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Review

Machine and Deep Learning Trends in EEG-Based Detection and Diagnosis of Alzheimer's Disease: A Systematic Review

Marcos Aviles *, Luz María Sánchez-Reyes , José Manuel Álvarez-Alvarado and Juvenal Rodríguez-Reséndiz *

Facultad de Ingeniería, Universidad Autónoma de Querétaro, Querétaro 76240, Mexico; luzmsr@ieee.org (L.M.S.-R.); jmalvarez@uaq.mx (J.M.Á.-A.)
* Correspondence: marcosaviles@ieee.org (M.A.); juvenal@uaq.edu.mx (J.R.-R.)

Abstract: This article presents a systematic review using PRISMA methodology to explore trends in the use of machine and deep learning in diagnosing and detecting Alzheimer's disease using electroencephalography. This review covers studies published between 2013 and 2023, drawing on three leading academic databases: Scopus, Web of Science, and PubMed. The validity of the databases is evaluated considering essential factors such as the arrangement of EEG electrodes, data acquisition methodologies, and the number of participants. Additionally, the specific properties of the databases used in the research are highlighted, including EEG signal classification, filtering, segmentation approaches, and selected features. Finally, the performance metrics of the classification algorithms are evaluated, especially the accuracy achieved, offering a comprehensive view of the current state and future trends in the use of these technologies for the diagnosis of Alzheimer's disease.

Keywords: deep learning; diagnosis of Alzheimer's disease; EEG; machine learning; systematic review

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1. Introduction

Alzheimer's disease (AD) is a neurodegenerative pathology that progresses over time and mainly affects older people. Its symptoms vary among those affected but include memory loss, confusion, and extensive cognitive impairment [1,2]. Early identification and accurate diagnosis are essential to provide appropriate medical care and improve the quality of life of patients [3,4]. With technological progress in capturing brain signals, such as the electroencephalogram (EEG), more accurate and effective diagnostic methods have been developed. Due to its non-invasive nature, the EEG records the brain's electrical activity through electrodes on the scalp, offering valuable insights into brain alterations linked to Alzheimer's disease [5–7].

Machine learning (ML) and deep learning (DL) techniques for classifying EEG signals have been established as an expanding area of research. These methods allow the analysis of large volumes of EEG data to identify non-obvious patterns, potentially facilitating the early diagnosis of AD [8,9]. However, the effective implementation of these techniques needs to be improved. Critical factors such as the appropriate choice of EEG databases, a correct arrangement of the electrodes, the selection of an appropriate number of participants, the identification of relevant features for the analysis, the choice of appropriate classification algorithms, and a rigorous evaluation of its performance is decisive in the quality and reliability of the results obtained [10].

This work aims to carry out a systematic review of current trends in the use of ML and DL to detect and diagnose AD through the use of EEG. Fundamental aspects such as preparation prior to data collection is addressed, including the selection of the EEG database, the electrode placement strategy, data acquisition methodologies, and the selection of the number of volunteers. A detailed analysis of ML and DL methods will be carried out, including everything from filtering and segmentation techniques to feature selection. The evaluation metrics used to determine the effectiveness of the classification algorithms are also reviewed. This article offers a comprehensive overview of the advances and methodologies in applying ML and DL in EEG analysis to diagnose and detect AD early.

The main contributions of the work are:

- Artificial intelligence is a booming branch that offers an alternative to understanding diseases. However, it is susceptible to the input data and its processing. This work analyzes these critical points described in the state of the art.
- No work has been carried out in the last ten years with this approach to analysis; before the application of artificial intelligence algorithms, their selection and classification levels focused on Alzheimer's disease.
- This review covers the analysis of EEG signal databases for use in AI, the demographic data of the patients that comprise them, and the data acquisition paradigms, resulting in a necessary tool for future research.

The structure of the current work is divided as follows: Section 2 exposes the sequential steps that must be followed to implement the proposed review. The results and discoveries obtained are presented in Section 3. Section 4 analyzes and interprets the results. Finally, in Section 5, the areas covered by the scope of this work are exposed.

2. Materials and Methods

The article selection and screening methodology are described in this section. The inclusion and exclusion criteria are detailed to select relevant studies. The searches in scientific databases and the screening process are discussed and divided into two main stages: an initial review based on titles and abstracts and a full-text review. The selection was based on the relevance and relationship to the topic of interest.

Search Strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines were used in this systematic review [11]. The systematic search was conducted to identify studies investigating the use of ML and DL methods in the diagnosis of mild cognitive impairment (MCI) and Alzheimer's Disease using EEG. Articles written in English and published between 2013 and 2023 were exclusively selected. The search strategy used the PubMed, Scopus, and Web of Science databases. The following key terms were combined using Boolean operators:

- TITLE-ABS-KEY ((mci OR (mild AND cognitive AND impairment) OR (amnestic AND mild AND cognitive AND impairment) OR Alzheimer) AND (eeg OR electroencephalography) AND (detection OR diagnosis OR classification OR diagnostic) AND ((deep AND learning) OR (machine AND learning)) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (PUBYEAR, 2023) OR LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017))).

Three independent reviewers removed duplicates and applied eligibility criteria to select relevant articles. Those who met the following criteria were included:

- Use of AD or MCI databases.
- Use of EEG data.
- Use of classification methods based on ML or DL algorithms.
- The works presenting objective performance measures were included, which allows an accurate evaluation of ML and DL's capacity to diagnose MCI and AD.

Relevant data were extracted from each selected study, including diagnostic methods prior to database acquisition, study groups, sample size, mean age, EEG electrode placement, acquisition, classification techniques used, signal processing, features used for classification, feature evaluation metrics, and the classification percentages obtained. These data allow it to comprehensively analyze the selected studies and evaluate their contribution to diagnosing MCI and AD using EEG. To ensure a systematic and transparent process in this review, the PRISMA methodology was followed. Initially, 425 articles from the PubMed (107), WOS (141), and Scopus (177) databases were included. Duplicates were subsequently removed, resulting in 241 unique articles. Then, the exclusion criteria were strictly applied, which included cohorts other than Alzheimer's or MCI, the non-use of EEG, the absence of machine learning or deep learning techniques, volunteers with conditions additional to MCI or AD, and the lack of presentation of performance metrics such as algorithm efficiency and incomplete information. After this evaluation, 109 articles met all criteria and were included in this review. The Figure 1 illustrates this selection process in detail.

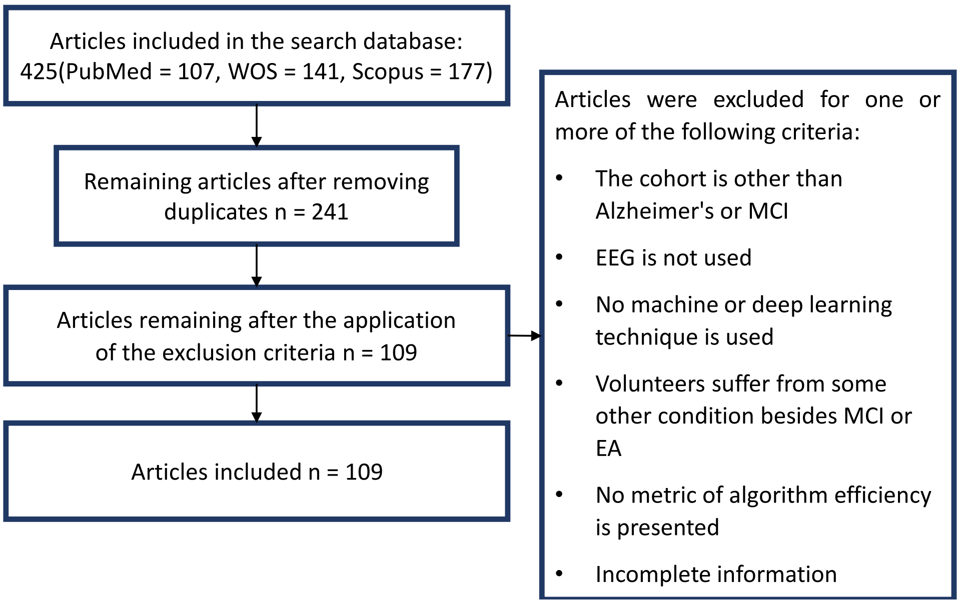

Figure 1. General methodology for the selection of articles.

Additionally, to ensure data integrity and methodological consistency, the following steps were adopted:

- Study selection criteria: Only studies that met predefined inclusion criteria, which guaranteed the use of EEG, were included. These criteria included specifying the EEG acquisition methodology, using cohorts diagnosed with Alzheimer's or MCI, and applying standardized machine learning or deep learning techniques.
- Review of methodologies: The methodologies used in each study for the acquisition and processing of EEG data were reviewed in detail. This included the evaluation of recording parameters, experimental conditions, and preprocessing procedures, ensuring that they met the standards established in the scientific literature.
- Peer review: All studies selected for review underwent a peer review process, ensuring the additional scrutiny of the validity and reliability of the data and methods used.
- Transparency and reproducibility: Studies were considered that provided sufficient detail about their methods and data, allowing the reproducibility of the experiments. Transparency in the presentation of results and analysis methods was also an important criterion for inclusion.

3. Results

In the results section, the findings obtained are presented. This section details significant advances, identifies emerging patterns and trends in current research, and highlights the most effective methodologies and areas requiring further research.

3.1. Traditional Alzheimer's Diagnosis Techniques for Database Formation

The database quality implemented for the classifiers' training is a critical point in ML and DL. In this section, an exhaustive analysis of the diagnostic techniques implemented before the ML and DL methodology is carried out to diagnose the volunteers and confirm which cohort they belong to. An incorrect diagnosis before the application of artificial intelligence algorithms affects the accuracy of the results and makes it difficult to obtain solid conclusions. If a participant is misdiagnosed, either by classifying them as healthy when they have early disease symptoms or by labeling them as Alzheimer's patients when they are not, the results of classifiers trained with such a database could be biased and lead to wrong conclusions.

In analyzing the diagnostic techniques used in the reviewed studies, several tools and methods widely used to detect dementia and cognitive impairment were identified. The Mini-Mental State Examination (MMSE) is the most used diagnostic technique in 50% of the analyzed studies [5–7,12–19]. This test is used to detect the presence of dementia in psychiatric patients through systematic screening. In addition, it is used to follow the evolution of cognitive deterioration in patients with dementia over time.

Another relevant diagnostic technique is the Montreal Cognitive Assessment (MoCA) [20–24]. This brief screening test assesses cognitive function in six domains: memory, visuospatial capacity, executive function, attention, concentration, working memory, language, and orientation. This test was used in 15% of the papers analyzed and comprehensively assessed cognitive function. As for imaging tests, it was found that magnetic resonance imaging (9.5%), positron emission tomography (4.25%), computed tomography (3.77%), and single-photon emission tomography (2.83%) techniques were also used in the diagnosis of dementia. These techniques allow for the visualization and analysis of the brain to identify possible structural and functional abnormalities.

In addition to these tools, other diagnostic tests were used to a lesser extent. The Neuropsychiatry Unit Cognitive Assessment Tool (NUCOG) was presented in 3.7% of the papers [14,21,25], while the Wechsler Memory Scale represented 2.83% and the Boston Naming Test 1.88%. These tests assess specific aspects of cognitive function and contribute to the accurate diagnosis of dementia. It is essential to highlight that some studies do not specify the initial diagnostic process for creating the database. In these cases, the presence of unspecified brain images was demonstrated in 4.71% of the works, unspecified neurological examinations in 11.3%, diagnosis made by experts in 9.43%, interviews in 5.66%, and 11.3% did not describe any prior diagnostic methodology.

Concerning the diagnostic criteria used in the studies analyzed, several standards and metrics widely used in detecting and diagnosing dementia were identified. One of the most used criteria was the National Institute of Neurological and Communicative Disorders and Stroke and the AD and Related Disorders Association (NINCDS-ADRDA), present in 20.75% of the papers analyzed [26–30]. This criterion establishes the clinical and neuropathological standards for diagnosing AD.

Another main diagnostic criterion was the Dementia Rating (CDR), which was used in 12.26% of the studies [31–35]. The CDR is a clinical tool that assesses and classifies dementia severity across multiple cognitive domains and provides a standardized and reliable measure for diagnosing and monitoring cognitive impairment. The Diagnostic and Statistical Manual of Mental Disorders (DSM), a widely used reference manual in mental health, was also mentioned in 9.43% of the papers. This manual provides diagnostic criteria for various mental disorders, including Alzheimer's disease.

Regarding the National Institute on Aging-Alzheimer's Association (NIA-AA) Criteria, its presence was found in 7.5% of the papers analyzed [36,37]. These criteria have been developed by a collaboration between the National Institute on Aging and the Alzheimer's Association, as well as ongoing updates and consensus for diagnosing and classifying AD. Finally, the RedLat (Standardized Diagnostic Assessment of the Multipartner Consortium to Expand Dementia Research in Latin America) was identified in 1.88% of the studies [23].

This criterion is part of a consortium that aims to standardize the diagnostic evaluations of dementia in Latin America.

These different diagnostic criteria reflect the importance of reliable tools and standards for accurately detecting and classifying dementia in the context of machine research and deep learning. Choosing the appropriate diagnostic criteria is crucial to guarantee the consistency and comparability of the results obtained in the studies.

3.2. Demographic Data of the Participants from the Databases

Three main aspects are examined: the average age of the participants, the percentage of males and females that make up the sample, and the average education level of the subjects. It is essential to highlight that only some reviewed papers reported the information necessary for these analyses. Of the 109 papers analyzed in this systematic review, 19 articles that did not provide the required statistics were identified [16,38–47]. This lack of information may be due to different reasons, such as the need for greater standardization in the presentation of demographic data.

Regarding the average age of the participants, significant differences were observed between the groups of healthy volunteers, those with MCI, and Alzheimer's patients. The average age for healthy volunteers was 68.53 years, with a standard deviation of 6.18. In the MCI group, the mean age was 70.52 years, with a standard deviation of 5.68. Finally, in the group of patients with Alzheimer's, the average age was 73.66 years, with a standard deviation of 5.58. These differences in average age reflect the progressive nature of Alzheimer's disease, which tends to manifest itself later in life.

Regarding the years of education, it was observed that the healthy volunteers had an average of 11.24 years, with a standard deviation of 2.98. On the other hand, MCI patients had an average of 9.67 years of education, while Alzheimer's disease patients had an average of 9.36 years, with a standard deviation of 2.84. These data indicate that the study participants had varied educational levels, which is essential to remember when interpreting the results and considering possible influences of education on cognitive performance.

Concerning the gender distribution in the databases, differences in the proportion of males and females were found. On average, the databases comprised 47.35% male, with a standard deviation of 10.12, and 53.57% female, with a standard deviation of 12.13. This indicates that, in general, the databases include a slightly higher proportion of females. In addition, the gender distribution by cohort was analyzed in healthy volunteers, MCI, and Alzheimer's patients. For healthy volunteers, it was found that, on average, 24.19% were female, and 18.87% were male. In the MCI group, the proportion of females was 20.47%, while the ratio of males was 19.68% on average. Finally, in the group of Alzheimer's disease patients, the proportion of females was 24.19%, and the balance of males was 21.86% on average. These differences in gender distribution by cohort may be significant in understanding possible variations in disease patterns and clinical manifestations.

This analysis of databases used in Alzheimer's disease screening and diagnosis studies using ML and DL techniques reveals differences in mean age, years of education, and gender distribution between healthy volunteers, MCI, and patient groups with Alzheimer's disease. These findings provide important information about the demographic features of the samples used in the studies, which is essential to interpret and generalize the results obtained.

The balance in the number of cases in the databases impacts the robustness of the model. According to the analysis of the percentages for control cases against cases with the disease, 50.47% of the databases show a difference of less than 10% between the number of cases with the disease and the control cases, which suggests that most of the methods reviewed used a balanced database [12–14,17,20,26,43,48,49]. On the other hand, in 8.5% of the databases, the total number of cases with the disease represents between 70 and 90% of the total cases, that is, they used a database with a bias in the number of cases [7,15,50,51].

3.3. EEG Acquisition

This section analyzes the number of electrodes used, sampling frequencies, and acquisition activities carried out by the volunteers who created the databases.

3.3.1. Number of Electrodes in the Acquisition of EEG Signals

In this context, 63 databases have been analyzed to understand the most used configurations and their relative proportions in scientific papers. Four main configurations were identified from the 63 analyzed databases representing the most used amounts of electrodes. The first uses 19 electrodes, the most frequently used in 19% of the works. As the second most used configuration, the use of 16 electrodes was found to be present in 17.46% of the total databases analyzed. This relatively minor number of electrodes may be due to studies focused on specific brain areas or restrictions in the equipment available for research. Thirdly, it is observed that implementing 32 electrodes is another standard option, being used in 14.28% of the analyzed databases. This configuration offers a greater density of information about brain activity, which is valuable for studies that seek a high level of detail.

On the other hand, it was identified that 21 electrodes also represent a common choice, present in 7.93% of the works analyzed. This configuration may be preferred in studies that seek a balance between information density and available technical resources. It is interesting to note that two configurations that stand out for their high electrode density were found. First, using 64 electrodes in 9.52% of the databases offers much information about brain activity, which is especially useful in research seeking comprehensive coverage. Secondly, it was identified that the configuration of 128 electrodes, although less frequent, was present in 6.34% of the analyzed databases.

Finally, less common configurations were found, corresponding to 25.46%. These include sensor configurations such as 1, 7, 30, and 33, among others. All the above configurations correspond to the international 20–10 system. Table 1 shows the electrode configurations found in the analysis.

Table 1. Electrode configurations in AD analysis.

Ref.	Electrode Configuration
[4,5,7,8,12,13,16,51–59]	19
[29,49,60–65,65]	16
[6,20,35,66–71]	32
[3,72–76]	21
[42,50]	64
[2,23,77,78]	128
[36,37,46,79–83]	Less common configurations

3.3.2. Analysis of Activities in Patients for Clinical Data Collection

In the context of the early detection of AD, the careful examination of the activities of patients becomes crucially important. This detailed analysis of daily actions allows for detailed stratification and helps design a valuable instrument for identifying patterns and early signs of the disease.

The above highlights the relevance of tasks, specifically resting with eyes closed at 58.67%, as a fundamental strategy for acquiring EEG signals. This highlights the importance of these controlled conditions to obtain and record more precise and consistent brain signals to evaluate more precise patterns for feature extraction. According to [84], these activities evidence the synchronous activation of multiple cortical neurons that coordinate to produce signals of considerable amplitude.

Acquisition with eyes open is another popular technique with 9.64% of the reviewed works. Other activities, such as analyzing responses to sound and visual stimuli or cognitive tasks, are intended to evaluate cognitive abilities in older people, represented by 11.73%. This approach not only enables the early detection of patterns associated with Alzheimer's disease, but also facilitates the continuous monitoring of disease progression. Furthermore, these techniques allow the design of a plan for particular interventions and the development of specific therapies and, ultimately, improve the quality of life of those affected by this neurological condition [85].

The other activities involve more specific studies, such as analyzing signals before sleep or after some physical activity, which represent 1.53% and 2.04%, respectively. Table 2 shows some works that apply the various acquisition paradigms for EA classification.

Table 2. Techniques and activities in the acquisition of EEG signals.

Ref.	Acquisition Paradigm
[5,16,18,21,22,24,25,28,29,32,33,38,57–59,70,72,82,83,86,87]	Closed eyes
[2,6,12,27,35,42,47,54,71,73–75,77,79,88–90]	Open eyes
[20,26,33,80,91,92]	Responses to stimuli and cognitive tasks
[19,41,93]	Sleep
[48,49,64]	Physical activity

3.3.3. Sampling Frequencies of EEG Signals

The analysis of the sampling frequencies implemented in the 63 databases reveals that preferences and trends in this field have been obtained. Of the sample frequencies analyzed, it stands out that the most used is 256 Hz, present in a considerable 22.22% of the works reviewed. This choice may be because 256 Hz is a widely accepted standard frequency in the scientific community to accurately and efficiently acquire brain activity data. In second place, there is the frequency of 500 Hz, corresponding to 20.63% of the databases. Thirdly, the 1024 Hz frequency is present in 14.28% of the acquisitions. This choice relates to research seeking a high temporal resolution to capture brain signals. Two other sample rate values used in a similar percentage are 1 kHz and 200 Hz, present in 11.11% and 12.68% of the databases, respectively.

On the other hand, the highest and lowest sampling frequencies found were the 128 Hz frequency used in 6.34% of the cases, while the 5 kHz frequency was used in 3.17% of the databases. These frequencies are related to specific investigations that require very fast or slow sampling to detect particular phenomena in the brain. In the remaining 6.34%, some frequencies were used only once, such as 10 kHz, 2 kHz, and 83.3 Hz. Finally, it is essential to note that a small percentage of works did not report their sampling frequency, in 3.175% of the cases. This highlights the importance of transparency and adequate documentation in the presentation of research results since the sampling frequency is a crucial aspect of the interpretation and replicability of the studies. Table 3 shows the sampling frequencies most implemented in Alzheimer's detection.

Table 3. Sampling frequencies of EEG signals in the analyzed databases.

Ref.	Sampling Frequency
[3,5,7,13,16,28,30,40,51,54–59,63,70,72,73,75,76,87,88,93,94]	256 Hz
[6,12,20,32,36,37,47,69,71,92,95–97]	500 Hz
[8,18,23,49,56,58,60,62,65,66,87,93,98,99]	1024 Hz
[45,48,67,77]	1 kHz
[4,23,61,72,76,90,100]	128 Hz
[91,92]	5 kHz
[26,27,78,79,100]	Frequencies ***

Frequencies *** refer to frequencies of 10 kHz, 2 kHz, and 83.3 Hz.

3.4. Filtering Methods for Signal Processing

The studies analyzed show a significant preference for the combined use of Band-pass and Notch filters, with low cut-off frequencies ranging from 0.1 Hz to 1 Hz, with the most common option being 0.5 Hz, followed by 1 Hz. Finally, the most used low-cost frequency is 0.1 Hz.

On the other hand, high cut-off frequencies are between 30 Hz and 45 Hz. The most used high cut-off frequency is around 30 Hz. The second most used frequencies are close to 45 Hz. Table 4 shows the most common outage frequencies.

Table 4. Low and high cutoff frequencies in the use of filters.

Ref.	Cutoff Frequency
[15,16,23,25,36–41,44,48,49,51,57,60,67,101]	0.5 Hz high pass
[7,9,20,22,52,53,55,56,63,65,69,81,86,92,102,103,103]	1 Hz high pass
[8,12,19,33,34,50,83,99,104]	0.1 Hz high pass
[4,8,16,19,22,25,35,38,40,41,46,56,57,59,60,63,66,79,86,90,96,97,101,103,105]	30 Hz low pass
[7,15,18,23,48–50,53,55,65,70,80,81,89,95,102,106]	45 Hz low pass

Filter type selection varies widely among studies, reflecting differences in analytical needs and methodological preferences, with the most common being the Butterworth filter. Butterworth filters are valued for their flat response in the passband, allowing minimal distortion within the frequency range of interest.

Independent component analysis (ICA) is another frequently cited method used not only as a filter per se but as a technique for artifact removal, underscoring the importance of signal cleaning in EEG preprocessing. This technique is beneficial for identifying and removing signal the components associated with blinks, eye movements, and other non-brain artifacts. Additionally, the specific applications of filters such as Chebyshev, Wavelet, and finite impulse response (FIR) are identified, which are selected for their unique properties that may be particularly beneficial under certain study conditions, such as the need for filters with highly selective frequency responses or the ability to decompose the signal into frequency components for detailed analysis. The choice of filters and preprocessing techniques in EEG analysis is a critical decision that directly influences the quality and interpretation of the collected data. Table 5 shows the most common filter types in the processing of EEG signals for patients with AD.

Table 5. Summary of filters and techniques in AD studies.

Ref.	Filter
[3,4,6,12,14,15,17,26,34,36,46,47,52,62,70,78,91,97,102]	Butterworth
[9,20,33,35,48,59,75,81,83,95,106,107]	ICA
[44,78]	Chebyshev
[28,34]	Elliptical
[31,45]	Wavelet
[4,8,16,19,22,25,35,38,40,41,46,59,60,63,66,79,86,97,101,103]	FIR

3.5. Feature Extraction

The selection and analysis of features represent a fundamental pillar in studying EEG signals from people with AD. This process allows us to identify distinctive patterns in patients' neurological conditions and facilitate discrimination between the different cognitive states and stages of the disease. Through EEG processing and analysis, we seek to extract relevant information hidden in the raw signals, transforming the data into information applicable to diagnosis [108].

Analyzing the features in the time, frequency, and time–frequency domains is a critical task. Each domain offers a unique perspective on brain activity, from the temporality and amplitude of signals to their spectral composition and the interaction between different frequencies over time. It has been determined that 36.49% of the reviewed works focus on analyzing the frequency domain. As for the most-used frequency feature, it is the calculation of power spectral density (PSD) [3,36–38,56,78,95,106]. Another feature in this domain is the coefficients of the Fourier transform [34,58,87]. Likewise, research that focuses on the temporal features of EEG signals makes up 22.97% of the analyzed works. Among the most used time features are statistical indicators such as mean, variance, kurtosis, skewness, and standard deviation [16,17,41,44,109]. Another of the most used features is entropy [22,30,44,76] and principal component analysis [43,47,61,70]. Furthermore, studies that integrate analysis in both the time and frequency domains represent 16.22%. By combining both domains, the calculation of the spectral power and entropy is used [15,19,67,75,83,96,102]. The PSD was also used together with the raw signal [5] or it was used together with the fractal dimension [59,73].

Brain connectivity, which examines the interactions between various brain regions, constitutes 10.81% of the works. Only 6.76% of the research jointly addresses frequency and brain connectivity or time. The most popular features of brain connectivity are network resilience, network clustering coefficient, or versatility [4,18,33,57,62]. Other implemented features are phase locking value and phase lag index [33,77,100]. Finally, a segment equivalent to 6.76% is categorized under various methodologies, including innovative or less conventional approaches in EEG analysis, such as 2D images to save the spatial structure, multiple color channels to represent the spectral dimension [32], and the writing features [42,81]. The left temporal volume and the cortical thickness of the frontal, parietal, and occipital lobes were also used [54].

3.6. Classification Techniques Approach for Alzheimer Detection

Different techniques performed in diagnosing Alzheimer's using classification models are presented in this section. According to [110], patients with Alzheimer's manifest neurological changes that cause physical changes, which is detected through brain signals. With this, classification techniques help detect these symptoms. According to the analysis of the 109 articles in the literature, different techniques associated with the classification of signals have been found. Figure 2 displays the most used classification techniques in the disease of Alzheimer's.

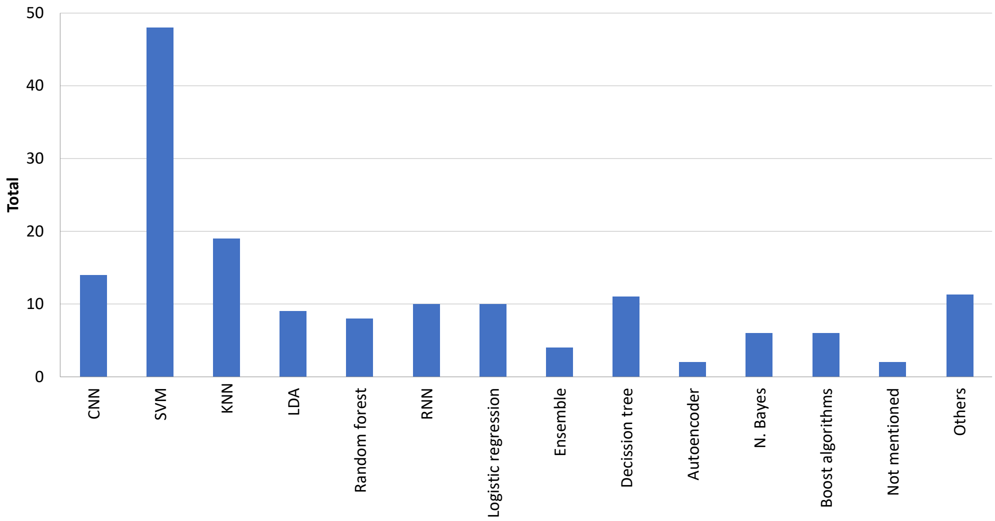

Figure 2. Classification techniques most used in the diagnosis of Alzheimer.

It is found that support vector machine (SVM) is the most popular technique used with around 30.57% of the works. It can handle nonlinear data using kernel functions, allowing complex relationships between features to be represented and improving the classification accuracy [111]. Then, the K-nearest neighbors (KNN) algorithm presents about 12.1% of usage according to the literature. This finding is noteworthy as both methods are supervised training algorithms commonly employed in ML for classification tasks.

Likewise, in recent years, the use of convolutional neural networks (CNN) has been increasing. Among the articles studied, its use is around 8.91%. The tendency to integrate

CNN is because they can automatically learn relevant features of the images or input signals using the convolution and pooling layers. This allows the model to autonomously identify complex and significant patterns in the data [112]. On the other hand, decision tree algorithms (DT) present about 7% in the analysis of AD. The recurrent neural network (RNN) algorithms are another trend technique, which represent 6.36%. RNNs benefit from directly operating on raw data, eliminating the need for a feature extraction step and providing faster responses [113].

One of the current deep learning techniques implemented is the graph neural network (GNNs). Among the analyzed works, only 2.8% used GNN networks. Linear regression algorithms are used in 6.36% of the analyzed works. Random forest (RF) is also another alternative used for extracting features with 5.73%. Other works, such as boost algorithms or latent Dirichlet allocation present about 3.82% and 5.73%, respectively. Another technique employed are the Bayesian-based algorithms, that are presented in 3.82%. Other conventional and not specified works represents the 6.36% of the analyzed works. Finally, ensemble algorithms are used in 2.54% and autoencoder algorithms in 1.27%. Table 6 shows the works where each of the classifiers were implemented.

Table 6. Deep and machine learning classifiers used for EA detection.

Ref.	Classification Technique
[2,4,6,7,13,15–18,20,25,28,29,31,34,36,37,41,44,46,49,54–57,59,62,67,68,70,73,75,78,80,81,83,86,88,89,92,96,103,105,106,109,114]	SVM
[7,13,15,25–27,34,43,44,46,56,57,59,73,89,94,99,104,105]	KNN
[3,7,8,32,38,39,42,45,69,79,90,93,107]	CNN
[7,15,21,34,55,56,58,59,73,78,87]	DT
[24,34,40,50,52,55,61,64,71,91]	RNN
[12,22,41,51,66,78,82,83,97,109]	Linear regression
[1,15,23,33,34,47,78,81,89]	RF
[57,78,81]	Boost
[34–37,44,52,76,83,95]	Latent Dirichlet allocation
[7,15,34,59,83,98]	Bayesian
[7,63,73,83]	Ensemble
[41,109]	Autoencoders
[77,100,115]	GNN
[5,60,65,72,101,102,116]	Other works

3.7. Evaluation Metrics

Accuracy shows the percentage of cases that the model got right. According to Figure 3, it is the most used metric, followed by precision and specificity. Although accuracy is the most used metric, it does not mean that it is the most representative metric of the model. As a complement to accuracy, it is recommended to use precision, recall, and F1 to represent the model regarding prediction quality, quantity, and the visualization of the types of errors. The 55% of the articles use at least three of the metrics, while 20% do not indicate the evaluation metrics [68,71,74,80,82,91,94,99,116].

3.8. Results in the Classification Achieved

In addition to the diversity in methodological approaches, it is crucial to highlight the classification percentages achieved in each domain, which provides insight into the effectiveness of the different techniques. Studies focused on the frequency domain achieved a classification average of 86.82%, while those focused on temporal analysis achieved a similar average of 86.81%. This suggests that both approaches, regardless of their orientation towards frequency spectrum or temporal features, offer comparable results in terms of classification ability. On the other hand, research exploring brain connectivity showed an average classification of 88.58%, indicating a slight advantage in applying this approach to discern between different conditions or brain states. Most notably, studies that combined analyses over time and frequency presented an average classification of 89.72%, suggesting that integrating multiple dimensions of analysis provide a more complete and detailed understanding of brain activity, reflected in a higher classification accuracy. Papers incorporating time, frequency, and brain connectivity analysis achieved an average classification of 89.07%. Finally, the methods classified as diverse achieved the highest average classification, with 92.575%.

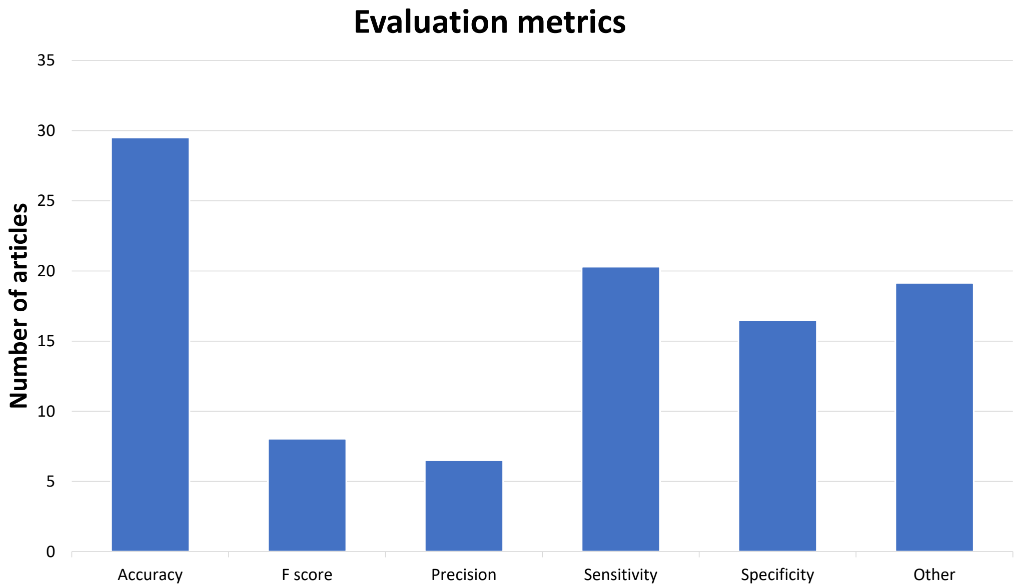

Figure 3. Comparison of the frequency of use of the various evaluation metrics in scientific articles.

4. Discussion

Table 7 highlights the main works analyzed, showing the various classification models used. In addition to selecting specific filtering ranges, sample size and rankings were also obtained.

Table 7. Summary of the main works analyzed.

Reference	N° Volunteers	Classification Model	Filtering Range (Hz)	Performance
[55]	11 healthy, 8 MCI, 19 AD	SVM with radial kernel, multilayer perceptron (MLP) and DT	1–40	DT 94.88% SVM 95.10% MLP 95.55%
[70]	120 healthy and 175 EA	SVM	0.2–47	95%
[64]	28 healthy and 7 MCI	Bidirectional LSTM	3–30	91.93%
[45]	15 healthy and 16 MCI	CNN	8–30	79.66%
[13]	16 healthy and 11 MCI	GRU	0–32	96.91%
[14]	16 healthy and 11 MCI	LSTM	0.5–50	96.41%
[18]	21 healthy and 28 MCI	SVM with Gaussian kernel	0–40	86.6%
[89]	89 EA	SVM with linear and Gaussian kernels, RF and KNN	0.5–45	RMSE of 1.682 between predicted and actual MMSE values when measuring disease progression
[75]	13 healthy, 16 MCI, 15 EA	SVM with Gaussian kernel	0.5–65	88%
[46]	50 healthy and 50 EA	SVM and KNN	0.5–30	94%

Table 7. *Cont.*

Reference	N° Volunteers	Classification Model	Filtering Range (Hz)	Performance
[107]	Synthetic EEG signals were generated from 8 healthy patients and 1 using EA generative adversarial networks and variational autoencoders	EEGNet, DeepConvNet, and EEGNet SSVEP	4–40	50.2%
[73]	15 healthy, 16 MCI and 16 EA	KNN	Iterative filtering	92%
[78]	17 healthy and 19 AD	Logistic regression, SVM, RF, extra trees, DT, stochastic gradient descent, Ada boosting, and gradient boosting	0.4–115 Hz	95.6%
[27]	20 healthy and 20 EA	KNN	2–680	90%
[8]	23 healthy, 56 MCI and 63 AD	CNN	0.1–30	80%
[61]	15 healthy and 20 EA	LSTM	-	97.9%
[81]	39 healthy and 40 MCI	SVM with Gaussian kernel, RF and Xgboost	1–45	XGboost 87.34% SVM 93.7% RF 84.81%
[19]	20 healthy and 20 EA	Cubic SVM and bidirectional GRU (Bi-GRU)	0.1–30	Cubic SVM 90.51% Bi-GRU 93.46%
[7]	11 healthy, 8 MCI and 19 EA	CNN, ensemble, KNN, SVM, naive Bayes, discriminant analysis and DT	1–40	57%
[102]	9 healthy, 6 MCI and 11 EA	MLP	1–45	82.5%
[100]	20 healthy and 20 AD	GNN	0.1–51	92%

Due to the nonlinear nature of EEG signals, models implemented in nature have proven to be robust in terms of their accuracy, since at least a classification model is expected to present a performance of at least 80% based on its precision. With this, it is possible to observe that SVMs are commonly used models for these tasks due to their kernel-based architecture. Furthermore, recent years have seen the implementation of RNN-based classification models, particularly with GRU and LSTM configurations. These models report at least 92% accuracy according to Table 7. It is important to note that the tendency of these models to present prominent results is based on the treatment of the signal and configuration of the parameters, so the remaining models can improve their accuracy if they are correctly adapted.

The analysis of EEG signals for the early diagnosis of the AD using machine and deep learning highlights the importance of carefully selecting databases and analysis methodologies. The adequate preparation and the choice of clear diagnostic criteria are essential to avoid bias in the results. There is a preference for using 19-electrode configurations and selecting specific activities such as rest periods with eyes closed. Different EEG electrode configurations can significantly affect classification results. High-density configurations, which use more electrodes, offer better spatial resolution and brain coverage, allowing for the more precise and subtle details of brain activity to be captured. This may improve the accuracy of diagnoses and the identification of robust features for the detection of AD [67]. However, these configurations also have disadvantages, such as greater complexity, which could make the classification task more complex, longer configuration time, patient discomfort, and higher economic and computational costs [117]. On the other hand, configurations with fewer electrodes, although more practical and comfortable, can limit the amount of information available and affect the effectiveness of machine and deep learning algorithms. Variability in electrode configurations introduces challenges when comparing results between studies, as different configurations may capture the different aspects of brain activity [118]. Given the above, it is important to standardize electrode configurations or provide detailed analyses on how these configurations can affect the results to improve the comparability and replicability of studies in the field.

Demographic data, such as age and gender distribution, can significantly influence the results of EEG studies used to diagnose AD. The information in this paper shows that notable differences in the mean age of participants were observed between the groups of healthy volunteers, patients with MCI, and patients with Alzheimer's, reflecting the progressive nature of the disease. Specifically, Alzheimer's disease patients had a higher mean age (73.66 years) compared to healthy volunteers (68.53 years) and MCI patients (70.52 years). These age differences may affect EEG results, as aging may influence brain activity patterns regardless of the presence of AD.

Regarding gender, the general distribution showed a slight majority of women (53.57%) in the databases analyzed. Furthermore, the proportion of women and men varied between the different cohort groups, with a higher proportion of women in the healthy volunteer and Alzheimer's patient groups. This gender distribution may be relevant to the results of EEG studies, as there are gender differences in the incidence and progression of AD, which may influence the patterns of brain activity recorded.

The average educational level also varied between groups: it was higher in healthy volunteers than in patients with MCI and Alzheimer's. Education has been identified as a factor that can influence cognitive reserve and, therefore, the results of EEG studies. People with more education may show different patterns of brain activity due to a greater capacity for cognitive compensation against the effects of AD.

The different methods of EEG data acquisition, such as being awake with eyes open, awake with eyes closed, asleep, and responses to cognitive stimuli and tasks, may influence the reliability of the data for diagnosing AD. The most commonly used method is being awake with eyes closed due to its ability to provide a stable baseline and minimize eye noise, thereby facilitating the identification of brain activity patterns indicative of AD, such as generalized slowing of brain waves [119]. This approach is particularly useful for detecting the changes in brain connectivity and complexity characteristic of AD. However, other methods, such as responses to stimuli and cognitive tasks, can offer additional information about cognitive decline and the dynamics of neural networks, although they require more complex experimental designs and are more susceptible to individual variations. A combination of these methods is suggested to obtain a more complete and reliable assessment of brain status in AD.

Regarding the filtering and analysis of the signals, the combination of band-pass and notch filters stands out as a way to maintain valuable information and eliminate noise. This approach is complemented by analysis in the time and frequency domains, prioritizing PSD and descriptive statistics to identify patterns related to Alzheimer's. Exploring brain connectivity also provides deep insights, suggesting that a multidimensional analysis significantly improves classification.

The choice and calibration of classifiers play a crucial role in the effectiveness of the diagnosis. Different classifiers produce varying results on the same data set due to how their parameters are tuned, underscoring the need for careful selection and optimization. Adequate adaptation of the classifier to the features of the dataset is decisive in achieving high classification rates. This aspect and an evaluation of metrics beyond simple accuracy offer a complete view of the classifier's performance and highlight the importance of advanced techniques for artifact removal and feature selection.

Despite its apparent simplicity, accuracy is considered the most used metric as an indicator of success. Accuracy provides a general measure of model performance, indicating the proportion of correct predictions over the total number of cases analyzed. In addition, it is complemented by sensitivity and specificity. Sensitivity measures the model's ability to correctly identify subjects with AD, which is crucial for early diagnosis and timely treatment. On the other hand, specificity evaluates the model's ability to correctly identify healthy subjects, avoiding false positives that could cause unnecessary anxiety and additional procedures.

The Figure 4 shows that SVM techniques are the predominant technique in the analysis of Alzheimer's. In addition, band-pass filters are the most commonly used when data acquisition is required with eyes-closed patients. It also is observed that the bands with relevant information are those ranging from 1 to 32 Hz. This suggests that the identification of patterns in resting or relaxed conditions is found with this model.

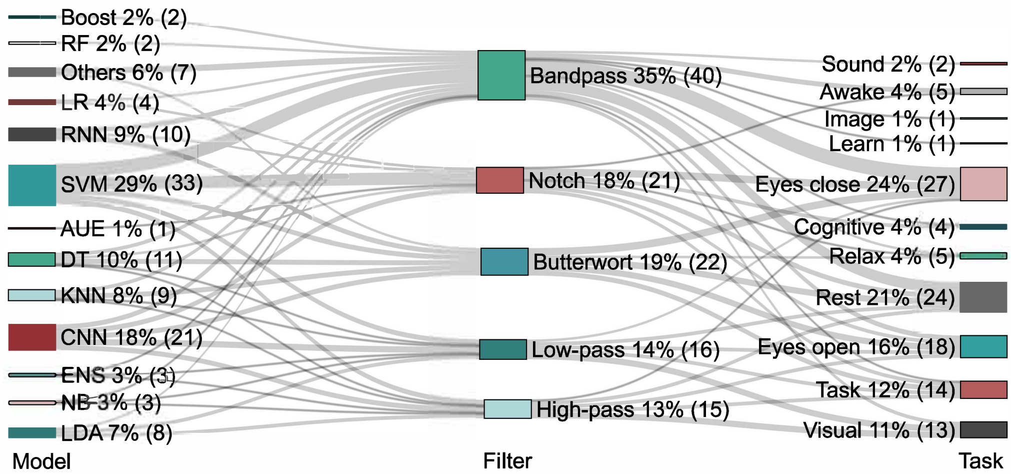

Figure 4. Sankey plot analysis of AI techniques in acquisition tasks.

This analysis suggests that the approaches combining analyses across time, frequency, and brain connectivity, supported by a well-prepared database and the choice of appropriate classifiers, provide the most detailed understanding of brain activity and the greatest accuracy in the classification. Integrating these elements strengthens the ability to detect Alzheimer's in its early stages and improves the development of artificial intelligence models that significantly contribute to combating this disease. In summary, the research highlights the need for a careful approach to data preparation, method selection, and classifier optimization to advance the use of artificial intelligence technologies in ongoing efforts to tackle Alzheimer's disease.

5. Conclusions

The review of recent works in artificial intelligence applied to detecting AD highlights the importance of these technologies in understanding this condition. The studies analyzed have shown promising results, significantly contributing to understanding the disease and developing advanced methodologies for its early detection. In particular, it has been shown that signal processing plays an essential role in improving data collection, highlighting the importance of adjusting data acquisition to specific frequency bands for the design of more accurate and efficient algorithms.

The proposal to adopt strategies that integrate various methodologies promises to increase the effectiveness of traditional methods and to revolutionize the current paradigm towards a more precise and robust classification of EEG signals in people with Alzheimer's. These innovations open new directions in research and development, facilitating the personalization of treatment and disease management with information obtained through advanced AI techniques. In the long term, these technologies provide more accessible and reliable diagnostic tools for early detection.

The importance of the careful analysis of EEG signals using machine and deep learning is highlighted, underlining the need to select databases and analysis methodologies to avoid biases appropriately. The preparation of data and choosing clear diagnostic criteria are essential. The demographic conformation of the databases and the selection of filtering and analysis methods, such as the combination of band-pass and notch filters, and an analysis in the time and frequency domains, are essential to identify patterns related to Alzheimer's. Furthermore, the precise adaptation and calibration of classifiers highlight the need for careful selection and meticulous optimization to achieve high classification rates.

The combination of detailed analysis in time, frequency, and brain connectivity, supported by a well-prepared database and adequately selected and tuned classifiers, provides a deep understanding of brain activity and the highest classification accuracy. This research emphasizes the need for a rigorous approach in data preparation, methodology selection, and classifier optimization to advance the application of AI technologies in the fight against Alzheimer's, demonstrating the transformative potential of these technologies in personalized medicine and patient management.

The generalization of these findings presents several challenges, given that the manifestation of Alzheimer's can vary significantly depending on genetic, lifestyle, and environmental factors. First, the studies reviewed often use cohorts that may not represent global genetic diversity, limiting the applicability of the results to populations with different backgrounds. Additionally, lifestyle factors such as diet, physical activity level, and sleep habits can influence brain health and EEG patterns. Differences in these factors between the populations studied, and other populations may lead to variations in results and reduce the generalizability of the findings. Environmental factors, such as exposure to toxins, level of education, and access to medical care, also play a crucial role in the manifestation of Alzheimer's. These factors may modify disease progression and associated EEG patterns, making the models developed in one specific context not directly applicable to other settings.

It is important to note that many studies need to detail these aspects in the description of their populations, which adds a layer of uncertainty about the generalizability of the findings. The lack of specific information on genetic, lifestyle, and environmental factors in the cohorts studied may limit the interpretation and application of the results to broader contexts. Although the findings of our review provide a valuable basis for the EEG-based diagnosis of AD, their generalization to different populations requires the careful consideration of multiple variables not anticipated in this review. To improve generalizability, future research should include more diverse cohorts and consider these factors when developing and validating diagnostic models.

Finally, according to our review, a key trend is the application of advanced deep learning techniques, which have shown great potential but are still relatively underexplored compared to more traditional methods such as CNNs, RNNs, and GNNs.

Another promising area is the development of new feature extraction and filtering methods. Advanced preprocessing techniques, such as adaptive filtering, can improve the quality of EEG signals. Feature extraction using nonlinear and multifractal methods can also capture complex brain dynamics indicative of AD. Integrating these techniques with deep learning models can significantly improve the accuracy and effectiveness of the diagnosis.

One of the main challenges for applying deep and machine learning in AD diagnosis is the need for large labeled datasets, which are essential for effectively training deep learning models. Variability in electrode configurations and data acquisition protocols between different studies must be more consistent, making comparing results and replicating studies difficult. Additionally, EEG signals are susceptible to artifacts and noise from various sources, such as eye and muscle movements, which complicates effectively removing these artifacts without losing relevant information.

Another limitation of deep learning models, often called black boxes, is their interpretability. This makes it difficult to understand how and why a model makes certain decisions, a crucial aspect of medical applications. Generalizing the models to different populations is also problematic due to genetic, lifestyle, and environmental differences that may need to be adequately represented in the study cohorts. The computational requirements to train and deploy deep learning models are significant, requiring specialized hardware and access to high-performance computing infrastructures.

While deep and machine learning techniques present exciting opportunities for EEG-based AD detection, their application is an ongoing area of research and development. Researchers should continue to focus on optimizing and adapting these emerging technologies, as well as developing new feature extraction and filtering methods, to advance the accuracy and effectiveness of Alzheimer's disease diagnosis.

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