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Impact of EEG Parameters Detecting Dementia Diseases: A Systematic Review

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ABSTRACT Dementia diseases are increasing rapidly, according to the World Health Organization (WHO), becoming an alarming problem for the health sector. The electroencephalogram (EEG) is a non-invasive study that records brain electrical activity and has a wide field of applications in the medical area, one of which is the detection of neurodegenerative diseases. The objective of this work is to present the results of a thorough review of the use of EEG systems for the detection of dementia diseases. Around 82 published papers between 2009 and 2020 were reviewed, and compared among them obtaining data such as sampling time, the number of electrodes, the most popular processing, classification, and validation techniques, as well as an analysis of the reported results. The relationship of the selected parameters with the efficiency obtained is shown, some more common combinations in the reviewed articles that demonstrated to have reliability levels greater than 90% and details to be considered at each stage of the process. An overview of the most commonly used classification tools and processing techniques is also described.

INDEX TERMS EEG systems, detection reliability, neurodegenerative diseases, automatic/semi-automatic detection, biomedical applications.

I. INTRODUCTION

According to studies conducted by the World Health Organization (WHO), it is estimated that there are more than 46.8 million cases of dementia, which will double by 2030 and triple by 2050. Dementia is one of the main causes of dependency and disability among the elderly. It is a syndrome that involves intellect, the deterioration of memory, the ability, and behavior to perform activities of daily living. It is a growing challenge for health systems [1]–[4].

Alzheimer's disease (AD) is the most common form of dementia, accounting for between 70% and 80% of cases. It is one of the irreversible neurodegenerative diseases characterized by a decrease in memory, thinking, orientation, understanding, calculation, learning capacity, language, and judgment. The importance of early detection lies in allowing soon and optimal treatment. Early cognitive stimulation contributes to slow down the decline of higher functions and the appearance of conduct disorders. It improves the quality of life not only of the person who suffers from it but also of their relatives. The EEG information can be used to obtain clinically relevant information for the identification, monitoring, and even prediction of diseases such as dementia diseases, brain tumors, sleep disorders, non-epileptic pathologies, encephalopathies, infections of the central nervous system, among others [5]–[12].

The EEG is the recording of voltage oscillations caused by intra and extraneuronal ionic currents of a neuron population with a certain spatial distribution. Neurons are responsible for transmitting and receiving information through an electrochemical process called a synapse, the EEG records post-synaptic events and this information allows to understand the dynamics and functioning of the brain [13]–[16]. The identification of pathologies using EEG data is carried out by searching for anomalies during the recording that are represented by paroxysms, they are waveforms that do not correspond to the nature of the signals [17]–[34].

The EEG is a non-invasive, cheap, fast study that has shown high levels of reliability compared to techniques such as magnetoencephalography, the study of cerebrospinal fluid, or neuropsychological tests that require waiting for people to have data on cognitive deterioration and are subject to clinical bias. As show in Figure 1, in the last decade, according to PubMed® (National Library of Medicine, National Institutes of Health) research related to EEG has increased by more than 50% due to the wide field of applications and its contributions to solving social problems. The combination of processing techniques such as Wavelet Transform (WT) or Fast Fourier Transform (FFT) and deep learning techniques for classification have achieved precision levels greater than 92%, robust systems and with high levels of efficiency [1], [35]–[51].

This work focuses on the applications for automatic and semi-automatic detection of dementia diseases using EEG information as the main tool. The paper is organized as follows: Methods II contains the description various processing and classification techniques for clinical applications of EEG. Results III includes the analysis of information and discussions. Finally, in Conclusions IV shows the contributions of the article and future work on EEG systems for the automatic detection of dementia diseases.

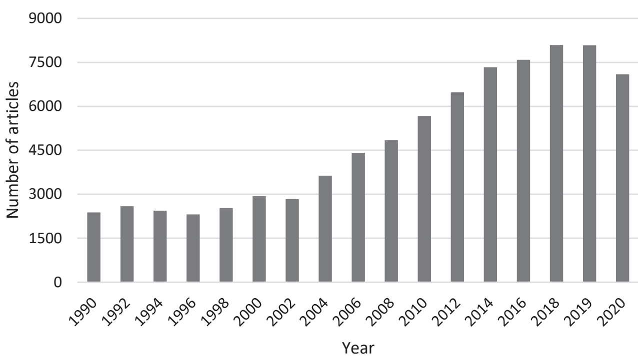

FIGURE 1. Articles published in the last 10 years related to EEG applications.

II. MATERIALS AND METHODS

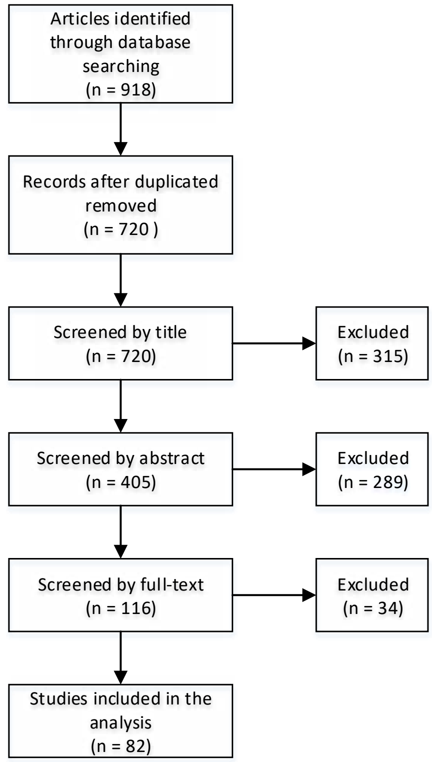

FIGURE 2. A diagram of the selected items, n is the number of articles.

A. SELECTION OF ARTICLES

For this review, a survey on English journal articles published between January 2009 and February 2020 was made. The database consulted was Scopus; using the following keywords in *AND* and *OR* combinations:

- EEG
- diagnosis
- dementia disorders
- biomarkers
- automatic/semi-automatic detection

Around 918 articles were identified, of which 198 were removed because they were duplicates and 638 were excluded in the three filters. The first filter was by title, this should refer to research focused on the quantitative analysis of the EEG and mention dementia diseases, some specific or symptoms thereof. The second filter was abstract, where the exclusion criterion was to remove the articles that did not mention the quantifiable results of the application performance. The last filter was by full-text which discarded all the articles that did not mention the processing and classification techniques used, leaving a total of 82 articles, Figure 2.

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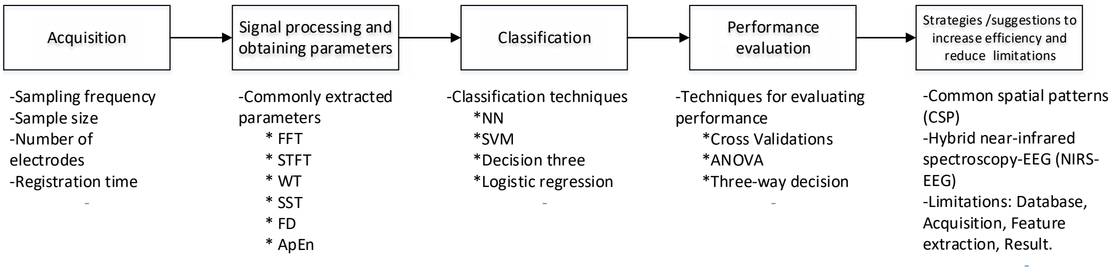

FIGURE 3. Data extracted from each paper divided by process stages.

B. FEATURE EXTRACTION

Parameters of all stages of the process were extracted: acquisition, processing, classification and performance evaluation. Figure 3 illustrates the parameters extracted in each stage. The elements marked with "*" are those that were repeated the most in the articles reviewed and are described in a general way in the following section. The relationship of the extracted parameters and the results of efficiency, advantages and associated cost is also identified, an analysis is described in the section III.

Table 1 displays a compilation of parameters and results of investigations focused on the detection of diseases by EEG. The last column of Table 1 illustrates the limitations separated into four categories: Database (1), Acquisition (2), Feature extraction (3), Results(4). Table 2 describes the limitations in each category. The information shown in Tables 1 and 2 contains the combinations whose parameters showed greater repeatability in the reviewed articles, and they are also ordered by the efficiency value obtained. In the next section, each column is discussed in detail, starting with the sample size.

III. RESULTS AND DISCUSSION

A. EEG SIGNAL ACQUISITION

The acquisition stage is crucial for the system because the information it retrieves will be used for the identification of EEG patterns, also called biomarkers. By having erroneous measurements, the results are altered and the reliability, quality and repeatability of the information is lost, which would lead to identifying erroneous patterns or not being able to identify any pattern. Due to the above, it is essential to have bases in the metrology area to be able to apply it in the project or review the reliability of the database used [59]–[73]. The Figures 4, 5, 6, 7 show the results of the extraction of characteristics for the acquisition stage, comparing the number of articles published with respect to the sampling frequencies, the number of electrodes, registration time, and size of the database used, respectively.

The sampling frequency reported in each article varies from 128 Hz to 1024 Hz, the highest repeatability was in the range of 128-256 Hz, Figure 4 (a). The Nyquist theorem is one of the key elements to determine which frequency is suitable for the application, this theorem is also known as the sampling theorem and shows that mathematically it is possible to reconstruct a continuous periodic baseband signal from its samples if the signal is band limited and the sampling rate is more than twice its bandwidth [74]. The normal EEG in humans displays activity in a range of frequencies, between 1 Hz to 100 Hz, considering the upper limit of the frequency range in combination with the Nyquist theorem corresponds to 256 Hz being among the most used frequencies.

On the other hand, the number of electrodes reported in each article varies from 2 to 128 pieces, the value that was repeated the most was 19 using the positioning of System 10-20, Figure 5. Determining how many electrodes are recommended for the application depends on the budget for the project of the type of application since the electrodes are metallic discs that are commonly made of gold and that greatly increases their cost [75]. The type of application is important because reviewing the literature and the reported evidence, can guide the researcher in defining the key areas to record, such as the frontal, parietal, occipital, or other areas. It is also important to consider that the more elements recorded, the greater the treatment and handling of information is required.

S. Jianga et al. applied two tests to detect dementia disorders. The first is a test to assess attention, memory, language, and spatial orientation. Study number two is the EEG; the recording was done while watching a movie and only those studies where the patient answered the questions about the movie correctly were considered. They applied the EEG with 32 electrodes, to evaluate the performance of the proposed method, used analysis of variance techniques, and found a significant difference between patients and control cases in the frontal-central zone [54]. Results such as those obtained by ref help the reader to define the areas to be covered during the registration.

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TABLE 1. Elements extracted from articles focused on the detection of neurodegenerative diseases using EEG. Column six contains the stages in which the limitations are concentrated: Database (1), Acquisition stage (2), Feature extraction (3), Results (4).

Year	Classification pathology	Processing technique	Efficiency	Subjects sample	Limitations
2016	Parkinson's disease	Test/frecuency-bands	Reliability levels	45 [52]	3, 4
2018	Parkinson's disease	Event-related potentials/Analysis of variance (ANOVA)	—	36 [53]	3
2019	Mild Cognitive Impairment (MCI)	Multimodal physiological signals	81.51%	336 [54]	4
2018	Huntington's disease	Fast Fourier Transform (FFT)	83.00%	51 [48]	2, 4
2019	MCI and Alzheimer's disease (AD)	—	89.23%	23 [17]	2, 3
2018	AD and Dementia with Lewy bodies and Parkinson's disease	FFT	89.85%	52 [21]	3, 4
2016	AD	Sum-adjacent amplitudes	90.76%	52 [41]	2, 4
2018	AD and MCI	FFT, Wavelet Transform (WT)	79-92%	86 [55]	2, 4
2017	Vascular dementia disease and Stroke-related with MCI	Independent component analysis (ICA)-WT	91.48%	35 [43]	2, 4
2013	MCI	ICA	91.76%	— [56]	2, 3
2017	AD	Hilbert Transform	88-92%	40 [57]	2, 3, 4
2017	Parkinson's disease	Discrete Wavelet Transform (DWT)	92.86%	42 [45]	2, 4
2018	AD	Automatic discrimination	93.13%	169 [40]	2, 4
2019	AD	Finite Impulse Response (FIR) filters	88-96%	24 [23]	2, 3
2020	MCI	Piecewise aggregate approximation, Permutation entropy (PE) and auto-regressive	98%	27 [58]	2, 3

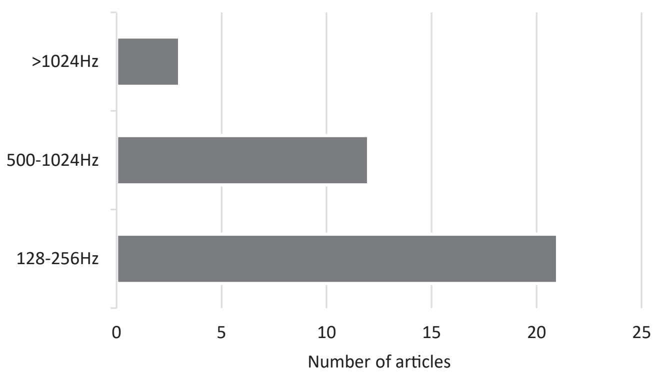

FIGURE 4. Most common characteristics in the reviewed articles: sample rates for the acquisition of EEG signals.

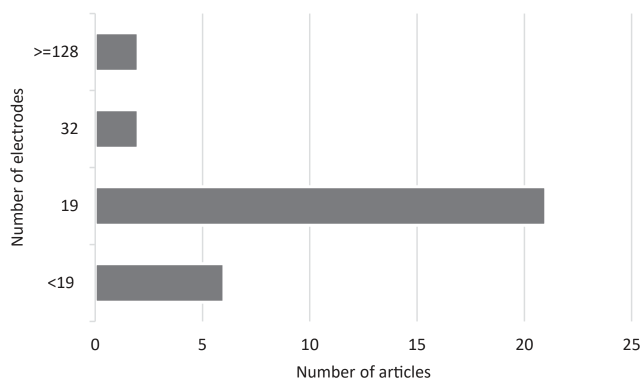

FIGURE 5. Most common characteristics in the reviewed articles: electrode parts used for EEG recording for dementia disease detection application.

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TABLE 2. Description of the limitations classified into four groups: database, acquisition, feature extraction and result.

Category	Limitations
Database (1)	Number of subjects in the study lower than the reporting average in the reviewed articles. Merged databases are different due to local implementations. Missing information (age, gender and/or education). The database includes subjects taking dementia medications. Complete diagnoses of the patients are not available and/or diagnoses are not reliable. Heterogeneous samples.
Acquisition stage (2)	Differences in data due to manual handling of artifacts. Low number of electrodes for connectivity analysis. Wrong sample rate for logging protocol. Wrong decoding of data. Loss of information in the acquisition. There is no serious dementia disease that difficult to perform an EEG recording. Presence of dominant alpha activity during EC condition.
Feature extraction (3)	The techniques and configuration of the processing techniques used are not mentioned. Classification tools include semiautomatic methods combined with specialist interpretation. Application of processing techniques without the minimum requirements, window size, samples used in training and validation.
Results (4)	Low levels of efficiency (less than 90%). Incomplete reporting of parameters in the performance evaluation (mostly they only mention precision). Incomplete information on the tools used in the algorithm. Lack of longitudinal approach for populations. Classification of limited dementia types.

The registration time reported in each article varied greatly, from 5 to more than 30 minutes, Figure 6. In the acquisition stage, the registration time is one of the parameters that can change the most between one application and another, since the minimum registration time is determined depending on the type of study planned. According to the articles reviewed, some recorded while doing a questionnaire, solving some mental task, generating stimuli, among other activities.

Finally, the size of the sample varied enormously, from 20 subjects to more than 89 as illustrated in Fig-

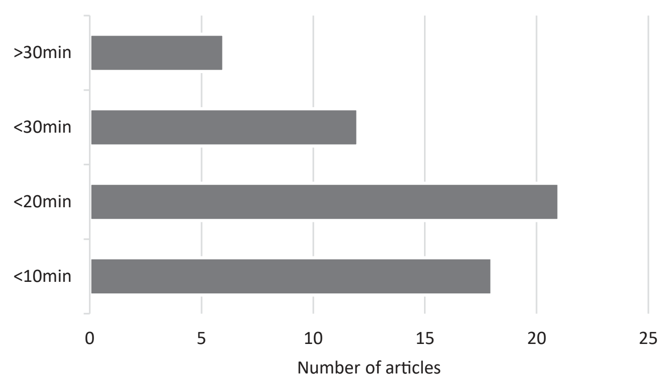

FIGURE 6. Most common characteristics in the reviewed articles: EEG recording time for the detection of dementia diseases.

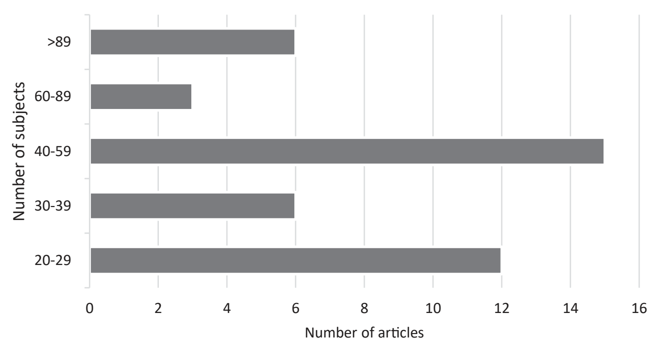

FIGURE 7. Sizes of the most common databases in the articles reviewed.

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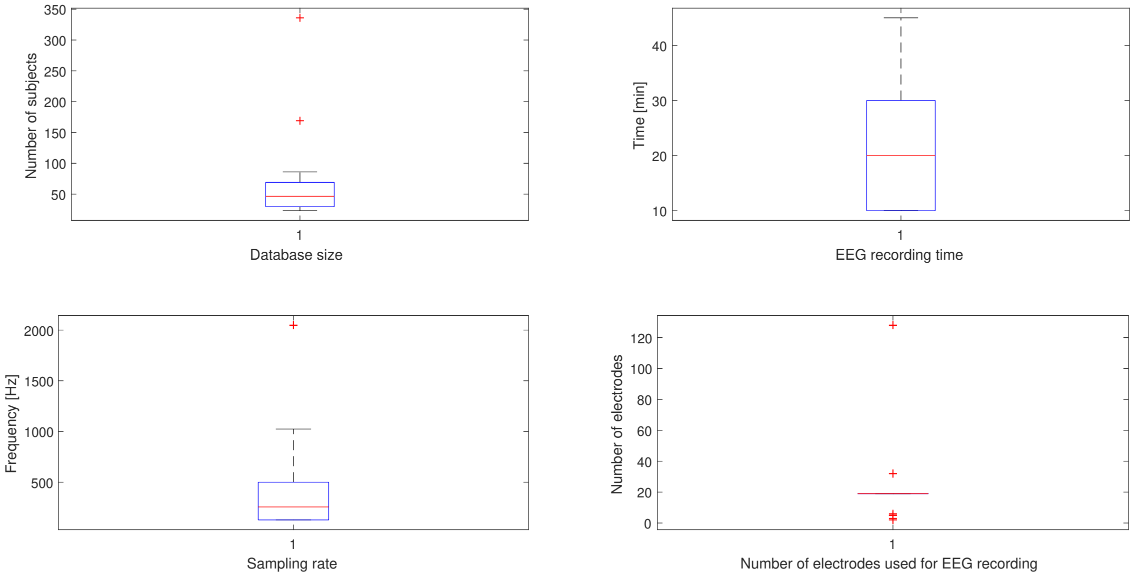

FIGURE 8. Box and whisker plots summarizing the sample characteristics.

ure 7. Most of the articles use databases that are not freely accessible, which makes it difficult to compare the results achieved. Also, another important data is that usually, the articles reported for automatic/semi-automatic detection for dementia diseases focus the investigation only on the application or on the acquisition of data, this due to the amount of effort, knowledge, and equipment that each requires exercise. In Figure 8, the results of Figures 4, 5, 6, 7 are shown in box-and-whisker plot format summarizing characteristics such as mean, range, and out-of-range points.

In addition to the data mentioned above, it is important to take care of the type of analog and digital filter, as well as the Analog to Digital Covert (ADC) converter and the protection and preparation status of the patient from inferences of metallic elements, involuntary movements and the patient history as they can alter the results. Once the acquisition stage is concluded, the data is processed, classified and validated, which are discussed in the following sections.

B. SIGNAL PROCESSING AND PARAMETER EVALUATION

The EEG patterns/biomarkers are used to classify data between control cases and cases with pathology. During the data processing, the aim is to highlight the patterns associated with dementia diseases. Figure 9 illustrates the incidence of the most commonly used techniques in EEG signal processing that allow the evaluation of parameters associated with dementia diseases. More than 25% of the papers reported suggest the use of more than one tool to achieve higher levels of reliability, such as more than one processing technique, sometimes questionnaires or studies such as magnetoencephalography. The following subsections describe the tools mentioned in Figure 9 in a way.

D. Reddy et al. were working to detect Creutzfeldt-Jakob disease, where one of the main symptoms is memory loss and personality changes. The detection is carried out with the application of several studies, EEG, magnetic resonance imaging, and studies of the cerebrospinal fluid. The results indicate that the EEG shows abnormal periodic slow and sharp waves that can only be observed in the first 8-12 weeks after the onset of symptoms; using the EEG alone, a sensitivity of 66% and a specificity of 74.5% were achieved. Accompanying the EEG of other methods, the sensitivity achieved rose to 97% with 100% specificity [6]. This research project illustrates an example of improvements of up to 20% that can be achieved with a combination of detection methods.

G. Fiscon et al. were able to distinguish patients affected by mild cognitive impairment from control cases with an efficiency close to 92%. They applied a monopolar montage EEG with 19 channels and a sampling frequency of 256 Hz. The FFT and the WT were applied, considering five levels of decomposition. The mother wavelets used were the Daubechies and the Symlets [55]. They combined FFT and WT, two processing techniques to analyze signals in the frequency domain, achieving efficiency levels higher than 90%.

The following describes an overview of the parameters used in the processing stage that showed greater repeatability in the reviewed articles:

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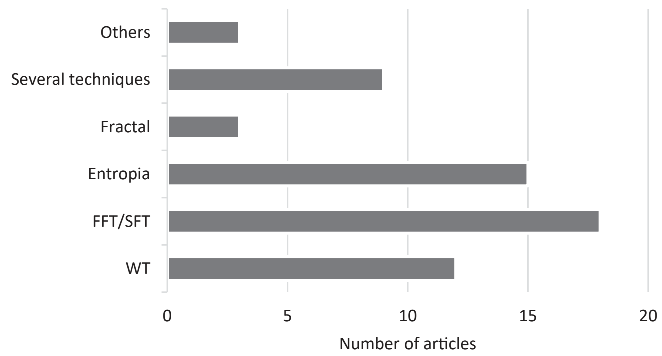

FIGURE 9. Tools for processing EEG signals that allow evaluating parameters associated with dementia diseases.

- FFT: The Fast Fourier Transform (FFT), which is also widely used in EEG signal processing to analyze signals in the frequency domain, using this tool, efficiency levels greater than 90% have been achieved in the detection dementia diseases [21]. The Discrete Fourier Transform (DFT), a variant of the FFT, requires $O(n_2)$ computational procedure, but when using the FFT only $O(nlog_2 n)$ are required. The computational procedure is an advantage for FFT, it achieves a lower computational demand, fast and efficient results that are very similar to those obtained with the DFT.
  Once the FFT or the DFT is applied, the results of the frequency domain analysis are compared in search of patterns/biomarks corresponding to the cases of dementia diseases and using this information to classify them from the control cases. EEG patterns are characterized by the frequency and amplitude of electrical activity. An example could be that the group of records belonging to people with the disease presented 30% higher activity in theta band frequencies according to the analysis of the frequency spectrum.
- STFT: The Short-Time Fourier Transform (STFT) is another variant of the FT, the STFT complements the limitations of the FFT, divides the signal into small segments, and calculates the FT of each of the segments separately in order to be able to represent the data in time-frequency. By having the information in its time-frequency representation, the temporal location can be obtained. In Eq. 1 the definition of the STFT is shown. Figure 10 visually shows the stages of applying the STFT, it has the time-domain signal (amplitude-time), the length of the window is identified, Eq. 1 is applied and finally, the signals in time-frequency.

$$\begin{aligned} STFT\{x(t)\} &= X(\tau,\omega) \\ &= \int_{\infty}^{\infty} x(t)\omega(t-\tau)e^{-i\omega t}\,d\tau \end{aligned} \tag{1}$$

  Where ω: frequency parameter, τ: time parameter, $x(t)$: signal to be analyzed, $\omega(t-\tau)$: windowing function, $e^{(-i\omega t)}$: FT kernel (basic function).
  The STFT as well as the WT are some of the most used techniques for non-stationary signals in the time-frequency domain. One of the limitations of the STFT is the limitation of the window width, which establishes that it is impossible to know an exact time-frequency representation of a signal, that is, it is not possible to determine what frequency value exists at a given instant of time. It is only possible to know what frequency components exist within the time interval determined by the Heisenberg uncertainty principle. The principle states that a signal cannot be located with high precision in both frequency and time [76], [77]. The STFT, like FFT or DFT, helps in the identification of EEG patterns, with the difference that it is possible to have identified the frequency value associated with the time in which it occurs, which in cases such as the application of stimuli could be relevant information.
- WT: The Wavelet Transform (WT) consists of decomposing the signal into scaled and displaced versions of the mother Wavelet, it was developed in the mid-'80s and an important advantage is that it does not have problems with non-stationary and fast-transient signals. The Mother Wavelets are families of functions that are defined and are used as analysis functions, examining the signal of interest in the time-frequency plane. The Continuous Wavelet Transform (CWT) is defined in Eq. 2 and the Discrete Wavelet Transform (DWT) is defined by passing the signal through a series of high and low pass filters in Eq. 3 and Eq. 4 respectively [78], [79].

$$W_s(a,b) = \frac{1}{\sqrt{|a|}} \int s(t)\psi^*(\frac{t-b}{a})\,d\tau \tag{2}$$

  Where b: translation parameter, a: scale parameter, $s(t)$: signal to be analyzed, $\frac{1}{\sqrt{|a|}}$: normalization constant, $\psi^*(\frac{t-b}{a})$: mother wavelet, $W_s(a,b)$: coefficients representing concentrated time-frequency.

$$y_{high}(n) = \sum s[k]h[2n-k] \tag{3}$$

$$y_{low}(n) = \sum s[k]g[2n-k] \tag{4}$$

  Where $y_{high}(n)$: detail coefficients, h: high-pass filter, $y_{low}(n)$: approximation coefficients, g: low-pass filter, $s[k]$: signal to be analyzed.
  According to 3, the WT is generated by the dilation and translation through the temporal axis of the mother Wavelet, Figure 11 illustrates the previously described behavior. Among the main

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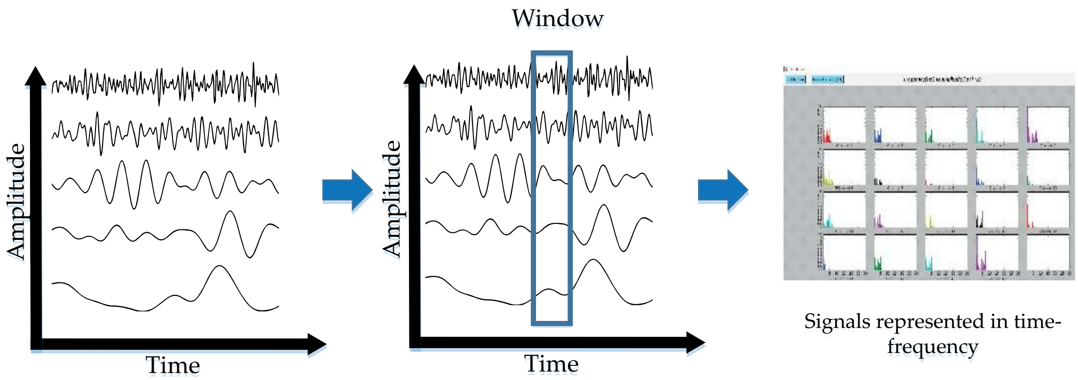

FIGURE 10. Stages of time-amplitude change to time-frequency using the STFT.

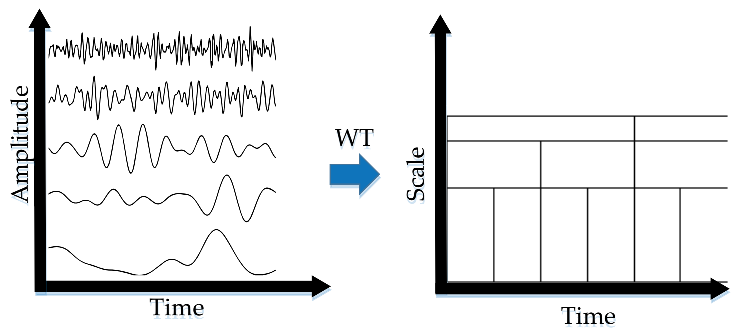

FIGURE 11. Stages of time-amplitude change to time-frequency using the WT.

mother Wavelets are Meyer, Daubechies, Coiflets, Symlets, Biortoganales, Morlet, and Mexican Hat. The use of WTs has increased in recent years due to its advantages for working with non-stationary signals, one of the main applications is in clinical EEG, but they are also found in the analysis of structures or robotics [80]–[89].

- SST: Synchrosqueezing Transform (SST) is a variant of Time Frequency Representation (TFR), invertible, and adaptive transform that improves quality. It is resistant to noise and allows to analyze signals in the frequency spectrum. SST concentrates the energy content in a spectral band and is suitable for the localization of FT. In the literature, high levels of reliability and efficiency are reported in the processing of EEG signals using this tool, [47], [90] the detailed steps for its implementation are described.
- FD: In general terms, the Fractal Dimension (FD) is used to quantify the degree of irregularity and fragmentation of a geometric set or natural object. Adapting the concept to EEG signal processing allows measuring the complexity of the neuronal cell profiles. FD is associated with a healthier or adaptive system [47].
  The calculation of the FD index is widely used in combination with techniques for analyzing signals in the frequency domain (FT or WT), thanks to this combination, higher levels of efficiency have been reported than those obtained separately. The higher the FD value, the greater the irregularity of the series. The FD can take values greater than 1 and less than 2 ($1 < DF < 2$), for this reason, that the FD for a time series is greater than the Euclidean dimension of a straight line, and less than that of a surface.
  Let the time series be: $X = x[1], x[2], \ldots, x[N]$. Form k new time series.

$$X_k^m = \{x[m], x[m+k], x[m+2k], ..., x[m + int\left(\frac{N-m}{k}\right) \times k]\} \tag{5}$$

Where the new series are described in Eq. 6 and $m = 1, 2, \ldots, k; k = 1, 2, \ldots, k_{max}$:

$$L(m,k) = \frac{1}{k}\left(\sum_{i=1}^{int\frac{N-m}{k}} |x[k+ik] - x[m+(i-1)\times k]|\right) \times \left[\frac{N-1}{int\frac{N-m}{k} \times k}\right] \tag{6}$$

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The mean length $L(k)$ is given by:

$$L(k) = \frac{1}{k}\left(\sum_{m=1}^{k} L(m,k)\right) \quad (7)$$

FD is the slope of $ln[L(k)]$ over $ln(\frac{1}{k})$. The selection of the appropriate ht value for k_{max} is done by plotting the FD values against the range of k_{max}. The point where the FD plateaus observed is taken as the saturation point, and the value is selected as k_{max}. [91], [92] the steps of the process to calculate the index in FD are described in detail.

- ApEn: The Approximate Entropy (ApEn) is a measure of regularity and complexity of a system, it reflects the "order" of the signal and is useful in biomedical applications in the detection of events associated with cerebral rhythms ranging from dementia diseases, sleep disorders, epilepsy among others. A lower ApEn is the quantification of predictability, while a higher ApEn indicates the unpredictability of a time series. For the EEG signals, an adaptation of the entropy calculation has been made, making it dependent on time. [45], [93]–[96] considering the algorithm proposed by Picus, let N point time series $x(1)$, $x(2)$,..., $x(N)$ with embedding space R^m, ApEn is defined as:

$$ApEn(m,r,N) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} logC_i^m(r) - \frac{1}{N-m}\sum_{i=1}^{N-m} logC_i^{m+1}(r) \quad (8)$$

Where $C_i^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} logC_i^m(r) - \frac{1}{N-m}\sum_{i=1}^{N-m} logC_i^{m+1}(r)$, N is the time series length, m is the comparing length of the sequences and r is the tolerance level.

C. CLASSIFICATION

The classification of data is the penultimate stage of the process in the detection of dementia diseases, the tool used plays an important role in the levels of efficiency and reliability achieved. According to Figure 13, one of the main classification techniques is Support Vector Machine (SVM) followed by Neural Networks (NN).

- SVM: It is a classification-regression method, developed in the 90's. SVM has become very popular in multiple application and regression problems due to its results, according to Figure 13 it is one of the main classification techniques in EEG signal applications. SVM is one of the most elegant solutions in machine learning, based on the hyperplane concept, which in turn is related to the "Maximal Margin Classifier". A hyperplane is a flat and affine subspace of dimensions $p-1$. Considering a $p-dimensional$ space. During the training, the aim is to create a classifier based on a hyperplane that, although it does not perfectly separate the classes, is robust and has a high predictive capacity [97]. One of the best-known tools for working with a difficult-to-classify data set is the use of kernels to aid in the optimization of predictions. A kernel is a function that returns the product point result between two vectors realizing in a new dimensional space different from the original one in which the vectors are found. By substituting the dot product for a kernel, the support vectors are obtained directly. Some examples of kernels are : linear, polynomial, and RBF. Currently, there is a wide variety of libraries that simplify the use of SVM in different programming languages that help users without extensive knowledge of SVM to use it to solve their classification problems [97].
- NN: Another popular method for classifying EEG data are NN, it is a model inspired by the human being. The NN is made up of a set of nodes known as artificial neurons that are connected and transmit signals to each other. Figure 12 displays an example of the basic parts for the architecture of a neural network, the architecture is the topology, structure, or connection pattern of the neural network. In the input layer, the neurons receive the data or signals; in the hidden layer it has no direct connection with the environment, it is responsible for providing degrees of freedom to the neural network in order to model the characteristics of the environment; finally, the output layer is made up of neurons that provide the response of the neural network. Some examples of NN architectures are unidirectional networks or recurring networks [98].

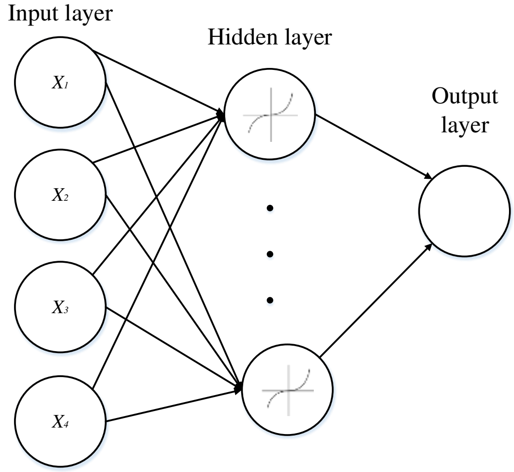

FIGURE 12. Basic elements of the NN architecture: Input layer, hidden layer and output layer.

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The internal structure or model of the NN is composed of a set of inputs x_j; synaptic weights w_{ij}, with $j = 1, ..., n$; a propagation rule h_i defined from the set of inputs and weights; an activation function, which simultaneously represents the neuron output and its activation state. As in SVM, there are currently libraries in different programming languages that make it possible for people without deep knowledge of NN to easily use them in troubleshooting [99]–[101].
Two examples of very common neural networks in EEG applications are described in a general way below:

1) Adaptive Neuronal Network (ANN): It is a type of neural network applied in dynamic environments [102]. It is characterized by one-line learning. The adaptation of the neural network can be presented by modifying the weight, neural property and / or structure of the network. [103] describes an example in the application of ANN in the classification of EEG signals.
2) Convolutional Neural Network (CNN): it is a neural network with supervised learning. CNN is a variation on the multilayer perceptron, uses two-dimensional matrices and is very effective in classification, computer vision and image segmentation applications. [104], [105] an example of the application of CNN in EEG signals is described.

- k-nearest neighbors (KNN):This is a supervised, non-parametric machine learning algorithm. It technique has stood out for its simplicity of application and the results obtained in classification efficiency. KNN assumes that something similar exists in the vicinity and depends on this assumption being true enough to make the algorithm useful. [106], [107] described the method.
- Decision tree: It is widely used in classification for its speed and competitive efficiency levels. A key element in this method is the attribute selection problem due to the spatial feature selection. In general, the process to apply this method is divided into building the tree to reduce the characteristics and pruning of the tree to avoid excessive adjustment.
  This is a non-parametric method, which has a high capacity to handle missing values, a very common problem in biomedical data. A disadvantage of the method is that it does not consider univariate statistics [108], [109].
- Logistic regression (LR): It is a tool for classification that consists of a specific case of a generalized linear regression model. In general, LR consists of quantifying the relationship between a variable with binary response and one/more dichotomous or continuous predictors. A linear relationship between the predictors and the result is obtained by transforming the probability of being correct into the logarithm of the probabilities that the primary answer is correct to incorrect. LR is classified as a type of regression with categorical results, which are expressed as multinomial or binomial [110]–[112].

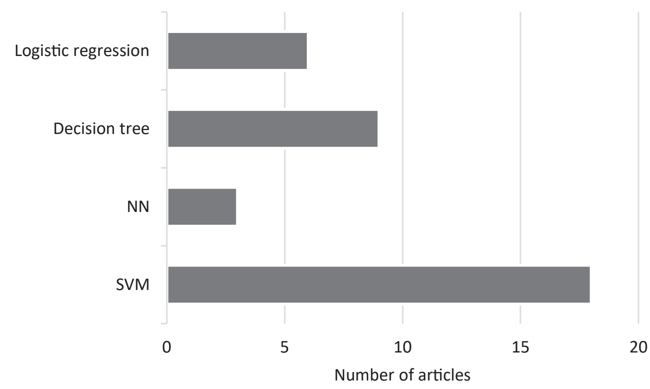

FIGURE 13. Tools for processing EEG signals that allow classification parameters associated with dementia diseases.

During the selection of classification technique, it is suggested that the researcher review the size of the database first, since often when there are few information vectors it can lead to overfitting and bias in the classification. It is also important to review how and with whom the work is required to be compared to have a real comparison of the research.

D. PERFORMANCE EVALUATION

The validation stage is the last phase of the process and serves to evaluate the performance of the application. In the field of pathology detection using EEG, precision, sensitivity, specificity, among others, are usually reported. According to Figure 14, the main validation method is Cross-Validation.

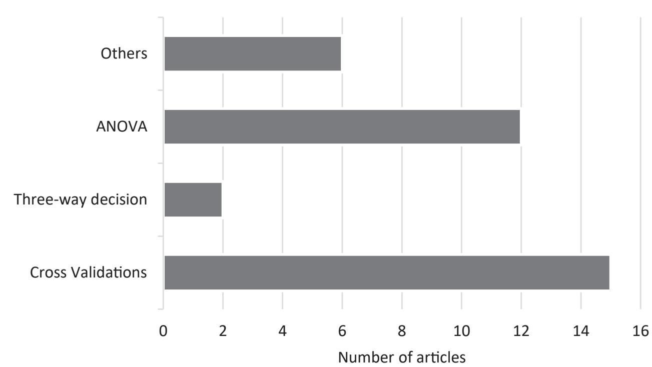

FIGURE 14. Tools for processing EEG signals that allow evaluating parameters associated with dementia diseases.

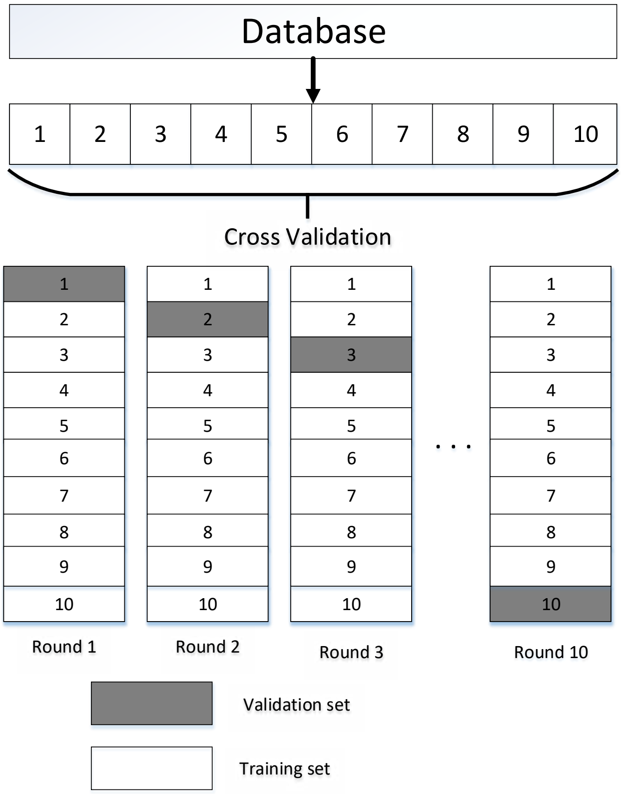

FIGURE 15. Cross validation considering 10 rounds.

- Cross-validation, k-fold, consists of taking the data set and creating two separate groups from it: a training set and a validation set. Later, the training set is divided into n subsets and, at the time of training, each subset is taken as a test set of the model, while the rest of the data is considered a training data. The process is repeated n times, and at each iteration, a different test set is selected, while the remaining data will be used as the training data. During each iteration, the aforementioned metrics are calculated [113]. Figure 15 illustrates an example of cross-validation considering 10 rounds.
- ANOVA: It is a technique for analysis of variance that can be used in the study of one or more factors. The statistical test consists of comparing the means of the groups, the null hypothesis from which the different types of ANOVA start is that the mean of the variable is the same in the groups and the alternative hypothesis that at least two means differ in a way significant [114].
  In most of the reviewed works where ANOVA is used, the information is presented with a value for p-value, this is the probability that quantifies the evidence against the null hypothesis. The smaller the p-value, the stronger the evidence against the null hypothesis and indicates that there is significant evidence to affirm that the means of the groups are statistically different [115].
- Three-way decisions: It is based on the notions of acceptance, rejection and non-commitment; an extension of the binary decision model with an option added. The applications of this method are concentrated in areas of computing where the objective is to divide into three regions: positive, borderline and negative. The challenge in this tool is to be able to calculate the thresholds, where in most of the reported cases it is solved from the loss functions determined in the experience of the experts [45]

E. STRATEGIES TO INCREASE EFFICIENCY AND SUGGESTIONS TO SOLVE THE LIMITATIONS

In addition to the elements discussed in the previous sections, another tool that has been shown to achieve improvements in efficiency levels is the combination of EEG with other acquisition techniques [116], [117].

- Common spatial patterns (CSP): They are algorithms used for the extraction of characteristics in Brain-Computer Interfaces (BCI). The objective of this technique is to find spatial filters that can maximize the projected variance relationship between the covariance matrices of the EEG signals corresponding to mental tasks. This technique has been shown to increase efficiency levels in the detection of EEG patterns/biomarks [118].
- Near-infrared spectroscopy (NIRS) or the functional near-infrared spectroscopy (FNIRS): These are non-invasive brain imaging techniques that use the near-infrared (NIR) light spectrum (wavelength 600-1000 nm) to measure the hemodynamic response, and high robustness to noise. Hermodynamic variations due to brain activity are used to relate them to specific patterns. These techniques help in the disadvantage of EEG in poor spatial resolution for precise localization. The combination of EEG with NIRS or FNIRS has been shown to increase efficiency levels in the detection of movement patterns. Which suggests that this combination could increase efficiency levels in the detection of dementia diseases [116], [117].
- Finally, in Table 3 lists a set of recommendations for resolving limitations in the following categories: database, acquisition, feature extraction, and results. Removing the limitations contributes to achieve more solid, robust, and reliable developments.

IV. CONCLUSIONS

The information provided by the EEG has become a key element in the health sector, due to the wide field of applications and the results in terms of efficiency and reliability. From the reviewed works, it was found that

TABLE 3. Recommendation to resolve limitations in future EEG-base dementia studies.

Category	Limitations
Database (1)	Provide detailed characteristics of the population. Describe how the diagnosis of dementia disease was made. Do not use heterogeneous samples. Detail the description of the EEG experiment in duration and phases. Use guidelines for the positioning of EEG electrodes. Provide information on the positioning of the channels. Verify the reliability of the patient's diagnosis and exclude patients who are taking medications.
Acquisition stage (2)	Describe artifact management strategies. Train the personnel who will apply the EEG. Periodically verify and calibrate the EEG acquisition system. Perform a reliability analysis of the acquisition system.
Feature extraction (3)	Define EEG feature extraction and processing in more detail. Train the person in charge of this stage with the basic knowledge in the identification of biomarks/EEG patterns. Use more than one parameter/processing techniques for classification. Check the data used for the configuration and application of the processing techniques agree with the data of the sampling time, the size of the recorded segments and the EEG record number. Use deep learning techniques to achieve automatic classification with higher levels of efficiency.
Results (4)	Extracting more than one feature in combination with deep learning techniques (NN, SVM) reported high levels of efficiency. Describe in detail the results obtained considering precision, sensitivity and specificity. Verify that the methodologies with which they will be compared have similar conditions.

EEG data in combination with processing techniques (FT, FFT, STFT, WT) and machine learning tools such as SVM and NN have been shown to achieve applications with a efficiency greater than 90%, a competitive tool for solving problems in this field of study, Table 1.

The measurements help to accurately indicate the degree of difference between two bodies, which in our case study will be two signals or electrode channels of the electroencephalogram, although there is no deep description of the acquisition stage, it is an indispensable element and that requires the attention of the project since it will be the raw material of the following stages.

According to the extraction of characteristics for the signal acquisition stage, Figure 4, it is observed that the most used frequency range is between 128-256 Hz. Considering the mathematical foundation as the Nyquist theorem, as well as the nature of the EEG signals meets at least the minimum requirements and also the electronic requirements imply a lower cost compared to higher frequencies.

In the case of the number of electrodes, the highest repeatability fell to 19 electrodes. The 10-20 system allows the 19 electrodes to be distributed evenly around the scalp, allowing a high-approximation panorama in all areas. According to the literature reviewed, it is shown that using this number of electrodes, efficiency levels have been achieved in the classification higher than 90%. In addition, the number of electrodes is in a medium-range for details such as cost, application time, and processing time.

Time, one of the parameters with the greatest variability, according to the articles reviewed. An average value was 20 min, however, the key element is the type of stimulus or state of the patient to be recorded, which in general terms is in accordance with the application and signal processing. In the sample size, according to Table 1 is associated with efficiency and reliability, in Figure 6, the range with more repeatability was between 40-56 subjects. It is essential to consider that the smaller the sample, it could be reflected in a bias and low levels of efficiency, so it is important to take into account statistical principles that offer criteria to estimate the size of the sample in order to obtain information on various characteristics of interest that can be generalized from the sample to the population.

The parameters or measurements that are possible to extract during the processing of the EEG signals, vary from obtaining the frequency spectra, time-frequency, values such as entropy, fractal average or combination of more than one parameter. According to Figure 9, more than 25% of the articles reviewed use more than one technique and thanks to them they achieve better levels of reliability; some of the combinations are WT/Entropy, FFT/Entropy, WT or FFT in combination with patient questionnaires. The objective of the processing stage is to extract relevant information that allows the identification of EEG patterns/biomarks that, during the classification stage, contribute to achieving higher levels of efficiency.

The following stages, which are the classification strategy and validation, are closely related because, according to the selected classification strategy, they are the options that can be used for validation. In the case of using deep learning tools for classification, one of the most used validation techniques is Cross-Validation according to Figure 14.

Collecting the results of the stage to define parameters in signal acquisition, processing and classification, an example of combination that resulted with high levels of efficiency, low cost and low computation time is: 19 electrodes, 20 min of acquisition, with a sample of 40-56 subjects, more than one processing parameter (WT/Entropia, FFT/Fractals) and using SVM as classification.

In recent years, it has not only been found that the use of EEG information helps in the arrest of pathologies but also in their prediction, which is why the study of this area of research is suggested. The prediction of pathologies, solve the limitations of Table 2, and tools such as CSP or NIRS-EEG are part of the challenges and future applications of EEG in the detection of dementia diseases.

The aforementioned data serve to guide the reader who begins a study in the development of an application using the EEG, to suggest some options that have shown outstanding results and also others that can become limitations. Several methods to achieve automatic or semi-automatic detection of dementia diseases have been presented in this review. Each proposal has its merits and disadvantages, and the most suitable medium must be selected based on the specific application in mind.

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