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Automatic Detection of EEG as Biomarker using Deep Learning: A review

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Abstract

Automated Electroencephalography (EEG) is a dynamic signal that can take years of training to interpret correctly, as well as advanced signal processing and feature extraction methodologies. Due to its ability to learn good feature representations from raw data, deep learning (DL) has recently shown great promise in helping make sense of EEG signals. The question of whether DL genuinely provides advantages over more conventional EEG processing methods remains unanswered. In this paper, we examine 154 papers that use deep learning to analyses EEG data, with applications ranging from epilepsy to sleep to brain–computer interfaces to cognitive and affective monitoring. In order to inform future research and formulate recommendations, we extracted trends and highlighted DL approaches from this broad body of literature.

Keywords: EEG, electroencephalogram, deep learning, review, neural-networks.

1. Introduction

1.1. Measuring brain activity with EEG

Electroencephalography (EEG) is a brain mapping and neuroimaging technique that is commonly used both within and outside the clinical domain. It measures the electrical fields generated by the active brain. When tiny excitatory post-synaptic potentials formed by pyramidal neurons in the cortical layers of the brain sum together, EEG detects electric potential differences on the order of tens of V that enter the scalp. As a result, the potentials measured represent neuronal activity and can be used to investigate a variety of brain processes. EEG has excellent temporal resolution due to the high speed at which electric fields propagate.

Usually, events occurring on millisecond timescales may be recorded. However, EEG has a low spatial resolution because the electric fields produced by the brain are smeared by tissues between the sources and the sensors, such as the skull. As a consequence, EEG channels are often spatially associated. The inverse problem, also known as the source localization problem, is a research field in which algorithms are being developed to reconstruct brain sources from EEG recordings [78]. EEG has a wide variety of applications. EEG is often used in clinical settings to research sleep cycles [1] or epilepsy [3].

The most common montage used for EEG recording for dementia is the referential montage, which is used to record the voltage difference between the active electrode on the scalp and the reference electrode on the earlobe, as shown in Figure 1 [4, 5]. The EEG of dementia patients

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was registered in a specialized clinical unit state, while resting with eyes comfortably closed, using the 10–20 method of the international federation, which is adopted by the American EEG Society, as shown in Figure 2.

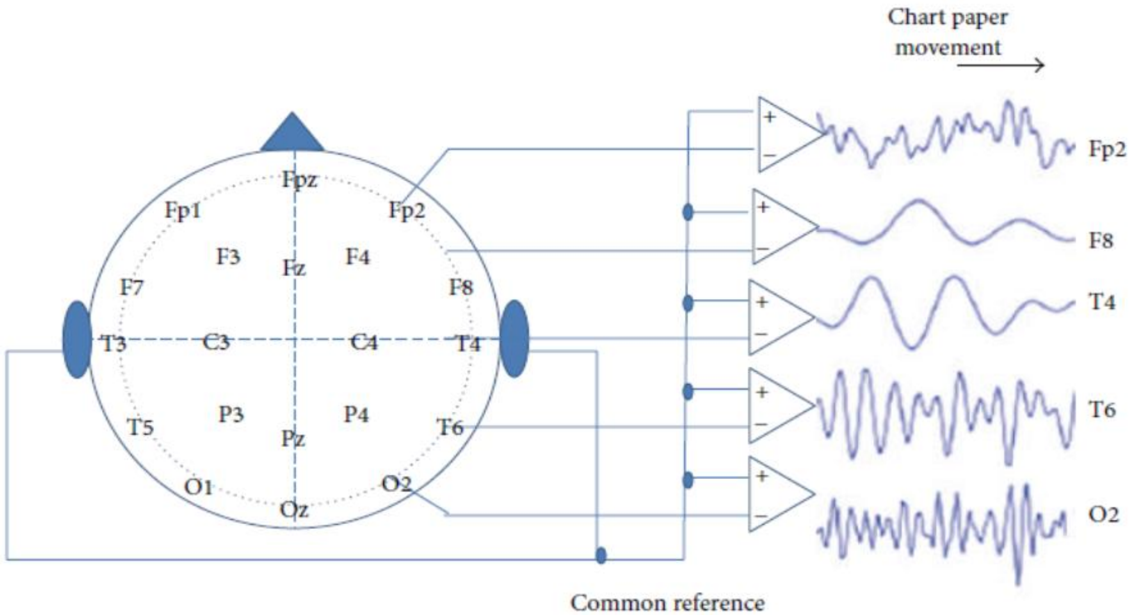

Fig 1: EEG referential montage

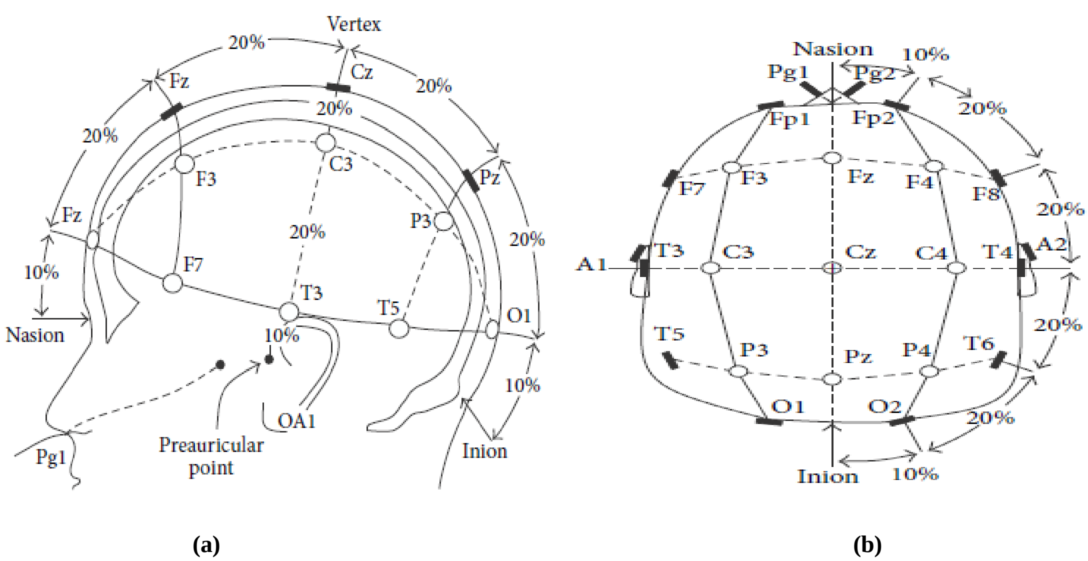

Figure 2: The 10–20 EEG electrodes placement system. (a) and (b)Three-dimensional side view and top view, respectively [6].

Various disorders have also been related to changes in electrical brain activity, so EEG can be used to track these changes to varying degrees. Attention deficit hyperactivity disorder (ADHD)

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[6], consciousness disorders [7, 8], depth of anesthesia [68], and so on are examples of these. EEG is also commonly used in neuroscience and psychology studies because it is a great method for understanding the brain and how it works. Cognitive and affective monitoring systems are very interesting because they could provide unbiased measurements of an individual's exhaustion, mental workload, mood, or emotions [9]. Finally, EEG is commonly used in brain–computer interfaces (BCIs)—communications between the brain and the computer.

1.2. Current challenges in EEG processing

While EEG has proven to be a powerful tool in a number of fields, it still has some limitations that make it difficult to analyses or process. First, EEG has a low signal-to-noise ratio (SNR) [9, 10], since the brain activity detected is often buried under numerous sources of environmental, physiological, and activity-specific noise of equal or greater amplitude, collectively known as "artefacts." To and the effect of these noise sources and remove true brain activity from the recorded signals, various filtering and noise reduction techniques must be used.EEG is a non-stationary signal [11, 12], which means that its statistics shift over time. As a result, a classifier trained on a dataset was developed.

This is a significant challenge for real-world EEG applications, which frequently require working with limited data sets. Finally, high inter-subject variability reduces the utility of EEG applications. This phenomenon arises as a result of physiological differences between individuals, which vary in magnitude but can have a significant impact on the performance of models designed to generalise across subjects [13]. Because the ability to generalise from one set of individuals to a second, unseen set is critical to many practical applications of EEG, much effort is being put into developing methods that can deal with inter-subject variability.

1.3. Improving EEG processing with deep learning

To overcome the aforementioned challenges, new approaches to EEG processing are required in order to achieve better generalization capabilities and more flexible applications. Deep learning (DL) [14] could significantly simplify processing pipelines in this context by allowing automatic end-to-end learning of preprocessing, feature extraction, and classification modules, while also achieving competitive performance on the target task. Indeed, in recent years, deep learning architectures have been very successful in processing complex data such as images, text, and audio signals , resulting in state-of-the-art performance on multiple public benchmarks such as large scale visual recognition. DL is a subfield of machine learning that studies computational models that learn hierarchical representations of input data through successive non-linear transformations [15]. Deep neural networks (DNNs), which were inspired by earlier models such as the perceptron [16], are models in which: (1) stacked layers of artificial 'neurons' each apply a linear transformation to the data they receive, and (2) the result of each layer's linear transformation is fed through a non-linear activation function.

Importantly, these transformations' parameters are discovered by explicitly minimizing a cost function. Despite the fact that the word "deep" implies the presence of several layers, there is no agreement on how to quantify depth in a neural network and thus on what really constitutes a deep network [17]. Figure 3 shows an overview of how EEG data (and other multivariate time

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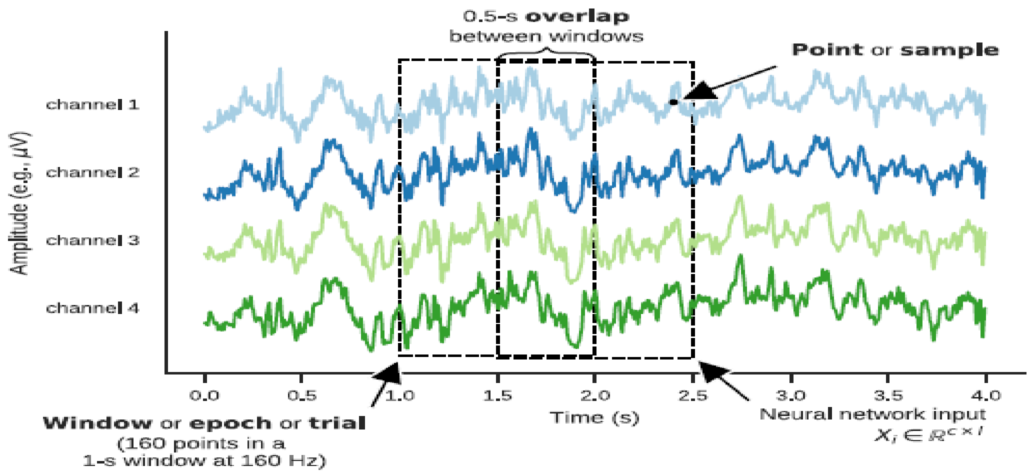
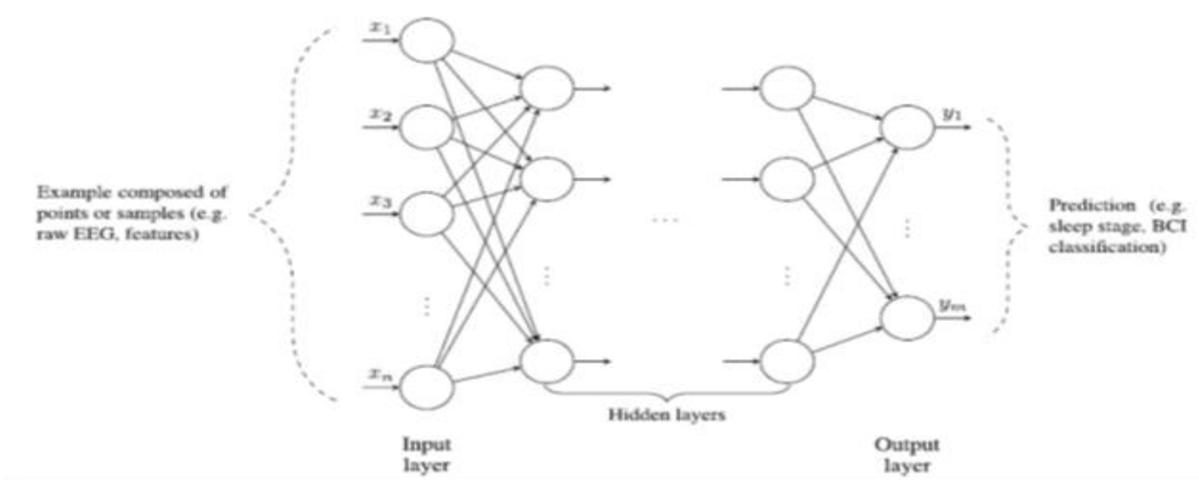
series) can be formatted for feeding into a DL model, as well as some key terminology and generic neural network architecture. When c channels are available and a window has length l samples, a neural network's input for EEG processing typically consists of an array containing the samples corresponding to each channel's window. This two-dimensional array can be used directly for training a neural network, or it can be unrolled into an n-dimensional array as shown in figure 3. (b).



(a)



(b)

Figure 3. Deep learning-based EEG processing pipeline and related terminology. (a) Overlapping windows (which may correspond to trials or epochs in some cases) are extracted from multichannel EEG recordings. (b) Illustration of general neural network architecture.

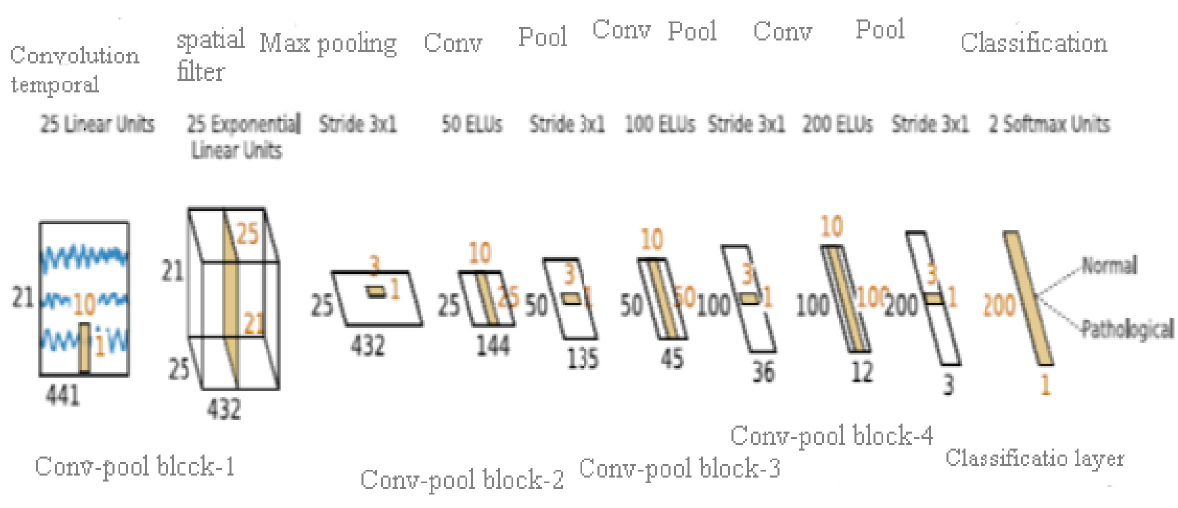


Fig.4. Four-layered BD-Deep4 as introduced by Schirrmeister et al. (2017b). Initial separated convolution is followed by several convolution and max-pooling blocks.

An initial separated convolution6 (first temporal, then spatial) is used in the BD-Deep4 architecture in Fig.4. Following that, it uses exponential linear units as activation functions and has multiple blocks consisting of convolution and max-pooling. It's a wide architecture that's been shown to work well for a variety of EEG decoding tasks, including motor (imagery) decoding [22], velocity and speed decoding, and pathology decoding. We used BD-Deep4 without making any improvements to its architecture.DNN-learned features may be more powerful or expressive than human-engineered features. Second, as in the many domains where DL has outperformed previous state-of-the-art, it has the potential to produce higher levels of performance on various analysis tasks. Third, DL makes it easier to develop tasks that are less commonly attempted with EEG data, such as generative modeling [23] and domain adaptation [18]. Deep learning-based methods enabled the synthesis of high-dimensional structured data like images [24] and speech. Generative models can be used to learn intermediate representations or to supplement data [23].When it comes to domain adaptation, deep neural networks combined with techniques like correlation alignment [25] allow for end-to-end learning of domain-invariant representations while maintaining task-dependent knowledge. Similar strategies can be applied to EEG data in order to learn better representations and thus improve the performance of EEG-based models across different subjects and tasks.On the other hand, there are a variety of reasons why DL may not be optimal for EEG processing, which may justify the scepticism of some in the EEG community. First and foremost, the datasets typically available in EEG research contain far fewer examples than what has led to the current situation.What has contributed to the new state-of-the-art in DL-intensive domains like computer vision (CV) and natural language processing (NLP)? Since data collection is costly, and data accessibility is often hampered by privacy concerns—especially with clinical data—openly accessible datasets of comparable sizes are uncommon. Despite this, several programmes have attempted to address the issue [26]. Second, EEG data differs from other forms of data (such as images, text, and speech) because of its peculiarities, such as its low SNR. As a result, existing DL architectures and strategies just cannot be readily applicable to EEG processing.

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2. Methods

This review focused on standard journal and conference articles, as well as electronic preprints, published. The first category includes the article's source, such as whether it was published in a journal, a conference, or a preprint repository, as well as the first author's affiliation nation. This provides a brief overview of the various types of publications covered in this study, as well as the major players in the field. The reasoning group, on the other hand, focuses on the study's application domains. This knowledge is useful for assessing the scope of research in the field and recognizing patterns across and within domains in our study. Third, the data type covers all applicable data used by the chosen papers. In addition to the amount of data available in each analysis, this involves both the source of the data and the data collection parameters. We hope to explain the data requirements for using DL on EEG through this portion. The fourth group, EEG processing parameters, illustrates the common transformations needed when applying preprocessing steps, artefact handling methodology, and function extraction are all covered from DL to EEG. Preprocessing measures, artefact handling technique, and function extraction are all covered. Fifth, the DL methodology is outlined in depth, including architecture design, training procedures, and inspection methods, to direct the interested reader through cutting-edge techniques. The sixth group, published results, discusses the results of the selected papers, as well as how they were reported, with the intention of assessing how DL compares to conventional processing pipelines in terms of output. Finally, the reproducibility of the chosen articles is assessed by looking at the data and code that is available. The findings of this section back up a key point in our discussion.

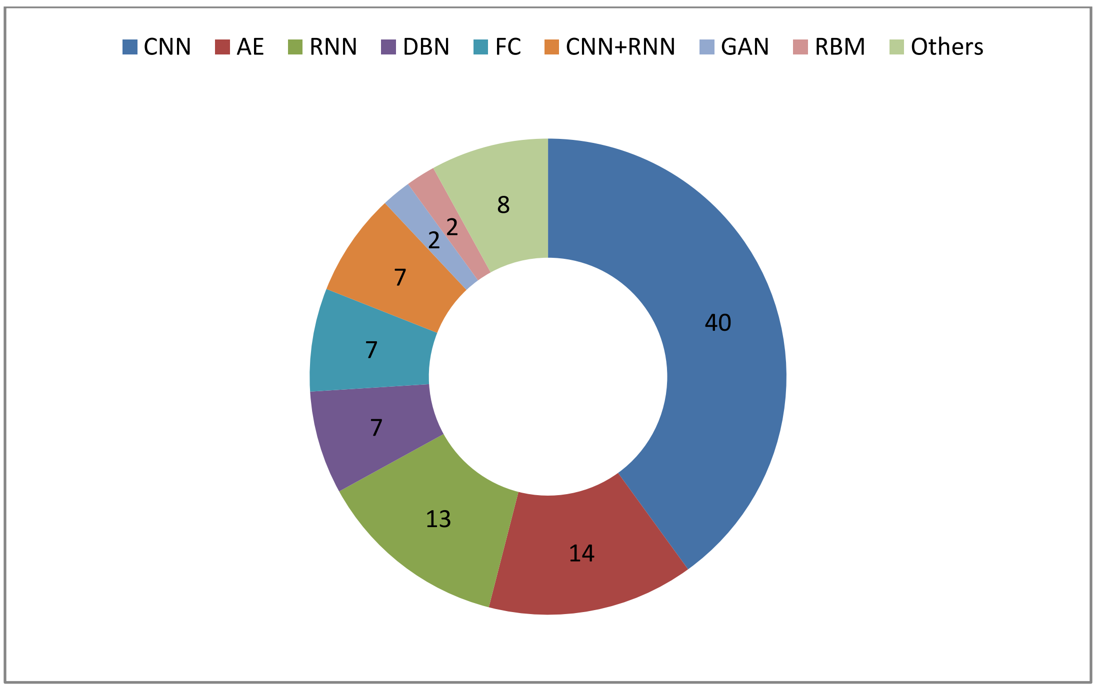

Figure 5.Deep learning architectures used in the selected studies. ‘

The neural network architecture to be used in the DL-based EEG processing pipeline is a critical decision. We divided and assigned the architectures used in the 154 papers into the following

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categories to address the first three questions: CNNs, RNNs, AEs, RBMs (restricted Boltzmann machines), DBNs, GANs, FC networks, CNN + RNN combinations, and 'Others' for every other architecture or combination not included in the aforementioned categories.The percentage of studies that used the various architectures is shown in Figure 5. CNNs were used in 40% of the papers, while RNNs and AEs were used in around 13% of the works, respectively. In contrast, 7 percent of the studies used a combination of CNNs and RNNs.RBMs and DBNs accounted for almost 10% of the architectures. Just 6% of the articles used FC neural networks. GANs and other architectures were found in 6% of the cases examined. It's worth noting that only 4% of the papers examined did not specify their preferred architecture. Deep neural networks are generally made up of layers stacked on top of one another to provide hierarchical processing.While it might seem that the use of deep neural networks implies a large number of layers in the architecture, there is no absolute agreement in the literature on this concept. In this paper, we look into this issue and show that in many of the studies examined, the number of layers is not inherently high, i.e. greater than three.

3. Results

Depending on how epochs are extracted, the amount of EEG data used in different studies ranges from less than ten minutes to thousands of hours, and the number of samples used during network training ranges from a few hundreds to many millions. We discovered that over half of the studies used publicly accessible data, and that there has been a clear change from intra-subject to inter-subject approaches in recent years. Convolutional neural networks (CNNs) were used in 40% of the experiments, while recurrent neural networks (RNNs) were used in 13%, with the most common layer count being 3–10 layers.Moreover, nearly half of the studies used raw or preprocessed EEG time series to train their models.Finally, across all related research, the median improvement in accuracy of DL approaches over conventional baselines was 5.4 percent. More significantly, we found that studies have a low reproducibility rate: the majority of papers would be difficult or impossible to replicate due to a lack of data and code importance.

4. Discussion

The electroencephalogram (EEG) is a valuable instrument for measuring brain activity. The aim of this review is to look at how EEG can be used as a physiological biomarker to diagnose dementia in its early stages and classify its severity using EEG signal analysis and processing. The identification and diagnosis of dementia in its early stages has sparked a lot of concern. This could be done by integrating diagnostic criteria with accurate biomarkers. Neuropsychological tests and biomarkers measured against different dementia symptoms will assist in capturing both the early stages and the spectrum of dementia before serious mental deterioration [26– 29].

An accurate, precise, and cost-effective biomarker to diagnose dementia is urgently needed. Because of its low cost and noninvasive nature, the EEG is an appealing method for early detection and differentiation of AD and VaD. The emphasis of this review was on the use of EEG as a physiological biomarker to help diagnose dementia in its early stages. Due to the subjective experience of neurologists, EEG assessment by visual examination is vulnerable to errors. Furthermore, it is time consuming and may not be able to detect subtle changes in the

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EEG, while computerized EEG signal analysis may simplify medical doctors' work and contribute to improving patient outcomes the assessments additional objective.

The principles of EEG signal processing were demonstrated in this study, as well as useful techniques for improving recorded EEG signals. To extract artefacts from EEG signals, a number of signal preprocessing and denoising techniques are used. To remove various forms of noise, methods such as WT and ICA have been used. On the one hand, ICA has some benefits as a higher order statistics system because of its ability to split a collection of mixed signals into its sources. ICA, on the other hand, may have difficulty deciding the ICs' order. It is, however, an effective tool for artefact removal that can be used offline.WT, on the other hand, is suitable for no stationary signals such as EEG, which provide a linear combination of the sum of wavelet coefficients and mother wavelet with frequency and localization details, and WT uses a multiresolution decomposition algorithm to break the signal into sub bands (approximation and detail). ICA-wavelet hybrid techniques have been used in recent years to address the limitations of each individual system, and they may prove to be a more efficient denoising method. When the redundancy is higher and the frequency domain features are completely used, the data can be projected into a new space to increase the performance of ICA and WT. This reduces the amount of data; it also allows WT to eliminate any noise overlapping in the EEG signals that ICA can't filter out.

This analysis also looked at strategies for extracting linear and nonlinear characteristics, as well as dimensionality reduction methods. Table 1 provides a description of the results of the most powerful linear and nonlinear processes.Following that, the methods for classifying EEG signals based on the dementia continuum (i.e., CIND, MCI, and dementia) were updated. The symptoms of dementia on the EEG can be described as a reduction in EEG sophistication and synchrony, as well as a slowing of the EEG. Based on its applicability in many fields and empirically good accuracy and generalization, the SVM classifier is recommended as a suitable technique for classifying the features of EEG signals. SVM's advantages in dealing with vast feature spaces have helped many researchers. Other researchers have combined classification algorithms to see if they can improve the effectiveness, sensitivity, and specificity of the best clinical opinion for dementia early detection and classification.

5. Conclusions

EEG has been described as a research tool and possible biomarker for detecting dementia and classifying its severity in this study, by presenting concise details about brain activity and how it is affected by AD and VaD. It should be noted that the study has occasionally concentrated on results relating to Alzheimer's disease. This is due to the fact that the literature on Alzheimer's disease is much more detailed. Despite extensive studies into the use of EEG for dementia screening, it is still not widely used in clinical practice [26–29]. Furthermore, the analyzed datasets were often small, necessitating additional analysis to validate the promising findings.

Several researches, on the other hand, have praised the EEG as a valuable clinical assessment method for separating Alzheimer's disease from dementia. EEG-based identification of dementia development and severity classification is a highly attractive screening technique in clinical

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practice because of its low cost and portability, making it a promising technique that can be used to tailor or personalize appropriate therapeutic services for dementia patients.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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