Intelligent Approaches for Alzheimer's Disease Diagnosis from EEG Signals: Systematic Review

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Abstract

This systematic review explores the emerging field of Alzheimer's disease (AD) diagnosis using recent advances in machine learning (ML) and deep learning (DL) methods using EEG signals. This review focuses on 38 key articles published between January 2020 and February 2024, critically examining the integration of computational intelligence with neuroimaging to improve diagnostic accuracy and early detection of AD.

AD poses significant diagnostic and treatment challenges, which are exacerbated by the aging of the global population. Traditional diagnostic methods, while comprehensive, are often limited by their time-consuming nature, reliance on expert interpretation, and limited accessibility. EEG is emerging as a promising alternative, providing a non-invasive, cost-effective way to record the brain's electrical activity and identify neurophysiological markers indicative of AD.

The review highlights the shift towards automated diagnostic processes, where ML and DL techniques play a crucial role in analyzing EEG data, extracting relevant features and classifying AD stages with extremely high accuracy. It describes different methods for preprocessing EEG signals, feature extraction and application of different classifier models and demonstrates the complexity of the field and the nuanced understanding of EEG signals in the context of AD.

In summary, although the review demonstrates several advantageous developments, it has highlighted critical challenges and limitations. For example, the AI needs more extensive and more diverse datasets to increase model generalizability and multi-modal data integration to achieve a more comprehensive AD diagnosis. Undoubtedly, its preprocessing techniques and classification techniques must be developed because of the complex nature of EEG data and AD pathology.

To conclude, this review portrays EEG-based AD diagnosis as a promising field fueled by computational breakthroughs. Yet the insufficient literature and investigation require additional scientific inquiries and further research. Numerous outlooks highlight co-investigating EEG with complementary biomarkers and investigating innovative ML/DL approaches. Through the compilation of EEG prowess and computational cognition, the future appears bright for inclusive, precise, and early AD detection. Hence, the forthcoming possibilities of prompt intervention and individualized care are unfolding.

Keywords: Alzheimer's Disease, EEG, Machine Learning, Deep Learning, AD Diagnosis.

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1. Introduction

Healthcare- innovations boost life span, and population rise means more- elderly folks. With age come- disorders like Alzheime-r's disease affecting many. Global population could hit 11.2 billion by 2100[1]. In 2050, around 2 billion will be- 60 or older, which is 21% of people. As more- live longer, age-re-lated illnesses like- Alzheimer's become- increasingly common. Evolving medical science- extends human lives, ye-t presents challenge-s with conditions tied to aging[2].

AD is the most common form of dementia constituting about 60 - 80 percent of all dementia cases[3]. AD is characterized by cognitive decline, memory loss, and other neuropsychiatric symptoms. However, there is no clear understanding regarding the causes of the disease; it is believed that genetic factors are important in its pathogenesis [4]. There is a consensus among experts that mild cognitive impairment (MCI) serves as the first stage in a continuum of AD though not everyone who develops MCI goes on to develop AD Alzheimer s Association.; approximately 15 or 20% of those over sixty-five present with MCI. Thus, within five years, nearly thirty to forty percent among them will advance into AD [5]. Medical diagnosis for AD involves laboratory tests, looking into one’s health record and use of neuroimaging techniques – fMRI among others. Despite this the methods are time consuming, call for highly trained personnel, not available in some places.

Improving the medical diagnosis as well as diagnosis for people with mental deterioration is an immediate necessary. Surprisingly as much as 20% of people might be misdiagnosed emphasizing the vital requirement for even more precise analysis techniques[6].Relying entirely on medical monitoring’s as well as neuropsychological screening to separate very early mental deterioration signs is naturally subjective and also vulnerable to mistakes. In the lack of reliable therapies extra requirements should be developed to verify Alzheimer's condition, and also very early discovery arises as an essential aspect in sample condition development[7].

Quick recognition of AD is important for prompt treatment as well as accessibility to ideal healthcare solutions. It not just assists in aggressive preparation yet additionally, in the period of disease-modifying therapies a very early as well as specific medical diagnosis overviews treatment approaches relocating us closer to an individualized medication standard[8]. Neuroimaging a non-invasive device commonly incorporated right into professional technique plays an essential duty in sustaining mental deterioration medical diagnosis. Different neuroimaging strategies are released, boosting our analysis toolbox together with boosting our capacity to resolve this complex problem[9].

Neuroimaging devices such as magnetic resonance imaging (MRI), calculated tomography (CT), plus PET allow clinics to explore the level of mind damages connected with Alzheimer's condition in vivo. Nevertheless by the time architectural damages attributable to the condition ends up being obvious with these strategies, AD is currently in an innovative phase, defined by prevalent mind degeneration. Additionally these neuroimaging techniques are expensive lengthy, as well as require skilled treatment[10].

Subsequently there has actually been a remarkable change in the direction of the expedition of electroencephalography (EEG) as an appealing accessory device for AD medical diagnosis. EEG holds substantial possibility because of its non-invasive nature, price, as well as family member simplicity of usage[11]. It uses the benefit of catching real-time electric task in the mind giving understandings right into neural working as well as irregularities related to AD. Therefore, EEG stands for an important enhancement to the analysis, armamentarium supplying the capacity for earlier and also extra available discovery of AD pathology[12].

Electroencephalography (EEG) has actually arised as a encouraging device for deciphering the complex problems in brainwave signaling observed in individuals with Alzheimer's illness. By discovering the modifications in analytical cortex signaling EEG information has actually come to be crucial in identifying the problem in its beginning[13].Resting-state EEG signals work as an entrance to deciphering the enigmas bordering AD, with unique regularity bands clarifying condition development[14][15].

EEG is a strategy that includes tape-recording modifications with time in the electric task of the analytical cortex, produced by postsynaptic possibilities from hundreds of nerve cells with comparable spatial alignment. These electric possibilities are gauged by electrodes positioned on the scalp. The spatial resolution of EEG is carefully connected to the variety of electrodes made use of together with their positioning or design on the scalp. One of the most commonly utilized design is the global 10-20 system, normally including 21 electrodes. Furthermore, greater thickness versions such as the 10-10 along with 10-5 systems typically with 64 plus 128 electrodes specifically, are likewise utilized. Different formats like the Maudsley plus Geodesics placing systems are utilized also supplying additional alternatives for electrode positioning along with boosting spatial resolution in EEG recordings[16][17].

EEG signal reading around is naturally distributed into 5 distinct frequency bands: delta (δ) between 0.1 and 4 Hz, theta (θ) between 4 and 8 Hz, alpha (α) between 8 and 12 Hz beta (β) between 12 and 30 Hz and gamma (γ) is above 30 Hz. In addition, within these bands added partitions are thought about such as reduced alpha high alpha reduced beta, and more; nonetheless the certain regularity limitations for these sub-bands do not have standardization throughout researches. Each regularity band shares unique details concerning mind performance plus synchronization[18].

Via EEG signal evaluation, scientists can find variances in mind feature that might suggest the existence of Alzheimer's condition prior to professional signs materialize[19]. Researches recommend a rise in delta as well as theta waves together with a reduction in alpha power in EEG signals from people at different phases of the condition showing the capacity for distinction in between healthy and balanced people as well as those impacted by AD. Nevertheless, obstacles occur in recording dependable EEG signals as a result of human variables together with ecological disruptions[15].

To satisfy the need for impartial medical decision-making additional to the capacity to identify AD as well as its phases from regular controls (NCs) a multi-class category system is necessary[20]. Current innovations in EEG-based analysis systems have actually resolved this obstacle by incorporating artificial intelligence (ML) along with deep discovering formulas to boost the precision and also dependability of Alzheimer's condition discovery[21]. ML formulas make it possible for the automation of neuroimaging analysis, possibly minimizing predisposition plus improving medical decision-making. Neuroimaging information are especially fit for ML evaluation specifically deep understanding, because of their high dimensionality, non-linear nature, as well as high covariance within the information[22].

These automated systems use EEG signal handling to draw out purposeful functions efficient in differentiating in between various phases of Alzheimer's illness with high accuracy[23]. By taking advantage of the power of ML and also deep understanding, EEG-based analysis systems hold assurance for helping with earlier plus much more precise medical diagnosis of AD thus enhancing client end results plus improving our understanding of the condition development[24].

With the combination of EEG evaluation with artificial intelligence formulas scientists have actually accomplished amazing category accuracies of approximately 99.9%, threatening the possibility of EEG as an useful biomarker for very early discovery of Alzheimer's disease[25][26].Nevertheless conventional artificial intelligence strategies have actually come across difficulties in successfully browsing the intricacies of advertisement discovery. The capability to differentiate certain functions within comparable mind patterns is vital yet formidable[27][28].

In the last few years, substantial strides in deep discovering formulas, equipped by the sophisticated handling abilities of graphics refining devices (GPUs), have actually reinvented efficiency throughout varied domain including object recognition[29][30], detection[31] [32] tracking[33] , segmentation[34] , and classification[35] [36]. Deep learning can be considered as a technology of artificial intelligence which depend on the human brain and the way it processes information and recognizes patterns. Therefore, great importance is attached to the field of deep learning in medical data analysis.

Unique deep finding out methods supply a brand-new opportunity for anticipating AD by removing topological functions of useful mind networks or checking out latent variables with variational self-encoders. These techniques intend to refine the accuracy of AD forecast by evaluating EEG signals in cutting-edge methods[15].

Research study ventures have actually focused on establishing computer-aided category methods that harness EEG signals to identify in between AD individuals, healthy and balanced people as well as those with moderate cognitive disability. Distinct attributes noted in EEG signals influenced by AD consist of reduced patterns, minimized communication and also reduced intricacy[37][25]. By leveraging the power of artificial intelligence and also deep knowing these initiatives look for to boost our capability to spot plus predict AD eventually progressing our understanding coupled with administration of this incapacitating problem[38][39].

1.2. Aim of the Review

The major goal of this study is to give an overview the latest research studies carried out aimed at predicting cognitive decline due to Alzheimer's using machine and deep learning models [40]. The present study conducted to examine how these approaches have been used in diagnosing and predicting neurodegenerative diseases, the advancements in this field, the challenges faced in methodology, and the future directions for implementing ML and DL methods in dementia care.

This paper looks into contemporary approaches that are employed while dealing with Alzheimer's detection using DL technique. The notion behind using DL both in supervised and unsupervised categories is to understand AD better. By going through the most recent studies and directions, AD detection using DL within this manuscript is presented [41]. It discusses the methodologies and approaches used in ML/DL for AD detection. The analysis of recent research aims to understand the progress in this field. Utilizing DL models in order to find the valuable information related to AD is investigated in order to shed light on the current situation.

After conducting a thorough review of existing literature, we have gathered and combined the latest findings on utilizing deep learning to detect AD. Our investigation delves into various supervised and unsupervised deep learning methods, assessing their efficacy and the opportunities they offer to enhance the accuracy of AD detection. Furthermore, we explore the prevailing patterns in using DL for AD detection, pinpointing noteworthy areas of focus and advancement. By gaining a comprehensive view of the present landscape, our goal is to offer valuable perspectives on the trajectory of research and progress in this swiftly advancing domain[42].

In this systematic review, the attention will be on recent research studies regarding Intelligent methods for diagnosing AD using EEG signals. The review will delve into and compare the key steps in EEG-based AD diagnosis. It will also highlight differences and similarities in common practices, as well as consensus on the use of EEG, reported limitations, and recommendations for various stages of experiments. These range from the characteristics of the study population to reporting results for future research. It is expected that this review will contribute to progressing research in this area, resulting in more dependable techniques for diagnosing AD using EEG[43]. The following sections of this article will outline the methods and strategies. Finally, the conclusions are presented in Section 4.

2. Methods

In this analysis, we will thoroughly examine and consolidate the latest developments in Alzheimer's disease detection through ML and DL approaches. Our focus will be on research articles released from January 2020 to February 2024, with the goal of presenting a comprehensive summary of cutting-edge techniques, their effectiveness, and their possible impact on AD detection.

2.1 Information sources

We conducted a thorough search for electronic literature to find relevant articles for this systematic review paper. The search was carried out in popular scientific databases like Scopus, IEEE Xplore, Google Scholar, ACM Digital Library, PubMed, Springer open, ScienceDirect, and Semantic Scholar. https://www.semanticscholar.org, springer Link, https://link.springer.com, mdpi(https://www.mdpi.com), hindawi (https://www.hindawi.com), IOPScience (https://iopscience.iop.org), Frontiers in Neuroinformatic (https://www.frontiersin.org/journals/neuroinformatics), Alzheimer's Research & Therapy (https://alzres.biomedcentral.com/articles).

The search focused only on English language studies during a specific timeframe. It covered papers released from January 2020 to December 2024. Additionally, studies known to the authors that fit the review criteria were included, even if they were not found through the search strategy.

2.2 *Search Strategy*

The Full search terms for each database included variations the following search terms:
(1) EEG. (2) Electroencephalogram (3) Alzheimer (4) Diagnosis
Which were then combined using the rule (1 OR 2) AND 3 AND 4.

2.3 Eligibility criteria

Below are the inclusion and exclusion criteria used in the screening process to decide on what studies are going to be included in systematic review:

Inclusion criteria:

Article where included based on passing all the selection criteria

1. Published as Primary research paper only.
2. Involving (EEG) data

3. Describe the application and verification of machine or deep learning methods for diagnosing and/or forecasting cognitive-related neurodegenerative diseases.

Exclusion criteria: Article were excluded if they

1. Studies that include other neurodegenerative disease.
2. Non English language studies.
3. Included the massive use of neurophysiological tests
4. Published book chapters and Conference abstracts.
5. Papers not having a primary research section, such as reviews
6. Articles where accessing the full text is difficult despite the attempts to access it.
7. he studies that did not make use of any machine learning or deep learning approaches.
8. Some articles that report on the utilization of automated segmentation methods which are not related to AD disease detection.

Finally, a few articles were excluded after a thorough review of the papers because they did not align with the criteria for inclusion. To help manage the important details while reviewing the articles, A data extraction sheet was created. So that for each selected article, there were 21 data points which could be extracted and categorized into 5 different sections-: the purpose of the study, characteristics of the participants, the setup of the experiment, processing of EEG data, and the results reported.

2.4 PICOS framework

The elements of this review were Structured based on the PICOS model:

- **Participants**: Patients suffering from Alzheimer's as a result of neurodegenerative diseases.
- **Index**: ML and/or DL based EEG signal data evaluation for diagnosing.
- **Comparator**: ML diagnosis, DL diagnosis
- **Outcome**: The accuracy of diagnosing and/or predicting progress.
- **Study design**: Controlled study.

2.4. Data Extraction and Synthesis

We collected data from chosen articles using a standard information-gathering form. This data helped us draw a comprehensive conclusion about the methods and effectiveness of detecting AD using EEG signals.

2.5 Data Analysis

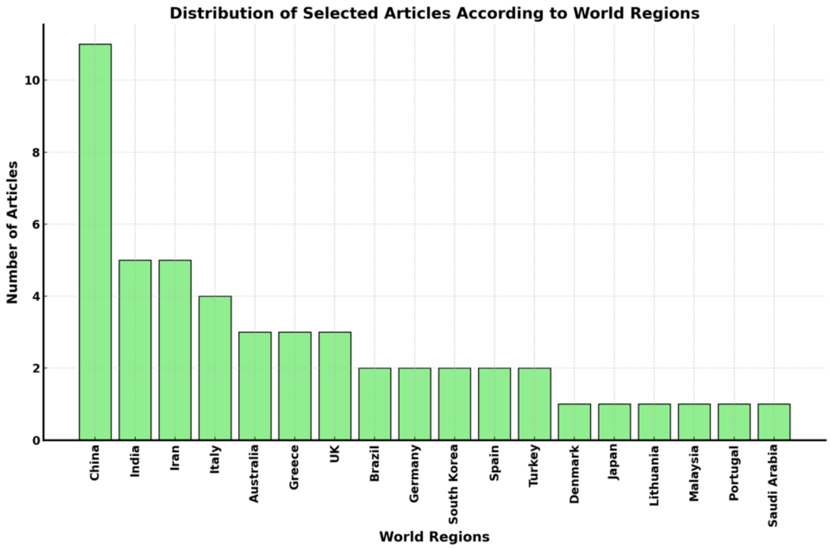
The artificial intelligence processed information was compiled in a story-like manner to uncover typical patterns, hurdles, and progressions in Alzheimer's disease detection through the designated methods. We followed the given framework to evaluate how well the techniques discussed in the studies performed.

2.6. Reporting

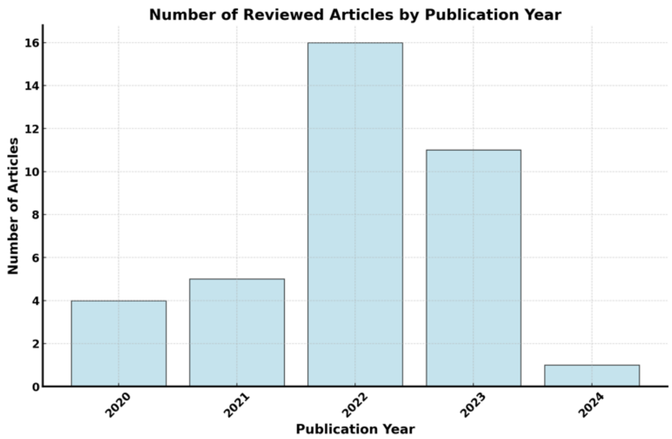
The review, whose results were presented according to PRISMA guidelines, details recent progress in Alzheimer's diagnosis methodology based on machine learning technology, deep learning among others. [44]

3. Results and Discussion

In the database searches, 62 journal articles were chosen. After reviewing titles and abstracts, 24 articles were excluded for not meeting the criteria. After thoroughly examining full texts, we included 38 articles that met all criteria in my systematic review. The papers were then classified according to institutional affiliation of their first authors as shown in Figure 1.



The temporal distribution of articles published between January 2020 and February 2024 is given in Figure 2.



3.1. Study Goal

Recent studies on AD diagnosis using EEG signals focus on advancing computer-aided diagnosis systems. The goal is to detect AD early, accurately, and automatically by leveraging EEG data. These studies aim to automate diagnostic processes and improve system accuracy and efficiency with innovative signal processing techniques and sophisticated machine learning models.

Furthermore, the study highlights a focused push to identify important patterns in EEG signals and use advanced methods for classifying AD from MCI and healthy individuals. By integrating deep learning

technologies like CNNs and LSTM networks, researchers are showing a shift towards more sophisticated diagnostic approaches. This research indicates a shift towards stronger, more precise, and earlier detection methods, showcasing the promise of EEG signals in combating AD.
According to the reported aim of the articles, study goals were determined and the articles related to each study goal are enlisted in Table 3.

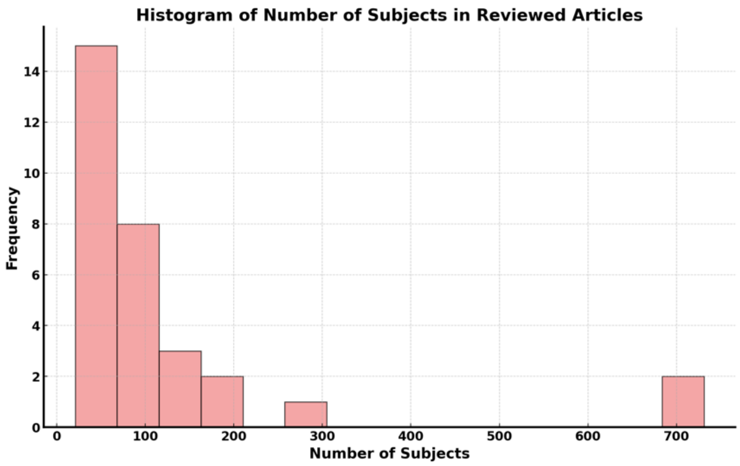
#	Author(s) & Year	Study Goal
[45]	Khalil Alsharabi et al., 2022	Create a computer-assisted diagnostic system that uses EEG data for detecting AD
[46]	Yue Ding et al., 2022	Completely automate the detection of AD by examining resting-state EEG signals
[47]	Digambar Puri et al., 2022	Detect AD by choosing the right EEG channels with tunable Q-wavelet transform
[48]	Digambar Puri et al., 2022	Use Wavelet Transform to detect AD and select the optimal EEG channel for the same purpose
[49]	Digambar Puri et al., 2022	Use Wavelet Transform to detect AD and select the optimal EEG channel for the same purpose
[50]	Kai Li et al., 2021	Use a variational auto-encoder along with latent factors of EEG to extract features for identifying AD
[51]	Daniele Pirrone et al., 2022	Diagnose AD at an earlier stage using signal processing of the EEG and supervised machine learning
[52]	Haitao Yu, et al.,	To detect AD using EEG signals accurately, the research will apply a new machine learning algorithm based on complex network theory and a TSK fuzzy system
[53]	Michele Alessandrini, et al., 2022	Diagnosis of AD based on EEG data denoising with Robust Principal component Analysis and classification using LStM RNN.
[23]	Caroline L Alves et al., 2022	Auto-diagnosis for AD and Schizophrenia (SZ) will be developed that uses Electroencephalography (EEG) functional connectivity data together with deep learning.
[54]	Dovile Komolovaitė et al., 2022	The classification of visual stimuli into categories could be possible by applying Convolutional Neural Networks (CNN's) for analyzing Electroencephalography (EEG) signals from normal individuals as well as those with AD on different categories of visual stimuli.
[55]	Morteza Amini et al., 2021	Detection or diagnosis of Alzheimer's dementia can be performed in an easy due to utilizing an EEG-based.
[56]	Saman Fouladi et al., 2022	Apply deep learning models to EEG signals to classify AD and MCI
[57]	Cameron J Huggins et al., 2021	Use DL model to classify AD, MCI and healthy ageing classes using resting-state EEG data
[58]	Wei Xia et al., 2023	Implement deep pyramid CNN that can help detect AD from EEG signals
[59]	Sadegh-Zadeh et al., 2023	Introduce AI-based technique for diagnosing AD by using EEG signals. One method of addressing this imbalance is to use variational autoencoders (VAEs) and add noise
[60]	Yuseong Hong et al., 2023	Upgrade AI model's stability when making a difference between normal and abnormal ADD subjects through the use of diverse QEEG features both at the channel-and source -level.
[61]	Chen, Wang, Zhang, Zhang, Tao, 2023	To make a predictive method for AD through EEG signals in resting state with a mixture of many features which CNNs, ViTs have their respective roles coupled with dedicated(specific) area(s) within the brain at which attention is paid so as to help improve upon this project.
[62]	Tawhid et al., 2023	The aim here was being on locating those significant sub-bands in an indicator Electroencephalogram associated with MCI. This was done within a structure that tested out how different bands affected accuracy when detecting MCI cases during this specific process.
[63]	Yu et al., 2020	The study has put forward an innovative analytic idea which joined together the fuzzy learning and complex networks as a mechanism in forecasting Alzheimer's disorder with reference to multiple sites recorded by scalp electrodes' EEG signals.
[64]	You et al., 2020	Develop an AD prediction method by combining both gait and EEG data streams within a cascade neural network.
[65]	Duan et al., 2020	Investigate the significant differences among early AD patients as well as controls through the use of functional connectivity which relies upon frequency domain and spatial properties in MCI and mild AD datasets

[66]	Xia et al., 2023	In diagnosing AD, the study focused on classifying at rest-state different EEGs namely ADs, mild cognitive impairment (MCIs) and normal people, by means of Deep Pyramid Convolutional Neural Network (DPCNN).
[67]	Puri et al., 2023	The purpose of this research is to develop a novel automatic framework aimed at early detection of AD, with the use of dual decomposition (DWT-VMD) of Electroencephalogram (EEG) signals into Intrinsic Mode Functions (IMFs) which are then analyzed by Multiscale Permutation Entropy (PE) features.
[68]	Mazrooei Rad et al., 2021	AI would like to detect Alzheimer's premature phase by studying EEG brainwaves and Event-Related Potentials (ERP) through linear and nonlinear classifiers.
[69]	Siuly et al., 2020	To come up with a system that automatically differentiate MCI patients from their healthy counterparts through EEG data.
[70]	Aslan & Akşahin, 2024	The aim here was detecting AD as well as Mild Cognitive Impairment (MCI) individuals by means of analyzing EEG signals with special concentration on developing feature extraction methods based on Poincare and Entropy followed by categorization within machine learning models.
[71]	Khare & Acharya, 2023	Create an interactive and understandable program that can automatically spot Alzheimer's Disease through EEG signals; this program is called Adazd-Net.… Also, proposed an explanation tool, in order to create trustful relationships with patients or doctors. This research introduces the Adaptive Flexible Analytic Wavelet Transform (AFAWT) for adaptive dynamic EEG signal analysis and incorporates explanation features to promote trust in machine learning predictions.
[72]	Hong, Jeong, Park, Kim et al., 2023	For an AI model that distinguishes between Alzheimer's Disease Dementia (ADD) and non-ADD (NADD) using quantitative EEG features both at channel and source levels, it is important to increase its resilience.
[73]	Alves et al.,, 2022	This research seeks to diagnose AD and Schizophrenia (SZ) in patients. The previous work employed the fusion of EEG functional connectivity matrices with Convolutional Neural Networks (CNN) to achieve high classification accuracies
[74]	Göker, 2023	Another study focuses on using from EEG signals to detect AD using multitaper method for feature extraction as well as using ensemble learning methods for classification.
[75]	Alessandrini, Biagetti, et al., 2022	The aim of this study was to create an automatic AD detection system from EEG signals which combines Robust Principal Component Analysis and LSTM RNN. Particularly, we investigated the ability of RPCA to remove noise from contaminated EEG thus improving accuracy in detecting AD using LSTM network.
[76]	Araújo, Teixeira, Rodrigues, 2022	Make a smart data driven system for classifying different stages of AD using EEG signals.
[26]	Miltiadous, et al., 2021	Study EEG to identify brain and thinking changes in dementia – particularly AD and Frontotemporal Dementia (FTD) – by analyzing signals.
[77]	Pirrone, et al., 2022	Establish an approach that employs EEG signals alongside supervised machine learning so as to identify AD at its early stages.
[78]	Wang, et al.,, 2023	Develop an original AD recognition system based on deep learning from EEG signals.
[79]	Perez-Valero, et al.,, 2022	Use a commercial EEG system to assess auto methods of AD detection in conjunction with machine learning on EEG waveforms.
[80]	Jennings et al., 2022	We aimed to assess the potential of using eyes open (EO) relative to eyes closed (EC) resting state EEG for aiding the delineation of various dementia types, with a particular focus on the differential diagnosis of Lewy body dementia as opposed to common types of dementia such as AD.

3.2 Population Characteristics

Number of Subjects, Group, Age, and Gender Matching.

In 38 research articles on AD diagnosis using EEG signals, there is a diverse range of sample sizes, group compositions, age ranges, and gender matches. The variance in sample sizes, ranging from 21 to 731 participants, shows the different scales of studies and how it can affect the reliability and applicability of the findings as shown in figure 3.



Furthermore, there is a noticeable amount of diversity in the makeup of the study participants. Many studies focus on differentiating between individuals with AD, those with mild cognitive impairment (MCI), and those who are healthy. However, the specific classifications and subgroupings can vary. While some studies strive to match participants based on age and gender, this information is not always consistently reported. Some studies provide detailed information on the distribution of genders among the control and AD groups, while others offer broader age ranges without specifying gender breakdowns.

In the realm of AD diagnosis research, there is a diverse range of methodologies and demographics utilized across studies, showcasing the complexity of the field. It is crucial to take into account demographic factors when analyzing EEG signals for AD diagnosis. The varying sample sizes and group compositions in studies may impact the results and their relevance to larger populations. Nevertheless, the combined efforts emphasize the importance of advancing AD diagnosis through EEG analysis to improve early detection and comprehension of the neurophysiological foundations of AD in diverse demographic settings, as detailed in Table 2.

#	Author(s) & Year	Number of Subjects	Group	Age	Gender Matching
[45]	Khalil Alsharabi et al., 2022	86	Control: 35 Mild-AD: 31 Moderate AD: 20	Control: mean age 66.89 Mild-AD: mean age 75.23 Moderate AD: mean age 73.77	Control: 16 males, 19 females Mild-AD: 12 males, 19 females Moderate AD: 7 males, 15 females
[46]	Yue Ding et al., 2022	301	NC: 113 Amnestic MCI: 11 Probable AD: 72	NC: mean age 67.79 MCI: mean age 68.17 AD: mean age 73.37	NC: 61 males, 52 females MCI: 45 males, 71 females AD: 29 males, 43 females
[47]	Digambar Puri et al., 2022	23	AD: 12 NC: 11	AD: mean age 72.8 ± 8.0 NC: mean age 72.7 ± 6.2	AD: 7 females, 5 males NC: 4 females, 7 males
[48]	Digambar Puri et al., 2022	Not specified	AD: 12 NC: 11 (Derived from context)	AD: mean age 72.8 ± 8.0 NC: mean age 72.7 ± 6.2 (Derived from context)	Not specified
[49]	Digambar Puri et al., 2022	Not specified	AD: 12, NC: 11 (Derived from context)	AD: mean age 72.8 ± 8.0, NC: mean age 72.7 ± 6.2 (Derived from context)	Not specified
[50]	Kai Li, et al., 2021	40	- AD: 20 patients Control: 20 subjects	AD: 74-78 Control: 70-76	- AD: 8 males, 12 females Control: 10 males, 10 females
[51]	Daniele Pirrone, et al., 2022	105	- AD: 48 patients MCI: 37 patients HC: 20 subjects	Not specified	Not specified

[52]	Haitao Yu, et al.,	Not specified	Not specified	N/A	N/A
[53]	Michele Alessandrini, et al., 2022	35	- AD: 20 Normal: 15	N/A	N/A
[54]	Caroline L Alves et al., 2022	Not specified	AD patients and SZ patients vs. healthy controls	N/A	N/A
[55]	Dovile Komolovaitė et al., 2022	Not specified	AD patients and healthy controls	N/A	N/A
[56]	Morteza Amini et al., 2021	Not specified	Mild Cognitive Impairment, AD, Healthy Controls	N/A	N/A
[57]	Saman Fouladi et al., 2022	Not specified	AD patients, MCI patients, and healthy controls	N/A	N/A
[58]	Cameron J Huggins et al., 2021	141	52 AD, 37 MCI, 52 HA	AD: 82.3 ± 4.7, MCI: 78.4 ± 5.1, HA: 79.6 ± 6.0	Not specified in the provided text
[59]	Wei Xia et al., 2023	100	49 AD 37 MCI, 14 HC	N/A	N/A
[60]	Sadegh-Zadeh et al., 2023	168	59 AD, 7 MCI, 102 HC	AD: 70.5 ± 4.9 years, MCI: 67 ± 7.67 years, HC: 72.2 ± 5.3 years	AD: 28M/31F; MCI: 3M/4F; HC: 43M/59F
[61]	Yuseong Hong et al., 2023	594 NADD and 137 ADD subjects	- NADD ADD	Not specified	Not specified
[62]	Chen, Wang, Zhang, Zhang, Tao, 2023	88	36 AD, 23 FTD, 29 Control	Not specified	AD: 22M/14F; FTD: 21M/2F; Control: 11M/18F
[63]	Tawhid et al., 2023	Dataset 1: 27; Dataset 2: 109	MCI and HC (Healthy Control) groups	Dataset 1: MCI (66.4 ± 4.6 years), HC (65.3 ± 3.9 years); Dataset 2: MCI (67 ± 7.6 years), HC (72.2 ± 5.3 years)	Not specified
[64]	Yu et al., 2020	60	(30 AD patients and 30 healthy controls)	AD group: 74 -78; Control group: 70 - 76	AD group: 18 females and 12 males; Control group: 10 females and 20 males
[65]	You et al., 2020	87	(35 HC, 35 MCI, 17 AD)	Not specified in the excerpt provided.	Not specified
[66]	Duan et al., 2020	MCI dataset: 60 ; Mild AD dataset: 41	MCI dataset: 60 (22 MCI patients, 38 controls); Mild AD dataset: 41 (17 mild AD patients, 24 healthy controls)	Not explicitly mentioned for each group	Not specified
[67]	Xia et al., 2023	100	(49 AD, 37 MCI, 14 HC)	Not specified	AD: 20M/29F; MCI: 17M/20F; HC: 9M/5F
[68]	Puri et al., 2023	168	(59 AD, 7 MCI, 102 NC)	AD: 67 ± 7.6 years, MCI: 70.5 ± 4.9 years, NC: Not specified	AD: 28M/31F; MCI: 3M/4F; NC: 43M/59F
[69]	Mazrooei Rad et al., 2021	40	Healthy, Mild and Severe AD patients	60-88 years (mean 68.43 ± 8.86)	19 Healthy, 11 Mild AD, 10 Severe AD (Equal number of participants in each gender)
[70]	Siuly et al., 2020	27	(16 healthy controls, 11 MCI patients)	60-77 years	Not specified
[71]	Aslan & Akşahin, 2024	35	(11 Healthy, 16 MCI, 8 AD)	65-90 years	AD: 5M/3F; MCI: 7M/9F; Healthy: 5M/6F
[72]	Khare & Acharya, 2023	23	(11 Healthy, 12 AD)	Not specified	AD: 5M/7F; Healthy: 7M/4F

[73]	Hong, Jeong, Park, Kim et al., 2023	731	(594 NADD, 137 ADD)	60 years and above	Equal number of participants in each gender not explicitly mentioned
[74]	Alves, et al., 2022	AD dataset: 48 subjects; SZ dataset: 84 subjects	AD dataset: 48 subjects; SZ dataset: 84 subjects (39 healthy, 45 with SZ)	AD: 69 ± 16 years; SZ: 11 to 14 years	Not specified
[75]	Göker, 2023	48	24 AD, 24 Healthy	Not specified	AD: 5M/19F; Healthy: Not specified
[76]	Alessandrini, et al., 2022	35	20 AD, 15 Normal	Not specified	Not specified
[77]	Araújo, et al., 2022	38	11 C, 8 ADA, 8 MCI, 11 ADM	Not specified	Not specified in the provided text
[78]	Miltiadous, et al., 2021	28	10 AD, 10 FTD, 8 Control	Mean ages: AD 70.5, FTD 67.5, Control 68.5	AD: 6M/4F; FTD: 6M/4F; Control: 4M/4F
[79]	Pirrone, et al., 2022	105	48 AD, 37 MCI, 20 HC	Not specified	AD: 5M/19F; MCI: Not specified; HC: Not specified
[80]	Wang, et al., 2023	30	15 AD, 15 Control	AD: 77.6 ± 3.4 years, Control: 72.2 ± 1.9 years	AD: 8F/7M; Control: 9F/6M
[81]	Perez-Valero, et al., 2022	21	Mild AD, MCI-non-AD, Control	Not specified	AD: 5M/5F; Control: 7F/1M; MCI-non-AD: 5M
[82]	Jennings et al., 2022	55	40 dementia patients and 15 healthy controls	74.42 - 76.93 years for dementia groups, 76.93 years for HC	AD: 22M/10F; DLB: 21M/5F; PDD: 20M/2F; HC: 11M/7F

3.3 Experimental Setup

The items defined are concerned with here have been extracted from each article. In the following subsections Table 3 these items across the reviewed articles are compared directly.

3.3.1 Number of EEG Electrodes and Layout

The arrangement of EEG electrodes employed in studies regarding the diagnosis of AD spans a broad spectrum, indicating a seemingly personalized approach to the acquisition of relevant brain activity. They may include IEEE 10-20- and 10-10-compliant, simple setups of on around 16 electrodes, or more sophisticated configurations containing up to 64 electrodes compliant with the 10-10 system and formatted in various caps layouts for additional spatial specificity . The variety behind the type and manner of usage of EEG electrodes is illustrative of a compromise between the desire of highly detailed mapping of brain activity and the necessity of managing the received data. Thus, while more extensive electrode arrangements provide a more detailed picture of neural dynamics – possibly crucial for diagnostic purposes – they also make it harder to manage the data analysis and interpretation. The selection of electrode layout is thus a pivotal methodological decision that directly influences the research outcomes, dictating the level of detail and the potential insights into the brain's functioning.

3.3.2 Experiment/Signal Duration

In studies on Alzheimer's Disease EEG, the lengths of recordings can vary greatly. Some segments are short, lasting only a few seconds, while others can extend up to 10 minutes. Short segments are usually used to capture specific, momentary brain events, while longer sessions aim to give a more complete picture of brain activity, potentially shedding light on cognitive states or resting patterns. This variety in recording durations is due to different research objectives, ranging from detailed analyses within specific time frames to observing larger trends in brain activity over time. When deciding how long to record data for a study, it's important to consider how this choice will affect the analysis and interpretation of results. Matching the duration of data collection to the research goals is crucial for accurately capturing patterns of brain activity associated with Alzheimer's Disease.

3.3.3 Resting-State Recording Conditions

In EEG studies of Alzheimer's Disease, researchers usually try to create a standardized setting where subjects are calm and have their eyes closed. However, the exact conditions can differ. Most studies make sure that subjects are sitting comfortably in a controlled space to reduce outside distractions and errors. But the specific details, like the level of lighting or instructions given to subjects to prevent muscle movements, can vary and may not always be clearly described.
The inconsistency in recording conditions can affect the quality and comparability of EEG data in different studies. It is important to strike a balance between controlling external factors and allowing subjects to be in a natural resting state. Detailed and consistent documentation of recording conditions is crucial for improving study reproducibility and making it easier to analyze EEG data in larger studies or reviews.

#	Author(s) & Year	Number of EEG Electrodes and Layout	Experiment/Signal Duration	Resting-State Recording Conditions
[45]	Khalil Alsharabi et al., 2022	20 electrodes are placed according to the international 10-20 system. Also to the two electrodes above the earlobe (A1 and A2)	At least 28 epochs of eight seconds each	Subjects were awake and sitting comfortably with their eyes closed
[46]	Yue Ding et al., 2022	There are 62 channels (60-channel EEG and dual-channel electromyography (EOG)) according to the established international 10-20 system with the reference electrode on the mastoid bilaterally.	About 5 minutes (300±22.1 seconds)	Subjects were sitting comfortably with their eyes closed
[47]	Digambar Puri et al., 2022 (IJECS)	16 electrodes placed according to the 10–20 electrode placement method.	5 seconds sampled at 256 Hz	Subjects were sitting comfortably in resting state with their eyes closed
[48]	Digambar Puri et al., 2022 (DASA)	Initially it uses 16 channels, with the best selection reduced to 6 channels.	5 minutes (with at least 28.8±15.5 epochs of 5 seconds each)	Subjects were awake with eyes closed, in a resting state
[49]	Digambar Puri et al., 2022 (Wavelet Transform)	Same dataset as in Digambar Puri et al., 2022 (DASA), with 16 initial channels and optimal selection to 6 specific channels	Similar to Digambar Puri et al., 2022 (DASA), with at least 5 minutes of EEG data taken from each person.	Subjects were remain awake with visual screens off, while remaining still to reduce the presence of artifacts.
[50]	Kai Li et al., 2021	The sixteen channels are Ag-AgCl scalp electrodes, in addition to the earlobe which is connected to A1 and A2 as a reference.	10 minutes collected for each subject.	Subjects sat in a semi-dark room, awake with closed eyes, and were told not to make unnecessary body movements.
[51]	Daniele Pirrone et al., 2022	19 electrodes are placed according to a 10-20 system in a monopolar connection connected to the earlobe electrode as a reference.	Approximately 300 seconds (for each subject, 150 seconds for the cleaned EEG).	I close my eyes behind closed eyelids in the middle IRCCS Centro Neurolesi.
[52]	Haitao Yu et al., No Year Specified	Not Specified	Not Specified	Subjects with closed eyes achieved 97.3% accuracy and subjects with open eyes achieved 94.78% accuracy in AD identification

[53]	Michele Alessandrini et al., 2022	There are 37 inputs total. 22 of them are unipolar and 8 are bipolar AC/DC inputs in accordance with the standard 10–20 system.	Not Specified	Not Specified
[54]	Caroline L Alves et al., 2022	AD: 19 channels (recorded at 128 Hz; SZ: 16 channels recorded at 128 Hz.	AD: 8 seconds per individual; SZ: 1 minute per individual	AD and SZ: Data collected under controlled conditions, specifics not detailed in the excerpt provided.
[55]	Dovile Komolovaitė et al., 2022	64 electrodes were made of the 10–10 international system, but with extra electrodes for monitoring blinks and eye movements..	Visual stimulus presented for 300 ms with a pause of 1000 ms between trials. Total number of stimuli trials per subject was 576, after artifact removal approximately 477 trials remained on average per control subject.	Not specified explicitly but involved minimizing noise from head and eye movements during the experiments. Subjects were likely in a controlled, stationary position for the recordings.
[56]	Morteza Amini et al., 2021	The configuration used was based on the international 10-20 system, with additional details not specified in the document.	180 seconds of EEG data taken into account in a subject	Not specified in the document.
[57]	Saman Fouladi et al., 2022	Sixty-one healthy subjects, fifty-six MCI, and sixty-three AD subjects were subject to 19-channel electroencephalogram recording (EEG).	The time and frequency (TFR) used to extract features are represented. Convert CWT with the Mexican hat function (MHf) used for the given TFR.	Subjects were likely in a resting state during recordings, specific details about recording conditions such as eyes open or closed are not provided. The focus is on scalp EEG recordings for early diagnosis of MCI and AD.
[58]	Cameron J Huggins et al., 2021	Subjects were classified into AD, MCI, and healthy aging (HA) groups based on their resting-state scalp EEG signals. Time-frequency histograms resulted from continuous wavelet transform using native Morse wavelets.	587 seconds (approx. 10 minutes), varied based on subject	EEG recordings were performed under resting-state conditions, with the exact environmental setup not detailed in the provided text. The focus is on using DL for three-class classification of AD, MCI, and HA.
[59]	Wei Xia et al., 2023	EEG data of 100 subjects (49 AD, 37 MCI, 14 HC) were augmented using overlapping sliding windows on one-dimensional EEG data.	180 seconds	Resting-state EEG of AD, MCI, and healthy control classified using a modified deep pyramid convolutional neural network (DPCNN), with an average accuracy rate of 97.10% and an F1 score of 97.11%.
[60]	Sadegh-Zadeh et al., 2023	19 EEG electrodes, following the 10–20 system	Not explicitly mentioned	Participants sat comfortably, eyes closed, using Medelec Valor digital amplifier with a sampling rate of 256 Hz
[61]	Yuseong Hong et al., 2023	19 EEG electrodes according to the international 10–20 system	Not explicitly mentioned	Patients were instructed to keep their eyes closed and relax throughout the patient examination
[62]	Chen, Wang, Zhang, Zhang, Tao, 2023	19 EEG electrodes, following the 10–20 system	The EEG data were separated into 10 time divisions, each lasting 4 seconds, including the signal from a single electrode channel; for everyone, there were extracted the following frequency ranges: Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–25 Hz), Gamma (25–45 Hz)	Participants' EEG signals were recorded in resting state. Details on additional conditions (like eyes open/closed) were not explicitly mentioned
[63]	Tawhid et al., 2023	Two types of EEG data that are publicly available for MCI were used. One admitted to the Cardiac Catheterization Department in Isfahan, Iran, with 27 subjects (11 MCI, 16 HC), and another consisting of 109 subjects (7 MCI, 102 HC). Data from 19 channels were saved in the canonical 10-20	A sampling rate of 256 Hz was used to record 19 channels of resting-state EEG data following the International 10-20 System.	no data were published that could identify participants or jeopardize their confidentiality.

		system with a sampling rate of 256 Hz.		
[64]	Yu et al., 2020	16 EEG electrodes, according to the international 10–20 system	30 minutes, with selected 10-minute EEG without artifacts for analysis	Participants were in a semi-dark room, eyes closed, and asked to stay awake.
[65]	You et al., 2020	64-channel EEG electrodes are placed on the patient's scalp in specific standard locations	EEG data collected for 8 min each with eyes open and eyes closed	EEG signals that have been sampled at 5000 Hz can be down-sampled to 250 Hz. After removing artifacts from the data, re-referencing it, 120 epochs are extracted from each subject's EEG data.
[66]	Duan et al., 2020	21 electrodes (MCI dataset) and 19 electrodes (mild AD dataset), following the 10-20 international system or the Maudsley system respectively.	Resting-state, 5 minutes recording, with a selected 20-second artifact-free segment for analysis.	all subjects were awake and resting with their eyes closed.
[67]	Xia et al., 2023	19 electrode positions according to the international 10–20 system, 300 s of resting-state EEG with eyes closing were collected.	180 seconds selected from 60s to 240s, after preprocessing	Not Specified
[68]	Puri et al., 2023	21-channel digital EEG setup according to a 10-20 electrode placement system, sampled at 128 Hz.	Not explicitly mentioned, signals recorded in standard conditions with eyes closed and in rest position.	EEG signals recorded under standard conditions with eyes closed and in rest position using a digital EEG setup.
[69]	Mazrooei Rad et al., 2021	Three channels (Pz, Cz, Fz) were used to record brain signals, as per the standard 10–20 system with a sampling rate of 1000 Hz. Plus EOG signal for artifact evaluation.	Recording involved several stages, including closed eyes, open eyes, recall, and stimulation tasks, totaling approximately 10 minutes per participant.	Brain signals recorded in various tasks, including closed eyes, open eyes, recall of displayed images, and auditory stimulation with target and non-target sounds.
[70]	Siuly et al., 2020	19 EEG channels, following the International 10-20 System, with a sampling rate of 256 Hz.	EEG signals were recorded over 30 minutes while the subjects were comfortably seated in a quiet room with their eyes closed.	People with major psychiatric disorders or medical conditions were excluded
[71]	Aslan & Akşahin, 2024	19 EEG electrodes, according to the 10–20 international system plus EOG signal for artifact evaluation.	7 minutes of EEG data recorded in resting eyes-closed condition	EEG data recorded from AD, MCI, and healthy individuals using a Nihon Kohden-Neurofax EEG 1200. Participants were screened for other neurological, psychiatric, or serious medical conditions and excluded if present.
[72]	Khare & Acharya, 2023	EEG data composed of 23 subjects with 11 NC and 12 AZD. 16-channel EEG recorder built in-accordance with the international 10–20 system.	Electroencephalograms were captured at a sampling rate of 256 Hz for each of 5 minutes. The subjects were awake with their eyes closed.	The participants were at rest with their eyes shut while the recording took place. A medical specialist was brought in to select the EEG epochs that had the lowest levels of electromyographic activity and fewer artifacts from electrooculography channels or eye blink movement artifact.
[73]	Hong, Jeong, Park, Kim et al., 2023	19 channel-EEG data acquired in accordance with the international 10–20 system.	Not explicitly mentioned	Subjects were instructed to keep their eyes closed and relax throughout the measurement.
[74]	Alves, et al., 2022	AD: 19 channels recorded at 128 Hz, 8 seconds; SZ: 16 channels recorded at 128 Hz, over 1 minute	AD: 8 seconds; SZ: over 1 minute	Not explicitly mentioned
[75]	Göker, 2023	We extracted 49 features from the power spectral density of frequencies in 1-49 Hz range in 24 healthy controls and 24 AD patients using EEG signals.	Not explicitly mentioned but involves calculating PSD over the EEG signal frequencies.	EEG signals recorded from subjects divided into groups of healthful people and Alzheimer's patients, the use of a Biologic Systems Brain Atlas III Plus laptop labelled in step with an

				international 10–20 machine at a 128 Hz sampling price.
[76]	Alessandrini, et al., 2022	Data from 35 hospitalized subjects, 20 AD patients and 15 controls, collected with electrodes placed according to the standard 10–20 system.	Not explicitly mentioned but involves analyzing EEG data for feature extraction.	EEG statistics recorded using a Galileo BE Plus PRO Portable Light version, imparting 37 overall inputs with 22 unipolar and eight bipolar AC/DC inputs.
[77]	Araújo, et al., 2022	19 electrodes positioned on the scalp using the common reference electrode at CPz in keeping with the 10–20 system.	EEG data segments of 5 seconds, sampled at 256 Hz.	all the study subjects were relaxed and with their eyes closed.
[78]	Miltiadous, et al., 2021	EEG recordings from 28 participants: 10 AD patients, 10 FTD patients, and 8 healthy controls, using the standard 10–20 system.	Not explicitly mentioned but involves processing of EEG signals for AD and FTD classification.	the subjects were at rest and the sample eye was closed.
[79]	Pirrone, et al., 2022	19 electrodes located consistent with the ten–20 device in monopolar connection with the earlobe electrode as a reference.	Approximately 300 seconds, sampled at 256 Hz	Not explicitly mentioned
[80]	Wang, et al., 2023	16-channel EEG data from 15 AD patients and 15 healthy controls, sampled at 1024 Hz, bandpass filtered between 0–60 Hz.	Data of the middle length (2–4 min) of the eyes closed state in the first 5 minutes as the analysis object.	Participants had been seated upright, stored unsleeping in a semi-dark, quiet room with electromagnetic defensive, and had been told to avoid any moves such as body actions, eye moves, and blinking
[81]	Perez-Valero, et al., 2022	16 electrodes placed according to the extended 10–20 system, referenced to the left earlobe, sampled at 256 Hz.	6 minutes (3 recordings of 2 minutes each)	EEG recordings conducted in three sessions before and after cognitive tests, focusing on the middle 2-min window to avoid edge effects. Subjects were relaxed with eyes closed during the recordings.
[82]	Jennings et al., 2022	The EEG was recorded by using a Waveguard cap having 128 sintered Ag/AgCl electrode placed on a 1015 positioning system at 1024Hz.	150 seconds of resting state EEG collected, with segments analyzed over 5 cortical regions (F, C, T, P, O).	Participants included 32 AD patients, 26 DLB patients, 22 PDD patients, and 18 age-matched healthy controls. EEG data segmented into 2-s windows with a 1-s overlap. Pre-processing and cleaning steps detailed, including baseline subtraction, bad channel deletion, artefact removal, and referencing to average.

3.4. EEG Signal Processing

The required data were extracted in Table 4, and the following subsections were presented with a direct comparison of these elements across the articles studied.

3.4.1 Filter/Preprocessing

In the various research projects, a range of methods are used to filter and process data, including band-pass filtering in specific frequency ranges like 0.1 Hz to 95 Hz, as well as more sophisticated techniques like Robust Principal Component Analysis (RPCA) and Independent Component Analysis (ICA) for removing artifacts. Notably, notch filters at 50 Hz are often used to get rid of power line noise, and elliptic digital filters are commonly employed for band-passing. These preprocessing steps play a crucial role in improving the quality of the signals and guaranteeing that subsequent analyses are performed on clean, artifact-free data.

3.4.2 EEG Bandwidth

Studies generally study EEG data as a rule of thumb, by concentrating on particular frequency ranges such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz). The selection of these frequency ranges is driven by the belief that changes in brain activity associated with Alzheimer's disease are better reflected in them.

3.4.3 Artifact Handling

Dealing with artifacts in EEG data involves a combination of manual and automated techniques. Skilled neurophysiologists are typically responsible for manually removing artifacts, while automated tools like Fieldtrip and EEGLAB are commonly used for preprocessing. Independent Component Analysis (ICA) is a popular automated method for detecting and eliminating artifacts caused by eye movements, muscle activity, and other non-brain signals. The Artifact Subspace Reconstruction (ASR) method is also highlighted as a useful technique for enhancing the quality of EEG data.

3.4.4 Effective Sampling Frequency

The studies show a variety of sampling frequencies, ranging from 128 Hz to 1024 Hz, with some researchers lowering the frequency to 256 Hz for analysis. This decision balances between capturing detailed data and handling the computational workload of analyzing big sets of data. The sampling frequency chosen affects the resolution of EEG data and the ability to detect subtle changes in brain activity.

3.4.5 EEG Epoching

Different studies use varying strategies for segmenting data, with certain ones choosing 5-second epochs, while others prefer longer segments. Some studies do not specify their epoching method. The choice of epoch length and use of overlapping windows impact the quantity of data for analysis and the level of detail in which brain activity patterns can be studied.

3.4.6 EEG Features

The studies extract a diverse range of EEG features, such as power spectral density, band power ratios, fractal dimensions, entropy measures, and connectivity metrics, to capture the complexity of brain activity and the impact of AD on neural function. Statistical features like mean, standard deviation, kurtosis, and energy are commonly used, along with more advanced measures like permutation entropy and wavelet transform coefficients. This wide variety of features shows the comprehensive approach to understanding brain activity and identifying biomarkers for Alzheimer's Disease.

#	Author(s) & Year	Filter/Preprocessing	EEG Bandwidth	Artifact Handling	Effective Sampling Frequency	EEG Epoching	EEG Features
[45]	Khalil Alsharabi et al., 2022	Band-pass elliptic digital filter	0.1 Hz to 60 Hz	Manual removal by skilled neurophysiologists	200 Hz	At least 28 epochs of 8 seconds	The power of bands should be measured by log. Normalization must be done by dividing it with the kurtosis or average energy combined with RMS, standard deviation and root mean square calculations based on variance.
[46]	Yue Ding et al., 2022	Band-pass filtering (0.1-95 Hz), notch filter (50 Hz), detrended, downsampled to 500 Hz, first and last 2s removed	1-30 Hz for functional connectivity analysis	Automated preprocessing with Fieldtrip and EEGLAB toolboxes, ICA for artifact removal	500 Hz (downsampled from 1000 Hz)	15s epochs without overlap	Band power ratio, Continuous Wavelet Transform (CWT) features, complexity measures (Permutation Entropy, Sample Entropy, Wavelet Entropy, LZ complexity), useful connectivity (correlation coefficient, move-strength spectral density)
[47]	Digambar Puri et al., 2022 (IJECS)	Band-pass filtering (0.1-95 Hz), notch filter (50 Hz), automated preprocessing with Fieldtrip and EEGLAB toolboxes, ICA for artifact removal, detrending, downsampled to 500 Hz.	Delta (δ: 0.5-4 Hz), Theta (θ: 4-8 Hz), Alpha (α: 8-13 Hz), Beta (β: 13-30 Hz)	Automated artifact removal using ICA based on EEGLAB and Fieldtrip toolboxes.	256 Hz	Not explicitly mentioned, but EEG recordings were segmented into epochs for processing.	Katz's fractal dimension, Tsallis entropy, Renyi's entropy, Kurtosis extracted from nine subbands (SBs) decomposed using Tunable Q-wavelet Transform (TQWT).
[48]	Digambar Puri et al., 2022 (DASA)	Wavelet packet analysis for sub-band energy and entropy calculation, Bandpass filtering (alpha and beta bands)	Delta (δ: 0.5-4 Hz), Theta (θ: 4-8 Hz), Alpha (α: 8-13 Hz), Beta (β: 13-30 Hz)	Visual inspection by a professional physician, minimization of artifacts through protocol	256 Hz	5 seconds epochs selected from at least 5 minutes of recording per subject	Standard deviation, mean, kurtosis, minimum value, power and maximum value for each subband of the wavelet packet
[49]	Digambar Puri et al., 2022 (Wavelet Transform)	Band-pass filtering for alpha (8-13Hz) and beta (13-32Hz) bands using a Hamming windowed order 70 bandpass filter	Delta (δ: 0.5-4 Hz), Theta (θ: 4-8 Hz), Alpha (α: 8-13 Hz), Beta (β: 13-30 Hz), Gamma (γ: 30-100 Hz)	Visual inspection by a physician and protocol for minimizing artifacts	256 Hz	5 seconds (based on a total of at least 5 minutes of EEG data collection per subject)	Mean, standard deviation, kurtosis, minimum, maximum and energy of each wavelet packet sub-band, computed using Wavelet Packet Transform (WPT)
[50]	Kai Li et al., 2021	Band-skip filtering (0.Five-30 Hz) the usage of a finite impulse virtual filter primarily based on wavelet package deal (Morlet wavelet), ICA for artifact removal	Delta (δ: 1-4 Hz), Theta (θ: 4-8 Hz), Alpha (α: 8-12 Hz), Beta (β: 12-30 Hz)	Independent population analysis (ICA) method for artifact removal	-	-	Power spectrum characteristics, Latent factors extracted using Variational Auto-Encoder (VAE), Energy features of sub-frequency bands
[51]	Daniele Pirrone et al., 2022	The high pass filter is at 1 Hz and the low pass filter is at 30 Hz	Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), Gamma (30-40 Hz)	It is identified by visual inspection	Normalized to 256 Hz	-	For distinguishing between AD, MCI, and HC classes, their absolute differences are used to indicate power intensity for both high- and low-frequency bands.

[52]	Haitao Yu et al., No Year Specified	Construction of functional networks from EEG	Not explicitly mentioned	Not explicitly mentioned	Not explicitly mentioned	Closed eyes and open eyes conditions	Local efficiency, clustering coefficient of functional networks
[53]	Michele Alessandrini et al., 2022	Robust Principal Component Analysis (RPCA) for preprocessing to remove outliers and artifacts, standardization of signals (mean=0, standard deviation=1), and Principal Component Analysis (PCA) for feature extraction from EEG signal segments.	Not specified	RPCA for artifact and outlier removal in EEG signals.	128 Hz (based on EEG data standard sampling rate)	Split into windows of fixed size with optional overlapping. Window size and overlap not specified in the snippet provided.	
[54]	Caroline L Alves et al., 2022	-	Not specified	Not specified	128 Hz	Not specified	Matrices of connections built using Granger causality, Pearson's and Spearman's correlations
[55]	Dovile Komolovaitė et al., 2022	FIR bandpass filter (4-40 Hz), Baseline correction	Not specified	Rejected if peak-to-peak signal > 150 µV	250 Hz	200 ms before to 800 ms after stimulus	Raw EEG signals used with architectures: EEGNet, DeepConvNet, and EEGNet SSVEP; Artificial EEG data generated using VAE
[56]	Morteza Amini et al., 2021	-	Not explicitly mentioned	Rejected if peak-to-peak signal > 150 µV	256 Hz	Not specified	Time-Dependent Power Spectrum Descriptors (TD-PSD) including logarithmic transformations of zero-order moment, second and fourth-order moments, sparseness, irregularity factor, covariance, and Teager energy operator (TEO) for feature extraction
[57]	Saman Fouladi et al., 2022	Band-pass filtered between 0.5 and 32 Hz to set the bands related to AD assessment, Continuous Wavelet Transform (CWT) with Mexican hat function for TFR	Not explicitly mentioned	Manually removed small and big artifacts or unanticipated action	256 Hz	2-second epochs without overlap	Time–Frequency Representation (TFR) using CWT for feature extraction, Deep Learning models (CNN and Conv-AE) for classification
[58]	Cameron Jj Huggins et al., 2021	Band-pass FIR filter (1-60 Hz), ICA, nootch filters at 21 and 42 Hz	Not explicitly mentioned, but preprocessing suggests a focus on frequencies between 1-60 Hz	ICA for noise and artifact removal	200 Hz	5 seconds epochs, with adjustments for start/end signal removal	Time-frequency maps using Continuous Wavelet Transform with Morse mother wavelet, converted into RGB images for DL
[59]	Wei Xia et al., 2023	It was band-pass filtered from 0.5 to 48 Hz, down sampled to 256 Hz, and ICA to delete artifacts.	Not explicitly mentioned but focuses on 0.5-48 Hz	ICA for oculoelectric and electromyographic artifacts removal	256 Hz	-	Fourier coefficients as frequency domain features, 16 Fourier coefficients selected per channel resulting in 304 features per subject
[60]	Sadegh-Zadeh et al., 2023	Band-pass filter (1-50 Hz), EEGLAB toolbox for preprocessing, Artifact Subspace Reconstruction (ASR) for artifact removal	1-50 Hz	ASR plugin for EEG artifacts removal	128 Hz	Not specified	Power Spectrum Density (PSD), mean, variance, and zero-crossing rate (ZCR) from 19 channels
[61]	Yuseong Hong et al., 2023	Band-pass FIR filter (1-60 Hz), ICA, notch filters at 21 and 42 Hz for artifact removal	1-60 Hz	Components are analyzed (ICA) and bad eras are eliminated	Not specified	Eyes closed, relax throughout	Spectra of power of 19 channels, source-level power spectra, functional brain networks, features turned into pictures for

						the measurement	deep neural network training with regard to channel, spectral power at a source level and functional brain networks for training a tree-based machine learning algorithm are items to be covered in this course.
[62]	Chen, Wang, Zhang, Zhang, Tao, 2023	Band-pass FIR filter (1-60 Hz), ICA, notch filters at 21 and 42 Hz	1-60 Hz	ICA and bad epoch rejection	250 Hz	40s time window segmented into ~10 segments	Feature-level fusion strategy using CNN and ViT, spatial and channel attention mechanisms
[63]	Tawhid et al., 2023	Stationary wavelet transformation for denoising, segmented into small time frames, spectrogram photo generation	Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-16 Hz), Beta (16-32 Hz)	Artifact Subspace Reconstruction for artifact removal	256 Hz	3-second time segments, each considered as an independent data sample	Spectrogram images generated for five separate frequency bands including full band and four sub-bands
[64]	Yu et al., 2020	Not explicitly detailed but includes preprocessing for noise and artifact removal	Not specified	Artifact Subspace Reconstruction (ASR)	1024 Hz (downsampled as needed)	Not explicitly detailed but mentions segmentation into epochs	"Clustering Coefficient, Average Number of Connections, Graph Index Complexity, Distribution of Connections, Network Entropy, Modularity, Local Efficiency, Average Path Length"
[65]	You et al., 2020	Not explicitly detailed but includes preprocessing for noise and artifact removal	Not specified	Artifact Subspace Reconstruction (ASR)	1024 Hz (downsampled as needed)	Not explicitly detailed but mentions segmentation into epochs	average path length, local efficiency, network entropy, degree distribution index, degree of complexity of a graph, average weighted degree, clustering coefficient
[66]	Duan et al., 2020	Band-pass FIR filter (0.5-250 Hz), online digital bandpass filtering between 0.5 and 30 Hz	Delta (0.1-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz)	Artifact Subspace Reconstruction (ASR) for artifact removal	200 Hz for MCI dataset, 128 Hz for mild AD dataset	20 seconds segment chosen from 5 min recording, eyes closed, resting condition	Functional connectivity (FC) metrics including low-ranking and high-ranking, 4 metrics (clustering coefficient, node strength, characteristic path length, betweenness centrality), network resilience, connectivity level metrics, and multiplicity
[67]	Xia et al., 2023	Band-pass filtered from 0.5 to 48 Hz, downsampled to 256 Hz, ICA to remove artifacts.	0.5-48 Hz	ICA for oculoelectric and electromyographic artifacts removal	256 Hz	Segmented using overlapping sliding windows	Fourier coefficients as frequency domain features, 16 Fourier coefficients selected per channel resulting in 304 features per subject
[68]	Puri et al., 2023	EEG signals are divided into 5 subscales using DWT transform, then variable mode decomposition (VMD) for further decomposition.	Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-16 Hz), Beta (16-32 Hz), Gamma (32-48 Hz)	Artifact Subspace Reconstruction (ASR) for artifact removal	128 Hz	Not specified	Features of the measured multi-permutation entropy (PE): Shannon PE (SPE), Tsalli's PE (TPE), and Renyi PE (RPE) measured from each original mode function (IMF).
[69]	Mazrooei Rad et al., 2021	Band-pass FIR filter (0.5-45 Hz), elimination of rapid signal changes and baseline fluctuations	Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz),	Artifact Subspace Reconstruction (ASR) for artifact removal	1000 Hz	Closed eyes, open eyes, recall, and stimulation modes with various	The power intensity in frequency bands, plus the mean, median, mode, maximum, minimum, standard deviation, variance, Lyapunov exponent, correlation dimension, and dynamic changes of brain signal.

			Beta (13–30 Hz)			tasks including responding to auditory stimuli	
[70]	Siuly et al., 2020	Noise removal (baseline drift and power line interference removal), SWT for denoising, segmentation, data compression	0.5-32 Hz	SWT for baseline drift and power line interference removal	256 Hz	2-second sliding windows, non-overlapping	Piecewise Aggregate Approximation (PAA) for data compression, Permutation Entropy (PE), Auto-regressive (AR) model features
[71]	Aslan & Akşahin, 2024	Not explicitly detailed, segmentation into epochs	Not explicitly mentioned	Not explicitly mentioned but involves preprocessing for noise and artifact removal	Not explicitly mentioned	Segmentation into epochs for feature extraction on each epoch	Poincare and Entropy methods including Permutation Entropy (PerEn), Approximate entropy (AppEn), Sample Entropy (SamEn), Spectral Entropy (SpecEn), and others for feature extraction
[72]	Khare & Acharya, 2023	Adaptive Flexible Analytic Wavelet Transform (AFAWT) with automatic adjustments to changes in EEGs, employing evolutionary optimization for parameter selection.	Not explicitly mentioned	Not detailed, but preprocessing includes noise and artifact removal	Not specified	Segmentation into epochs for feature extraction	Statistical, nonlinear, entropy features, and features from sub-bands obtained through AFAWT, totaling 85 features across 16 channels.
[73]	Hong, Jeong, Park, Kim et al., 2023	Noise reduction via bad epoch rejection and ICA, Fourier transform for frequency domain conversion, division into 8 frequency bands, sLORETA for source-level signals	Delta (1–4 Hz) to Gamma (30–45 Hz), divided into 8 bands	ICA for periodic noise removal, bad epoch rejection	Not specified	Eyes closed and relaxed throughout the measurement	Channel-level and source-level absolute and relative power spectra, functional brain networks through iCoh between ROIs, transformed into images for deep neural network training and numerical values for tree-based algorithm training
[74]	Alves, et al., 2022	EEG signals were collected and then the correlation between electrodes was calculated, yielding matrices of connections which encompass the functional connectivity between brain regions.	Not explicitly mentioned	Not detailed, but preprocessing includes noise and artifact removal.	128 Hz for AD dataset; 128 Hz for SZ dataset over 1 min	Not specified explicitly, but matrices of connections derived from EEG time series	Matrices of connections built using Granger causality, Pearson's and Spearman's correlations to represent the functional connectivity between brain regions. These matrices served as input for a convolutional neural network (CNN) model to enable the automatic classification of individuals.
[75]	Göker, 2023	Multitaper method for calculating power spectral density (PSD) from 1-49 Hz	1-49 Hz	Artifact Subspace Reconstruction (ASR) for artifact removal	128 Hz	Segmentation into epochs for feature extraction	49 features extracted from the PSD of frequencies between 1-49 Hz
[76]	Alessandrini, et al., 2022	Robust Principal Component Analysis (RPCA) for preprocessing to put off outliers and artifacts, standardization of alerts (mean=zero, standard deviation=1), and Principal Component Analysis (PCA) for characteristic extraction from EEG sign segments.	Not specified	RPCA for artifact and outlier removal in EEG signals.	Not specified	Segmentation into epochs for feature extraction	Statistical, nonlinear, entropy features, and features from sub-bands obtained through RPCA and PCA, focusing on enhancing signal quality and data representation for LSTM RNN processing.
[77]	Araújo, et al., 2022	Noise removal, Wavelet Packet Decomposition for nonlinear multi-band analysis	1-49 Hz	Artifact Subspace Reconstruction (ASR) for artifact removal	256 Hz	5-second segments	Classic Machine Learning (ML) and Deep Learning (DL) techniques used for information type in keeping with EEG channel, extracting numerous features from every examine institution

[78]	Miltiadous, et al., 2021	Noise removal, down-sampling from 500 Hz to 250 Hz, Butterworth band-pass filter (0.5-48 Hz)	0.5-48 Hz	Marked and removed automatically for blinking, swallowing, muscle activity; severe artifacts removed manually	250 Hz	5-second epochs with 2.5-second intervals	Time and frequency domain metrics including mean, variance, IQR, and energy in delta, theta, alpha, beta, gamma
[79]	Pirrone, et al., 2022	To remove noise, normalize to 256 Hz, and filter at the 1 Hz low-cut (high-pass) and at the 30 Hz high-cut (low-pass)	1-30 Hz	Visual inspection for artifact rejection	256 Hz	For each subject, 150 seconds of clean EEG were taken, extracted from the central part of the EEG signal.	The range of high and low frequencies becomes per power density using absolute differences
[80]	Wang, et al., 2023	Noise removal, down-sampling from 500 Hz to 250 Hz, Butterworth band-pass filter (0.5-48 Hz)	0.5-48 Hz	Marked and removed automatically for blinking, swallowing, muscle activity; severe artifacts removed manually	250 Hz	5-second epochs with 2.5-second intervals	Phase Synchronization Index (PSI) for constructing brain functional networks, leading to 14 topological features (e.g., Degree, Node Betweenness, Clustering Coefficient, Shortest Path Length, etc.)
[81]	Perez-Valero, et al., 2022	FIR filter with 1–45 Hz bandpass, segmentation into 4-s epochs, Autoreject and ICA for artifact rejection	1-45 Hz	Automatic rejection algorithm and ICA are used to remove artifact regions	256 Hz	4-s epochs with automated artifact rejection	Relative power (RP), Hjorth complexity (HC), Spectral entropy (SE) from 16 channels
[82]	Jennings et al., 2022	Baseline subtraction, bandpass filtering (0.3-54 Hz), artifact removal using ICA, interpolated deleted channels, referenced to average reference	0.5-48 Hz	ICA for eye artifacts, muscle activity, and heartbeats removal	1024 Hz downsampled to 250 Hz	2-s windows with 1-s overlap, ensuring at least 20 s of clean data for analysis	Relative spectral density in the delta, theta, high theta, alpha and beta bands; It becomes the dominant frequency (DF) and its variance (DFV) across 5 cortical areas (F, C, T, P, O)

3.5. Reported Outcomes.

In the literature on classification performance, three aspects were taken into consideration: classification type, validation strategy, accuracy, and preprocessing method, as detailed in Table 5

3.5.1 Preprocessing Method

The reviewed studies employ an array of preprocessing techniques for improving the quality of the EEG recordings. Techniques like Discrete Wavelet Transform (DWT) and Robust Principal Component Analysis (RPCA) are commonly utilized for denoising the EEG signals and the removal of artifacts. EEG recordings can be noisy with various types of artifacts. The primary goal of preprocessing is to separate the actual neural signals recorded by the EEG equipment from the noise. There are numerous noise sources that are existent. Common physiological artifacts include muscle activity, eye movements, magnetic and electrical artifacts as well as the cardiac activity among others. Preprocessing techniques are responsible for removing artifacts. Depending on the task at hand, this could be done through manual intervention of the experimenters or automatically using processing and filtering techniques that can extract useful information from the artifact contaminated data. Some methods concentrate on how to extract meaningful characteristics from the frequency domain of EEG. It is an important aspect since frequency domain of EEG recording is helpful in making machine learning and deep learning techniques effective." The variety of preprocessing techniques is an illustration of the adaptive and flexible approach of the studies in their approach to dealing with the particular EEG signal analysis challenges in Alzheimer's Disease identification.

3.5.2 ML/DL Approach

Most of the studies use Machine Learning (ML) methods, some of which employ Deep Learning (DL) techniques. The decision to use ML or DL is based on the complexity of the EEG data and the aim of the study - from feature extraction to the classification of AD stages.

3.5.3 Validation Strategy

The validation strategy in the studies is used to check the reliability and generalizability of the predictive models. Some studies adopt one of the two most commonly used strategies: 10-fold Cross-Validation and 5-fold Cross-Validation, which split the dataset into multiple subsets to ensure that the model is trained and tested on different segments of the data, thus avoiding overfitting and providing a more reliable performance estimation of the model when applied to new data. Few studies do not report their validation strategy. In the absence of a reported validation strategy, it is hard to say whether the findings are robust and generalizable, which is crucial for applying the outcome to clinical practice.

3.5.4 Classifier Types

Among the studies, we encountered a myriad variety of algorithms that serve the purpose of EEG data classification. The K-Nearest Neighbors classifier, Support Vector Machines, Decision Trees, Convolutional, and Long Short-Term Memory Recurrent Neural Networks are some of the modes for this purpose. The selection of an appropriate classifier is usually influenced by the nature of the information as well as its complexity. Its utility critically hinges on handling it correctly."

3.5.5 Accuracy

The pronounced accuracies inside the research variety extensively, applicable to the level of trouble in growing robust models for Alzheimer's Disease analysis with EEG alerts. Some research mentioned close to-one hundred% accuracies and Area Under the Curve (AUC) rankings implying that the models are near-best in discriminating AD patients and normal controls, or among exceptional degrees of the ailment. Other studies reported accuracies as low as 80% which suggest that these EEG models are not robust enough to work poorly when tested with other datasets and diagnostic criteria. These differences in accuracies demonstrates the need for more rigorous experiments and calls for better preprocessing techniques, feature selection algorithms, and classifier optimization to improve the diagnostic potential of EEG in Alzheimer's Disease.

#	Author(s) & Year	(preprocessing)Method	ML/DL	Validation Strategy	Classifier Types	Accuracy
[45]	Khalil Alsharabi et al., 2022	DWT and ML Approaches	ML	10-fold Cross-Validation	KNN	99.98% (AUC 100%)
[46]	Yue Ding et al., 2022	Spectral power and connectivity	ML	5-fold Cross-Validation	RF	AUC up to 80.08%
[47]	Digambar Puri et al., 2022 (IJECS)	TQWT for EEG feature extraction	ML	10-fold Cross-Validation	EBT	96.20%
[48]	Digambar Puri et al., 2022 (DASA)	EMD and Hjorth parameters	ML	10-fold Cross-Validation	SVM	97.50%
[49]	Digambar Puri et al., 2022 (Wavelet Transform)	Optimal EEG channel selection with Wavelet Transform	ML	10-fold Cross-Validation	SVM	97.50%
[50]	Kai Li et al., 2021	Latent factors with auto-encoder	ML	Not mentioned	Takagi-Sugeno-Kang	98.10%
[51]	Daniele Pirrone et al., 2022	FIR filtering in time domain	ML	10-fold Cross-Validation	DT, SVM, KNN	Varied accuracies
[52]	Haitao Yu et al., No Year Specified	Network-based fuzzy learning	ML	Not mentioned	N-TSK	Highest accuracy of 97.3%
[53]	Michele Alessandrini et al., 2022	Robust-PCA and LSTM RNN	DL	Cross-validation	LSTM RNN	Over 99%
[54]	Caroline L Alves et al., 2022	EEG functional connectivity and DL	DL	Not mentioned	CNN	Close to 100%
[55]	Dovile Komolovaitė et al., 2022	CNN for visual stimuli classification	DL	Not specified	DeepConvNet, EEGNet	Not provided
[56]	Morteza Amini et al., 2021	Time-Dependent Power Spectrum Descriptors and CNN	DL	Not specified	CNN	82.3% accuracy, with 85% detection in MCI, 89.1% in AD, and 75% in HC correctly diagnosed
[57]	Saman Fouladi et al., 2022	Modified CNN and Convolutional Autoencoder (Conv-AE) NN	DL	Not specified	CNN, Conv-AE	CNN: 92%, Conv-AE: 89%
[58]	Cameron J Huggins et al., 2021	Deep learning of resting-state EEG signals	DL	10-fold Cross-Validation	AlexNet	98.9% ± 0.4% for AD vs MCI vs HA
[59]	Wei Xia et al., 2023	Deep Pyramid CNN	DL	5-fold Cross-Validation	Deep Pyramid CNN (DPCNN)	97.10%
[60]	Sadegh-Zadeh et al., 2023	PSD features and SVM classifier	ML	Not specified	SVM	The category accuracy of the models elevated by 2 to 7% with facts augmentation. For AD, MCI vs. HC, accuracy reached ninety seven.2%, and for AD+MCI vs. HC, it turned into ninety six.2%.
[61]	Yuseong Hong et al., 2023	Ensemble learning of EEG features	DL	Not specified	Deep neural networks, tree-based ML	88.5%
[62]	Chen, Wang, Zhang, Zhang, Tao, 2023	Multi-feature fusion learning	DL	Not specified	CNN and ViT	80.23%
[63]	Tawhid et al., 2023	Frequency Band-based Biomarkers for MCI Detection	DL	Not specified	CNN	Not provided
[64]	Yu et al., 2020	WVG Network-Based Fuzzy Learning	ML	Not specified	TSK fuzzy system	97.12% accuracy
[65]	You et al., 2020	NN relay using gait and EEG data	DL	Not explicitly mentioned	Cascade Neural Network (CNN with AST-GCN for gait and ST-CNN for EEG)	91.07% for HC, MCI, AD; 93.09% for HC vs. MCI/AD

[66]	Duan et al., 2020	Topological Network Analysis on EEG	DL	Not specified	ResNet-18	MCI: 98.33% (best), 93.42% (average); mild AD: 100% (best), 98.54% (average)
[67]	Xia et al., 2023	Deep Pyramid CNN	DL	5-fold Cross-Validation	Deep Pyramid CNN (DPCNN)	97.10%
[68]	Puri et al., 2023	Dual Decomposition: DWT-VMD and MPEs	ML	10-fold Cross-Validation	EBT	95.20% for three-class; 97.70% for two-class
[69]	Mazrooei Rad et al., 2021	EEG and ERP Analysis using LDA, Elman NN, and CNN	ML/DL	Not specified	LDA, Elman NN, CNN	LDA: 59.4%-66.4%, Elman NN: 92.3%-94.1%, CNN: 97.5%-99%
[70]	Siuly et al., 2020	Piecewise Aggregate Approximation (PAA), Permutation Entropy (PE), and Auto-regressive (AR) model	ML	10-fold Cross-Validation	ELM, SVM, KNN	ELM: 98.78%
[71]	Aslan & Akşahin, 2024	Poincare and Entropy Methods	ML	Not specified	Not specified	Not provided
[72]	Khare & Acharya, 2023	Adaptive Flexible Analytic Wavelet Transform (AFAWT)	ML	10-fold Cross-Validation	XBM	99.85%
[73]	Hong, Jeong, Park, Kim et al., 2023	Ensemble learning of EEG features	ML/DL	Not specified	Ensemble of DNN and tree-based ML	88.5%
[74]	Alves, et al., 2022	EEG functional connectivity and deep learning	DL	Not specified	CNN	Not specified
[75]	Göker, 2023	Multitaper and Ensemble Learning	ML	Not specified	Logit Boost	93.04%
[76]	Alessandrini, et al., 2022	EEG-based ad detection using RPCA and LSTM RNN	DL	Not specified	LSTM RNN	Improvement of about 5% over baseline PCA
[77]	Araújo, et al., 2022	Smart-Data-Driven System, EEG Nonlinear Analysis	ML/DL	Leave-One-Out	Decision Trees, SVM, CNN, etc.	Up to 93.8% (various comparisons)
[78]	Miltiadous, et al., 2021	Classification of EEG Signals	ML	K-fold CV, Leave-One-Patient-Out	Decision Trees, Random Forests, etc.	AD: 78.5% with DT, FTD: 86.3% with RF
[79]	Pirrone, et al., 2022	EEG Signal Processing and Supervised ML	ML	70% training/30% test split	DT, SVM, KNN	AD vs HC: 97%, HC vs MCI: 95%, MCI vs AD: 83%, Three-class: 75%
[80]	Wang, et al., 2023	MOPSO-GDM algorithm for EEG-based functional network analysis.	ML	10-fold cross-validation strategy.	SVM, Naive Bayes, Discriminant Analysis.	Excellent classification error rate of 6.7 (93.3% accuracy) with feature vector size reduced to 20.
[81]	Perez-Valero, et al., 2022	Automated pipeline the usage of industrial EEG machine and automated class.	ML	Leave-one-subject-out cross-validation.	SVM and LR, with SVM performing best.	It is comparable to the best reported studies on AD detection by automated processing and commercial EEG systems.
[82]	Jennings et al., 2022	Spectral properties from EO and EC EEG signals were used to improve dementia diagnosis accuracy. KNN and SVM models were employed to differentiate groups using spectral data.	ML	10-fold cross-validation.	KNN, SVM, Logistic Regression.	The KNN model achieved a specificity of 87% and a sensitivity of 92% in distinguishing between AD and dementia (HC), in addition to a specificity of 75% accompanied by a sensitivity of 91% in distinguishing between dementia with DLB and AD (Advertisement).

3.5. Reported Limitations and Recommendations.

3.5.1 Reported Limitations

The reported constraints throughout the evaluated short articles generally emphasize worries relating to data dimension, generalizability of searching's for, as well as the specifics of information evaluation. An usual style is the restricted dimension of datasets made use of in the researches which increases concerns concerning the durability coupled with generalizability of the outcomes. Such restraints are kept in mind throughout numerous research studies highlighting the difficulty of getting huge plus varied datasets in AD research study. This problem is worsened by the intricacy of advertisement medical diagnosis as well as the irregularity in EEG signal attributes amongst individuals.

The category of AD specifically without precise in-vivo proof offers an additional layer of intricacy with some research studies recognizing the restrictions of classifying just possible AD situations. This indicate the requirement for a much more nuanced technique that includes a larger range of analysis proof. A couple of research studies particularly point out the obstacle of overfitting as a result of the high dimensionality of EEG function collections, emphasizing the significance of advanced information handling together with design recognition techniques to make certain that searchings for are not artefacts of the evaluation procedure yet are genuinely a measure of hidden neurophysiological patterns.

Furthermore, particular researches keep in mind the lack of thorough group details for topics coupled with the absence of expedition right into the influences of elements such as education and learning degree, sex matching and also age varieties on the EEG evaluation. This non-inclusion recommends a requirement for even more detailed information collection as well as evaluation to totally just how these variables might affect EEG signals along with AD medical diagnosis.

Additionally the exemption of extra professional info such as education and learning size or suggested medicine in some research studies restricts the deepness of evaluation. Info on outliers with uncommon EEG analyses which can be medically pertinent is additionally usually ignored, mentioning a prospective location for additional examination.

In recap, while the examined short articles add considerably to the area of EEG-based research study in AD, they likewise highlight the requirement for improvements in data source collection, preprocessing strategies together with analytical techniques. Attending to these constraints might bring about extra exact, trusted along with detailed devices for AD medical diagnosis plus understanding. By assembling the various constraints reported in all the examined write-ups it is feasible to have a suggestion of the concerns that require to be dealt with in the list below years to progress EEG-based research study on AD. Table 6 offers the above- stated restrictions.

#	Author(s) & Year	Reported Limitations
[45]	Khalil Alsharabi et al., 2022	Limited by dataset size and the scope of EEG data analysis.
[46]	Yue Ding et al., 2022	The study might have limitations due to the classification of only probable AD without definitive in-vivo evidence.
[47]	Digambar Puri et al., 2022 (IJECS)	Dataset size is small, affecting the generalizability of the findings.
[48]	Digambar Puri et al., 2022 (DASA)	Not explicitly mentioned
[49]	Digambar Puri et al., 2022 (Wavelet Transform)	Not explicitly mentioned
[50]	Kai Li et al., 2021	Small dataset size not including MCI subjects, reliance on sensor-level EEG analysis
[51]	Daniele Pirrone et al., 2022	The study highlights the challenges related to data splitting, especially considering data imbalance, loss, and concept drift.
[52]	Haitao Yu et al., No Year Specified	The study does not specify the number of subjects involved or their demographic details

[53]	Michele Alessandrini et al., 2022	Not explicitly mentioned
[54]	Caroline L Alves et al., 2022	The study does not specify limitations
[55]	Dovile Komolovaitė et al., 2022	Not explicitly mentioned
[56]	Morteza Amini et al., 2021	Not explicitly mentioned
[57]	Saman Fouladi et al., 2022	Not specified in the provided text
[58]	Cameron J Huggins et al., 2021	Not specified
[59]	Wei Xia et al., 2023	Not specified
[60]	Sadegh-Zadeh et al., 2023	The main limitations include a small dataset size and unbalanced dataset distribution, which may affect the generalizability of the results.
[61]	Yuseong Hong et al., 2023	Not specified
[62]	Chen, Wang, Zhang, Zhang, Tao, 2023	Previous literature acknowledges the challenge posed by the limited data set size, which may affect the generalizability of findings.
[63]	Tawhid et al., 2023	The study's limitations include the limited size and diversity of the datasets, which may affect the generalizability of the findings. The impact of different education levels, gender matching, or age ranges wasn't deeply explored.
[64]	Yu et al., 2020	The EEG feature set's high dimensionality could overfit and was therefore stated as the main limitation. Furthermore, the generalizability of study findings in question may be restricted by the specific attributes of such an experimental database.
[65]	You et al., 2020	It is limited by the specific features of the EEG dataset used.
[66]	Duan et al., 2020	The generalizability of the study may be negative due to the restricted characteristics of the EEG data used.
[67]	Xia et al., 2023	The main limitations include the challenges of data augmentation and potential model overfitting due to the high dimensionality of EEG feature sets.
[68]	Puri et al., 2023	The study's main limitation is the relatively small dataset size, especially for MCI patients.
[69]	Mazrooei Rad et al., 2021	The study acknowledges the challenge of data augmentation and the potential for model overfitting due to high dimensionality of EEG feature sets.
[70]	Siuly et al., 2020	The small size of the dataset may affect the generalizability of the results.
[71]	Aslan & Akşahin, 2024	The fundamental problem is the small dataset size which may affect the generalizability of the consequences. Additionally, the observe became carried out on uncooked EEG statistics with out preprocessing for noise reduction.
[72]	Khare & Acharya, 2023	The main limitation is the use of a single dataset with a small number of subjects, which may affect the generalizability of the findings.
[73]	Hong, Jeong, Park, Kim et al., 2023	The research's core concern is the EEG data while additional clinical information like the period of education and the prescription drugs are important as they can improve the study's quality. Moreover, it also talks about the outliers showing abnormally high or low absolute powers that could be very much significant clinically but they are not discussed.
[74]	Alves, et al., 2022	The study acknowledges the small dataset size, which is a common issue in disease classification studies, but highlights that even with this limitation, the proposed method showed high accuracy.
[75]	Göker, 2023	The small sample size have negative effects on the generalization of the results
[76]	Alessandrini, et al., 2022	The main limitation is the small training data set, which affects the generalizability of the results

[77]	Araújo, et al., 2022	The smaller size of the utilized dataset affects the generalizability of the results
[78]	Miltiadous, et al., 2021	The ability to generalize is affected by the size of the used data
[79]	Pirrone, et al., 2022	An important factor that affects the generalizability of results is when the data set is small.
[80]	Wang, et al., 2023	What may negatively affect the generalizability of the results is when the data set is small,
[81]	Perez-Valero, et al., 2022	The small size of the data set may affect the generalizability of the results. Other conditions that could overlap with AD symptoms are not included.
[82]	Jennings et al., 2022	Small sample size, exclusion of subjects due to insufficient clean EEG data, and potential overlap of dementia symptoms not accounted for in the study.

3.5.2 Reported Recommendations

Numerous future research directions on EEG-based medical diagnosis of AD have appeared in previous discussions in Table 7 in the form of direct points. Typical points include:

1. Combination of Multi-modal Data Sources: Many researches advise including hereditary, imaging along with various other pen information together with EEG signals to supply an extra extensive sight of advertisement's neurophysiological effects. This incorporated method might dramatically boost analysis precision and also our understanding of the condition.
2. Development of Dataset Size and also Diversity: A persisting style is the need for bigger as well as extra varied datasets. Broadening data source dimension plus variety is critical for boosting the generalizability of searchings for as well as making certain versions are durable throughout various populaces as well as phases of AD.
3. Work of Deep Learning Techniques: Several suggestions highlight the possibility of deep understanding methods to boost analysis devices for AD. By immediately removing intricate patterns from EEG signals deep understanding versions can supply substantial improvements in recognizing refined neurophysiological pens of the condition.
4. Optimization of Feature Selection and also Classification Methods: Optimizing the choice of EEG functions as well as the application of category formulas is an additional location determined for future research study. Boosted function choice might decrease computational prices together with boost the precision as well as interpretability of analysis designs.
5. Expedition of Advanced EEG Analysis Methods: Suggestions consist of discovering deep knowing approaches, complicated network approaches together with artificial intelligence strategies customized to EEG information. These progressed logical strategies can open brand-new understandings right into EEG signals' analysis and also analysis worth in AD.
6. Addition of Clinical along with Demographic Information: Incorporating added medical information such as medicine background, cognitive analysis ratings and also group information, might improve EEG evaluations. This extra context might assist to much better and also translate the neurophysiological modifications related to AD.
7. Resolving Data Augmentation and also Model Overfitting: Balancing data sources amongst AD, MCI as well as healthy and balanced control topics as well as utilizing automated criterion optimization strategies are suggested to boost design generalization. Attending to the difficulties of information enhancement and also version overfitting is vital for establishing trusted analysis devices.

8. Application to Other Neurological Disorders: Extending the methods established for AD medical diagnosis to various other neurological problems is viewed as a guaranteeing instruction. This strategy can result in wider applications of EEG evaluation in neurology plus psychiatry.
9. Real-time Diagnosis coupled with Embedded Device Implementation: Some researches recommend the advancement of real-time analysis systems as well as their application on ingrained gadgets. This might settle the reduced expense, easily accessible analysis devices that can be utilized in professional as well as residence setups.

Together, the ideas highlighted here indicate how lively and progressive such work can be; which areas should be next studied so that diagnosis could be improved by EEG, expanded its use beyond what it has already accomplished and thus enhance patient prognosis in AD.

#	Author(s) & Year	Recommendations
[45]	Khalil Alsharabi et al., 2022	Explore the integration of multi-modal data sources, including genetic and imaging data, for a more comprehensive analysis. Use of deep learning techniques could enhance diagnostic performance.
[46]	Yue Ding et al., 2022	Suggests further studies with larger datasets and the potential integration of deep learning techniques for better diagnostic tools.
[47]	Digambar Puri et al., 2022 (IJECS)	Future work to include larger datasets and explore deep learning methods for AD diagnosis.
[48]	Digambar Puri et al., 2022 (DASA)	The study emphasizes the efficiency of using a reduced number of EEG channels for diagnosing AD, suggesting a potential direction for further optimizing EEG-based AD detection methodologies.
[49]	Digambar Puri et al., 2022 (Wavelet Transform)	The study emphasizes the efficiency of using a reduced number of EEG channels for diagnosing AD, suggesting a potential direction for further optimizing EEG-based AD detection methodologies.
[50]	Kai Li et al., 2021	Future research should concentrate on fine-tuning algorithmic methods to accurately diagnose Alzheimer's' disease from EEG data by combining complex network measures with machine learning
[51]	Daniele Pirrone et al., 2022	The study suggests further exploration of the feature extraction method for AD diagnosis and its potential application on embedded devices for real-time diagnosis.
[52]	Haitao Yu et al., No Year Specified	This research points to local efficiency and clustering coefficient as key aspects in AD identification via EEG signals and recommends further optimization of network attributes used in N-TSK fuzzy classifiers."
[53]	Michele Alessandrini et al., 2022	Demonstrates the potential of RPCA preprocessing in enhancing AD diagnosis accuracy with corrupted EEG data.
[54]	Caroline L Alves et al., 2022	Highlights the potential of DL and EEG connectivity for diagnosing neurological disorders
[55]	Dovile Komolovaitė et al., 2022	Highlighted the effectiveness of CNNs and the potential of synthetic data augmentation for improving classification accuracy
[56]	Morteza Amini et al., 2021	Further studies on enhancing feature extraction and classification methods to identify AD using EEG signals.
[57]	Saman Fouladi et al., 2022	To confirm the effectiveness of DL models in interpreting electroencephalograms in order to make early diagnosis of cognitive impairment and mild AD.
[58]	Cameron J Huggins et al., 2021	Not specified
[59]	Wei Xia et al., 2023	Not specified
[60]	Sadegh-Zadeh et al., 2023	The study suggests future work could include the application of this method to larger and more balanced datasets, as well as the exploration of other neurological disorders using the proposed approach.
[61]	Yuseong Hong et al., 2023	Continuous analysis of independent QEEG features for neurological disorders diagnosis
[62]	Chen, Wang, Zhang, Zhang, Tao, 2023	Future work could include validating the model on larger, more diverse datasets to enhance its predictive accuracy and reliability. The method's potential applicability to other forms of dementia besides AD is also suggested for further exploration.
[63]	Tawhid et al., 2023	Recommendations for future studies include using larger and more diverse datasets to validate the findings. Investigating the role of education, age, and gender in MCI detection through EEG is also recommended, as well as exploring other machine learning models and frequency bands for deeper insights.

[64]	Yu et al., 2020	Future research need to focus on optimizing function choice to decorate model accuracy and interpretability. There's additionally a advice for similarly validation of the proposed model across more various and large patient datasets to strengthen the findings' generalizability.
[65]	You et al., 2020	Extend framework to other neurological diseases; optimize EEG data collection for HC.
[66]	Duan et al., 2020	Future work should focus on gathering more data from MCI patients and mild AD patients using these same instruments so as to get a better analysis done Future research is needed regarding the similarities of MCI and mild AD datasets.
[67]	Xia et al., 2023	Future work includes balancing the dataset among AD, MCI, and HC subjects, enhancing model generalization through diverse EEG datasets, and employing automatic parameter optimization techniques.
[68]	Puri et al., 2023	Future work could extend this dual decomposition technique for diagnosing other neurodegenerative disorders such as epilepsy, various sleep disorders, Parkinson's disease , and major depressive disorders. Also, implementing deep learning models on the EEG datasets could enhance diagnostic accuracy.
[69]	Mazrooei Rad et al., 2021	Future work should focus on enhancing the model's generalizability by incorporating a wider range of EEG datasets, including exploring other neural network architectures and combining EEG with other types of biomarkers for more accurate AD diagnosis.
[70]	Siuly et al., 2020	Expanding the scope of modifying the method to larger data and seeing its utility in multi-class situations, such as distinguishing between mild cognitive impairment, healthy control, and advertising subjects
[71]	Aslan & Akşahin, 2024	The study suggests further research could focus on optimizing the feature selection process to reduce computation costs and enhance the model's accuracy. Implementing deep learning techniques and expanding the dataset are also recommended for future studies.
[72]	Khare & Acharya, 2023	Future research could validate the proposed model across larger and more diverse datasets. The adaptability and explainability of the model offer promising directions for enhancing automatic AD detection and providing understandable machine learning predictions for clinical use.
[73]	Hong, Jeong, Park, Kim et al., 2023	The study emphasizes the potential of combining various EEG-derived features to improve performance in diagnosing neurodegenerative disorders, suggesting the utility of deep learning and machine learning techniques for this purpose. It calls for further research to incorporate additional clinical data and address the challenge of outliers in EEG data analysis
[74]	Alves, et al., 2022	The paper suggests the method is generalizable and can be adapted for any brain disorder with available EEG data. It recommends further research to include larger datasets and additional clinical information for an enhanced diagnosis process.
[75]	Göker, 2023	Further development of the model to include more diverse and larger datasets for improved generalization and application to different biomedical signals for early diagnosis of various diseases.
[76]	Alessandrini, et al., 2022	The paper suggests the method is generalizable and could be adapted for any brain disorder with available EEG data. It recommends further research to include larger datasets and additional clinical information for an enhanced diagnosis process.
[77]	Araújo, et al., 2022	Enhance the system by incorporating larger datasets and additional clinical information for diagnosis.
[78]	Miltiadous, et al., 2021	Many tests must be performed on a larger sample of clinical EEG records to validate the methodology. In doing so, the classification of different types of other dementias and the possible expansion and differentiation of seizure waveforms for dementia will be explored.
[79]	Pirrone, et al., 2022	The combination of devices is the future development of low-cost, real-time diagnosis.
[80]	Wang, et al., 2023	Expansion to larger clinical datasets for validation, exploration of other neurological disorders using the proposed method, and enhancement of algorithm efficiency for real-time diagnosis.
[81]	Perez-Valero, et al., 2022	Further research with larger sample sizes and inclusion of typical patients seen in neurological services to validate the method's effectiveness in a clinical setting.
[82]	Jennings et al., 2022	A validation cohort is recommended for further validation of findings, suggesting future research to include larger datasets and potentially additional clinical information for improved diagnostics.

4. Conclusion

The organized testimonial of smart strategies for AD medical diagnosis from EEG signals mirrors a crucial stride in the direction of leveraging technical breakthroughs in neuroimaging together with computational formulas to deal with the expanding obstacle of prompt along with exact AD discovery. The cumulative evaluation attracted from 38 short articles highlights the appealing combination of artificial intelligence (ML) as well as deep discovering (DL) methods with EEG information to improve analysis precision, supplying understandings right into the condition's neurophysiological underpinnings.

The presented study has actually highlighted substantial success in the area, such as the growth of innovative computer-aided medical diagnosis systems that efficiently make use of EEG signals for very early precise as well as automated AD recognition. These systems have actually shown the possibility of EEG as a beneficial pen for AD, showcasing improvements in signal handling methods along with the application of intricate logical structures. Significantly the evaluation recognized a varied range of preprocessing techniques, reliable use ML/DL techniques, differing recognition techniques, , and also reported accuracies showing the breadth of approaches used to boost analysis abilities.

In spite of these improvements, the evaluation additionally highlights a number of restrictions and also difficulties that continue in the present research study landscape. These consist of the requirement for bigger together with extra varied datasets to boost the generalizability of searchings for, the combination of multi-modal information resources for an extra extensive evaluation as well as the expedition of innovative EEG evaluation techniques and also deep discovering formulas to resolve the intricacies of AD discovery.

The suggestions supplied by the assessed write-ups propose a plan for future research study emphasizing the growth of dataset dimension as well as variety, the capacity of incorporating hereditary, imaging, as well as professional information together with EEG signals and also the expedition of cutting-edge ML/DL strategies. These tips intend to conquer the existing obstacles coupled with open brand-new opportunities for research study that might bring about much more durable, exact plus, very early analysis abilities.

Finally, this evaluation envelops the present state of EEG-based AD medical diagnosis research study highlighting both its encouraging success and also the difficulties that exist in advance. By dealing with the determined constraints and also accepting the suggested instructions for future researches, the area is positioned for substantial improvements. The combination of EEG with sophisticated computational versions holds the possible to change AD medical diagnosis leading the way for prompt treatments and also boosted results for people influenced by this devastating condition.

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