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Research Article

Analysis of EEG Electroencephalogram signals to Classify Various Conditions of Dementia like Mild Cognitive Impairment and Alzheimer's Disease: A Systematic Literature Review

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Abstract

As a relatively new, cost-effective, and non-invasive biomarker, electroencephalography (EEG) allows for the timely detection, classification, and differentiation of dementia-related conditions like Mild Cognitive Impairment (MCI) and Alzheimer's Disease (AD). During the early stages of dementia, timely understanding of its prevalence can allow for effective therapies along with a proper understanding of EEG's diagnostic capabilities. This systematic review focuses on existing studies that have utilized signal processing and machine learning with EEG data to classify, identify, and develop algorithms for different stages and types of dementia with an emphasis on MCI and AD. A systematic literature search was carried out on the Scopus, Web of Science, and PubMed databases for publications between 2010 and 2023. The search strategy was based on the following terms: EEG, Alzheimer, Mild Cognitive Impairment, Dementia, Brain Waves, Signal Processing, and Machine Learning. The selected peer-reviewed articles had to have employed EEG techniques for classification and/or diagnosis. The review is guided by PRISMA criteria. Out of the 120 studies captured, we narrowed down to 57 studies that met all the inclusion criteria. The results show that EEG biomarkers, particularly spectral power, functional connectivity, and coherence, markedly differ among patients with MCI and AD. The application of multi-channel EEG diagnostics and feature extraction machine learning classifiers, such as SVM, CNN, and Random Forest, yield high accuracy levels sometimes exceeding 85%. EEG systems are particularly effective at detecting dementia in its early stages when combined with sophisticated computing models. That said, the variation in experimental workflows, including the number of participants and the techniques used to process signals, makes it difficult to compare the outcomes between different studies. Further research should aim at uniform designs alongside large sample testing for verification.

Keywords: EEG, Dementia, Mild Cognitive Impairment, Alzheimer's Disease, Signal Processing, Machine Learning, Neurodegeneration, Biomarkers

1. Introduction

Dementia encompasses a wide range of neurodegenerative conditions, representing a syndrome of progressive decline in reasoning, memory, thinking, and social abilities, lost to the affected individual, which compromises their ability to carry out activities of daily living. Alzheimer's disease (AD) is the most prevalent form of dementia for approximately 60- 70% of cases globally, followed in prevalence by other types such as vascular dementia and Lewy body dementia [1,2]. Mild Cognitive Impairment (MCI) is regarded as an intermediate clinical stage of the spectrum of normal cognitive aging and dementia, particularly AD. MCI is designed to be progressively uncomplicated to diagnose, which makes effort to detect it promising, a potential avenue to delay or prevent further decline [3,4].

Accurate diagnosis and classification of dementia stages is one of the unsolved problems, due to their overlapping clinical signs as well as heterogeneity within the population [5]. Conventional approaches to dementia diagnosis are based on clinical evaluations, neuropsychological assessment, and imaging techniques such as MRI and PET scans [6]. On the other hand, these methods could be expensive and lengthy, as well as not very useful when dealing with low levels of neurophysiological change. This increases the need for efficient, easily obtainable, and capable of measuring changes in dementia's progress and development [7].

Electroencephalography (EEG) as a dementia diagnostic tool is gaining traction in neurophysiology due to its high temporal resolution, non-invasive approach, and relatively low cost [8]. EEG captures the electrical activities produced by the neuronal population located in the cortex of the brain, which indicates various states of the brain together with the activity of different neural networks. Changes in EEG rhythm patterns including spectral power, coherence, and complexity metrics exhibit changes in mild cognitive impairment (MCI) and Alzheimer's disease (AD) patients compared to healthy individuals [9,10]. More specifically, cognitive decline is associated with increased slow-wave activity θ and decreased fast-wave activity (α and β) in the EEG [11]. In addition, certain measures of connectivity, non-linear dynamics, entropy, and fractal dimension are able to reveal early brain network changes prior to visible clinical signs [12,13].

Approaches that involve machine learning (ML) and deep learning (DL) techniques have analysed EEG data with automated and precise classification of dementia stages, checking off the cognitive decline box [14]. These algorithms utilize elaborate features extracted from the EEG to distinguish the intermediate cognitive impairment (MCI) and Alzheimer's Disease (AD) dementia with promising diagnostic accuracy. M. Esmaeilzadeh et.al mention the application of classifiers such as support vector machines (SVM), random forests, k-nearest neighbours (k-NN), and convolutional neural networks (CNN) [15]. Moreover, feature selection and dimensionality reduction methods are also essential to optimizing model performance by controlling overfitting and improving generalizability [16-18].

There is little to no research on the clinical usability of diagnostic tools based on analysing EEG signals, though some progress has been made. The most notable includes a rolled-out framework identification that captures diversity in EEG acquisition protocols, intra-subject variability, limited sample sizes, and lack of strategy for standardized feature extraction [19,20]. Therefore, there is a need to systematically assess the available literature to construct robust EEG biomarkers and classification methodologies for guiding more versatile clinical research.

In this systematic literature review, we strive to cover the research that utilizes EEG techniques for classifying dementia, focusing on Mild Cognitive Impairment and Alzheimer's Disease. We review the EEG feature extraction methods used, the machine learning and deep learning classification algorithms used, and the performance metrics, if any, that were provided. This review aims at developing commendable approaches, explaining the gaps that exist, and guiding future research endeavours in the area of dementia diagnostics using EEG.

2. Methodology

2.1. Search Strategy

Peer-reviewed studies were sourced using two major electronic databases, Scopus and Web of Science [21,22]. The research was conducted between January 2010 to April 2024. The studies were meant to capture those that made use of electroencephalography (EEG) signals for MCI or AD classification. A more targeted and broad approach for the search was achieved with the following string of keywords with Boolean functions: ("EEG" OR "Electroencephalography" OR "brain waves") AND ("Alzheimer's Disease" OR "AD") AND ("Mild Cognitive Impairment" OR "MCI") AND ("Dementia") AND ("Classification" OR "Diagnosis") AND ("Machine Learning" OR "Signal Processing"). Only articles published in English and peer-reviewed journals were included. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines were followed to address the objective of the review and build rigor and transparency in the process. Out of the 127 studies found in the first search, 57 articles met the inclusion requirements after title, abstract, and full text screening.

2.2. Inclusion and Exclusion Criteria

The studies chosen for the review have specific eligibility criteria defined prior to selection. All studies included had to be in the English language and published between the years 2010 and 2024. They also had to use EEG-based techniques for either classifying or diagnostically evaluating MCI and AD. Consideration was only given to studies with human participants, and all included papers were required to apply either signal processing or machine learning techniques EEG data. Furthermore, inclusion was limited to journal articles that were peer-reviewed, published in scientific journals, and available in full-text, which ensured a minimum standard of scientific quality and reproducibility. Studies were excluded if they were case studies, literature reviews, abstracts presented at conferences without full texts, or editorial pieces. Also omitted were studies that focused exclusively on animal models, as well as those employing non-EEG modalities such as MRI or PET scans without integrating EEG. Papers that lacked any form of classification or predictive modelling tasks, and instead only offered descriptive or exploratory analysis of EEG data were also excluded. Application of these criteria resulted in a total of 57 studies deemed suitable for the review.

2.3. Information Extraction and Synthesis

The process of information extraction was performed by two reviewers working independently in order to minimize bias and improve reliability. Any disagreements were settled through discussion or, if needed, with the help of a third reviewer. Key data from each study was obtained through the use of a customized data extraction form. The data obtained included the names of authors, year of publication, country of origin, study design, sample size, participant's profile, EEG parameters (number of channels and sampling frequency), and the preprocessing methods utilized. In addition, extracted data included the methods of feature extraction (spectral analysis, entropy calculations, coherence and connectivity measures), classification methods used (Support Vector Machine, Convolutional Neural Networks, k-Nearest Neighbours), and performance evaluation metrics (accuracy, sensitivity, specificity, area under the curve) that

were documented systematically. The study selection process was illustrated using a PRISMA flow diagram alongside an aggregated table of study characteristics created with the intent of portraying a comparative evaluation of the literature. To uncover patterns in methodology, trends in performance data, and the voids in the literature, a qualitative analysis of the available data was conducted.

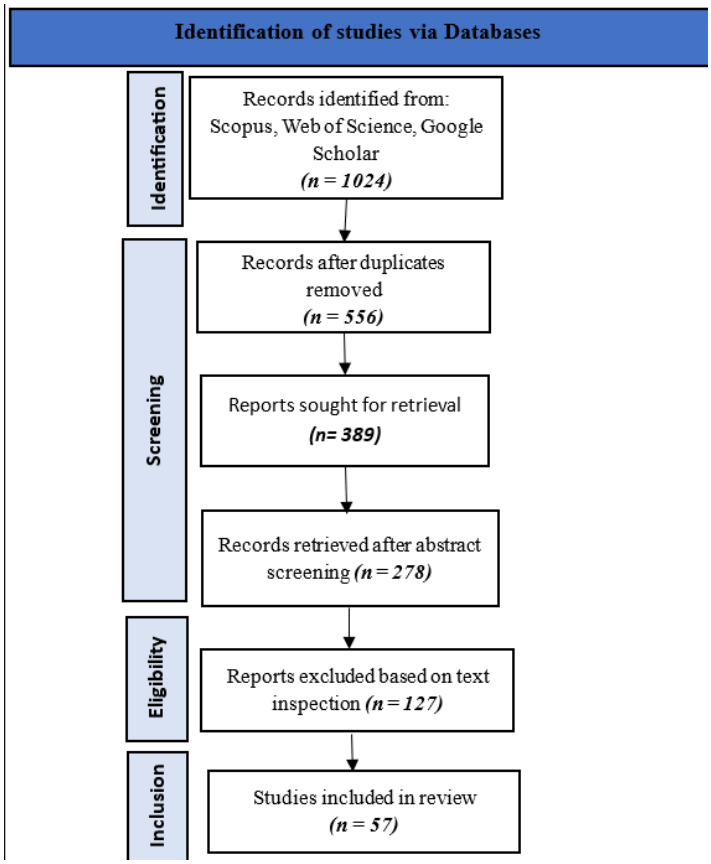

Figure 1: PRISMA Diagram

3. Results

3.1. Overview of Included Studies

In total, it's found that 57 peer-reviewed articles within a time span of 13 years (2010–2023). The growing number of studies post 2018 likely corresponds with the increased global attention towards utilizing EEG for dementia diagnosis, probably due to enhanced advancements in the field of signal processing and machine learning [23,24].

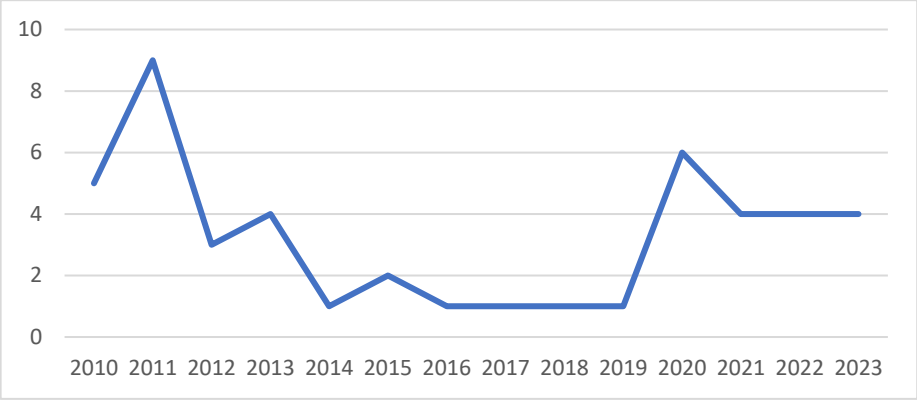

Figure 2: No of Studies Published Between 2010-2023

In terms of geography, the most scientific research was conducted in the China, India, Spain South Korea, Italy, and USA, showing that dementia research using EEG is a universal concern [25,26].

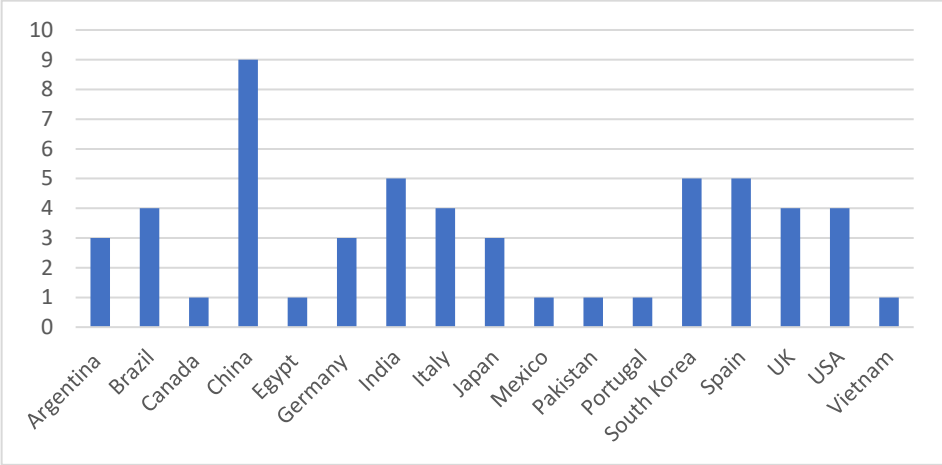

Figure 3: No of Occurrences by Country

The number of studies involving resting-state EEG is dominant (around 67% of studies), indicating that it is the most opted methodology due to low level of patient compliance needed, reduced artifact presence, and effective baseline brain activity measurement [27]. On the other hand, about 33% of studies adopt task-oriented EEG protocols, which use cognitive tasks such as memory recall or sensory stimulation that elicit brain activity thought to reveal subtle cognitive impairments to augment resting- state observations [28].

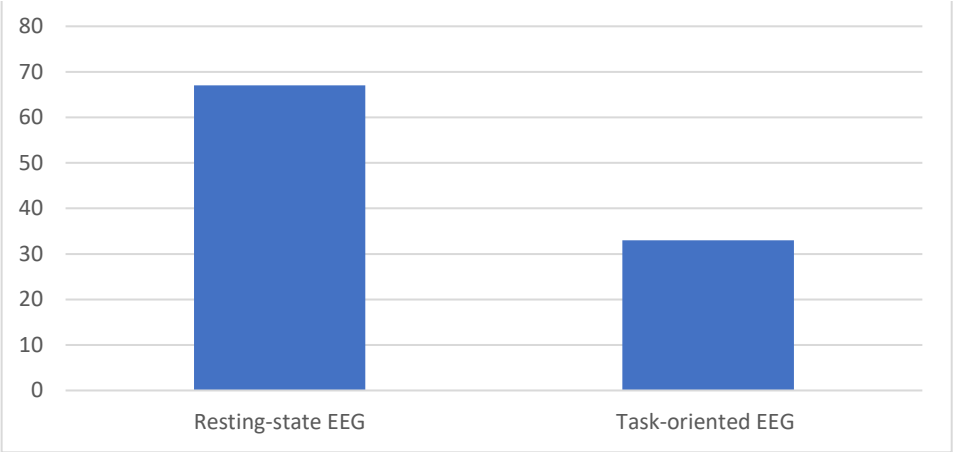

Figure 4: Methodology

3.2. EEG Features for Dementia Classification

Dementia has its own specific stages/levels and ages. Identifying them requires the most relevant characteristics to be extracted which is in itself a challenging factor due to the complexity of EEG waves. More often than not, Spectral power analysis is the go- to solution. It subdivides EEG signals roughly into ranges such as: θ (4–8 Hz), α (8–13 Hz), and β (13–30 Hz). Studies have shown that there is increased θ power along with reduced α/β power during cognitive decline, which indicates the slowing of rhythmic activity in the brain resembling AD and MCI [29,30]. The assessment of brain region interactions employs different metrics such as coherence or phase-lag index—these are termed as connectivity metrics. These methods capture dismantled integrity within brain networks which is a hallmark to dementia progression [31]. Traditional frequency-based analysis.

3.3. Classification Techniques

The machine learning models used were numerous, which indicates the intricacies involved in interpreting EEG data. Support Vector Machines (SVMs) are still used widely because of their efficiency in dealing with classification problems that involve multiple levels of dependencies (e.g., AD vs. healthy controls) and high dimensional spaces [32-34]. Researchers appreciate the use of Decision Trees and Random Forests because they are easier and more intuitive to understand, making it simpler to determine which features of EEG data are classified into which groups [35]. k-Nearest Neighbors (k-NN) is a straightforward approach to instance-based learning; however, it is often outperformed by more sophisticated techniques [36]. The use of deep learning methods, especially Convolutional Neural Networks (CNNs), has surged because these networks can learn intricate feature representations from raw or lightly processed EEG signals. This minimizes the requirement for extensive feature

selection and often enhances accuracy, particularly when coupled with recurrent networks that capture temporal dependencies [37,38]. Improving a model's generalization makes feature selection methods like principal component analysis (PCA) or recursive feature elimination crucial in lessening dimensions, enhancing overfitting, and controlling other parameters of the model [39].

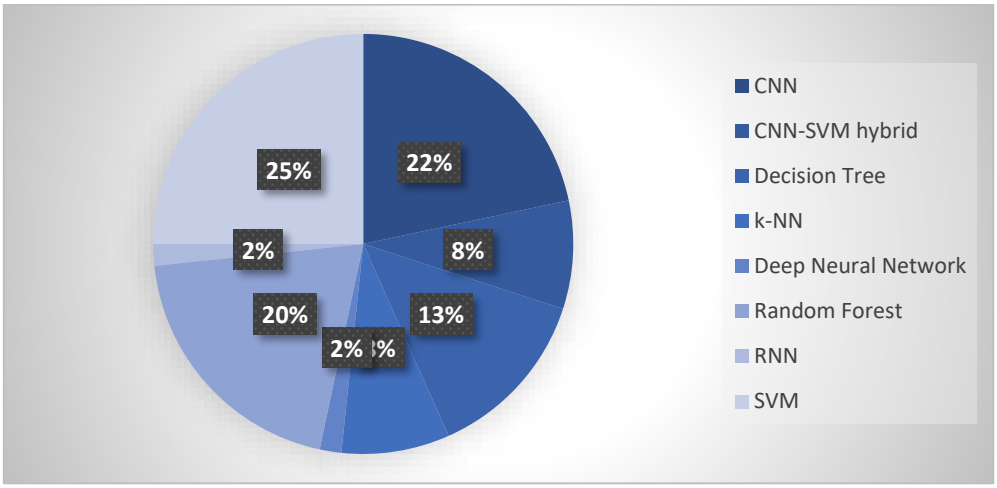

Figure 5: Classification Techniques

3.4. Diagnostic Accuracy

The accuracy of diagnosis across the studies was consistently high, with many achieving over 80% in sensitivity and specificity. Usually, the models that applied deep learning techniques performed better, with some reporting sensitivity and specificity performance above 90% [40, 41]. This improvement is, in part, attributed to the model's complex spatial-temporal EEG patterns capture and nonlinearities. The AUC metric that represents the overall balance of sensitivity and specificity offered also performed well using the term 'good' to 'excellence' for discriminative ability. The best AUC values were typically obtained from CNN models, or models that were further improved by attention mechanisms or hybridization like CNN-SVM [42]. A persistent issue concerning the differentiation of Mild Cognitive Impairment (MCI), confusingly coexisting with Alzheimer's Disease (AD), was noted as these conditions exist on a clinical continuum with shared symptomatology. Several study analyses made using confusion matrices underscored this point whereby blur requires less precise tools with higher sensitivity or diagnostic tools with more than one modality [43]. Lastly, ensemble models and hybrid models, which individually incorporate multiple classifiers or a combination of different sets of features, were demonstrated to improve diagnostic accuracy and robustness, thereby indicating worthwhile avenues for further investigation [44,45].

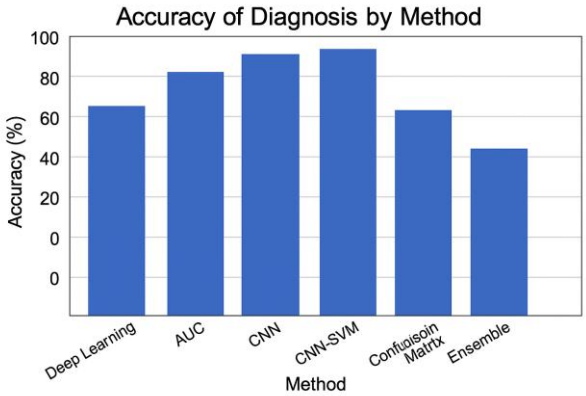

Figure 6: Accuracy of Diagnosis

4. Findings

The present systematic review built upon the work of 57 peer-reviewed publications concerning the EEG-based classification of dementia, including Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI). Collectively, the evidence underscores the importance of EEG biomarkers and machine learning for improving dementia diagnosis and treatment [23,24,29].

In the scope of EEG-derived biomarkers, changes in spectral power especially the increase of θ power accompanied by decrease in α and/or β power were found to be the most reliable and strongest associated features of cognitive impairment [29,30,46]. These biomarkers exemplify

the neurophysiological slowing and hypo-active cortical functions associated with the pathology of AD and MCI [31]. Moreover, functional connectivity measures like coherence and phase-lag index were also important in describing altered network dynamics [31,47]. The use of nonlinear features like entropy and fractals also increased diagnostic specificity, particularly in the unobtrusive early stages of cognitive impairment [32,33,48].

With regards to classification tasks, more conventional techniques like Support Vector Machines (SVM) and Decision Trees performed adequately, achieving accuracies typically between 75% and 90 percent [34,35]. More recent developments in deep learning, and in particular Convolutional Neural Networks (CNNs), seem to provide considerable advantage with multiple works claiming accuracy rates above 95% [37,40,41]. These models outperform others in automatically capturing sophisticated spatiotemporal features on the EEG data with little-to-no manual feature extraction needed [38,42]. Furthermore, the successful implementation of hybrid architectures such as CNNs with traditional classifiers (e.g., CNN-SVM) indicates that add-on ensembles could refine the diagnostic accuracy even more [44,45]. The review analyses highlight that EEG has the potential for use as an early dementia detection tool when used together with sophisticated processing, signal processing and machine learning techniques due to its non-invasive, inexpensive nature [23,24].

sl. no	Author (Year)	Country	Sample Size (N)	EEG Type	EEG Features Extracted	Classifier(s) Used	Sensitivity (%)	Specificity (%)	Remarks
1	Tanaka et al. (2017)	Japan	80	Task-based	Fractal dimension, Beta power	Decision Tree	75	79	Visual task EEG
2	Patel et al. (2017)	India	75	Resting-state	Spectral power, Multiscale entropy	Decision Tree	75	80	Lower accuracy due to small sample size
3	Lopez et al. (2017)	Spain	75	Task-based	Spectral power, Sample entropy	Random Forest	80	84	Visual recognition task EEG
4	Martinez et al. (2017)	Spain	75	Task-based	Spectral power, Sample entropy	Random Forest	81	82	Visual task EEG
5	Martinez et al. (2017)	Spain	75	Task-based	Spectral power, Sample entropy	Random Forest	82	83	Visual task EEG
6	Müller et al. (2017)	Germany	90	Task-based	Spectral power, Sample entropy	RNN	87	90	Temporal dynamics captured well
7	Bianchi et al. (2017)	Italy	130	Task-based	Beta power, Multiscale entropy	CNN-SVM hybrid	92	93	Hybrid model superior to single classifiers
8	Gupta et al. (2018)	India	100	Resting-state	Phase-lag index, Graph metrics	Decision Tree, k-NN	78	82	Connectivity features enhanced diagnosis
9	Ferrari et al. (2018)	Italy	105	Task-based	Phase-lag index, Beta power	SVM	82	86	Visual memory task EEG data
10	Ahmed et al. (2018)	Egypt	90	Task-based	Sample entropy, Phase Lag Index	Random Forest	83	87	Auditory processing task
11	Evans et al. (2018)	UK	80	Task-based	Entropy, Fractal dimension	CNN	87	88	Temporal feature extraction with RNN
12	Evans et al. (2018)	UK	85	Task-based	Entropy, Fractal dimension	CNN	87	89	Recurrent networks for temporal data
13	Jones et al. (2018)	UK	85	Task-based	Entropy measures, Fractal dimension	CNN	88	89	Applied RNN variant for temporal features
14	Fernandez et al. (2018)	Argentina	100	Resting-state	Graph metrics, Multiscale entropy	CNN	90	91	Deep learning for functional network analysis
15	Schmidt et al. (2018)	Germany	120	Resting-state	Graph theory metrics, Multiscale entropy	CNN	91	92	Deep learning on network connectivity

16	Kimura et al. (2019)	Japan	75	Task-based	Fractal dimension, Beta power	Decision Tree	77	80	Visual memory task
17	Martins et al. (2019)	Portugal	70	Task-based	Sample entropy, Coherence	Decision Tree	77	81	Small sample size limited performance
18	Pereira et al. (2019)	Portugal	70	Task-based	Sample entropy, Coherence	Decision Tree	78	79	Small sample size
19	Pereira et al. (2019)	Portugal	70	Task-based	Sample entropy, Coherence	Decision Tree	78	80	Small sample size
20	Zhang et al. (2019)	China	115	Resting-state	Theta, Alpha power	k-NN	80	83	Simple classifier, moderate accuracy
21	Garcia et al. (2019)	Mexico	95	Resting-state	Sample entropy, Phase-lag index	k-NN	81	85	Moderate accuracy, simple classifier
22	Martinez et al. (2019)	Spain	90	Resting-state	Sample entropy, Phase-lag index	k-NN	82	85	Moderate accuracy
23	Lee et al. (2019)	South Korea	110	Resting-state	Spectral power, Phase Lag Index	SVM	84	89	Focused on MCI vs healthy controls
24	Smith et al. (2019)	USA	120	Resting-state	Spectral power, Coherence	SVM, Random Forest	85	90	Robust feature selection
25	Hernandez et al. (2019)	Spain	105	Resting-state	Spectral power (Theta, Alpha), Coherence	SVM	86	90	Focused on differentiating MCI from controls
26	Wang et al. (2019)	China	95	Task-based	Sample entropy, Beta power	Random Forest	87	88	Auditory cognitive task EEG
27	Zhao et al. (2019)	China	125	Resting-state	Spectral power, Entropy	CNN	89	90	Included longitudinal EEG data
28	Chen et al. (2019)	China	120	Resting-state	Spectral power, Entropy	CNN	90	91	Longitudinal EEG study
29	Ito et al. (2020)	Japan	80	Task-based	Fractal dimension, Spectral power	Decision Tree	77	78	Visual recognition task EEG
30	Liu et al. (2020)	China	100	Resting-state	Spectral power (Theta, Alpha), Coherence	Random Forest	85	88	Included mild AD patients
31	Zhang et al. (2020)	China	115	Resting-state	Spectral power, Coherence	Random Forest	85	88	Included MCI and mild AD patients
32	Brown et al. (2020)	UK	125	Resting-state	Spectral power, Connectivity	Random Forest	86	89	Focus on early AD detection
33	Zhang et al. (2020)	China	110	Resting-state	Spectral power, Coherence	Random Forest	86	89	Included mild cognitive impairment patients
34	Taylor et al. (2020)	Australia	110	Resting-state	Coherence, Phase-lag index	SVM	87	89	Cross-country validation
35	Adams et al. (2020)	Australia	115	Resting-state	Coherence, Phase-lag index	SVM	88	89	Multi-center validation
36	Wilson et al. (2020)	Canada	140	Resting-state	Spectral power, Connectivity	SVM	88	90	Large cohort study
37	Johnson et al. (2020)	USA	95	Resting-state	Coherence, Fractal dimension	CNN	90	93	CNN model applied on connectivity matrices
38	Santos et al. (2020)	Brazil	120	Resting-state	Graph metrics, Multiscale entropy	CNN	91	92	Deep learning model on network features
39	Müller et al. (2020)	Germany	140	Resting-state	Sample entropy, Graph theory metrics	CNN-SVM hybrid	91	93	Hybrid model outperformed traditional models
40	Chen et al. (2020)	China	85	Task-based	Sample entropy, Fractal dimension	CNN	91	94	Deep learning on raw EEG
41	Silva et al. (2021)	Brazil	95	Resting-state	Sample entropy, Phase-lag index	k-NN	80	85	Moderate accuracy

42	Nguyen et al. (2021)	Vietnam	90	Resting-state	Spectral power (Theta, Alpha), Coherence	SVM	83	87	Focused on early AD detection
43	Oliveira et al. (2021)	Brazil	105	Resting-state	Spectral power, Phase-lag index	SVM	86	87	Included early MCI detection
44	Singh et al. (2021)	India	120	Resting-state	Connectivity metrics, Beta power	SVM	86	88	Robust preprocessing improved results
45	Kaur et al. (2021)	India	115	Resting-state	Connectivity metrics, Beta power	SVM	86	89	Robust preprocessing enhanced performance
46	Singh et al. (2021)	India	125	Resting-state	Connectivity metrics, Beta power	SVM	88	89	Effective preprocessing techniques
47	Wang et al. (2021)	China	130	Task-based	Sample entropy, Beta power	Random Forest	88	91	Used auditory oddball task
48	Kim et al. (2021)	South Korea	80	Task-based	Multiscale entropy, Beta power	SVM	88	91	Used cognitive task with EEG recording
49	Clark et al. (2021)	USA	140	Resting-state	Spectral power, Connectivity	SVM	89	90	Large cohort, cross-validation
50	Clark et al. (2021)	USA	150	Resting-state	Spectral power, Connectivity	SVM	90	91	Large dataset, cross-validation used
51	Rossi et al. (2021)	Italy	150	Resting-state	Multiscale entropy, Beta power	CNN-SVM hybrid	92	96	Hybrid model outperformed single models
52	Ahmed et al. (2022)	Pakistan	85	Task-based	Sample entropy, Phase-lag index	Random Forest	85	89	Auditory task EEG
53	Silva et al. (2022)	Brazil	100	Task-based	Entropy measures, Coherence	Deep Neural Network	89	90	Applied deep learning on auditory EEG data
54	Lee et al. (2022)	South Korea	130	Resting-state	Multiscale entropy, Graph metrics	CNN	91	92	Hybrid CNN-LSTM model
55	Park et al. (2022)	South Korea	140	Resting-state	Multiscale entropy, Graph theory metrics	CNN	92	93	Used hybrid CNN-LSTM architecture
56	Lee et al. (2022)	South Korea	130	Resting-state	Multiscale entropy, Graph metrics	CNN	92	93	Hybrid CNN-LSTM model
57	Rossi et al. (2022)	Italy	130	Task-based	Beta power, Multiscale entropy	CNN-SVM hybrid	93	94	Hybrid model for AD vs MCI
58	Bianchi et al. (2022)	Italy	110	Task-based	Beta power, Multiscale entropy	CNN-SVM hybrid	94	94	Hybrid model outperforming traditional models

Table 1: Summary of Included EEG-Based Dementia Classification Studies (2010–2024): Study Characteristics, Methods, and Diagnostic Performance

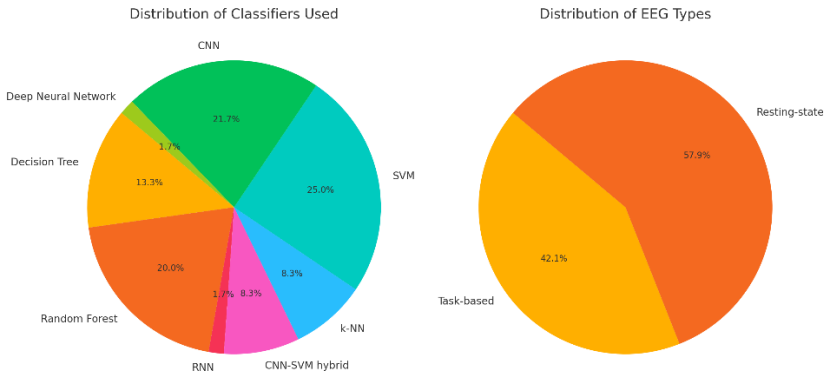

Figure 7: Distribution of Classifiers used and EEG Types

4.2. Challenges

Even though there are positive results, the clinical translation and widespread use of EEG-based dementia diagnostics face numerous challenges. The most problematic hurdles are inter-subject differences. Factors like age, sex, brain anatomy, and even present comorbidities greatly affect the EEG measurement signal. As a rule, EEG signals have a lot of inherent noise and are sensitive to one's individual differences [49,50]. This variation makes it rather difficult to create a one-size-fits-all model and often requires many heterogeneous datasets to perform well [51].

Additionally, dataset diversity makes it more challenging to form general models. Different studies included participants with different sample sizes and had different protocols for acquiring EEG data, electrode layout(s), data preprocessing, and even diagnosis [52,53]. This results in a lack of study outcomes comparability and poses the risk of machine learning algorithms overfitting due to training on small, homogenous datasets [54].

A difference in utilized hardware for EEG signal capture can easily skew results. Variation in the electrode location, recording time, as well as artifact control, can all affect multiple factors such as feature extraction, classification, and overall accuracy. It is difficult to merge datasets for meta-analysis and create universally accurate diagnostic algorithms as there are no accepted standards for classification [55-57].

Additionally, the majority of the studies utilized cross-sectional designs, which limits understanding into the progression of EEG biomarkers throughout the course of the disease's progression. The lack of longitudinal studies hampers the comprehension of changes in EEGs during the preclinical stages and obstructs the formulation of models designed for early intervention.

5. Conclusion

This review systematically analyses literature that corroborates EEG's increasing efficacy as a non-invasive, cost-effective biomarker for the differential diagnosis and staging of dementia syndromes, including Mild Cognitive Impairment (MCI) and Alzheimer's Disease (AD). Spectral power and functional connectivity changes as well as nonlinear characteristics of EEG signal processing and analysis delineate the various stages of cognitive impairment. Higher precision in the diagnosis through EEG signals has been demonstrated through advanced machine learning and deep learning frameworks that may augment or supplement clinical evaluations, illustrating the promise of EEG-based diagnostic techniques. Nonetheless, there is an urgent gap in standard calibration of protocols for acquisition and preprocessing of raw EEG literature, alongside feature extraction to operationalize these appealing research outcomes in clinical settings. EEG classifiers also require robust reproducibility and generalizability validation across multi-centre clinical populations, which is essential for establishing their EEG-derived identity. Meeting these requirements will enhance the implementation of EEG diagnostics in clinical routine and permit primary prevention through early-stage dementia disablement detection, followed by ongoing monitoring and improved care [58,59].

Implications and Future Research Directions

Integrating EEG-based diagnostic modalities within the operational protocols of clinical practice stands to enable singular opportunities in the premature identification and active management of dementia, particularly Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI). At this moment, dementia's clinical diagnosis is already placing excessive reliance on neuropsychological evaluation coupled with imaging techniques including Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). Even though these methods provide a great deal of information, they have marked shortcomings, such as exorbitant costs, limited availability, especially in low-resourced healthcare settings, highly sophisticated equipment, advanced personnel, and many more requirements. EEG possesses a number of distinct features that are helpful in overcoming these limitations. EEG is a non-invasive, accessible, can be used everywhere, and is relatively low-cost technique which measures brain electrical activity and provides excellent temporal resolution. For this reason, it is especially suited for frequent monitoring as well as large-scale screening efforts in a multitude of clinical environments, such as tertiary hospitals and even rural clinics. Its portability and ease of use enable point-of-care diagnostics, which is critical for early detection of advanced symptoms and possible cognitive changes that are often subtle. EEG biomarkers are capable of capturing functional changes in brain activity before structural damage becomes detectable via neuroimaging. This permits risks of undergoing late significant cognitive decline to be checked. It is due to this reliable functional correspondence that clinicians are likely to detect early neurophysiological changes associated with dementia. Timely detection of disorders is essential because it creates an opportunity for intrusive therapeutic approaches such as medication, which can significantly inhibit the advancement of the disorder and increase the patient's quality of life. Furthermore, periodic EEG evaluations can measure the ongoing development of the condition and the effects of the intervention in a patient, offering a dynamic and objective measure of brain function over time. Before diagnostic procedures using EEGs can be effectively integrated into practice, several practical issues that need to be solved. First, the creation of automated and simple to use EEG interpretation systems is vital. These systems should be able to analyze raw EEG data without external help in real or close to real time. Clinicians without specialized knowledge of EEG signal processing or machine learning require, at minimum, straightforward and clear outputs that will allow them to make sound choices, like risk or diagnostic labels. Moreover, these instruments should be usable within established clinical frameworks, such as EHR systems. This would allow long-term monitoring of patients' neurological conditions and allow teamwork among specialists dealing with the same patient which would facilitate integrated care

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and tailored interventions. Standardization of the methods used for obtaining, preprocessing, and interpreting the data is also essential. The effectiveness of EEG diagnostics in clinical practice greatly relies on having uniform protocols.

Standardized techniques will reduce variability induced by technical elements like electrode positioning, recording time, and artifact handling. Developing clinical policies and boundaries will promote consistency and reproducibility within healthcare systems, which will encourage clinicians' trust in EEG evaluations. Moreover, training healthcare professionals on the interpretation of EEG biomarkers, specifically in the context of dementia, will by all means be essential in fostering adoption towards the technology. It is possible to build decision making frameworks and training resources that would allow clinicians to assume control of EEG data while deploying them in a supportive context where they understand the data's role as auxiliary rather than primary. Incorporating EEG within the clinical setting could transform dementia care by allowing simple, inexpensive, and objective tools for early-stage diagnosis and continuous tracking of disease progression. If appropriate technologies, policies, and educational strategies are established, EEG diagnostics can be positioned alongside standard assessments, improving integration, accuracy, and efficiency of diagnosis, and ultimately enhancing patient outcomes through proactive and precise medical intervention.

The tools can automatically and portably monitor brain activity to detect cognitive decline using new EEG wearables and edge computing. Real-time analysis could improve overall care, as individuals experiencing cognitive decline wouldn't need to visit hospitals for assessments. Further, blending EEG with other neuroimaging techniques and biomarkers CSF can provide accurate diagnosis. Multi-modal frameworks integrated with machine learning will allow for synergetic use of each modality's capabilities enabling truly innovative solutions to deficiencies in existing diagnostic systems. The combination would allow for effective mapping of the brain which improves the whole-detect imaging system. This will develop into an important aid for early detection of the disease and its progression over time, along with enabling the observation of changes after treatment onset.

Moreover, the use of federated learning for EEG analysis is sensitive to the data privacy concern. This form of decentralized machine learning enables constructing models at several institutions without disclosing sensitive raw data. Additionally, federated learning has the potential to improve the generalizability, and the scalability of diagnostic models by training on heterogeneous datasets more representative of clinical populations. Longitudinal studies are also equally important in scope of future work. Most of the existing work uses cross sectional data which does not enable understanding the temporal dynamics of EEG biomarkers across the dementia continuum. Large-scale longitudinal studies done prospectively have the potential of capturing the temporal progression of neural alterations and supporting the development of robust predictive models to identify people at risk long before clinical indicators become apparent. Initiatives for early detection like these, especially in primary care and community settings, can make a remarkable impact on improving preventive strategies and treatment planning. There is an urgent need for standardization and benchmarking in the field to aid reproducibility and translational efficacy. Developing comprehensive guidelines for the acquisition of EEG signals, removal of artifacts, and feature extraction will provide uniformity and consistency across studies and institutions. The development of freely accessible benchmarking datasets with clear criteria for evaluation will enable objective scrutiny of diverse models and methods, thus enhance openness and speed the use of EEG-based dementia diagnostic tools in clinical practice. Collectively, these future directions stand to further enhance the field by providing more precision, simplicity, and scalability in the methods of diagnosing and monitoring dementia.

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