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Review Article

A comparative analysis of signal processing and classification methods for different applications based on EEG signals

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ABSTRACT

Electroencephalogram (EEG) measures the neuronal activities in the form of electric currents that are generated due to the synchronized activity by a group of specialized pyramidal cells inside the brain. The study presents a brief comparison of various functional neuroimaging techniques, revealing the excellent neuroimaging capabilities of EEG signals such as high temporal resolution, inexpensiveness, portability, and non-invasiveness as compared to the other techniques such as positron emission tomography, magnetoencephalogram, functional magnetic resonance imaging, and transcranial magnetic stimulation. Different types of frequency bands associated with the brain signals are also being summarized. The main purpose of this literature survey is to cover the maximum possible applications of EEG signals based on computer-aided technologies, ranging from the diagnosis of various neurological disorders such as epilepsy, major depressive disorder, alcohol use disorder, and dementia to the monitoring of other applications such as motor imagery, identity authentication, emotion recognition, sleep stage classification, eye state detection, and drowsiness monitoring. After reviewing them, the comparative analysis of the publicly available EEG datasets and other local data acquisition methods, preprocessing techniques, feature extraction methods, and the result analysis through the classification models and statistical tests has been presented. Then the research gaps and future directions in the present studies have been summarized with the aim to inspire the readers to explore more opportunities on the current topic. Finally, the survey has been completed with the brief description about the studies exploring the fusion of brain signals from multiple modalities.

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1. Introduction

EEG transforms Electroencephalogram means it is the continuous recording of the electrical activity of the brain by placing the metal electrodes over the scalp. The neuronal cells spontaneously communicate with each other via generating the electrical currents and remain active all the time even if a person is sleeping or relaxing. The low cost, high flexibility, high temporal resolution, non-invasiveness, ease of use, portability and safe nature make EEG a powerful tool for the brain imaging task as compared to the other functional neuroimaging techniques such as positron emission tomography (PET), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI), and transcranial magnetic stimulation (TMS).

Hans Berger (1873–1941), the German Physician [1] coined the term 'electroencephalogram' to define the electrical potentials occurring in the human brain. He took the first EEG readings from the patients with "palliative trepanations" or having some defects in the skull by making use of metal strips and galvanometer [2]. He was able to characterize the α ("slower and larger") and β ("faster and smaller") rhythms and concentrated on the changes occurring in the EEG patterns while associating with the mental attention and cerebral injuries. His findings opened the gateway for most of the applications that are presently based on the EEG signals as he observed that these brain signals were not irregular and inconsistent, instead electrical changes revealed some periodic patterns that help to deduce the occurrence of some activity, e.g. changing the state from sleep (slow, very low frequency, and high amplitude waves) to wakefulness (fast, high frequency, and low amplitude waves). He was also responsible for investigating the effects of anesthesia and epilepsy on the EEG recordings [1].

EEG can record only those potential changes that occur due to the synaptic transmissions. When the action potential reaches at the axon terminal, neurotransmitters are released at the synapses site [3], causing the exhibitory post synaptic graded potentials (EPSPs) or the inhibitory post synaptic graded potentials (IPSPs) [4,5] to occur at the postsynaptic cells. These potentials lead to the flow of ionic currents in the extracellular space of the cell membrane, thus generating the local field potentials with very small magnitudes. Research studies conclude that the detection of electric fields is possible only due to the synchronized activity by a group of few specialized pyramidal neurons that are present in the cortical regions of the brain [6,7]. The currents generated inside these cells do not cancel out the effect of each other due to their unique and stable orientation. The overall electric field becomes much stronger when the postsynaptic graded potentials for such group of neurons are summed up. This summation actually helps in the measurement of EEG signals.

Different types of rhythms such as theta, delta, alpha, beta, and gamma can be observed in the brain waves depending upon the different functional states of the brain. Any subtle changes in the frequency patterns of these waves help in the diagnosis of certain neurological disorders or to conclude the occurrence of some neuronal activity in response to some external stimuli. The slow brain waves indicate the deep sleep stage [8] in the humans or less power in alpha and theta bands [9] in all the regions (central, occipital, frontal, parietal, and temporal) are observed for the depressed patients when compared to the normal subjects.

EEG signals are non-linear and non-stationary in nature. The small variations in the voltage fluctuations of the EEG measurements conclude the happening of some neuronal activity. So the visual inspection of these signals varies with the expertise experience. Moreover, the long EEG recordings require a lot of time for their manual review and sometimes the results may be inaccurate due to the presence of artifacts in the signals. So the processing and the analysis of these signals can be done with the help of computer-aided technologies in order to get fast and accurate results. The use of computer-aided technologies with EEG signals has gained a widespread popularity, especially in the diagnosis of various neurological and neuropsychiatric disorders such as epilepsy [10,11], major depressive disorder (MDD) [12,13], alcohol use disorder (AUD) [14,15], and dementia [16,17] such as Alzheimer, mild cognitive impairment (MCI), Parkinson, and dementia with Lewy bodies (DLB). EEG based application of Motor Imagery has opened a new gateway in the field of neuroprosthesis [18,19]. Apart from this, other research domains such as identity authentication [20,21], sleep stage classification [22], emotion recognition [23,24], eye state detection [25,26], and drowsiness monitoring [27] are getting prominent results with the use of physiological data such as EEG.

The EEG signal processing and analysis is basically performed in four steps: preprocessing the raw signals with the help of filtering or some other techniques, then extracting the most important information in the form of features from them, further applying the feature selection methods for more optimized results, and finally at the result analysis phase, the disease diagnosis or the recognition of the different functional states of the brain is made through the machine learning models or the statistical tests. So the main aim of this research study is to target the maximum number of EEG based research applications available in the literature and to perform the comparative analysis for:

(a) Different data collection methods in the form of publicly available EEG datasets and other local data acquisition studies.
(b) Various pre-processing methods such as down-sampling, artifact handling, and feature scaling.
(c) Different categories of features using various feature extraction methods.
(d) Post-processing methods such as feature selection and dimensionality reduction techniques.
(e) Result analysis methods in the form of classification algorithms and statistical tests.

The rest of the paper is organized as follows: the taxonomy of the proposed study is explained in Section 2, the brief comparison of the various functional neuroimaging techniques is provided in Section 3, different types of brain rhythms in Section 4, data collection process in Section 5, EEG signal processing and analysis in Section 6, then the other EEG based research studies with their findings are explained in Section 7, Section 8 summarizes the research gaps and the future directions in the given studies, then a brief description about the multi-modal fusion of brain signals has been given in Section 9, and finally the paper has been concluded with its future scope in Section 10. The list of acronyms and abbreviations as summarized in Table 21 are provided in Appendix A.

2. Taxonomy of the proposed study

The main aim of the present study is to inspire the readers with the excellent neuroimaging capabilities of the EEG signals and how the computer-aided technologies are used to monitor the numerous applications by using a variety of signal processing and classification algorithms. The idea is to explode the market with the automated machine learning recognition systems based on brain signals. This analysis is completed in the following manner (as shown in Fig. 1): A total of 131 research papers have been surveyed to complete the current study. Except four, all the studies are from the years 1999 to 2019. 3 handbooks, 103 journal papers, 9 book chapters, 13 conference papers, 1 Ph.D. thesis, 1 web-link, and 1 tutorial file constitute the total number of studies. Apart from that, 15 web-links are included in the study for accessing the publicly available datasets for various applications. Further categorizing the studies on the basis of the explained topics – there are 12 research studies for the comparison of various functional neuroimaging techniques, 90 studies for the EEG applications based on computer-aided technologies, 16 studies for brain rhythms (out of 16, 8 are already included in the application studies), 5 studies based upon multi-modal fusion of brain signals, and the remaining 16 are based on the basic knowledge related to the EEG signals such as history, generation of electric currents inside the brain, types of artifacts, comparison of feature extraction methods, and non-linear analysis studies for EEG signals. The main purpose of the present literature review is to target the maximum number of EEG applications and explore a variety of signal processing and classification algorithms used in those studies. Out of 90 application studies, 17 give the description about the public datasets that are available online and 73 are further categorized on the basis of applications for which the EEG signals are used – 14 are for epilepsy and seizures, 10 for depression, 9 for MI, 8 for emotion state recognition, 8 for eye state recognition, 6 for sleep stage classification, 5 for alcoholism, 5 for dementia, 3 for driver drowsiness, 2 for identity authentication, 1 for multi-class task recognition, and 4 for others (visual comfort level of images, BCI based spelling interface, autism, and one study based on reduced number of electrodes using the concept of ERP), the total actually makes 75 because two studies are based on multiple applications such as one study based on epilepsy with alcoholism and another on epilepsy with autism, so are counted twice. Also all the application studies are classified on the basis of source of datasets used - 38 are based upon using the publicly available datasets and 35 are acquiring data locally, out of total, 2 are based upon the both. So, this makes a total of 71 studies. Out of 73, the information about the datasets is not given in the two studies. After reviewing all the studies, firstly a brief comparison of various functional neuroimaging techniques has been given, then the description about the different brain rhythms has been summarized briefly, and finally, the available EEG application studies based on computer-aided technologies are analysed from signal processing and classification perspective, with the target to extract the maximum information in the form of four stages- preprocessing techniques, categories of features, post-processing methods, and finally the result analysis using classification algorithms and statistical tests. For preprocessing stage, 44 studies are mentioned in Table 5 for artifact handling and 7 have been explained in separate section of preprocessing details for public datasets for artifact handling, 8 for downsampling (out of 8, 3 are based upon preprocessing for public datasets), and 8 in Table 6 for feature scaling. For feature extraction, 28 studies are based on statistical features (Table 8), 19 for spectral (Table 9), 21 for non-linear (Table 10), and 7 for functional-connectivity based features (Table 11). For postprocessing, 23 studies are mentioned in Table 12 using different types of feature selection techniques and 12 for dimensionality reduction in Table 13. For result analysis, 51 are based on the classification techniques (Table 16) and 14 on statistical tests (Table 17). Apart from that, there are about 13 studies that have been chosen separately and explained in Table 18 with their

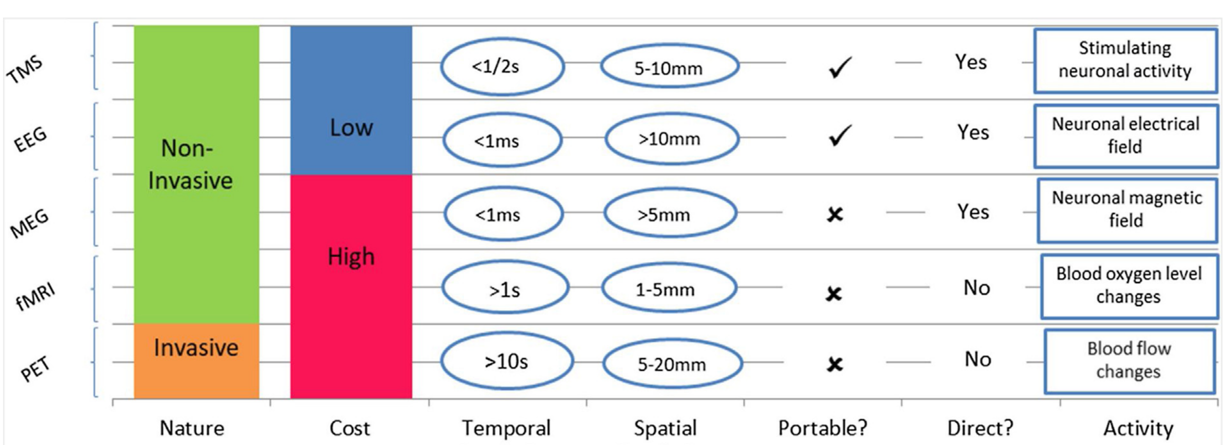

Fig. 1 – Taxonomy of the proposed study.

important findings. These number of studies are also depicted in Fig. 3. There are 5 studies focusing on the multi-modal fusion of brain signals, that have been summarized in Table 20.

The idea is to make the readers aware that what level of research has already been done on EEG signals, from signal processing and classification perspective and how more number of opportunities can be explored on this topic.

3. Comparison of functional neuroimaging techniques

Functional neuroimaging is a brain imaging method that encompasses a wide variety of technologies that are directly or indirectly used to investigate the functional information of the central nervous system. It is used to represent the metabolic and physiological processes occurring inside the brain. It includes various techniques: positron emission tomography (PET), magnetoencephalogram (MEG), functional magnetic resonance imaging (fMRI), electroencephalogram (EEG), and transcranial magnetic stimulation (TMS) [28–30]. These techniques are used to detect the various biomarkers that are helpful in the diagnosis of various neuropsychiatric and neurological disorders [31–34,29] such as Alzeihmer, Parkinson, alcoholism, schizophrenia, Huntington's disease, Tourette syndrome, stress and mood disorders, etc. This is done by identifying the dysfunctioning in the release of certain substances like serotonin, dopamine, etc. in the brain. The comparison of various functional neuroimaging techniques has been graphically represented through Fig. 2.

Comparison of functional neuroimaging techniques

(a) *Measuring the neuronal activity indirectly/directly*

PET involves the generation of cross-sectional 2D and 3D images of the brain giving the measurement of radiations emitted by the "radiotracers" that are injected into the blood stream [31,32]. The use of tracers helps to map the blood flow differences in order to visually represent the pathological conditions and functions of the brain. fMRI aims at tracking the amount of blood oxygen levels in the brain [35] and gives information about the active brain regions during certain activities. It is performed by using a signal method called as BOLD (Blood Oxygenation Level Depredent signal) [33,29,36,32,30], i.e. the variations occurring in the intensities of the signal as a result of changing oxygen levels in the blood due to the occurrence of some neuronal activity. In order to understand the complex brain functionality, the subjects are made to perform certain tasks in response to stimuli (visual, auditory and so on) while present in the scanner. Thus, both fMRI and PET give an indirect measurement of the brain's electrical activities. MEG [36,30] is used to directly measure the brain functionality by recording the magnetic fields with the help of highly sensitive magnetometers called as SQUIDs (superconducting quantum interference devices). EEG directly records and interprets the electrical activity of the brain by using the metal electrodes placed over the scalp. The electric currents are generated by the synchronization of millions of active neurons. Then, TMS is also based upon the direct

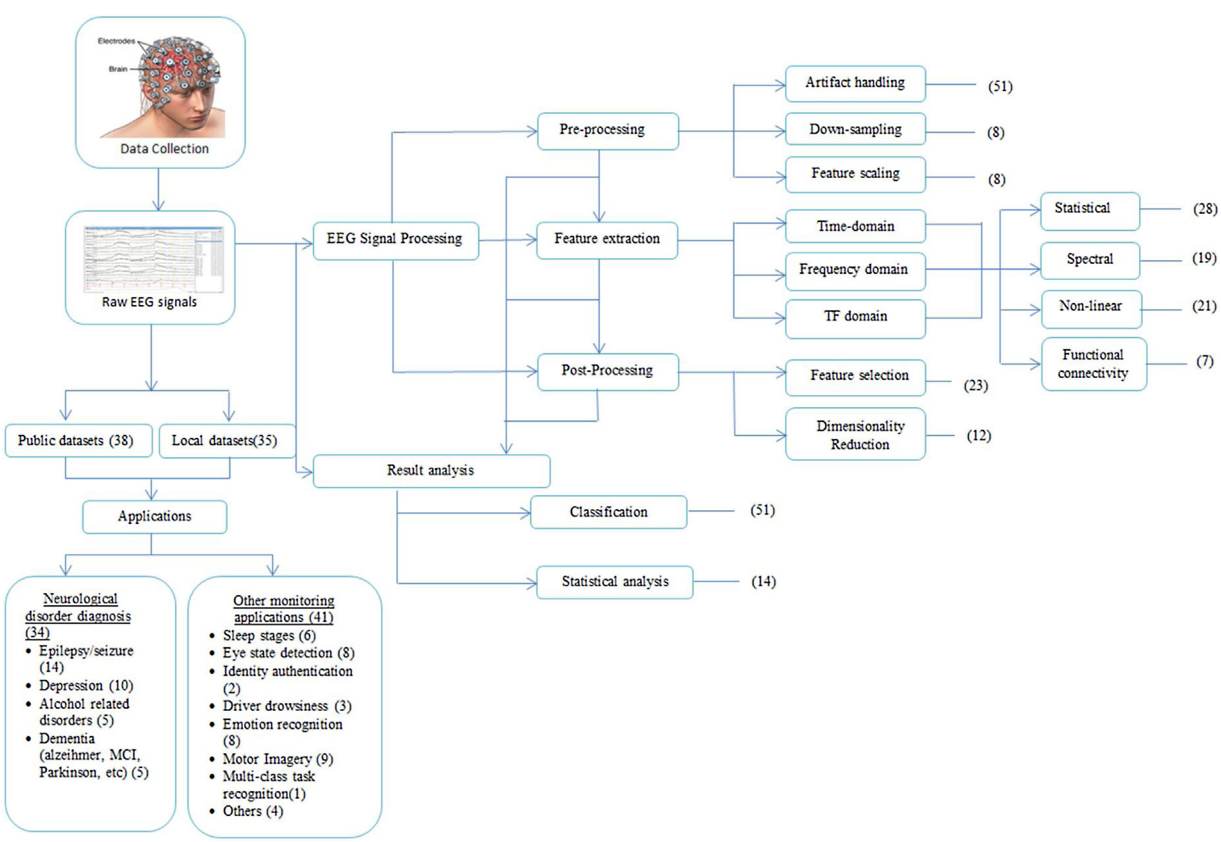

Fig. 2 – Comparison of functional neuroimaging techniques.

measurement of the neuronal activity by stimulating the nerves cells of the brain with the electric simulator. The functionality of the specific brain areas can be tested through the process of "virtual lesions" in which the disruptions to the different brain areas is made temporarily and in a reversible manner [37].

(b) *Based on invasive/non-invasive*

In PET, it is required to inject a radioactive and positron emitting contrast elements into the subject's body, thus making it an invasive methodology while all other techniques are based upon non-invasive methodology.

(c) *Based on spatial/temporal resolution*

fMRI has high temporal resolution than that of PET but less than that of EEG, MEG, and TMS [38,30,37]. fMRI and PET can never match the temporal resolution [36,38] of electrophysiological signals because it involves the indirect measurement of the brain activity through the hemodynamic changes. The temporal resolutions for the methods PET, fMRI, MEG, EEG, and TMS are of the order of >10 s [36,30,37], >1 s [36,30], <1 ms [36,30,37], <1 ms [36,30,37], and <1/2 s [37], respectively.

fMRI has the highest spatial resolution [30,35] (order of millimetres) than that of PET, MEG, EEG, and TMS, thus helps to do the good quality anatomy analysis of images. MEG has high spatial resolution than EEG [30]. The spatial resolutions for the methods PET, fMRI, MEG, EEG, and TMS are of the order of 5–20 mm [37], 1–5 mm [36,37], >5 mm [37], >10 mm [37], and 5–10 mm [37], respectively.

MEG and EEG offer the highest temporal resolution than other techniques that is highly demanded in measuring the complex functional events occurring dynamically in the brain.

(d) *Cost*

Except EEG and TMS, the other functional imaging techniques are very expensive [36,30]. Like for MEG, the strength of magnetic field inside the brain is very weak, so it is important to have magnetically shielded devices and rooms in which those are measured thus, making the MEG devices highly expensive (in millions of dollars) whereas EEG and TMS are comparatively inexpensive (in thousands).

(e) *Portability*

EEG and TMS are portable techniques while PET, fMRI, and MEG have to be performed in some confined place [30].

Unlike PET and fMRI, EEG directly measures the electrical activity of the brain and does not require the subject to be exposed to any magnetic fields or injected with any radiotracers, thus making the EEG tests to be very safe. The excellent temporal resolution and the reasonable spatial resolution make EEG a perfect candidate for recording the complex neuronal activities occurring dynamically on a temporal scale of milliseconds [39]. Although MEG has comparable temporal resolution as that of EEG but it has its own limitations. MEG is insensitive to some of the sources that are radially oriented while EEG has higher sensitivity than MEG so it is equally able to detect all the source orientations very well. EEG has the capability to deeply analyse the sources while MEG detects the sources superficially. EEG is less expensive and portable in nature as compared to the other techniques except TMS. But TMS is having its own drawbacks such as, it is not suitable for studying the functions in the temporal lobe because the temporalis muscle is contracted painfully with the TMS stimulation [37] and secondly, headaches or seizures may occur if the safety measures are not followed while undergoing TMS [30]. Thus, the low cost, high flexibility, high temporal resolution, non-invasiveness, ease of use, portability, and high density recording capability make EEG a powerful tool for the brain imaging task, especially for studying the dynamically occurring complex processes of the brain.

4. Brain rhythms

Due to the extremely complex patterns generated by the firing of billions of neurons, the signals consist of a mixture of various base frequencies. The researchers have classified those varied frequency ranges into some sub-groups, known as the frequency bands. Each of these frequency bands represents a different cognitive or attentional state of a brain. The history of these waves [5,8] can be briefly traced as – in 1929, Berger introduced the term "alpha" and "beta" [1]. In 1934, Adrian and Matthews gave a significant contribution that the alpha rhythms of 10–12 Hz are dominant in the human brain when a person is in the resting state with his eyes closed and are mainly identified from the occipital region of the cerebral cortex [41]. In 1938, the term "gamma" was introduced by Jasper and Andrews with the frequencies of greater than 30–35 Hz. In 1936, Walter introduced the term "delta" for all those frequencies which lie below the alpha band. He also defined the frequency range of 4–7.5 Hz for "theta" waves. The idea of theta was clearly introduced in 1944 by Walter and Dovey [42]. The fuzzy upper and lower frequency limits are available for these frequency bands in the literature. So, various brain rhythms with their frequency ranges [8], regions of occurrence and characteristics [5,8,43,44] have been generalized in Table 1.

The other research studies have used some other variants of the above brain rhythms depending upon the requirement of certain frequency bands for the analysis of particular application. These are summarized in Table 2.

5. Data collection studies

The different research applications based on EEG signals have either used the publicly available datasets or have themselves created their own datasets but have not released them publicly. So, the data collection process can be divided as: publicly available datasets and other locally collected data acquisition methods. These are shown in Fig. 3.

5.1. *Publicly available EEG datasets*

Table 3 gives the description about the publicly available datasets including – the name with which that dataset is available online, their web links, number of classes in which the EEG signals have been distinguished, number of subjects involved in the experiments, devices used for collecting the EEG signals, and the sampling rate with which the data has

Table 1 – Brain rhythms.

Rhythm	Frequency range (in Hz)	Regions	Characteristics
Gamma (γ)	>30	Fronto-central areas [5]	• Sometimes known as fast beta waves. • Rarely occur in the brain area, so can be used as an indicator to diagnose certain neurological disorders. • Having the highest frequencies with the lowest amplitudes. • Functional integration of activities occurring transiently. • Help to get the brain locations responsible for voluntary movements (such as movement of left and right index finger, right toes, etc.)
Beta (β)	14–30	Parietal, somatosensory, frontal, and motor areas [43]	• Mostly found in normal adults. • Increased attention and alertness. • Increasing levels of beta may be obtained in panic condition. • May be increased due to the bone defects or in the regions with tumours. • Amplitudes generally less than 30 μV [5,8].
Alpha (α)	8–13	Occipital and parietal regions [44]	• Relaxed with closed eyes and wakefulness state. • Greatly affected during the menstrual cycle • Attenuation in alpha frequencies can be used for assessing the anxiety and emotional tension of the subjects. • Generally have an amplitude of less than 50μV [5].
Theta (θ)	4–7.5	Hippocampus region [8]	• Abnormal in adults, common for young children below 13 years. • Sub-conscious activity of the brain. • Deeply relaxed and meditated mind state. • An increase in the theta band power under testing condition depicts the memory demands [43]. • Arise of these waves in normal subjects shows the change from conscious to the drowsy state.
Delta (δ)	0.1–3.5	Mostly in thalamus region [8]	• Predominate in new born babies, rarely present in adults with normal state during waking condition. • Observed at third sleep stage known as slow wave sleep (SWS). • Artifacts generated from the muscles of the jaw and the neck are generally confused with the delta rhythms. • "Slow" waves having the "highest" amplitudes (75–200 μV) [43].

Table 2 – Other brain rhythms.

Purpose	Sub-bands with frequency limits (in Hz)	References
Sleep stage classification	• Sigma waves (12–16) and k-complex waves	[45]
	• β1 (14–22) and β2 (22–31)	[46]
Emotion recognition	• Low alpha (8–10)	[47]
Depression or stress recognition	• Low beta (13–15), beta (15–20) and high beta (20–38)	[48]
	• Theta (Fc − 6) to (Fc − 2) and beta (Fc + 2) to (Fc + 26) where Fc is the central maximum frequency in alpha band	[49]
Alcoholism	• Beta (12–25) and high beta (25–30), gamma (30–40) and high gamma (40–50)	[50]
Dementia (Alzeihmer, MCI and DLB)	• Beta 1 (13–19) and beta 2 (19–30)	[51]
	• Alpha 1 (8–10) and alpha 2 (10–13)	[52]

been stored. The last column gives the references of different research studies that have used these datasets for different purposes such as alcoholism, eye state detection, epilepsy and seizure detection, motor imagery, emotion recognition, sleep stage classification, identity authentication, multi-task recognition, and drowsiness detection.

5.2. *Local data acquisition studies*

Table 4 gives the description about the various data acquisition studies that have themselves created their own datasets and have not released them publicly. The description includes-purpose of EEG data collection, details of subjects involved in the experiments, devices used, number of EEG channels used for data acquisition, sampling rate/recording time/electrode impedance (EI), state in which the data has been collected (can be relaxed or task based), references of the research studies that have carried that process. The reviewed studies for these locally collected datasets include the applications such as dementia, depression, motor imagery, emotion recognition, identity authentication, alcoholism, eyes state detection, driver drowsiness/fatigue detection, and multi-class task recognition.

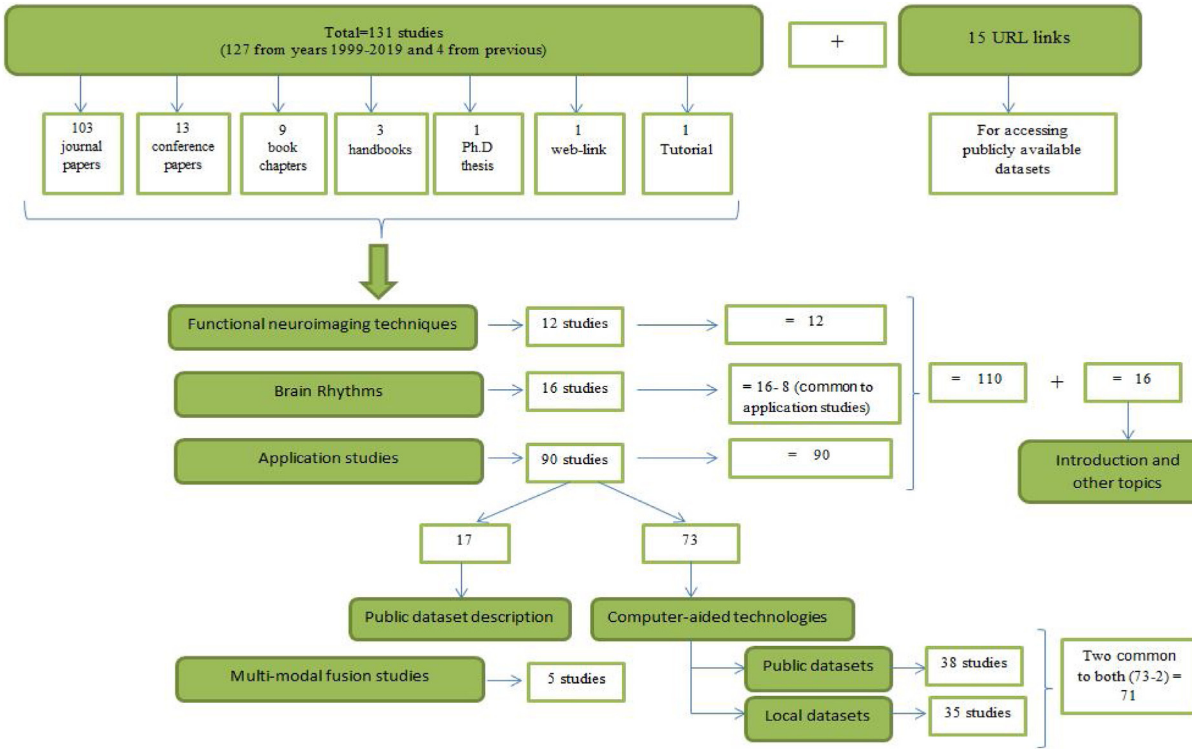

Fig. 3 – EEG data collection, signal processing, and result analysis.

6. EEG signal processing and analysis

The dynamically changing functional states of the brain are easily captured in the small variations of the EEG readings. Also, the EEG of the normal person differs from the abnormal one. So it is very important to identify those changes by applying a series of signal processing and analysis mechanisms with the help of computer-aided technologies. This is carried out in four stages – pre-processing, feature extraction, post-processing and result analysis. These are shown in Fig. 3. The raw signals can be directly fed to the result analysis phase for classification or statistical analysis, i.e. any of the first three stages can be skipped in the processing mechanism depending upon the requirement of the application. Like in some of the research studies where the deep neural architectures are used for the data analysis, any feature extraction or feature selection is not required to be performed manually. Also in other cases, if the data is already pre-processed or the features are already extracted, especially for the publicly available datasets, then any of those steps can also be skipped. Again if the extracted feature set is small, then there is no need for post-processing that involves the feature selection or dimensionality reduction methods. Finally, at the result analysis phase, the classification or the statistical analysis is made with the aim of diagnosing some abnormality or recognizing the different functional states of the brain to monitor some application. The values inside the parenthesis in Fig. 3 gives the information about the number of application studies that have worked upon the corresponding techniques.

6.1. *Pre-processing*

The pre-processing methods applied in the research studies can be broadly divided into three categories- downsampling, artifact handling and feature scaling, as explained below:

(a) *Downsampling*

The data collected by the different EEG devices is downsampled to certain ranges depending upon the requirement of an application. Downsampling to 16 Hz [105], 64 Hz [21], from 512 to 64 Hz [18], 256 to 16 Hz [104], and 2400 to 600 Hz [20] is done in the research studies depending upon the requirement of an application.

(b) *Artifact handling*

Artifacts are not generated from the cortical activity but due to the errors originated from the experimental settings, environment noise or biological artifacts. The artifact signals can be broadly categorized into two classes depending upon their origin [40,115] [116]: *(i) Technical or extrinsic artifacts:* These arise due to the technical issues or some external factors in the data collecting environment such as due to the misplacement of electrodes, powerline interference (50–60 Hz) or the electromagnetic interference in the cables or other devices, etc., and *(ii) Physiological or intrinsic artifacts:* Different types of physiological signals generated inside the human body act as the artifacts during the EEG data collection process.

These include eye movements or blinks (or electro-oculogram (EOG) artifacts), muscle activities (or electro-myogram (EMG) artifacts), cardiac activities (or

Table 3 – Public datasets.

Dataset	Web link	No. of classes	Subjects	Device	Sampling rate (in Hz)	References
UCI dataset for Alcohol [53]	http://kdd.ics.uci.edu/databases/eeg/eeg.data.html	2 (Control and alcohol)	122	61 electrode cap (ECI, Electrocap International) + 3 reference channels + horizontal and vertical EOG	256	[14,54,55]
UCI dataset for Eye State [56]	https://archive.ics.uci.edu/ml/datasets/EEG+Eye+State	2 (Eyes open and close)	1	Neuroheadset EmotivEpoc– 14 channels	128	[57–59,26]
Bonn university database [60]	http://www.meb.unibonn.de/epileptologie/science/physik/eegdata.html	3 (Control, interictal and ictal/epileptic)	10	128-Channel amplifier system	173.61	[55,61–68,10,11]
Bern Barcelona Database [69]	https://www.upf.edu/web/mdm-dtic/datasets	2 (intercranial signals with categories- "focal" and "non-focal")	5	Intracranial strip along with depth electrodes manufactured by AD-TECH (Racine, WI, USA)	512	[70]
Seizure-Prediction data [71]	https://www.kaggle.com/c/seizure-prediction/data	2 (pre-ictal and inter-ictal)	5 dogs and 2 patients	16 sub-dural conductors inserted into canine's head (for dogs) Patient 1 = 8 depth electrodes, patient 2 = 3 * 8 sub-dural electrodes	400 (for dogs), 5000 Hz (2 patients)	[72]
CHB-MIT Scalp EEG Database [73]	https://archive.physionet.org/pn6/chbmit/	2 (seizure and non-seizure)	23	An array of 23-EEG channels	256	[67,74]
Autism dataset by KAU, Saudi Arabia [75]	https://malhaddad.kau.edu.sa/Pages-BCI-Datasets-En.aspx	2 (normal and autistic)	19	16 Ag/Agcl electrodes, g.tec EEG cap, g.tec GAMMAbox, g.tec USBamp and BCI2000	256	[67]
BCI competition II Dataset-III [76]	http://www.bbci.de/competition/ii/	2 (Left or Right hand imagery movement)	1	G.tec amplifier and a set of Ag/Agcl electrodes	128	[77,78]
DEAP database [79]	http://www.eecs.qmul.ac.uk/mmv/datasets/deap/	Labels- valence, arousal, dominance and liking	40	Biosemi ActiveTwo with 32 EEG channels	512	[80,47,81,21]
BCI Competition III dataset IV-a [82]	http://www.bbci.de/competition/iii/	2 (Right foot and right hand)	5	BrainAmp amplifier system with 128 channel electrode cap	100	[83,84]
Physionet EEG Motor Movement/Imagery [85] [86]	https://physionet.org/pn4/eegmmidb/ and http://www.bci2000.org	Contains the two baseline tasks and four motor imagery tasks	109	BCI 2000 system consisting of 64 channels	160	[87,25,88]
Sleep EDF	https://physionet.org/physiobank/database/sleep-edf/	Sleep stages according to rules by Rechtschaffen and Kales (Wake, REM, Stage 1, Stage 2, Stage 3, and Stage 4)	8 PSGs (sleep edf)	Four channel cassette recorder and telemetric system and contains two EEG channels (FpzCz and PzOz), horizontal EOG data and EMG signals	100	[45,22,46,89]
Sleep EDF Database [Expanded] [90,86] [91] [92]	https://physionet.org/physiobank/database/sleep-edfx/		197 PSGs (expanded)			
MIT-BIH Polysomnographic Database [93] [86]	https://physionet.org/physiobank/database/slpdb/	Sleep stages defined according to rules by Rechtschaffen and Kales	16	3 channels – C3-O1, C4-A1 and O2-A1	250	[94,95]
Sleep Heart Health Study (SHHS)-1 [96]	https://sleepdata.org/datasets/shhs/pages	Sleep stages defined according to rules by Rechtschaffen and Kales-Wake, N1, N2, N3, N4, and REM	5,793	Gold cup electrodes for two EEG channels (C4/A1) and (C3/A2)	125	[97]

Table 4 – Other data acquisition studies.

Purpose	Subjects	Device	Channels	Sampling rate/ Recording time/EI	Recording state	Refs.
Dementia (Alzheimer, MCI, Parkinson, and DLB)	HC: 37 (M: 12, F: 25, age = 76), MMSE = 29, MCI: 37 (M: 16, F: 21, age = 76.6), MMSE = 27.25, AD: 37 (M: 12, F: 25, age = 81.55), MMSE = 21.5, Total: 111	19-channel system (XLTEK®, Natus Medical, Plesanton, CA, USA)	19	200 Hz/5 min	Relaxed awake with eyes closed	[51]
	HC: 30 (age = 70–76), MMSE = 28–30, AD: 30 (age = 74–78), MMSE = 12–15	Symtop amplifier	16 + 2 Ref (linked earlobes A1 and A2)	1024 Hz/30 min/ EI ≤ 3 KΩ	EC, EO	[17]
	ADhall+: 36 (M:17, F: 19, age: 69.41 ± 7.74), MMSE = 19 (*n* = 33), ADhall-: 108 (M: 51, F: 57, age: 69.41 ± 7.37), MMSE = 21 (*n* = 108), DLBhall+: 29 (M: 20, F: 9, age: 70.76 ± 9.51), MMSE = 23 (*n* = 24)	OSG digital equipment (Brainlab and BrainRT®; OSG B.V.Belgium)	21	500 Hz/20 min/ EI < 5 KΩ	Resting state awake	[52]
	AD: 10 (M: 5, F: 5, age = 69.4 ± 9.2), MMSE = 16.2, HC: 10 (M: 4, F: 6, age = 68.7 ± 7.7), MMSE = 30	TrueScan 32	21	200 Hz	EC	[98]
	PD: 20 (59.05 ± 5.64, M: 10, F: 10, MMSE: 26.90 ± 1.51), HC: 20 (58.10 ± 2.95, F: 11, M: 9, MMSE: 27.15 ± 1.63)	Emotiv Epoc	14	128 Hz/5 min	EC	[16]
Depression or stress	HC: 18 (M: 18, F: 0, college aged)	Emotiv Epoc neuroheadset	14 + 2 Ref	128 Hz	Mild stress is induced in response to stimuli presentation module under congruent and incongruent conditions	[23]
	HC: 13 (M: 5, F: 8, age = 38.7 ± 15.8), MDD: 13 (M: 5, F: 8, age = 38.7 ± 15.8)	Neuroscan synamps2 (compumedics, NC, USA)	30 + avg (M1, M2) taken as reference + Horizontal EOG + Vertical EOG	1000 Hz/2 min (EO) and 30 min (EC)/EI < 10 KΩ	EO and EC	[49]
	HC: 30 (age = 38.227 ± 15.64), MDD: 33 (age = 40.33 ± 12.861)	EEG cap attached to Brain Master systems	19 (1 Linked ear ref)	256 Hz/5 min each EO and EC	EO and EC	[9]
	7 subjects out of 11 with high cortisol levels (M: 11, F: 0, age = 37.9 ± 8.8)	Emotiv Epoc+	14	128 Hz	Under working condition at onsite and offsite construction site	[48]
	HC: 45 (M: 20, F: 25, age = 33.7 ± 10.2), MDD: 45 (M: 22, F: 23, age = 33.5 ± 10.7)	19 electrodes placed over the scalp	19	256 Hz/5 min	EC	[99]
	HC: 15 (age = 20–50), MDD: 15 (age = 20–50)	1 bipolar EEG channels from left and right hemisphere each	2	256 Hz/5 min (EO and EC each)	EO and EC	[100,13]
	HC: 30 (M: 21, F: 9, age = 38.227 ± 15.64), MDD: 34 (M: 16, F: 18, age = 40.33 ± 12.861)	EEG sensor cap with amplifier from Brain Master system	19 (1 Linked ear ref)	256 Hz/5 min each EO and EC	EO and EC	[12]
	HC: 204 (M: 68, F: 136, age = 27.46 ± 9.61), MDD: 144 (M: 58, F: 86, age = 27.65 ± 9.50)	MUSE EEG headband	5 (FPz as ref)	220 Hz	Task based on watching 8 short videos	[101]

Table 4 (*Continued*)

Purpose	Subjects	Device	Channels	Sampling rate/ Recording time/EI	Recording state	Refs.
	HC: 23 (M: 23, age = 18–28)	Mistar system, MCScap-26 hat for EEG, 30 Ag/Agcl electrodes	5 (FPz as ref)	256 Hz/1 min	Recording during EC and EO, before, immediately after, and after 20 min of the test (TSST – trier social stress test)	[102]
Motor imagery	HC:10 (M: 5, F: 5, age = 26.3 ± 5.4)	EEG cap with four g.USBamp amplifiers (g.tec, Graz, Austria)	60 + 3 EOG, Ref on left ear and ground on right ear	512 Hz/EI < 5 KΩ	Paradigm where the participants have to look at goal on screen and do movements accordingly	[103]
	HC:3 (M: 1, F: 2 age = 22–24)	EEG cap with 5 g.USBamp amplifiers (g. tec, Graz, Austria)	68 + 3 EOG, Ref on left mastoid and ground on right mastoid	512 Hz	Based on self-paced center out reaching task	[18]
	HC:9 (M: 5, F: 4, age = 26.1 ± 4.3)	EEG cap with 5 g.USBamp amplifiers (g. tec, Graz, Austria)	68 + 3 EOG, Ref on left mastoid and ground on right mastoid	256 Hz	Based on imagining rhythmic movements of the right arm in horizontal and vertical plane in response to arrow on the screen	[104]
	HC: 15	EEG cap with g.USBamps (g.tec, Austria)	61 channels	–	Based on performing the hand movements according to the presented cues on the screen	[105]
Emotion recognition	HC: 28 (M: 13, F: 15, avg age = 23.62)	MUSE headband	4	220 Hz (raw data), 10 Hz (features)	Based on video stimuli	[24]
	HC: 15 (M: 8, F: 7, age = 29.42 ± 4.02), MDD:15 (M: 8, F: 7, age = 30.92 ± 3.65)	EasyCap with BrainAmp DC (Brain Products, Munich, Germany)	16	250 Hz/15 min (3 min each for different condition)/EI < 10 KΩ	Resting state + In response to audio stimuli (noise and music)	[106]
	HC: 24	Biopac provided electrode cap with 10 Ag/Agcl electrodes and MP 150 system	3 electrodes (Fz, Cz, Pz)	500 Hz	The emotions have been evoked by using images from IAPS belonging to the four quadrants (LVHA, HVHA, HVLA, LVLA).	[107]
	HC: 10 (M: 8 and F:2, mean age = 30.6 years and SD = 13.73 years)	Emotiv Epoc+	14	128 Hz	images from MUG database from categories of happy, angry, and neutral were shown to the participants	[108]

Table 4 (Continued)

Purpose	Subjects	Device	Channels	Sampling rate/ Recording time/EI	Recording state	Refs.
Identity authentication	HC: 45 (age = 22.4 ± 2.1, User: 15, Imposter: 30)	g.USBamp amplifier with electrodes	16	2400 Hz, EI < 5 KΩ	Based on rapid visual presentation of images of fare and non-fare users	[20]
Alcoholism	HC: 30 (M: 18, F: 12, age = 42.67 ± 15.90), AUD: 30 (M: 16, F: 14, age = 55.4 ± 12.87)	Discovery 24E system	19	256 Hz/5 min for each EO and EC	EO and EC	[15]
	HC: 15 (age = 42.67 ± 15.90), Alcoholics: 18 (age = 46.80 ± 9.29), Alcoholic abusers: 12 (age = 56.70 ± 15.33)	(1) Discovery 24E	(1) 19 + 1 grd + 2 ref + 2 for event synchronization	256 Hz and 500 Hz for (1) and (2) resp./5 min each for EO and EC/ EI < 10 KΩ for (1)	EO and EC	[50]
		(2) Enobio System	(2) 19 + 1 External + 2 mastoid ref			
Eyes state detection	HC: 2 (M: 1, F: 1)	Mindwave headset	1	16 min (two 4 min for each EO and EC)	EO and EC	[109]
	HC: 20 (M: 8, F: 12, age = 18–30)	NeuroScan SynAmps2	30 + 1 electrode A2 + 1 ref (A1) + Vertical EOG + Horizontal EOG	sampled DC to 70 Hz and digitized at 1 KHz/ 2 min each for EO and EC/EI < 5 KΩ	EOand EC	[110]
Driver drowsiness/ fatigue detection	HC: 13 (M: 13, F: 0, age = 22–25)	Nihon-Koden EEG 2110	9 + 2 Earlobe channels (A1, A2) + 2 EOG	256 Hz	To make some mental calculation during the experiment	[27]
	HC: 8 (age = 20–24)	Neuroscan device	30 + 2 Ref + Horizontal and vertical EOG	1000 Hz/60 min	Simulated driving Environment	[111]
Multi-class task recognition	HC: 5 (M: 3, F: 2, age = 24–30)	Emotiv Epoc+	14	128 Hz	Tasks in response to mark on the screen	[87]
Others	HC: 5 with normal vision (age = 21.6 ± 5.32)	BioAmp2 wireless recording system	Oz-Cz	250 Hz	Subjects were asked to look at the RVS source.	[112]
	HC: 28 (M: 25, F: 3 age = 19–37 years and SD = 4)	Neurosky Mindwave headset	1 EEG channel + eye tracking data	300 Hz	Data collected under the effect of visual stimuli, images selected from IVY LAB stereoscopic 3D image database.	[113]
	50 evoked potentials from healthy participants (age: 28–53 years, all males)	Mobile device, LiveAmp (by Brain vision)	32 channels and 3 axis sensor for body movement detection	500 Hz	Visual, auditory, and somatosensory stimulations	[114]
	HC: 10	64 channel g.Gamma cap with g.tech software	60	256 Hz/5 min	EO	[67]

Table 5 – Artifact removal methods.

Application Artifact removal technique	Depression	Alcoholism	Dementia	MI/MT	Emotion recognition	Sleep stage	Identity authentication	Epilepsy	Drowsiness	Eyes open/closed	Others
Notch filter (50 Hz powerline interference removed)							[101,12,9,100,13,99]	[15]	[51]	[103,18,104]	[108]
×	×	×	×	×	[112]						
Notch filter (60 Hz powerline interference removed)	[48]	×	×	×	[108]	×	×	×	×	×	×
Bandpass filter	2–36 Hz [101], 0.5–70 Hz [12,9], 0.5–64 Hz [48], 0.5–46 Hz [49]	0–70 Hz [15]	0.5–60 Hz [98], 0.5–30 Hz [17], 1–70 Hz [51]	×	0.5–50 Hz [106], 4–45 Hz [47], 0.2–45 Hz [108]	0.3–45 Hz [45]	0.1–55 Hz [21]	0–50 Hz [68]	1–50 Hz [111]	×	×
Chebyshev filter	Transition width = 1 Hz, passband ripple = 1 dB, Stopband ripple = 80 dB [23]	×	×	8th order, 0.01–200 Hz [103,18]	×	×	Passband ripple = 40 Hz, Stopband ripple = 49 Hz [20]	×	×	×	×
Elliptic band pass filter	×	×	×	0.5–50 Hz [78]	×	×	×	0.5–60 Hz [67]	×	×	0.5–60 Hz [67]
Bandstop filter	×	×	49–51 Hz [98]	×	×	×	×	×	×	×	×
Low pass filter	×	×	70 or 100 Hz [52]	×	40 Hz [107]	×	×	×	×	×	×
High pass filter	×	×	×	×	0.5 Hz [107]	×	×	×	×	×	×
Butterworth filter	×	×	6th order, 1–49 Hz (bandpass) [16]	4th order, 1–70 Hz [103], 4th order, 0.3–100 Hz [18], 4th order, 0.3–3 Hz [18], 4th order, 0.3–3 Hz [105], 8th order, 0.01–100 Hz, 4th order, 0.2–70 Hz, 2nd order, 0.4–0.6 Hz [104]	3th order, 0.5–15 Hz [108]	20th order, 1–60 Hz [22] 8th order, 0.5–35 Hz [89]	×	×	2nd order, 0.5–60 Hz [94]	5th order, 40 Hz (low pass) [25], 5th order, 0.5 Hz (high pass) [26]	5–80 Hz [112], 4th order, 0.01–45 Hz [113]
Accelerometer module along 3-axis	To track and reject artifacts due to head movements [101]	×	×	×	×	×	×	×	×	×	×
Multiple source modelling technique	[12,9]	[15]	×	×	×	×	×	×	×	×	×
Manual removal by experts after visual inspection or visual selection of artifact free data	[100,13,99,49]	×	[52,17,51]	[103,87]	[106]	×	×	×	[27]	[26]	×

Table 5 (*Continued*)

Application Artifact removal technique	Depression	Alcoholism	Dementia	MI/MT	Emotion recognition	Sleep stage	Identity authentication	Epilepsy	Drowsiness	Eyes open/closed	Others
Semi-automatic detection method	×	Physiological noise removed with contribution of both user and machine, segments with SHR score > 0.90 selected [50]	×	×	×	×	×	×	×	×	×
PCA	×	×	×	[18]	×	×	×	×	×	×	×
ICA	[48]	×	[51]	[103,18,105,104]	×	×	×	×	[111]	×	×
Automatic removal	×	×	×	×	[106,47]	×	×	×	×	×	×
Thresholding technique	×	×	Segments with voltage > 150 μV [17], Segments with voltage > 80 μV [16]	Median absolute deviation [18,104]	Epochs with peak value > 70 μV were rejected [108]	×	×	×	×	×	×
Wavelet method	×	×	×	×	×	DWT ('db4') with adaptive threshold and soft threshold function [22]	×	×	×	Threshold denoising using heuristic method [57]	×
Revised aligned artifact average	×	×	×	×	×	×	×	×	×	[110]	×
Regression based correction method	×	×	×	[103,104]	×	×	×	×	×	×	×
Adaptive filters	×	×	×	×	FIR filter with LMS optimization algorithm [117]	×	×	×	Biological noise and line interference handled [94]	×	×
Wavelet modified ICA method	×	×	×	×	×	×	×	×	×	×	[113]

electrocardiogram (ECG) artifacts), etc. All these kinds of artifacts are generally handled by applying a variety of artifact removal/reduction methods. These have been tabulated in Table 5 – the type of artifact removal technique has been mentioned in the first column, while the rest of the columns denote the type of application in which the corresponding method has been applied for filtering. The symbol (×) denotes that the particular artifact removal method has not been used in any of the studied research papers.

(c) *Feature scaling*

It is very important to scale the features of the dataset in order to exhibit the symmetrical behaviour. Normalization is one of the most commonly used feature scaling methods in the studied papers. The scaling is performed either on the raw/filtered values or on the extracted features. Table 6 gives the description about the feature scaling methods.

Pre-processing on publicly available datasets

The pre-processing was also performed on some of the publicly available datasets during their data collection process before they were publicly released. These involve:

i. In UCI dataset for alcohol, the trials with amplitudes greater than 73.3 μV, indicating extreme eye and body movements were discarded.
ii. In Bonn University dataset for epileptic seizure, only those segments of the collected data were chosen through the visual inspection that were free from the eye movement and muscle artifacts. Bandpass filters with frequency range 0.53-40Hz were also applied.
iii. In Bern Bercelona database for epilepsy, the signals with a sampling rate of 1024 Hz were downsampled to 512 Hz and then were filtered with Butterworth bandpass filters of 4th order with the frequency range of 0.5–150 Hz.
iv. For DEAP dataset for emotion recognition, a preprocessed form of the original data is also made available online by the authors in which the downsampling of data to 128Hz had been performed followed by the removal of EOG artifacts by blink source separation technique. Then the band pass filtering with frequency range of 4–45 Hz had been applied, followed by some segmentation and reordering steps. The pre-processed dataset can be acquired from the same web-link as mentioned in Table 3 for the original dataset.
v. For BCI Competition II Dataset-III, the readings for the electrode channels were filtered with the bandpass filter of frequency range 0.5–30 Hz.
vi. For BCI Competition III dataset-IVa, the sampling rate was 1000 Hz which was downsampled to 100 Hz. The signals were filtered with the band pass filter of frequency range 0.05–200 Hz.
vii. For autism dataset given by King Abdulaziz University, Saudi Arabia, band pass filters with frequency range 0.1–60 Hz and notch filter at 60 Hz stop band frequency are used for preprocessing the data.

6.2. *Feature extraction*

A number of feature extraction methods are used to perform time domain, frequency domain, and time-frequency domain analysis of the signals. Some of them are empirical mode decomposition (EMD), fast Fourier transform (FFT), wavelet transform (WT), wavelet packet decomposition (WPD), and so on. The feature extraction methods have been studied in three categories- spectral estimation methods, family of transforms, and time decomposition methods (see Fig. 4). A comparative analysis of different feature extraction methods has been briefly summarized in Table 7. Different types of band pass filters are also used to decompose the signals into various frequency sub-bands, from which then the features are extracted for more detailed analysis.

Four categories of features can be reviewed from the studied applications that are named as – statistical/wavelet, spectral, non-linear, and functional connectivity based features. These have been precisely summarized in Fig. 4. These features can be directly extracted from the raw or preprocessed signals. But for more deeper analysis, a number of feature extraction methods (as summarized in Table 7) are applied to obtain various detailed sub-bands that are used to extract the different types of features from them. A complete survey for different category of features using different feature extraction methods for various applications has been explained as:

(a) *Statistical/wavelet features*

Table 8 gives the description about the statistical/wavelet features – the name of features, reference of the studies which have worked upon those features, name of the feature extraction methods (if applied), sub-bands

Table 6 – Feature scaling methods.

Normalization method	Before/after extracting features	References	Purpose
Max-Min	Before	[87]	Multi-class task recognition
	After	[24]	Emotion recognition
Z-score (mean = 0, Std Dev = 1)	Before	[87]	Multi-class task recognition
		[62]	Seizure/epilepsy
		[13]	Depression
	After	[9,12]	Depression
		[15,50]	Alcoholism
Unity	before	[87]	Multi-class task recognition

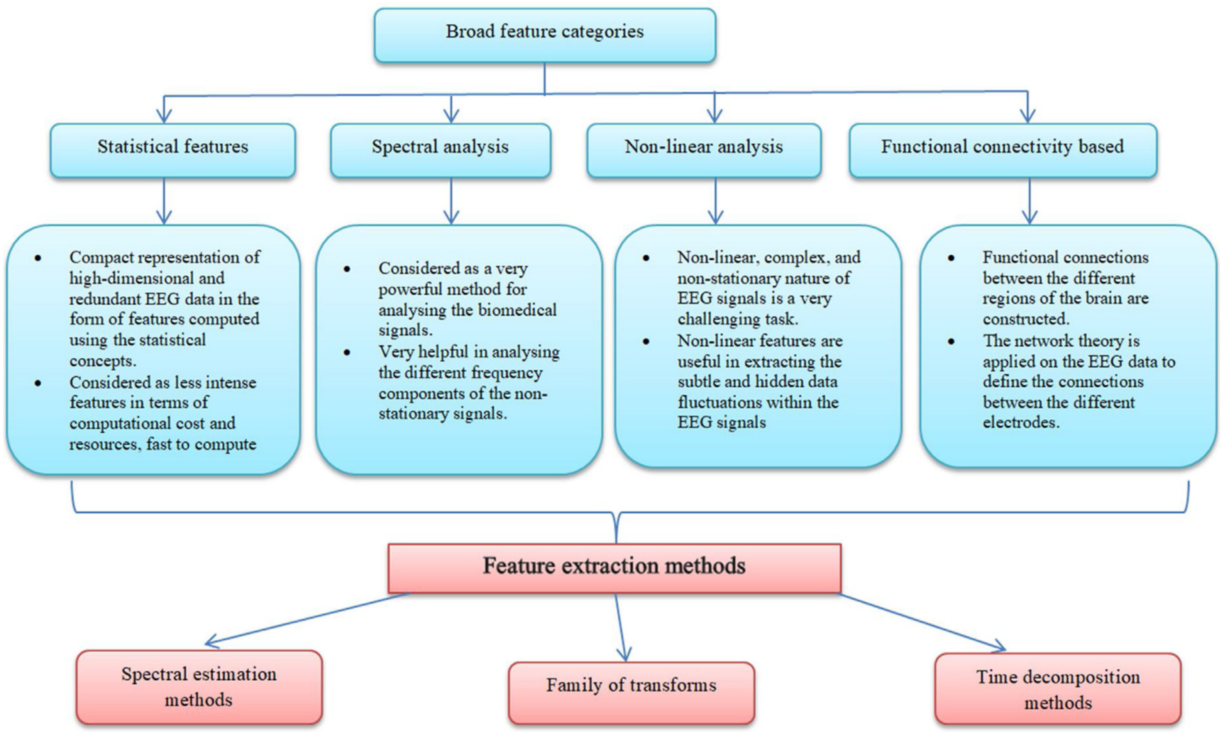

Fig. 4 – Types of features extracted with various extraction methods.

from which the corresponding features have been extracted after applying the corresponding feature extraction method (if applied), and the purpose or the application of the EEG study. In some of the applications, no feature extraction method has been used, instead the raw or the preprocessed signals have been directly used for the result analysis, therefore, no sub-band divisions are performed for them.

(b) *Spectral features*

The spectral analysis of the features can be done by using either parametric (Yuler-walker or Burg's Method) or non-parametric approach (Welch method with FFT) [118,55]. These features have been explained in Table 9 giving the information about the- name of the spectral parameters, any decomposition method if applied, name of the sub-bands from which the respective spectral features can be extracted, and the purpose of the study.

(c) *Non-linear features*

Different categories of non-linear features [125,126] are available that are important to understand the non-linear features and complex nature of the EEG signals. Table 10 gives an explanation about those features as- category of the non-linear features, name of the features extracted from the particular category, reference of the studies which have worked upon those features, name of the feature extraction methods (if applied), sub-bands from which the features have been extracted after applying the corresponding feature extraction method (if applied), and the purpose or the application of the EEG study. In some of the applications, no feature extraction method has been used, instead the raw or the preprocessed signals have been directly used for the result analysis, therefore, no sub-band divisions are performed for them.

(d) *Functional connectivity based features*

By applying the network theory on the collected EEG data, the functional networks of the brain are constructed and the connectivity inside them is measured with the help of various features. The functional connectivity based metrics that are derived from the EEG data are described in Table 11, along with the application study and their references in which they are computed.

6.3. *Postprocessing*

Post-processing can be done either through the feature selection methods or the dimensionality reduction methods.

(a) *Feature selection*

A number of feature selection methods are available in the studied applications that aim to improve the quality of the result analysis phase. Table 12 shows the feature selection methods along with the application and reference of the study in which they have been used.

(b) *Dimensionality Reduction*

EEG application studies using the different dimensionality reduction methods have been provided in Table 13.

6.4. *Result analysis*

A variety of machine learning algorithms are used for the diagnosis of neurological disorders (such as epilepsy/seizure,

Table 7 – Comparison of feature extraction methods.

Feature extraction method type	Name	Description/Advantages	Disadvantages/challenges
Spectral estimation methods [40,118,55]	Non-parametric or classical approach	• Estimation of auto-correlation sequence is done from a given set of data and then applying the Fourier transformation to it.	• Concept of windowing creates the spectral leakage effects.
		• Welch method is one of the most popular spectral estimation method: - The sequences are allowed to overlap and the data windows are applied. - Modified periodiograms are generated for each sequence. - Their average gives an estimation of power spectrum.	• Not good for the spectral estimation of short EEG segments. • Suffers from a problem of noise sensitivity.
	Parametric or non-classical approach	• Model based power spectrum estimation method.	• Suffers from a problem of selecting an optimal model order as:
		• Overcomes the problem of spectral leakage thus leading to better frequency resolution	- Higher order induces false peaks and
		• Estimation of the parameters of the linear system is done.	- Lower order leads to the smoothing of spectra.
		• AR models, linearly stochastic in nature, are considered as the most preferred ones for estimating the PSD graphs.	• Highly vulnerable to heavy biases and larger variability.
		• The parameters such as sampling rate, model order, etc. can be estimated by using two methods: - Yulk-Walker - Burg's method • Best for spectral estimation of shorter data segments.	
Family of transforms [119,120,118]	Fourier Transform (FT)	• Transforms the raw time domain signals into frequency domain by using exponential function of varying frequencies as an analysing function for transformation.	• Has zero temporal resolution.
		• Captures the different frequency components of the signals.	• Not good for non-stationary signals i.e. FT is not a good tool for real time applications where representation of time varying spectra is required.
		• Appropriate for stationary signals.	• Discontinuities in the signals cannot be represented appropriately.
		• Achieves high frequency resolution.	
	STFT	• Windowed version of FT.	• Choosing a width of the window is a very difficult problem as:
		• Concept of 'windows' is used, i.e. short time stationary data segments from the non-stationary ones are chosen and FT is applied to those segments.	- Shorter time window leads to low frequency and high temporal resolution.
		• Gives both time and frequency representation of the signals.	- Longer time window leads to high frequency and low temporal resolution. • Also the window size is fixed, thus the fixed resolution throughout the time.
	CWT	• Alternative method of transformation to STFT.	• Parameters, a and b, vary continuously over the whole time during the calculation of the wavelet coefficients.
		• Time-varying window sizes according to the different spectral components.	• Thus, involves a lot of redundancy and effort for analysing and reconstructing the signal, thus wastage of computational time and resources.
		• Time localization of various frequencies can be obtained. • Good for non-stationary signals. • Signal is multiplied with the mother wavelet to get the transformed signal. • Transformed signal is represented as a function of two parameters, a and b, called as the "scale" and "translation" respectively. • Mother wavelet defines the varying finite length window functions by changing the "scale" and "translation". •Examples of mother wavelet for CWT are Morlet and Mexican hat.	

Table 7 (*Continued*)

Feature extraction method type	Name	Description/Advantages	Disadvantages/challenges
	DWT	• Easier to implement than CWT. • Signal is analysed at different scales w.r.t. time. • Involves the significant amount of information for analysing and reconstructing the signal, thus useful for designing the less intense models in terms of computational time and resources. • A series of low and high pass filters are used to study the signal at different "scales". • "Level wise" decomposition is involved in which the lists of detailed and approximation coefficients with half the sampling rate are obtained corresponding to the high and low frequency components respectively. • Some of the popular wavelet functions are symlet, daubechies (db1, db2, db4, db6, and db8), and Haar. • DWT is the most commonly used method than CWT for EEG based epilepsy diagnosis application.	• Choosing the correct choice of "wavelet" is a tedious task. • It suffers from some other limitations such as sensitive to translation, shift variance, aliasing, and lack of directionality [121,66]. • The extent of frequency resolution achieved by DWT is considered to be coarse for analysing the signals in practical scenarios.
	DD-DWT [66]	• Better time-frequency representation method than traditional DWT. • Based on the structure of "dual-wavelets". • Input signal is passed through DD-DWT to obtain the low frequency sub-component and two high frequency sub-components at each level of decomposition. • The subtle changes in the EEG signals can be revealed and localized more accurately through this method. • Outperformed DWT by having properties of anti-aliasing and shift invariance.	–
	WPD [121,122]	• "Wavelet Packets" are generated, given some wavelet function with orthogonal property. • It is an extension to DWT: - In WPD, signal is passed through more number of filters as compared to DWT. - In DWT, only the approximation coefficients are decomposed further at each level. - In WPD, at each level of decomposition, both the detailed and approximation coefficients are decomposed into high and low frequency components, thus offering much richer signal analysis. - For n levels of decomposition, WPD produces 2^n sets of wavelet coefficients as compared to $(n+1)$ sets as in DWT.	• Lacks of improved directionality and sensitive to location w.r.t. time. • Involves complex data structures.
	TQWT [123,124]	• Efficient in analysing the subtle variations in the oscillatory signals. • Basically involves the 3 parameters – Q (Q-factor), r (redundancy), and j (number of decomposition levels). • A signal with frequency rate f_s, is decomposed into low and high pass sub-bands. • Low pass filter and low pass scaling parameter (α) are responsible for generating low pass sub-band with sampling frequency αf_s, similarly, high pass filter and high pass scaling parameter (β) are responsible for generating high pass sub-band with sampling frequency, βf_s. • Q describes the extent of signal resonance and is tuned depending upon the oscillatory nature of the signal. • High value of Q is suitable for high frequency signals and low for low frequency signals. • Can be implemented with FFTs in case of discrete time signals.	• One should have complete understanding to finely tune the Q-factor for TQWT. • Number of levels should be chosen carefully because as the number of levels become too large, it becomes difficult to interpret the resulting coefficients.

Table 7 (Continued)

Feature extraction method type	Name	Description/Advantages	Disadvantages/challenges
Time domain • It is a time-domain based		decomposition decomposition method that helps to effectively analyse the non-linear and non-periodic signals. • The signal is decomposed into a set of intrinsic mode functions (IMFs) that are used as sub-signals. • Represents the intrinsic modes present inside the signals w.r.t. time, thus giving better temporal resolution.	EMD [46] • For EEG signals, where the data is simultaneously captured using the multiple channels, EMD is not enough to analyse the cross-channel interdependence [26].

Table 8 – Statistical/wavelet features.

Features	Reference	Feature Extraction method (if applied)	Sub-bands	Purpose
Mean	[45,46]	Raw/ Preprocessed signals	No sub-band divisions	Sleep stage classification
	[48]	Raw/ Preprocessed signals	No sub-band divisions	Depression
	[14]	FAWT	D2, D3, D4, D5 and A5	Alcoholism
	[63,10]	DWT (Db4, Levels = 5)	D3, D4, D5, A5	Seizure/epilepsy
	[72]	Low pass, high pass, band pass and band stop filters	10 sub-bands – δ, θ, α, β, low γ, full spectrum excluding 57–63 Hz, 63 Hz to maximum frequency, 100 Hz to maximum frequency, 200 Hz to possible complete spectrum, full spectrum	Seizure/epilepsy
	[68]	DWT (symlet, levels = 4)	δ, θ, α, β, γ	Epilepsy
Median	[47]	Raw/preprocessed signals	No sub-band divisions	Emotion recognition
	[48]	Raw/preprocessed signals	No sub-band divisions	Depression
	[14]	FAWT	D2, D3, D4, D5 and A5	Alcoholism
	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
Variance	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[48]	Raw/preprocessed signals	No sub-band divisions	Depression
	[95]	Band pass filters	δ, θ, α, β, γ	Sleep stage classification
	[72]	Low pass, high pass, band pass and band stop filters	10 sub-bands – δ, θ, α, β, low γ, full spectrum excluding 57–63 Hz, 63 Hz to maximum frequency, 100 Hz to maximum frequency, 200 Hz to possible complete spectrum, full spectrum	Seizure/epilepsy
Standard deviation	[46]	FIR bandpass filters	δ, θ, α, $\beta 1$, $\beta 2$, k-complex, spindle wave	Sleep stage classification
	[46]	EMD	7 IMFs	Sleep stage classification
	[47]	Raw/preprocessed signals	No sub-band divisions	Emotion recognition
	[48]	Raw/preprocessed signals	No sub-band divisions	Depression
	[14]	FAWT	D2, D3, D4, D5 and A5	Alcoholism
	[94]	Raw/preprocessed signals	No sub-band divisions	Drowsiness detection
	[25]	DWT (db4, levels = 5)	δ, θ, α, β, γ	Eyes state detection
	[61]	Multi-basis MODWPT	-	Seizure/epilepsy
	[63,10]	DWT (Db4, levels = 5)	D3, D4, D5, A5	Epilepsy/seizure
	[67]	DWT (levels = 6)	D3, D4, D5, D6, and A6	Epilepsy and autism
	[68]	DWT (symlet, levels = 4)	δ, θ, α, β, γ	Epilepsy
	[22]	DWT (Db4, levels = 4)	δ, θ, α, β	Sleep stage classification
Kurtosis	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[46]	FIR bandpass filters	δ, θ, α, $\beta 1$, $\beta 2$, k-complex, spindle wave	Sleep stage classification
	[46]	EMD	7 IMFs	Sleep stage classification
	[47]	Raw/preprocessed signals	No sub-band divisions	Emotion recognition
	[48]	Raw/preprocessed signals	No sub-band divisions	Depression
	[14]	FAWT	D2, D3, D4, D5 and A5	Alcoholism
	[22]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[72]	Low pass, high pass, band pass and band stop filters	10 sub-bands – δ, θ, α, β, low γ, full spectrum excluding 57–63 Hz, 63 Hz to maximum frequency, 100 Hz to maximum frequency, 200 Hz to possible complete spectrum, full spectrum	Seizure/epilepsy

Table 8 (*Continued*)

Features	Reference	Feature Extraction method (if applied)	Sub-bands	Purpose
Maximum	[45,46]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[94]	Raw/preprocessed signals	No sub-band divisions	Drowsiness detection
	[61]	Multi-basis MODWPT	-	Seizure/epilepsy
	[22]	DWT (Db4, levels = 4)	δ, θ, α, β	Sleep stage classification
Minimum	[46]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[94]	Raw/preprocessed signals	No sub-band divisions	Drowsiness detection
	[61]	Multi-basis MODWPT	-	Seizure/epilepsy
RMS	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[48]	Raw/preprocessed signals	No sub-band divisions	Depression
	[23]	Bandpass filters	θ, α, β	Depression
	[25]	DWT (db4, levels = 5)	δ, θ, α, β, γ	Eyes state detection
Skewness	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[46]	FIR bandpass filters	δ, θ, α, β1, β2, k-complex, spindle wave	
	[14]	FAWT	D2, D3, D4, D5 and A5	Alcoholism
	[22]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[72]	Low pass, high pass, band pass and band stop filters	10 sub-bands – δ, θ, α, β, low γ, full spectrum excluding 57–63 Hz, 63 Hz to maximum frequency, 100 Hz to maximum frequency, 200 Hz to possible complete spectrum, full spectrum	Seizure/epilepsy
Energy	[46]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[45]	IIR Butterworth bandpass filters: 0.5–45 Hz	δ, θ, α, sigma, β, γ	
	[46]	EMD	7 IMFs	
	[46]	FIR bandpass filters	δ, θ, α, β1, β2, k-complex, spindle wave	
	[117]	DWT (Db4, levels = 5)	δ, θ, α, β, γ	Emotion recognition
	[78]	DWT (Db4, levels = 3)	Level 3	Motor imagery
	[57]	WPD (Db4, levels = 5)	A5, D5, D4, D3	Eyes state detection
	[61]	Multi-basis MODWPT	-	Seizure/epilepsy
	[22]	DWT (Db4, levels = 4)	δ, θ, α, β	Sleep stage classification
	[17]	WPD	δ, θ, α, β	Dementia
	[72]	Low pass, high pass, band pass and band stop filters	10 sub-bands – δ, θ, α, β, low γ, full spectrum excluding 57–63 Hz, 63 Hz to maximum frequency, 100 Hz to maximum frequency, 200 Hz to possible complete spectrum, full spectrum	Seizure/epilepsy
Average rectified value	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
Peak-to-peak amplitude	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[45]	IIR Butterworth bandpass filters: 0.5–45 Hz	δ, θ, α, sigma, β, γ	
Forward prediction error	[72]	Low pass, high pass, band pass and band stop filters	10 sub-bands – δ, θ, α, β, low γ, full spectrum excluding 57–63 Hz, 63 Hz to maximum frequency, 100 Hz to maximum frequency, 200 Hz to possible complete spectrum, full spectrum	Seizure/epilepsy
Zero crossings	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[48]	Raw/preprocessed signals	No sub-band divisions	Depression
	[94]	DWT (Db2, levels = 5)	Scales – 3 (β), 4 (α), 5 (θ)	Drowsiness detection
Mean square amplitude	[117]	DWT (Db4, levels = 5)	δ, θ, α, β, γ	Emotion recognition
Moving slope	[117]	DWT (Db4, levels = 5)	δ, θ, α, β, γ	Emotion recognition
Integrated EEG	[94]	DWT (Db2, levels = 5)	Scales- 3 (β), 4 (α), 5 (θ)	Drowsiness detection
Hjorth Parameters: (mobility and complexity)	[45]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	[46]	FIR bandpass filters	δ, θ, α, β1, β2, k-complex, spindle wave	
	[46]	EMD	7 IMFs	
	[47]	Raw/preprocessed signals	No sub-band divisions	Emotion recognition
	[22]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
Energy ratios	[45]	IIR Butterworth bandpass Filters: 0.5-45 Hz	δ, θ, α, sigma, β, γ	Sleep stage classification

Table 8 (*Continued*)

Features	Reference	Feature Extraction method (if applied)	Sub-bands	Purpose
Cumulative max and min, Smallest window elements, moving median, max to min difference, Root sum of squares peak and other related	[48]	Raw/ Preprocessed signals	No sub-band divisions	Depression
Auto-regressive coefficients	order = 6 [21]	Raw/preprocessed signals	No sub-band divisions	Identity authentication
AAR coefficients with RLS	order = 6 or 12 [77]	Raw/preprocessed signals	No sub-band divisions	Motor imagery
	order = 6 [78]	Raw/ Preprocessed signals	No sub-band divisions	
Wavelet coefficients	[80]	DWT (Db8)	δ, θ, α, β, γ	Emotion recognition
	[81]	DWT (Db8)	δ, θ, α, β, γ	Emotion recognition
	[83]	WPD	-	Motor imagery
	[57]	WPD	A5, D5, D4, D3	Eyes state detection
	[64]	DWT (db1, db2, db4, db6, Haar)	-	Seizure/epilepsy
	[74]	Wavelet filter bank (scales = 6, db4)	Upper 5 scales- δ, θ, α, β, γ	Seizure/epilepsy
Energy (delta/alpha)	[22]	DWT (Db4, levels = 4)	δ, θ, α, β	Sleep stage classification
Wavelet entropy	[78]	DWT (Db4, levels = 3)	Level 3	Motor imagery
Maximum and minimal singular value	[11]	GST and SVD	-	Seizure/epilepsy

Table 9 – Spectral features.

Features	Feature extraction method	Sub-bands	Purpose
Mean frequency	Welch method [45]	MEAN frequency from the whole power spectrum for 1 s epoch	Sleep stage classification
Band power	Welch method + IIR Butterworth bandpass filters: 0.5-45 Hz [45]	δ, θ, α, sigma, β, γ	Sleep stage classification
	[47]	θ, low (α), α, β, γ	Emotion recognition
	FFT [24]	δ, θ, α, β, γ	Emotion recognition
	Welch method + Butterworth bandpass [99]	δ, θ, α, β	Depression
	[48]	δ, θ, α, low (β), β, high (β), γ	Depression
	[9] Welch method	δ, θ, α, β	Depression
	FFT [50]	δ, θ, α, β, high (β), γ, high (γ)	Alcoholism
	Elliptic bandpass [78]	δ, θ, α, β, γ,	Motor imagery
	DWT (db4, 5 levels) [63,10]	D3, D4, D5, A5	Seizure/epilepsy
	DWT (levels = 6) [67]	D3, D4, D5, D6, and A6	Epilepsy and autism
Normalized band power	FFT [24]	δ, θ, α, β, γ,	Emotion recognition
SASI, APV, RGP	[49]	Modified θ, α, modified β, γ,	Depression
Peak power and their corresponding peak frequencies	FFT (Welch method),	Peak values from the whole PSD graph	Epilepsy, alcoholism
	Yuler-walker, Burg's Method [55]		
Relative power	FFT [50]	δ, θ, α, β, high (β), γ, high (γ)	Alcoholism
	[51]	δ, θ, α, β-1, β-2, γ	Dementia
Median frequency	[51]	Median frequency of the whole PSD graph	Dementia
	[48]	Median frequency of the whole PSD graph	Depression
Individual alpha frequency	[51]	Only α band	Dementia

Table 9 (*Continued*)

Features	Feature extraction method	Sub-bands	Purpose
Lowest, mean and highest relative power and peak frequencies from all sub bands and in range (4–13 Hz) respectively, theta/alpha ratio	FFT [52]	δ, θ, $\alpha 1$, $\alpha 2$, β	Dementia
Central frequency, Q1F, Q3F, ratio H/L, RH/L, SSD, IR, MaxF, AC, kurtosis coefficient	Burg's method with order = 20 [94]	δ, θ, α, β, γ	Drowsiness detection
Other PSD parameters	[21]	From the PSD graph, but sub-bands not mentioned	Identity authentication
Max to min power ratio	DWT (db4, levels = 5) [117]	δ, θ, α, β, γ	Emotion state recognition
Power ratios, product of powers	IIR Butterworth bandpass filters: 0.5–45 Hz [45]	δ, θ, α, sigma, β, γ,	Sleep stage classification
Valence, arousal	[48]	From α and β sub-bands	Depression
EEG alpha interhemispheric asymmetry	FFT (Welch method) [9]	From α band	Depression
DE, DASM, RASM	[24]	δ, θ, α, β, γ	Emotion recognition
Power percentage, gravity frequency, frequency variability	FFT [27]	δ, θ, α, β, γ	Drowsiness detection

Table 10 – Non-linear features.

Category	Features	Reference	Feature extraction method (if applied)	Sub-bands	Purpose
Entropy based features	Spectral entropy	[45]	Welch method	From the whole power spectrum	Sleep stage classification
		[51]	Not mentioned	From the whole power spectrum	Dementia
	Renyi Entropy	[45]	Welch method	From the whole power spectrum	Sleep stage classification
		[27]	DWT (db4)	A5, D5, D4, D3, D2	Drowsiness detection
	Kraskov entropy	[46]	FIR band pass filter	δ, θ, α, $\beta 1$, $\beta 2$, k-complex, spindle wave	Sleep stage classification
		[46]	EMD	7 IMFs	Sleep stage classification
	Shannon entropy	[106]	Raw/preprocessed signals	No sub-band divisions	Emotion recognition
		[67]	DWT (levels = 6)	D3, D4, D5, D6, and A6	Epilepsy and autism
	Centered correntropy	[54]	TQWT	Last detailed subband	Alcoholism
	Sample entropy	[51]	Raw/preprocessed signals	No sub-band divisions	Dementia
		[27]	DWT (db4)	A5, D5, D4, D3, D2	Drowsiness detection
		[22]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
		[22]	DWT (db4, levels = 4)	δ, θ, α, β	Sleep stage classification
	MSE	[88]	Raw/preprocessed signals	No sub-band divisions	Eye state recognition
		[89]			Sleep stage classification
	Fuzzy entropy	[51]			Dementia
		[66]	DD-DWT (levels = 5)	15 sub-bands – c1, c2, c3, c4, c5, d11, d21, d31, d41, d51, d12, d22, d32, d42, and d52	Epilepsy/seizure
		[22]	Raw/preprocessed signals	No sub-band divisions	Sleep stage classification
	Permutation entropy	[98]			Dementia
		[22]			Sleep stage classification

Table 10 (*Continued*)

Category	Features	Reference	Feature extraction method (if applied)	Sub-bands	Purpose
	MPE	[88]			Eye state recognition
	Tsallis entropy	[22]			Sleep stage classification
	Singular value entropy 1	[11]	GST and SVD		Seizure/epilepsy
	Singular value entropy 2				
	Approximate entropy	[27]	DWT (db4)	A5, D5, D4, D3, D2	Drowsiness detection
	Dispersion entropy	[95]	Band-pass filter	δ, θ, α, β, γ	Sleep stage classification
Fractral dimension	KFD	[46]	FIR band pass filter	δ, θ, α, $\beta 1$, $\beta 2$, k-complex, spindle wave	Sleep stage classification
		[46]	EMD	7 IMFs	Sleep stage classification
		[106]	Raw/preprocessed signals	No sub-band divisions	Emotion recognition
	PFD	[46]	FIR band pass filter	δ, θ, α, $\beta 1$, $\beta 2$, k-complex, spindle wave	Sleep stage classification
		[46]	EMD	7 IMFs	Sleep stage classification
	HFD	[46]	FIR band pass filter	δ, θ, α, $\beta 1$, $\beta 2$, k-complex, spindle wave	Sleep stage classification
		[46]	EMD	7 IMFs	Sleep stage classification
		[106]	Raw/preprocessed signals	No sub-band divisions	Emotion recognition
		[99]			Depression
		[49]			Depression
	FD	[47]			Emotion recognition
		[22]			Sleep stage classification
Fractral analysis	DFA	[46]	FIR band pass filter	δ, θ, α, $\beta 1$, $\beta 2$, k-complex, spindle wave	Sleep stage classification
		[46]	EMD	7 IMFs	Sleep stage classification
		[99]	Raw/preprocessed signals	No sub-band divisions	Depression
		[49]			Depression
Other complexity measures	LZC	[106]			Emotion recognition
		[49]			Depression
		[51]			Dementia
		[22]			Sleep stage classification
	KC	[106]			Emotion recognition
	CD	[99]			Depression
	Large Lyapunov exponents	[99]			Depression
		[22]			Sleep stage classification
	Hurst exponent	[22]			Sleep stage classification
		[66]	DD-DWT (levels = 5)	15 sub-bands – c1, c2, c3, c4, c5, d11, d21, d31, d41, d51, d12, d22, d32, d42, and d52	Epilepsy/seizure
	CTM	[51]	Raw/preprocessed signals	No sub-band divisions	Dementia
	AMI	[51]			Dementia
	Area parameters from RPS plots of rhythms using CTM	[70]	EWT	δ, θ, α, β, γ	Seizure/epilepsy
	LL2N	[100]	Six length BDL TCOWFB	7 wavelet sub bands	Depression
	Bispectrum features using HOS	[16]	Raw/preprocessed signals	No sub-band divisions	Dementia
	RQA	[27]	DWT (db4)	A5, D5, D4, D3, D2	Drowsiness detection
	LLE	[67]	DWT (levels = 6)	D3, D4, D5, D6, and A6 and db4	Epilepsy and autism

Table 11 – Functional connectivity based features.

Features	EEG application	References
Topological features based on PSI such as E_{global}, E_{local}, C, B_{nodal}, and B_{edge}	Dementia	[17]
RWECN	Fatigue classification	[111]
SL	Alcoholism	[15]
	Depression or stress	[12,102]
Phase lag index	Dementia	[52]
Cross-correlation	Epilepsy and autism	[67]

Table 12 – Feature selection methods.

Technique	EEG application	References
mRMR	Emotion recognition	[47]
	Sleep stage classification	[45]
Genetic algorithm	Emotion recognition	[47]
	Identity authentication	[20]
	Depression	[99]
Fast correlation-based filter solution	Dementia	[51]
	Sleep stage classification	[22]
Sequential forward floating selection	Identity authentication	[21]
	Sleep stage classification	[22]
Wrapper subset evaluation	Emotion recognition	[24]
Rank based Selection using ROC	Depression	[12,9]
	Alcoholism	[15]
Student *t*-test	Depression	[100]
	Alcoholism	[50]
	Parkinson	[16]
	Sleep stage classification	[95]
Correlation based method	Depression	[48]
Wrapper method	Depression	[48]
Kruskal Wallis test	Epilepsy/seizure	[70]
	Sleep stage classification	[46]
FDM, Kullback–Leiber, Bhattacharya distance, Gini Index, DM	Motor imagery	[77]
LDA	Drowsiness detection	[94]
ANOVA test	Eyes state detection	[109]
	Epilepsy	[66]
CfscSubset Eval Evaluator (weka toolkit)	Eyes state detection	[57]
Fisher Score	Sleep stage classification	[22]
Sequential forward selection	Sleep stage classification	[22]
RF	Sleep stage classification	[46]

Table 13 – Dimensionality reduction methods.

Dimensionality reduction method	Application	References
PCA	Depression	[99,48]
	Alcoholism	[54,50]
	Epilepsy/seizure	[61,63,64,68]
	Sleep stage classification	[45]
ICA	Epilepsy/seizure	[61,63]
KPCA, ISOMAP, LLE, and LE	Epilepsy/seizure	[61]
LDA	Epilepsy/seizure	[63]
Autoencoder	Multi-class task recognition	[87]
Generalized Gaussian distribution	Epilepsy/seizure	[74]
Compensation distance evaluation technique	Stress	[102]

Table 14 – Classification algorithms.

Classifiers	Applications	References
SVM		[12,48,9,100,101,47,117,14,15,50,77,83] [25,26,16,17,63,64,66,68,87,27,21,46]
LR		[12,9,99,49,101,100,23,15,26]
NB		[12,9,14,15,83,16,17,46]
LDA		[99,50,17,74,87,21]
KNN		[99,48,100,23,24,83,17,16]
GDA		[48]
LS-SVM		[100,14,54,70,61]
LD		[100]
Complex tree		[100]
Bagging		[100,78,46,21]
RF		[24,83,57,11,68,87,22,46,101]
CNN		[13,84,62,87,97]
QDA		[23]
MLP		[80,24,59,10,50]
DNN		[81,95]
LMT		[50]
Ensemble classifier		[77,78,22]
DT		[83,16,46,87]
ANN		[83,26,94]
Boosting		[78,22,87,46]
DBN		[59]
Dropout NN		[59]
Fuzzy KNN		[16]
PNN		[16]
Weighted/unweighted N-TSK		[17]
ME		[10]
Proposed USVM and UTSVM, USVM, TWSVM, UTSVM		[64]
MK-LSVM		[61]
Optimized SVM (GA-SVM)		[66]
GRNN		[72]
GBM		[68]
RNN		[87]
FLDA		[111]
ELM		[27]
GBDT		[22]
LSTM RNN		[45]
Hierarchical classification based on probabilistic output SVM and proportion based clustering		[89]
HDCA, optimized HDCA		[20]
GSLT-CNN, CV-CNN		[21]

MDD, AUD, etc.) or monitoring of other applications (such as emotion recognition, sleep stage classification, etc.) with the help of EEG signals. The machine learning classifiers such as supervised, unsupervised, deep learning neural architectures, and ensemble learning models are used for the classification purposes in various EEG research studies. Some important findings have also been concluded in the following sub-heading that have applied the statistical tests on the extracted features or other parameters for result analysis. The result analysis phase can be explained through classification models and statistical analysis as below:

(a) *Classification models*

The survey for classification algorithms for various EEG applications has been done into two parts:

(a) Table 14 gives an idea to the readers about the extent the particular classification algorithm has been explored for various applications. Ist column gives the name of the classification algorithm, second column signifies the applications which have worked upon these algorithms, and the third gives the reference of the application study. The color coding for the Table 14 has been explained in Table 15 where each color signifies the type of an EEG application.

(b) Table 16 summarizes the details of the best performing algorithms in the corresponding application

Table 15 – Color coding scheme for EEG applications.

Color	Application
	Depression
	Alcoholism
	Dementia
	MI
	Eye state recognition
	Identity authentication
	Emotion recognition
	Epilepsy
	Multi-class task recognition
	Drowsiness detection
	Sleep stage classification

Table 16 – Classification algorithms.

Classifiers	References	Application	Class labels	Division	ACC	SEN	SPEC	F-score	Others
SVM	[12]	Depression	2 (Normal and MDD)	10-fold CV	98	99.9	95	0.97	–
	[48]	Depression	2 (High stress and low stress)	10-fold CV	80.32	–	–	–	–
	[9]	Depression	2 (Normal and MDD)	10-fold CV	98.4	96.66	100	–	–
	[47]	Emotion Recognition	2, 3, and 5 classes each for Valence (V) and Arousal (A)	8-fold	2 Classes – 73.06 (A), 73.14 (V), 3 classes – 60.7 (A), 62.33 (V), 5 classes – 46.69 (A) 45.32 (V)	–	–	–	–
	[15]	Alcoholism	2 (AUD and normal)	10-fold CV	98	99.9	95	0.97	–
	[77]	Motor Imagery	2 (Left and right hand imagery movements)	Holdout and 5-times 10-fold CV	80 (Holdout), 78.57 (10-fold)	–	–	–	–
	[25]	Eye state detection	2 (EO and EC)	2-fold CV	86.08	–	–	–	–
	[16]	Dementia	2 (Parkinson and not)	10-fold CV	96.62	100	99.25	0.98	99.38 (Precision)
	[63]	Epilepsy	2 (Normal and epileptic)	800 samples for training and 800 for testing	100	100	100	–	–
LR	[99]	Depression	2 (Normal and depressed)	LOOCV	90	–	–	–	–
	[49]	Depression	2 (Normal and depressed)	LOOCV	92	–	–	–	–
	[101]	Depression	2 (Normal and MDD)	0.8–0.2	72.41	86.21	–	0.7576	67.57 (Precision)
	[23]	Depression	2 (Congruent and incongruent conditions)	LOOCV	81.1	–	–	–	–
	[26]	Eye state detection	2 (EO and EC)	5-fold CV	88.2	–	–	0.882	Detection of eye states takes 2 s
Weighted N-TSK	[17]	Dementia	2 (AD and control)	Data for 46 subjects used as training and 16 as testing	97.30	95.48	98.32	–	–
LS-SVM	[100]	Depression	2 (Normal and depressed)	10-fold CV	99.58	98.66	99.38	–	1 (AUC), 0.991 (MCC)
	[14]	Alcoholism	2 (Alcoholic and non-alcoholic)	10-fold CV	99.17	99.17	99.17	99.16	99.44 (Precision), 0.9833 (MCC), 0.9933 (AUC)
	[54]	Alcoholism	2 (Alcoholic and normal)	10-fold CV	97.02	96.53	97.5	–	0.9494 (MCC)
	[70]	Epilepsy	2 (Focal and non-focal)	10-fold CV	90	88	92	–	–

Table 16 (*Continued*)

Classifiers	References	Application	Class labels	Division	ACC	SEN	SPEC	F-score	Others
	[61]	Epilepsy	2 (interictal and ictal)	10-fold CV	99.67	–	–	–	–
CNN	[13]	Depression	2 (Normal and depressed)	0.9–0.10/10-fold	95.49	94.99	96	–	1 (AUC), 0.991 (MCC)
	[84]	Motor imagery	2 (Right hand and right foot)	0.80–0.20	99.35	98.80	100	0.994	0.9869 (Kappa coefficient)
	[62]	Epilepsy	3 (Normal, pre-ictal and seizure)	0.9 (0.70–0.30)–0.10 with 10-fold CV	88.67	95	90	–	–
	[97]	Sleep stage classification	5 (Wake, N1, N2, N3 and REM)	0.5–0.2–0.3	87	–	–	0.87 (F1-micro), 0.78 (F1-macro)	0.81 (Kappa)
MLP	[80]	Emotion Recognition	2 (Happy and sad)	Out of 32 subjects, data for 30 used as training and 2 as testing	58.5	–	–	–	–
LMT	[50]	Alcoholism	2 or 3(Alcoholics, alcohol abusers, and controls)	10-fold	96	97	93	0.97	0.97 (AUC)
KNN	[24]	Emotion recognition	2 (Boredom and non-boredom)	10-fold	86.73	–	–	–	0.92 (AUC)
	[83]	Motor imagery	2 (Right hand and right foot)	10-fold	94.57	–	–	–	–
DNN	[81]	Emotion recognition	Low/high each for Valence (V) and Arousal (A)	Out of 32 subjects, data for 30 used as training and 2 as testing	62.50 (V), 64.25 (A)	–	–	–	–
	[95]	Sleep stage classification	4 and 2 from stages (W, S1, S2, S3, S4 and REM)	10-fold	sleep vs wake: 85.51, light sleep vs deep sleep: 94.03, NREM vs REM: 95.71	–	–	–	–
	[26]	Eye state detection	2 (EO and EC)	5-fold	88.2	–	–	0.882	Detection of eyes state takes 2 s
	[94]	Drowsiness detection	2 (Alert and drowsy)	0.70–0.30	85.5	–	–	–	–
RF	[57]	Eye state detection speed = 639.5 samples/s	2 (EO and EC)	0.66-0.34	99.8	–	–	–	Classification
	[11]	Epilepsy	2 and 3 (Normal, interictal, and ictal)	10-fold	99.63 (seizure vs non-seizure)	–	–	–	–
	[46]	Sleep stage classification	5 (N1, N2, N3, REM, W)	2-fold	89.4	–	–	–	–
Dropout NN	[59]	Eye state detection	2 (EO and EC)	Holdout (0.8–0.1–0.1), 10-fold CV, LOOCV	97.5 (Holdout)	–	–	–	Classification speed = 1.9 s
ME	[10]	Epilepsy	2 (Epileptic and normal)	1000 samples for training and 600 for testing	94.5	95	94	–	–

Table 16 (Continued)

Classifiers	References	Application	Class labels	Division	ACC	SEN	SPEC	F-score	Others
Proposed UTSVM	[64]	Epilepsy	2 (Healthy and seizure)	0.5–0.5	99	–	–	–	Training time = 0.01756 s
MKLSVM	[61]	Epilepsy	2 (Interictal and ictal)	10-fold CV	99.83	–	–	–	–
GA-SVM	[66]	Epilepsy	2 or 3 (healthy, inter-ictal. ictal), (inter-ictal and ictal), (seizure and non-seizure)	10-fold CV	–	100	100	–	100 (PPV)
GRNN	[72]	Epilepsy	2 (pre-ictal and inter-ictal)	Training and testing: approximately half (labelled training data, unlabelled testing)	–	–	–	–	Prediction rate = 91.6%
GBM	[68]	Epilepsy	3 (ictal, intermittent, and healthy)	10-fold CV	96.5	–	–	–	0.9695 (AUC)
LDA	[74]	Epilepsy	2 (seizure and non-seizure)	LOOCV	–	98	88	–	Average detection latency of 4 s thus very fast method
XGBoost	[87]	Multi-class task recognition	5 tasks (public dataset)	532,000 samples for training and 28,000 for testing	0.794	0.781	–	0.7883	0.9456 (AUC)
	[87]		6 tasks (local dataset)	155,520 samples for training set and 17,280 samples for testing	0.7485	–	–	–	–
FLDA	[111]	Drowsiness detection	2 (Alert and fatigue)	10-fold	–	–	–	–	Proposed method shows improved performance than traditional approach
ELM	[27]	Drowsiness detection	2 (Alert and drowsy)	LOOCV	95.6	96.8	94	–	Accuracy = 96.9 (EEG + EOG)
Ensemble classifier	[22]	Sleep stage classification	6 (awake, NREM1, NREM2, NREM3, NREM4, REM)	0.70–0.30 with 5-fold CV	96.67	–	–	–	0.96 (Kappa coefficient)
	[77]	Motor Imagery	2 (Left and right hand imagery movements)	Holdout and 5-times 10-fold CV	80 (Holdout), 78.57 (10-fold)	–	–	–	–
	[78]	Motor Imagery	2 (Left and right hand movement)	0.5–0.5 (holdout technique)	85.71(Adaboost (Mix boost ensemble))	–	–	–	–
LSTM RNN	[45]	Sleep stage classification	5, 4 and 2 (N1, N2, N3, REM, W)	0.80–0.10–0.10 with 10-fold CV	86.74 (five classes)	–	–	–	–

Table 16 (Continued)

Classifiers	References	Application	Class labels	Division	ACC	SEN	SPEC	F-score	Others
Hierarchical classification based on probabilistic output SVM and proportion based clustering	[89]	Sleep stage classification	5 (W, S1, S2, SWS, and REM)	2-fold CV	91.4	–	–	–	–
Optimized HDCA	[20]	Identity authentication	2 (self-face and non-self-face)	5-fold CV	94.26	–	–	–	–
GSLT-CNN	[21]	Identity authentication	2 (self-face and non-self-face)	5-fold CV	96 (157 subjects)	–	–	–	–

studies as- name of the algorithm, reference of the study, type of an application, class labels, division of the dataset into training, validation (in some cases) and testing datasets or name of the Cross Validation (CV) technique if used for computing the performance parameters, and the rest of the columns give performance of the classifiers in the form of various parameters such as accuracy (ACC) in (%), sensitivity (SEN) in (%), specificity (SPEC) in (%), f-score, and other parameters (such as precision (%), MCC, etc.).

(b) *Statistical analysis*

There are some application studies that have used different statistical tests for EEG signal analysis. Table 17 describes the name of the statistical test, features or parameters on which the test is applied, results, and purpose or the application for which the tests are used along with their references.

7. Other research studies

There are some research studies that have been separately summarized in Table 18 with their important findings. Some of them have worked upon the ERP measures or the evoked potentials [107,112,114] for developing various applications based on EEG signals, while we came across two studies that are based upon classifying two neurological disorders simultaneously – (epilepsy and autism) [67] and (epilepsy and alcoholism) [55], another study is using a combination of ECG and EEG signals to classify the sleep stages [95], then stress analysis is done using EEG, salivary cortisol level test, and VAT [102], one study is proposing the circuit to make reliable ERP measurements using low cost Emotiv Epoc+ headset [108], then the visual comfort level for stereoscopic images are predicted using a combination of EEG signals and eye tracking data [113], images are used instead of signals for classifying the MI tasks [84], and the MDD patients are classified from normal subjects by using a combination of EEG signals, GSR, and eye tracking data in another study [101]. For the attribute 'Dataset' in Table 18, the description for the data collection has already been summarized in Section 5.

8. Research gaps and future directions

Unlike the other functional neuroimaging techniques, that are only useful in diagnosing various neurological disorders, EEG signals are successful in monitoring the other applications too, such as identity authentication, emotion state recognition and designing the BCI systems. The subtle variations that come in the long EEG recordings are very difficult to analyse, time consuming, and their analysis depend upon the human expertise. The signal processing and machine learning algorithms based on computer aided technologies have been proven as the beneficial tools for the research. These extract the most important ncharacteristics from the EEG signals and help to design the automated systems that can reduce the human burden and increase the accuracy of the models. In healthcare, the brain signals of the patients can be fed to the

Table 17 – Statistical analysis.

Method	Feature	Result	Purpose
t-test	Alpha band power for both the hemispheres for depressed and normal	Significant difference of $p < 0.05$ for alpha band power is found between two groups (depressed and normal) in: • Five electrodes (C3, P3, O1, F7, T3) of left hemisphere. • One electrode (O2) of right hemisphere. • Higher values for depressed than normal.	Depression [99]
Statistical test	Power, Alpha interhemispheric for depressed and normal	• Less power in alpha and theta bands in all the regions (central, occipital, frontal, parietal and temporal) for depressed than normal. • For MDD, it is more in right region than left for frontal region and for rest of regions it is vice-versa. For normal, both the cases are reverse. • Significant difference of $p < 0.01$ for both parameters is found between two groups (depressed and normal).	Depression [9]
Mann–Whitney test	SASI, APV, RGP, HFD, DFA, LZC for normal and depressed	• Higher values for parameters for depressed than normal. • Significant difference ($p < 0.05$) found for APV, RGP and HFD between two groups (depressed and normal).	Depression [49]
ANOVA, ROC	KFD, HFD, LZC for MDD and normal	• Higher values of complexity measures are found for MDD than normal – significant difference of $p < 0.01$, $p < 0.05$ and $p = 0.05$ are found for features of KFD, HFD and LZC respectively in frontal and parietal locations. • When subjected to noise, MDD show more complexity than normal. • For MDD, more complexity seen when subjected to noise than music. • For normal, significant difference found in frontal ($p < 0.05$) and parietal ($p = 0.05$) regions for the parameters when subjected to music than restline state. • For MDD, significant difference found in frontal region ($p < 0.05$) for KFD and LZC when subjected to music than restline state.	Emotional state recognition [106]
t-test, chi-square	Power, SDS score and other parameters for normal and depressed	• No significant difference between age, gender and marital status. • Significant difference found for SDS score ($p < 0.01$) between two groups. • Significant difference of ($p < 0.05$) found in EEG power of theta, alpha, beta and gamma bands, lower values are observed for MDD.	Depression [101]
Wilcoxon signed ranked test, Friedman test, Bonferroni-corrected	Stress is induced under external stimuli for normal subjects. Reaction times were observed for congruent and incongruent condition for subject and also performance of classifiers is also observed under the two conditions	Significant differences ($p < 0.01$) found in: • Reaction time of subject for congruent and incongruent condition. • LR and QDA work superior to 3-NN for fused features. Significant differences ($p < 0.05$) found in: • Classifier for four electrodes (F3, F4, F7 and O2).	Depression [23]
t-test	AP and RP for both EO and EC	• For AUD and controls, significant difference of $p < 0.01$ for AP and RP for theta band in both EO and EC. • For alcoholics and alcoholic abusers, significant difference of $p < 0.01$ for AP and RP for delta band in both EO and EC. • Overall, RP shows more significant results than AP.	Alcoholism [50]
One-way ANOVA	MSE	• Eight values for MSE were chosen according to their *p*-values ($p < 0.001$ and $p < 0.5$) for each classification level of hierarchy. • MSE curves for two channels (Fpz-Cz and Pz-Oz) are same for healthy people and people with mild difficulty in sleeping.	Sleep stage classification [89]
Bonferroni test	Cortisol level	• Its value increases immediately after the stress test and after the recovery of stress with a significant difference of $p < 0.001$ as compared to the pre-stress condition	Stress [102]

Table 17 (*Continued*)

Method	Feature	Result	Purpose
ANOVA test, ROC	Peak powers, their corresponding frequencies and ratio of peak power and frequency derived from PSD for normal, epileptic and alcoholic using Welch, Yulker walker and Burg's method	• Very low p-values for the features for burg's method. • For ROC, burg's method gives the most distincting results.	Alcoholism and epilepsy [55]
t-test	EPN	• Significant difference of $p < 0.001$ is observed values of EPN for occipital electrodes O1 and O2 under the emotion effects	Emotion state recognition [108]
Mann-Whitney test, ROC	MPE and MSE for EO and EC	• Higher significant results found for MPE ($p < 0.05$) than MSE. Higher significant difference for MPE found at electrodes: F5 0.00001 Fp1 0.000028 F2 0.00001 F4 0.00013 Fp2 0.00017 P4 0.0163 P3 0.0179 O1 0.023 • For ROC, maximum value of AUC at F5 (AUC = 0.90750) and we get p value for F5 = 0.00001	Eye state recognition [88]
Wilcoxon rank-sum test	PSI	• Significant difference of $p < 0.01$ between AD and control for PSI value. • Lesser PSI value for Alzheimer patients depicts the weaker functional connections than healthy subjects. • Significant difference of $p < 0.01$ between AD and control for E_{global}, E_{local} and C, the values of these parameters are lower for AD patients than normal subjects. • Significant difference of $p < 0.01$ between AD and control for B_{nodal} and B_{edge}, the values of these parameters are higher for AD patients than normal subjects.	Dementia [17]
t-test	Wavelet entropy and RWECN	For states alert and fatigue, significant difference of $p < 0.01$ for wavelet entropy and RWECN.	Driver drowsiness [111]

models that give automated decisions about their disorder, thus reducing the time of the patients as well as the doctors in hospitals. Even the prediction models can be developed using EEG signals that keep on monitoring the mental state of the person and depending upon the change in behaviour, a warning system can be generated that help the patients to reduce the risk of the disease. Suppose in one case, if the seizure attacks of a person can be predicted in advance, a lot of accidents or injuries can be prevented and in another case, the progression of the disease can also be measured like MCI can lead to the Alzeihmer if not taken seriously or normal stress can lead to MDD if not diagnosed in advance. In other applications too, the different functional states of the brain can be analysed by the automated systems based on EEG signals and help to design the applications such as authenticating the identity of the person, designing the warning systems to alert the drivers about their drowsy state and so on. The BCI systems based on EEG signals can help the disabled people a lot to perform their daily tasks such as controlling their wheel chairs, closing or opening the doors of the lifts with their motor imaginary based brain signals, controlling the television screen in their houses or work environments to perform different tasks and so on. The various research gaps and the future directions have also been suggested by the authors in their studies based on different applications of EEG signals. These have been summarized in Table 19. The most common ones are:

(a) The unavailability of larger datasets for most of the applications that restricts the validation of the models for practical use and restricts their feasibility for clinical use.
(b) The need of the hour is to develop the mobile, portable and cheap models that are computationally less intensive and requires less storage space.
(c) The model should be simple and consists of least number of EEG channels.
(d) The real time data is full of artifacts, so very efficient filtering techniques need to be proposed that help to reduce the noise and increase the performance of the models.
(e) A variety of feature extraction techniques and machine learning classifiers can be explored for different datasets.

Table 18 – Other research studies.

Purpose	Dataset	Methodology	Findings
Emotion recognition [107]	Own dataset	Single trial ERP and latency features + SVM (polynomial)	• The ERP attributes have been directly obtained from the filtered EEG signals at different latencies. • 4 class emotion classification has been performed with good accuracies under the subject independent as well as subject dependent scenario. • The proposed methodology in this study motivates to develop the real time applications based on emotion classification with reduced processing time.
brain computer interface [112]	Own dataset	SSVEP responses	• An asynchronous SSVEP based BCI system for spelling interface for high frequency RVS has been developed using a single EEG channel. • LASSO algorithm has been adopted as the frequency detection method to evaluate the SSVEP responses in the range 6-60 Hz. • The frequency set of 35-40 Hz is best suited for BCI with best accuracy of 99.2%, ITR of 67.1 bit/min and maximal user comfort level of 80%.
Visual, auditory, and somatosensory stimulations [114]	Own dataset	VEP, AEP, and SEP measured under different stimulating conditions.	• The best positions on the scalp have been investigated for the measurement of the evoked potentials so that the wearables with few electrodes can be used for real time EEG applications. • The activities occurring due to the visual, auditory, and somatosensory stimulations are detected in the Lobus Occipitalis and Lobus temporalis. • The combination of VEP, AEP, and SEP can be detected at Oz, O1, O2, TP9, and TP10. • It is also investigated that segmentation frequency should match the stimulation frequency with an accuracy of at least 99.92% for VEP detection and 99.95% for AEP and SEP detection.
Epilepsy and autism [67]	Own + public dataset	DWT, Shannon entropy and KNN	• Based on two class scenario: Epileptic vs normal for single channel and autistic vs normal for single and multi-channel, as well as three class scenario: epileptic vs normal vs autistic for single and multi-channel. • Thus it is able to classify the data for two neurological disorders (autism and epilepsy) at the same time. • It gives an overall accuracy of 94.6% for the three class classification scenario.
Alcoholism and epilepsy [55]	Public dataset	PSD using Welch method and AR model	• Analysis has been done to distinguish the normal, epileptic and alcoholic subjects using ROC method. • Burg's method gives the most distinguishing features.
Sleep stage classification [95]	Public dataset	ECG (IMFs) + EEG (sub-bands): (RQA, dispersion entropy and variance) + Deep neural architecture	• The proposed method is able to get the highest classification accuracies for different combinations of classes using the features from both the RR-time series (ECG) as well as EEG data. • Uses only the single channel data recordings of both EEG and ECG data. • Simulation time for evaluating the features from RR time series and EEG signals take 0.03 and 4.89 s respectively, classification using both the features takes 0.275 s.
Stress [102]	Own dataset	SL + CDET + SVM (RBF)	• Salivary cortisol levels and VAT are also measured along with EEG to check the stress level changes during the three different scenarios. • The effect of stress vanishes after 20 min of the test. • Accuracies for EO and EC for alpha waves are 74.32% and 91.21% respectively, i.e., alpha waves are more sensitive to anxiety in EC state. • Accuracies for EO and EC for beta waves are 92.31% and 93.62% respectively. • Good classification accuracies for alpha and beta bandwidths are observed for monitoring the stress levels.

Table 18 (*Continued*)

Purpose	Dataset	Methodology	Findings
Emotion state recognition [108]	Own dataset	ERP and stimuli display timestamps, EPN	• The marking circuit for determining the stimuli display time stamps has been proposed for attaining the reliable ERP measurements in case of low cost Emotic Epoc+ headset. • Differences can be observed for EPN components under the effect of different facial expressions using the proposed modifications. • The proposed scheme can be a very good solution to carry out the research using the low cost EEG devices.
Visual comfort level of images [113]	Own dataset	Multi-taper method + Eye tracking features and EEG activity from frontal lobe	• This aims at finding the set of significant features for predicting the visual comfort level for stereoscopic images. • The best results are found for 2-s and 5-s pre-DPI windows for the selected feature set. • Increased activity was observed for beta, theta-alpha ratio, alpha-high beta ratio in case of visually uncomfortable stereoscopic perception.
Motor imagery [84]	Public dataset	Signals transformed to images using STFT and CWT + AlexNet	• The EEG signals are not directly used instead the transformed images are fed to the deep CNN to classify the motor imagery tasks. • CWT performs better than the STFT transform. • Overall accuracy of 99.35% is achieved through the proposed approach.
Depression [101]	Own dataset	EEG, GSR, Eye tracking data + LR	• Using only EEG signals gives an f1 score of 75.76% for classification of MDD and normal. • The combination of EEG, eye tracking and GSR data achieves an improved performance with f1 score of 80.70%.

Table 19 – Research gaps and future directions.

Purpose	Research gaps and future directions
Depression	• Hospitalized MDD patients can be explored for more realistic results [101,12,9]. • The depression study is still under-diagnosed among the older subjects, so there is a scope to carry further study on the depressed older patients [101]. • Smaller dataset is the limitation of the most of the studies [12,100,99,49,9,48]. • For more detailed analysis, EEG can be combined with other modalities such as fMRI or fNIRS. • More heterogeneous dataset can be collected covering the different severity stages for depression and people of varied age groups and genders [100,13,49]. • The most effected regions of the brain due to depression need to be found and also EEG data can be collected under varied conditions instead of rest state only [99]. • The various modalities such as EEG, GSR, and eye-tracking can be integrated to get high performance for the classifier models. • Significant hemispheric asymmetry can be observed in MDD patients by including more number of EEG channels [101]. • Apart from low and high, more number of classes of stress can be studied further by using voting algorithms, etc. [48]. • To the best of our knowledge, there are no public datasets available for depression based on EEG signals, so it is a challenging task to collect the own heterogeneous dataset of MDD patients for different age groups using the different EEG headsets. • Most of the research studies are carried out under the laboratory conditions, they need to be tested in mobile and non-laboratory environment for real time deployment of research models in daily life. • For more detailed analysis, EEG data can be combined with the other parameters such as heart rate, blood pressure, breathing patterns, and body posture. • The levels of various biomarkers such as cortisol, alpha amylase enzyme and catecholamine should also be observed for more validated results. • To the best of our knowledge, no datasets are available for depression and stress, so efforts can be made to collect the own dataset covering the various levels of the problem in varied age groups such as workers at construction sites, children in school or the youth taking the drugs due to the various life stresses.
Alcoholism	• The work can be carried further on the bigger datasets with proper selection of participant's biological characteristics such as age group, gender, etc. [14,15,54,50]. • Systems consuming lesser storage space need to be designed [54].

Table 19 (*Continued*)

Purpose	Research gaps and future directions
	• The automated machine learning methods can be combined with various traditional alcohol screening methods such as questionnaire based to achieve higher efficiency of the system and make its deployment feasible in clinical practice [50].
Epilepsy/seizure	• Most of the research studies have focused on the dataset provided by Bonn University, Germany. It has been made available publicly for more the last 15 years and is small and less comprehensible. So, it is required to work upon more larger and comprehensible datasets. • The intracranial EEG recordings for epilepsy need to be replaced with more effective and simpler solutions based on scalp EEG. • New methods can be proposed in order to automate the selection of optimized kernel parameters for LS-SVM used in the study [70]. • The performance can be further improved by working on larger datasets, extracting much better features, using more pre-processing methods and using more machine learning classifiers [70,61,62,11,66]. • A work can be done to design new muscle artifact removal techniques in order to filter the epileptic dataset used in the study [61]. • Apart from epilepsy, the proposed methodology can be used for the diagnosis of various neurological disorders based on EEG signals such as Alzheimer, coronary artery disease [61,11]. • Bagging algorithms can be used to increase the performance of the proposed work [62]. • Efforts should be made to develop the research models that use least number of electrodes in order to make the wearable, portable and mobile applications to be deployed in real time applications. • Work can be done to improve the computational time of the study and to solve the multi-class classification problems based on EEG signals [64]. • Research on seizure studies can be extended to work upon more different number of time-frequency transforms [64]. • Optimized-SVM can be used for the diagnosis of other classification problems due to its splendid ability of classification [66]. • Different severity stages of the disease can be studied for deeper analysis or for understanding the progression of the disease [67]. • Alzeihmer can also be included in the given classification problem along with epilepsy and autism [67]. • Optimized GSO can be used for the automatic selection of optimized parameters for different classifiers [68] or even some other optimization algorithms can also be used for the selection procedure. • Prediction models based on early warnings before the onset of epileptic seizures can be designed that can help to avoid severe accidents or injuries. • The long-term EEG recordings can be used for thorough evaluation of the proposed work [74]. • The false positives that occur due to the noise and random peaks in the epileptic signals can be handled by adding the regularization parameters at the training stage [74]. • It is necessary to track the dynamic offsets arising due to the seizures because they lead to the degradation in classification performance [74]. • The source location for EEG signals is required in order to characterize the spatio-temporal wave patterns [74].
Identity authentication	• The bigger datasets containing data for multiple days, tasks, and sessions are needed to build more validated models for biometric identification [21]. • The authentication models needs to be designed for personal needs keeping in mind the requirements such as high performance and low cost. • Portable EEG devices such as Emotiv Epoc can be used for the research purposes so that the models can be deployed in practical scenarios [20]. • The performance of the system can be improved further by choosing a set of more random people who are not a part of the training phase, thereby giving more realistic results [20].
Alzeihmer	• Large and heterogeneous dataset for MCI needs to be collected and analysed for MCI and its various sub-types. Also the study about the progression of MCI to Alzheimer can be worked upon [51]. • More advanced classification algorithms such as spiking neural networks and SVMs can be included in the work as an extension [51]. • The combination of fuzzy systems and functional networks can be used as an effective tool for the automatic diagnosis of various neurological diseases by making use of various machine learning algorithms [17]. • The potential biomarkers for AD can be explored with the help of N-TSK system [17]. • The early warning systems of AD with the help of machine learning algorithms can be designed. • The concept of network theory can be integrated with the unsupervised or semi-supervised learning methods to improve the identification performance.
Sleep stage classification	• The accuracy for the NREM1 stage can be improved by using different feature extraction and analysis techniques [46]. • Analysis can be done on the patients with sleep related disorders. • Large and heterogeneous databases can be used for more validated results. • Sleep stage classification can be improved by using multiple channels of EEG and more physiological signals such as EMG and EOG can be combined with the EEG signals for improved performance [97,46]. • The combination of RNN and CNN can be used where the raw signals are fed to the CNN for the feature extraction and RNN does the classification task [45].

Table 19 (*Continued*)

Purpose	Research gaps and future directions
	• CNN and RNN can be used for the spatial and the temporal extraction of features respectively [45]. • Classification performance for the 'wake' stage can be improved and also the layer by layer errors that arise in the hierarchical structure needs to be handled [89]. • More non-linear features such as HOS, entropies and teager energy as well as the deep learning architectures can be used for high performance results [95]. • Study for sleep stage classification can be done on the patients with disorders such as bruxism, epilepsy, and insomnia using various non-linear features [95].
Motor imagery	• An adaptive scheme for selection of k-value (parameter for selecting the feature sub-set in the FDM) is required to be developed with the aim to increase the discernibility between the decision classes [77]. • Various time-frequency methods can be used to convert the signals into the images [84]. • The study can be extended on exploring the various CNN models such as VGGNet, ResNet and GoogleNet [84]. • The different types of classifiers can be ensemble in a mixture mode to get more improved performance results [78]. • Bigger datasets can be explored for the research work for more validated results. • A lot of scope is there to carry research studies on neuroprosthesis for designing the BCI systems for disable people.
Eye state recognition	• Many of the research studies are based upon the UCI dataset for eye state recognition which is a very small dataset containing the data samples for a single user. So, the research can be extended on bigger datasets for more validated results. • Temporal RBMs for time-series data models can be used for more improved learning [59]. • Work can done to increase the classification speed of the proposed models by following the algorithms having the less intense and fast computations. • The ensemble of deep learning architectures may be proven as the effective models for the classification problems based on time-series data [59]. • The dataset for eye state recognition can be used for controlling various applications such as BCI, driver drowsiness, and home automation. • The fuzzy cognitive maps generated using LSTM and GA can be merged with IoT to provide person-centric monitoring in the healthcare applications [58].
Emotion state recognition	• Work can be done on more than two emotional states so that the model can be deployed to control the real-time applications such as brain controlled wheel-chairs, video-games, etc. [80,47]. • More number of classifiers can be explored as an extended research work [80]. • Bigger and balanced datasets can be used for the research. • Overfitting issues can be solved for improved performance results [24]. • GSR data can be combined with EEG to gain higher accuracies [24]. • More model design parameters such as the different frequency bands, number of subjects, etc., can be varied for the testing the performance of the study [47]. • More number of complexity measures such as RQA, HOS, and sample entropy can be used to analyse the MDD patients under different emotional states [106]. • The proposed methodology can be applied to the other neurological disorders such as schizophrenia, epilepsy, and bipolar depression with the aim to compare the findings for all the studies [106]. • The factors such as level of severity, gender and the medication status of the subjects should also be considered in the research work as a part of more detailed analysis [106]. • Deep neural architectures such as RNN can be used for the classification [81]. • Advanced filtering techniques and averaging methods can be designed in order to pre-process the data taken using the Emotiv Epoc+ headset in the research studies [108].
ERP related	• The concept of evoked potentials can be leveraged to find the least number of electrodes for various EEG applications [114]. • The various machine learning techniques can be combined with the ERP features for improving the classification performance [108].

Deep learning and ensemble architectures can help to improve the accuracy of the models.

(f) Non-linear and functional connectivity features can be studied for various applications to understand the complexity of the EEG signals.

9. Multi-modal fusion of brain signals

Integrating the brain signals from different neuroimaging modalities can give better understanding and analysis of neuronal activities. This fusion gives a more clear picture of the neuronal structure and functions and can help in finding the more accurate biomarkers for diagnosing various neurological and neuropsychiatric disorders. For an instance, EEG and fMRI as the single modalities may not give high spatial and temporal resolutions respectively. But their fusion can achieve both. Now-a-days, the fusion of data from multiple modalities is considered as a new research challenge because different modalities may represent the data in the form of uncommon patterns and with different orders and it is not easy to directly fuse them. In the present work, we have explored some of the research studies which have contributed in proposing the

Table 20 – Multi-modal fusion of brain signals.

Application	Data	Methodology	Future scope/limitations
Schizophrenia [127]	• EEG + fMRI + sMRI • HC: 21, Schizophrenia patients: 11 during an auditory oddball task (AOD).	• Structure-revealing CMTF (coupled matrix and tensor factorization) method (advanced CMTF), as a fusion method, has been used to exploit the potential biomarkers for diagnosis of schizophrenia. • It aims at finding the unique features for identifying the patients using multi-modal data with shared and unshared patterns. • It is able to provide excellent temporal and spatial resolution.	• Done on limited number of patients. • Study can be carried forward to different neurological disorders. • Pre-processing the fused data is a new area of interest.
Brain–computer interface [128]	• EEG + NIRS (near-infrared spectroscopy) • HC: 14 (right-handed participants) under cue-based paradigm	• An asynchronous BCI system has been developed to accurately detect an idle class. • Two subject-dependent classification algorithms have been proposed. • Two subject-dependent classification algorithms have been proposed. • The hybrid EEG-NIRS model is not only successful in improving the classification performance but also improves the delays of the overall model that are caused due to the slow hemodynamic response of NIRS.	• The model needs to be validated in real-time asynchronous BCI-based paradigm.
Alzeihmer [129]	•MRI + PET + CSF • 200 normal instances, 400 MCI instances, 200 AD patients	• Zero-masking method has been used to fuse the data from multiple modalities. • A deep learning architecture combining the multi-modal data for computer-aided diagnosis of AD has been presented. • A performance gain has been achieved for binary and multi-class classification scenario.	• Four-class classification performance is required to be improved for deployment of the model in clinical scenarios. • More number of training samples with smaller variance are required to check the validity of the model.
Alzeihmer [130]	• Voxel based morphometry (VBM) + fluorodeoxyglucose positron emission tomography (FDG) + F-18 florbetapir PET scans amyloid imaging (AV45)	• The present fusion methods have following limitations: – unable to preserve the structure information while fusing the data from different modalities, – the contributions of the samples from different data is considered as equal in the fused data. • To address the above problems, a latent correlation embedded multi-modal fusion (LLM2F) algorithm has been proposed. • This method is able to provide compact representation of the multi-modal data by exploring the latent correlations among the different modalities and fusing the data into a common feature level. • To dynamically evaluate the contribution of each sample in the fused model, a self-optimized learning method has been adopted.	• In future, focus can be laid on solving the non-convex optimization problem in multi-modal fusion models.
Epilepsy [131]	• EEG + fMRI	• At the time of data fusion from multiple modalities, a joint BSS (blind source separation) problem arises. This has been mathematically formulated in the present work.	• In future, efforts will be made to better understand why jointICA and CMTF are able to provide stable EEG and fMRI voxel signatures respectively.

Table 20 (*Continued*)

Application	Data	Methodology	Future scope/limitations
	• Epilepsy patients: 5 (right temporal) and 5 (left temporal)	• To solve the above issue, different approaches such as joint independent component analysis (jointICA) and coupled matrix-tensor factorization (CMTF) have been presented as solutions. • These have been used to fuse EEG and fMRI data for analysing the interictal activities with high spatio-temporal resolution.	• Efforts will be made to explore more advanced models such as advanced matrix-tensor decomposition (ACMTF).

solutions for fusing the data from multiple modalities. These have been tabulated in Table 20.

10. Conclusion

The functional neuroimaging capabilities such as excellent temporal resolution, non-invasiveness, inexpensiveness, and safe nature makes the study of EEG to be very crucial for understanding the dynamically changing complex processes of the brain. The varied frequency rhythms are associated with different functional states of the brain. Any minute changes in the frequencies of these rhythms can be well captured by the EEG signals. These signals are analysed with the help of computer-aided technologies with greater accuracies and speed.

The present study explores a number of data acquisition methods for wide variety of applications based on EEG signals. A comparative analysis of the signal processing methods has been made that involves a number of pre-processing, feature extraction, and postprocessing techniques. Then, the result analysis stage is discussed, mainly focusing on the classification methods based upon various machine learning models. From the studies, it can be concluded that every stage has its own crucial role in processing the raw EEG signals. Each of the stages- preprocessing, feature extraction, post-processing, and result analysis play a very significant role in processing the raw time-domain EEG signals for developing the computer-aided automated decision models. Pre-processing the raw signals at the first stage diminishes the unwanted frequency components and noise from the signals, thereby, enhancing the quality of the signals. At next stage, various feature extraction methods are adopted to represent the high-dimensional EEG data in the form of most discriminating features, without this step, the performance of the decision model might get degraded. Then, if the data is still very high dimensional or suffers from a problem of overfitting, feature selection and reduction algorithms play their significant role, thereby reducing the burden on the computational resources and cost of the model. The signals are still of no use, unless they are not processed through the classification models (such as traditional algorithms or deep learning architectures) or the statistical tests for some decision making or deducing some findings through them. From the survey, it can be concluded that maximum number of studies are preprocessing the signals with the help of artifact handling methods, then for feature extraction studies, maximum studies have worked upon the statistical features and in future, there is a greater scope to work upon the functional connectivity based features, then post-processing is done with the aim to reduce the computational burden, for that, maximum studies are based upon selecting the most significant features with the help of various feature selection methods, and lastly, for the result analysis phase, maximum number of studies are focusing on the classification algorithms for developing the automated recognition systems for various applications.

It is very time consuming and tedious task to manually analyse the complex and non-stationary EEG signals and the analysis results vary a lot depending upon the expertise experience of the visualizers. So, now-a-days, a lot of research is going on analysis the EEG signals using various computer-aided technologies that could automate the analysis task thereby giving fast and highly accurate results. From the survey, it can be concluded that these computer-based systems make use of various signal processing and machine learning schemes to automatically conclude the happening of some neuronal activity using EEG signals. Computer-based programming languages or softwares such as MATLAB, python, R, WEKA, and so on are used to implement these signal processing methods and machine learning techniques. It can be concluded that EEG based computer-aided systems have shown their potential successfully in various research applications, covering the diagnosis of different neurological disorders such as epilepsy/seizure, alcohol related disorders, depression, and dementia to the monitoring of other applications including emotion recognition, identity authentication, sleep stage classification, eye state detection, motor imagery and drowsiness monitoring. Then, the future scope of the various studies has been summarized in order to inspire the readers to take the study of EEG signals based on computer-aided technologies to more higher level of research. Finally, some of the research studies have been explored that focuses on the fusion of brain signals from multiple modalities.

In future, efforts will be made to explore more advanced applications on EEG signals and study a wide variety of signal processing and classification methods used in their analysis. There are various applications that are least or not covered in the present study that are working upon EEG based computer-aided methods in their analysis. Such as study of EEG signals for patients with neurological disorders like Huntington's disease, Schizophernia, Autism, Strokes, Rett syndrome, attention deficit hyperactivity disorder (ADHD), and sleep related disorders. Efforts will be made to cover the extent of research going on signal processing and classification methods used in these applications. It has been observed that maximum number of studies on EEG based diagnosis of epilepsy using computer-aided methods have worked upon a very small dataset containing the EEG signals for only 5 patients. So, in future, efforts will be made to collect the data for more number of epileptic patients from a renowned hospital to create huge and heterogeneous (data of patients with varying age, gender, and so on) dataset. Advanced signal processing methods and classification methods will be used to process these signals with the aim to get more validated results and higher classification accuracies. Next, to the best of our knowledge, it has been studied that no EEG dataset is publicly available for Major Depressive Disorder (MDD) that has led to the limited research on this field. As a part of future work, it has been planned to extend the work on EEG based depression diagnosis by creating the huge dataset of the patients and working towards their analysis using various signal processing and classification methods.

Authors' contribution

Ashima Khosla: conceptualization, writing – original draft preparation, writing – reviewing and editing, visualization. Padmavati Khandnor: writing – reviewing and editing, supervision. Trilok Chand: writing – reviewing and editing, supervision.

Conflict of interest

None declared.

Appendix A. List of acroynms and abbreviations

The list of abbreviations and acroynms has been summarized in Table 21.

Table 21 – List of acroynms and abbreviations.

Acronynm/ abbreviation	Full form	Acronynm/ abbreviation	Full form
AAR	Adaptive auto-regressive	KFD	Katz fractral dimension
AC	Asymmetry coefficient	KNN	K-nearest neighbor
AD	Alzheimer's disease	KPCA	Kernel principal component analysis
ADhall+	AD with hallucinations	LD	Linear discriminant
ADhall-	AD without hallucinations	LDA	Linear discriminant analysis
AEP	Auditory evoked potentials	LE	Laplacian eigenmaps
AMI	Auto-mutual information	LMS	Least mean square
ANN	Artificial neural network	LLE	Locally linear embedding
ANOVA	One-way analysis of variance	LL2N	Logarithm of L2 norm
AP	Absolute power	LMT	Logistic model tree
APV	Alpha band power variability	LOOCV	leave one out cross validation
AUC	Area under curve	LR	Logistic regression
AUD	Alcohol use disorder	LSTM	Long short – term memory
BCI	Brain computer interface	LS-SVM	Least square support vector machine
BDL	Bandwidth-duration localized	LASSO	Least absolute shrinkage and selection operator
BOLD	Blood oxygenation level depredent signal	LVHA	Low valence high arousal
B_{edge}	Edge betweeness	LVLA	Low valence low arousal
B_{nodal}	Node betweeness	LZC	Lempel-ziv complexity
C	Clustering coefficient	M	Male
CD	Correlation dimension	MaxF	Maximum frequency
CDET	Compensation distance evaluation technique	MCC	Matthews correlation coefficient
CWT	Continuous wavelet transform	MCI	Mild cognitive impairment
CNN	Convolutional neural network	MDD	Major depressive disorder
CTM	Central tendency measure	ME	Mixture of experts
CV	Cross validation	MEG	Magnetoencephalogram
DASM	Differential asymmetry	MKLSVM	Multiple kernel learning SVM
DBN	Deep belief network	MLP	Multi-layer perceptron
DD-DWT	Double-density discrete wavelet transform	MLPNN	Multi-layer perceptron neural networks
DE	Differential entropy	MMSE	Mini Mental State Examination
DEAP	Database for Emotion Analysis using Physiological Signals	MODWPT	Maximal overlap discrete wavelet package transform

Table 21 (Continued)

Acronynm/ abbreviation	Full form	Acronynm/ abbreviation	Full form
DLB	Dementia with Lewy bodies	mRMR	Minimum redundancy maximum relevance
DLBhall+	Dementia with Lewy bodies with hallucinations	MSE	Multiscale sample entropy
DFA	Defrended fluctuation analysis	MPE	Multiscale permutation entropy
DM	Discernibility matrix	NB	Naïve Bayesian
DNN	Deep neural network	NN	Neural network
DPI	Depth perception indication	NREM	Non-rapid eye movement
DT	Decision tree	N-TSK	Network based Takagi–Surgeno–Kang
DWT	Discrete wavelet transform	PCA	Principal component analysis
EC	Eyes closed	PD	Parkinson disease
ECG	Electrocardiogram	PET	Positron emission tomography
EEG	Electroencephalogram	PFD	Petrosian fractral dimension
EI	Electrode impedance	PNN	Probabilistic neural network
EMD	Empirical mode decomposition	PPV	Positive predictive value
EMG	Electromyogram	PSD	Power spectral density
ELM_sig	Extreme learning machine with sigmoid activation function	PSI	Phase synchronization index
ELM_RBF	Extreme learning machine with RBF kernel	QDA	Quadratic discriminant analysis
EO	Eyes open	Q1F	First quartile frequency
EOG	Electrooculogram	Q3F	Third quartile frequency
EPN	Early posterior negativity	RASM	Rational asymmetry
EPSPs	Exhibitory post synaptic graded potentials	RBF	Radial basis function
ERP	Event related potentials	RBM	Restricted Boltzmann machine
EWT	Empirical wavelet transform	REM	Rapid eye movement
E_{global}	Global efficiency	RF	Random forest
E_{local}	Local efficiency	RGP	Relative gamma power
F	Female	RLS	Recursive least square
FAWT	Flexible analytical wavelet transform	RNN	Recurrent neural network
FD	Fractral dimension	ROC	Receiver operating curve
FDM	Fuzzy discernibility matrix	RP	Relative power
FFT	Fast Fourier transform	RPS	Reconstructed phase space
FIR	Finite impulse response	RQA	Recurrence quantification analysis
FLDA	Fisher linear discriminant analysis	RVS	Repetitive visual stimulus
fMRI	Functional magnetic resonance imaging	RWECN	Relative wavelet entropy in complex networks
fNIRS	Functional near infrared spectroscopy	SASI	Spectral asymmetry index
GBDT	Gradient boosting decision tree	SDS	Self-rating depression score
GBM	Gradient boosting machine	SEP	Somatosensory evoked potentials
GDA	Gaussian discriminant analysis	SHHS	Sleep Heart Health Study
GGD	Generalized Gaussian distribution	SHR	Split-half-reliability
GRNN	Generalized regression neural network	SSVEP	Steady-state visual evoked potentials
GSLT-CNN	CNN with global spatial and local temporal filter	SQUIDs	Superconducting quantum interference devices
GSO	Grid search optimizer	SSD	Spectral standard deviation
GSR	Galvanic skin response	STFT	Short time Fourier transform
GST	Generalized Stockwell transform	SVD	Single value based decomposition
HC	Healthy control	SVM	Support vector machine
HDCA	Hierarchical discriminant component analysis	SWS	Slow wave sleep
HE	Hurst exponent	TCOWFB	Three-channel orthogonal wavelet filter bank
HFD	Higuchi fractral dimension	TMS	Transcranial magnetic stimulation
HOS	Higher order spectra	TSST	Trier social stress test
HVHA	High valence high arousal	TWSVM	Twin SVM
HVLA	High valence low arousal	TQWT	Tunable-Q wavelet transform
IAPS	International Affective Picture System	UCI	University of California Irvine
ICA	Independent component analysis	USVM	Universum SVM
IIR	Infinite impulse response	UTSVM	Universum twin SVM
IMFs	Intrinsic mode functions	VAT	Visual analog test
IPSPs	Inhibitory post synaptic graded potentials	VEP	Visually evoked potentials
IR	Interquartile range	WT	Wavelet transform

Table 21 (*Continued*)

Acronynm/ abbreviation	Full form	Acronynm/ abbreviation	Full form
ISOMAP	Isometric feature mapping	WPD	Wavelet packet decomposition
KC	Kolmogorov complexity	XGBoost	Extreme gradient boosting

REFERENCES

[1] La Vaque T. The history of EEG Hans Berger: psychophysiologist. A historical vignette. J Neurother 1999;3(2):1–9.

[2] Bronzino JD. Biomedical engineering handbook, vol. 2. CRC Press; 1999.

[3] Kandel ER, Schwartz JH, Jessell TM, D. of Biochemistry, Jessell MB, Siegelbaum S, et al. Principles of neural science, vol. 4. New York: McGraw-Hill; 2000.

[4] Beres AM. Time is of the essence: a review of electroencephalography (EEG) and event-related brain potentials (ERPS) in language research. Appl Psychophysiol Biofeedback 2017;42(4):247–55.

[5] Novik O, Smirnov F, Volgin M. Structures of the brain. Electromagnetic Geophysical Fields. Springer; 2019. p. 69–89.

[6] Das S, Tripathy D, Raheja JL. An insight to the human brain and EEG. Real-Time BCI System Design to Control Arduino Based Speed Controllable Robot Using EEG. Springer; 2019. p. 13–24.

[7] Teplan M, et al. Fundamentals of EEG measurement. Meas Sci Rev 2002;2(2):1–11.

[8] Da Silv FL. Electroencephalography: basic principles, clinical applications, and related fields. Lippencott Wlliams & Wilkins; 2005.

[9] Mumtaz W, Xia L, Ali SSA, Yasin MAM, Hussain M, Malik AS. Electroencephalogram (EEG)-based computer-aided technique to diagnose major depressive disorder (MDD). Biomed Signal Process Control 2017;31:108–15.

[10] Subasi A. Eeg signal classification using wavelet feature extraction and a mixture of expert model. Expert Syst Appl 2007;32(4):1084–93.

[11] Zhang T, Chen W, Li M. Generalized Stockwell transform and SVD-based epileptic seizure detection in EEG using random forest. Biocybern Biomed Eng 2018;38(3):519–34.

[12] Mumtaz W, Ali SSA, Yasin MAM, Malik AS. A machine learning framework involving EEG-based functional connectivity to diagnose major depressive disorder (MDD). Med Biol Eng Comput 2018;56(2):233–46.

[13] Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H, Subha DP. Automated EEG-based screening of depression using deep convolutional neural network. Comput Methods Programs Biomed 2018;161:103–13.

[14] Anuragi A, Sisodia DS. Alcohol use disorder detection using EEG signal features and flexible analytical wavelet transform. Biomed Signal Process Control 2019;52:384–93.

[15] Mumtaz W, Kamel N, Saad MNbM, Ali SSA, Malik AS. An EEG-based functional connectivity measure for automatic detection of alcohol use disorder. Artif Intell Med 2018;84:79–89.

[16] Yuvaraj R, Acharya UR, Hagiwara Y. A novel Parkinson's disease diagnosis index using higher-order spectra features in EEG signals. Neural Comput Appl 2018;30 (4):1225–35.

[17] Yu H, Lei X, Song Z, Liu C, Wang J. Supervised network-based fuzzy learning of EEG signals for Alzheimer's disease identification. IEEE Trans Fuzzy Syst 2019.

[18] Ofner P, Müller-Putz GR. Movement target decoding from EEG and the corresponding discriminative sources: a preliminary study. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE; 2015. p. 1468–71.

[19] Müller-Putz GR, Ofner P, Schwarz A, Pereira J, Pinegger A, Dias CL, et al. Towards non-invasive EEG-based arm/hand-control in users with spinal cord injury. 2017 5th International Winter Conference on Brain–Computer Interface (BCI). IEEE; 2017. p. 63–5.

[20] Zeng Y, Wu Q, Yang K, Tong L, Yan B, Shu J, et al. EEG-based identity authentication framework using face rapid serial visual presentation with optimized channels. Sensors 2019;19(1):6.

[21] Chen J, Mao Z, Yao W, Huang Y. EEG-based biometric identification with convolutional neural network. Multimedia Tools Appl 2019;1–21.

[22] Wang Q, Zhao D, Wang Y, Hou X. Ensemble learning algorithm based on multi-parameters for sleep staging. Med Biol Eng Comput 2019;1–15.

[23] Blanco JA, Vanleer AC, Calibo TK, Firebaugh SL. Single-trial cognitive stress classification using portable wireless electroencephalography. Sensors 2019;19(3):499.

[24] Seo J, Laine TH, Sohn K-A. Machine learning approaches for boredom classification using EEG. J Amb Intell Human Comput 2019;1–16.

[25] Kaur B, Singh D, Roy PP. Eyes open and eyes close activity recognition using EEG signals. International Conference on Cognitive Computing and Information Processing. Springer; 2017. p. 3–9.

[26] Saghafi A, Tsokos CP, Goudarzi M, Farhidzadeh H. Random eye state change detection in real-time using EEG signals. Expert Syst Appl 2017;72:42–8.

[27] Chen L-l, Zhao Y, Zhang J, Zou J-z. Automatic detection of alertness/drowsiness from physiological signals using wavelet-based nonlinear features and machine learning. Expert Syst Appl 2015;42(21):7344–55.

[28] Brašic´ JR, Mohamed M. Human brain imaging of autism spectrum disorders. Imaging of the human brain in health and disease. Elsevier; 2014. p. 373–406.

[29] Ewers M, Sperling RA, Klunk WE, Weiner MW, Hampel H. Neuroimaging markers for the prediction and early diagnosis of Alzheimer's disease dementia. Trends Neurosci 2011;34(8):430–42.

[30] Crosson B, Ford A, McGregor KM, Meinzer M, Cheshkov S, Li X, et al. Functional imaging and related techniques: an introduction for rehabilitation researchers. J Rehabil Res Dev 2010;47(2). vii.

[31] Wong DF, Gründer G, Brašic´ JR. Brain imaging research: does the science serve clinical practice? Int Rev Psychiatry 2007;19(5):541–58.

[32] Malhi G, Lagopoulos J. Making sense of neuroimaging in psychiatry. Acta Psychiatr Scand 2008;117(2):100–17.

[33] Mier W, Mier D. Advantages in functional imaging of the brain. Front Human Neurosci 2015;9:249.

[34] Walsh V, Cowey A. Transcranial magnetic stimulation and cognitive neuroscience. Nat Rev Neurosci 2000;1(1):73.

[35] He B, Yang L, Wilke C, Yuan H. Electrophysiological imaging of brain activity and connectivity – challenges and opportunities. IEEE Trans Biomed Eng 2011;58 (7):1918–31.

[36] Babiloni C, Pizzella V, Del Gratta C, Ferretti A, Romani GL. Fundamentals of electroencefalography, magnetoencefalography, and functional magnetic resonance imaging. Int Rev Neurobiol 2009;86:67–80.
[37] Braisby N. Cognitive psychology: a methods companion. Oxford University Press; 2005.
[38] Rossini PM, Dal Forno G. Integrated technology for evaluation of brain function and neural plasticity. Phys Med Rehabil Clin 2004;15(1):263–306.
[39] Michel CM, Murray MM. Towards the utilization of EEG as a brain imaging tool. NeuroImage 2012;61(2):371–85.
[40] Sörnmo L, Laguna P. Bioelectrical signal processing in cardiac and neurological applications, vol. 8. Academic Press; 2005.
[41] Adrian ED, Matthews BH. The berger rhythm: potential changes from the occipital lobes in man. Brain 1934;57 (4):355–85.
[42] Walter WG, Dovey VJ. Electroencephalography in cases of sub-cortical tumour. J Neurol Neurosurg Psychiatry 1944;7 (3–4):57. Jul.
[43] Campisi P, La Rocca D. Brain waves for automatic biometric-based user recognition. IEEE Trans Inform Forensics Secur 2014;9(5):782–800.
[44] Kumar JS, Bhuvaneswari P. Analysis of electroencephalography (EEG) signals and its categorization – a study. Proc Eng 2012;38:2525–36.
[45] Michielli N, Acharya UR, Molinari F. Cascaded lstm recurrent neural network for automated sleep stage classification using single-channel EEG signals. Comput Biol Med 2019;106:71–81.
[46] Jiang D, Lu Y-n, Yu M, Yuanyuan W. Robust sleep stage classification with single-channel EEG signals using multimodal decomposition and hmm-based refinement. Expert Syst Appl 2019;121:188–203.
[47] Atkinson J, Campos D. Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers. Expert Syst Appl 2016;47:35–41.
[48] Jebelli H, Hwang S, Lee S. EEG-based workers' stress recognition at construction sites. Autom Constr 2018;93:315–24.
[49] Bachmann M, Päeske L, Kalev K, Aarma K, Lehtmets A, Ööpik P, et al. Methods for classifying depression in single channel EEG using linear and nonlinear signal analysis. Comput Methods Programs Biomed 2018;155:11–7.
[50] Mumtaz W, Vuong PL, Xia L, Malik AS, Rashid RBA. Automatic diagnosis of alcohol use disorder using EEG features. Knowl-Based Syst 2016;105:48–59.
[51] Ruiz-Gómez S, Gómez C, Poza J, Gutiérrez-Tobal G, Tola-Arribas M, Cano M, et al. Automated multiclass classification of spontaneous EEG activity in Alzheimer's disease and mild cognitive impairment. Entropy 2018;20 (1):35.
[52] Dauwan M, Linszen MM, Lemstra AW, Scheltens P, Stam CJ, Sommer IE. EEG-based neurophysiological indicators of hallucinations in Alzheimer's disease: comparison with dementia with Lewy bodies. Neurobiol Aging 2018;67:75–83.
[53] Zhang XL, Begleiter H, Porjesz B, Wang W, Litke A. Event related potentials during object recognition tasks. Brain Res Bull 1995;38(6):531–8.
[54] Patidar S, Pachori RB, Upadhyay A, Acharya UR. An integrated alcoholic index using tunable-q wavelet transform based features extracted from EEG signals for diagnosis of alcoholism. Appl Soft Comput 2017;50:71–8.
[55] Faust O, Acharya R, Allen AR, Lin C. Analysis of EEG signals during epileptic and alcoholic states using AR modeling techniques. IRBM 2008;29(1):44–52.
[56] Rösler O, Suendermann D. A first step towards eye state prediction using EEG. Proc of the AIHLS; 2013.
[57] Zhou Z, Li P, Liu J, Dong W. A novel real-time EEG based eye state recognition system. International Conference on Communications and Networking in China. Springer; 2018. p. 175–83.
[58] Duneja A, Puyalnithi T, Vankadara MV, Chilamkurti N. Analysis of inter-concept dependencies in disease diagnostic cognitive maps using recurrent neural network and genetic algorithms in time series clinical data for targeted treatment. J Amb Intell Human Comput 2018;1–9.
[59] Reddy TK, Behera L. Online eye state recognition from EEG data using deep architectures. 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE; 2016. p. 000712–7.
[60] Andrzejak RG, Lehnertz K, Mormann F, Rieke C, David P, Elger CE. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state. Phys Rev E 2001;64(6):061907.
[61] Zhang T, Chen W, Li M. Classification of inter-ictal and ictal EEGs using multi-basis MODWPT, dimensionality reduction algorithms and LS-SVM: a comparative study. Biomed Signal Process Control 2019;47:240–51.
[62] Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. Comput Biol Med 2018;100:270–8.
[63] Subasi A, Gursoy MI. EEG signal classification using PCA, ICA, LDA and support vector machines. Expert Syst Appl 2010;37(12):8659–66.
[64] Richhariya B, Tanveer M. Eeg signal classification using universum support vector machine. Expert Syst Appl 2018;106:169–82.
[65] Faust O, Acharya UR, Adeli H, Adeli A. Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis. Seizure 2015;26:56–64.
[66] Li M, Chen W, Zhang T. Automatic epilepsy detection using wavelet-based nonlinear analysis and optimized SVM. Biocybern Biomed Eng 2016;36(4):708–18.
[67] Ibrahim S, Djemal R, Alsuwailem A. Electroencephalography (EEG) signal processing for epilepsy and autism spectrum disorder diagnosis. Biocybern Biomed Eng 2018;38(1):16–26.
[68] Wang X, Gong G, Li N. Automated recognition of epileptic EEG states using a combination of symlet wavelet processing, gradient boosting machine, and grid search optimizer. Sensors 2019;19(2):219.
[69] Andrzejak RG, Schindler K, Rummel C. Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients. Phys Rev E 2012;86(4):046206.
[70] Bhattacharyya A, Sharma M, Pachori RB, Sircar P, Acharya UR. A novel approach for automated detection of focal EEG signals using empirical wavelet transform. Neural Comput Appl 2018;29(8):47–57.
[71] Brinkmann BH, Wagenaar J, Abbot D, Adkins P, Bosshard SC, Chen M, et al. Crowdsourcing reproducible seizure forecasting in human and canine epilepsy. Brain 2016;139 (6):1713–22.
[72] Sudalaimani C, Sivakumaran N, Elizabeth TT, Rominus VS. Automated detection of the preseizure state in EEG signal using neural networks. Biocybern Biomed Eng 2019;39 (1):160–75.
[73] Shoeb AH. Application of machine learning to epileptic seizure onset detection and treatment. Massachusetts Institute of Technology; 2009 [Ph.D. thesis].
[74] Quintero-Rincón A, Pereyra M, D'Giano C, Risk M, Batatia H. Fast statistical model-based classification of epileptic EEG signals. Biocybern Biomed Eng 2018;38 (4):877–89.

[75] Alhaddad MJ, Kamel MI, Malibary HM, Alsaggaf EA, Thabit K, Dahlwi F, et al. Diagnosis autism by fisher linear discriminant analysis flda via EEG. Int J Bio-Sci Bio-Technol 2012;4(2):45–54.
[76] BCI-competition-II, dataset III. Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology Graz; 2004, http://www.bbci.de/competition/ii/.
[77] Chatterjee R, Maitra T, Islam SH, Hassan MM, Alamri A, Fortino G. A novel machine learning based feature selection for motor imagery EEG signal classification in internet of medical things environment. Fut Gen Comput Syst 2019;98:419–34.
[78] Chatterjee R, Datta A, Sanyal DK. Ensemble learning approach to motor imagery EEG signal classification. Machine Learning in Bio-Signal Analysis and Diagnostic Imaging. Elsevier; 2019. p. 183–208.
[79] Koelstra S, Muhl C, Soleymani M, Lee J-S, Yazdani A, Ebrahimi T, et al. Deap: a database for emotion analysis; using physiological signals. IEEE Trans Affect Comput 2011;3(1):18–31.
[80] Pandey P, Seeja K. Emotional state recognition with EEG signals using subject independent approach. Data Science and Big Data Analytics. Springer; 2019. p. 117–24.
[81] Pandey P, Seeja K. Subject-independent emotion detection from EEG signals using deep neural network. International Conference on Innovative Computing and Communications. Springer; 2019. p. 41–6.
[82] Blankertz B, Muller K-R, Krusienski DJ, Schalk G, Wolpaw JR, Schlogl A, et al. The BCI competition III: validating alternative approaches to actual BCI problems. IEEE Trans Neural Syst Rehabil Eng 2006;14(2):153–9.
[83] Behri M, Subasi A, Qaisar SM. Comparison of machine learning methods for two class motor imagery tasks using EEG in brain–computer interface. 2018 Advances in Science and Engineering Technology International Conferences (ASET). IEEE; 2018. p. 1–5.
[84] Chaudhary S, Taran S, Bajaj V, Sengur A. Convolutional neural network based approach towards motor imagery tasks EEG signals classification. IEEE Sens J 2019;19 (12):4494–500.
[85] Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. Bci2000: a general-purpose brain-computer interface (BCI) system. IEEE Trans Biomed Eng 2004;51 (6):1034–43.
[86] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, et al. Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. Circulation 2000;101(23): e215–20.
[87] Zhang X, Yao L, Zhang D, Wang X, Sheng QZ, Gu T. Multi-person brain activity recognition via comprehensive EEG signal analysis. Proceedings of the 14th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services. ACM; 2017. p. 28–37.
[88] Hussain L, Aziz W, Saeed S, Shah SA, Nadeem MSA, Awan IA, et al. Complexity analysis of EEG motor movement with eye open and close subjects using multiscale permutation entropy (MPE) technique. Biomed Res 2017;28 (16).
[89] Tian P, Hu J, Qi J, Ye X, Che D, Ding Y, et al. A hierarchical classification method for automatic sleep scoring using multiscale entropy features and proportion information of sleep architecture. Biocybern Biomed Eng 2017;37(2):263–71.
[90] S. C. C. O. T. J. S. O. S. R. S. (JSSR), Hori T, Sugita Y, Koga E, Shirakawa S, Inoue K, et al. Proposed supplements and amendments to 'a manual of standardized terminology, techniques and scoring system for sleep stages of human subjects', the rechtschaffen & kales (1968) standard. Psychiatry Clin Neurosci 2001;55(3):305–10.
[91] Mourtazaev M, Kemp B, Zwinderman A, Kamphuisen H. Age and gender affect different characteristics of slow waves in the sleep EEG. Sleep 1995;18(7):557–64.
[92] Kemp B, Zwinderman AH, Tuk B, Kamphuisen HA, Oberye JJ. Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the EEG. IEEE Trans Biomed Eng 2000;47(9):1185–94.
[93] Ichimaru Y, Moody G. Development of the polysomnographic database on CD-ROM. Psychiatry Clin Neurosci 1999;53(2):175–7.
[94] Correa AG, Orosco L, Laciar E. Automatic detection of drowsiness in EEG records based on multimodal analysis. Med Eng Phys 2014;36(2):244–9.
[95] Tripathy R, Acharya UR. Use of features from RR-time series and EEG signals for automated classification of sleep stages in deep neural network framework. Biocybern Biomed Eng 2018;38(4):890–902.
[96] Quan SF, Howard BV, Iber C, Kiley JP, Nieto FJ, O'Connor GT, et al. The sleep heart health study: design, rationale, and methods. Sleep 1997;20(12):1077–85.
[97] Sors A, Bonnet S, Mirek S, Vercueil L, Payen J-F. A convolutional neural network for sleep stage scoring from raw single-channel EEG. Biomed Signal Process Control 2018;42:107–14.
[98] Tylová L, Kukal J, Hubata-Vacek V, Vyšata O. Unbiased estimation of permutation entropy in EEG analysis for alzheimer's disease classification. Biomed Signal Process Control 2018;39:424–30.
[99] Hosseinifard B, Moradi MH, Rostami R. Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from EEG signal. Comput Methods Programs Biomed 2013;109 (3):339–45.
[100] Sharma M, Achuth P, Deb D, Puthankattil SD, Acharya UR. An automated diagnosis of depression using three-channel bandwidth-duration localized wavelet filter bank with EEG signals. Cogn Syst Res 2018;52:508–20.
[101] Ding X, Yue X, Zheng R, Bi C, Li D, Yao G. Classifying major depression patients and healthy controls using EEG, eye tracking and galvanic skin response data. J Affect Disord 2019;251:156–61.
[102] Lotfan S, Shahyad S, Khosrowabadi R, Mohammadi A, Hatef B. Support vector machine classification of brain states exposed to social stress test using EEG-based brain network measures. Biocybern Biomed Eng 2019;39(1):199–213.
[103] Pereira J, Ofner P, Müller-Putz GR. Goal-directed or aimless? EEG differences during the preparation of a reach-and-touch task. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE; 2015. p. 1488–91.
[104] Ofner P, Müller-Putz GR. Using a noninvasive decoding method to classify rhythmic movement imaginations of the arm in two planes. IEEE Trans Biomed Eng 2014;62 (3):972–81.
[105] Ofner P, Schwarz A, Pereira J, Müller-Putz GR. Movements of the same upper limb can be classified from low-frequency time-domain EEG signals. Proceedings of the Sixth International Brain-Computer Interface Meeting: BCI Past, Present, and Future (June 2016); 2016.
[106] Akar SA, Kara S, Agambayev S, Bilgiç V. Nonlinear analysis of EEGs of patients with major depression during different emotional states. Comput Biol Med 2015;67:49–60.
[107] Singh MI, Singh M. Development of a real time emotion classifier based on evoked EEG. Biocybern Biomed Eng 2017;37(3):498–509.

[108] Kotowski K, Stapor K, Leski J, Kotas M. Validation of emotiv EPOC+ for extracting ERP correlates of emotional face processing. Biocybern Biomed Eng 2018;38(4):773–81.
[109] Öner M, Hu G. Analyzing one-channel EEG signals for detection of close and open eyes activities. 2013 Second IIAI International Conference on Advanced Applied Informatics. IEEE; 2013. p. 318–23.
[110] Karamacoska D, Barry RJ, Steiner GZ. Using principal components analysis to examine resting state EEG in relation to task performance. Psychophysiology 2019;56(5): e13327.
[111] Gao Z, Li S, Cai Q, Dang W, Yang Y, Mu C, et al. Relative wavelet entropy complex network for improving EEG-based fatigue driving classification. IEEE Trans Instrum Meas 2018.
[112] Ajami S, Mahnam A, Abootalebi V. Development of a practical high frequency brain-computer interface based on steady-state visual evoked potentials using a single channel of EEG. Biocybern Biomed Eng 2018;38(1):106–14.
[113] Abromavicius V, Serackis A. Eye and EEG activity markers for visual comfort level of images. Biocybern Biomed Eng 2018;38(4):810–8.
[114] Stehlin SA, Nguyen XP, Niemz MH. Eeg with a reduced number of electrodes: where to detect and how to improve visually, auditory and somatosensory evoked potentials. Biocybern Biomed Eng 2018;38(3):700–7.
[115] Grundlehner B, Mihajlović V. Ambulatory EEG monitoring; 2019.
[116] Jiang X, Bian G-B, Tian Z. Removal of artifacts from EEG signals: a review. Sensors 2019;19(5):987.
[117] Ghare PS, Paithane A. Human emotion recognition using non linear and non stationary EEG signal. 2016 International Conference on Automatic Control and Dynamic Optimization Techniques (ICACDOT). IEEE; 2016. p. 1013–6.
[118] Al-Fahoum AS, Al-Fraihat AA. Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains. ISRN Neurosc 2014.
[119] Borisagar KR, Thanki RM, Sedani BS. Fourier transform, short-time fourier transform, and wavelet transform. Speech enhancement techniques for digital hearing aids. Springer; 2019. p. 63–74.
[120] Polikar R. The wavelet tutorial – part I, 2nd ed.
[121] Sović A, Seršić D. Signal decomposition methods for reducing drawbacks of the DWT. Eng Rev 2012;32(2):70–7.
[122] Cohen I, Raz S, Malah D. Orthonormal shift-invariant wavelet packet decomposition and representation. Signal Process 1997;57(3):251–70.
[123] Selesnick IW. Wavelet transform with tunable q-factor. IEEE Trans Signal Process 2011;59(8):3560–75.
[124] Huang W, Sun H, Wang W. Resonance-based sparse signal decomposition and its application in mechanical fault diagnosis: a review. Sensors 2017;17(6):1279.
[125] Paraschiv-Ionescu A, Aminian K. Nonlinear analysis of physiological time series. Advanced biosignal processing. Springer; 2009. p. 307–33.
[126] Faust O, Bairy MG. Nonlinear analysis of physiological signals: a review. J Mech Med Biol 2012;12(04):1240015.
[127] Acar E, Schenker C, Levin-Schwartz Y, Calhoun VD, Adali T. Unraveling diagnostic biomarkers of schizophrenia through structure-revealing fusion of multi-modal neuroimaging data. Front Neurosci 2019;13:416.
[128] Lee M-H, Fazli S, Mehnert J, Lee S-W. Subject-dependent classification for robust idle state detection using multi-modal neuroimaging and data-fusion techniques in BCI. Pattern Recogn 2015;48(8):2725–37.
[129] Liu S, Liu S, Cai W, Che H, Pujol S, Kikinis R, et al. Multimodal neuroimaging feature learning for multiclass diagnosis of alzheimer's disease. IEEE Trans Biomed Eng 2014;62(4):1132–40.
[130] Zhu Q, Xu X, Yuan N, Zhang Z, Guan D, Huang S-J, et al. Latent correlation embedded discriminative multi-modal data fusion. Signal Process 2020;107466.
[131] Hunyadi B, Van Paesschen W, De Vos M, Van Huffel S. Fusion of electroencephalography and functional magnetic resonance imaging to explore epileptic network activity. 2016 24th European Signal Processing Conference (EUSIPCO). IEEE; 2016. p. 240–4.