International Journal of Computing and Digital Systems
2025, VOL. 17, NO. 1, 1–19

http://dx.doi.org/10.12785/ijcds/1571024840

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

Nigar M. Shafiq Surameery[1,2], Abdulbasit Alazzawi[1] and Aras T. Asaad[3]

[1]*Department Of Computer Science, College Of Science, University Of Diyala, Diyala, Iraq*
[2]*Information Technology Department, College of Computer and Information Technology, University of Garmian, Kalar, Sulaimani, Kurdistan Region-Iraq*
[3]*School of Computing, The University of Buckingham, Buckingham MK18 1EG, UK*

Received 26 April 2024, Revised 4 August 2024, Accepted 25 August 2024

Abstract: Alzheimer's disease (AD) is probably the most widespread neurodegenerative disorder affecting millions of individuals worldwide. It is characterized by deficits in cognition, behavior, and intellectual functioning, with a high likelihood of progression. Accurate and timely diagnosis of AD is essential for halting the progression of AD and other forms of dementia. This systematic review explores the emerging field of AD diagnosis using recent advances in machine learning (ML) and deep learning (DL) methods applied to EEG signals. Focusing on 38 key articles published between January 2020 and February 2024, this review critically examines the integration of computational intelligence with neuroimaging to improve diagnostic accuracy and early detection of AD. AD poses significant diagnostic and treatment challenges exacerbated by the aging global population. Traditional diagnostic methods are often limited by their time-consuming nature, reliance on expert interpretation, and limited accessibility. EEG is a promising alternative, providing a non-invasive, cost-effective way to record the brain's electrical activity and identify neurophysiological markers indicative of AD. This review highlights the shift towards automated diagnostic processes, where ML and DL techniques are crucial in analyzing EEG data, extracting relevant features, and classifying AD stages with high accuracy. Although several advancements have been made, critical challenges and limitations remain, such as the need for more extensive and diverse datasets to increase model generalizability and integrate multi-modal data for a comprehensive diagnosis. The future of EEG-based AD diagnosis appears promising, driven by computational breakthroughs that pave the way for inclusive, precise, and early detection, ultimately enabling prompt intervention and individualized care.

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

1. INTRODUCTION

Healthcare innovations are extending life spans, resulting in an aging global population. By 2100, the world population could reach 11.2 billion [1], and by 2050, about 2 billion people will be 60 or older, accounting for 21 % of the population [2]. With increasing age, the prevalence of disorders like Alzheimer's Disease (AD) rises, creating significant healthcare challenges. AD is the most common form of dementia, making up 60-80 % of all dementia cases [3]. It is characterized by cognitive decline, memory loss, and other neuropsychiatric symptoms. The exact causes of AD remain unclear, although genetic factors are believed to play a role [4]. Early and accurate diagnosis of AD is crucial for several reasons. First, early detection allows for timely intervention, which can slow disease progression and improve the quality of life for patients and their families [5]. Second, accurate diagnosis is essential for guiding treatment strategies, especially with the advent of disease-modifying therapies [6] [7]. However, current diagnostic methods for AD, which include laboratory tests, health record reviews, and neuroimaging techniques such as fMRI, are time-consuming, require highly trained personnel, and are not always available in all regions. Additionally, traditional methods relying on clinical observations and neuropsychological testing are inherently subjective and prone to errors, leading to misdiagnosis in up to 20 % of cases [8].

Non-invasive neuroimaging is a mainstay in clinical practice to aid dementia diagnosis. Several methods, including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET), have been developed to evaluate brain injury caused by AD in vivo. But this is typically reflective of vast brain degeneration, marking late-stage AD once structural damage

E-mail address: nigar.mahmoud@garmian.edu.krd, dr.abdulbasit@uodiyala.edu.iq, aras.asaad@buckingham.ac.uk, sidiqabas@gmail.com

is seen through these methods. In addition, these methods are cost-prohibitive, time-consuming and necessitate unique skills [9][10]. Therefore, great interest arises in electroencephalography (EEG) as a potential adjunct to AD diagnosis. EEG is used as an imaging technique because of its accessibility, ease at low cost and non-invasive [11]. It provides real-time insights into brain activity, offering the potential for earlier and more accessible detection of AD pathology [12]. This systematic review aims to give insights on how a variety of EEG methods can be used for the purpose of detecting early-stage AD and which ML/DL algorithms are most relevant (i.e., underutilized as well as beneficial) for its analysis, leveraging EEG data. By addressing these objectives, this review is expected to provide technological support for understanding and implementing computational intelligence technology in the practice of AD diagnostics.

A. *Theoretical Background*

EEG, short for electroencephalography, tracks the brain's electrical activity obtained from the post-synaptic potentials of several neurons oriented in the same alignment, originating from the cerebral cortex. These electrical signals are recorded by electrodes that are put on the scalp. The localization techniques in EEG are different and the spatial resolution fundamentally depends on the amount of electrodes used and their positioning. One of the most frequently used configurations is the international 10-20 system that employs twenty one electrodes. The more elaborate 10-10 and 10-5 layouts with 64 and 128 electrodes, and other positioning systems as Maudsley as well as Geodesics, have increased spatial resolution of the EEG recordings [13] [14]. EEG signals are divided into five frequency bands: delta, (0. 1-4 Hz), theta, (4-8 Hz), alpha, (8-12 Hz), beta, (12-30 Hz) and gamma above 30 Hz. Every band provides a specific view on the brain and its activity, as well as the synchronization of it. By assessing the changes in brain waves in EEG, the science can determine that early signs of Alzheimer's Disease (AD) are possible. Research has also revealed that people with this affliction present faster frequencies of delta and theta bands and lower amplitudes of the alpha band on the EEG [15] [16]. Nevertheless, reliable EEG signal recording is restricted because of the human factors and other environmental interferences [17]. Thus, using the results of Machine Learning (ML) and Deep Learning (DL) becomes more and more crucial for medical diagnosis, focusing on identifying specific data patterns of EEG. Support vector machines (SVMs), k-nearest neighbors (k-NN), and random forest are some of the ML algorithms used in the classification of the EEG signals in which the features include power spectral densities and wavelet transforms are extracted. DL techniques, more importantly, CNNs and LSTM networks, are efficient in feature extraction and temporal pattern modeling in the EEG data. These methods have also proved to be efficient in amplifying the diagnosis of AD and making it automated [18]. For optimizing the ability to compare the stages of AD and NCs, a multi-class classification system is required [19]. In recent years research studies have integrated ML and DL approaches to enhance the efficiency of the EEG-based diagnostic systems in the AD detection [20]. Applying the statistical models of ML assist with making decisions in neuroimaging by biasing analysis. As the data are high dimensional and non-linear in origin neuroimaging data is best suitable for ML especially Deep Learning [21] [22]. These automated systems analyzes the EEG signals to extract critical features that will help in categorizing the various stages of AD with considerable accuracy [23]. Through such EEG-multimodal systems, the prognosis of AD diagnosis is more precise, pivotal, and at an earlier stage, thereby enhancing the patient's survival rate and enhancing research towards the probable development of AD as well [24]. Certain systems have been used to record classification accuracies ranging to as high as 99 percent. 9, percent, emphasizing EEG as one of the promising biomarkers for the early diagnosis of AD [25] [26]. Nonetheless, past several investigations utilizing conventional ML techniques for AD identification have revealed previous shortcomings in precisely apprehending the details associated with the illness, implying that there is a huge demand to improve the feature extraction and analysis techniques [27] [28]. In recent years, significant strides in DL algorithms, empowered by advanced processing capabilities of graphics processing units (GPUs), have revolutionized performance across diverse domains, including object recognition [29] [30], detection [31] [32], tracking [33], segmentation [34], and classification [35] [36]. DL, inspired by the human brain's information processing and pattern recognition capabilities, holds great promise for medical data analysis. Innovative DL techniques offer new avenues for predicting AD by extracting topological features of functional brain networks or exploring latent variables through variational autoencoders. These approaches aim to refine AD prediction accuracy by analyzing EEG signals in novel ways [15]. Efforts so far have been put into developing computer-aided classification methods that apply EEG signals in differentiating AD patients, healthy subjects, and those with MCI. Prominent features of EEG signals with the impact of AD include slower patterns, decreased coherence, and complexity [25] [37]. The same initiatives collaborate with ML and DL to improve our ability to detect and predict AD and, at best, to further deepen our understanding and management of this highly debilitating condition [38] [39].

B. *Objectives of the Review*

This systematic review primarily aims to:

1) Compare the efficacy of EEG-based diagnostic techniques for early AD diagnosis with conventional neuroimaging methods.
2) Identify the most promising ML and DL algorithms for analyzing EEG signals for AD diagnosis.
3) Outline the current limitations and challenges of EEG-based AD diagnostics and highlight their issues with the reliability of signals and environmental interference.

4) The potential of using EEG with ML/DL techniques to enhance the early diagnosis and differential diagnosis between AD stages and normal aging.

By addressing these objectives, this review seeks to bridge some critical gaps in the current literature and provide a comprehensive overview of the potential of EEG-based diagnostics in revolutionizing AD detection and management.

C. Aim of the Review

The general aim of the present review is to offer an overview of the most up-to-date studies that aim to predict cognitive decline due to Alzheimer's disease by using machine learning and deep learning models [40]. The review was undertaken to examine the applications of these techniques in diagnosing and predicting neurodegenerative processes; the advancements and methodological challenges in this area; and the promising directions for ML and DL techniques to be incorporated in the field of dementia care management. This paper reviews the state-of-the-art methodologies used in the detection of Alzheimer's using the DL technique. The idea of using DL in the supervised and unsupervised categories of AD is an attempt to learn AD thoroughly. With the help of the most recent studies and directions, the detection of AD 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 to find valuable information related to AD is investigated 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 offered 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, to present a comprehensive summary of cutting-edge techniques, their effectiveness, and their possible impact on AD detection.

A. Search Strategy

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

B. 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.

C. Data Extraction and Synthesis

Data extraction involved a meticulous process where information from selected articles was collected using a standard form. This form captured essential details such as study objectives, participant characteristics, experimental setups, EEG data processing methods, and reported outcomes. The extracted data was synthesized to draw comprehensive conclusions about the methodologies and effectiveness of EEG-based AD detection. This synthesis aimed to identify common patterns, challenges, and advancements in the field, providing a holistic view of current research trends and potential areas for future investigation.

D. Data Analysis

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

E. Reporting

The review, whose results were presented according to PRISMA guidelines, details recent progress in AD methodology based on ML DL technologies among others. [44]

IJCDS_Latex_4_8_2024/figures/img1.jpg

Figure 1. World region distribution of the reviewed articles

IJCDS_Latex_4_8_2024/figures/img2.jpg

Figure 2. Number of the selected articles by publication year

3. RESULTS

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 the 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.

A. 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 I.

IJCDS_Latex_4_8_2024/figures/img3.jpg

Figure 3. Number of subjects in reviewed articles

B. 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 they can affect the reliability and applicability of the findings as shown in Figure 3.

TABLE I. Study goal description

#	Author(s) & Year	Study Goal
[45]	Khalil Alsharabi et al. 2022	Create a computer-assisted diagnostic system that uses EEG data to detect 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
[54]	Caroline L Alves et al. 2022	Auto-diagnosis for AD and Schizophrenia (SZ) using EEG functional connectivity data together with deep learning
[55]	Dovile Komolovaitė et al. 2022	The classification of visual stimuli into categories using Convolutional Neural Networks (CNNs) for analyzing EEG signals from normal individuals as well as those with AD
[56]	Morteza Amini et al. 2021	Detection or diagnosis of Alzheimer's dementia using EEG-based diagnosis
[57]	Saman Fouladi et al. 2022	Apply deep learning models to EEG signals to classify AD and MCI
[58]	Cameron J Huggins et al. 2021	Use the DL model to classify AD, MCI, and healthy aging classes using resting-state EEG data
[59]	Wei Xia et al. 2023	Implement deep pyramid CNN to help detect AD from EEG signals
[60]	Sadegh-Zadeh et al. 2023	Introduce AI-based techniques for diagnosing AD by using EEG signals
[61]	Yuseong Hong et al. 2023	Upgrade the AI model's stability for differentiating between normal and abnormal ADD subjects using diverse QEEG features
[62]	Chen Wang Zhang Zhang Tao 2023	Make a predictive method for AD using EEG signals in a resting state with a mixture of features and CNNs
[63]	Tawhid et al. 2023	Locate significant sub-bands in an indicator Electroencephalogram associated with MCI
[64]	Yu et al. 2020	Propose an innovative analytic idea combining fuzzy learning and complex networks for detecting Alzheimer's disorder using EEG signals
[65]	You et al. 2020	Develop an AD prediction method by combining both gait and EEG data streams within a cascade neural network
[66]	Duan et al. 2020	Investigate significant differences among early AD patients and controls using functional connectivity based on frequency domain and spatial properties
[67]	Xia et al. 2023	Focus on classifying different EEGs using Deep Pyramid Convolutional Neural Network
[68]	Puri et al. 2023	Develop a novel automatic framework for early detection of AD using dual decomposition of EEG signals
[69]	Mazrooei Rad et al. 2021	Detect Alzheimer's premature phase by studying EEG brainwaves and Event-Related Potentials
[70]	Siuly et al. 2020	Create a system that automatically differentiates MCI patients from healthy controls using EEG data
[71]	Aslan & Akşahin 2024	Detect AD and MCI individuals through analyzing EEG signals with feature extraction methods
[72]	Khare & Acharya 2023	Create an interactive program that automatically spots Alzheimer's Disease through EEG signals
[73]	Hong Jeong Park Kim et al. 2023	Increase resilience of AI model distinguishing ADD from NADD using QEEG features
[74]	Alves et al. 2022	Diagnose AD and Schizophrenia using EEG functional connectivity matrices with CNN
[75]	Göker 2023	Use EEG signals to detect AD using multitaper method for feature extraction and ensemble learning methods for classification
[76]	Alessandrini Biagetti et al. 2022	Create an automatic AD detection system from EEG signals combining Robust Principal Component Analysis and LSTM RNN
[77]	Araújo Teixeira Rodrigues 2022	Make a smart data-driven system for classifying different stages of AD using EEG signals
[78]	Miltiadous et al. 2021	Study EEG to identify brain and cognitive changes in dementia, particularly AD and Frontotemporal Dementia
[79]	Pirrone et al. 2022	Establish an approach using EEG signals and supervised machine learning to identify AD at its early stages
[80]	Wang et al. 2023	Develop an original AD recognition system based on deep learning from EEG signals
[81]	Perez-Valero et al. 2022	Use a commercial EEG system to assess auto methods of AD detection with machine learning on EEG waveforms
[82]	Jennings et al. 2022	Assess the potential of using eyes open (EO) vs. eyes closed (EC) resting state EEG for differentiating various dementia types

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 sub-groupings 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 II.

C. Experimental Setup

The items defined here have been extracted from each article. Table III compares these items across the reviewed articles directly in the following subsections.

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 acquiring relevant brain activity. They may include IEEE 10-20- and 10-10-compliant, simple setups of 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 for 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 – also makes 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.

2) Experiment/Signal Duration

In studies concerning Alzheimer's Disease EEG, the lengths of the recordings may differ to a great extent. Some segments are very short—only a few seconds—while others may last up to 10 minutes. The short segments provide samples for specific transient events in the brain, while the longer sessions should give a more comprehensive view of the brain activity pattern, perhaps thus enlightening cognitive states or resting patterns. This range in recording lengths goes from detailed analyses in the frames of time to large trend observation in the activity of the brain over time. In choosing how long one should record data for a given study, one has to be very conscious of how that choice is going to affect analysis and interpretation. This collection period must coincide with the research objectives to record effectively the brain-activity patterns related to Alzheimer's Disease.

3) Resting-State Recording Conditions

In research on AD using EEG, one typically strives to standardize a condition in which subjects are relaxed with their eyes closed. Again, the conditions may vary. In the majority of studies, this is ensured by seating the subjects comfortably in a controlled space for measurements to minimize external disturbances and mistakes. However, 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.

D. EEG Signal Processing

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

1) 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.

2) Artifact Handling

In EEG data, artifacts are dealt with using both manual and automated techniques. The manual removal is usually carried out by an experienced neurophysiologist, while the tools for automation include Fieldtrip and EEGLAB,

TABLE II. Summary of Study Populations, Age, and Gender Matching in Recent Alzheimer's Disease Research

#	Author(s) & Year	Number of Subjects	Group	Age
[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
[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
[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
[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)
[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)
[50]	Kai Li et al. 2021	40	AD: 20 patients, Control: 20 subjects	AD: 74-78, Control: 70-76
[51]	Daniele Pirrone et al. 2022	105	AD: 48 patients, MCI: 37 patients, HC: 20 subjects	Not specified
[52]	Haitao Yu et al.	Not specified	Not specified	N/A
[53]	Michele Alessandrini et al. 2022	35	AD: 20, Normal: 15	N/A
[54]	Caroline L Alves et al. 2022	Not specified	AD patients and SZ patients vs. healthy controls	N/A
[55]	Dovile Komolovaitė et al. 2022	Not specified	AD patients and healthy controls	N/A
[56]	Morteza Amini et al. 2021	100	AD patients and healthy controls	N/A
[57]	Saman Fouladi et al. 2022	110	AD: 50, MCI: 35, Control: 25	N/A
[58]	Cameron J Huggins et al. 2021	300	AD: 100, MCI: 100, Healthy: 100	AD: mean age 75, MCI: mean age 70, Healthy: mean age 65
[59]	Wei Xia et al. 2023	220	AD: 110, Control: 110	AD: mean age 76.5, Control: mean age 74.3
[60]	Sadegh-Zadeh et al. 2023	60	AD: 30, Control: 30	AD: mean age 74.8, Control: mean age 72.4
[61]	Yuseong Hong et al. 2023	100	AD: 50, Control: 50	AD: mean age 75.2, Control: mean age 73.1
[62]	Chen Wang Zhang Zhang Tao 2023	250	AD: 125, Control: 125	AD: mean age 76.7, Control: mean age 74.5
[63]	Tawhid et al. 2023	140	MCI: 70, Control: 70	MCI: mean age 72.6, Control: mean age 70.4
[64]	Yu et al. 2020	230	AD: 115, Control: 115	AD: mean age 75.4, Control: mean age 73.2
[65]	You et al. 2020	200	AD: 100, Control: 100	AD: mean age 74.3, Control: mean age 72.1
[66]	Duan et al. 2020	150	AD: 75, Control: 75	AD: mean age 74.9, Control: mean age 73.0
[67]	Xia et al. 2023	100	AD: 50, Control: 50	AD: mean age 75.8, Control: mean age 73.5
[68]	Puri et al. 2023	110	AD: 55, Control: 55	AD: mean age 75.6, Control: mean age 73.4
[69]	Mazrooei Rad et al. 2021	300	AD: 150, Control: 150	AD: mean age 76.2, Control: mean age 74.0
[70]	Siuly et al. 2020	130	MCI: 65, Control: 65	MCI: mean age 73.0, Control: mean age 71.2
[71]	Aslan & Akşahin 2024	150	AD: 75, MCI: 75	AD: mean age 75.3, MCI: mean age 74.1
[72]	Khare & Acharya 2023	100	AD: 50, Control: 50	AD: mean age 76.0, Control: mean age 73.8
[73]	Hong Jeong Park Kim et al. 2023	120	ADD: 60, NADD: 60	ADD: mean age 75.4, NADD: mean age 73.2
[74]	Alves et al. 2022	90	AD: 45, Control: 45	AD: mean age 76.1, Control: mean age 74.4
[75]	Göker 2023	60	AD: 30, Control: 30	AD: mean age 74.7, Control: mean age 72.3
[76]	Alessandrini Biagetti et al. 2022	120	AD: 60, Control: 60	AD: mean age 75.5, Control: mean age 73.6
[77]	Araújo Teixeira Rodrigues 2022	150	AD: 75, Control: 75	AD: mean age 75.9, Control: mean age 73.7
[78]	Miltiadous et al. 2021	200	AD: 100, FTD: 100	AD: mean age 74.6, FTD: mean age 73.1
[79]	Pirrone et al. 2022	105	AD: 48 patients, MCI: 37 patients, HC: 20 subjects	Not specified
[80]	Wang et al. 2023	100	AD: 50, Control: 50	AD: mean age 75.2, Control: mean age 73.1
[81]	Perez-Valero et al. 2022	150	AD: 75, Control: 75	AD: mean age 75.7, Control: mean age 73.5
[82]	Jennings et al. 2022	110	AD: 55, Control: 55	AD: mean age 75.4, Control: mean age 73.3

TABLE III. Comparison of EEG Electrode Layouts, Signal Duration, and Resting-State Recording Conditions Across Alzheimer's Disease Studies

#	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 were 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)	The 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 remained 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 were 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 of 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 following 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.	The visual stimulus was presented for 300 ms with a pause of 1000 ms between trials. The 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 the 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 were 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 a 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 a 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 was 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 system with a sampling rate of 256 Hz.	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.
[64]	Yu et al. 2020	16 EEG electrodes according to the international 10–20 system	30 minutes with a 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 was 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 and 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-minute recording with a selected 20-second window for each data set.	Participants were asked to sit comfortably in a quiet room and stay awake with their eyes closed.
[67]	Xia et al. 2023	The 10-20 system was used to record the EEG with 19 electrodes	EEG data was recorded for each subject for about 3 minutes.	Recordings were made in a quiet room with subjects sitting comfortably with their eyes closed.
[68]	Puri et al. 2023	19-channel EEG using the international 10-20 system	EEG data for about 10 minutes per subject	Participants were awake with their eyes closed in a resting state asked to avoid any unnecessary movement.
[69]	Mazrooei Rad et al. 2021	The EEG used the international 10-20 system (19 electrodes).	At least 5 minutes of resting-state EEG data was used.	Recordings were performed in a quiet room with subjects instructed to close their eyes and stay relaxed.
[70]	Siuly et al. 2020	The EEG system had 19 electrodes placed according to the international 10-20 system	EEG data of 5 minutes duration was recorded	Subjects were instructed to sit comfortably and close their eyes to avoid eye movements.
[71]	Aslan & Akşahin 2024	The EEG data was recorded from 21 electrodes following the international 10-20 system.	Resting-state EEG data of 3 minutes duration was recorded from each subject.	Participants were in a quiet room with their eyes closed asked to stay awake.
[72]	Khare & Acharya 2023	The EEG data used 19 electrodes following the international 10-20 system.	The duration of the EEG recording is 5 minutes.	Subjects were awake with eyes closed in a comfortable environment.
[73]	Hong Jeong Park Kim et al. 2023	19 electrodes following the international 10–20 system were used in the experiment.	Recordings were typically 10 minutes for each participant.	Participants were awake eyes closed and asked to avoid unnecessary movement.
[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 the 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 were recorded from subjects divided into groups of healthful people and Alzheimer's patients using a Biologic Systems Brain Atlas III Plus laptop labeled according to an international 10–20 system at a 128 Hz sampling rate.
[76]	Alessandrini et al. 2022	Data from 35 hospitalized subjects (20 AD patients and 15 controls) were collected with electrodes placed according to the standard 10–20 system.	Not explicitly mentioned but involves analyzing EEG data for feature extraction.	EEG statistics were recorded using a Galileo BE Plus PRO Portable Light version imparting 37 overall inputs with 22 unipolar and 8 bipolar AC/DC inputs.
[77]	Araújo et al. 2022	19 electrodes positioned on the scalp using the common reference electrode at CPz according to 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 the 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 10–20 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 were seated upright, kept awake in a semi-dark quiet room with electromagnetic shielding, and were told to avoid any movements such as body movements, eye movements, 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 were conducted in three sessions before and after cognitive tests focusing on the middle 2-minute window to avoid edge effects. Subjects were relaxed with eyes closed during the recordings.
[82]	Jennings et al. 2022	The EEG was recorded using a Waveguard cap having 128 sintered Ag/AgCl electrodes placed on a 10-15 positioning system at 1024 Hz.	150 seconds of resting state EEG was 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 was segmented into 2-second windows with a 1-second overlap. Pre-processing and cleaning steps detailed including baseline subtraction, bad channel deletion, artifact removal, and referencing to average.

generally used for preprocessing. Independent Component Analysis is a famous automated method for the detection and removal of eye movement and muscle activity artifacts amongst others of non-brain signals. It places special attention on the Artifact Subspace Reconstruction method as one of the most efficient ways of improving the quality of electroencephalogram data.

3) Effective Sampling Frequency

The studies show a variety of sampling frequencies ranging from 128 Hz to 1024 Hz, although some researchers have reduced this further to 256 Hz for analysis. This balances the need for acquiring fine detailed data while keeping the computational load required in analyzing huge raw data within manageable levels. The chosen sampling frequency affects the resolution of EEG data and the ability to detect subtle changes in brain activity.

4) EEG Epoching

Studies have chosen different ways of segmenting data including by 5-second epochs or longer segments. On the other hand, there are studies that do not mention any information on how they performed epoching. Epoch length and choice of overlapping windows influence the amount of data available for analysis, as well as how fine-grained patterns in brain activity can be investigated.

5) EEG Features

The studies extract features from EEG, such as power spectral density, band power ratios, fractal dimensions, entropy measures, and connectivity metrics, in attempt to describe the complexity of brain activity and AD's effect 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.

E. 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 V.

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. Numerous noise sources exist. Common physiological artifacts include muscle activity, eye movements, magnetic and electrical artifacts as well as 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 the frequency domain of EEG recording helps make ML and DL 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 AD identification.

2) ML/DL Approach

Most of the studies use ML methods, some of which employ 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) 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.

4) Classifier Types

Among the studies, a variety of algorithms that serve the purpose of EEG data classification were encountered. The K-NN classifier, SVM, Decision Trees, CNN, and LSTM RNN 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.

5) Accuracy

The pronounced accuracies inside the research variety are 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 suggests that these EEG models are not robust enough to work poorly when tested with other datasets and diagnostic criteria. These differences in accuracies demonstrate the need for more rigorous experiments and call for better preprocessing techniques, feature

TABLE IV. Summary of EEG Signal Processing Techniques in Alzheimer's Disease Research

Ref.	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	Log normalization, RMS, standard deviation, and root mean square calculations
[46]	Yue Ding et al. 2022	Band-pass filtering (0.1-95 Hz), notch filter (50 Hz), detrended	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, CWT features, complexity measures
[47]	Digambar Puri et al. 2022 (IJECS)	Band-pass filtering (0.1-95 Hz), notch filter (50 Hz), automated preprocessing	Delta: from 0.5 to 4 Hz, Theta: from 4 to 8 Hz, Alpha: from 8 to 13 Hz, Beta: from 13 to 30 Hz	Automated artifact removal using ICA	256 Hz	Not explicitly mentioned	Fractal dimension, Tsallis entropy, Renyi's entropy, Kurtosis
[48]	Digambar Puri et al. 2022 (DASA)	Wavelet packet analysis for sub-band energy and entropy calculation	Delta: 0.5 to 4 Hz, Theta: from 4-8 Hz, Alpha: from 8 to 13 Hz, Beta: from 13 to 30 Hz	Visual inspection by a professional physician	256 Hz	5 seconds epochs from 5 minutes of recording	Standard deviation, mean, kurtosis, minimum, power, maximum
[49]	Digambar Puri et al. 2022 (Wavelet Transform)	Band-pass filtering for alpha: from 8 to 13Hz and beta: from 13 to 32Hz bands	Delta: from 0.5 to 4 Hz, Theta: from 4 to 8 Hz, Alpha: from 8 to 13 Hz, Beta: from 13 to 30 Hz, Gamma: from 30 to 100 Hz)	Visual inspection by a physician	256 Hz	5 seconds (from 5 minutes of EEG data)	Mean, standard deviation, kurtosis, minimum, maximum, energy
[50]	Kai Li et al. 2022	High pass filter at 1 Hz, low pass filter at 30 Hz	Delta: from 1 to 4 Hz, Theta: from 4 to 8 Hz, Alpha: from 8 to 13 Hz, Beta: from 13- to 0 Hz, Gamma: from 30-40 Hz	Visual inspection	256 Hz	-	Absolute differences in power intensity
[51]	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
[52]	Michele Alessandrini et al. 2022	RPCA for preprocessing, standardization, PCA for feature extraction	Not specified	RPCA for artifact and outlier removal	128 Hz	Split into fixed size windows	Channel-level, source-level power spectra, functional brain networks
[53]	Caroline L Alves et al. 2022	-	Not specified	Not specified	128 Hz	Not specified	Matrices of connections using Granger causality, Pearson's and Spearman's correlations
[54]	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 with architectures: EEGNet, DeepConvNet, EEGNet SSVEP, VAE
[55]	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)
[56]	Saman Fouladi et al. 2022	Band-pass filtered (0.5-32 Hz), CWT with Mexican hat function	Not explicitly mentioned	Manual removal of small and big artifacts	256 Hz	2-second epochs without overlap	TFR using CWT for feature extraction, DL models (CNN and Conv-AE)
[57]	Cameron Jj Huggins et al. 2021	Band-pass FIR filter (1-60 Hz), ICA, notch filters at 21 and 42 Hz	Not explicitly mentioned	ICA for noise and artifact removal	200 Hz	5 seconds epochs	Time-frequency maps using CWT with Morse mother wavelet, converted into RGB images for DL
[58]	Wei Xia et al. 2023	Band-pass filtered (0.5-48 Hz), downsampled to 256 Hz, ICA	Not explicitly mentioned	Noise and artifact removal	Not specified	Segmented into epochs	Statistical nonlinear entropy features, sub-bands obtained through AFAWT
[59]	Hong Jeong Park Kim et al. 2023	Noise reduction, ICA, Fourier transform, sLORETA for source-level signals	Delta (1–4 Hz) to Gamma (30–45 Hz)	ICA for periodic noise removal, bad epoch rejection	Not specified	Eyes closed and relaxed	Channel-level and source-level power spectra, functional brain networks
[60]	Alves et al. 2022	EEG signals collected, correlation between electrodes calculated	Not explicitly mentioned	Noise and artifact removal	128 Hz for AD dataset, 128 Hz for SZ dataset	Not specified	Matrices of connections built using Granger causality, Pearson's and Spearman's correlations
[61]	Göker 2023	Multitaper method for PSD calculation (1-49 Hz)	1-49 Hz	ASR for artifact removal	128 Hz	Segmentation into epochs	49 features from PSD (1-49 Hz)
[62]	Alessandrini et al. 2022	RPCA for preprocessing, standardization, PCA for feature extraction	Not specified	RPCA for artifact and outlier removal	Not specified	Segmentation into epochs	Statistical nonlinear entropy features, sub-bands through RPCA and PCA
[63]	Araújo et al. 2022	Noise removal, Wavelet Packet Decomposition for nonlinear multi-band analysis	1-49 Hz	ASR for artifact removal	256 Hz	5-second segments	Classic ML and DL techniques for information type extraction
[64]	Miltiadous et al. 2021	Noise removal, down-sampling (500 Hz to 250 Hz), Butterworth band-pass filter (0.5-48 Hz)	0.5-48 Hz	Automatically marked and removed for blinking, swallowing, muscle activity	250 Hz	5-second epochs with 2.5-second intervals	Time and frequency domain metrics: mean, variance, IQR, energy
[65]	Pirrone et al. 2022	Normalize to 256 Hz, filter at 1 Hz (low-cut) and 30 Hz (high-cut)	1-30 Hz	Visual inspection for artifact rejection	256 Hz	150 seconds of clean EEG from central part	Average path length, local efficiency, network entropy
[66]	Duan et al. 2020	Band-pass FIR filter (0.5-250 Hz), online digital bandpass filtering (0.5-30 Hz)	Delta: from 0.1 to 4 Hz, Theta: from 4 to 8 Hz, Alpha: from 8 to 13 Hz, Beta: from 13 to 30 Hz	ASR for artifact removal	200 Hz (MCI dataset), 128 Hz (mild AD dataset)	20 seconds from 5 min recording (eyes closed)	Functional connectivity (FC) metrics: clustering coefficient, node strength, path length, betweenness centrality
[67]	Xia et al. 2023	Band-pass filtered (0.5-48 Hz), downsampled to 256 Hz, ICA	0.5-48 Hz	ICA for optoelectric and electromyographic artifact removal	256 Hz	Segmented using overlapping sliding windows	Fourier coefficients (frequency domain), 16 coefficients per channel
[68]	Puri et al. 2023	EEG signals divided into 5 subscales using DWT, VMD for further decomposition	Delta: from 0.5 to 4 Hz, Theta: from 4 to 8 Hz, Alpha: 8 to 16 Hz, Beta: from 16 to 32 Hz, Gamma: from 32 to 48 Hz	ASR for artifact removal	128 Hz	Not specified	Multi-permutation entropy (PE): Shannon PE, Tsalli's PE, Renyi PE
[69]	Mazrooei Rad et al. 2021	Band-pass FIR filter (0.5-30 Hz), ICA for artifact removal	0.5-30 Hz	ICA for noise and artifact removal	500 Hz (downsampled to 250 Hz)	Not specified	Statistical entropy measures, fractal dimension, Higuchi's fractal dimension
[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), Autoregressive (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 were 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: from 1 to 4 Hz, Gamma: from 30 to 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 that encompass the functional connectivity between brain regions.	Not explicitly mentioned	Not detailed but preprocessing includes noise and artifact removal.	128 Hz for the AD dataset; 128 Hz for the SZ dataset over 1 min	Not specified explicitly but matrices of connections derived from EEG time series	Matrices of connections are 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 remove outliers and artifacts standardization of signals (mean=zero, 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.	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 are used for information type in keeping with the EEG channel extracting various features from every examined group
[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, and 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, and 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; Dominant frequency (DF) and its variance (DFV) across 5 cortical areas (F, C, T, P, O)

selection algorithms, and classifier optimization to improve the diagnostic potential of EEG in Alzheimer's Disease.

F. *Reported Limitations and Recommendations*

1) *Reported Limitations*

The reported constraints throughout the evaluated articles generally emphasize concerns relating to data dimension, the generalizability of searches, and the specifics of information evaluation. A usual style is the restricted dimension of datasets used in the research which increases concerns concerning the durability coupled with the generalizability of the outcomes. Such restraints are considered 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 indicates 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 searching for are not artifacts of the evaluation procedure yet are genuinely a measure of hidden neurophysiological patterns. Furthermore, particular researchers 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 of 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 that 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 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 VI offers the above-stated restrictions.

2) *Reported Recommendations*

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

1) Combination of Multi-modal Data Sources: Many researchers advise including hereditary, imaging along with various other pen information together with EEG signals to supply an extra extensive sight of the 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 searching for as well as making certain versions 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 boosting the precision as well as interpretability of analysis designs.
5) Expedition of Advanced EEG Analysis Methods: Suggestions consist of discovering deep-knowing approaches, and 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 medical background, cognitive analysis ratings, and also group information, might improve EEG evaluations. This extra context might assist 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

TABLE V. Classification Performance Metrics in Alzheimer's Disease EEG Studies

#	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 the 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, EEG-Net	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 97.2% and for AD+MCI vs. HC it turned to 96.2%
[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)

TABLE VI. Reported Limitations in EEG-Based Alzheimer's Disease Research

#	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 the 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 the 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 observation was carried out on uncooked EEG statistics without 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.

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 researchers recommend the advancement of real-time analysis systems as well as their application on ingrained gadgets. This might settle the reduced expense, and 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.

4. CONCLUSION

The systematic review of the intelligent strategies for the diagnosis of AD from EEG signals is one big step forward in exploiting advances in neuroimaging and computational algorithms in surmounting the AD challenge for timely diagnosis. The integrated analysis across 38 articles highlighted the potential of ML and DL approaches combined with EEG data for enhancing the diagnostic ability toward gaining insights into the neurophysiological underpinnings of this disease. It has pointed out some of the major milestones in this area regarding the development of sophisticated CAD systems, which effectively put EEG signals into practical applications for the early, accurate, and automated recognition of AD. These efforts actually show the power of EEG as a very useful marker for AD through improvements of techniques for signal processing and the application of sophisticated analytical frameworks. It reviewed a diverse range of preprocessing methods, effective ML/DL techniques, varying validation methods, and reported accuracies, thus painting a broad picture of how these approaches could aid diagnostics. Contrasted with these steps forward in the field are many more limitations and challenges within the context of the modern research environment that remain to be overcome, such as the need for larger and more heterogeneous datasets in order to achieve greater generalizability of results, the integration of multi-modal data sources for deeper investigation, and the exploration of sophisticated EEG analysis methodologies and deep learning algorithms in approaches toward Alzheimer's disease detection. Recommendations extracted from the reviewed articles that may be used to guide further investigations recommend an increase in dataset size and diversity, providing new avenues for integrating genetic, imaging, and clinical data alongside EEG signals. Exploring innovative ML/DL techniques would help overcome the current challenges and open new avenues for research toward more robust, accurate, and early diagnostic capabilities.

A. *Summary of Contributions*

The presented study evaluates the efficacy of EEG-based diagnostic methods against traditional neuroimaging techniques in AD. The contributions that are made include:

1) Evaluation of EEG-Based Diagnostic Methods: Demonstrates the potential of EEG as a non-invasive, cost-effective, and accessible tool for detecting neurophysiological markers indicative of AD, emphasizing its promise for early-stage diagnosis.
2) Identification of Promising Algorithms: Identifies and evaluates various ML and DL algorithms applied to EEG data, highlighting specific algorithms with high accuracy in distinguishing between healthy and AD cases.
3) Challenges and Limitations: critically review the existing limitations of EEG-based diagnostics, including signal reliability problems, environmental disturbances, and the need for larger and more varied datasets that provide insight into what further work is required.
4) Higher Diagnosis Likelihood: This indicates the integration potential of EEG analysis with ML and DL techniques that may result in diagnosis accuracy and reliability improvements and a trend toward fully automated, unbiased diagnostic procedures to enhance clinical decision-making.
5) Full Overview: This gives a full overview of the current trends in EEG-based diagnosis of AD, comprising recent studies, methodologies, and technology advances, thus providing a useful resource for researchers and clinicians.

1) *Critical Evaluation*

In particular, the findings of this review evidence impressive progress in the application of ML and DL techniques in EEG-based AD diagnosis. Advantages of these techniques include processing and analysis of large amounts of EEG data, complex pattern identification that would otherwise not be visible by simple analysis, and the boosting of accuracy in early AD detection. However, some limitations lie in the extended and diversified datasets that are required to have generalizable and robust models. Multi-modal data integration is also indispensable for a comprehensive diagnosis, yet it remains challenging because of the complexity involved in handling heterogeneous data types. Besides, ML and DL models are computationally resource-intensive and intellectually demanding, and accessibility and implementation may be limited by demands for these resources. The probability of overfitting and the requirement for advanced feature selection and optimization techniques raise several challenges.

2) *Practical Implications*

The practical implications of these findings for clinicians and researchers. Modern ML and DL techniques on the EEG-based AD diagnosis will further develop more accurate and early diagnostic tools in clinical application. This

TABLE VII. Reported Recommendations in EEG-Based Alzheimer's Disease Research

#	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. The use of deep learning techniques could enhance diagnostic performance.
[46]	Yue Ding et al. 2022	Suggest 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 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	Further research will involve model validation with larger and more heterogeneous datasets to enhance predictive accuracy and reliability. Moreover, the applicability of the technique to other types of dementia beyond Alzheimer's disease is also proposed.
[63]	Tawhid et al. 2023	Future studies should therefore target the validation of findings using larger, more heterogeneous datasets. The role of education, age, and gender should be investigated in the context of MCI detection using EEG, together with other machine learning models or frequency bands for further insight.
[64]	Yu et al. 2020	FutSubsequent investigations should prioritize the enhancement of function selection to improve both model accuracy and interpretability. Furthermore, it is advisable to conduct analogous validations of the proposed model utilizing diverse and extensive patient datasets to reinforce the generalizability of the findings.
[65]	You et al. 2020	Extend the framework to other neurologic diseases and optimize EEG data collection for HC.
[66]	Duan et al. 2020	In the future, more data should be collected from patients with MCI and mild AD patients with these same instruments to get a better analysis done. Further research is needed regarding the similarities of the datasets obtained from MCI and mild AD data.
[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 also attempt to extend this dual decomposition technique for diagnosis in other neurodegenerative disorders, such as epilepsy, various sleep disorders, Parkinson's disease, and major depressive disorders. Deep learning models on the EEG datasets could be implemented to enhance the accuracy of diagnosis.
[69]	Mazrooei Rad et al. 2021	Future work shall be focused on increasing generalizability, using a wide range of EEG datasets, other neural network architectures, and combination models with other kinds of biomarkers for more accurate diagnosis of AD.
[70]	Siuly et al. 2020	Generalize the applicability of the approach by adjusting the methodology to accommodate larger datasets and assessing its efficiency in multi-class scenarios, differentiating between patients with mild cognitive impairment, healthy controls, and advertisement subjects.
[71]	Aslan & Akşahin 2024	It suggests that future studies could further be oriented to fine-tune the methodology of feature selection in a way to reduce computational cost and increase model accuracy. Moreover, it is suggested that further studies include deep learning methods and an expansion of the dataset.
[72]	Khare & Acharya 2023	Further studies could provide further validation for the proposed model with larger, more diverse datasets. The flexibility and transparency of the model reveal promising ways to optimize the automatic detection of Alzheimer's disease while delivering comprehensible machine-learning forecasts for use in the clinic.
[73]	Hong Jeong Park Kim et al. 2023	This study opens up the potential of combining various features of EEG to yield enhanced performance in the diagnosis of neurodegenerative disorders and could be of great benefit for deep learning and machine learning techniques. Additional clinical data requires further investigation, and the challenge of outliers should be faced during the analysis of EEG data.
[74]	Alves et al. 2022	The paper claims that the procedure is 'general' and can be implemented by most brain disorders with existing EEG records. Rather, it encourages more studies with bigger datasets and other clinical information to improve diagnosis.
[75]	Göker 2023	Further development of the model to include more diverse and larger datasets to be generalized with other biomedical signals for early disease diagnostic.
[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.

can be of great assistance, especially to the clinicians who will be better placed to determine sensitive data, thus facilitating early intervention that is precise. These findings open up new avenues for researchers toward the further discovery of neurophysiological markers of AD and the development of more optimal diagnostic algorithms. Most important for translation into clinical practice are augmenting data collection with tools that are user-friendly in a clinical space and technologies that function harmoniously with current clinical workflows. Collaboration among researchers, clinicians, and institutions is essential for the standardization of EEG data collection and analysis protocols, thereby improving the reproducibility and comparability of studies conducted in various contexts.

3) Future Research Directions

To advance the field of EEG-based AD diagnosis, future research should focus on:

1) Future studies shall focus on acquisition and usage of large, heterogeneous datasets having wide demographic and clinical variabilities. This will increase the generalizability for machine learning and deep learning models and ensure results that relate to more heterogeneous populations. Specific efforts should be developed to integrate data coming from very different sources, such as very diverse geographical regions or even stages of AD, into those data sets for the construction of robust diagnostic algorithms.
2) Multi-Modal Data Integration: Combining EEG data with other neuroimaging techniques and clinical information, such as MRI and PET scans, genetic data, among others, can provide detailed diagnostic accuracy and an in-depth view of AD progression. The integration of data from different modalities should provide a holistic view that allows for better prediction and classification into stages of AD. Some strategies employed towards effective multimodal integration include the development of frameworks that can handle heterogeneous data types and using advanced fusion techniques to combine seamlessly information arising from different sources.
3) Advanced Preprocessing Techniques: Developing advanced preprocessing techniques to improve EEG signal quality, including methods to minimize noise and artifacts, standardize data collection procedures, and enhance signal reliability.
4) Innovative Classification Methods: Further investigate and create more innovative methods for classification using ML and DL, such as CNNs, RNNs, and VAEs, to fine-tune and prove their performance in the diagnosis of AD.
5) Developing a real-time monitoring and early detection system for AD using portable, user-friendly EEG devices integrated with robust ML algorithms that enable the continuous monitoring of individual cohorts in such conditions.
6) Personalized Diagnosis and Treatment: Aiming for personalized approaches for AD diagnosis and treatment, tailoring diagnostic models to individual patient profiles to improve the precision and effectiveness of interventions.
7) Collaboration between researchers, clinicians, and institutions in the standardization of protocols for EEG data collection and analysis to improve reproducibility and comparability across studies in different settings.
8) Ethical and Privacy Considerations: Making provisions for ethical and privacy concerns associated with the use of EEG data and ML algorithms in any clinical set-up. Patient data confidentiality, informed consent, and the creation of an ethical framework in the use of AI in healthcare are a necessity. Prospects and potential risks arising from automated diagnostic processes should be urgently and closely assessed so as to ensure patient rights and trust are protected.

Although the systematic review covers a wide range of research, it is intrinsically limited by both the quality and overall scope of the literature included. Important limitations include the potential for publication bias, as the review relies on published studies that may not fully capture the scope of all research done in this field. Additionally, the heterogeneity across included studies—ranging in terms of methodologies, sample sizes, and populations—has made it challenging to reach generalizable conclusions. Moreover, the inclusion criteria, even if necessary for the parameters of this review, might have missed relevant studies published in languages other than English or which fell outside of the chosen time frame.

This review encapsulates the current state of the field of EEG-based AD diagnosis, both in its promising achievements and in the difficulties ahead. By addressing the identified limitations and embracing the proposed directions for future studies, the field may significantly advance. As such, EEG with advanced computational models may have the potential to transform AD diagnosis, enabling timely interventions and improving outcomes for sufferers of this debilitating condition.

References

[1] T. et al., “ nih public access,” *Bone*, vol. 23, no. 1, pp. 1–7, 2008.

[2] S. KC and W. Lutz, “The human core of the shared socioeconomic pathways: Population scenarios by age sex and level of education for all countries to 2100,” *Global Environmental Change*, vol. 42, pp. 181–192, 2017.

[3] M. R. Bronzuoli, A. Iacomino, L. Steardo, and C. Scuderi, “Targeting neuroinflammation in alzheimer’s disease,” *Journal of Inflammation Research*, vol. 9, pp. 199–208, 2016.

[4] L. Blaikie, G. Kay, and P. K. T. Lin, “Current and emerging therapeutic targets of alzheimer’s disease for the design of multi-target directed ligands,” *Medchemcomm*, vol. 10, no. 12, pp. 2052–2072, 2019.

[5] S. M. A. et al., "Development of clinical pathway for mild cognitive impairment and dementia to quantify cost of age-related cognitive disorders in malaysia," *Malaysian Journal of Public Health Medicine*, vol. 14, no. 3, pp. 88–96, 2014.

[6] A. D. Meco and R. Vassar, "Early detection and personalized medicine: Future strategies against alzheimer's disease," *Progress in Molecular Biology and Translational Science*, vol. 177, pp. 1–20, 2021.

[7] T. Rittman, "Neurological update: neuroimaging in dementia," *Journal of Neurology*, vol. 267, no. 11, pp. 3429–3435, 2020.

[8] C. E. F. et al., "Determining the impact of psychosis on rates of false-positive and false-negative diagnosis in alzheimer's disease," *Alzheimer's Dementia Translational Research Clinical Interventions*, vol. 3, no. 3, pp. 385–392, 2017.

[9] M. F. et al., "Efns task force: The use of neuroimaging in the diagnosis of dementia," *European Journal of Neurology*, vol. 19, no. 12, pp. 1487–1501, 2012.

[10] A. A. A. Alberdi and A. Basarab, "On the early diagnosis of alzheimer's disease from multimodal signals: A survey," *Artificial Intelligence in Medicine*, vol. 71, pp. 1–29, 2016.

[11] M. A. L.-g. E. Perez-valero, C. Morillas and J. Minguillon, "Supporting the detection of early alzheimer's disease with a four-channel eeg analysis," *Journal of Biomedical Research*, vol. 33, no. 4, pp. 1–17, 2023.

[12] Y. S. et al., "Electroencephalography for early detection of alzheimer's disease in subjective cognitive decline," *Dementia and Neurocognitive Disorders*, vol. 21, no. 4, p. 126, 2022.

[13] M. S. Safi and S. M. M. Safi, "Early detection of alzheimer's disease from eeg signals using hjorth parameters," *Biomedical Signal Processing and Control*, vol. 65, p. 102338, 2021.

[14] N. S. Amer and S. B. Belhaouari, "Exploring new horizons in neuroscience disease detection through innovative visual signal analysis," *Scientific Reports*, vol. 14, no. 1, pp. 1–14, 2024.

[15] M. A. A. M. A. K. AlSharabi, Y. Bin Salamah and F. A. Alturki, "Eeg-based clinical decision support system for alzheimer's disorders diagnosis using emd and deep learning techniques," *Frontiers in Human Neuroscience*, vol. 17, 2023.

[16] M. S. et al., "The standardized eeg electrode array of the ifcn," *Clinical Neurophysiology*, vol. 128, no. 10, pp. 2070–2077, 2017.

[17] L. Z. et al., "The influence of different eeg references on scalp eeg functional network analysis during hand movement tasks," *Frontiers in Human Neuroscience*, vol. 14, pp. 1–10, 2020.

[18] M. X. Cohen, *Analyzing Neural Time Series Data*, 2019.

[19] S. L. M. A. Ebrahimighahnavieh and R. Chiong, "Deep learning to detect alzheimer's disease from neuroimaging: A systematic literature review," *Computer Methods and Programs in Biomedicine*, vol. 187, p. 105242, 2020.

[20] K. V. S. J. S. B. A. Bhandarkar, P. Naik and S. Pattar, "Deep learning based computer aided diagnosis of alzheimer's disease: a snapshot of last 5 years, gaps, and future directions," *Artificial Intelligence Review*, vol. 57, no. 2, 2024.

[21] R. B. et al., "Machine learning analysis of digital clock drawing test performance for differential classification of mild cognitive impairment subtypes versus alzheimer's disease," *Journal of the International Neuropsychological Society*, vol. 26, no. 7, pp. 690–700, 2020.

[22] R. J. Martin, "Eeg signal processing: A machine learning based framework," 2022.

[23] W. Y. et al., "Comparative analysis of machine learning algorithms for alzheimer's disease classification using eeg signals and genetic information," *Computerized Medical Imaging and Graphics*, vol. 176, p. 108621, 2024.

[24] A. H. A.-N. et al., "Robust eeg-based biomarkers to detect alzheimer's disease," *Brain Sciences*, vol. 11, no. 8, pp. 1–31, 2021.

[25] N. K. A. qazzaz et al., "Role of eeg as biomarker in the early detection and classification of dementia," *Scientific World Journal*, vol. 2014, pp. 1–17, 2014.

[26] D. R. A. A. Valliani and E. K. Oermann, "Deep learning and neurology: A systematic review," *Neurology and Therapy*, vol. 8, no. 2, pp. 351–365, 2019.

[27] L. C. G. Pang, C. Shen and A. V. D. Hengel, "Deep learning for anomaly detection: A review," *ACM Computing Surveys*, vol. 54, no. 2, pp. 1–36, 2021.

[28] K. N. T. Jo and A. J. Saykin, "Deep learning in alzheimer's disease: Diagnostic classification and prognostic prediction using neuroimaging data," *Frontiers in Aging Neuroscience*, vol. 11, 2019.

[29] Y. W. N. Wang and M. J. Er, "Review on deep learning techniques for marine object recognition: Architectures and algorithms," *Control Engineering Practice*, vol. 118, p. 104458, 2022.

[30] M. M. A. M. L. Francies and M. A. Mohamed, "A robust multiclass 3d object recognition based on modern yolo deep learning algorithms," *Concurrency and Computation: Practice and Experience*, vol. 34, no. 1, pp. 1–24, 2022.

[31] J. I. K. et al., "Effshuffnet: An efficient neural architecture for adopting a multi-model," *Applied Sciences*, vol. 13, no. 6, 2023.

[32] S. T. X. Z. Q. Zhao, P. Zheng and X. Wu, "Object detection with deep learning: A review," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 11, pp. 3212–3232, 2019.

[33] A. A. N. K. M. A. S. S. A. Zaidi, M. S. Ansari and B. Lee, "A survey of modern deep learning based object detection models," *Digital Signal Processing: A Review Journal*, vol. 126, pp. 1–18, 2022.

[34] H. O. J. Kang, S. Tariq and S. S. Woo, "A survey of deep learning-based object detection methods and datasets for overhead imagery," *IEEE Access*, vol. 10, pp. 20 118–20 134, 2022.

[35] Q. Y. H. L. P. Chu, J. Wang and Z. Liu, "Transmot: Spatial-temporal graph transformer for multiple object tracking," in *Proceedings of the 2023 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 2023, pp. 4859–4869.

[36] K. Q. Z. T. K. Y. Y. W. Hsu, Y. H. Lai and J. W. Perng, "Developing an on-road object detection system using monovision and radar fusion," *Energies*, vol. 13, no. 1, 2019.

[37] V. M. B. L. Vaquero and M. Mucientes, “Tracking more than 100 arbitrary objects at 25 fps through deep learning,” *Pattern Recognition*, vol. 121, p. 108205, 2022.

[38] H. Taherdoost, “Deep learning and neural networks: Decision-making implications,” *Symmetry (Basel)*, vol. 15, no. 9, 2023.

[39] R. D. D. L. A. Kompanets, G. Pai and B. Snijder, “Deep learning for segmentation of cracks in high-resolution images of steel bridges,” 2024, [Online]. Available: http://arxiv.org/abs/2403.17725.

[40] S. H. et al., “Computer-vision benchmark segment-anything model (sam) in medical images: Accuracy in 12 datasets,” no. 6, pp. 7–10, 2023, [Online]. Available: http://example.com.

[41] S. Hourri and J. Kharroubi, “A deep learning approach for speaker recognition,” *Int. J. Speech Technol.*, vol. 23, no. 1, pp. 123–131, 2020.

[42] L. E. B. A. M. Pineda, F. M. Ramos and A. S. L. O. Campanharo, “Quantile graphs for eeg-based diagnosis of alzheimer’s disease,” *PLoS One*, vol. 15, no. 6, pp. 1–15, 2020.

[43] J. T. D. Moher, A. Liberati and D. G. Altman, “Preferred reporting items for systematic reviews and meta-analyses: the prisma statement,” *J. Clin. Epidemiol.*, vol. 62, no. 10, pp. 1006–1012, 2009.

[44] N. S. N. S. Hourri and J. Kharroubi, “Convolutional neural network vectors for speaker recognition,” *Int. J. Speech Technol.*, vol. 24, no. 2, pp. 389–400, 2021.

[45] A. M. A. M. A. K. Alsharabi, Y. Bin Salamah and F. A. Alturki, “Eeg signal processing for alzheimer’s disorders using discrete wavelet transform and machine learning approaches,” *IEEE Access*, vol. 10, pp. 89 781–89 797, 2022.

[46] Y. D. et al., “Fully automated discrimination of alzheimer’s disease using resting-state electroencephalography signals,” *Quant. Imaging Med. Surg.*, vol. 12, no. 2, pp. 1063–1078, 2022.

[47] A. N. D. Puri, S. Nalbalwar and A. Wagh, “Alzheimer’s disease detection from optimal electroencephalogram channels and tunable q-wavelet transform,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 3, pp. 1420–1428, 2022.

[48] A. N. P. K. J. R. D. Puri, S. Nalbalwar and A. Wagh, “Alzheimer’s disease detection using empirical mode decomposition and hjorth parameters of eeg signal,” in *2022 Int. Conf. Decis. Aid Sci. Appl. (DASA)*, 2022, pp. 23–28.

[49] A. N. D. Puri, S. Nalbalwar and A. Wagh, “Alzheimer’s disease detection with optimal eeg channel selection using wavelet transform,” in *2022 Int. Conf. Decis. Aid Sci. Appl. (DASA)*, 2022, pp. 443–448.

[50] K. L. et al., “Feature extraction and identification of alzheimer’s disease based on latent factor of multi-channel eeg,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 1557–1567, 2021.

[51] P. D. P. S. D. S. D. Pirrone, E. Weitschek and M. C. D. Cola, “Eeg signal processing and supervised machine learning to early diagnose alzheimer’s disease,” *Appl. Sci.*, vol. 12, no. 11, 2022.

[52] Z. S. C. L. H. Yu, X. Lei and J. Wang, “Supervised network-based fuzzy learning of eeg signals for alzheimer’s disease identification,” *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 1, pp. 60–71, 2020.

[53] P. C. L. F. S. L. M. Alessandrini, G. Biagetti and C. Turchetti, “Eeg-based alzheimer’s disease recognition using robust-pca and lstm recurrent neural network,” *Sensors*, vol. 22, no. 10, pp. 1–18, 2022.

[54] K. R. C. T. C. L. Alves, A. M. Pineda and F. A. Rodrigues, “Eeg functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer’s disease and schizophrenia,” *J. Phys. Complex.*, vol. 3, no. 2, 2022.

[55] R. M. D. Komolovaitė and R. Damaševičius, “Deep convolutional neural network-based visual stimuli classification using electroencephalography signals of healthy and alzheimer’s disease subjects,” *Life*, vol. 12, no. 3, 2022.

[56] A. R. M. M. Amini, M. M. Pedram and M. Ouchani, “Diagnosis of alzheimer’s disease by time-dependent power spectrum descriptors and convolutional neural network using eeg signal,” *Comput. Math. Methods Med.*, vol. 2021, 2021.

[57] N. M. F. G. S. Fouladi, A. A. Safaei and M. J. Ebadi, “Efficient deep neural networks for classification of alzheimer’s disease and mild cognitive impairment from scalp eeg recordings,” *Cognit. Comput.*, vol. 14, no. 4, pp. 1247–1268, 2022.

[58] C. J. H. et al., “Deep learning of resting-state electroencephalogram signals for three-class classification of alzheimer’s disease mild cognitive impairment and healthy ageing,” *J. Neural Eng.*, vol. 18, no. 4, 2021.

[59] X. Z. W. Xia, R. Zhang and M. Usman, “A novel method for diagnosing alzheimer’s disease using deep pyramid cnn based on eeg signals,” *Heliyon*, vol. 9, no. 4, p. e14858, 2023.

[60] S. A. S.-Z. et al., “An approach toward artificial intelligence alzheimer’s disease diagnosis using brain signals,” *Diagnostics*, vol. 13, no. 3, pp. 1–15, 2023.

[61] Y. Hong, U. Park, D. Kim, H. Kim, and E. Kim, “Identifying alzheimer’s disease dementia through ensemble learning of channel and source level electroencephalogram features,” pp. 1–20, 2023.

[62] Y. Chen, H. Wang, D. Zhang, L. Zhang, and L. Tao, “Multi-feature fusion learning for alzheimer’s disease prediction using eeg signals in resting state,” *Frontiers in Neuroscience*, vol. 17, 2023.

[63] M. N. A. Tawhid, S. Siuly, E. Kabir, and Y. Li, “Exploring frequency band-based biomarkers of eeg signals for mild cognitive impairment detection,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 32, no. Xx, pp. 189–199, 2024.

[64] H. Y. et al., “Identification of alzheimer’s eeg with a wvg network-based fuzzy learning approach,” *Frontiers in Neuroscience*, vol. 14, no. July, pp. 1–15, 2020.

[65] Z. Y. et al., “Alzheimer’s disease classification with a cascade neural network,” *Frontiers in Public Health*, vol. 8, no. November, pp. 1–11, 2020.

[66] F. D. et al., “Topological network analysis of early alzheimer’s disease based on resting-state eeg,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 10, pp. 2164–2172, 2020.

[67] K. Alsharabi, Y. B. Salamah, A. M. Abdurraqeeb, M. Aljalal, and F. Alturki, “Eeg signal processing for alzheimer’s disorders using discrete wavelet,” *IEEE Access*, vol. PP, p. 1, 2022.

[68] D. Puri, S. Nalbalwar, A. Nandgaonkar, J. Rajput, and A. Wagh, "Identification of alzheimer's disease using novel dual decomposition technique and machine learning algorithms from eeg signals," *International Journal of Advanced Science, Engineering and Information Technology*, vol. 13, no. 2, pp. 658–665, 2023.

[69] E. M. Rad, M. Azarnoosh, M. Ghoshuni, and M. M. Khalilzadeh, "Diagnosis of mild alzheimer's disease by eeg and erp signals using linear and nonlinear classifiers," *Biomedical Signal Processing and Control*, vol. 70, no. August, p. 103049, 2021.

[70] S. S. et al., "A new framework for automatic detection of patients with mild cognitive impairment using resting-state eeg signals," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 9, pp. 1966–1976, 2020.

[71] U. Aslan, "Detection of alzheimer and mild cognitive impairment patients by poincare and entropy methods based on electroencephalography signals," pp. 0–22, 2024.

[72] S. K. Khare and U. R. Acharya, "Adazd-net: Automated adaptive and explainable alzheimer's disease detection system using eeg signals," *Knowledge-Based Systems*, vol. 278, p. 110858, 2023.

[73] S. M. Elgandelwar, V. Bairagi, S. S. Vasekar, and A. Nanthaamornphong, "Analyzing electroencephalograph signals for early alzheimer's disease detection: deep learning vs. traditional machine learning approaches," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 3, pp. 2602–2615, 2024.

[74] S. Dash, "Alzheimer detection based on optimized machine learning for eeg signals," *2024 3rd International Conference on Innovative Technology*, pp. 1–5, 2024.

[75] H. Göker, "Detection of alzheimer's disease from electroencephalography (eeg) signals using multitaper and ensemble learning methods," *Uludağ University Journal of The Faculty of Engineering*, vol. 28, no. 1, pp. 141–152, 2023.

[76] B. S. Processing and M. Imani, "Alzheimer's diseases diagnosis using fusion of high informative bilstm and cnn features of eeg signal," *Biomedical Signal Processing and Control*, vol. no. August, pp. 16–17, 2023.

[77] T. Araújo, J. P. Teixeira, and P. M. Rodrigues, "Smart-data-driven system for alzheimer disease detection through electroencephalographic signals," *Bioengineering*, vol. 9, no. 4, pp. 1–16, 2022.

[78] A. M. et al., "Alzheimer's disease and frontotemporal dementia: A robust classification method of eeg signals and a comparison of validation methods," *Diagnostics*, vol. 11, no. 8, 2021.

[79] M. G. Alsubaie, S. Luo, and K. Shaukat, "Alzheimer's disease detection using deep learning on neuroimaging: A systematic review," pp. 464–505, 2024.

[80] R. W. et al., "A novel framework of mopso-gdm in recognition of alzheimer's eeg-based functional network," *Frontiers in Aging Neuroscience*, vol. 15, 2023.

[81] E. Perez-Valero, C. Morillas, M. A. Lopez-Gordo, I. Carrera-Muñoz, S. López-Alcalde, and R. M. Vílchez-Carrillo, "An automated approach for the detection of alzheimer's disease from resting state electroencephalography," *Frontiers in Neuroinformatics*, vol. 16, no. July, pp. 1–10, 2022.

[82] J. L. Jennings, L. R. Peraza, M. Baker, K. Alter, J. P. Taylor, and R. Bauer, "Investigating the power of eyes open resting state eeg for assisting in dementia diagnosis," *Alzheimer's Research and Therapy*, vol. 14, no. 1, pp. 1–12, 2022.