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SURVEY

EEG Signal Processing for Medical Diagnosis, Healthcare, and Monitoring: A Comprehensive Review

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ABSTRACT EEG is a common and safe test that uses small electrodes to record electrical signals from the brain. It has a broad range of applications in medical diagnosis, including diagnosis of epileptic seizure, Alzheimer's, brain tumors, head injury, sleep disorders, stroke, and other seizure and neurological disorders. EEG can also be used to help diagnose death in people who are in a persistent coma. The use of digital signal processing and machine learning to improve EEG analysis for medical diagnosis has gained traction in recent years. This is because EEG visual analysis can be complex and time-consuming, as it mostly involves high dimensions and consists of large datasets. The development of novel sensors for EEG recording, digital signal processing algorithms, feature engineering, and detection algorithms increases the need for efficient diagnostic systems. An extensive review of the recent approaches for EEG preprocessing, extraction of features, and diagnosis of brain disorders is provided. In this paper, the main focus is to identify reliable algorithms for preprocessing, feature engineering, and classification of EEG, applied to medical healthcare and diagnosis, providing practitioners with insights into the most effective strategies, as well as potential future directions for improving accuracy of the automatic diagnostic systems. The study of reliable feature extraction and classification algorithms is crucial for a more accurate analysis of EEG signals. This paper can provide valuable information to researchers and practitioners working in the fields of EEG analysis and machine learning, as it provides a summary of recent developments and highlights key areas for future research. This paper can help researchers and clinicians to stay up-to-date on the latest developments in this field.

INDEX TERMS Classification, electroencephalogram (EEG), feature extraction, machine learning, preprocessing.

I. INTRODUCTION

According to the World Health Organization (WHO), of the one billion people affected by neurological disorders worldwide, 50 million are affected by epilepsy and 24 million by other brain diseases and dementias [1]. These Neurological and brain disorders can affect individuals of all ages, genders, educational backgrounds, and income levels regardless of where they live in the world. Figure 1 depicts a report of the main causes of death globally, as published by WHO on December 9, 2020. Women are disproportionately affected by Alzheimer's disease and other forms of dementia, accounting for two-thirds of the cases Globally. The neurological and brain disorders and other non-communicable diseases claim about 43.5% of deaths globally.

The main brain disorder epilepsy is characterized by recurrent seizures, which can affect people of all ages. About 4-10 people per 1000 individuals experience active epilepsy at any given time [1]. In addition to epilepsy and Alzheimer's, the WHO estimates that 1 in 100 children has autism, which is a disorder that affects the development of the nervous system and brain and can cause problems with

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behavior, sociability, and intercommunication [2]. Mental disorders are also prevalent worldwide, with approximately 1 in 8 individuals, or 970 million people, living with a form of mental disorder. Anxiety and depression are the most common disorders, and the COVID-19 pandemic has led to an increase in persons living with these conditions [3].

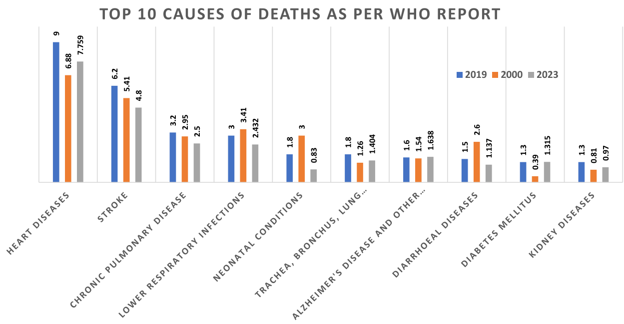


FIGURE 1. Summary of the statistical report of WHO regarding leading causes of deaths globally for the year 2000 and up to 2023.

Psychiatric disorders, including bipolar disorder, schizophrenia, eating disorders, ADHD, and autism spectrum disorder (ASD), are characterized by significant difficulties in thinking, emotional regulation, and behavior.

Various projects have been conducted globally to manage these disorders and identify potential prevention strategies by diagnosing brain activity. However, the brain consists of billions of cells, with neurons and non-neuron cells called glia being the most common types of cells [4]. Neurons in the brain are closely linked, with synapses as entryways for either inhibitory or excitatory activity. Activity at a synaptic junction generates tiny voltages known as a postsynaptic potential [1]. While it is impossible to detect the burst of a single neuron without direct contact due to its small size, the synchronous activity of hundreds of millions of neurons with similar spatial orientations can be recognized on the scalp's surface. During volume conduction, many neurons simultaneously push ions, and the energies of the ions push and pull electrons onto the electrodes. Voltmeters can measure the difference between any two electrodes' push and pull voltages because metals conduct electrons efficiently. The differences in voltage between electrodes in the brain create EEG signals, which are used to analyze brain activity [2].

EEG signals are vital in biomedical healthcare because these represent brain activity mainly utilized for the identification of epilepsy, Alzheimer's, mental stress, autism, ADHD, and other brain and neurological disorders. Early detection and precise identification of these brain conditions can help save lives across the globe. We were motivated to conduct a comprehensive assessment of EEG signals by the desire to save lives and reduce the symptoms and disabilities associated with brain disorders.

The EEG signal is very low amplitude and is commonly enhanced with amplifiers during acquisition. Due to low amplitude, noise sources usually contaminate the signal; thus, denoising is applied to get a clean signal. Sometimes, if the noise is dominant and deficient, the signal is discarded and recorded by experimenting again. Further, depending on the application, filtering and processing are applied to EEG. EEG signals are then analyzed by extracting features that consider the complexity of brain dynamics. EEG signals are currently being studied to improve preprocessing and feature extraction methods, which can be applied to EEG processing, enabling the extraction of reliable features [3].

In this study, we aim to develop a comprehensive reference tool for EEG researchers by covering various topics related to EEG signal processing, feature extraction, and classification. The paper's contents are organized as follows: Section II begins with a brief history of EEG, its techniques and applications, and a description of the mechanisms and methods involved. This section also provides an overview of the current challenges associated with EEG processing. Section III presents the available datasets, Section IV reviews EEG artifacts and their types, and Section V discusses the preprocessing techniques used to remove these artifacts. Section VI focuses on the features of EEG and the methods used for their extraction. Section VII discusses the most commonly used classification techniques, and Section VIII presents an overview of existing review papers. Finally, Section IX discusses future research directions and concludes the paper. Overall, this study provides up-to-date and comprehensive references based on influential articles published in scholarly journals and prime academic conferences after 2017 while highlighting open challenges and possibilities that should be addressed to enhance the accuracy of the models.

A. MAIN CONTRIBUTIONS OF THIS STUDY

This study provides new insights into the potential of EEG signals for diagnosing, monitoring, and managing brain disorders. While many survey articles have been published on EEG signal processing, these articles often focus on general aspects of the field and do not provide a comprehensive overview of EEG for medical diagnosis. In 2022, Orban et al. [5] provided a comprehensive review of EEG; however, it also discusses the development of natural interaction strategies, with a specific emphasis on EEG recording, preprocessing, classification of diseases, and control strategies. It does not provide insight into EEG in medical healthcare and diagnosis. In [6], the researchers presented an extensive review of EEG signaling but mainly focused on the general applications of EEG-controlling devices. Reference [7] provides a review of using DL models for EEG signal processing; however, it only focuses on signal denoising and processing. The literature review reveals a lack of an extensive review of EEG signals for medical diagnosis, healthcare, and monitoring; this study presents a comprehensive review with the following main contributions.

1) Ascribe a detailed review of all the stages of the EEG Analysis for medical diagnosis,
2) Describes the types of common artifacts that contaminate EEG signals and the techniques for attenuating them.
3) Outlines the preprocessing techniques applied to EEG,
4) Discusses the EEG filtering and feature extraction techniques for medical diagnosis.
5) Provides a comprehensive examination of EEG-based traditional ML/DL approaches for medical diagnosis and healthcare, 6) Additionally, we furnish a synopsis of the common datasets employed in EEG signal processing and the existing challenges within EEG signal processing methods are underscored, accompanied by proposed remedies and promising avenues for future research.

II. EEG BACKGROUND

The invention of the electroencephalogram (EEG) is attributed to Hans Berger, a German scientist, who acquired the EEG from human subjects for the first time, marking the beginning of clinical electroencephalography. Gibbs, Davis, and Lennox further characterized interictal signals and patterns of clinical seizures, contributing to the growth of EEG's clinical and scientific use. The development of machine learning in the 1960s [8] led to increased usage of EEGs in research and medical practice, culminating in the invention of the recurrent neural network in 1982 [9]. Since then, mathematical frequency analysis [10], frequency reduction [11], and classification techniques [9], [12] have advanced EEG analysis, alongside technical improvements such as videotape recording and remote real-time reading in the 1990s. Complex algorithms such as multi-class support vector machines and probabilistic neural networks were introduced in the 2000s, aimed at reducing artifacts and improving classification [13], complementing the feature extraction techniques described in Section II.

A. OVERVIEW OF EEG

EEG is a painless procedure that uses electrodes placed on the scalp to measure the electric current by neurons in the brain to study its operation [14]. Each electrode is connected to a single wire to detect voltage fluctuations or electric potential differences resulting from the flow of ionic currents inside the neurons of the brain [15], [16].

EEG signals show oscillations at various frequencies, which can be classified into five main bands as shown in Table 1 [17]. Different frequency bands of EEG are linked to various brain activities and functions, and their amplitudes and relative power can help detect neurological and brain disorders.

To measure EEG signals, electrodes are placed on specific scalp locations following a 10-20 international system, as shown in Figure 2, which maintains consistency in laboratory procedures worldwide [18]. The EEG from the electrodes is fed into amplifiers that filter and amplify the signal before being displayed. EEG is typically used to detect brain activity in a bandwidth from 0.1 Hz to 100 Hz, as shown in Figure 3.

However, EEG processing faces various challenges, including artifact removal, signal processing and analysis, individual differences, and interpretation and validation. Despite these challenges, EEG has multiple applications in clinical practice, such as diagnosing and monitoring epilepsy, sleep disorders, and other neurological and psychiatric conditions. EEG also studies brain function and connectivity, including memory, attention, and language. Therefore, EEG has become a vital tool in neuroscience and clinical practice.

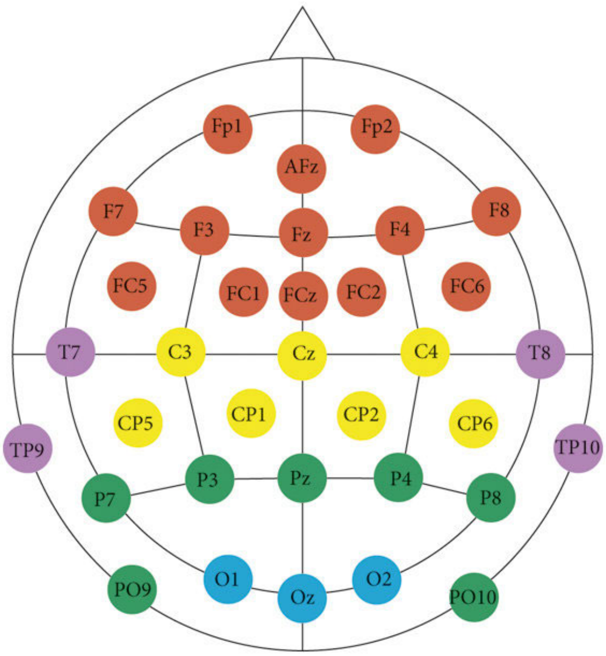


FIGURE 2. The actiCAP: a 32-electrode EEG cap that uses the international 10–20 system for electrode placement [18].

B. EEG APPLICATIONS

EEG applications are diverse and range from clinical to non-clinical settings. Clinical applications of EEG include studying sleep patterns, seizures, comas, brain death, attention deficit hyperactivity disorder (ADHD), disorders of consciousness, and the depth of anesthesia [17], [19] [20], [21], [22]. EEG is also used to diagnose and monitor various neurological and psychiatric conditions alongside these brain disorders.

In addition to clinical applications, EEG is used in neuromarketing and psychological studies to evaluate a patient's cognitive state, such as mood and anxiety. For example, brain-computer interface (BCI) involves moving the cursor on the screen using the brain, wheelchairs, and military scenarios [21]. EEG is recognized as one of the most efficient imaging methods for detecting brain electric currents

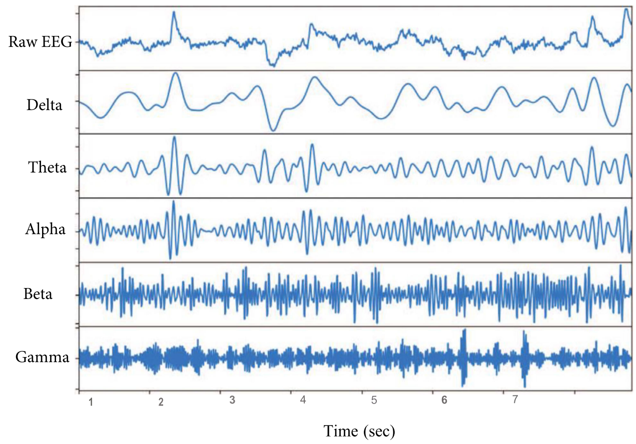


FIGURE 3. EEG of a healthy subject recorded for 200 seconds, broken down into the five main frequency bands of cerebral oscillations, also called brainwaves.

TABLE 1. The five bands of EEG signals.

Waves	Frequency band Hz	Brain State
$Deltawaves(\delta)$	$0.5 - 4$ slowest	Deep sleep Dreaming Mental Comma State
$Thetawaves(\theta)$	$4 - 8$	Creative thought Stress Deep Meditation Drowsiness
$Alphawaves(\alpha)$	$8 - 12$	Calm Mental states Relaxation Restful
$Betawaves(\beta)$	$12 - 30$	Busy active mind Attention Coordination
$Gammawaves(\gamma)$	> 30	Motor functions Problem solving Concentration Simultaneous/ Multitasking work

due to the coordinated actions of hundreds of neurons. This approach offers high temporal resolution, which may be viewed on the screen as a digital representation of a continuous voltage flow. This technique can determine cortical activity even at the lowest time intervals. EEG is an essential tool for clinical and non-clinical settings, and ongoing research continues to explore its potential applications.

C. CURRENT CHALLENGES IN EEG PROCESSING

Processing EEG signals poses several challenges that must be addressed for accurate analysis. One of the most significant challenges is the Signal to Noise Ratio (SNR), and the presence of different noise sources, such as artifacts or interference, which makes signal preprocessing difficult [23], [24]. The SNR of the EEG is sensitive to external factors, including light, smells, blinking, movement, temperature, and controlled lab environments. These inherited noise sources complicate their analysis as the EEG processing algorithms work on an adequate quality of the signals. Various techniques can be utilized to overcome the challenge of low SNR and external noise sources in EEG processing. These techniques include using high-quality electrodes, optimal electrode placement, advanced signal filtering and denoising algorithms, and improved experimental setups and stimulation techniques [22].

Additionally, EEG signals are *unique* in nature, making their processing complex due to non-stationarity, non-linearity, and the higher likelihood of artifacts, which makes it challenging to study their internal relationships directly. Therefore, preprocessing steps are required to remove artifacts from the signal before post-processing, commonly called artifact subtraction (AS) [25].

Another challenge is the *data dimensionality* that arises from collecting numerous electrodes. Thus, fusion and merging of data are critical for reducing dimensionality and improving classification results. Noise reduction algorithms and methods like multiple-source Electrooculography (EOG) [26], non-linear recursive least squares [27], Fisher scores, and principal component analysis (PCA) are commonly applied to remove noise and decrease data dimensions, with PCA being the most widely used method for separating the data into independent components.

The *lack of data* is another challenge as statistics change over time for the same patient, and physiological differences between patients can lead to high inter-subject variability [28], negatively affecting the generalization of models. Various processing pipelines, such as adaptive and Riemannian-geometry-based classifiers [29], are applied to EEG for denoising, feature engineering, and classification, although this area of research remains active. The stages of EEG data analysis as shown in Figure 4, are discussed in the following sections.

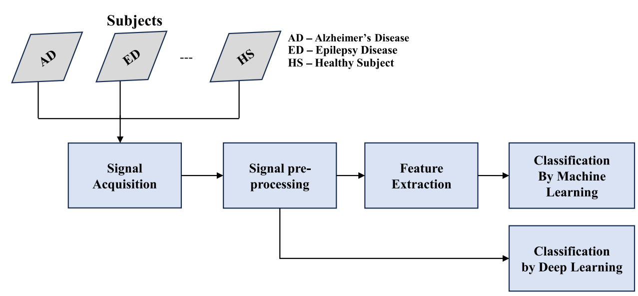


FIGURE 4. Various steps used in EEG digital signal processing and classification for medical diagnosis.

III. DATASETS

Freely downloadable EEG datasets make them more accessible to researchers, medical doctors, and clinicians for medical diagnosis and research. Numerous well-known EEG datasets have been made available for research purposes and have been utilized by researchers. These datasets are publicly available and have been used in many research studies. Some of these datasets include Melbourne, CHB-MIT, Bonn, European Epilepsy datasets, EEG dataset for Alzheimer, American Epilepsy Society dataset, and other datasets as listed in Table 2. The details of these datasets are summarized in the following subsections.

A. CHB-MIT DATASET

EEGs of children were acquired at the Boston Children's Hospital and Massachusetts Institute of Technology (MIT) [30]. The data are publicly accessible and are available on the website Physionet.org. EEG is recorded for 916 hours from 22 pediatric participants with intractable seizures for a total of one hour or four hours. Five males and 17 females participated in this research, ranging in age from 3-22 years and 1.5-19 years, respectively. The number of electrodes varied between 23 to 28 electrodes for different patients. The sampling rate for EEG was set to 256 samples per second, with 23 EEG signals per file, and 198 seizures were annotated with their beginning and end times. There are 23 channels in most records, with a few having 24 and 26; Figure 5 shows seizures and non-seizures records. The files can be downloaded as ZIP files (42.6 GB) using European Data Format (.edf) [31], which can be accessed via a terminal or Google Cloud Storage Browser. Preictal and interictal labels were not included in this dataset, but could be extracted from the meta-data files for each patient [32]. It is a widely used dataset for epilepsy research. However, there are several challenges associated with this dataset. One of the main challenges is the presence of artifacts, including motion artifacts, electrode artifacts, and muscle artifacts, which can affect the accuracy of the analysis. Another challenge is the interictal and ictal classification of EEG signals, which requires domain knowledge and can be time-consuming. Additionally, the dataset only contains a limited number of patients, which can limit the generalizability of the findings to a larger population.

B. UNIVERSITY OF BONN DATASET

Bonn dataset has five sub-datasets (A-E) for healthy people and patients with epilepsy. The data can be downloaded for free from http://epileptologie-bonn.de/. 100 EEG signal recordings last for 23.6 seconds per channel in each dataset. Four phases are measured: surface EEG with open and closed eyes and intracranial EEG with interictal and seizure phases. Each channel contains 4097 samples, sampled at a rate of 173.61 samples per second. The zip files of the datasets are available with labels. The Bonn dataset is not chosen for the development of epilepsy prediction algorithms as it is only one channel and recorded for a shorter duration.

C. AMERICAN EPILEPSY SOCIETY DATASET

This dataset [33] consists of EEG recordings of seven participants for 1300 hours. The subjects are two humans and five canines with channels from 15 to 24 per subject. The EEG recordings include a line noise of 60 Hz that could be fixed using a notch filter [34].

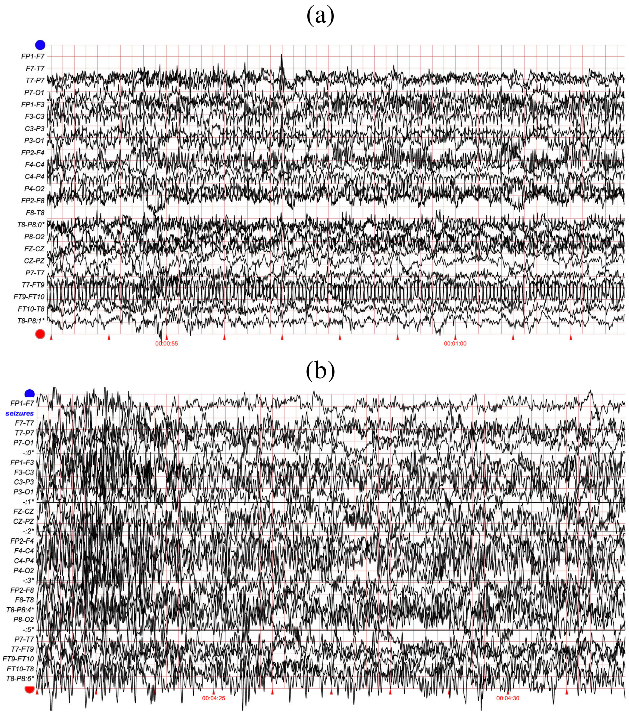


FIGURE 5. Two records for EEG tracing of CHB12_23: (a) no seizure, (b) seizure [31].

D. EUROPEAN EPILEPTIC DATASET

The European Epileptic Dataset, part of the EU-funded project "EPILESIAE" [35], is one of the most comprehensive data sources currently available. This dataset contains EEG signals recorded for 300 subjects aged 13 to 67 years, representing a wide spectrum of epilepsy symptoms. A total of 6488 hours of EEG recordings with more than 250 seizures were included in the dataset, of which 50 included intracranial recordings with up to 122 channels. Datasets are available on http://epilepsy-database.eu/, but they must be paid for. They are saved in.edf format. Moreover, the dataset is not labeled as preictal, ictal, or interictal but can be analyzed based on the timing information of the seizures.

E. EEG DATASET FOR ALZHEIMER

Alzheimer's disease (AD) is a neurodegenerative disorder that causes memory loss, changes in behavior, and other cognitive problems. They are most common in people over 65 but can occur at younger ages. Recently a new dataset of EEG signals for Alzheimer's has been developed by Miltiadous et al. [36]. The EEG dataset has signal acquired for 88 subjects resting with closed eyes. Of these, 36 were AD patients, 23 with frontotemporal dementia (FTD), and 29 with cognitive normal. The neurological state of each participant was evaluated using a test called Mini-Mental State Examination (MMSE)—this standardized test scores cognitive decline from 0 to 30, where 0 is for more severe cases.

F. EEG DATASETS FOR PARKINSON'S DISEASE

The open-source and publically available dataset of EEG for Parkinson's disease is the San Diego dataset (31 subjects, 93 min) [37]. EEG is recorded from subjects sitting in a comfortable state with their eye relaxed while focused on a screen. The dataset has two sub-datasets: the first subset has EEGs from 16 healthy individuals, and the second group contains EEGs from 15 Parkinson's disease (PD) persons, which were similar to the healthy subjects in terms of gender, right-handedness, cognition, and age, as recognized by MMSE.

G. EDPMSC DATASET

Another dataset analyzed in this study is the Perceived Mental Stress Classification (EDPMSC) dataset [38]. The data is available for anyone to use and contains EEG signals labeled with one of two categories: stress or not stress. The data is collected from 28 subjects aged between 18 and 40 years, comprising 13 men and 15 women, using a Muse headband with only four channels (AF7, AF8, TP9, TP10). Signals were acquired using a sampling frequency of 256 samples/s for three minutes across three experiments: a pre-active phase consisting of three minutes of recording in a quiet room with a relaxed position and open eyes, an activity phase during a presentation in front of people, and a post-activity phase involving three minutes of recording in the same room. To categorize the groups as stressed or not stressed, the Perceived Stress Scale (PSS) was employed. The groups were classified as either stressed (PSS>=20) or not stressed (PSS20) based on their PSS scores.

IV. EEG ARTIFACTS

Several physiological and non-physiological sources of noise attenuate EEG. These artifacts refer to signal records that are not of neural origin. Detecting and removing artifacts is crucial to ensure adequate quality of EEG signals, as they can often mimic actual brain abnormalities or seizures. Artifacts can be classified into two types: physiological, which are from the body of the subject, and non-physiological, due to the surroundings [51]. Figure 6 illustrates the most common types of EEG artifacts. The details are in the next subsections.

A. PHYSIOLOGIC ARTIFACTS

1) ELECTROMYOGRAM (EMG)

EMG refers to the electrical noise produced by muscle movements. Myogenic potentials are the most common artifacts generated by the muscles near the scalp, like the frontalis, orbicularis, and temporalis muscles surrounding the eyebrows, eyelids, and jaw [53]. Muscle artifacts that mimic cerebral activity are due to different disorders like essential tremor, PD, and hemifacial spasm and can be identified based on their duration, morphology, and frequency [54]. An example of such artifacts is depicted in Figure 7.

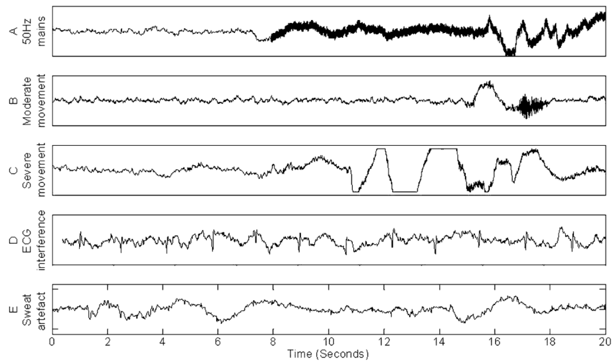


FIGURE 6. Common EEG Artifacts: (A) Superposition of 50Hz main waves of EEG appears as thickened signal, (B) Movement Artifact causes sudden deviation from the EEG background, (C) The EEG could be cut short by sudden movement, (D) When the ECG's pulses are overlapped on the EEG, a pulsed EEG is the visible result, (E) Sweat artifacts show up on EEGs as a little shift in the baseline [52].

2) ELECTROOCULOGRAPHY (EOG)

Electrical impulses called electrooculograms (EOGs) are generated by eye movements and blinking. These artifacts are only helpful in determining sleep modes [55]. Otherwise, the EEG is affected by these artifacts, leading to inaccurate interpretations [56]. EOG and EEG contaminated by movement artifacts from an infant are shown in Figure 7 [57].

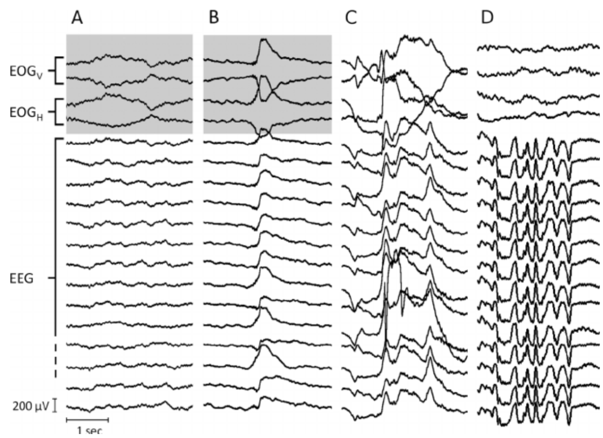


FIGURE 7. Panel: (A) Eye movement, (B) Eye Blink, (C) Head Movement, (D) Comforter/nursing Movement [57].

3) GLOSSOKINETIC ARTIFACTS

These artifacts are caused by tongue movement during the acquisition of EEG while talking, chewing, or sucking, as depicted in Figure 7. These artifacts are commonly seen in young patients and those with dementia [53].

4) ELECTROCARDIOGRAM (ECG OR EKG) ARTIFACT

Electrocardiogram artifacts refer to the heart activity that may be detected on the scalp during EEG recordings [58]. Sharp waves or spikes characterize them and are most prominent in individuals with short and wide necks. These artifacts can

TABLE 2. A list of EEG public datasets for various brain and neurological disorders.

Name	Kind	Length	Year	Size	# Patients	# Channels	Sampling Frequency	EEG segments, States
Physionet [39]	Motor/imagery	Two 1-min	2008		109	64	160Hz	Eyes open, Eyes closed
DEAP [40]	Emotion Recognition	40 (1-min long)	2012	5.8GB	32	48	512Hz	Arousal, Valence, Like, Dislike, Dominance, Familarity
	Physionet [41]	Motion Artifact contaminated EEg data	-	2013	649.9 MB	-	2	200 Hz
SEED [42]	Emotion Recognition	4 min	2015	-	15	62	200Hz	Negative,Positive,Neutral
SEED IV [42]	Emotion Recognition	4s sessions	2019	-	15	62	200Hz	Happy, Sad, Neutral, Fear
EDPMSC [38]	Emotion Recognition	3min	2019	-	28	4	256Hz	Non-stressed, stressed, mildly-stressed
Kaggle [43]	Autism	200ms	2020	6GB	15	-	250Hz	
DREEM [44]	Miscellaneous	10 sec epochs Nx1261 matrix	2020	-	25	-	125Hz	0, 1, 2
NEMAR [45]	Recognition	20ms	2020	4GB	14	32	1000Hz	Go-no
Mendeley [46]	Emotion Recognition	5 min- total 20 min	2020	1737MB	28	14	-	Arousal, Valence
DEAR-MULSEMEDIA [47]	Emotion recognition	4 clips<33s to 58s	2020	-	18	4	256Hz	Valence, Arouse,9-point scale
Zenodo	Epilepsy	-	2021	16GB	24	24	-	Ictal, Pre-ictal, Post-ictal, Non seizure
SEED-V [48]	Emotion Recognition	50 min	2021	-	16	62	200Hz	Happy, Sad, Disgust, Neutral, Fear
Openneuro [49]	Sleep,emotion, mental health	20ms	2021	30.67GB	60	-	500Hz	Health, control
King Abdulaziz University [50]	Autism	12-40 min (autistic) 5-27(non autistic)	2012	-	18	16	156Hz	Autistic, Non Autistic
EEG Alzheimer [36]	ALzheimer and FTD	13.5 min	2023	-	88	19	500Hz	ALzheimer and FTD
San-Diego dataset [37]	Parkinson	93 min	2021	-	31	32	512Hz	Alzheimer and FTD

be distinguished based on duration and morphology unless the EEG signal coincides with abnormal cerebral activity, making it difficult to differentiate the two [59].

5) EEG PULSE ARTIFACT

The placement of an electrode over a pulsating blood vessel can cause an EEG pulse artifact, resulting in the appearance of slow waves on the EEG graph. The main QRS spike in the ECG represents the heart's electrical component, which appears between 200 and 300 ms before the pulse artifact [59]. To address this issue, the electrode can be repositioned to a different location.

6) SKIN ARTIFACTS

The large baseline is a skin artifact observed in EEG and is primarily due to sweating. Other potential causes may include skull defects and subgaleal hematomas [58].

B. NON-PHYSIOLOGIC ARTIFACTS

These types of artifacts are often referred to as non-biological or technological artifacts. Powerline interference, electrode pop, cable movement, improper reference positioning, and erroneous placement of electrodes are all potential causes of such artifacts that degrade the quality of EEG and thus limit its applications. An example of EEG signals with these artifacts is depicted in Figure 8.

1) ELECTRODE ARTIFACTS

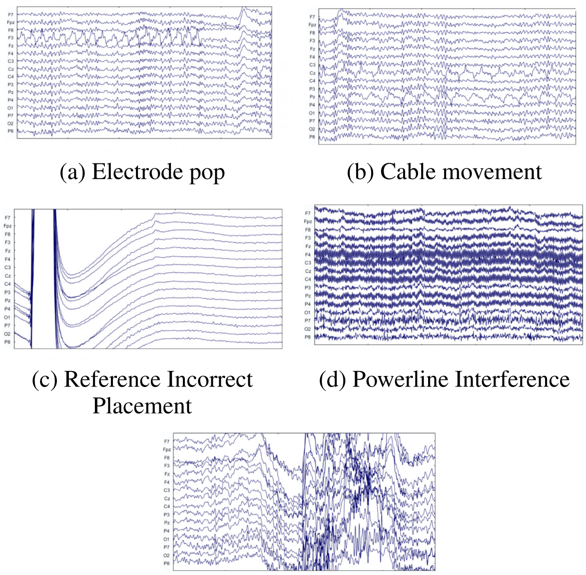
The sudden disconnection or movement of the electrode is one of the most common electrode artifacts. This can result in either incorrect acquisition of the EEG signal or a transient vertical path associated with a single electrode due to an abrupt change in impedance and can be visually identified [59].

2) MOVEMENTS IN THE ENVIRONMENT

Movements in the environment, such as the movement of a person around the patient, electrostatic effects on the drops, respirators, radio, and television radiation, or interference of other equipment, such as electromagnetic sources like infusion pumps that use electricity, can affect EEG signals [61]. This can result in the deflection of the pens and make it difficult to record EEG signals unless the interfering devices are turned off [62].

3) ALTERNATING CURRENT ARTIFACT

An alternate current artifact refers to a specific type of artifact that arises from technical complications, such as unintentionally high impedance [63]. These complications can lead to the emergence of a 50 Hz or 60 Hz artifact, depending on the frequency standards followed. Notably, countries like the USA operate on a frequency of 60 Hz. Therefore, any technical issues resulting in artifacts within



(a) Electrode pop (b) Cable movement

(c) Reference Incorrect Placement (d) Powerline Interference

(e) Body Movements

FIGURE 8. (a) Electrode Pop with a distortion in F3 produced by touching the sensor, (b) Cable Movement producing distortion in Cz or Pz that are not eeg-related, (c) Reference Incorrect Placement producing a high amplitude abrupt, (d) Powerline Interference with a peak at 50Hz overlapping the EEG data, (e) Head Movement effect overlaps low frequencies of eeg in all channels [60].

the USA would typically produce a 60 Hz artifact. It is essential to recognize that this frequency disparity stems from variations in electrical systems and standards across different countries.

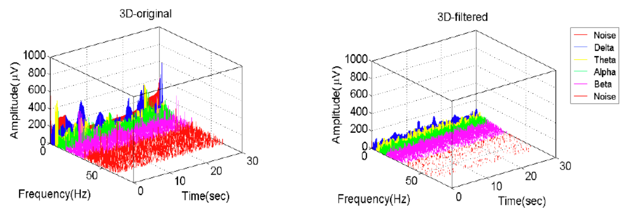
V. EEG PREPROCESSING AND FILTERING

To prepare raw EEG signals for feature extraction and classification, it is crucial to clean them from noise and artifacts through preprocessing and proper filtering to enhance the extraction of relevant information. EEG signals are biomedical signals that reflect brain activity and are susceptible to external interference during collection because of their high time-varying nature and low amplitude. This interference can come from eye movement, blinking, ECG, and EMG sources. These interferences are often called artifacts.

EEG analysis is complex in the presence of these artifacts. They can also affect EEG features, detection, and classification if not attenuated. Due to the low amplitude and the complex nature of EEG signals, attenuating them is also more complex. Thus, it is expected to perform some preprocessing and filtering on the signal before using it to classify diseases. To make it convenient, first, the frequency contents of the EEG are visualized to check for the existence of noises. As depicted in Figure 9, the 3D plot shows the contents of the signals with respect to time and frequency. At this stage, the spatiotemporal characteristics of EEG signals [64] play a significant role since they can help select a suitable preprocessing and filter technique [23], [65], [66], [67] [68], [69]. Artifacts originate from external sources, including physiologic and non-physiologic sources,

Filters are systems that attenuate unwanted frequencies from EEG signals, amplify desired frequencies, or do both. A high-pass filter passes high frequencies of EEG while attenuating lower frequencies (noises), while a notch filter stops power line interference. Low-pass filters smooth the input signals by removing high-frequency noises. Thus, filtering provides a tool for improving the signal SNR, which measures how much of the signal is to noise. By removing noise from a signal, the SNR can be improved.

Filters work by taking advantage of the difference between the frequency spectrum of the noise and that of the target signal. Frequency spectra is a graphical representation of the frequencies that are present in a signal. Filters attenuate those frequencies in the spectrum that are dominated by noise more than those frequencies that are dominated by the target signal. This can significantly improve the SNR of the signal. Some of the filter and preprocessing techniques used for EEG are discussed in detail in the next sections and are summarized in Table 3.



(a) EEG with Noise (b) Filtered EEG

FIGURE 9. Time-frequency 3D plot of EEG: (a) Not filtered, (b) Filtered [92].

A. POWER LINE INTERFERENCE REMOVAL

The frequency of line noise artifact is typically found in the gamma band of the EEG at 50 Hz or 60 Hz, as shown in Figure 10. A notch filter, which blocks off a specific frequency range, is commonly used to eliminate this artifact. However, the use of a notch filter can introduce spurious oscillations with parasitic frequencies and potentially distort the signal [70], [71], [93]. Spectral interpolation [70] is also a good option however, it also sometimes introduces extra frequencies in the signal while performing the phase interpolation.

A smoothing filter of cut-off frequency less than 50 Hz or 60 Hz can be a solution. However, it can lead to an incorrectly denoised signal with missed causalities [95] and alteration of the signal's temporal structure [96]. To overcome this issue, a multi-taper decomposition can be utilized to estimate the spectral energy, which helps to minimize broadband variations [97], as depicted in Figure 11. The entire process is carried out in three key stages: Firstly, a short-time window is slid over the data using discrete prolate spheroidal sequences (DPSS) tapers, and multiple independent projections of the data are extracted [98].

TABLE 3. A Summary of the preprocessing, Artifacts Removal, and digital filtering techniques applied to EEG signals.

S. No.	Type and Ref.	preprocessing, Artifact removal, and Filtering Techniques	Limitations	Concluding remarks
1	Spectrum interpolation [70]	FFT and spectrum interpolation to remove 50 or 60 Hz and its harmonics	Phase interpolation sometimes introduce new frequencies in the signals	A good alternative to Notch filter as it removes the signal 60 Hz also
2	Noise Cancellation [71]	Adaptive noise cancellation (ANC) method with Linear regression and modified Independent Component Analysis (ICA)	Although good but very sensitive to the SNR of the signal	According to statistical evaluation, ANC method shows good results. The lowest residual of the simulated line noise artifact corresponds to 0.0005 microvolts squared per hertz.
3	Regression [72]	Estimation of regression coefficients on epoch data with the evoked response subtracted out	Reference channel required Not feasible for EEG Limited artifact sources Can work automatically	Limited artifacts Not feasible for muscle artifacts
4	Blind source Separation [73] [74] [75] separation (BSS)	ICA CCA MCA PCA	Signals should be statistically independent Computational complexity Automation problem for selecting artifacts, Solution: using kurtosis, temporal, spatial, and spectral features for ICs detection [73] [76] MCA is limited to morphology Not sufficient as an individual method [76]	ICA, PCA, Ocular artifacts CCA, Muscle artifacts
5	Wavelet Analysis (WT) [77]	DWT CWT WPT SWT	Time frequency-based analysis Based on a selection of mother wavelets DWT-ST is best for single-channel applications	Ocular artifacts DWT-ST fastest execution time
6	Empirical Mode Decomposition (EMD) [78]	EEMD MEMD	Flexible and adaptive Best for highly contaminated signals and EMG noise [78] [79] Overlapping of modes Data - driven Not good for online applications High sensitivity to noise Computational complexity	EEMD best works on a single channel with reduced computational complexity [80] MEMD for muscle artifacts using few channels [81]
7	Adaptive Filtering [82]	LMS RLS	Self-modifying system A reference signal is required Uses optimization algorithms (ex: least mean square)	Ocular artifacts
8	Digital Filtering [83]	IIR, FIR, Notch filters	Good for stationary signals Not good for EEG as it introduces dc offset [84] Uses regression analysis Very time-consuming for ocular artifacts	EMG artifacts are unsuitable for real-life applications unless used with other features (spatial, spectral)
9	Hybrid methods [72]	BSS- WT [85] BSS-WT-combined with EMD or SVM [86] [87] Wavelet and adaptive filter [82] EMD-adaptive filter [88] WT and Kalman filter [89] EEMD-CCA [80] VMD-CCA [90]	Extra complicated calculations [91]	ocular artifacts muscular artifacts only if the initial methods are a type of regression or adaptive filtering [72]

Secondly, the single-taper spectra for each projection are computed, representing the spectral energy within each band. Finally, a regression-based model is utilized to calculate the component's mean and approximate phase and amplitude (50 Hz or 60 Hz).
The following equation describes multi-taper analysis:

$$\tilde{x}_k(f) = \sum_{1}^{N} w_t(k) x_i e^{(-2\pi i f t)} \quad (1)$$

where:

$w_t(k)$: k orthogonal taper functions N: length of taper w: frequency brandwidth parameter

The third step involves using the Thompson F-test to determine the statistical significance of the non-zero regression coefficient since the precise frequency and phase of the sinusoidal component (50 Hz or 60 Hz) could slightly vary over time in the second step. This method can identify frequencies with maximum F-statistics above a defined significance threshold (> 0.05), and the sinusoid can be removed from the affected time series, as shown in Figure 12 [23].

B. REFERENCING

Referencing is a crucial step in EEG preprocessing since it affects the amplitude measurement of the signal. When one electrode is used as a reference for another electrode, it can introduce a mixture of brain activity and noise. To address this issue, different referencing methods can be used, such as the Average Reference (AV) and the Common Average

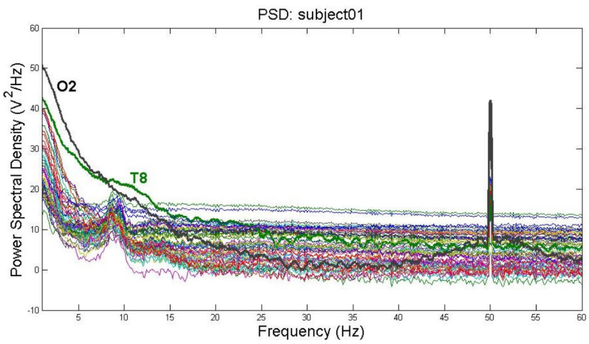


FIGURE 10. **Electromagnetic interference at 50 Hz (Take into account that certain nations, such as the USA, operate on a 60Hz frequency.). To get rid of them, a notch filter can be applied to the raw signal with MNE to cut off frequencies at or around 50 Hz and their multiples [94].**

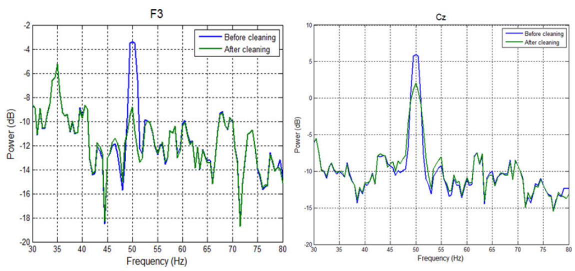


FIGURE 11. **The difference in the frequency spectra of the F3 (left) and Cz (right) electrodes before (blue) and after (green) multi-taper line noise-cleaning [99].**

Reference (CAR), which are commonly used in BCI design, where a single reference point is positioned distantly from the other electrodes. However, this can lead to a single-point failure, so detecting and removing outlier channels should be done first. The AR method subtracts the average brain activity across all EEG electrodes, with the assumption that the sum of the overall brain activity is zero at a particular time. Another referencing method is the current source density (CSD) estimation, which uses Laplacian to calculate the changing rate of current in the scalp. However, this method is only valid if the electrodes are positioned at equal distances in a 2-D plane. Selection of the referencing method can change the interpretation of EEG, thus should be selected carefully [98], [100], [101], [102].

C. BAD CHANNELS DETECTION

An electrode popping up from its location on the scalp or movement artifacts can cause bad channels [103]. Noise information is propagated to all channels, thereby making it difficult to detect and remove artifacts. To eliminate bad channels, statistical characteristics, including power spectral density(PSD), kurtosis, and variance, must be considered. A bad channel can also be detected by using the robust z-score, correlation, soft F1 score, and binary cross-entropy to calculate the loss function for a given channel. A series of interpolation schemes are then employed to replace high-frequency components above the threshold, including radial basis functions [104], nearest neighbor averaging [105], and spherical spline interpolation [106].

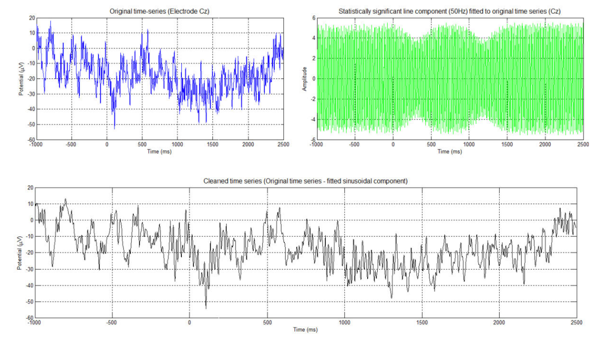


FIGURE 12. **The original time series is fitted with the major line component (identified by the F-test). From the original, noisy time series, this signal will be removed [99].**

D. ARTIFACT REMOVAL

Several factors must be considered while eliminating artifacts from EEG data, which necessitates a significant amount of processing power and computing time, which becomes problematic when employed in "real-world applications." [91]. As an area of investigation within the field of artifact removal, there is still no optimal approach that can be used for the effective removal of artifacts. In terms of the methods that are currently in place can be categorized as follows:

1) REGRESSION ANALYSIS

Regression analysis can be applied to EEG in any domain and is based on estimating the artifacts from the EEG data and subtracting them from the data [72]. This method has some limitations, including the need for a channel to serve as a reference and the in-feasibility of its use for applications involving EEG-like signals that are non-stationary. It is limited to certain artifacts rather than all categories of artifacts.

2) DIGITAL FILTERING

1) Time domain filters: attenuate either very high- or low-frequency bands while leaving behind the required frequencies [107]. Temporal filters de-noise the EEG and improve its quality by avoiding artifacts caused by interference from power lines and improper polarization of scalp electrodes [108].
   Long-duration brain signals are filtered using DFT or FFT by eliminating all coefficients that do not correspond to the frequency band of EEG signals. Subsequently, a backward DFT is used to convert it back into a time domain signal.
   To generate a filtered EEG signal $s(n)_{FIR}$, FIR filters use last M input samples from a recorded EEG signal $s(n)$ as follows:

$$s(n)_{FIR} = \sum_{k=0}^{M\tilde{-}1} a_k s(n-k) \tag{2}$$

where:

$\{a_k\}$ represents the filter coefficients and M represents the total number of coefficients of the FIR filter.

Similarly, recursive IIR filters use the most recent N output samples and the most recent M input samples from a raw EEG signal, requiring fewer coefficients than FIR filters [109].

$$s(n)_{IIR} = \sum_{k=0}^{M-1} a_k s(n-k) + \sum_{k=1}^{N-1} b_k s(n-k)_{IIR} \tag{3}$$

where

$\{a_k\}$ and $\{b_k\}$ are filter coefficients and M and N respectively represent the recent input samples and the most recent recursive, i.e., feedback output samples.

A review of the state-of-the-art digital filtering applied to EEG is summarized in Table 3.

2) Spatial Filters: Utilize CAR and the surface Laplacian (SL) filters to eliminate the noise from the background brain activity for pattern recognition, especially imagined motor activities [110]. A spacial filter is used for space reduction, signal filtering, and original brain signal recovery [62]. This is defined as follows:

$$\tilde{x} = \sum_i w_i x_i = wX \tag{4}$$

where:

$\tilde{x}$: spatial filtered signal x_i: Signal from EEG channel i w_i: channel weight in a spatial filter and w is a vector representing all channel weights X: original EEG brain signal matrix from all channels

3) Surface Laplacian Filtering: uses topographical power spectral distributions with respect to frequency [111] to differentiate between the brain and muscle signals. These techniques approximate the localized current density passing perpendicularly into the scalp [111]. The surface Laplacian can also be used to estimate the cortical surface potential and source identification. Laplacian methods are all reference-independent [112].
4) Adaptive filtering: a self-modifying system that uses an optimization algorithm to adjust filter parameters while comparing the reference and output signals [91]. As a result, it estimates noise and subtracts it from the raw EEG signals through feedback.

3) BLIND SOURCE SEPARATION (BSS)

The BSS is a commonly used method for ocular artifact suppression. Reference [113] from statistically independent [73] signals, incorporates the following:

1) Independent component analysis (ICA): A method of analyzing data that involves first centering and whitening the data. This is followed by optimization, which aims to minimize the nongaussianity of the independent sources. The advantages of ICA include its independence from reference channels [114]. One of the major drawbacks of ICA is that it is computationally complex and must be manually selected in terms of its artifacts. This can be fixed by the use of kurtosis, along with spatial, spectral, and temporal features to detect ICs automatically [73].
2) Canonical Correlation Analysis (CCA): utilizes correlation; it splits the contaminated signals while utilizing statistics of the second order (SOS) [75] to calculate the maximized correlation by canonical variables. It is efficient in detecting muscle artifacts but still has automation with fewer complexity problems than ICA [115].
3) Morphological component analysis (MCA): depends on the artifact database that has been decomposed according to its morphological properties, thus making it insufficient as an individual technique on its own [76].
4) Principle Component Analysis (PCA): transforms a correlated signal in the time domain into uncorrelated principal components via orthogonal transformation (PCs) [74]. Artifacts can be removed only if they are uncorrelated with the EEG [75].

4) FREQUENCY DECOMPOSITION

Wavelet transform decomposition is a time-frequency analysis method that decomposes a signal into a series of wavelets localized in both time and frequency. This allows for separating highly correlated wavelets from artifacts that are not correlated with the basis mother wavelet [116]. Several wavelet transforms exist, including continuous wavelet transform (CWT), wavelet packet transform (WPT), stationary wavelet transform (SWT), and discrete wavelet transform (DWT). DWT with statistical threshold (ST) functions is suitable for ocular artifacts removal [77], with a fast execution time when working on single-channel applications.

5) EMPIRICAL MODE DECOMPOSITION

A method that can adapt to different datasets and tasks [78]. To remove the noisy intrinsic mode functions (IMFs) from the signals, these are divided into IMFs and use complex computations. This method is most suitable for highly contaminated data [79]. However, the model overlap is one of its significant drawbacks. An ensemble-EMD approach (EEMD) is used to overcome this issue in which the IMF component is determined by averaging the ensembles of trials [80] in one channel, while a multivariate empirical mode decomposition (MEMD) is based on identifying muscle artifacts over a small number of channels.

6) HYBRID METHODS

A combination of multiple methods is often used to obtain superior outcomes. For instance, BSS-AF, and (BBS-WT) [85], [117], [118] have been found to be more effective than using the BSS technique alone, particularly when combined with EMD or SVM [86], [119], [120]. Additionally, the combined use of wavelet and adaptive filters can mitigate certain limitations and eliminate ocular artifacts [82]. Moreover, VMD-CCA [90] has shown superior performance over EEMD and ICA and EEMD and CCA across various SNRs and channels, while AWCCR has demonstrated higher efficacy than CCR [121].

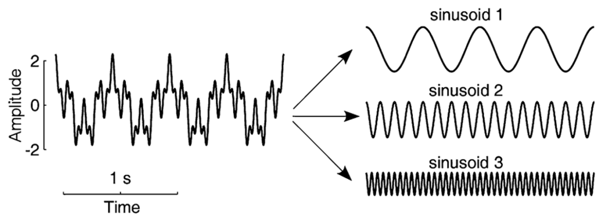
VI. EEG FEATURES AND FEATURE EXTRACTION METHODS

EEG data often has long recordings of multiple channels, thus generating massive data. The use of feature extraction helps simplify this dataset by identifying attributes. This approach has the advantage of reducing burdens and minimizing overfitting risks. When studying brain activity, EEG recordings are typically collected from individuals with brain function and those with conditions, resulting in a large amount of data for analysis. EEG signal features represent values that capture signal characteristics observed at sampling frequencies ranging from 100 to 1000 Hz. The individual features are then aggregated into a feature vector. Extraction of features from either an EEG signal or a collection of signals requires the application of diverse methodologies. Feature engineering methods prepare the data for classification stages, enabling the identification of synchronization instances, recognition of prominent low-frequency bands during peak periods, and identification of frequencies indicative of specific pathologies, like epilepsy, tumors, and injuries. Figure 13) depicts time-frequency and non-linear features. A summary of the features used for automatic diagnosis of various brain disorders is summarized in Table 4.

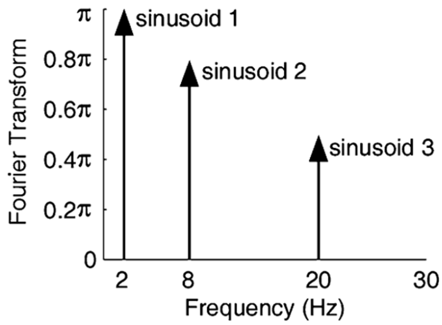
A. TIME-DOMAIN FEATURES

Variable features of time-domain parameters [122] include mean, median, variance, RMS, peak-to-peak, standard deviation, auto-correlation, absolute value, and zero-crossing (ZC) [147]. Below are a few more time domain features:

1) EEG histogram: It demonstrates the typical spread of EEG.
2) The kurtosis of a frequency distribution curve represents the peak's sharpness compared with that of a Gaussian curve.
3) Skewness: The degree to which the distribution curve deviates from what would be expected if the data were distributed according to a Gaussian distribution.
4) Fractal dimensions: This term is also known by its other name, the Hurst exponent, and it refers to the capacity of a time series to store information for a longer time.
5) Entropy characterizes the degree of randomness in the time series. It simultaneously specifies the uniformity of the waves and the uncertainty of the alterations.
6) The Hjorth parameter measures the variability of EEG derivatives, such as mobility coefficient and complexity coefficient [148].
7) K-complexes [136] are standard waveforms in non-rapid eye phase two.



(a) Time-Domain



(b) Frequency-Domain

FIGURE 13. Representation of Signals (a) with respect to time and (b) with respect to frequency [146].

B. FREQUENCY-DOMAIN FEATURES

The frequency domain is where signals are analyzed based on frequency rather than time. A frequency-domain representation has amplitude and phase of the signal's frequency components. Specifically, this representation can include information on the phase shift required to recombine the frequency components and obtain the original time signal [137].

The power spectral density (PSD) [129] can also be used to get the features of the signal in the frequency domain. Fourier transforms [149], convert signals into sinusoidal components, where wavelet decomposition, as explained in Section **C** incorporates a mother wavelet function into the decomposition process [134].

Fourier Transform It involves decomposing the signal into sub-spectral components covering the frequency spectrum. These subspectral components represent peaks with respect to frequency. The peaks in this domain are then collected and computed using the FFT algorithm, as given in Figure 14 [130].

C. TIME FREQUENCY FEATURES

Analyzing a two-dimensional signal in both time and frequency domains is powerful because it can exhibit non-stationary characteristics [131], [148]. The spectral characteristics of a signal can change over time, and it is essential to observe frequency changes over time to understand the signal better.

Time-frequency analysis provides a way to analyze signals in time-frequency domains. One of the most straightforward techniques for observing a signal and calculating its frequency components is the short-time Fourier transform

TABLE 4. **A review of the features and feature extraction methods used for classification of brain disorders from EEG.**

Reference	Feature Extraction Methods and Features	Brain disorder/state	Accuracy
[122]	multimodal signal decomposition	Sleep stage	–
[123]	Entropy (ApEn), Fuzzy Entropy (FuzzyEn), Sample Entropy (SampEn), and Standard Deviation (STD)	Epelipsy	100%
[124]	Spatio-temporal features	Parkisnson's Disease	99.2%
[125]	Scalogram images using CWT	Parkinson's Disease	99.46%
[126]	automated tunable Q wavelet transform features	Parkinson's Disease	98.56%
[127]	wavelet coherence and quantile graphs	Alzheimer Disease	100%
[128]	Discrete Wavelet Transform and Fourier Transform features	Alzheimer Disease	92%
[129]	Frequency and Time-Frequency Domains Features	Epilepsy	-
[130]	peaks of FFT	Epilepsy	99.96%
[131]	twelve time-frequency features (TFFs)	–	96.67%
[132]	discrete short-time Fourier transform	Epileptic Seizure	97.9%
[133]	wavelet transform features	Schizophrenia (SCH), and Obsessive Compulsive Disorder (OCD)	71%
[134]	continuous wavelet transform features	–	–
[135]	min-entropy-based feature, wavelet packet transformation	Eye open Close classification	–
[136]	K-complex occurences as features, Multitaper-based KC detection	Sleep Monitoring	82.1%
[137]	Fourier Transform, Wavelet features	General purpose	–
[138]	Singular Value Decomposition, Rhythmic absolute energy, alpha peak freq	Autism Diagnosis	92.66%
[139]	Deep feature using one-dimensional local binary pattern	Autism Diagnosis	96.44%
[140]	Multi-feature fusion of power spectrum analysis, bicoherence, entropy, and coherence methods	Autism Diagnosis	91.38%
[140]	Multi-feature fusion of power spectrum analysis, bicoherence, entropy, and coherence methods	Autism Diagnosis	91.38%
[141]	The neighbor composition analysis (NCA), entropy, and variance of each sub-band.	Sleep Apnoea	95.24%
[142]	Alpha band Energy, Beta band energy, PCA, ICA	Brain Disorders	–
[143]	Time-frequency analysis of PSD approach applied on EEG signals using channel ROC-LOC	Insomnia Sleep Disorder	–
[144]	Discrete wavelet transform (DWT), the logarithmic band power (LBP), standard deviation, variance, kurtosis, and Shannon entropy (SE)	epilepsy and an autism spectrum disorder	99.9%, 97%
[145]	Connections between two brain regions are quantified by three different methods: (i) Granger causality test, the Pearson's, Spearman's correlation measures	Alzheimer's disease and schizophrenia	75%, 55.5%

(STFT), which uses uniform separation and obtains a spectrogram [131]. More sophisticated methods have also been developed for data with uneven spacing, such as wavelet transform [134], which uses variable window sizes based on spectral frequencies and least-squares spectral analysis. These techniques provide valuable insight into the spectral characteristics of a signal with respect to time.

1) SHORT TIME FOURIER TRANSFORM

STFT, as illustrated in Figure 15, enables the description of the frequency information of a signal with respect to time, thereby improving classification accuracy [132]. Unlike the standard FT, which evaluates the whole signal at once, STFT uses time-shifting window frames [146] to divide the data into several short signals and then find its frequency contents individually.

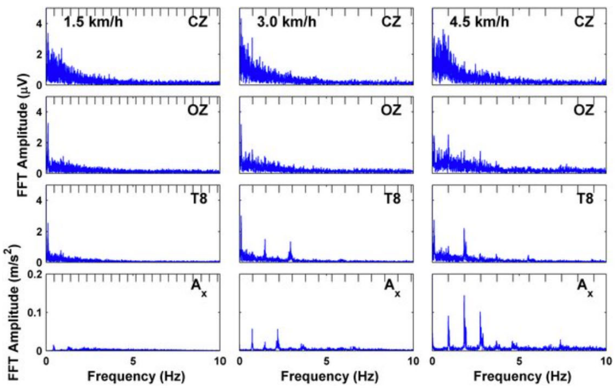


FIGURE 14. An EEG signal with its Fourier Transform [150].

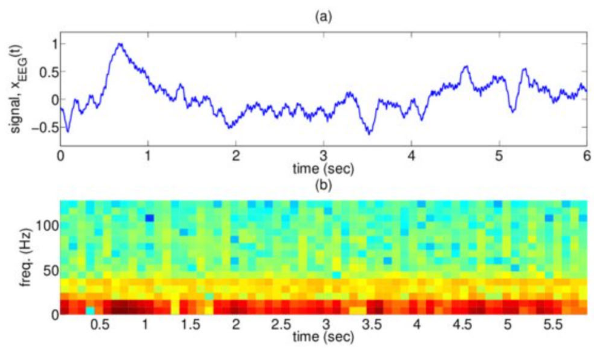


FIGURE 15. (a) EEG signal, (b) STFT of the signal [151].

2) PROGRESSIVE FOURIER TRANSFORM (PFT)

The Progressive Fourier Transform (PFT) [152], as depicted in Figure 16, is an innovative technique in time-frequency analysis based on the concept of the Short-Time Fourier Transform (STFT). It efficiently converts time-domain signals into the frequency domain by adaptively considering a specific window of values. PFT gradually computes the STFT by sliding a predetermined window size across the signal, focusing solely on the values within the window. The rest of the signal values outside the window are effectively disregarded. PFT is a valuable tool for analyzing time-frequency characteristics in signals using the following equation:

$$X(f, u) = \int_{-\infty}^{u} e^{-j2\pi ft} x(t) 1_{\{t<u\}} dt \tag{5}$$

where f and u represent the signal frequency and time; e is a mathematical constant that represents the base of the natural logarithm; j is an imaginary unit; and $1_{t\in I}(t)$ is equal to one if t belongs to the interval I and is zero otherwise [152]

3) WAVELET TRANSFORM (WT)

The WT is an extension of the Fourier transform that overcomes the limitations of STFT by providing multi-scale analysis, as shown in Figure 17. In WT, the signal is divided into a family of basis functions known as wavelets, which are then used to reconstruct the original signal. This decomposition process allows for identifying low-frequency and high-frequency components of the signal at different scales.

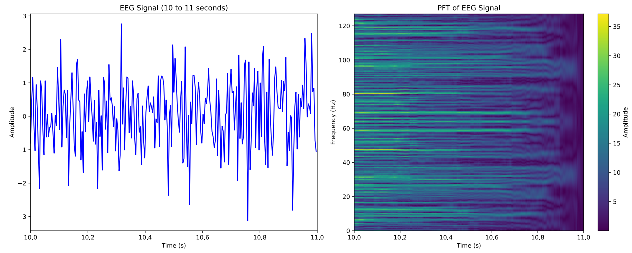


FIGURE 16. PFT [152].

Wavelets can be created from an existing wavelet by stretching, compressing, and reshaping the mother wavelet, which makes it possible to customize wavelets to fit specific signal characteristics [133]. This flexibility, combined with the ability to analyze signals at different scales, makes wavelet analysis a powerful tool for signal processing and analysis.

a: MOTHER WAVELET

$$\psi_{a,b} = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right); a > 0, -\infty < b < \infty$$

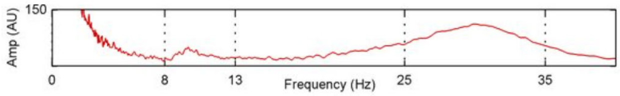
where a is the scale parameter and b determines the location of the wavelet [153].

The WT delivers precise frequency information at low frequencies and accurate time information at high frequencies using 3D representations. Numerous mother wavelets are used in a wide variety of WT types used in practice. Below are some types used with EEG signals.

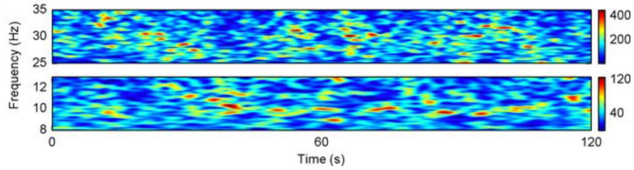
b: CONTINUOUS WAVELET TRANSFORM (CWT)

The Continuous Wavelet Transform (CWT) technique analyzes non-stationary signals by examining signal portions at different scales and positions. Unlike the traditional Fourier Transform, which focuses on frequency components, the CWT captures the frequency content of the signal at varying resolutions by convolving it with a scaled and translated version of a mother wavelet function, often the "Morlet" function [154]. This adaptability enables the CWT to accommodate the dynamic characteristics of non-stationary signals, making it a valuable tool in signal processing, image analysis, time-series analysis, and biomedical signal analysis. The resulting scalogram provides a visual representation of the signal's energy distribution across different scales and times [134] as seen in Figure 18, aiding in the identification of localized frequency variations and time-frequency patterns. By continuously varying the location and scale parameters, the CWT allows for selecting and examining different signal parts for different scale variations. Overall, the CWT and scalograms offer valuable insights into the complex dynamics of time-varying signals.

$$W_f(a, b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}^{*}(t)dt = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}\psi_{a,b}^{*}\left(\frac{t-b}{a}\right)f(t)dt$$



(a) EEG signal



(b) Wavelet Transform

FIGURE 17. (a) EEG signal- awake, (b) Wavelet Transform [155].

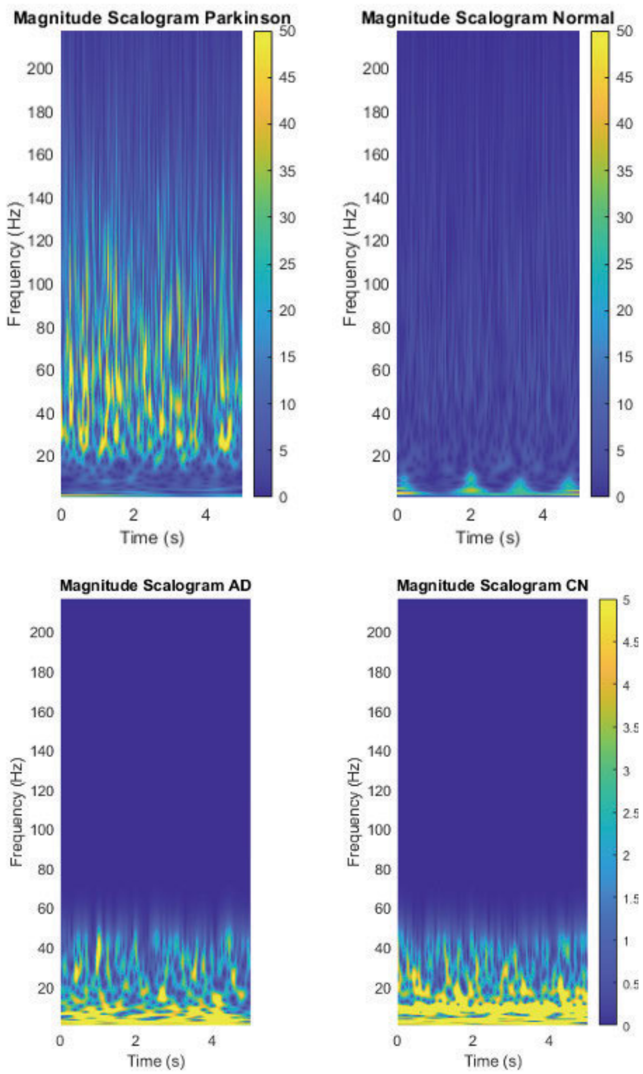


FIGURE 18. Scalograms for Alzheimer and Parkinson.

c: DWT

Different mother wavelets can be used with DWT, and wavelet scales and translations can be customized depending on the sampled value for an efficient signal decomposition [153]. An important difference between the DWT and CWT is that the signal is broken up into a collection of wavelets that are orthogonal to one another across all discrete scales by using the DWT transform. This is expressed as follows:

$$\psi_{i,k}(u) = 2^{-i/2}\psi\left(2^{-i}u - k\right)$$

The coefficients are obtained using the following expression:

$$W_{i,k} = W\left(2^i, k2^i\right) = 2^{-i/2}\int_{-\infty}^{\infty} f(u)\overline{\psi\left(2^{-i}u - k\right)}du$$

d: WAVELET PACKET DECOMPOSITION (WPD)

WPD is a general form of the wavelet decomposition, Figure 19, it gives a richer signal analysis and a higher frequency resolution [156], decomposing both the approximation and detail components of the signal at every level using two-scale equations [157].

$$\psi_{j,k}^{2i}(t) = \frac{1}{\sqrt{2}}\psi^{2i}\left(\frac{2^j k - t}{2^j}\right) = \sum_n h(n)\psi_{j-1,2k-n}^{i}(t)$$

$$\psi_{j,k}^{2i+1}(t) = \frac{1}{\sqrt{2}}\psi^{2i+1}\left(\frac{2^j k - t}{2^j}\right) = \sum_n g(n)\psi_{j-1,2k-n}^{i}(t)$$

where i is the node's counter, j is the level of decomposition; h and g represent filters used as quadrature mirrors. The coefficients are computed using recursion equations [157].

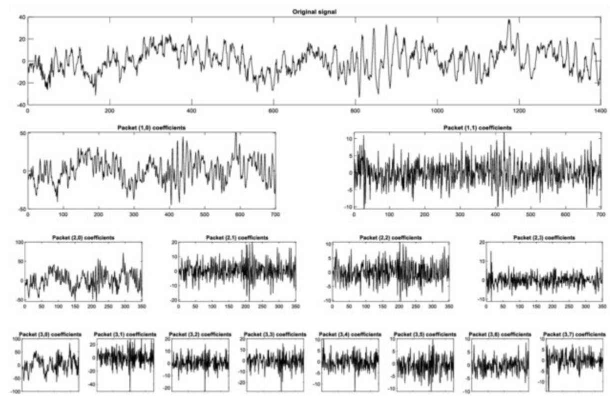


FIGURE 19. Wavelet packet decomposition of an electroencephalogram (up to level 3) [135].

D. NON-LINEAR FEATURES

The complex nature of the brain's electrical activity and its non-linear dynamic characteristics result in diverse EEG patterns. Breaking down the signal into smaller subsystems can potentially modify the irregular patterns and dynamic attributes of the signal. Thus, different non-linear statistical features are extracted from EEG [215]. Fractal geometry provides a perspective for studying EEG signals due to the property of self-similarity or scaling invariance. Several fractal dimensions can be estimated in EEG signal analysis using multifractal time-series analysis, such as the Hurst exponent [158], [159], Renyi scaling exponent [148], [160], [161], Katz fractal dimension (KFD) [162], Petrosian fractal

dimension (PFD) [163], and Higuchi fractal dimension (HFD) [164]. Similarly, Hjorth's parameters can discriminate EEG based on their slope, amplitude, and complexity [165]. These features are helpful in EEG analysis for medical diagnosis and achieve high accuracy in classifying diseases.
The Lyapunov exponent (LE) [166] is a number that measures the linearity, complexity, and stability of a dynamic system by evaluating the exponential divergence between two trajectories over time [119]. Non-linear features of the Lyapunov exponent can be extracted using WT [167], EMD, and multivariate EMD [168]. These features can then be fed into the Hilbert transform [169] for classification. Similarly, the divergence (Div) follows a similar trend [170]. Another measure is the entropy of the recurrence plot.

E. ENTROPIES

The entropy, first introduced by Shannon [171] in 1948, measures the randomness or uncertainty of the data using the equations $-sum_j p_j \log\left(p_j\right)$, where p_j is the pdf of the signals. Different forms of information entropy are utilized in EEG analysis to isolate relevant data from the background noise [172]. Several entropies can be used to analyze EEG data. These include Renyi's entropy [173] given as $-\frac{\alpha}{1-\alpha}\sum \log p_k^{\alpha}$, with $\alpha > 0$ and $\alpha \neq 1$ and Tsallis' entropy [174] given by $\frac{k}{q-1}\left(1-\sum_i p_i^q\right)$, with k as a positive constant and q is the nonextensity parameter. Later entropies serve as a basis for calculating other entropies such as Kraskov's entropy [50], spectral entropy [175], and Renyi's spectral entropy [176]. Log energy entropy (LogEn) and wavelet entropy (WE) are similar to spectral entropy but differ in a few important aspects. Meanwhile, Kolmogorov's entropy [177] is calculated by adding the positive Lyapunov exponents, which makes it computationally difficult. Entropy is the rate at which information is lost, as well as the regularity of the attractor. There are several methods to estimate Kolmogorov's entropy [178] with less computational expense, including non-linear forecasting entropy [179], maximum-likelihood entropy [180], and approximate entropy (ApEn) [181].

VII. CLASSIFICATION OF BRAIN DISORDERS USING TRADITIONAL ML AND DL APPROACHES

ML techniques can be applied to classify EEG for various brain disorders. This can be done using supervised or unsupervised learning methods. Supervised learning (SL) methods use input and output data to train models that can estimate the outcome of unseen data. Unsupervised learning uses data to find patterns or clusters in it.
SL methods are typically more accurate than unsupervised for diagnosing brain disorders from EEG signals. However, the accuracy of a single classification method can be limited to specific use cases. Multimodal integration algorithms that combine multiple classification methods can also be used to improve accuracy. ML algorithms can lead to bias, which can affect accuracy. ML methods have been used to classify EEG signals for diagnosing diseases (e.g., epilepsy, Alzheimer's, Parkinson's, depression, stroke) and rehabilitation interventions.
Reliable classification techniques are pivotal in enhancing our comprehension of real-world signal analysis applications in medical diagnosis. Various supervised machine learning classifiers are frequently employed for this purpose, encompassing linear/non-linear classifiers, non-linear Bayes classifiers, neural networks, nearest-neighbor classifiers, and hybrid classifiers such as Support Vector Machines (SVM) combined with nearest-neighbor methods [8]. SVM and nearest neighbors are used in almost 40 percent of the studies. A detailed list of the classification methods used for classifying various brain disorders is listed in Table 5.

A. LINEAR CLASSIFIERS

Linear classifiers employ algorithms based on linear discriminants to classify a collection of data points by combining the predictor variables linearly to distinguish between various classes. Examples of such linear classifiers include SVM and LDA.

1) LINEAR DISCRIMINANT ANALYSIS (LDA)

It is an approach that employs hyperplanes to classify EEG data, as illustrated in Figure 20. This method involves segregating classes by leveraging their respective mean values while maximizing their separation distance. Nevertheless, LDA's effectiveness diminishes when dealing with intricate non-linear EEG signals, and it can also be susceptible to overfitting issues [182].

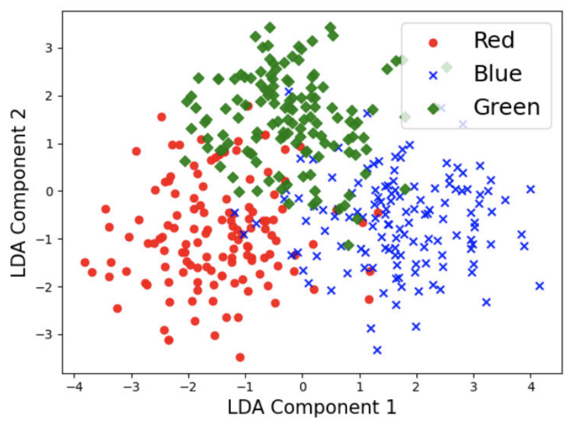


FIGURE 20. Feature separation using LDA [183].

2) SUPPORT VECTOR MACHINE(SVM)

SVMs use a discriminant hyperplane to determine classes with higher speed, better performance, and better generalization abilities while maximizing the margin and varying the kernel value, as shown in Figure 21.
When the hyperplane dimension changes from 1D to the nth dimension, differentiation becomes challenging. However,

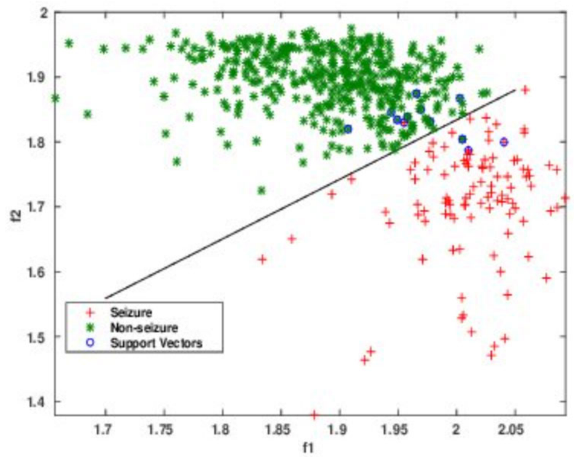


FIGURE 21. SVM classification of ictal and non-ictal EEG data [184].

with the kernel trick, SVM can be used for non-linear data classifications [103]. The Kernel function G(x,y) provides a mapping to a higher dimension. Generally, three types of kernels are selected for data: linear kernels, polynomial kernels, Gaussian kernels, and radial basis functions.

$$K(x, y) = \exp\left(\frac{-\|x-y\|^2}{2\sigma^2}\right)$$

B. NON-LINEAR BAYESIAN CLASSIFIERS

These are classifiers based on Bayes' theorem and involve probabilistic reasoning. They are employed for predicting probabilities of class membership, thereby facilitating class classification. However, their computational demands become significant when dealing with numerous items and situations involving zero probabilities, which represents their main limitation. The two prevalent forms of Bayesian classifiers are Bayesian quadratics and Markov models, also known as Hidden Markov Models (HMM) [182]. These classifiers are used for EEG classification for various brain disorders, including epilepsy and Alzheimer's.

1) BAYES QUADRATIC

The Bayes Quadratic algorithm is used to determine the most likely class for the feature vector [182]. It is mostly used in mental task classification.

2) HIDDEN MARKOV MODEL (HMM)

It is an intelligent classifier for social network sequence classification, speech recognition, and analysis [185]. It predicts unknown data points from given input data points.

C. NEAREST NEIGHBOR CLASSIFIERS

Nearest-neighbor classifiers are successful for a large number of classification problems. It uses uniform weights, which means looking at the samples closest in the distance to the new point to predict its label.

K-Nearest Neighbor (KNN) is a straightforward method to gauge the probability of a data point's association with a particular group. This determination is based on the nearest neighbor principle, as depicted in Figure 22. However, KNN's efficacy diminishes when confronted with datasets that possess high dimensions or are substantial in size, owing to the considerable prediction expenses involved. Primarily, KNN finds its utility in pattern recognition and statistical estimation [8].

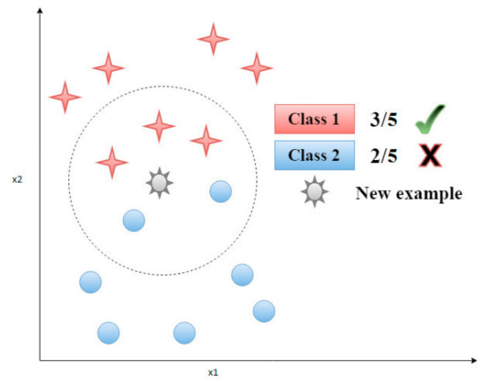


FIGURE 22. K-nearest neighbor [186].

These classifiers are utilized by the researchers to automatically diagnose brain disorders, including ADHD, epilepsy, Alzheimer's, Parkinson's, sleep apnea, etc. The use of these state-of-the-art classifiers for automatically detecting these diseases is discussed in the next section.

D. DEEP LEARNING-BASED CLASSIFICATION OF BRAIN DISORDERS FROM EEG

Due to the non-stationary nature of EEG, a classifier trained on a smaller dataset from one particular individual may not be able to generalize well to data collected from the same subject at a different time. This is a challenge for traditional machine learning classifiers to classify brain disorders from EEG, which may have to work with a limited number of data. Another problem with EEG signals is the high degree of inter-subject variability, which degrades the performance of traditional ML algorithms discussed in the above subsections. The reason for this phenomenon is that there are physiological differences between individuals. The variability of EEG signals across subjects can be challenging for models trained to generalize to new subjects [187].

Traditional machine learning methods for processing EEG data have limitations, such as limited generalization capabilities and flexibility. Deep learning (DL) could significantly improve the processing of EEG data by automatically learning end-to-end pipelines that include automatic extraction of features and diagnosis of diseases directly from EEG. This could lead to better performance in diagnosis of various diseases. DL models are very effective in dealing with complex data, such as text, audio images, and biomedical signals/images. DL models have high performance on multiple public benchmark challenges [188], Deep Learning delves into the exploration of computational models that acquire layered representations of input data. These representations are constructed by means of sequential non-linear conversions [188]. Deep neural networks are frameworks in which (1) successive tiers of artificial 'neurons' employ linear transformations on incoming data, and (2) the output of each tier is channeled across non-linear activation functions. Significantly, the parameters steering the transformations are fine-tuned by minimizing a defined cost function. Figure 23 depicts the architecture of a deep learning model having EEG signals as input, with deep layers and the output classification layer, which give the classification probabilities for each class, i.e., the brain disease. Different DL models like auto-encoders (AE), Generative adversarial networks (GAN), Transformers, Recurrent Neural Networks, etc., are different variants of the DL that are used for EEG analysis. Some of the DL model diagnoses of brain disorders like Alzheimer's, Parkinson's, epilepsy, etc. are listed at the bottom of Tables 4 and 5. Graph neural networks (GNN), auto-encoders (AE), Recurrent neural networks (RNN), Deep belief networks (DBN), Convolutional neural networks (CNN), Long short term memory (LSTM), and optimized deep neural networks are used for diagnosis of epilepsy and other brain disorders. These are discussed in the next subsections.

1) CONVOLUTIONAL NEURAL NETWORKS (CNNS)

CNNs have four primary feature layers, with the first layer being a convolutional layer that comprises multiple feature maps [189] and a ReLU layer that trains several times faster by changing all negative activation values to zero using the formula f(x) = max(x,0) [190]. Pooling layers reduce the dimensionality of feature maps, which makes the feature extraction more robust to noise and distortions. The fully connected layer is the final output layer, which incorporates all neurons from previous layers. An example of CNN is shown in, Figure 23.

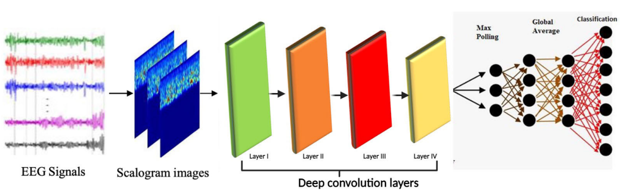


FIGURE 23. Architecture of CNN for automatic diagnosis of brain disorders using EEG.

2) GRAPH NEURAL NETWORKS (GNNS)

GNNs are ANNs that can learn from data hat is organized as a graph. In recent years, GNNs have been applied to detect brain disorders from EEG signals. In [191], the author used GNN to classify Alzheimer's Disease from EEG. They used Functional-Connectivity-Based Brain Graph Inference as input to GNNs. The EEG is used to represent the brain as a graph network, with the electrode as a node, and the time samples recorded for each electrode are the features of that node. They achieved an accuracy of 98.4% for Alzheimer's detection.

3) RECURRENT NEURAL NETWORKS (RNNS)

RNNs are deep-learning models that have been around for decades. However, their full potential was not realized until the 1990s when long short-term memory (LSTMs) were advanced. LSTMs are able to learn longer dependencies, which is essential for time series classification like EEG and other biomedical signals. RNNs are similar to the human brain in their behavior because they can process sequential data, which is something that the human brain is very good at. An example of RNN models is shown in Figure 24.

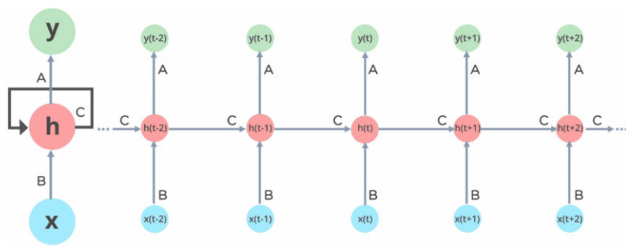


FIGURE 24. Structure of RNNS.

VIII. CURRENT STATE-OF-THE-ART

This section provides an extensive review of the current state of the art in EEG analysis for seizure and other brain disorders detection from 2017 to 2023, focusing on the studies published in Science Direct, Web of Science, PubMed, and IEEE Xplore databases, summarized in Table 5. The studies were screened and filtered in three iterations to exclude duplicates and articles outside the scope according to their titles, abstracts, and domain.

Sharma and Pachori [192] proposed a tunable Q-wavelet-transform (TQWT) method based on a single-channel dataset from the University of Bonn. This method decomposes the EEG signals into subbands, and the fractal dimensions (FDs) are computed for each subband. The features are then fed to the least squares SVM. The authors achieved 100% accuracy for automatic detection of epilepsy, but the method was not tested on multi-channel EEG datasets.

Gupta et al. [193] developed an automated system based on difference and flexible analytic wavelet transform for the Bern Barcelona database. After decomposing the signal into sub-bands, cross correntropy, SURE entropy, and Log Energy Entropy are entered into an SVM. The accuracy was 94.4% for this method. Similarly, the authors proposed a sparse discriminative ensemble learning paradigm for emotion recognition from EEG [194], where kernel-based representations were calculated from training EEG recordings and linear discriminant objective functions for ensemble learning. SVM showed better accuracy of 77.27% and 74.53% in the 2-class classification setting using the DEAP dataset.

Furthermore, Chen et al. [119] developed a new model that identifies the optimized DWT to improve the performance on

TABLE 5. Summary of Machine and Deep Learning based methods for classification of brain disorder from EEG signals.

Author(s)	Method	Dataset(s)	Classifier	Accuracy	Brain disorder
[192]	TQWT	University of Bonn	LS-SVM	98.5%	Epelipsy
[193]	FAWT	Ben Barcelona Database	SVM with RBF Kernel	94.4%	Epelipsy
[194]	SDEL	DEAP dataset	SVM	77.27% and 74.53%	Emotions
[195]	Wavelet based appraoch	University of Bonn	K-NN	97.50%	Epelipsy
[196]	DWT based on Hurst exponent	Bonn dataset	SVM	99%	Epelipsy
[197]	CAD based on Hurst exponent	Bonn dataset	k-NN	100%	Epelipsy
[198]	Hamsi-Pat	Bonn dataset	k-NN	99% for 4 classes- 100% for others	Epelipsy
[199]	DWT	Bonn dataset	SVM - ANN	100%-two class problems and 98.7% three-class problem	
[200]	WPD	TUH EEG Corpus	GBDT	87.68%	
[201]	EMD EEMD	-	SVM, KNN, naive Bayes, and logistic regression classifiers	94.56%, 95.63%, 96.8%, and 96.25% 96.06%, 97%, 97%, and 96.25%	
[202]	EMD	CHB MIT dataset	5 classifiers	99.6%, 99.8%, and 99.6%	
[203]	EMD	Bonn dataset	IMFs, FD, SVM	99.7%	
[204]	EMD	CHB MIT dataset	PHA	98.84%	
[205]	DFT with sliding window	-	SVM	98.45%	
[206]	TQWT	TUH dataset	ANN	95.1% accuracy, 97.4% accuracy, and 88.8% accuracy	
[207]	Novel method TQWT-autoencoder	Bonn dataset Freiburg dataset	ANFIS	99.46% 99.28%	
[208]	NeuCube	DEAP dataset SEED	SNN	74%, 78%, 80%, and 86.27% over DEAP dataset and 96.76% over SEED dataset	
[130]	FDM	BONN and CHB-MIT datasets	SVM	99.96% and 99.94%	Mental Stress
[123]	CNN and Random Forest	Bonn and New Delhi datasets	CNN and Random Forest	100% and 100%	Epelipsy
[126]	Q wavelet transform	openneuro dataset	SVM, LDA, KNN	92% , 96%,85%	Parkinson
[209]	Hybrid Model	-	CNN	99.2%	Parkinson
[124]	Deep learning	own dataset	CRN,GRU CNN	99.2%	Parkinson
[125]	Gabor transformation	OpenNeuro	CNN	100% and 100%	Parkinson
[128]	Fourier and Wavelet Transform	OpenNeuro	Decision Tree	92%	Alzheimer
[127]	Wavelet and fractal features	Florida State University dataset	Statistical analysis	100%	Alzheimer

the test data. To create an optimal setting for DWT, the authors combined factors: the mother wavelet, the frequency band, the decomposition level, and the features. The CHB-MIT datasets and UBonn were tested using this method. They achieved 92.3% and 99.33% accuracy, respectively on these datasets.

Harender and Sharma [195] tested a wavelet-based technique over the University of Bonn single channel, where three statistical features were determined after the wavelet decomposition. The authors claimed that KNN got an average accuracy of 97.50%, but they did not test their approach on CHB-MIT or any other multi-channel dataset. Madan et al. [196] employed a DWT to extract features from the Bonn dataset based on the Hurst exponent (HE). As a result of their approach, the SVM produced a higher accuracy of 99% compared to the KNN. Similarly, Lahmiri and Shmuel [197] presented a new automated detection system (computer-aided diagnostic-CAD system) based on the Hurst exponent to differentiate intracranial EEG with non-seizure and seizure periods. Using KNN with tenfold cross-validation and testing on the Bonn dataset, they achieved 100% accuracy. Tuncer [198] developed a novel biomedical EEG classification method called Hamsi-Pat that uses a non-linear feature extractor based on the Hamshi hash function of the substitution box. A Hamsi-Pat feature generator, TQWT decomposition method, iterative neighborhood component analysis (INCA), and a kNN classifier were used in the proposed method. The authors claimed 99.20% accuracy for five class cases and 100% accuracy for others on the Bonn dataset. Selvathi and Meera [210] achieved 95.6% accuracy over the CHB MIT dataset by decomposing the EEG signal into seven levels using DWT and extracting statistical characteristics of the alpha band for SVM classification. Within the same context, Omidvar and colleagues [199] used DWT to divide the Bonn University dataset into five sub-bands and achieved 100% accuracy in two-class problems and 98.7% accuracy in three-class problems by combining SVM and ANN. Similarly, using wavelet packet decomposition (WPD) to extract statistical features, Albaqami et al. [200] utilized WPD to decrease the feature's dimension and demonstrated that GBDT could achieve an accuracy of 87.68% on the TUH EEG Corpus dataset. EMD and its derivatives were used in many studies as a baseline method to divide EEG signals into intrinsic mode functions (IMFs) and extract relevant features from those derivatives to classify the signal. According to Cura et al. [201], using EMD analysis, they achieved, 95.63%, 96.25%, 94.56% and 96.8%for KNN, logistic regression SVM and Naive Bayes respectively. Meanwhile, 96.06%, 97%, 97%, and 96.25% of the classifications were achieved using the EEMD and the same classifiers, respectively. Kaleem et al. [202] used a new model on the CHB-MIT scalp EEG dataset, with accuracy, sensitivity, and specificity values to achieve accuracy values of 99.6%, 99.8%, and 99.6%, respectively. Wijayanto et al. [203] claimed to achieve 99.7% accuracy using the Bonn University dataset with five IMFs, FD, and SVM in combination with EMD. Belhadj et al. [204] used the EMD tool and the rapid potential-based hierarchical agglomerative (PHA) clustering technique. The Euclidian, Batacharay, and Kolmogorov distances between the IMFs were calculated and fed into the PHA cluster to achieve an accuracy of 98.84% over the CHB-MIT datasets. In their study, Wang et al. [205] used a directed transfer function-based method for detecting epilepsy. They used the sliding window technique and the DFT method to determine cerebral function connectivity and calculate the brain's information outflow. The SVM classifier was later utilized to differentiate between ictal and interictal EEG signals with 98.45% accuracy. Multi-channel EEG datasets such as those from Bonn.

George et al. [206] proposed a tunable Q-wavelet transform-based method that divides a signal into sub-bands, entropies based on the non-linear features are calculated, optimal features are then selected using particle swarm optimization, and ANN is then used to classify the signals. Over the Temple University Hospital (TUH) dataset, the method achieved 95.1% accuracy, 97.4% accuracy, and 88.8% accuracy.

Shoeibi et al. [207] also proposed a novel procedure on the basis of deep learning and fuzzy logic. A tunable-Q-wavelet transform is proposed to decompose the EEG into sub-bands, and 13 different entropies are calculated and their computational complexity is considered for the purpose of choosing the best one. The dimensionality was reduced using a six-layer autoencoder (AE). Finally, for classification, the classic adaptive neuro-fuzzy inference system (ANFIS) techniques of the grasshopper optimization (ANFIS-GOA), particle swarm optimization (PSO), and breeding swarm optimization (BSO) were utilized to achieve an accuracy of 99.46% for the Bonn EEG dataset and 99.28% for the Freiburg EEG dataset.

The classification technique NeuCube on the basis of spiking ANN was put forward by Luo et al. [208]. The authors integrated Ben's spiker rule with other rules. The EEG data were processed using DWT and FFT for feature extraction. An SNN classifier was then used, with accuracies of 96.76% for the SEED dataset and 86.27% for the DEAP dataset. In their study, Mehla et al. [130] proposed the Fourier decomposition method (FDM) for EEG classification. FDM was used to divide EEG data into Fourier intrinsic band functions (FIBFs), and the Kruskal-Wallis test was applied for feature extraction. SVM was trained with the features and 99.96% and 99.94% accuracies were obtained for BONN and CHB-MIT datasets.

In [123], the authors proposed a model for epileptic EEG classification. The method combines random RF and CNN for the classification of epileptic seizures. The model was validated using EEG signals of the Bonn dataset and Indian New Delhi dataset. The accuracy, specificity, and sensitivity were 99.9%, 99.80%, and 100%, respectively for the C-E case.

Many studies have used EEG signals and machine learning techniques to detect Parkinson's disease (PD). 5, also summarizes these studies, the models, and the results they obtained. Most of these studies in used DL methods [124], [125], [209]. Khare [126] got higher accuracy using a smoothed pseudo-Wigner-Ville distribution of EEG combined with CNN with an accuracy of 100%.

Several studies have demonstrated encouraging outcomes in the identification of neurological disorders like Alzheimer's disease. Although there is no specific cure for AD, the timely identification of the condition may help enhance the quality of life for those affected. Fiscon and Weitschek implemented a methodology that leverages techniques for extracting distinctive attributes and categorizing EEG [128]. They differentiate between patients afflicted with AD, those experiencing mild AD, and individuals in a healthy group. A total of 109 samples spanning AD, MCI, and HC categories are converted to scalograms using both Fourier and Wavelet Transforms. Through the utilization of Wavelet-based feature extraction, they attained classification accuracies of 83% for AD and normal cases,92% for health and mild AD cases, and 79% for Mild and AD classification scenarios.

In [127], authors employed six computational techniques for analyzing time-series data i.e. EEG of 160 subjects with AD and 24 with HC. Findings derived from both the original and wavelet-filtered EEG signals to sub-bands indicate that some validated methods, such as wavelet-coherence and quantile graphs, exhibit a robust capacity to differentiate between AD patients and healthy elderly participants with high accuracy. The authors of [211] proposed graph theoretical approaches to analyze brain functional or cortical connectivity from EEG signals. Brain networks were modeled as graphs based on super edges [212], which take all possible paths between a pair of nodes, allowing the characterization of the properties of the networks within the graphs. In the proposed method, current densities of various dipoles were averaged using linear inverse problems (distributed inverse methods) and Brodmann's mapping criterion based on MRI images and EEG recordings. In the later stages, multivariate autoregressive models (MVAR) were used to estimate the frequency domain, which was then modeled by a graph. After using PCA for dimensionality reduction and decorrelation of heavily correlated measurements, each frequency band was projected into a three-dimensional space, allowing for further analysis and interpretation of the data. According to the results obtained for the dataset [213], [214], the p-value yielded a value of 0.066.

In the study titled "PFT: A Novel Time-Frequency Decomposition of BOLD fMRI Signals for Autism Spectrum Disorder Detection," the authors of [152] proposed a new approach called Progressive Fourier Transform (PFT) for detecting Autism Spectrum Disorder (ASD) using fMRI signals. They utilized the temporal dynamics of the BOLD (blood oxygen level-dependent) data from specific brain areas for ASD categorization. The PFT was employed to derive the temporal dynamic features of the BOLD signals. This approach aimed to address the limitations of existing ASD detection systems by incorporating time-frequency components and improving feature extraction and classification. The study used the Autism Brain Imaging Data Exchange dataset for model validation, demonstrating better results with the proposed PFT model compared to existing models, including an increase in accuracy to 96.7%. This research highlights the potential of the PFT technique for analyzing rs-fMRI data from various brain diseases of the same type.

In summary, various methods have been proposed for EEG signal processing and classification for various brain disorders, including time-frequency analysis, wavelet transforms, empirical mode decomposition, spiking neural networks, and graph theoretical approaches. These methods are robust i and have the potential to be used for various applications, such as detecting epileptic seizures and analyzing brain connectivity. Further research and experimentation are necessary to increase the accuracy of these methods and to explore their applicability for diagnosing other brain and neurological disorders.

IX. PROBLEMS, CHALLENGES AND WAY FORWARD

EEG of individuals or selected from a dataset can have a lot of noise. This is because EEG signals are often multi-channel and of longer duration. As a result, signal denoising, preprocessing, and analysis can be challenging. Accurate computer-based processing of EEG is also challenging due to its low amplitude and susceptibility to high frequency and other noises. In this work, we highlighted the main problems and complexities caused by various common artifacts, their automatic detection, and attenuation methods in detail. We also discussed the limitations of current signal processing methods and how they can be improved.

We are of the opinion that a single model may not be able to remove all possible artifacts from EEG. Thus the selection of a proper filter and preprocessing technique for removal of each possible noise is required. ML/DL-based techniques may be used in the future first to classify the type of noise contaminating EEG signals, and then in run time, a proper filter may be applied to attenuate the noise to get a better quality signal. In some cases, the noise may only be present in one portion of the EEG, which needs to be identified first, and then filtering may be applied to that portion of the EEG only.

The second main challenge is the feature engineering step. Traditional handcrafted feature engineering methods struggle to detect reliable features from EEG signals due to low EEG amplitude and SNR. Another challenge is the selection of the number of features, which increases the computational cost. Thus, the main challenges in EEG are computational cost, high dimensionality, and classification accuracy for brain disorders. The best approach to overcome these challenges is to select features depending on the specific application and the desired trade-off between processing time and accuracy. We propose that new optimization techniques may be applied to EEG signals to select the most relevant features rather than using traditional EEG signal processing systems. This includes developing new feature selection and transformation methods and improving the efficiency of existing methods.

Recently, ML/DL has proven to be immensely worthwhile for interpreting EEG signals. Nevertheless, the incorporation of ML/DL techniques into clinical practices presents a range of technical challenges. A primary hurdle involves achieving data standardization. The broad compatibility of EEG data is inevitably hindered by variations in the types of EEG input data available, storage formats employed, and interpretation protocols applied. These variations stem from differences in data collection sources, whether from ambulatory devices, bedside apparatus, or mobile devices, resulting in potential discrepancies and divergences during data analysis. A significant constraint faced by AI algorithms is their reliance on substantial amounts of high SNR data to yield correct outcomes, especially when proposing models for managing brain disorders having limited datasets. Occasionally, the SNR of the signals can be compromised by factors like incompleteness, heterogeneity, or noise, thereby introducing missing values, redundancies, or data sparsity. Furthermore, AI models typically demand advanced processors to function effectively, leading to increased computational complexities. As a consequence, there exists a trade-off in the design of a system.

EEG datasets are often small, which can make it difficult to train machine learning algorithms. This is because EEG signals are typically recorded from a small number of subjects, and each subject may only have a limited amount of data. This problem can be overcome by recording data for a relatively longer time but it is also sometimes not possible if the subject has severe epilepsy episodes or other chronic brain disorders. Another challenge is high dimensionality: EEG signals have a high dimensionality, i.e., signals are recorded with an electrode grid, with longer recordings. This can make it difficult to find the most important features for classification, and it can also make the training of machine learning algorithms computationally expensive. The non-stationary nature of EEG makes it difficult to classify EEG signals, as the classifier needs to adapt to the unexpected changes in the data with respect to time. Inter-subject variability is also a big challenge which can make it difficult to develop a classifier that works for everyone. This is because the features important for classifying EEG signals in one person may not be important in another person. Even though these challenges exist there has been significant progress in EEG processing in recent years. ML and DL algorithms, such as SVM, RF, LSTM, and Hybrid CNN-LSTM, have been shown to be helpful in classifying EEG signals for a variety of disorders. Recently developed transformer models may also be used to overcome these challenges.

X. CONCLUSION AND FUTURE WORK

This paper provides an extensive overview of the most popular datasets, feature domains, artifacts, and preprocessing methods used to perform more accurate analyses of EEG for the automatic detection of brain disorders, especially epilepsy. An examination of EEG characteristics and the procedures utilized to extract those characteristics, along with a discussion of the benefits and drawbacks of each method, are presented in this article. In addition, this study examines the current trends regarding feature engineering and classification techniques. Several academic papers have provided the source material for these methodologies and the findings associated with them. The time-frequency methods of the EEG do not provide as much detail as the frequency domain methods, while the frequency domain approaches do not provide satisfactory performance for a number of signals. Time-frequency is one of the most frequently utilized feature domains, and its analysis can be performed using either the STFT or CWT. It is important to choose accurate features and methods for analysis in accordance with the various mental tasks that are being carried out to improve the results.

As a future work, We believe that in the era of the medical internet of things, ML, and DL, EEG signal processing is poised to undergo significant advances and transformative changes. IoT allows for seamless connectivity of EEG devices, enabling real-time monitoring of brain activity. This is particularly valuable for remote patient monitoring, where EEG data can be transmitted to healthcare professionals for timely diagnosis and intervention. Similarly, With the increasing processing capabilities of edge devices, it becomes feasible to perform initial preprocessing and feature extraction directly on EEG devices. This will reduce the need to transmit huge raw data, minimizing bandwidth requirements and latency. In summary, the convergence of IoT, ML, and DL technologies has the potential to revolutionize EEG signal processing. This convergence opens up new opportunities for personalized healthcare, real-time monitoring, improved diagnostic accuracy, and a deeper understanding of brain activity and neurological conditions.

This paper provides a holistic evaluation of the existing EEG processing for medical diagnosis. It discusses several important research works in detail and Serves as a resource for researchers in this field of EEG processing for the diagnosis of health conditions. It also provides insight for future research on EEG analysis for healthcare. In conclusion, while there have been significant advancements in EEG analysis techniques, there are still challenges that need to be addressed, such as artifact and noise removal. As machine learning and deep learning continue to evolve, new approaches for robust artifact removal may become available. Developing a noise-reduction method and creating a custom metric for deep learning are also proposed as future directions. Additionally, attention should be given to other neurological disorders beyond epilepsy to find the best methods for EEG analysis. The use of graph neural networks and exploring new transformations like time-frequency decomposition are also suggested for improving EEG analysis. Overall, there is still much to be explored and developed in EEG analysis, and future research should continue to advance the field.

XI. CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] W. O. Tatum, G. Rubboli, P. W. Kaplan, S. M. Mirsatari, K. Radhakrishnan, D. Gloss, L. O. Caboclo, F. W. Drislane, M. Koutroumanidis, D. L. Schomer, D. K.-N. Trenite, M. Cook, and S. Beniczky, "Clinical utility of EEG in diagnosing and monitoring epilepsy in adults," *Clin. Neurophysiol.*, vol. 129, no. 5, pp. 1056–1082, May 2018.

[2] M. Elsabbagh, A. Yusuf, J. Zeidan, J. Scorah, E. Fombonne, M. S. Durkin, S. Saxena, and A. Shih, "The time has come for living systematic reviews in autism research," *Autism Res.*, vol. 15, no. 7, pp. 1187–1188, Jul. 2022.

[3] T. Wang, Y. Ma, R. Li, J. Sun, L. Huang, S. Wang, and C. Yu, "Trends of ischemic heart disease mortality attributable to household air pollution during 1990–2019 in China and India: An age-period-cohort analysis," *Environ. Sci. Pollut. Res.*, vol. 29, pp. 87478–87489, Dec. 2022.

[4] C. J. Stam, "Nonlinear dynamical analysis of EEG and MEG: Review of an emerging field," *Clin. Neurophysiol.*, vol. 116, no. 10, pp. 2266–2301, Oct. 2005.

[5] M. Orban, M. Elsamanty, K. Guo, S. Zhang, and H. Yang, "A review of brain activity and EEG-based brain–computer interfaces for rehabilitation application," *Bioengineering*, vol. 9, no. 12, p. 768, Dec. 2022. [Online]. Available: https://www.mdpi.com/2306-5354/9/12/768

[6] P. Wang, X. Cao, Y. Zhou, P. Gong, M. Yousefnezhad, W. Shao, and D. Zhang, "A comprehensive review on motion trajectory reconstruction for EEG-based brain-computer interface," *Frontiers Neurosci.*, vol. 17, Jun. 2023, Art. no. 1086472. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2023.1086472

[7] H. Altaheri, G. Muhammad, M. Alsulaiman, S. U. Amin, G. A. Altuwaijri, W. Abdul, M. A. Bencherif, and M. Faisal, "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: A review," *Neural Comput. Appl.*, vol. 35, no. 20, pp. 14681–14722, Jul. 2023.

[8] S. Pahuja and K. Veer, "Recent approaches on classification and feature extraction of EEG signal: A review," *Robotica*, vol. 40, no. 1, pp. 77–101, Jan. 2022.

[9] J. D. Bronzino, "Quantitative analysis of the EEG-general concepts and animal studies," *IEEE Trans. Biomed. Eng.*, vol. BME-31, no. 12, pp. 850–856, Dec. 1984.

[10] M. C. Houston, "Some aspects of a college health service," *Amer. J. Nursing*, vol. 42, no. 10, pp. 1183–1189, Oct. 1942.

[11] P. L. Nunez, "Representation of evoked potentials by Fourier-Bessel expansions," *IEEE Trans. Biomed. Eng.*, vol. BME-20, no. 5, pp. 372–374, Sep. 1973.

[12] A. C. Sanderson, J. Segen, and E. Richey, "Hierarchical modeling of EEG signals," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-2, no. 5, pp. 405–415, Sep. 1980.

[13] P. Herman, G. Prasad, T. M. McGinnity, and D. Coyle, "Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 4, pp. 317–326, Aug. 2008.

[14] S. Biswal, J. Kulas, H. Sun, B. Goparaju, M. B. Westover, M. T. Bianchi, and J. Sun, "SLEEPNET: Automated sleep staging system via deep learning," 2017, *arXiv:1707.08262*.

[15] R. Hari and A. Puce, *MEG-EEG Primer*. Oxford, U.K.: Oxford Univ. Press, 2017.

[16] D. L. Schomer and F. L. Da Silva, *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*. Philadelphia, PA, USA: Lippincott Williams & Wilkins, 2012.

[17] D. A. Engemann, F. Raimondo, J.-R. King, B. Rohaut, G. Louppe, F. Faugeras, J. Annen, H. Cassol, O. Gosseries, D. Fernandez-Slezak, S. Laureys, L. Naccache, S. Dehaene, and J. D. Sitt, "Robust EEG-based cross-site and cross-protocol classification of states of consciousness," *Brain*, vol. 141, no. 11, pp. 3179–3192, Nov. 2018.

[18] N. S. Bastos, B. P. Marques, D. F. Adamatti, and C. Z. Billa, "Analyzing EEG signals using decision trees: A study of modulation of amplitude," *Comput. Intell. Neurosci.*, vol. 2020, pp. 1–11, Jul. 2020.

[19] J. T. Giacino, J. J. Fins, S. Laureys, and N. D. Schiff, "Disorders of consciousness after acquired brain injury: The state of the science," *Nature Rev. Neurol.*, vol. 10, no. 2, pp. 99–114, Feb. 2014.

[20] S. Hagihira, "Changes in the electroencephalogram during anaesthesia and their physiological basis," *Brit. J. Anaesthesia*, vol. 115, pp. 27–31, Jul. 2015.

[21] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, "A review of classification algorithms for EEG-based brain–computer interfaces: A 10 year update," *J. Neural Eng.*, vol. 15, no. 3, Jun. 2018, Art. no. 031005.

[22] M. Rashid, N. Sulaiman, A. P. P. Abdul Majeed, R. M. Musa, A. F. A. Nasir, B. S. Bari, and S. Khatun, "Current status, challenges, and possible solutions of EEG-based brain-computer interface: A comprehensive review," *Frontiers Neurorobotics*, vol. 14, p. 25, Jun. 2020.

[23] N. Bigdely-Shamlo, T. Mullen, C. Kothe, K.-M. Su, and K. A. Robbins, "The PREP pipeline: Standardized preprocessing for large-scale EEG analysis," *Frontiers Neuroinform.*, vol. 9, p. 16, Jun. 2015.

[24] M. Jas, D. A. Engemann, Y. Bekhti, F. Raimondo, and A. Gramfort, "Autoreject: Automated artifact rejection for MEG and EEG data," *NeuroImage*, vol. 159, pp. 417–429, Oct. 2017.

[25] D. Steyrl and G. R. Müller-Putz, "Artifacts in EEG of simultaneous EEG-fMRI: Pulse artifact remainders in the gradient artifact template are a source of artifact residuals after average artifact subtraction," *J. Neural Eng.*, vol. 16, no. 1, Feb. 2019, Art. no. 016011.

[26] H. Zamanian and H. Farsi, "A new feature extraction method to improve emotion detection using EEG signals," *ELCVIA Electron. Lett. Comput. Vis. Image Anal.*, vol. 17, no. 1, pp. 29–44, Nov. 2018.

[27] K. D. Rao and D. C. Reddy, "On-line method for enhancement of electroencephalogram signals in presence of electro-oculogram artefacts using nonlinear recursive least squares technique," *Med. Biol. Eng. Comput.*, vol. 33, no. 3, pp. 488–491, May 1995.

[28] L. Cao, J. Li, Y. Sun, H. Zhu, and C. Yan, "EEG-based vigilance analysis by using Fisher score and PCA algorithm," in *Proc. IEEE Int. Conf. Prog. Informat. Comput.*, vol. 1, Dec. 2010, pp. 175–179.

[29] F. Lotte, L. Bougrain, and M. Clerc, "Electroencephalography (EEG)-based brain-computer interfaces," in *Wiley Encyclopedia of Electrical and Electronics Engineering*. Wiley, 2015, p. 44. [Online]. Available: https://hal.archives-ouvertes.fr/hal-01167515, doi: 10.1002/047134608X.W8278.

[30] A. Shoeb, *CHB-MIT Scalp EEG Database*. Accessed: Aug. 11, 2023. [Online]. Available: http://physionet.org/pn6/chbmit/

[31] A. H. Shoeb, "Application of machine learning to epileptic seizure onset detection and treatment," Ph.D. dissertation, Massachusetts Inst. Technol., Cambridge, MA, USA, 2009.

[32] R. Hussein, S. Lee, R. Ward, and M. J. McKeown, "Epileptic seizure prediction: A semi-dilated convolutional neural network architecture," in *Proc. 25th Int. Conf. Pattern Recognit. (ICPR)*, Jan. 2021, pp. 5436–5443.

[33] B. Hegermiller-Smith, P. Miller, A. Husain, and V. Neurodiagnostic, "American epilepsy society," *Epilepsia*, vol. 50, no. 11, pp. 1–502, 2009.

[34] R. Rahman, S. M. Varnosfaderani, O. Makke, N. J. Sarhan, E. Asano, A. Luat, and M. Alhawari, "Comprehensive analysis of EEG datasets for epileptic seizure prediction," in *Proc. IEEE Int. Symp. Circuits Syst. (ISCAS)*, May 2021, pp. 1–5.

[35] M. Ihle, H. Feldwisch-Drentrup, C. A. Teixeira, A. Witon, B. Schelter, J. Timmer, and A. Schulze-Bonhage, "Epilepsiae—A European epilepsy database," *Comput. Methods Programs Biomed.*, vol. 106, no. 3, pp. 127–138, 2012.

[36] A. Miltiadous, K. D. Tzimourta, T. Afrantou, P. Ioannidis, N. Grigoriadis, D. G. Tsalikakis, P. Angelidis, M. G. Tsipouras, E. Glavas, N. Giannakeas, and A. T. Tzallas, "A dataset of scalp EEG recordings of Alzheimer's disease, frontotemporal dementia and healthy subjects from routine EEG," *Data*, vol. 8, no. 6, p. 95, 2023. [Online]. Available: https://www.mdpi.com/2306-5729/8/6/95

[37] N. G. J. A. A. Rockhill, A. P. Jackson, and N. C. Swann, "UC San Diego resting state EEG data from patients with Parkinson's disease," Tech. Rep., 2021.

[38] A. Arsalan, M. Majid, A. R. Butt, and S. M. Anwar, "Classification of perceived mental stress using a commercially available EEG headband," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 6, pp. 2257–2264, Nov. 2019.

[39] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: A general-purpose brain-computer interface (BCI) system," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun. 2004.

[40] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "DEAP: A database for emotion analysis; Using physiological signals," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 18–31, Jan. 2012.

[41] K. T. Sweeney, H. Ayaz, T. E. Ward, M. Izzetoglu, S. F. McLoone, and B. Onaral, "A methodology for validating artifact removal techniques for physiological signals," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 5, pp. 918–926, Sep. 2012.

[42] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks," *IEEE Trans. Auto. Mental Develop.*, vol. 7, no. 3, pp. 162–175, Sep. 2015.

[43] M. Simoes, D. Borra, E. Santamaría-Vázquez, M. Bittencourt-Villalpando, D. Krzeminski, and A. Miladinovic, "BCIAUT-P300: A multi-session and multi-subject benchmark dataset on autism for P300-based brain-computer-interfaces," *Frontiers Neurosci.*, vol. 14, Sep. 2020, Art. no. 568104.

[44] A. Guillot, F. Sauvet, E. H. During, and V. Thorey, "Dreem open datasets: Multi-scored sleep datasets to compare human and automated sleep staging," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 9, pp. 1955–1965, Sep. 2020.

[45] A. Delorme, S. Makeig, M. Fabre-Thorpe, and T. Sejnowski, "From single-trial EEG to brain area dynamics," *Neurocomputing*, vols. 44–46, pp. 1057–1064, Jun. 2002.

[46] T. B. Alakus, M. Gonen, and I. Turkoglu, "Database for an emotion recognition system based on EEG signals and various computer games—GAMEEMO," *Biomed. Signal Process. Control*, vol. 60, Jul. 2020, Art. no. 101951.

[47] A. Raheel, M. Majid, and S. M. Anwar, "DEAR-MULSEMEDIA: Dataset for emotion analysis and recognition in response to multiple sensorial media," *Inf. Fusion*, vol. 65, pp. 37–49, Jan. 2021.

[48] W. Liu, J.-L. Qiu, W.-L. Zheng, and B.-L. Lu, "Comparing recognition performance and robustness of multimodal deep learning models for multimodal emotion recognition," *IEEE Trans. Cognit. Develop. Syst.*, vol. 14, no. 2, pp. 715–729, Jun. 2022.

[49] Y. Wang, W. Duan, D. Dong, L. Ding, and X. Lei, "A test-retest resting, and cognitive state EEG dataset during multiple subject-driven states," *Sci. Data*, vol. 9, no. 1, pp. 1–11, Sep. 2022.

[50] M. J. Alhaddad, M. I. Kamel, and H. M. Malibary, "Diagnosis autism by Fisher linear discriminant analysis FLDA via EEG," *Int. J. Bio-Sci. Bio-Technol.*, vol. 4, no. 2, pp. 45–54, 2012.

[51] M. Sazgar and M. G. Young, *Absolute Epilepsy and EEG Rotation Review: Essentials for Trainees*. Berlin, Germany: Springer, 2019.

[52] S. Motamedi-Fakhr, M. Moshrefi-Torbati, M. Hill, C. M. Hill, and P. R. White, "Signal processing techniques applied to human sleep EEG signals—A review," *Biomed. Signal Process. Control*, vol. 10, pp. 21–33, Mar. 2014.

[53] D. Moretti, "Computerized processing of EEG–EOG–EMG artifacts for multi-centric studies in EEG oscillations and event-related potentials," *Int. J. Psychophysiol.*, vol. 47, no. 3, pp. 199–216, Mar. 2003.

[54] K. Venkatachalam, A. Devipriya, J. Maniraj, M. Sivaram, A. Ambikapathy, and S. A. Iraj, "A novel method of motor imagery classification using EEG signal," *Artif. Intell. Med.*, vol. 103, Mar. 2020, Art. no. 101787.

[55] S. Sen Gupta, S. Soman, P. Govind Raj, R. Prakash, S. Sailaja, and R. Borgohain, "Detecting eye movements in EEG for controlling devices," in *Proc. IEEE Int. Conf. Comput. Intell. Cybern. (CyberneticsCom)*, Jul. 2012, pp. 69–73.

[56] T. W. Picton, P. van Roon, M. L. Armilio, P. Berg, N. Ille, and M. Scherg, "The correction of ocular artifacts: A topographic perspective," *Clin. Neurophysiol.*, vol. 111, no. 1, pp. 53–65, Jan. 2000.

[57] S. Hoehl and S. Wahl, "Recording infant ERP data for cognitive research," *Develop. Neuropsychol.*, vol. 37, no. 3, pp. 187–209, Apr. 2012.

[58] D. Craven, B. McGinley, L. Kilmartin, M. Glavin, and E. Jones, "Adaptive dictionary reconstruction for compressed sensing of ECG signals," *IEEE J. Biomed. Health Informat.*, vol. 21, no. 3, pp. 645–654, May 2017.

[59] S. R. Benbadis and K. Lin, "Errors in EEG interpretation and misdiagnosis of epilepsy," *Eur. Neurol.*, vol. 59, no. 5, pp. 267–271, 2008.

[60] (Mar. 2021). *All About EEG Artifacts and Filtering Tools*. [Online]. Available: https://www.bitbrain.com/blog/eeg-artifacts

[61] A. W. Lininger, M. R. Volow, and D. T. Gianturco, "Intravenous infusion motor artifact," *Amer. J. EEG Technol.*, vol. 21, no. 4, pp. 167–173, Dec. 1981.

[62] N. Elsayed, Z. Saad, and M. Bayoumi, "Brain computer interface: EEG signal preprocessing issues and solutions," *Int. J. Comput. Appl.*, vol. 169, no. 3, pp. 12–16, Jul. 2017.

[63] K. Majumdar, *A Brief Survey of Quantitative EEG*. Boca Raton, FL, USA: CRC Press, 2017.

[64] D. J. Krusienski, D. J. McFarland, J. C. Principe, and E. Wolpaw, "BCI signal processing: Feature extraction," in *Brain-Computer Interfaces: Principles and Practice*, J. R. Wolpaw and E. W. Wolpaw, Eds. New York, NY, USA: Oxford Univ. Press, 2012, pp. 123–146.

[65] H. Jäger, H. Witte, M. Galicki, C. Schelenz, M. Specht, K. Reinhart, M. Eiselt, and A. Doering, "Adaptable preprocessing units and neural classification for the segmentation of EEG signals," *Methods Inf. Med.*, vol. 38, no. 3, pp. 214–224, 1999.

[66] I. Rejer and P. Górski, "Independent component analysis for EEG data preprocessing-algorithms comparison," in *Proc. IFIP Int. Conf. Comput. Inf. Syst. Ind. Manag.* Cham, Switzerland: Springer, 2013, pp. 108–119.

[67] I. Winkler, S. Debener, K.-R. Müller, and M. Tangermann, "On the influence of high-pass filtering on ICA-based artifact reduction in EEG-ERP," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 4101–4105.

[68] D. Wu, J.-T. King, C.-H. Chuang, C.-T. Lin, and T.-P. Jung, "Spatial filtering for EEG-based regression problems in brain–computer interface (BCI)," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 2, pp. 771–781, Apr. 2018.

[69] L. Eeckhout, "Hot chips: Industry and academia cutting-edge microprocessors," *IEEE Micro*, vol. 37, no. 2, p. 4, Mar. 2017.

[70] S. Leske and S. S. Dalal, "Reducing power line noise in EEG and MEG data via spectrum interpolation," *NeuroImage*, vol. 189, pp. 763–776, Apr. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1053811919300266

[71] J. Strobl, M. Piorecky, V. Koudelka, T. Nagy, and V. Krajca, "Methods for removing of line noise artifact from EEG records with minimization of neural information loss," in *Proc. Medit. Conf. Med. Biol. Eng. Comput.* Cham, Switzerland: Springer, 2019, pp. 184–192.

[72] M. A. Klados, C. Papadelis, C. Braun, and P. D. Bamidis, "REG-ICA: A hybrid methodology combining blind source separation and regression techniques for the rejection of ocular artifacts," *Biomed. Signal Process. Control*, vol. 6, no. 3, pp. 291–300, Jul. 2011.

[73] A. Zachariah, J. Jai, and G. Titus, "Automatic EEG artifact removal by independent component analysis using critical EEG rhythms," in *Proc. Int. Conf. Control Commun. Comput. (ICCC)*, Dec. 2013, pp. 364–367.

[74] T. Zikov, S. Bibian, G. A. Dumont, M. Huzmezan, and C. R. Ries, "A wavelet based de-noising technique for ocular artifact correction of the electroencephalogram," in *Proc. 2nd Joint 24th Annu. Conf. Annu. Fall Meeting Biomed. Eng. Society*, vol. 1, 2002, pp. 98–105.

[75] V. Krishnaveni, S. Jayaraman, N. Malmurugan, A. Kandasamy, and D. Ramadoss, "Non adaptive thresholding methods for correcting ocular artifacts in EEG," *Academic Open Internet J.*, vol. 13, pp. 2–3, Mar. 2004.

[76] X. Yong, R. K. Ward, and G. E. Birch, "Artifact removal in EEG using morphological component analysis," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Apr. 2009, pp. 345–348.

[77] S. Khatun, R. Mahajan, and B. I. Morshed, "Comparative analysis of wavelet based approaches for reliable removal of ocular artifacts from single channel EEG," in *Proc. IEEE Int. Conf. Electro/Inf. Technol. (EIT)*, May 2015, pp. 335–340.

[78] R. B. Pachori, "Discrimination between ictal and seizure-free EEG signals using empirical mode decomposition," *Res. Lett. Signal Process.*, vol. 2008, pp. 1–5, Dec. 2008.

[79] D. Safieddine, A. Kachenoura, L. Albera, G. Birot, A. Karfoul, A. Pasnicu, A. Biraben, F. Wendling, L. Senhadji, and I. Merlet, "Removal of muscle artifact from EEG data: Comparison between stochastic (ICA and CCA) and deterministic (EMD and wavelet-based) approaches," *EURASIP J. Adv. Signal Process.*, vol. 2012, no. 1, pp. 1–15, Dec. 2012.

[80] K. T. Sweeney, S. F. McLoone, and T. E. Ward, "The use of ensemble empirical mode decomposition with canonical correlation analysis as a novel artifact removal technique," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 1, pp. 97–105, Jan. 2013.

[81] X. Chen, X. Xu, A. Liu, M. J. McKeown, and Z. J. Wang, "The use of multivariate EMD and CCA for denoising muscle artifacts from few-channel EEG recordings," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 2, pp. 359–370, Feb. 2018.

[82] B. Widrow and S. D. Stearns, *Adaptive Signal Processing*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1985.

[83] B. Kovavevic, Z. Banjac, and M. Milosavljevic, *Adaptive Digital Filters*. Berlin, Germany: Springer, 2013.

[84] G. Benmouyal, "Removal of DC-offset in current waveforms using digital mimic filtering," *IEEE Trans. Power Del.*, vol. 10, no. 2, pp. 621–630, Apr. 1995.

[85] M. Rakibul Mowla, S.-C. Ng, M. S. A. Zilany, and R. Paramesran, "Artifacts-matched blind source separation and wavelet transform for multichannel EEG denoising," *Biomed. Signal Process. Control*, vol. 22, pp. 111–118, Sep. 2015.

[86] J. P. Lindsen and J. Bhattacharya, "Correction of blink artifacts using independent component analysis and empirical mode decomposition," *Psychophysiology*, vol. 47, no. 5, pp. 955–960, 2010.

[87] V. Kamath, Y.-C. Lai, L. Zhu, and S. Urval, "Empirical mode decomposition and blind source separation methods for antijamming with GPS signals," in *Proc. IEEE/ION Position, Location, Navigat. Symp.*, 2006, pp. 335–341.

[88] X. Navarro, F. Porée, and G. Carrault, "ECG removal in preterm EEG combining empirical mode decomposition and adaptive filtering," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Mar. 2012, pp. 661–664.

[89] Y. Chen, Q. Zhao, B. Hu, J. Li, H. Jiang, W. Lin, Y. Li, S. Zhou, and H. Peng, "A method of removing ocular artifacts from EEG using discrete wavelet transform and Kalman filtering," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2016, pp. 1485–1492.

[90] Q. Chen, Y. Li, and X. Yuan, "A hybrid method for muscle artifact removal from EEG signals," *J. Neurosci. Methods*, vol. 353, Apr. 2021, Art. no. 109104.

[91] W. Mumtaz, S. Rasheed, and A. Irfan, "Review of challenges associated with the EEG artifact removal methods," *Biomed. Signal Process. Control*, vol. 68, Jul. 2021, Art. no. 102741.

[92] M.-T. Shih, F. Doctor, S.-Z. Fan, K.-K. Jen, and J.-S. Shieh, "Instantaneous 3D EEG signal analysis based on empirical mode decomposition and the Hilbert–Huang transform applied to depth of anaesthesia," *Entropy*, vol. 17, no. 3, pp. 928–949, Feb. 2015.

[93] J. A. DeLisa, B. M. Gans, and N. E. Walsh, *Physical Medicine and Rehabilitation: Principles and Practice*, vol. 1. Philadelphia, PA, USA: Lippincott Williams & Wilkins, 2005.

[94] "Pre-processing for ERP analysis," *CREx*, Feb. 2015. Accessed: Jul. 12, 2023. [Online]. Available: http://blricrex.hypotheses.org/ressources/eeg/pre-processing-for-erps

[95] E. Florin, J. Gross, J. Pfeifer, G. R. Fink, and L. Timmermann, "The effect of filtering on Granger causality based multivariate causality measures," *NeuroImage*, vol. 50, no. 2, pp. 577–588, Apr. 2010.

[96] R. VanRullen, "Four common conceptual fallacies in mapping the time course of recognition," *Frontiers Psychol.*, vol. 2, p. 365, Dec. 2011.

[97] B. Babadi and E. N. Brown, "A review of multitaper spectral analysis," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 5, pp. 1555–1564, May 2014.

[98] S.-P. Kim, "Preprocessing of EEG," in *Computational EEG Analysis*. Berlin, Germany: Springer, 2018, pp. 15–33.

[99] A. Turnip and E. Junaidi, "Removal artifacts from EEG signal using independent component analysis and principal component analysis," in *Proc. 2nd Int. Conf. Technol., Informat., Manag., Eng. Environ.*, Aug. 2014, pp. 296–302.

[100] D. Hagemann, E. Naumann, and J. F. Thayer, "The quest for the EEG reference revisited: A glance from brain asymmetry research," *Psychophysiology*, vol. 38, no. 5, pp. 847–857, Sep. 2001.
[101] T. Al-Ani, D. Trad, and V. S. Somerset, "Signal processing and classification approaches for brain-computer interface," in *Intelligent and Biosensors*. Rijeka, Croatia: Intech, 2010, pp. 25–66.
[102] J. Dien, "Issues in the application of the average reference: Review, critiques, and recommendations," *Behav. Res. Methods, Instrum., Comput.*, vol. 30, no. 1, pp. 34–43, Mar. 1998.
[103] P. N. Kumar and H. Kareemullah, "EEG signal with feature extraction using SVM and ICA classifiers," in *Proc. Int. Conf. Inf. Commun. Embedded Syst. (ICICES)*, Feb. 2014, pp. 1–7.
[104] J. Jäger, A. Klein, M. Buhmann, and W. Skrandies, "Reconstruction of electroencephalographic data using radial basis functions," *Clin. Neurophysiol.*, vol. 127, no. 4, pp. 1978–1983, Apr. 2016.
[105] N. Chauveau, J. P. Morucci, X. Franceries, P. Celsis, and B. Rigaud, "Resistor mesh model of a spherical head: Part 1: Applications to scalp potential interpolation," *Med. Biol. Eng. Comput.*, vol. 43, no. 6, pp. 694–702, Nov. 2005.
[106] F. Perrin, J. Pernier, O. Bertnard, M. H. Giard, and J. F. Echallier, "Mapping of scalp potentials by surface spline interpolation," *Electroencephalogr. Clin. Neurophysiol.*, vol. 66, no. 1, pp. 75–81, Jan. 1987.
[107] F. Lotte, "Study of electroencephalographic signal processing and classification techniques towards the use of brain-computer interfaces in virtual reality applications," Nat. Inst. Appl. Sci. (INSA), Rennes, France, 2008.
[108] D. Bansal and R. Mahajan, *EEG-Based Brain-Computer Interfaces: Cognitive Analysis and Control Applications*. Cambridge, MA, USA: Academic Press, 2019.
[109] S.-I. Park, M. J. T. Smith, and R. M. Mersereau, "A new directional filter bank for image analysis and classification," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process.*, May 1999, pp. 1417–1420.
[110] J. Müller-Gerking, G. Pfurtscheller, and H. Flyvbjerg, "Designing optimal spatial filters for single-trial EEG classification in a movement task," *Clin. Neurophysiol.*, vol. 110, no. 5, pp. 787–798, May 1999.
[111] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw, "Spatial filter selection for EEG-based communication," *Electroencephalogr. Clin. Neurophysiol.*, vol. 103, no. 3, pp. 386–394, Sep. 1997.
[112] P. L. Nunez, R. B. Silberstein, P. J. Cadusch, R. S. Wijesinghe, A. F. Westdorp, and R. Srinivasan, "A theoretical and experimental study of high resolution EEG based on surface Laplacians and cortical imaging," *Electroencephalogr. Clin. Neurophysiol.*, vol. 90, no. 1, pp. 40–57, Jan. 1994.
[113] W. De Clercq, A. Vergult, B. Vanrumste, W. Van Paesschen, and S. Van Huffel, "Canonical correlation analysis applied to remove muscle artifacts from the electroencephalogram," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 12, pp. 2583–2587, Nov. 2006.
[114] S. Makeig, T.-P. Jung, D. Ghahremani, and T. J. Sejnowski, "Independent component analysis of simulated ERP data," Inst. Neural Comput., Univ. California, Long Beach, CA, USA, Tech. Rep. INC-9606, 1996.
[115] V. Kumaravel, F. Paissan, and E. Farella, "Towards a domain-specific neural network approach for EEG bad channel detection," in *Proc. IEEE Signal Process. Med. Biol. Symp. (SPMB)*, Dec. 2021, pp. 1–4.
[116] P. A. Bizopoulos, T. Al-Ani, D. G. Tsalikakis, A. T. Tzallas, D. D. Koutsouris, and D. I. Fotiadis, "An automatic electroencephalography blinking artefact detection and removal method based on template matching and ensemble empirical mode decomposition," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 5853–5856.
[117] M. B. Hamaneh, N. Chitravas, K. Kaiboriboon, S. D. Lhatoo, and K. A. Loparo, "Automated removal of EKG artifact from EEG data using independent component analysis and continuous wavelet transformation," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 6, pp. 1634–1641, Jun. 2014.
[118] C. Zhao and T. Qiu, "An automatic ocular artifacts removal method based on wavelet-enhanced canonical correlation analysis," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2011, pp. 4191–4194.
[119] X. Chen, C. He, and H. Peng, "Removal of muscle artifacts from single-channel EEG based on ensemble empirical mode decomposition and multiset canonical correlation analysis," *J. Appl. Math.*, vol. 2014, pp. 1–10, Jun. 2014.
[120] L. Shoker, S. Sanei, and J. Chambers, "Artifact removal from electroencephalograms using a hybrid BSS-SVM algorithm," *IEEE Signal Process. Lett.*, vol. 12, no. 10, pp. 721–724, Oct. 2005.
[121] B. Abdi-Sargezeh, R. Foodeh, V. Shalchyan, and M. R. Daliri, "EEG artifact rejection by extracting spatial and spatio-spectral common components," *J. Neurosci. Methods*, vol. 358, Jul. 2021, Art. no. 109182.
[122] D. Jiang, Y.-N. Lu, Y. Ma, and Y. Wang, "Robust sleep stage classification with single-channel EEG signals using multimodal decomposition and HMM-based refinement," *Exp. Syst. Appl.*, vol. 121, pp. 188–203, May 2019.
[123] W. Chen, Y. Wang, Y. Ren, H. Jiang, G. Du, J. Zhang, and J. Li, "An automated detection of epileptic seizures EEG using CNN classifier based on feature fusion with high accuracy," *BMC Med. Informat. Decis. Making*, vol. 23, no. 1, p. 96, May 2023.
[124] S. Lee, R. Hussein, R. Ward, Z. J. Wang, and M. J. McKeown, "A convolutional-recurrent neural network approach to resting-state EEG classification in Parkinson's disease," *J. Neurosci. Methods*, vol. 361, Sep. 2021, Art. no. 109282.
[125] H. W. Loh, C. P. Ooi, E. Palmer, P. D. Barua, S. Dogan, T. Tuncer, M. Baygin, and U. R. Acharya, "GaborPDNet: Gabor transformation and deep neural network for Parkinson's disease detection using EEG signals," *Electronics*, vol. 10, no. 14, p. 1740, Jul. 2021.
[126] S. K. Khare, V. Bajaj, and U. R. Acharya, "Detection of Parkinson's disease using automated tunable Q wavelet transform technique with EEG signals," *Biocybernetics Biomed. Eng.*, vol. 41, no. 2, pp. 679–689, Apr. 2021.
[127] M. L. Vicchietti, F. M. Ramos, L. E. Betting, and A. S. Campanharo, "Computational methods of EEG signals analysis for Alzheimer's disease classification," *Sci Rep.*, vol. 13, no. 1, p. 8184, 2023.
[128] G. Fiscon, E. Weitschek, A. Cialini, G. Felici, P. Bertolazzi, S. De Salvo, A. Bramanti, P. Bramanti, and M. C. De Cola, "Combining EEG signal processing with supervised methods for Alzheimer's patients classification," *BMC Med. Informat. Decis. Making*, vol. 18, no. 1, pp. 1–10, Dec. 2018.
[129] A. S. Al-Fahoum and A. A. Al-Fraihat, "Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains," *ISRN Neurosci.*, vol. 2014, pp. 1–7, Feb. 2014.
[130] V. K. Mehla, A. Singhal, P. Singh, and R. B. Pachori, "An efficient method for identification of epileptic seizures from EEG signals using Fourier analysis," *Phys. Eng. Sci. Med.*, vol. 44, no. 2, pp. 443–456, Jun. 2021.
[131] R. Alazrai, A. Al-Saqqaf, F. Al-Hawari, H. Alwanni, and M. I. Daoud, "A time-frequency distribution-based approach for decoding visually imagined objects using EEG signals," *IEEE Access*, vol. 8, pp. 138955–138972, 2020.
[132] K. Samiee, P. Kovács, and M. Gabbouj, "Epileptic seizure classification of EEG time-series using rational discrete short-time Fourier transform," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 2, pp. 541–552, Feb. 2015.
[133] N. Hazarika, J. Z. Chen, A. C. Tsoi, and A. Sergejew, "Classification of EEG signals using the wavelet transform," *Signal Process.*, vol. 59, no. 1, pp. 61–72, May 1997.
[134] M. Rhif, A. Ben Abbes, I. Farah, B. Martínez, and Y. Sang, "Wavelet transform application for/in non-stationary time-series analysis: A review," *Appl. Sci.*, vol. 9, no. 7, p. 1345, Mar. 2019.
[135] M. A. Rahman, F. Khanam, M. Ahmad, and M. S. Uddin, "Multiclass EEG signal classification utilizing Rényi min-entropy-based feature selection from wavelet packet transformation," *Brain Informat.*, vol. 7, no. 1, pp. 1–11, Dec. 2020.
[136] G. H. B. S. Oliveira, L. R. Coutinho, J. C. D. Silva, I. J. P. Pinto, J. M. S. Ferreira, F. J. S. Silva, D. V. Santos, and A. S. Teles, "Multitaper-based method for automatic K-complex detection in human sleep EEG," *Exp. Syst. Appl.*, vol. 151, Aug. 2020, Art. no. 113331.
[137] M. Akin, M. Kiymik, M. Arserim, and I. Turkoglu, "Separation of brain signals using FFT and neural networks," in *Proc. Biyomut*, 2000, pp. 161–164.
[138] J. Zhao, J. Song, X. Li, and J. Kang, "A study on EEG feature extraction and classification in autistic children based on singular spectrum analysis method," *Brain Behav.*, vol. 10, no. 12, pp. 2651–2660, Dec. 2020.
[139] M. Baygin, S. Dogan, T. Tuncer, P. Datta Barua, O. Faust, N. Arunkumar, E. W. Abdulhay, E. Emma Palmer, and U. Rajendra Acharya, "Automated ASD detection using hybrid deep lightweight features extracted from EEG signals," *Comput. Biol. Med.*, vol. 134, Jul. 2021, Art. no. 104548.
[140] J. Kang, T. Zhou, J. Han, and X. Li, "EEG-based multi-feature fusion assessment for autism," *J. Clin. Neurosci.*, vol. 56, pp. 101–107, Oct. 2018.
[141] X. Zhao, X. Wang, T. Yang, S. Ji, H. Wang, J. Wang, Y. Wang, and Q. Wu, "Classification of sleep apnea based on EEG sub-band signal characteristics," *Sci. Rep.*, vol. 11, no. 1, p. 5824, Mar. 2021.

[142] R. Behzad and A. Behzad, "The role of EEG in the diagnosis and management of patients with sleep disorders," *J. Behav. Brain Sci.*, vol. 11, no. 10, pp. 257–266, 2021.

[143] M. M. Siddiqui, G. Srivastava, and S. H. Saeed, "Diagnosis of insomnia sleep disorder using short time frequency analysis of PSD approach applied on EEG signal using channel ROC-LOC," *Sleep Sci.*, vol. 9, no. 3, pp. 186–191, Jul. 2016.

[144] F. A. Alturki, K. AlSharabi, A. M. Abdurraqeeb, and M. Aljalal, "EEG signal analysis for diagnosing neurological disorders using discrete wavelet transform and intelligent techniques," *Sensors*, vol. 20, no. 9, p. 2505, Apr. 2020.

[145] C. L. Alves, A. M. Pineda, K. Roster, C. Thielemann, and F. A. Rodrigues, "EEG functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer's disease and schizophrenia," *J. Phys., Complex.*, vol. 3, no. 2, Apr. 2022, Art. no. 025001, doi: 10.1088/2632-072x/ac5f8d.

[146] L. Hu and Z. Zhang, *EEG Signal Processing and Feature Extraction*. Berlin, Germany: Springer, 2019.

[147] N. Michielli, U. R. Acharya, and F. Molinari, "Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals," *Comput. Biol. Med.*, vol. 106, pp. 71–81, Mar. 2019.

[148] I. Stancin, M. Cifrek, and A. Jovic, "A review of EEG signal features and their application in driver drowsiness detection systems," *Sensors*, vol. 21, no. 11, p. 3786, May 2021.

[149] M. Akin, "Comparison of wavelet transform and FFT methods in the analysis of EEG signals," *J. Med. Syst.*, vol. 26, no. 3, pp. 241–247, 2002.

[150] K. Nathan and J. L. Contreras-Vidal, "Negligible motion artifacts in scalp electroencephalography (EEG) during treadmill walking," *Frontiers Hum. Neurosci.*, vol. 9, p. 708, Jan. 2016.

[151] B. R. Joy, A. Amara, and A. Nakhmani, "Transform with no parameters based on extrema points for non-stationary signal analysis," *Circuits, Syst., Signal Process.*, vol. 37, no. 6, pp. 2535–2547, Jun. 2018.

[152] S. B. Belhaouari, A. Talbi, S. Hassan, D. Al-Thani, and M. Qaraqe, "PFT: A novel time-frequency decomposition of BOLD fMRI signals for autism spectrum disorder detection," *Sustainability*, vol. 15, no. 5, p. 4094, Feb. 2023.

[153] I. Daubechies, *Ten Lectures on Wavelets*. Philadelphia, PA, USA: SIAM, 1992.

[154] S. Mallat and C. Mallat, "7.2 classes of wavelet bases," in *A Wavelet Tour of Signal Processing*. Amsterdam, The Netherlands: Elsevier, 1999, pp. 241–254.

[155] A. C. Hale, T. Hansard, L. W. Sheppard, P. V. E. McClintock, and A. Stefanovska, "The Kuramoto model subject to a fluctuating environment: Application to brainwave dynamics," *Fluctuation Noise Lett.*, vol. 11, no. 1, Mar. 2012, Art. no. 1240011.

[156] M. Unser and A. Aldroubi, "A review of wavelets in biomedical applications," *Proc. IEEE*, vol. 84, no. 4, pp. 626–638, Apr. 1996.

[157] J.-Z. Xue, H. Zhang, C.-X. Zheng, and X.-G. Yan, "Wavelet packet transform for feature extraction of EEG during mental tasks," in *Proc. Int. Conf. Mach. Learn. Cybern.*, 2003, pp. 360–363.

[158] H. E. Hurst, "Methods of using long-term storage in reservoirs," *Proc. Inst. Civil Engineers*, vol. 5, no. 5, pp. 519–543, Oct. 1956.

[159] E. Lloyd, "Review of long-term storage: An experimental study," *J. Royal Stat. Soc. A Gen.*, vol. 129, no. 4, pp. 591–593, 1996. [Online]. Available: https://doi.org/10.2307/2982267

[160] H. Salat, R. Murcio, and E. Arcaute, "Multifractal methodology," *Phys. A, Stat. Mech. Appl.*, vol. 473, pp. 467–487, May 2017.

[161] H. Kantz and T. Schreiber, *Nonlinear Time Series Analysis*, vol. 7. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[162] D. P. Dash, M. H. Kolekar, and K. Jha, "Multi-channel EEG based automatic epileptic seizure detection using iterative filtering decomposition and hidden Markov model," *Comput. Biol. Med.*, vol. 116, Jan. 2020, Art. no. 103571.

[163] C.-T. Shi, "Signal pattern recognition based on fractal features and machine learning," *Appl. Sci.*, vol. 8, no. 8, p. 1327, Aug. 2018.

[164] R. Ferenets, T. Lipping, A. Anier, V. Jantti, S. Melto, and S. Hovilehto, "Comparison of entropy and complexity measures for the assessment of depth of sedation," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 6, pp. 1067–1077, Jun. 2006.

[165] R. Damasevicius, R. Maskeliunas, M. Wozniak, and D. Polap, "Visualization of physiologic signals based on Hjorth parameters and Gramian angular fields," in *Proc. IEEE 16th World Symp. Appl. Mach. Intell. Informat. (SAMI)*, Feb. 2018, pp. 91–96.

[166] I. I. Shevchenko, "Lyapunov exponents in resonance multiplets," *Phys. Lett. A*, vol. 378, nos. 1–2, pp. 34–42, Jan. 2014.

[167] A. Prochazka, J. Kukal, and O. Vysata, "Wavelet transform use for feature extraction and EEG signal segments classification," in *Proc. 3rd Int. Symp. Commun., Control Signal Process.*, Mar. 2008, pp. 719–722.

[168] S. Zou, T. Qiu, P. Huang, X. Bai, and C. Liu, "Constructing multi-scale entropy based on the empirical mode decomposition (EMD) and its application in recognizing driving fatigue," *J. Neurosci. Methods*, vol. 341, Jul. 2020, Art. no. 108691.

[169] M. Johansson, "The Hilbert transform," M.S. thesis. Växjö Univ., Suecia. Disponible en internet, Växjö, Sweden, 1999. Accessed: Aug. 31, 2023. [Online]. Available: http://yumpu.com/en/document/read/6683719/m-johansson-the-hilbert-transformpdf

[170] D. P. Subha, P. K. Joseph, R. U. Acharya, and C. M. Lim, "EEG signal analysis: A survey," *J. Med. Syst.*, vol. 34, no. 2, pp. 195–212, Apr. 2010.

[171] B. J. Strait and T. G. Dewey, "The Shannon information entropy of protein sequences," *Biophysical J.*, vol. 71, no. 1, pp. 148–155, Jul. 1996.

[172] U. R. Acharya, H. Fujita, V. K. Sudarshan, S. Bhat, and J. E. W. Koh, "Application of entropies for automated diagnosis of epilepsy using EEG signals: A review," *Knowl.-Based Syst.*, vol. 88, pp. 85–96, Nov. 2015.

[173] A. Rényi, "On measures of entropy and information," in *Proc. 4th Berkeley Symp. Math. Statist. Probab., Contrib. Theory Statist.*, vol. 4. Univ. of California Press, 1961, pp. 547–562.

[174] C. Tsallis, R. Mendes, and A. R. Plastino, "The role of constraints within generalized nonextensive statistics," *Phys. A, Stat. Mech. Appl.*, vol. 261, nos. 3–4, pp. 534–554, Dec. 1998.

[175] J. Fell, J. Röschke, K. Mann, and C. Schäffner, "Discrimination of sleep stages: A comparison between spectral and nonlinear EEG measures," *Electroencephalogr. Clin. Neurophysiol.*, vol. 98, no. 5, pp. 401–410, May 1996.

[176] N. Kannathal, M. L. Choo, U. R. Acharya, and P. K. Sadasivan, "Entropies for detection of epilepsy in EEG," *Comput. Methods Programs Biomed.*, vol. 80, no. 3, pp. 187–194, Dec. 2005.

[177] E. Guariglia, "Entropy and fractal antennas," *Entropy*, vol. 18, no. 3, p. 84, Mar. 2016.

[178] P. Grassberger and I. Procaccia, "Estimation of the Kolmogorov entropy from a chaotic signal," *Phys. Rev. A, Gen. Phys.*, vol. 28, no. 4, pp. 2591–2593, Oct. 1983.

[179] D. J. Wales, "Calculating the rate of loss of information from chaotic time series by forecasting," *Nature*, vol. 350, no. 6318, pp. 485–488, Apr. 1991.

[180] J. C. Schouten, F. Takens, and C. M. van den Bleek, "Maximum-likelihood estimation of the entropy of an attractor," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 49, no. 1, pp. 126–129, Jan. 1994.

[181] S. M. Pincus, I. M. Gladstone, and R. A. Ehrenkranz, "A regularity statistic for medical data analysis," *J. Clin. Monitor.*, vol. 7, no. 4, pp. 335–345, Oct. 1991.

[182] A. Subasi and M. I. Gursoy, "EEG signal classification using PCA, ICA, LDA and support vector machines," *Exp. Syst. Appl.*, vol. 37, no. 12, pp. 8659–8666, Dec. 2010.

[183] M. Chaudhary, S. Mukhopadhyay, M. Litoiu, L. E. Sergio, and M. S. Adams, "Understanding brain dynamics for color perception using wearable EEG headband," 2020, *arXiv:2008.07092*.

[184] M. Sharma, R. B. Pachori, and U. Rajendra Acharya, "A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension," *Pattern Recognit. Lett.*, vol. 94, pp. 172–179, Jul. 2017.

[185] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," *J. Neural Eng.*, vol. 4, no. 2, pp. R1–R13, 2007.

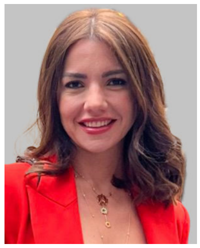
[186] A. Bablani, D. R. Edla, and S. Dodia, "Classification of EEG data using k-nearest neighbor approach for concealed information test," *Proc. Comput. Sci.*, vol. 143, pp. 242–249, Jan. 2018.

[187] M. Congedo, A. Barachant, and R. Bhatia, "Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review," *Brain-Comput. Interfaces*, vol. 4, no. 3, pp. 155–174, Jul. 2017.

[188] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015.

[189] W.-L. Mao, H. I. K. Fathurrahman, Y. Lee, and T. W. Chang, "EEG dataset classification using CNN method," *J. Phys., Conf.*, vol. 1456, no. 1, Jan. 2020, Art. no. 012017.

[190] D. Bardou, K. Zhang, and S. M. Ahmad, "Classification of breast cancer based on histology images using convolutional neural networks," *IEEE Access*, vol. 6, pp. 24680–24693, 2018.
[191] D. Klepl, F. He, M. Wu, D. J. Blackburn, and P. Sarrigiannis, "EEG-based graph neural network classification of Alzheimer's disease: An empirical evaluation of functional connectivity methods," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 2651–2660, 2022.
[192] M. Sharma and R. B. Pachori, "A novel approach to detect epileptic seizures using a combination of tunable-Q wavelet transform and fractal dimension," *J. Mech. Med. Biol.*, vol. 17, no. 7, Nov. 2017, Art. no. 1740003.
[193] V. Gupta, T. Priya, A. K. Yadav, R. B. Pachori, and U. R. Acharya, "Automated detection of focal EEG signals using features extracted from flexible analytic wavelet transform," *Pattern Recognit. Lett.*, vol. 94, pp. 180–188, Jul. 2017.
[194] H. Ullah, M. Uzair, A. Mahmood, M. Ullah, S. D. Khan, and F. A. Cheikh, "Internal emotion classification using EEG signal with sparse discriminative ensemble," *IEEE Access*, vol. 7, pp. 40144–40153, 2019.
[195] B. Harender and R. K. Sharma, "DWT based epileptic seizure detection from EEG signal using k-NN classifier," in *Proc. Int. Conf. Trends Electron. Informat. (ICEI)*, May 2017, pp. 762–765.
[196] S. Madan, K. Srivastava, A. Sharmila, and P. Mahalakshmi, "A case study on discrete wavelet transform based Hurst exponent for epilepsy detection," *J. Med. Eng. Technol.*, vol. 42, no. 1, pp. 9–17, Jan. 2018.
[197] S. Lahmiri and A. Shmuel, "Accurate classification of seizure and seizure-free intervals of intracranial EEG signals from epileptic patients," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 3, pp. 791–796, Mar. 2019.
[198] T. Tuncer, "A new stable nonlinear textural feature extraction method based EEG signal classification method using substitution box of the Hamsi hash function: Hamsi pattern," *Appl. Acoust.*, vol. 172, Jan. 2021, Art. no. 107607.
[199] M. Omidvar, A. Zahedi, and H. Bakhshi, "EEG signal processing for epilepsy seizure detection using 5-level Db4 discrete wavelet transform, GA-based feature selection and ANN/SVM classifiers," *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 11, pp. 10395–10403, Nov. 2021.
[200] H. Albaqami, G. M. Hassan, A. Subasi, and A. Datta, "Automatic detection of abnormal EEG signals using wavelet feature extraction and gradient boosting decision tree," *Biomed. Signal Process. Control*, vol. 70, Sep. 2021, Art. no. 102957.
[201] O. K. Cura, S. K. Atli, H. S. Türe, and A. Akan, "Epileptic seizure classifications using empirical mode decomposition and its derivative," *Biomed. Eng. OnLine*, vol. 19, no. 1, pp. 1–22, Dec. 2020.
[202] M. Kaleem, A. Guergachi, and S. Krishnan, "Patient-specific seizure detection in long-term EEG using wavelet decomposition," *Biomed. Signal Process. Control*, vol. 46, pp. 157–165, Sep. 2018.
[203] I. Wijayanto, R. Hartanto, and H. A. Nugroho, "Comparison of empirical mode decomposition and coarse-grained procedure for detecting pre-ictal and ictal condition in electroencephalography signal," *Informat. Med. Unlocked*, vol. 19, Jan. 2020, Art. no. 100325.
[204] S. Belhadj, A. Attia, A. B. Adnane, Z. Ahmed-Foitih, and A. A. Taleb, "Whole brain epileptic seizure detection using unsupervised classification," in *Proc. 8th Int. Conf. Model., Identificat. Control (ICMIC)*, Nov. 2016, pp. 977–982.
[205] G. Wang, D. Ren, K. Li, D. Wang, M. Wang, and X. Yan, "EEG-based detection of epileptic seizures through the use of a directed transfer function method," *IEEE Access*, vol. 6, pp. 47189–47198, 2018.
[206] S. T. George, M. S. P. Subathra, N. J. Sairamya, L. Susmitha, and M. J. Premkumar, "Classification of epileptic EEG signals using PSO based artificial neural network and tunable-Q wavelet transform," *Biocybernetics Biomed. Eng.*, vol. 40, no. 2, pp. 709–728, Apr. 2020.
[207] A. Shoeibi, N. Ghassemi, M. Khodatars, P. Moridian, R. Alizadehsani, A. Zare, A. Khosravi, A. Subasi, U. R. Acharya, and J. M. Gorriz, "Detection of epileptic seizures on EEG signals using ANFIS classifier, autoencoders and fuzzy entropies," *Biomed. Signal Process. Control*, vol. 73, Mar. 2022, Art. no. 103417.
[208] Y. Luo, Q. Fu, J. Xie, Y. Qin, G. Wu, J. Liu, F. Jiang, Y. Cao, and X. Ding, "EEG-based emotion classification using spiking neural networks," *IEEE Access*, vol. 8, pp. 46007–46016, 2020.
[209] S. A. A. Shah, L. Zhang, and A. Bais, "Dynamical system based compact deep hybrid network for classification of Parkinson disease related EEG signals," *Neural Netw.*, vol. 130, pp. 75–84, Oct. 2020.
[210] D. Selvathi and V. K. Meera, "Realization of epileptic seizure detection in EEG signal using wavelet transform and SVM classifier," in *Proc. Int. Conf. Signal Process. Commun. (ICSPC)*, Jul. 2017, pp. 18–22.
[211] F. D. V. Fallani, L. d. F. Costa, F. A. Rodriguez, L. Astolfi, G. Vecchiato, J. Toppi, G. Borghini, F. Cincotti, D. Mattia, and S. Salinari, "A graph-theoretical approach in brain functional networks. possible implications in EEG studies," in *Nonlinear Biomedical Physics*, vol. 4, no. 1. Berlin, Germany: Springer, 2010, pp. 1–13.
[212] L. D. F. Costa and F. A. Rodrigues, "What is there between any two nodes in a complex network?" 2008, *arXiv:0801.4068*.
[213] F. D. V. Fallani, L. Astolfi, F. Cincotti, D. Mattia, M. G. Marciani, S. Salinari, J. Kurths, S. Gao, A. Cichocki, A. Colosimo, and F. Babiloni, "Cortical functional connectivity networks in normal and spinal cord injured patients: Evaluation by graph analysis," *Hum. Brain Mapping*, vol. 28, no. 12, pp. 1334–1346, Dec. 2007.
[214] R. Sinatra, F. De Vico Fallani, L. Astolfi, F. Babiloni, F. Cincotti, D. Mattia, and V. Latora, "Cluster structure of functional networks estimated from high-resolution EEG data," *Int. J. Bifurcation Chaos*, vol. 19, no. 2, pp. 665–676, Feb. 2009.
[215] I. Stancin, N. Frid, M. Cifrek, and A. Jovic, "EEG signal multichannel frequency-domain ratio indices for drowsiness detection based on multicriteria optimization," *Sensors*, vol. 21, no. 20, p. 6932, 2021.



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