms of these disorders within a specific and practical framework.



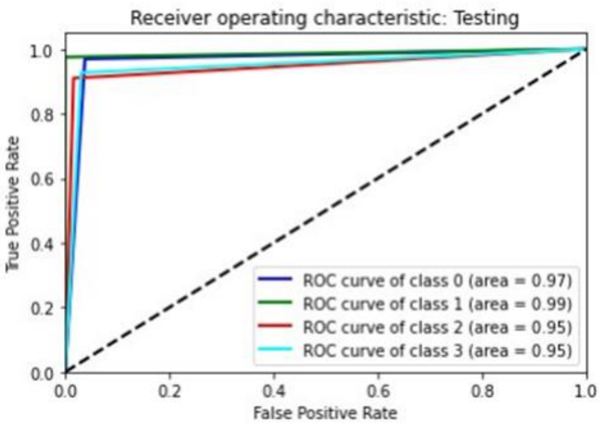

a)




b)




c)




d)

**Fig 3:** ROC curves representing classifier performance using One-vs-rest method: (a) KNN classifier with PCC extracted parameters, (b) RF classifier with PCC extracted parameters, (c) SVM classifier with PCC extracted parameters, (d) DNN classifier with PCC extracted parameters

### Conflicts of Interest

The authors declare no conflict of interest.

### Author Contributions

"Conceptualization, Rageshri Bakare and Virendra Shete; methodology, Rageshri Bakare and Virendra Shete; software, validation, and formal analysis, Rageshri Bakare; investigation, Rageshri Bakare; resources, Ioannis Kompatsiaris and Magda Tsolaki; data curation, Ioannis Kompatsiaris and Magda Tsolaki; writing—original draft preparation, Rageshri Bakare; writing—review and editing, Rageshri Bakare, Virendra Shete, Ioannis Kompatsiaris and Magda Tsolaki; visualization and supervision, Virendra Shete, Ioannis Kompatsiaris and Magda Tsolaki; project administration, Virendra Shete".

### Acknowledgments

The writers are thankful to Centre for Research and Technology Hellas - Information Technologies Institute (CERTH-ITI), Thessaloniki, Greece, and Greek Association of Alzheimer's Disease and Related Disorders (GAADRD), Thessaloniki, Greece, for giving them access to the repository of the EEG recordings.

## References

[1] Lazarou, S. Nikolopoulos, S. I. Dimitriadis, I. (Yiannis) Kompatsiaris, M. Spilioti, and M. Tsolaki, "Is brain connectome research the future frontier for subjective cognitive decline? A systematic review," Clinical Neurophysiology, vol. 130, no. 10, pp. 1762–1780, Oct. 2019, doi: 10.1016/j.clinph.2019.07.004.

[2] M. Ouchani, S. Gharibzadeh, M. Jamshidi, and M. Amini, "A Review of Methods of Diagnosis and Complexity Analysis of Alzheimer's Disease Using EEG Signals," BioMed Research International, vol. 2021. Hindawi Limited, 2021. doi: 10.1155/2021/5425569.

[3] B. Dubois et al., "Research criteria for the diagnosis of Alzheimer's disease: revising the NINCDS–ADRDA criteria.," 2007, doi: 10.1016/S1474.

[4] R. Cassani, M. Estarellas, R. San-Martin, F. J. Fraga, and T. H. Falk, "Systematic Review on Resting-State EEG for Alzheimer's Disease Diagnosis and Progression Assessment," Dis Markers, vol. 2018, 2018, [Online]. Available: https://api.semanticscholar.org/CorpusID:53211139

[5] J. Jeong, "EEG dynamics in patients with Alzheimer's disease," Clinical Neurophysiology, vol. 115, no. 7. pp. 1490–1505, Jul. 2004. doi: 10.1016/j.clinph.2004.01.001.

[6] F. Jessen et al., "The characterisation of subjective cognitive decline," Lancet Neurol, vol. 19, no. 3, pp. 271–278, 2020, doi: https://doi.org/10.1016/S1474-4422(19)30368-0.

[7] X. Delbeuck, M. Van der Linden, and F. Collette, "Alzheimer' Disease as a Disconnection Syndrome?," Neuropsychol Rev, vol. 13, pp. 79–92, 2003, [Online]. Available: https://api.semanticscholar.org/CorpusID:22021236

[8] Z. Song, B. Deng, J. Wang, and R. Wang, "Biomarkers for Alzheimer's Disease Defined by a Novel Brain Functional Network Measure," IEEE Trans Biomed Eng, vol. PP, p. 1, Sep. 2018, doi: 10.1109/TBME.2018.2834546.

[9] B. Jelles, Ph. Scheltens, W. M. van der Flier, E. J. Jonkman, F. H. L. da Silva, and C. J. Stam, "Global dynamical analysis of the EEG in Alzheimer's disease: Frequency-specific changes of functional interactions," Clinical Neurophysiology, vol. 119, no.

4, pp. 837–841, 2008, doi: https://doi.org/10.1016/j.clinph.2007.12.002.

[10] W. S. Pritchard et al., "EEG-based, neural-net predictive classification of Alzheimer's disease versus control subjects is augmented by non-linear EEG measures."

[11] N. Houmani et al., "Diagnosis of Alzheimer's disease with electroencephalography in a differential framework," PLoS One, vol. 13, no. 3, Mar. 2018, doi: 10.1371/journal.pone.0193607.

[12] O. Györfi et al., "Accuracy of high-density EEG electrode position measurement using an optical scanner compared with the photogrammetry method," Clin Neurophysiol Pract, vol. 7, pp. 135–138, Jan. 2022, doi: 10.1016/j.cnp.2022.04.002.

[13] E. C. Ketola, M. Barankovich, S. Schuckers, A. Ray-Dowling, D. Hou, and M. H. Imtiaz, "Channel Reduction for an EEG-Based Authentication System While Performing Motor Movements," Sensors, vol. 22, no. 23, Dec. 2022, doi: 10.3390/s22239156.

[14] M. Regeena BITS Pilani, "Signal Processing Methods of Diagnosing Alzheimer's Disease Using EEG A Technical Review Maining Safety Integrity Level of a Critical Safety Instrumented System Component through Employee Training View project Radar Signal Processing View project," 2018. [Online]. Available: https://www.researchgate.net/publication/327281761

[15] P. Durongbhan et al., "A dementia classification framework using frequency and time-frequency features based on EEG signals," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 5, pp. 826–835, May 2019, doi: 10.1109/TNSRE.2019.2909100.

[16] L. M. Sanchez-Reyes, J. Rodriguez-Resendiz, G. N. Avecilla-Ramirez, M. L. Garcia-Gomar, and J. B. Robles-Ocampo, "Impact of EEG Parameters Detecting Dementia Diseases: A Systematic Review," IEEE Access, vol. 9. Institute of Electrical and Electronics Engineers Inc., pp. 78060–78074, 2021. doi: 10.1109/ACCESS.2021.3083519.

[17] Lazarou et al., "A novel connectome-based electrophysiological study of subjective cognitive decline related to Alzheimer's disease by using resting-state high-density EEG EGI GES 300," Brain Sci, vol. 10, no. 6, pp. 1–29, Jun. 2020, doi: 10.3390/brainsci10060392.

[18] C. Lehmann et al., "Application and comparison of classification algorithms for recognition of Alzheimer's disease in electrical brain activity (EEG)," J Neurosci Methods, vol. 161, no. 2, pp. 342–350, Apr. 2007, doi: 10.1016/j.jneumeth.2006.10.023.

[19] M. Cejnek, O. Vysata, M. Valis, and I. Bukovsky, "Novelty detection-based approach for Alzheimer's disease and mild cognitive impairment diagnosis from EEG," Med Biol Eng Comput, vol. 59, no. 11–12, pp. 2287–2296, Nov. 2021, doi: 10.1007/s11517-021-02427-6.

[20] L. Trambaiolli, A. Lorena, F. Fraga, P. Kanda, R. Anghinah, and R. Nitrini, "Improving Alzheimer's Disease Diagnosis with Machine Learning Techniques," Clinical EEG and neuroscience : official journal of the EEG and Clinical Neuroscience Society (ENCS), vol. 42, pp. 160–165, Sep. 2011, doi: 10.1177/155005941104200304.

[21] M. Dauwan et al., "Random forest to differentiate dementia with Lewy bodies from Alzheimer's disease," Alzheimer's and Dementia: Diagnosis, Assessment and Disease Monitoring, vol. 4, pp. 99–106, 2016, doi: 10.1016/j.dadm.2016.07.003.

[22] B. M. Thejaswini, T. Y. Satheesha, and S. Bhairannawar, "EEG Classification Using Modified KNN Algorithm," in 2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC), 2023, pp. 1–4. doi: 10.1109/ICAISC58445.2023.10200104.

[23] R. B. Vallabhaneni et al., "Deep Learning Algorithms in EEG Signal Decoding Application: A Review," IEEE Access, vol. 9, pp. 125778–125786, 2021, doi: 10.1109/ACCESS.2021.3105917.

[24] F. C. Morabito et al., "Deep convolutional neural networks for classification of mild cognitive impaired and Alzheimer's disease patients from scalp EEG recordings," in 2016 IEEE 2nd International Forum on Research and Technologies for Society and Industry Leveraging a better tomorrow (RTSI), 2016, pp. 1–6. doi: 10.1109/RTSI.2016.7740576.

[25] H. Zhang et al., "The Significance of EEG Alpha Oscillation Spectral Power and Beta Oscillation Phase Synchronization for Diagnosing Probable Alzheimer Disease," Front Aging Neurosci, vol. 13, Jun. 2021, doi: 10.3389/fnagi.2021.631587.