A COMPREHENSIVE STUDY ON EEG SIGNAL PROCESSING-METHODS, CHALLENGES AND APPLICATIONS

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Abstract: Electroencephalogram (EEG) signals help us to analyse the various activities of a human brain. These signals reveals the excellent activity of a brain at certain states and these neuroimaging methods differs from other neuroimaging methods such as magnetoencephalogram, functional magnetic resonance imaging, Positron emission tomography by its capabilities like high temporal resolution in the millisecond range, low cost, portability and non-invasiveness. The patterns that are recorded by these EEG signals are mostly non-stationary, time and frequency variant type and with the increasing power of computing and enhanced processing capabilities of the recent tools, EEG signal analysis can be done efficiently and effectively. In recent days, EEG signal analysis through the classification models is utilized in different application areas like diagnosis of various neurological disorders in the medical field, emotion recognition, motor imagery and entertainment. A variety of signal processing techniques must be used to process such signals.This review offers an extensive study that explores the various stages of processing EEG signals such as data acquisition, pre-processing techniques which include artifacts removal, feature extraction methods of different domains, post processing techniques and the classification models in accordance with the different applications that utilize EEG signals.

***Keywords*: Electroencephalogram, Non invasive, Feature extraction, classification.**

1. Introduction

Human Brain is a significant part of which controls entire part of the human body. Human Brain consists of millions of neurons whose vital function is to control the behaviour of a human in respect to any external stimulus. ELECTROENCEPHALOGRAPHY is a popular way of measuring the electrical function of the human brain. EEG detects the behaviour of large groups of simultaneously active neurons. German neurologist namely Hans Berger first applied EEG assessing method to humans in the 1920's by attaching the electrodes to the scalp and recorded the net sum of all electric signals generated by the brain. EEG characterize as a mixture of rhythmic, sinusoidal-like fluctuations in voltage. The recordings of the EEG signals are done with the help of electrode arrays which comprises various sensor numbers that ranges from 10 to 512 electrodes and will vary from one experiment to another depends on its scope. The use of non-invasive and lightweight systems is currently the most portable method for monitoring the brain function. EEG signals have a fast response time and are inexpensive [1] compared to other approaches such as FMRI-Functional Magnetic Resonance Imaging, MEG - Magneto Encephalography. EEG is a significant bioinformatics indicator. EEG has been widely used in the field of medical diagnosis such as neurological disorders, brain-computer interface (BCI) systems which relay message between the human brain and an external system, education, entertainment and an effective strategy for human-machine interactions has been suggested [2]. The majority of the electrical signals generated underneath the skull and other tissues fade substantially, but these signals are quite powerful to reach certain regions and have amplifications around 10 - 100 microvolts on the skull. So, we can use a non –invasive method to measure these electrical impulses by means of directly placing the electrodes on the scalp. There are a few standard electrode positioning schemes that specify the positions of EEG channels, according to the head dimension of the participants in the experiment. These standard electrode placement schemes guaranteed that tests were reproducible and the findings of various subjects were compared. The 10–20 system is the most commonly adopted international electrode positioning system and it is shown in Figure 1, which locates up to 128 electrodes. In the 10-20 scheme, electrode names labelled with one or two characters such as C, T, F, O, P,Fp representing the central, temporal, frontal, occipital , parietal and frontal pole area of the brain in which the electrode is mounted. The two corresponding letters represent the electrodes that are located between two regions. Each electrode name ends with a number or letter represents the location of the electrode. The electrode name labelled with even numbers are typically placed in the right hemisphere and the odd numbers are used for the left hemisphere. The electrodes located at the midline are named with "z" for zero.

The EEG normally presents in the context of rhythmic movement which is separated into bands by frequency. EEG frequency bands [3] are categorized into five different types such as, the delta (δ) band ranges between 0.1 Hz and4 Hz are

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associated to deep sleep. The theta (θ)waves occur between 4Hz and 7 Hz appear in meditation and light sleep phases.The alpha ($\propto$) band confines between 8Hz and 12 Hz seems in relax and calm states of conscious subjects. whereas beta (β) waves lies between 14Hz and 25 Hz appear when the subject is in active thinking or decode the complicated problems, and the gamma(γ) waves occur between 26Hz and 50 Hz is connected to attention, cognition and learning processes.

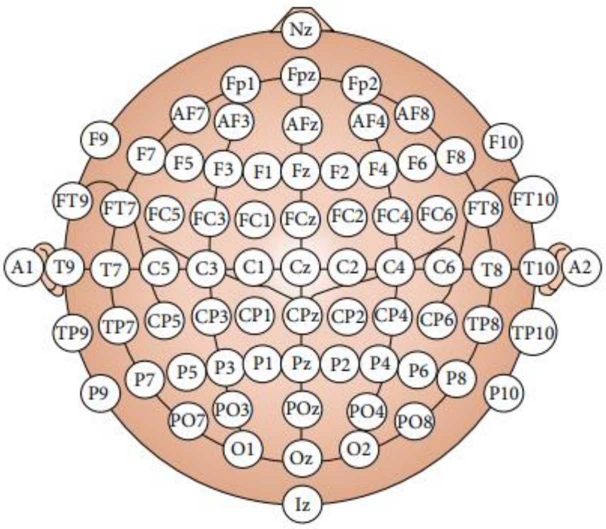

Fig 1 Standardized10-20 electrode placement scheme [4]

This paper presents a review of EEG signal processing methods. In section 2.1, EEG signal Acquisition and pre-processing with various methods have discussed. In section 2.2 Feature methods under various methods and summarizing their strengths and weaknesses has been summarized. Post processing techniques namely Feature selection and Dimensionality Reduction is discussed in section 2.3. In section 2.4 different classification methods has been studied.

2. Methods

The EEG signals are received by mounting the electrodes on the scalp. The recorded EEG signals are processed by extracting features using different methods under various domain and classification has done in order to obtain the desired results. The EEG signal classification in various stages have represented in the block diagram that depicted in Fig.2.

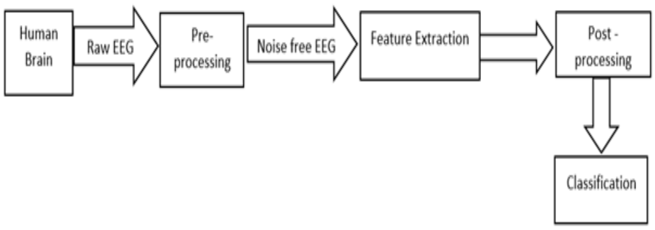

Fig 2 EEG System Block Diagram

2.1EEG signal Acquisition and pre-processing

2.1.1 EEG signal Acquisition

EEG signal collection can be done either in the way of using datasets that are available publicly or locally collected data. EEG signals can be collected by many devices [5, 6, 7, 8] where few are listed in Table 1.

Table 1 EEG Device Specification

Devices	**Channels Number**	**Sampling Rate**	**Bandwidth**
Neurosky Mindwave headset	1	512Hz	3-100Hz
EmotivEpoc+	14	128Hz-256Hz	0.16-43Hz
Emotiv INSIGHT	5	128Hz	0.5-43Hz
MUSE headband	4	220Hz	2-50Hz
TrueScan	21	200Hz	0.15-100Hz

2.1.2.EEG signal pre-processing

EEG raw signals are contaminated by noise and artifacts. Generally, pre-processing of artifacts has become an important method for collecting the enhanced significant information from raw EEG signals. and acts a primitive stage before the feature extraction stage.

2.2.1Artifact Handling

The set of electrical signals that are nonbrain source called artifacts are detected along with EEG recordings. Artifacts are mostly prone to EEG data. Compared to the size of the cortical signals of interest, the artifacts amplitude can be very high. The removal of artifacts [9] present in the EEG signals is necessary because it removes possible classification errors and the amount of information processed. On the other hand, while performing such a method, care must be taken, as valuable information in the signals could be damaged. Generally, artifact handling is divided into two categories namely Technical and Nontechnical artifacts.

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2.2.1.1 Technical artifacts

The noise signals occur due to electrode positions, power line interference, analog ground noise, ECG noise, environmental artifacts, noises from EEG equipment recording, improper handling of EEG systems.The other EEG artifacts mostly generated is by high-impedance electrodes.

2.2.1.2NonTechnical artifacts

The set of artifacts that are produced inside the body such as eye blinks, eye muscle movement, cardiac artifacts and muscular artifacts are referred as Nontechnical artifacts.

Most of the artifact removal methods used by the researcher

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• **Digital Filtering**: This method involves a wide number of various filters that can be linear or non-linear. The widely used approach to pre-process raw EEG is to use a band-pass filter for clearing the undesired bits. A digital Notch filter is used to remove high voltage interference from the signals. In order to reduce muscle artifacts and eliminate linear patterns, Butterworth filters, which are band-pass filters, are used. To eradicate the effects of the EOG and ECG artifacts where the frequency contents overlap with EEG spectrum [10], adaptive filters are used in addition to the linear filtering.

• **Wavelet Transform (WT):** Wavelet Transform break down the signal into its Wavelet components. The wavelet components containing artifacts are detected in each sub band by measuring the energy in it and adding a threshold [11]. After that the noisy and undesired bands are removed. A clean signal can be reconstructed using the remaining wavelet components by selecting the wavelet functions with highest resemblance to the nature of EEG in terms of frequency bands. Symmlet and Daubechies mother wavelets are the widely used wavelets for EEG processing**.**

However, the information loss and flawed reconstruction of clean signals might result while removing artifacts using wavelet transform. Several studies revealed that to improve the general method further, wavelet transform can be combined with other methods.

• **Blind Source Separation (BSS**): The BSS method comprises a range of unsupervised learning algorithms without any extra reference channels and no additional prior information.

• **Principal Component Analysis (PCA):** PCA, an algorithm which is based on Eigen values of covariance matrix is one of the simplest and broadly used Blind Source Separation methods [12]. This method initially uses orthogonal transformation to convert the correlated variables into uncorrelated variables and these converted variables are referred as principal components (PCs). A computational method namely Single Value Decomposition (SVD) is widely used to calculate PCs of EEG signals.

• **Independent Component Analysis (ICA):**ICA is a multivariate analysis which is one of the widely used BSS techniques that attempts to decompose the original signals into a brand-new set of linear signals called independent components (ICs) along with the artifacts detection in the given signal. ICA [13] generally detects artifacts in the given signal by using the following steps: initially, the ICs are formed from the given signal using decomposition method. Secondly, the ICs which are varying from each other are identified and removed from the set of signals. Lastly, the artifact free signal can be formed by concatenating the remaining ICs. The ICA can be expressed as:

$$x(t) = As(t) \tag{1}$$

Where A is called the mixing matrix (an unknown matrix), x (t), a vector that represents the observed signals and s (t), another vector represents the source signals.

• **Common Spatial Patterns: This** method defines the pattern exhibits by EEG signal by constructing spatial filters that increases the variance of one task and reduce the variance of another task. at the same time [14]. This approach works with multiple electrodes and by varying the electrode position, the classification performance may be affected.

2.2 FEATURE EXTRACTION

The content of a signal can be projected as descriptive values which are commonly referred as features. The extraction of informative, discriminating and related features is a critical part in creating a suitable set of values for a classifier. Features can be extracted from different domains namely Time, Frequency, Time-Frequency and Nonlinear domains and are briefly discussed below.

2.2.1Time Domain Features. The morphological characteristics of a signal can be represented by time domain features [15]. For real-time applications, this time domain features are clearly interpretable and relevant. Table 2 presents some of the general time domain features

Table 2 Time Domain Features

Time domain Features	**Equation**	**Description**
Mean	$x = \frac{1}{N}\sum_{N}^{n-1} X(n)$	X(n) is a time-series Where n ranges from 1 to n
Variance	$var = \frac{1}{N}\sum_{N}^{n-1}(X(n) -$	Variance is computed by finding the average of squared deviations from the mean
Standard Deviation	$\sigma_X = \sqrt{\frac{1}{N}\sum_{N}^{n-1}(X(n) -}$	Standard Deviation computed by finding the square root of the Variance.
Skewness	$skew = \frac{\sum_{i=1}^{N}(x_i - \bar{\bar{x}}}{(N-1)\sigma^3}$ $\bar{\bar{x}}$ - *Average value of EEG signal.*	Skewness is a way to measure the distortion. In given set of data which follows normal distribution, it checks whether the curve formed is either shifted left or right (Skewed).
Kurtois	$c = \sum \frac{(x_i - \bar{\bar{x}})^4}{\sigma^4}$ $\bar{\bar{x}}$ - *Average value of EEG signal.*	Kurtois is a measure that decides the degree of flatness of a distribution, examining the degree to which a given tails of distribution is differing from the tails of symmetric bell curve
Hjorth Activity	$ha = var(x(t))$	A variance measure of a time series (x)

Time domain analysis also provides great information on group synchronization of brain activity measured from various electrodes. These time domain features are providing only spatial information, but temporal information is not addressed.

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2.2.2 Frequency Domain Features.

Frequency is the measure of the occurrence of the events in specified time Frequency domain features are versatile features which are repeatedly utilized for describing changes in EEG signals. Spectral estimation was performed to transfer the time series to the frequency domain [16, 17]. There are many strategies for extracting frequency features, herewith summarized in the Table 3.

Table 3 Frequency domain Features

Approaches	Method	Inference	Advantages	Disadvantages
Non parametric approach	Fast Fourier transform-Welch method	The EEG data is analysed through the application of mathematical methods. The features of the EEG signals to be analysed are determined by the computation of power spectral density to selectively signify the EEG samples.	• It provides good tool for stationary signal processing. • In real time application it h • as an improved speed when compared with all other methods.	• Its performance is too weak on non-stationary EEG signals. analysis. • FF T has high noise sensitivity and no shorter data recording duration.
	Eigenvector	It determines the frequency and power of signals from artifact influenced measurements. Eigen decomposition is the core part of this approach to associate even artifact corrupted signal	• It offers sufficient resolution for the evaluation of the sinusoid from the results.	• In this approach false zeros are likely to be generated, and hence shows low statistical accuracy.
Parametric approach	Autoregressive	Autoregressive (AR) [18] method maps each EEG signal sample as a linear combination of prior signal samples. Yule-Walker method and Burg's method are the two common autoregressive methods used for PSD estimation by modelling the data as the output of linear system and identifies the parameters of the linear system.	• Th is technique provides good frequency resolution	• It is particularly vulnerable to extreme biases and high variability.

The frequency domain can only supply temporal features after the function has been windowed, The challenges in assessing window size are the main issue in frequency analysis.

2.2.3 TIME FREQUENCY FEATURES

Time-frequency features were derived from transformed EEG waveforms that included both time and frequency properties. Time frequency features are described in the Table 4

Table 4 Time Frequency Features

METHOD	DESCRIPTION	ADVANTAGES	LIMITATIONS
Short Time Fourier Transform (STFT)	STFT obtained by applying the proper windows to the Fourier functions [19]. FFT are assigned to each of the small chunks of data from the segregated signals.	• igh frequency resolution has been offered.	• hoosing a window width is quite complicated.
Continuous Wavelet Transform (CWT)	In CWT, to obtain the transformed signal, the signal is amplified with the mother wavelet. A short interval in the x-axis shifts the mother wavelet, and correlation coefficients are measured. It repeated the process for different scaling factors in the y-axis.A continuous variance of both translation and dilation variables is assessed for the CWT coefficients..	• indow sizes can differ in time according to the various frequency characteristics	• his requires a huge amount of redundancy to analyze and recreate the signal due to the parameters vary continuously, so depletion of computational time and resources.
Discrete Wavelet Transform (DWT)	In a first stage of decomposition, the DWT method decomposes a given signal into approximate and detailed coefficients. The coefficients of approximation in each step are further decomposed into the subsequent level of approximation and the detail coefficient [20]. The properties of the time series can be seen by the features derived from the detailed coefficients from various levels	• esigning less intense models on the basis of computational time and resources	• t is susceptible to translation, shift variation, aliasing, and shortage of directionality.
WPD	WPD [21] is a DWT extension. The decomposition of the detailed and approximation coefficients at each level into components representing higher and lower frequencies.	• t offers more efficient signal processing.	• It involves complex data structures
TQWT	The three parameters Q-factor, redundancy and decomposition levels count are used in TQWT [22]. Q determines the resonance degree of the signal which is tuned depending on the oscillatory nature of the signal.	• t is effective in the study of subtle oscillatory pattern variations.	• It is difficult to infer the resulting coefficient if the number of levels is too large.

Features extracted from the Time -frequency representation of the EEG signal that provides information which could contribute to effective and accurate classification systems, since they can use the additional information available in the time-frequency domain to exploit the non-stationary characteristics of the signal. [23]. It is difficult to infer such information directly from the representation of the signal in the time or frequency domain.

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2.2.4 NON- LINEAR FEATURES

The brain's pattern is non-linear and non-stationary. Non-linear features [24] can determine the complexity of nonlinear and non-stationary signals that described in Table 5.

Table 5 Non- Linear Features

Nonlinear Features	Description	Advantages	Disadvantages
Fractal dimension	Fractal dimension is a representation of the signal's complexity and self-similarity.	• t offers a good estimate of the fractal dimension for short signal segments. • t is computationally fast.	• he highest FD exists at a certain frequency in accordance with FD range, noise level, and window length.
Approximate Entropy (ApEn)	Approximate Entropy is a statistic for calculating the regularity and variability of a signal over time.	• It can be implemented in real time. • Lower computational demand • ess effect from noise	• he record length is targeted and is smaller for short records than expected. • t is poor in relative consistency
SampleEntropy (SampEn)	SampEn [25] estimates signal complexity by calculating the conditional probability that two sequences of a given length, m, share self-similar aspects within a specified tolerance when matches are not included.	• t is easy to implement . • t is usable for short, low-noise data sequences. • he system is able to isolate the large system variations.	• his method relates to an inconsistency of entropy for short data.
Largest Lyapunov Exponent (LLE)	The LLE method tests the exponential deviation of two initial adjacent phase space trajectories dependent on the Euclidean distance to attain an estimate of the degree of chaos in the signals.	• obust method even existence of noise.	• t is unreliable for small data sets. • t is relatively difficult to implement
Lempel-Ziv Complexity (LZC)	The LZC calculates the number of different segments and the event rate during the signal to measure the complexity.	• asy to measure	• t has higher amplitude values, results in slow variation in EEG rhythms. • t overlooks the higher frequency components.

The usage of nonlinear approaches has revealed New evidence that can better determine the complexity of the brain across a number of cognitive tasks, as well it improves the possibility of better describing the state of the brain

2.3 Post-processing

Post-processing techniques can be achieved by the processes of feature selection or the dimensionality reduction strategies.

2.3.1 Feature selection

Feature selection is an easy means to distinguish the most discriminatory features from the original features set. The selection of features not only provides the correct details, but also helps to reduce the total dimension of the data provided Table 6 describes various methods of Feature selection.

Table 6 Feature selection methods

Methods	Description
Genetic Algorithm [GA]	GA [26] uses a heuristic search technique, it selects random chromosomes and at each step tries to select the best individuals. These chromosomes then undergo mutation and crossover process to create a succeeding generation. This procedure continues till an optimal subset of features is formed. It deals specially for high dimensional data
student t -test	T-test functions in a way that operates around the ratio of the difference of means to the differences between the two classes. Feature Ordering can be achieved by using t-test in a binary classification problem.
Kullback–Leibler (K-L) divergence	This technique estimates for the variance of two probability distributions. The selection of features is done by choosing different subsets of features, so that the K-L distance is maximized between the resulting densities obtained from the conditional probabilities of the class.
Bhattacharyya distance	It tests the similarity of distributions or, precisely it calculates the degree to which two statistical samples overlap. In multiclass classification problem, the separability has been find using this method.
Gini index	Gini index is widely used for impurity measures. It is a criterion to minimize the probability of misclassification. This method employs in binary decision trees.
ANOVA Test	ANOVA [27] is a mathematical tool used to test if there are any substantial variations in the parameters. For each function, the test calculates a F measure, and the function with a relatively higher F will provide good discrimination. The features with the maximum F measure are sorted in the decreasing order.
Fisher Score	Fisher score (FS)[28] is a widely used technique for evaluating the features correlation. Find the score as F using the Fisher method for each feature first, then set a threshold as θ. If F>θ, then the feature will be selected; else it will not be selected.
minimum-Redundancy-Maximum Relevance (mRMR)	mRMR chooses the attributes that most correlate with a classification variable, reducing data redundancy. This approach chooses characteristics that are mutually distinct from each other, whereas the mRMR [29] selection task also has a high correlation by reducing redundancy using Mutual Information (MI) methods between bad and good features, such that it is possible to achieve a subset of features that better reflect the dataset.

2.3.2 Dimensionality reduction methods

Dimensionality reduction is the way toward changing from an extremely high-dimensional space to a low-dimensional space where the low-dimensional representation possesses certain meaningful features of the originally generated data. Dimensionality reduction methods [30,31] has been discussed in Table 7.

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Table 7 Dimensionality reduction methods

METHODS	DESCRIPTION
PCA	Principal Component Analysis (PCA) extends the data into a set of orthogonal components and it achieves maximum signal decorrelation. All the core components are orthogonal to each other, and therefore no redundant information is available.
ICA	Independent Component Analysis (ICA)is an empirical and statistical tool for finding hidden variables that are also used for random factors, measurements or signals resources for the analyzed multivariate results. ICA defines a productive model that is drawn from a broad sampling database.
LDA	Linear Discriminant Analysis (LDA) is another technique similar to PCA but furthermore we have driven on the axes that maximize the separation between multiple classes and most commonly it is used as dimensionality compression technique in the feature generation for pattern classification, this also results in reduce computational costs and consume less time for a train a model.

Feature selection and Dimensionality reduction algorithms play their significant role that avoids overfitting problem can reduced the computational resources and model cost. Relevant features not only decrease the processing time to train a classifier but also provide better generalization

2.4 Classification

Classification is an important method for classifying characteristics in order to identify the different forms of brain activity. Different supervised learning algorithms enable us to find the relation between the features and the target classes and some widely used classifier models used for EEG signal classification are listed in the Table 8

Table 8 Classification methods

Classifier type	**Proposed Method**	**Inference**
K-Nearest Neighbour classifier **(KNN)**	Fattah et al. [32] used KNN to classify alcoholic and non-alcoholic subjects based on reflection coefficients as features	The accuracy of classifier depends on increase in the number of reflex coefficients
Support Vector Machine **(SVM)**	Yang et al. [33] used Linear SVM with Radial Basis Function kernel function creates a hyperplane that maximizes the margin between the two data points of the binary classes.	Effective in classifying the epileptic and non-epileptic persons.
	Yan et al. [34] utilized the Linear SVM along with sparse auto encoders (SAE) for generalizing the hyperplane	The SVM + SAE showed an improved accuracy when handling with high dimension data sets
	A multiple kernel learning (MKL-SVM) was proposed by XiaoouLi [35], which uses a mixture of both polynomial kernels and the Radial Basis Function kernel function for the EEG Signals classification.	The combined MKL-SVM approach provided better classification efficiency compared to SVM based on a single kernel.
Random Forest	T. Zhang et al [36] employed an ensemble-based classifier, Random classifier which classifies the data samples based on Majority voting mechanism.	Random Forest with Random sampling with and without replacement techniques yielded the high accuracy for detecting epileptic seizure
Recurrent Neural Network **(RNN)**	RNN [37] classified EEG signals by using Eigen vector methods for feature extraction	RNN along with Eigen vector methods achieved good classification accuracy
Convolutional Neural Network **(CNN)**	Acharya et al [38] used a deep learning CNN algorithm with 13 layers to classify the EEG signals	This approach uniqueness is no separate feature processing step required
Convolutional Neural Network + MultiLayer Perceptron Neural Network **(RNN-MLPNN)**	Dong et al [39] used this hybrid approach to detect the sleep disorders	The hybrid approach detected the sleep disorder with high classification accuracy
Convolutional Neural Network + Recurrent Neural Network **(CNN-RNN)**	Bressch et al [40] classified the EEG signals using this hybrid approach to detect sleep states	This combined approach yields good classification accuracy based on single channel EEG data

A classifier's efficiency is improved by the performance of a model trained on a training dataset. A classifier can model the relationship between the classes and the appropriate features in order to distinguish new instances in an unseen training dataset. Classification efficiency is very subjective due to the various features and classifiers implemented.

2.5Applications

The growing usefulness of EEG signals has been used in the detection of different neurological disorders. Moreover, the usage of EEG results greatly in other fields of research such as Motor Imagery, identity authentication, sleep stage classification, emotion identification, stress identification and drowsiness monitoring. The various stages of EEG signal processing and analysis has been summarized in table 9 for few applications.

Table 9 Applications

Applications	Data Acquisition	Artifact Removal Techniques	Features Extraction	Feature Selection	Classification	Accuracy
Emotion state recognition [41]	DEAP Dataset	Empirical Mode Decomposition + Variational Mode Decomposition	• ntropy • iguchi's fractal dimension	-	CNN	94.93 %
Identity authentication [42]	RSVP datasets +DEAP dataset+ XB Driving	Band-pass filtering (0.1 to 55 Hz)	• uto-regression coefficients (AR) • ower spectrum	sequential floating forward selection	GSLT-CNN	96%

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			density (PSD)	(SFFS)		
Stress [43]	Physionet Dataset	Bandpass filter (0.5Hz-64 Hz)	***Time Domain*** • ean value • tandard deviation ***Frequency Domain*** • ean Power • alence	PCA	GS-SVM	80.32 %
Motor Imagery [44]	BCI competition-II Dataset-III	Elliptic bandpass filter (0.5 Hz–50 Hz	• daptive Auto-regressive	Fuzzy Discernibility Matrix	SVM	80%
Sleep stage Classification **[45]**	Sleep-EDF database	Wavelet Function +IIR filters	***Time Domain*** • jorth parameters • urtosis • kewness • tandard deviation ***Time-frequency*** • nergy Non-linear • uzzy entropy • ample entropy • ractal dimension • Z complexity • urst exponent • argest Lyapunov exponent • ermutation entropy	Fisher score + Fast Correlation-Based Filter .+ Sequential Forward Selection.	Ensemble classifier	96.67 %
Epilepsy [46]	Bonn University Dataset	Butterworth filtering	Symlet wavelet Transform	PCA + Grid search optimizer	Gradient Boosting Machine.	100%

3 Conclusion

The EEG study which exhibits characteristics such as excellent time resolution, non-invasive, portable and low cost is very useful for analysing dynamically varying complex cognitive processes. This review investigates the methods of signal processing which include different methods of data collection, different pre-processing techniques for noise removal, feature extraction in various domains, most relevant features using post-processing methods and classification approaches for various applications depending upon different models using machine learning. From various studies, it was discovered that each stage does its own critical role in the processing of the raw EEG signals. EEG devices have demonstrated their capability successfully in different research applications representing different diagnosis of neurodegenerative disorders, emotion recognition, stress identification, motor imagery, sleeping stage classification, drowsiness detection and the identity authentication. The maximum number of studies have been found to operate on a very limited dataset comprising EEG signals that limits the validation of models for realistic use. In the future, however, efforts to improve validation results and classification accuracy will be carried out on the basis of improved signal processing techniques and classifiers in the processing of EEG signals..

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