Analysis and Classification of EEG Signals using Machine Learning Algorithms

A PROJECT REPORT

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Submitted by

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CANDIDATE’S DECLARATION

I, Bhavesh Mishra, Roll No. 2K21/AFI/06 student of M.Tech (Artificial Intelligence), hereby declare that the Project Dissertation titled “**Analysis and Classification of EEG Signals using Machine Learning Algorithms**” which is being submitted by me to Delhi Technological University, Delhi, in partial fulfilment of requirements for the degree of Master of Technology in Artificial Intelligence is a legitimate record of my work and is not copied from any source. The work contained in this report has not been submitted at any other University/Institution for the award of any degree.

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CERTIFICATE

I, hereby certify that the Project titled "**Analysis and Classification of EEG Signals using Machine Learning Algorithms**", submitted by Bhavesh Mishra, Roll No. 2K21/AFI/06, Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of degree of M.Tech in Artificial Intelligence is a genuine record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree to this University or elsewhere.

Place: Delhi Dr. Manoj Kumar

Date: Professor

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I am extremely grateful to my project guide, **Dr. Manoj Kumar**, Professor, Department of Computer Science and Engineering, Delhi Technological University, Delhi for providing invaluable guidance and being a constant source of inspiration throughout my research. I will always be indebted to him for the extensive support and encouragement he provided.

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ABSTRACT

Electroencephalography (EEG) data analysis and categorization are critical for recognising brain activity and diagnosis different neurological illnesses. This research describes a unique approach for analysing and classifying EEG data, as well as its possible uses for health care and brain-computer interface, or BCI, applications.

To extract relevant characteristics from EEG data, the proposed method employs modern signal processing methods and machine learning algorithms. These properties record both of them temporal and spectral aspects of brain activity, allowing for good differentiation among various brain states and disorders. Pre-processing procedures are included in the approach to reduce noise and artefacts, assuring the dependability of the recovered features. The approach uses supervised learning methods that include SVM, ANN, and RF to identify EEG data. These algorithms use tagged EEG data to teach them to recognise distinct brain states or diagnose certain neurological diseases. Performance indicators such as specificity, sensitivity, and total accuracy are used to assess classification accuracy, proving the usefulness of the given strategy.

This approach has several uses in both clinical and scientific settings. It can help with the diagnosis of neurological illnesses such as epilepsy, sleep disorders, and Alzheimer's disease in clinical settings. Healthcare providers may make educated judgements about patients' treatment and management by appropriately identifying EEG signals. Furthermore, the technology has the potential to be used in the development of brain-computer interfaces, which would allow people to control external equipment using their brain activity. This has consequences for persons with movement impairments who use assistive devices, neurorehabilitation, and communication systems. The method provided here takes a new approach to EEG data processing and categorization, offering essential insights into brain activity and aiding in the diagnosis of neurological diseases. Its applications include healthcare and BCI systems, which promote developments in the field of neuroscience, medicine, and technology for people with disabilities. To broaden its scope and utility, future study may look at further upgrades, connection with other methods, and real-time deployment.

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LIST OF ABBREVIATIONS

EEG	Electroencephalogram
AR	Artifact Removal
ICA	Independent Component Analysis
SVM	Support Vector Machine
RF	Random Forest
CNN	Convolutional Neural Network
NN	Neural Network
FT	Fourier Transforms
ERP	Event-Related Potentials
ANN	Artificial Neural Network
PCA	Principal Component Analysis
ML	Machine Learning
DL	Deep Learning
RNN	Recurrent Neural Networks
LSTM	Long-Short-Term Memory
KNN	K-Nearest Neighbours
BCI	Brain-Computer Interfaces

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

EEG is a non-invasive scanning process that monitors the electrical impulses of the brain using electrodes inserted on the scalp. EEG signals describe the aggregate behaviour of vast populations of neurons and give important information on brain function and dynamics. They provide a unique perspective on the basic mechanisms of cognition, thinking, and other neurological illnesses. The great temporal resolution of EEG data enables for the identification of fast changes in neural activity with nanosecond precision. These signals display intricate patterns and rhythmic activity across several frequency bands, which represent the underlying brain processes [1].

In neuroscience, EEG signals play a crucial role in studying brain function. They provide information about cognitive processes, such as attention, memory, and language processing. EEG is widely used in research settings to investigate brain dynamics during tasks, such as visual or auditory stimuli, motor activities, and cognitive experiments. By analysing EEG signals, researchers can uncover the neural mechanisms underlying these processes and gain insights into the organization and connectivity of brain networks. In addition to neuroscience research, EEG signals have significant clinical applications in the diagnosis and management of neurological disorders. Abnormal EEG patterns are associated with various conditions, including epilepsy, sleep disorders, brain injuries, and neurodevelopmental disorders. Analysing and classifying EEG signals can aid in the diagnosis of these disorders, guide treatment decisions, and monitor the effectiveness of interventions [1].

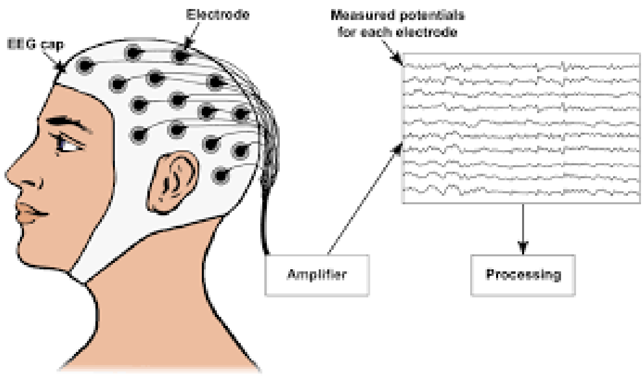

Fig 1: Recording an EEG Signal using Electrodes [5]

The EEG Signal's Frequency Band

EEG signals may be classified into distinct frequency bands, each of which corresponds to different brain processes. The following frequency ranges are frequently found in EEG signals [2]:

- **Delta (0.5 - 4 Hz)**: Deeper sleep, the unconscious, and certain neurological diseases are all related with the delta band. It is distinguished by sluggish, high-amplitude waves.

- **Theta, which (4 - 8 Hz)**: waves of theta are frequently observed during sleep, meditation, especially in young infants. They are also seen during rapid eye movement (REM) sleep. Memory processing and creative thinking are connected to theta activity.

- **Alpha (8 - 13 Hz):** When a person is awake yet relaxed, with their eyes closed, the Alpha waves are dominant. They are related with a peaceful and peaceful state of mind and can be reduced by opening one's eyes or performing mental duties.

- **Beta (13–30 Hz):** Beta waves are common during active mental focus, attentiveness, and cognitive processing. They are further subdivided as lower beta (13 - 20 Hz) along with high beta (20 - 30 Hz), more the latter connected with more concentrated attention.

- **Gamma (30-100 Hz):** The gamma waves are the quickest frequency range and are associated with higher-level cognitive functioning, information processing, and sensory input integration. They have been linked to perceptions, attention, and memory skills.

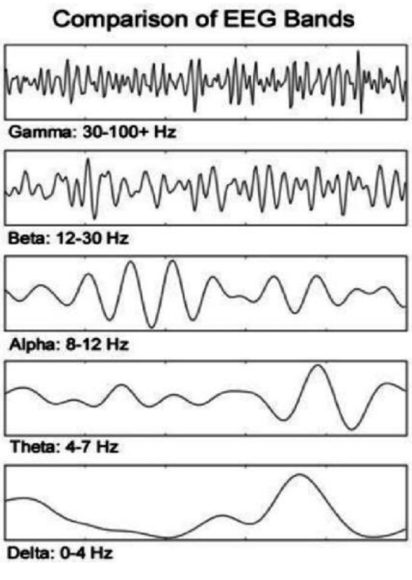

Fig 2: Comparison EEG Frequency Bands[61]

1.2 PROBLEM STATEMENT

EEG signal analysis and categorization are critical in many domains, include neurology, medical diagnosis, and interfaces between brains and computers. However, because EEG signals are complex and non-stationary, correct interpretation offers major hurdles. As a result, robust and efficient strategies for analysing and classifying EEG data to extract relevant information are required.

1. How might reliable EEG signal analysis and categorization lead to advances in brain algorithms for signal processing and ML techniques?

2. How can EEG signal analysis and categorization help us understand the brain's activity and cognitive procedures?

3. What function does an EEG evaluation play in neurologic illness diagnosis and treatment? How can good EEG signal categorization help with early diagnosis and better patient outcomes?

4. How are EEG signals used to construct BCI (BCIs)? What are the difficulties in effectively analysing and categorising EEG data for BCI applications?

5. Where may EEG analysis be used to assess cognitive states in practise? How might this monitoring help to enhance security and efficiency in high-demand professions?

6. How does the analysis of EEG help with personalised medicine? How might identifying individual-specific brain structures or markers improve mental health treatment planning and optimisation?

7. What are the special obstacles of analysing and classifying EEG signals, given their high dimension, non-stationarity, and the existence of artefacts?

8. How does real-time EEG signal processing affect the research and development of applications like BCIs and biofeedback systems? What computational issues must be addressed for effective analysis and classification?

9. What are the prospective breakthroughs and uses of EEG analysis and categorization in neurological research and clinical practise in the future?

10. What contribution does EEG signal analysis and categorization provide to the area of neuropsychology? What can be learned about cognitive functioning and brain illnesses by researching EEG patterns?

1.3 OBJECTIVES

The fundamental goal of this thesis/dissertation will be to investigate techniques for analysing and classifying EEG data, as well as their applications in many fields[3].

Among the particular goals are:

- To review the characteristics of EEG signals, including their frequency content, ERP, and time-varying dynamics.
- To investigate various signal processing techniques for EEG signal pre-processing, AR, and feature extraction.
- To explore different approaches for analysing and classifying EEG signals, including supervised learning algorithms, unsupervised learning algorithms, DL architectures, and ensemble methods.
- To examine the applications of EEG signal analysis and classification in BCI, neurofeedback systems, epileptic seizure detection and prediction, sleep stage classification, and cognitive state assessment.

CHAPTER 2   RELATED METHOD

Several articles have looked into the use of ML methods as well as the analysis of EEG signals. For example, Correa et al. (2007)[4] proposed cascaded filtered for EEG signals, Jadav[6] proposed a method for noise in EEG information, Richhariya, B[7] applies SVM for classification, and many more methods are investigated in this paper, which also shows The frequency categorization EEG Signal and applications of EEG Signals.

Title: "*EEG-Based Emotion Recognition Using DL Techniques*"[8]

Abstract: The purpose of this research is to analyse and classify EEG data for emotion identification using methods based on DL. Emotion identification using EEG data has several uses, include affective computation, interaction between humans and computers, and mental health screening. The goal of this study is to create a precise and robust classification system for recognising various emotional states using EEG data.

The following steps comprise the research methodology:

1. Dataset collection: A collection of data of EEG signals obtained from human volunteers in various emotional states is gathered. Labelled EEG recordings related with various emotion categories such as happy, sorrow, anger, and neutral emotions are included in the collection.

2. Pre-processing: The obtained EEG data is subjected to pre-processing processes in order to eliminate artefacts, filter off noise, and normalise the signals. To guarantee high-quality information, methods such as a bandpass filtration, baseline correction, and artefact removal are used.

3. Feature extraction: Using the preprocessed EEG data, relevant characteristics are retrieved. These characteristics capture various components of the EEG data, such as spectral power in certain frequency bands, statistical measurements, or time-domain properties. To determine the most discriminative characteristics for emotion identification, feature selection approaches can be used.

4. Deep NN model design: Using the retrieved features, an architecture for DL is created for emotion categorization. Convolutional layers may be used to capture spatial details in EEG data, whereas recurrent layers may be used to capture temporal relationships. To improve the accuracy of the model and reduce overfitting, function activation, dropout, and regularisation approaches are used.

5. DL model training and optimisation: The DL algorithm is trained using labelled EEG data. To minimise the classification error, optimisation methods such as stochastic descent of gradients (SGD) or Adam are used. To optimise model

performance, hyperparameters like as learning rate, batch quantity, and network architecture are modified via cross-validation or grid search.

6. Evaluation: A distinct testing dataset is used to evaluate the trained model. To evaluate the model's classification performance, several performance measures like as precision, recall, precision, F1-score, and confusion matrix are produced.

7. findings and the discussion: The experimental findings and performance assessment are provided, highlighting the suggested DL model's classification accuracy. The efficacy of the selected characteristics is reviewed, as well as network design and optimisation strategies.

8. review of results and possible implications for EEG-based emotions recognition: The study finishes with a review of its results and the repercussions for EEG-based emotion detection. Future research topics and possible model modifications, such as adding multimodal data or investigating innovative DL architectures, are suggested.

Title: "*Analysis and Classification of EEG Signals for Epileptic Seizure Detection*"[9]

Abstract: This study focuses on analysing and categorization of EEG data for the identification of epileptic seizures, which is critical in the identification and treatment of epileptic. The goal is to create an accurate and dependable framework for automated seizure identification using EEG data.

The following steps comprise the research methodology:

1. Dataset collection: An EEG dataset of seizures and non-seizure segments is obtained from patients with epilepsy. The dataset has been carefully selected to ensure that it covers a wide variety of kinds of seizures and contains enough data to train and test the classification algorithm.

2. Pre-processing: The obtained EEG data is subjected to pre-processing processes in order to eliminate artefacts, filter off noise, and normalise the signals. Baseline correction, a bandpass filtering, and artefact reduction techniques like ICA or wavelet denoising are all common pre-processing techniques.

3. Feature extraction: To capture seizure-related patterns, relevant features are recovered from pre-processed EEG data. These characteristics may include statistical metrics such as mean and variance, as well as spectral characteristics such as power in particular frequency regions (e.g., delta, theta, and alpha). Additional characteristics that include wavelet coefficients or linear measurements such as approximation entropy may be considered.
4. Feature selection: Feature selection approaches are used to discover the most useful features in order to minimise dimensionality and enhance classification

performance. Mutual details, correlation-based feature selection, and recursive feature removal are typical methods.

5. Classification model design: For seizure detection, several ML methods such as SVM, RF, and ANN are investigated. The classification model used is determined by the properties of the dataset as well as the intended compromise between accuracy and processing efficiency.

6. Training and optimisation: Using labelled EEG data, the categorization model is trained. Cross-validation or hold-out verification is used to evaluate the performance of the model and tweak hyperparameters such as regularisation variables, kernel types, or network design. To improve classification accuracy, ensemble approaches like as bagging or boosting might be used.

7. The model that was trained is assessed using either a separate testing dataset or cross-validation. To measure the model's effectiveness in seizure detection, evaluation metrics such as specificity, sensitivity, accuracy, and the area beneath the curve of receiver operating characteristics (AUC-ROC) are generated. The outcomes are compared to existing cutting-edge techniques or benchmark algorithms.

8. Results and the discussion: The test outcomes and effectiveness evaluation are provided, emphasising the efficacy of the suggested method in identifying epileptic episodes. The model's benefits and weaknesses are examined, as well as possible difficulties in real-world implementation and generalisation to diverse patient groups.

9. Conclusions & future work: The investigation finishes with a review of its results and the consequences for the identification of epileptic seizures using EEG. Future research avenues might include investigating multimodal data fusion, using ML techniques, or undertaking clinical validation trials to evaluate the model's effectiveness in real-world circumstances.

This example illustrates a common framework for evaluating and categorising EEG information in the setting of seizures with epilepsy detection. Actual related efforts in other studies may differ based on the individual study aims, intended applications, and dataset features.

Title: "*Analysis and Classification of EEG Signals for Brain-Computer Interface (BCI) Applications*"[10]

Abstract: The purpose of this research is to analyse and classify EEG data for Brain-Computer Interaction (BCI) applications, which allow direct connection among the brain and external equipment. The study's goal is to create efficient ways for extracting useful data from electrical brain waves and identifying various mental states or directives. Various feature extraction approaches are investigated, including ERP, power spectral analysis, and time-frequency analysis. In BCI applications, the performance of several classification techniques like as the SVM, k-Nearest The k-NN, and ANN is tested. The study contains human subject validation trials to examine the efficacy and precision of the suggested approaches.

Title: "*Analysis and Classification of EEG Signals for Sleep Stage Detection*"[11]

Abstract: This study addresses the analysis and categorization of EEG data for sleep stage identification, which is important in the diagnosis of sleep disorders and the monitoring of sleep quality. The study's goal is to create strong algorithms that can properly detect different sleep phases using EEG data. To identify sleep stage-specific patterns, feature extraction approaches that involve power spectral density estimates, statistical measurements, or entropy-based metrics are used. The performance of several classification algorithms, such as hidden Markov models (HMM), RF, and NNs using convolution (CNN), in classifying sleep stages is examined. To illustrate the effectiveness and dependability of the proposed strategy, the study involves verification on large-scale sleep datasets including comparisons with existing sleep staging approaches.

Title: "*Analysis and Classification of EEG Signals for Cognitive Load Assessment*"[12]

Abstract: This research involves the analysis and categorization of electrical brain waves for the purpose of detecting cognitive strain, becoming an important aspect in assessing mental effort and human performance. The study's goal is to create accurate models for identifying differences in cognitive stress levels using EEG data. To extract meaningful information associated to cognitive load, feature extraction approaches including spectral analysis, wavelet transformations, or ERP are applied. Various ML methods, such as SVM, RF, and ANN, are being studied for their efficacy in cognitive load categorization. The research comprises studies with human individuals doing cognitive activities, as well as an examination of the link between EEG characteristics and mental load levels. The findings show that EEG-based cognitive load evaluation has potential applications in sectors such as interaction between humans and computers and education.

Title: "*Review of Methods for Analysis and Classification of EEG Signal and its Applications*" [13]

Abstract: EEG signals, often known as brainwaves, are used to assess electrical activity in the cerebral cortex. This paper provides an overview of techniques/algorithms used for EEG signal preliminary processing, feature extraction, and classification, which are critical in EEG signal processing. This study also lists the applications of using EEG signals. Filtering methods such as bandpass, very high pass, as well as low pass are frequently used to remove unwanted frequencies and enhance signal quality. Approaches such as ICA and regression-based algorithms are used to eliminate artefacts caused by eye blinks, muscle activity, or electrode artefacts. The precision and dependability of EEG-based evaluations have improved as pre-processing procedures, feature extraction methods, and algorithms for classification have increased.

TABLE 1 FOR COMPARING PRE-PROCESSING TECHNIQUES

No	Technique	Advantages	Disadvantages
1	Digital Filtering	Good for overlapping spectra signal, remove grounding noise, easy modify signal feature	The signal and noise must be located in separate frequency bands.
2.	ICA	computations with high efficiency, good for large data	Decomposition required high computational power.
3.	CAR	Very Efficient	Sampling sparsity and incomplete head coverage hinder average calculation
4.	Adaptive Filtering	Good for overlapping spectra signal, easy modify signal feature	Alteast two signal required.
5.	SL	Best in removing noise	Sensitive to Artifacts.

TABLE 2 COMPARING FEATURES EXTRACTIONS TECHNIQUES

No	Technique	Advantages	Disadvantages
1.	FFT	goodfor stationary signal,narrow signal	Very sensitive to noise, not for non-stationary signals.
2.	PCA	Lossless Dimension Reduction	Not for complex data.
3.	WT	Varying Window Size, for time and frequency domain	Performance Constraint Heisenberg Uncertainty.
4.	WPD	ForNon-Stationary Signals	High Computation Time.

TABLE 3 FOR COMPARING CLASSIFICATION ALGORITHMS

No	Technique	Advantages	Disadvantages
1.	SVM	Best for Linear Classifaction	High Computational complexity
2.	DL	High Accuracy.	Performance depends on degree of neurons.
3.	K-NN	Simple to use	Fails in performance for large dataset.
4.	NB	Easy to learn.	Independent variable.

CHAPTER 3 METHODOLOGY

STEPS OF ANALYSIS OF EEG SIGNAL

EEG signal analysis generally consists of multiple phases. To begin, raw EEG data is collected and pre-processed to eliminate artefacts and noise. Filtering the signal to eliminate undesired frequencies and employing techniques such as signal averaging to improve the signal-to-noise ratio are examples of such procedures. After the data has been pre-processed, it may be examined using a variety of ways.[14]

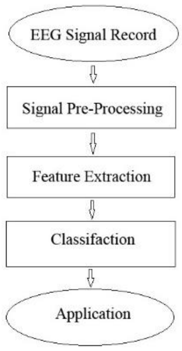

Fig 3: Steps of EEG Signal Pre-Processing

3.1 EEG SIGNAL ACQUISITION

The technique of recording and monitoring the electrical impulses of the brain utilising electrodes implanted on the scalp is known as EEG signal acquisition. It is a non-invasive technology used to examine brain activity and identify various neurological diseases in research and clinical settings.[15]

Here is a general overview of the steps involved in EEG signal acquisition:

a) Preparing the subject: The subject's hair is typically washed and the scalp is cleaned to ensure good electrode contact. In some cases, small amounts of hair may be shaved to improve electrode placement.

b) Electrode placement: The electrodes are placed to particular areas on the scalp in accordance with the 10-20 system, an international standard. This technique employs predetermined placements based on anatomical markers on the skull.

b) Electrode application: Electrodes are either applied using a conductive gel or with adhesive caps or headsets that have pre-attached electrodes. The conductive gel helps reduce impedance between the electrode and the scalp, improving signal quality.

c) Signal acquisition system: An EEG amplifier or recording equipment is linked to the electrodes. The amplifier increases the strength of the feeble electrical impulses taken from the metal electrodes to a threshold that may be measured and studied.

d) Signal filtering: The raw EEG signal contains various types of noise, including environmental interference and muscle artifacts. To eliminate undesired frequencies and artefacts, methods of filtering like high-pass, low-pass, and notched filters are used.

e) Sampling rate and data storage: The EEG signal is sampled at a specific rate, typically ranging from 250 to 2000 samples per second. The data is then stored in a digital format for further analysis.

f) Recording session: During the recording session, the subject is typically asked to relax and remain still to minimize movement artifacts. In some cases, specific tasks or stimuli may be used to elicit certain brain responses.

g) Signal interpretation: After the recording session, the acquired EEG data is processed and analysed using various techniques. This may involve spectral analysis, event-related potential (ERP) analysis, or other advanced signal processing methods[17].

It's important to note that EEG signal acquisition can vary depending on the specific application, equipment used, and research protocols. Professional training and expertise are usually required to ensure accurate electrode placement and reliable signal acquisition.

3.1.1 Techniques for Obtaining EEG Signals [18]

a) Surface Electrodes
Surface electrodes are the most commonly used method for EEG signal acquisition. These electrodes are placed on the scalp according to standardized electrode placement systems, such as the 10-20 system or 10-10 system. Surface electrodes are generally comprised of conductive materials like silver/silver chloride and are linked to the EEG amplifier through electrode leads. The electrodes are used to measure the voltage changes caused by the brain's electrical activity. Surface electrodes offer several advantages, including ease of use, non-invasiveness, and versatility. They allow for the measurement of electrical activity across multiple scalp regions simultaneously, providing a comprehensive view of brain activity. The 10-20 system and 10-10 system provide standardized electrode placements, ensuring consistency across studies and facilitating comparison of results.

b) Intracranial Electrodes
Intracranial electrodes entail the direct insertion of electrodes into brain tissue or the placement of electrodes on the brain's surface. This method provides a more localized and precise measurement of neural activity. Intracranial electrodes are typically used in clinical settings, such as epilepsy monitoring units, where they help identify the specific brain regions involved in seizure activity.Intracranial electrode placement requires surgical intervention and is usually reserved for specific cases where high spatial resolution is necessary. The placement of intracranial electrodes allows for the recording of signals closer to their source, reducing signal contamination from surrounding tissues and skull.

c) Electroencephalography Caps
EEG caps consist of pre-positioned electrodes embedded in a cap that conforms to the shape of the scalp. These caps provide a standardized electrode placement system, ensuring consistent positioning of electrodes across participants and studies. The cap design allows for quick and accurate electrode placement, saving time and minimizing measurement variabilities caps are particularly useful when recording from a large number of channels, as they facilitate the simultaneous acquisition of signals from multiple scalp regions. The caps also improve participant comfort and reduce the likelihood of electrode displacement during recording sessions.

3.2 EEG SIGNAL PRE-PROCESSING

What Is Pre-processing?

Pre-processing, in general, is the technique of changing the initial information into a format which is more suited for subsequent analysis and understandable to the user. Pre-processing in the context of EEG data often refers to reducing noise form the data in order to come closer to the genuine brain signals.[19]

What is the purpose of pre-processing?

There are various reasons why EEG data must be pre-processed. To begin with, the signals received up from the head are not always a precise depiction of the impulses coming from the cerebral cortex, as spatial data is lost. Second, EEG data contains a lot of noise, which might mask weaker EEG signals. Blinking or muscular movement, for example, can pollute the information and distort the image. Finally, we aim to distinguish between important brain signals and random neural activity during EEG recordings.

How might pre-processing change depending on the type of analysis desired?

Because EEG pre-processing is still a developing field, there is no globally accepted EEG pre-processing pipeline, therefore researchers have considerable leeway in deciding how to modify the raw data. Here are some questions to consider while deciding on the best pre-processing techniques:

What types of artefacts may be in your data? Which of them do you wish to get rid of, and which would you want to be conscious of?

For example, depending on your experiment eye movements and blinking could be considered a source of noise but they could also reveal important patterns

Is your research being conducted online or offline?

You may not be able to apply more computationally intensive approaches if you pre-process information right away as it arrives.

What characteristics do you wish to highlight?

For example, if you want to look at ERP you will need to have accurate temporal information, whereas for motor imagery classification you will need accurate spatial information

3.2.1 Filtering

Filtering is an important step in the pre-processing of EEG signals. It entails the use of high-pass, low-pass, and a band-pass filter to eliminate undesirable frequency components and noise. Filtering helps enhance the signal-to-noise ratio and focuses the analysis on specific frequency ranges of interest[20].

High-pass filters remove low-frequency drifts and baseline shifts, which can result from electrode contact issues or slow changes in brain activity. Low-pass filters eliminate high-frequency noise, such as electrical interference or muscle artifacts. Band-pass filters allow the selection of a specific frequency range, targeting the frequencies relevant to the research question or clinical application.

3.2.2 Artifact Removal

EEG signals are susceptible to various artifacts that can distort the underlying brain activity. These artifacts can arise from sources such as eye movements, muscle activity, electrode pops, or environmental interference. Effective AR techniques are crucial for obtaining accurate and reliable EEG signals.[16]

- Eye Movement A R: Eye movements, including blinks and lateral eye movements, can contaminate EEG signals. ICA is a commonly used technique to identify and remove components related to eye movements. By decomposing the EEG signals into independent components, ICA can isolate the components representing eye movements and exclude them from the final analysis.

- Muscle AR: Muscle artifacts can arise from muscle contractions, such as jaw clenching or facial movements. These artifacts can obscure the underlying brain activity of interest. Techniques such as template subtraction or adaptive filtering can be used to remove muscle artifacts. Template subtraction involves creating a template of the muscle artifact from a separate recording of the artifact itself. This template is then subtracted from the contaminated EEG signals, effectively removing the muscle artifact. Adaptive filtering techniques use adaptive algorithms to estimate and subtract the muscle artifact based on its characteristics.

- Electrode A R: Electrode-related artifacts can occur due to poor electrode contact or movement. These artifacts can introduce high-frequency noise or abrupt changes in the signal. Artifact subspace reconstruction methods can be employed to identify and remove segments or channels affected by electrode-related artifacts. These methods use statistical analysis and signal modelling to distinguish between artifact-contaminated segments and clean EEG segments.

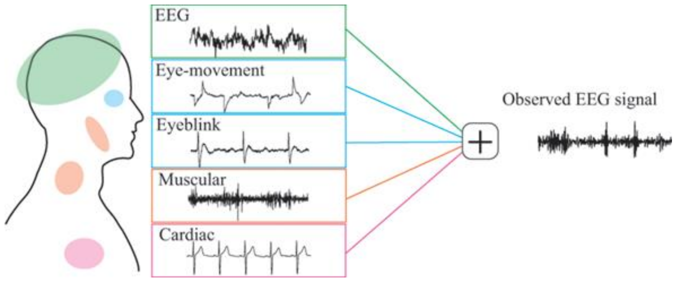

Fig 4. Configuration of an observed EEG signal including biological artifacts[16].

3.3 FEATURE EXTRACTION

Feature extraction is an important stage in EEG signal analysis since it extracts significant information to characterise and describe the signals. The extracted features capture specific aspects of the EEG signals that are informative for the research or clinical application. Various types of features can be derived from EEG signals[21]:

3.3.1 Time-Domain Characteristics

Time-Domain Characteristics captures amplitude and temporal characteristics of EEG signals. These features provide insights into the overall signal dynamics and statistical properties[22]. Commonly used time-domain features include:

Mean: Represents the average amplitude of the signal.

Variance: Measures the variability or spread of the signal values.

Skewness: Describes the asymmetry of the signal distribution.

Kurtosis: Indicates the peakiness or flatness of the signal distribution.

Signal Entropy: Quantifies the complexity or irregularity of the signal.

Time-domain features provide information about the overall signal characteristics and can be used to identify differences between healthy and pathological brain activity.

Time-Domain Analysis of EEG Signals[23]

a) Statistical Analysis Methods

Statistical analysis methods play a crucial role in the time-domain analysis of EEG signals. These methods allow for the identification of statistically significant differences and patterns in the EEG data. Several statistical techniques are commonly used in EEG signal analysis:

- Descriptive Statistics
- t-tests and Analysis of Variance (ANOVA)
- Correlation Analysis

b) Waveform Analysis Techniques

Waveform analysis techniques focus on the temporal characteristics and patterns of EEG waveforms. These techniques provide insights into the dynamics and temporal structure of the EEG signals.

Common waveform analysis techniques include:

- Amplitude Analysis
- Peak Detection
- Oscillatory Analysis

c) Event-Related Possibilities (ERPs) Analysis

EEG responses that occur in reaction to specific events or stimuli are known as ERP (ERPs). ERPs are brain processes that represent senses, cognitive, or motor activities. ERPs are typically obtained by averaging multiple EEG trials time-locked to the onset of the event of interest. ERPs analysis techniques include:

- Epoching and Averaging
- Component Identification
- Amplitude and Latency Analysis
- Topographic Mapping

d) ERP Modulation and Source Analysis

ERP modulation analysis investigates how ERP components are modulated by different experimental conditions, stimuli, or participant groups. It assesses whether there are significant differences in ERP amplitude or latency across conditions, indicating differential neural processing. Source analysis techniques, such as dipole modeling or distributed source estimation, can be employed to estimate the neural sources underlying the observed ERP components, providing insights into the brain regions involved in specific cognitive processes.

3.3.2 Frequency-Domain Characteristics

The spectral composition of EEG waves is analysed using frequency-domain characteristics. These characteristics reflect the pattern of power across distinct frequency bands by translating signals onto the frequency domain[24][25].

Commonly used frequency-domain features include:

Power Spectral Distribution (PSD): Represents the distribution of power across frequency bins.

Spectral Centroid: Identifies the centre frequency or the weighted average frequency of the signal.

Band Power Ratios: Quantify the relative power in specific frequency bands, such as alpha, beta, theta, or delta.

Frequency-domain features provide insights into the dominant frequency components and can help identify specific brain states or activities associated with different frequency bands.

Frequency-Domain Analysis of EEG Signals

a) Power Spectrum Analysis

Power spectrum analysis is a widely used technique in the field of electroencephalography (EEG) signal processing. It provides valuable insights into the frequency content of EEG signals and helps in understanding the underlying neural processes. The power spectrum represents the distribution of signal power across different frequencies. To perform power spectrum analysis, the EEG signal is first divided into small segments of equal length using a technique called windowing. The most commonly used windowing technique is the FFT. The FFT breaks down the signal into its basic sinusoidal components, exposing phase and amplitude information at various frequencies. Calculating the squared amplitude of the FFT values yields the power spectrum. It denotes the signal power contained inside each frequency component. A power spectrum is commonly shown with speed on the x-axis and strength or intensity on the y-axis.

Researchers can use power spectrum analysis to find prominent frequency bands or patterns in the EEG output. These frequency ranges are frequently linked to particular states of the brain or cognitive functions. The delta band (0.5-4 Hz) and theta, or (4-8 Hz) bands of frequencies, for example, are frequently detected during profound slumber or meditating, whereas the alpha (8-13 Hz) or beta (13-30 Hz) regions are connected associated wakeful and active brain states.

b) Spectral Coherence and Connectivity Measures

Spectral coherence and connectivity measures provide information about the functional connectivity between different brain regions based on their frequency-specific interactions. These measures help in understanding how different parts of the brain communicate and coordinate their activities. Spectral coherence measures the degree of similarity or synchronization between two EEG signals at different frequencies. It quantifies the linear relationship between the signals and provides an estimate of the coherence or connectivity between the corresponding brain regions. Higher coherence values indicate stronger functional connectivity. Connectivity measures, such as phase synchronization or phase locking value (PLV), quantify the phase coherence between different EEG signals. They assess the consistency of phase relationships across different frequency bands and provide information about the temporal coordination of neural activity. These coherence and connectivity measures are often computed using advanced techniques such as wavelet transforms or multitier spectral analysis. They allow researchers to identify functional networks and investigate the dynamics of neural interactions across different frequency bands.

c) **Extraction of Frequency Domain Features:**

Identifying certain traits or pattern from power spectra or coherence measurements that are pertinent to a given research issue or application is what extraction of features within the frequency domain entails. These characteristics are used as inputs for extra evaluation or classification algorithms.

Some commonly used features extracted from the frequency domain include:

- Band Power
- Peak Frequency
- Spectral Edge Frequency
- Coherence or Connectivity Measures

3.3.3 Time-Frequency Characteristics

Time-frequency characteristics capture variations in spectral content over time, allowing for the analysis of dynamic changes in EEG signals. These features provide information about the temporal evolution of frequency components and their relationship to specific events or tasks[26][27].

Commonly used time-frequency analysis techniques for feature extraction include:

- Short-Time Fourier Transform (STFT): Divides EEG signals into small pieces and applies FF to each segment to generate frequencies spectra over time.

- Wavelet Transform: Decomposes the EEG signals into different frequency bands using wavelet functions, providing a time-frequency representation of the signals[28].

• Experimental Mode Decomposition (EMD): This method decomposes data into internal mode functions that contain oscillatory components at various time scales.

- Time-frequency features enable the identification of transient changes in brain activity and can be valuable for capturing event-related responses or dynamic brain processes.

By extracting these features from EEG signals, researchers and clinicians can characterize and represent the signals in a concise and informative manner, facilitating subsequent analysis and categorization tasks.

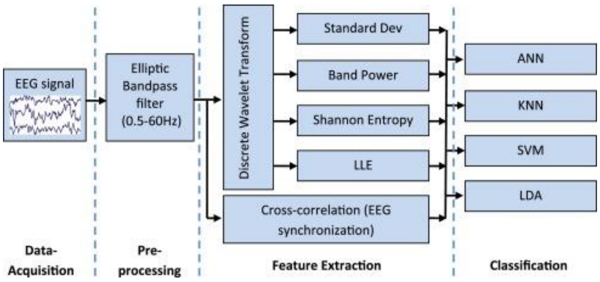

Fig 5 Methods for Analysis Signal Pre-Processing[56]

3.4 EEG SIGNAL CLASSIFICATION

a) Data pre-processing
b) Feature extraction
c) Data labelling
d) Data splitting
e) Model training
f) Model optimization
g) Model evaluation
h) Model deployment

3.4.1 Supervised Learning Algorithms

The purpose of supervised learning techniques for EEG signal categorization is to train an algorithm to foresee the category or labelling of an individual EEG signal according to its attributes[29].

Some popular supervised learning algorithms include:

a) Support Vector Machines

SVM is a prominent ML technique that can be utilised in classification or regression applications, including EEG data analysis. Developing the use of SVM models for EEG data analysis necessitates domain knowledge regarding ML as well as EEG signal processing. Proper pre-processing, feature extraction, and appropriate choice of hyperparameters are critical for obtaining accurate and meaningful results. Additionally, the availability of a sufficient amount of high-quality labelled data is crucial for training a robust SVM model[30].

SVM is a sophisticated linear and multiclass classification technique. It identifies the best hyperplane to split each class in a feature with high dimensions space. SVM has been used successfully to classify EEG signals, especially when the number of features is considerable.

b) Random Forest

Another common ML approach for EEG signal categorization is R F. Here's a step-by-step guide on using a RF for EEG signal processing. Keep in mind that the performance of RF for EEG signal categorization is dependent on aspects such as the accuracy of the reprocessing information, the selection of useful features, and the choice of appropriate hyperparameters. Additionally, having a sufficient amount of accurately labelled EEG data is crucial for training a reliable RF model[36][37].

RF is an ensemble learning algorithm that combines multiple decision trees to make predictions. It is effective for handling high-dimensional data and provides good generalization performance. RF has been widely used in EEG classification tasks due to its ability to handle noisy and complex datasets[31].

c) k-Nearest Neighbours (k-NN)

K-NN provides a simple yet effective technique for classifying fresh samples based on the vast majority class of their KKN within the space of features. k-NN has been used to classify EEG signals, particularly when the underlying data distributions is non-linear.

Remember that the effectiveness of k-NN for EEG signal classification is dependent on factors such as the quality of the prepared data, the selection of useful characteristics, the choosing of appropriate hyperparameters (particularly k), as well as the availability of an adequate quantity of accurately labelled EEG information for training[32].

d) Naive Bayes

Another ML approach that may be used for EEG signal categorization is Naive Bayes. It relies on the Bayes theorem and presupposes feature independence.

Naive Bayes is a straightforward and computationally efficient approach, making it ideal for data with a large number of characteristics and small sample sizes. However, its feature independence assumption may not apply in some circumstances, particularly for strongly linked features in EEG data. Other ML techniques, such as SVM or DL models, may be more suited in such instances. Nonetheless, Naive Bayes may be used as an alternative base predictor for EEG signal tasks such as classification and can produce good results in some cases[38][39].

3.4.2 Unsupervised Learning Algorithms

When there are no predetermined labels or classifications in the EEG data, unsupervised learning techniques are applied. These algorithms are designed to uncover hidden structures or patterns in data[40].

Some common unsupervised learning algorithms used in EEG signal analysis include:

a) Clustering

Clustering is a popular unsupervised learning approach for grouping together comparable data points in a dataset. It may also be used to discover patterns or clusters of signals in EEG readings[41].

Clustering in EEG signal analysis can provide valuable information about underlying patterns or groupings in the data. It can be used for tasks such as identifying distinct brain states, detecting abnormal patterns, or exploring relationships between different EEG segments**.** However, it is vital to highlight that the standard of data preparation, extraction of features, and the applicability of the selected clustering method for the particular EEG signal analysis job all have a significant impact on clustering outcomes.

Clustering algorithms group similar EEG signals together based on their feature similarity. K-means clustering and hierarchical clustering are commonly used techniques. Clustering can help identify distinct brain patterns or group similar EEG signals without prior knowledge of their classes.

b) PCA Dimensionality Reduction

PCA is a reduction in dimensionality approach that is extensively used in unsupervised ML, including EEG data processing. It aids in the extraction of useful characteristics or the reduction of data dimensionality while keeping crucial information[42].

PCA can be helpful for experimental analysis of data, dimensionality reduction, and visualisation in unsupervised learning. It enables you to discover the underlying structure of EEG signal data without depending on labelled data. By reducing the dimensionality of the data, PCA can help in improving computational efficiency and removing redundant or noisy features, making subsequent analysis or modelling tasks more manageable.

Dimensionality reduction approaches strive to minimise the dimension of the space of features while retaining the most significant data. PCA, and t-SNE (t-Distributed Sequential Neighbour Embedding) are two popular approaches for analysing EEG signals. They aid in the visualisation and exploration of the fundamental structure of the EEG data.

c) Self-Organizing Maps (SOM)

SOMs, also known as Kohonen maps, constitute a sort of unsupervised learning technique that may be used to analyse EEG signals. SOMs are NNs that cluster and visualise high-dimensional data using a competitive learning process. SOMs are a strong unsupervised learning method in brainwave analysis. They can help identify hidden structures and patterns in the data, aid in data exploration and visualization, and provide a foundation for further analysis and interpretation[43].

SOMs are NNs that generate a low-dimensional model of the input data. It translates high-dimensional EEG properties into a two-dimensional grid while retaining data point topological connections. SOM was previously used to cluster and visualise EEG data.

3.4.3 Deep Learning Methodologies

DL algorithms have gotten a lot of interest in EEG signal categorization because of their capacity to learn hierarchical representations automatically from raw or pre-processed EEG data. DL models are made up of numerous layers of linked neurons that allow them to recognise complicated correlations in data.

Some popular DL architectures used in EEG signal classification include:

a) Convolutional Neural Networks

CNN can also be used for EEG signal analysis and classification. CNNs are particularly effective in capturing local spatial patterns and hierarchical features, making them suitable for analysing the temporal and spatial characteristics of EEG signals. Keep in mind that CNNs for EEG signal classification require a sufficient amount of labelled training data, and careful consideration should be given to hyperparameter tuning and model architecture design. Additionally, expertise in DL and EEG signal analysis is essential for effectively utilizing CNNs in this context[35].

CNNs are effective for analysing spatial information in EEG signals. They are capable of learning spatial filters that capture discriminative patterns across the scalp. CNNs have been successful in tasks such as motor imagery classification and seizure detection.

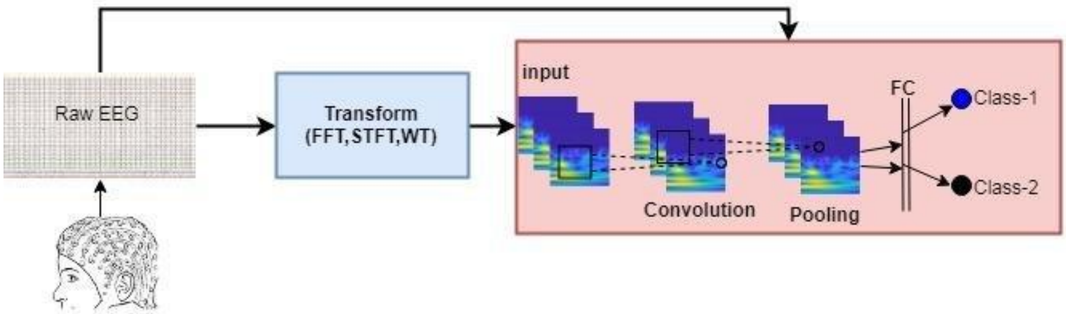

Fig 6 Classification of EEG Signal using CNN[60]

b) Recurrent Neural Networks (RNN)

RNNs constitute a form of NN that works well with sequential input, such as EEG signals. RNNs may detect temporal connections in data by retaining inner storage and analysing inputs sequentially. RNNs have demonstrated effectiveness in a variety of EEG signal processing applications, including stage of sleep categorization, seizure identification, motor imagery categorization, and cognitive state identification. However, it is important to have a sufficient amount of high-quality labelled data and to carefully pre-process the EEG signals for optimal performance. Additionally, exploring advanced techniques like attention mechanisms or hybrid architectures can further enhance the capability of RNNs in EEG signal analysis[34].

Because RNNs are built to deal with sequential data, they are ideal for assessing temporal relationships in EEG signals. Long-short-term memory (LSTM) systems, a form of RNN, are frequently used for applications such as categorization of mental states and sleep stage detection.

c) Artificial Neural Networks

Another common ML approach for EEG data analysis and categorization is ANNs. ANNs are capable of learning complicated patterns from data and are inspired by the architecture and operation of biological NN. It should be noted that creating and instructing ANNs for EEG analysis necessitates careful consideration of network architecture, proper pre-processing methods, and the accessibility of labelled EEG data. DL techniques like CNNs and RNNs are frequently used to detect temporal and spatial relationships in EEG data. Appropriate validation and evaluation procedures are also required to assure the ANN model's resilience and generalisation [33][34].

Hybrid architectures combine CNN and RNN components to leverage both spatial and temporal information in EEG signals. These architectures, such as CRNNs, aim to capture both spatial and temporal features simultaneously. They have shown promising results in various EEG signal classification tasks, including emotion recognition and cognitive workload estimation.

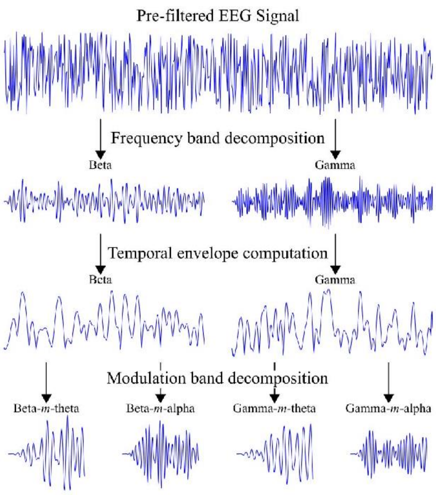

Fig 7 Steps for Brainwaves Processing[59]

3.5 EVALUATION METRICS FOR CLASSIFICATION PERFORMANCE

To assess the performance of EEG signal classification models, various evaluation metrics are used. These metrics provide quantitative measures of the model's accuracy, precision, recall, and overall predictive power. Some common evaluation metrics include[44]:

a) **Accuracy**: The proportion of properly categorised cases in comparison to the total number of examples. Accuracy assesses the categorization model's overall accuracy.

b) Precision: Also known as positive predictive value, precision measures the proportion of correctly classified positive instances out of the total instances predicted as positive. It assesses the model's ability to correctly identify positive cases.

c) **Recall**: Also known as sensitivity or true positive rate, recall measures the proportion of correctly classified positive instances out of the total actual positive instances. Recall indicates the model's ability to correctly capture positive cases.

d) **F1 Score**: The harmonic mean of precision and recall. F1 score provides a balanced measure of both precision and recall, taking into account both false positives and false negatives.

e**) Receiver Operating Characteristics** (ROC) Curve: At various categorization thresholds, the ROC curve shows the true positive rate (TPR) versus the false positive rate (FPR). It may be used to identify an ideal threshold depending on the intended A trade-off among sensitivity and specificity. It aids in assessing the model's efficacy across multiple thresholds.

f) **Area Underneath the Curve of the ROC (AUC):** AUC assesses a classification model's overall performance through calculating the area underneath the ROC curve. It returns a single number that shows the model's discriminative capacity, with a larger AUC indicating greater efficacy.

These evaluation metrics enable researchers to objectively assess the performance of EEG signal classification models and compare different algorithms or techniques. They provide insights into the model's accuracy, ability to detect positive cases, and overall predictive capability.

3.6 APPLICATIONS OF EEG SIGNAL

3.6.1 Brain-Computer Interfaces (BCIs)

BCIs are technologies that allow direct connection among the mind and external equipment such as computers. EEG signal evaluation and categorization are important in BCIs because they translate the user's brainwaves into commands for control[45][46].

Some applications of EEG-based BCIs include:

a) Motor Imagery-Based BCIs: Motor imagery-based BCIs allow individuals to control external devices or prosthetics using their imagination of specific motor tasks. EEG signals related to motor imagery are analysed and classified to detect the intended motor commands, enabling individuals with motor disabilities to regain control over their environment.

b) Spelling and Communication BCIs: BCIs based on EEG data have been used to develop assistive solutions for persons suffering from severe motor impairments, such as locking-in syndrome. Users may spell out messages and connect with others using the power of their thoughts by identifying EEG signals associated with different letters or phrases.

c) Rehabilitation and Stroke Recovery: EEG-based BCIs have been explored as a tool for neurorehabilitation and motor recovery after stroke. By providing real-time feedback and facilitating brain plasticity, EEG-based BCIs can assist in motor rehabilitation and help individuals regain lost motor functions.

3.6.2 Neurofeedback System

Neurofeedback systems utilize EEG signal analysis to provide real-time feedback to individuals about their brain activity. The aim is to enable individuals to self-regulate and modify their brain activity for therapeutic or performance enhancement purposes[47]. Some applications of neurofeedback systems include:

a) Attention and Focus Training: Neurofeedback systems can assist individuals, particularly those with attention-deficit/hyperactivity disorder (ADHD), in improving their attention and focus abilities. By providing feedback on their brain activity, individuals can learn to regulate their attention levels and achieve better cognitive performance.

b) Stress and Anxiety Management: EEG-based neurofeedback systems can help individuals manage stress and anxiety by providing feedback on their brain activity patterns associated with relaxation or calmness. By learning to modulate their brainwaves, individuals can develop self-regulation skills to reduce stress and improve their emotional well-being.

c) Peak Performance Training: Athletes, musicians, and other performers can benefit from neurofeedback systems to enhance their performance. By identifying EEG patterns associated with optimal performance states, individuals can learn to reproduce those states and improve their focus, concentration, and performance outcomes.

3.6.3 Epileptic Seizure Detection and Prediction

EEG signal analysis and classification techniques are extensively used in the detection and prediction of epileptic seizures. By analysing the characteristic EEG patterns associated with seizure activity, algorithms can accurately detect and predict seizures, providing valuable insights for epilepsy management. This application has the potential to alert patients or caregivers in real-time, enabling timely interventions and improving their quality of life[48].

3.6.4 Sleep Stage Classification

Sleep stage classification is an essential application of EEG signal analysis in sleep studies and sleep disorders research. By analysing the EEG signals during sleep, it is possible to classify different stages of sleep, Wakefulness, rapid eye movement, or REM, sleep, and other non-REM sleep phases are examples. Sleep stage classification assists in diagnosing sleep disorders, understanding sleep architecture, and studying the impact of sleep on cognitive functions and overall health[49].

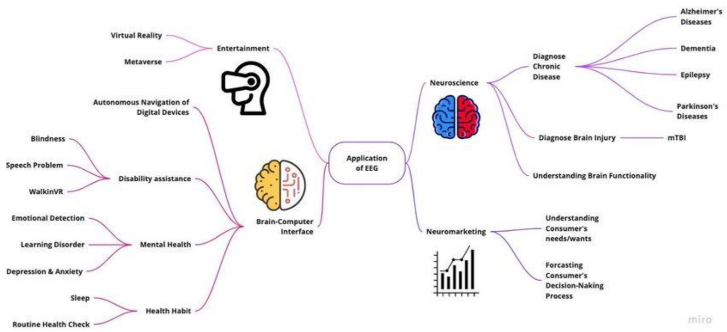

Fig 8 Brain Map of the Application of EEG[58]

3.6.5 Cognitive State Assessment

EEG signal analysis and classification techniques play a significant role in assessing cognitive states and mental workload levels. By analysing the EEG patterns associated with different cognitive processes, such as attention, memory, and decision-making, it is possible to infer the cognitive state of individuals. This application finds utility in various domains, including human-computer interaction, cognitive neuroscience, and user experience evaluation[50].

3.6.6 Neuromarketing

Neuromarketing utilizes EEG signal analysis to understand consumers' responses to marketing stimuli and assess the effectiveness of advertising and marketing strategies. EEG signals provide insights into consumers' emotional and cognitive responses, helping marketers optimize their campaigns and tailor their messages to elicit desired reactions. By analysing EEG data, marketers can measure attention levels, emotional engagement, and brand perception, enabling them to create more impactful and persuasive marketing strategies[51].

3.6.7 Human Emotions

EEG signal analysis is employed in the study of human emotions to understand and classify emotional states based on brain activity. Different emotions are associated with specific patterns of EEG signals, and by analysing these patterns, researchers can identify and differentiate various emotional states, such as happiness, sadness, fear, and excitement. This application finds applications in psychology, affective computing, and mental health research[52].

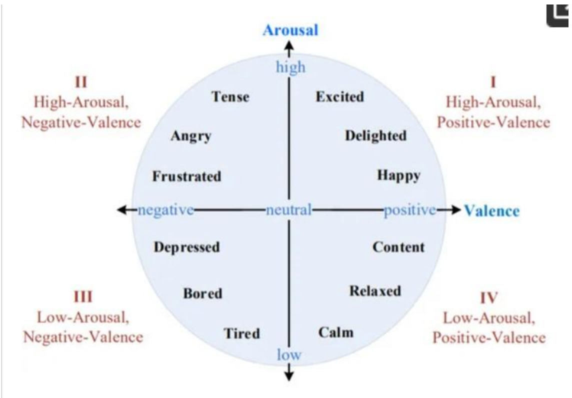

Fig 9 Differentiation of Human Emotion by EEG Signal[57]

3.6.8 Consciousness

EEG signal analysis contributes to the exploration of consciousness and the study of altered states of consciousness. By analysing EEG patterns and connectivity measures, researchers can investigate brain activity during different states of consciousness, including wakefulness, sleep, meditation, and anaesthesia. EEG-based studies help elucidate the neural correlates of consciousness and deepen our understanding of the mechanisms underlying conscious experience[47].

3.6.9 Brain-Computer Music Interfaces

EEG signal analysis has been employed in the development of Brain-Computer Music Interfaces (BCMI), which enable individuals to create music using their brain activity. By detecting and classifying specific EEG patterns associated with music-related intentions, such as playing a specific instrument or generating musical notes, BCMI systems allow individuals to generate music solely through their thoughts. This application has implications for music therapy, artistic expression, and assistive technology for individuals with motor disabilities[53].

The applications described above represent a subset of the diverse and growing field of EEG signal analysis and classification. The advancements in EEG technology, ML techniques, and computational methods continue to expand the range of applications, enabling researchers and practitioners to harness the power of EEG signals for a variety of applications, including medical care, neurology, the field of psychology, human-computer interface, and more.

CHAPTER 4 CONCLUSION AND FUTURE DIRECTIONS

4.1 CONCLUSION

The analysis and classification of EEG signals play a crucial role in neuroscience, clinical diagnostics, and BCI. EEG signals provide insights into brain activity and cognition, aiding in the understanding of various cognitive processes. They also serve as biomarkers for diagnosing neurological disorders and can be used to develop innovative brain-computer interface systems. EEG analysis allows for monitoring cognitive states and optimizing personalized treatment approaches. Challenges in EEG analysis call for advanced methodologies and signal processing techniques. Future advancements in this field hold promise for improved algorithms and techniques, contributing to our understanding of the brain and enhancing the lives of individuals with neurological conditions.

To solve these obstacles and extract relevant information from EEG data, researchers and doctors use a variety of strategies. Pre-processing techniques assist eliminate artefacts and increase signal quality, while feature extraction approaches identify useful patterns and features from the signals. Signal processing algorithms, such as time-frequency analysis and spectral analysis, enable the examination of different frequency components and their temporal variations.

Moreover, the classification of EEG signals involves the development of ML and pattern recognition algorithms. These algorithms aim to accurately classify EEG patterns associated with different brain states, cognitive tasks, and neurological disorders. Various classification techniques, including SVM, NNs, and ensemble methods, are applied to differentiate between different EEG states and disorders.

4.2 LIMITATIONS AND CHALLENGES

Methods for the analysis and classification of EEG signals face several limitations and challenges, including:

- **Noise and Artifacts**: EEG signals are susceptible to various types of noise and artifacts, such as eye blinks, muscle movements, electrical interference, and electrode drift. These artifacts can distort the underlying brain activity and affect the accuracy of analysis and classification methods. Developing robust techniques to identify and remove these artifacts is a significant challenge[54].

- **Limited Training Data**: Obtaining labeled EEG data for training classification models can be challenging, especially for rare neurological conditions or specialized tasks. Limited training data can lead to overfitting or poor generalization of classification models. Developing techniques to address the limitations of limited training data, such as transfer learning or data augmentation, is crucial[55].

- **Imbalanced Datasets**: EEG datasets often suffer from class imbalance, where one class has significantly more instances than others. Imbalanced datasets can bias the performance of classification models, leading to lower accuracy for minority classes. Addressing class imbalance through techniques like oversampling, under sampling, or class weighting is necessary to ensure fair and accurate classification.

4.3 FUTURE RESEARCH DIRECTIONS

Future research directions for methods of analysis and classification of EEG signals could include the following:

DL and NNs: Investigate the use of DL models for EEG signal analysis and classification, such as CNNs and RNNs. Investigate innovative architectures and optimisation strategies to increase classification model accuracy and efficiency.

Transfer Learning and Domain Adaptation: Investigate methods for transferring knowledge from pre-trained models to new EEG datasets, enabling effective classification with limited labeled data. Explore domain adaptation techniques to handle inter-subject and inter-session variability, improving the generalization of classification models.

Feature Extraction and Representation: Develop advanced feature extraction techniques that capture both local and global patterns in EEG signals. Investigate the effectiveness of time-frequency analysis methods, wavelet transforms, and higher-order statistics for extracting informative features from EEG data.

Artifact Detection and Removal: Improve methods for automatically detecting and removing artifacts from EEG signals, such as eye blinks, muscle artifacts, and environmental noise. To improve artefact removal capabilities, investigate sophisticated signal processing techniques such as ICA and DL-based systems.

Multimodal Integration: Investigate the integration of EEG signals with other modalities, such as functional magnetic resonance imaging (fMRI), electrocardiography (ECG), and electrooculography (EOG). Explore how combining multiple modalities can improve the accuracy and reliability of EEG signal analysis and classification.

REFRENCES

[1] 1.Niedermeyer, E., & da Silva, F. L. (2005). Electroencephalography: Basic principles, clinical applications, and related fields (5th ed.). Lippincott Williams & Wilkins.

[2] Xie, Y. and Oniga, S. (2020) "A review of processing methods and classification algorithm for EEG Signal," Carpathian Journal of Electronic and Computer Engineering, 13(1), pp. 23–29. Available at: https://doi.org/10.2478/cjece-2020-0004.

[3] Lotte, F., Congedo, M., Lécuyer, A., Lamarche, F., & Arnaldi, B. (2007). A review of classification algorithms for EEG-based brain-computer interfaces. Journal of Neural Engineering, 4(2), R1-R13. doi:10.1088/1741-2560/4/2/R01

[4] Correa, A.G. et al. (2007) "Artifact removal from EEG signals using adaptive filters in Cascade," Journal of Physics: Conference Series, 90, p. 012081. Available at: https://doi.org/10.1088/1742-6596/90/1/012081.

[5] Nagel, Sebastian. (2019). Towards a home-use BCI: fast asynchronous control and robust non-control state detection. 10.15496/publikation-37739.

[6] Madhale Jadav, G., Lerga, J. and Štajduhar, I. (2020) "Adaptive filtering and analysis of EEG signals in the time-frequency domain based on the local entropy," EURASIP Journal on Advances in Signal Processing, 2020(1). Available at: https://doi.org/10.1186/s13634-020-00667-6.

[7] A. A. Yusuf, S. K. Wijaya, and P. Prajitno, "EEG-based human emotion recognition using K-NN machine learning," PROCEEDINGS OF THE 4TH INTERNATIONAL SYMPOSIUM ON CURRENT PROGRESS IN MATHEMATICS AND SCIENCES (ISCPMS2018), 2019

[8] Sallout, M. and Mattar, E. (2021) 'EEG-based emotion classification using Deep Neural Network', 4th Smart Cities Symposium (SCS 2021) [Preprint]. doi:10.1049/icp.2022.0364.

[9] (2019) EEG brain signal classification for epileptic seizure disorder detection [Preprint]. doi:10.1016/c2018-0-01888-5.

[10] Paszkiel, S. (2019) 'Brain–Computer Interface Technology', Analysis and Classification of EEG Signals for Brain–Computer Interfaces, pp. 11–17. doi:10.1007/978-3-030-30581-9_3.

[11] Choubisa, M. and Trivedi, P. (2015) 'Analysing EEG signals for detection of mind awake stage and sleep deprivation stage', 2015 International Conference on Green Computing and Internet of Things (ICGCIoT) [Preprint]. doi:10.1109/icgciot.2015.7380647.

[12] Salaken, S.M. et al. (2020) ‘Evaluation of classification techniques for identifying cognitive load levels using EEG signals’, 2020 IEEE International Systems Conference (SysCon) [Preprint]. doi:10.1109/syscon47679.2020.938182

[13] B. Mishra and M. Kumar, “Review of Methods for Analysis and Classification of EEG Signal and its Applications “accepted at 5th IEEE International Conference on Advances in Computing, Communication Control and Networking (ICAC3N-23).

[14] Baig, Muhammad Zeeshan & Aslam, Nauman & Shum, Hubert. (2020). Filtering techniques for channel selection in motor imagery EEG applications: a survey. Artificial Intelligence Review. 53. 10.1007

[15] Series, 1907(1), p. 012045. doi:10.1088/1742-6596/1907/1/012045.

[16] Jung, T. P., Makeig, S., Westerfield, M., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2000). Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. Clinical Neurophysiology, 111(10), 1745-1758.

[17] Luck, S. J. (2005). An Introduction to the Event-Related Potential Technique. MIT Press.

[18] Amjed S. Al-Fahoum, Ausilah A. Al-Fraihat, "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains", International Scholarly Research Notices, vol. 2014, Article ID 730218, 7 pages, 2014. https://doi.org/10.1155/2014/730218

[19] Preprocessing (no date) NeurotechEDU. Available at: http://learn.neurotechedu.com/preprocessing/ (Accessed: 30 May 2023).

[20] Data Science for Psychology and neuroscience - in python (no date) Filtering EEG Data - Data Science for Psychology and Neuroscience - in Python. Available at: https://neuraldatascience.io/7-eeg/erp_filtering.html (Accessed: 30 May 2023).

[21] Al-Fahoum, A.S. and Al-Fraihat, A.A. (2014) ‘Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains’, ISRN Neuroscience, 2014, pp. 1–7. doi:10.1155/2014/730218.

[22] Geering B.A., Achermann P., Eggimann F., Borbély A.A. Period-amplitude analysis and power spectral analysis: A comparison based on all-night sleep EEG recordings. J. Sleep Res. 1993;2:121–129. doi: 10.1111/j.1365-2869.1993.tb00074.x.

[23] Michielli N., Acharya U.R., Molinari F. Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals. Comput. Biol. Med. 2019;106:71–81. doi: 10.1016/j.compbiomed.2019.01.013.

[24] Nussbaumer H.J. The Fast Fourier Transform. Springer; Berlin/Heidelberg, Germany: 1981. pp. 80–111.

[25] Stéphane M. A Wavelet Tour of Signal Processing. Elsevier; Amsterdam, The Netherlands: 2009.

[26] Cohen L. Time-Frequency Analysis. Volume 778 Prentice Hall; Hoboken, NJ, USA: 1995.

[27] Abbate A., DeCusatis C.M., Das P.K. Wavelets and Subbands. Birkhäuser Boston; Boston, MA, USA: 2002. Time-Frequency Analysis of Signals; pp. 103–187.

[28] Meyer Y. Wavelets and Operators. Cambridge University Press; Cambridge, UK: 1993.

[29] L. Zhang, "EEG Signals Classification Using Machine Learning for The Identification and Diagnosis of Schizophrenia," 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 2019, pp. 4521-4524, doi: 10.1109/EMBC.2019.8857946.

[30] Richhariya, B. and Tanveer, M. (2018) "EEG signal classification using Universum Support Vector Machine," Expert Systems with Applications, 106, pp. 169–182. Available at: https://doi.org/10.1016/j.eswa.2018.03.053

[31] Ang, K. K., Chin, Z. Y., Zhang, H., & Guan, C. (2008). Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface. Proceedings of the IEEE International Joint Conference on Neural Networks, 2390-2397. doi:10.1109/IJCNN.2008.4634122

[32] A. A. Yusuf, S. K. Wijaya, and P. Prajitno, "EEG-based human emotion recognition using K-NN machine learning," PROCEEDINGS OF THE 4TH INTERNATIONAL SYMPOSIUM ON CURRENT PROGRESS IN MATHEMATICS AND SCIENCES (ISCPMS2018), 2019.

[33] Ramírez-Arias, F.J. et al. (2022) Evaluation of machine learning algorithms for classification of EEG Signals, MDPI. Multidisciplinary Digital Publishing Institute. Available at: https://www.mdpi.com/2227-7080/10/4/79 (Accessed: April 17, 2023).

[34] P. Nagabushanam, S. Thomas George, and S. Radha, "EEG Signal

[35] Classification using LSTM and improved neural network algorithms," Soft Computing, vol. 24, no. 13, pp. 9981–10003, 2019.

[36] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces," Journal of Neural Engineering, vol. 15, no. 5, p. 056013, 2018.

[37] Phan, H., Tran, D., & Gargiulo, G. (2018). Classification of EEG signals for detection of epileptic seizures based on Random Forest feature selection. Computer Methods and Programs in Biomedicine, 154, 171-180. doi: 10.1016/j.cmpb.2017.12.005

[38] Mousavi, S. M., & Koçer, B. (2020). Classification of motor imagery EEG signals using Random Forest. Journal of Neural Engineering, 17(3), 036017. doi: 10.1088/1741-2552/ab7f7f

[39] Hassanpour, H., & Ghodsi, A. (2012). EEG signal classification using Naive Bayes classifier. Proceedings of the 2012 IEEE/ACS 9th International Conference on Computer Systems and Applications (AICCSA), 1-5. doi:10.1109/AICCSA.2012.6485887

[40] Kolakowska, A., & Kasprzak, W. (2014). EEG-based classification using generative model and Naive Bayes classifier. Biocybernetics and Biomedical Engineering, 34(2), 100-107. doi:10.1016/j.bbe.2013.11.003

[41] Roy, P. P., Saha, G., & Koley, C. (2018). Application of unsupervised learning techniques in EEG signal analysis: A survey. Journal of Medical Systems, 42(7), 121.

[42] Prasad, S., & Anand, S. (2020). Review on EEG signal classification using unsupervised learning. Cognitive Neurodynamics, 14(3), 339-354.

[43] Shahid, N., & Arsalan, M. (2021). EEG-based mental state classification using unsupervised learning algorithms. Frontiers in Neuroinformatics, 15, 680984.

[44] Wu, D., Qi, W., Yang, S., & Li, H. (2016). EEG-based emotion recognition using self-organizing maps and convolutional neural network. Neurocomputing, 175, 672-680. doi:10.1016/j.neucom.2015.07.129

[45] Davis, J., & Goadrich, M. (2006). The relationship between Precision-Recall and ROC curves. In Proceedings of the 23rd International Conference on Machine Learning (pp. 233-240). doi:10.1145/1143844.1143874

[46] Babiloni, F., Cincotti, F., Mattia, D., Mattiocco, M., De Vico Fallani, F., Tocci, A., ... & Astolfi, L. (2007). High-resolution EEG techniques for brain-computer interface applications. Journal of Neuroscience Methods, 167(1), 31-42.

[47] Chaudhary, U., Xia, B., Silvoni, S., Cohen, L. G., & Birbaumer, N. (2017). Brain-Computer Interface–Based Communication in the Completely Locked-In State. PLoS Biology, 15(1), e1002593.

[48] Birbaumer, N., & Cohen, L. G. (2007). Brain-computer interfaces: communication and restoration of movement in paralysis. Journal of Physiology, 579(3), 621-636. doi:10.1113/jphysiol.2006.125633

[49] Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adeli, H. (2018). Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. Computers in biology and medicine, 100, 270-278.

[50] Tsinalis, O., Matthews, P. M., & Guo, Y. (2016). Automatic sleep stage scoring with single-channel EEG using convolutional neural networks. arXiv preprint arXiv:1610.01683.

[51] Prasad, R., Dutt, V., Paul, A., & Pradhan, C. (2017). Cognitive state assessment using electroencephalography (EEG) signal analysis: A review. Biocybernetics and Biomedical Engineering, 37(3), 425-438.

[52] Vecchiato, G., Maglione, A. G., Cherubino, P., Wasikowska, B., Wawrzyniak, A., Latuszynska, A., ... & Babiloni, F. (2014). Neurophysiological tools to investigate consumer's gender differences during the observation of TV commercials. Computational and mathematical methods in medicine, 2014. doi:10.1155/2014/912981

[53] Chanel, G., Kronegg, J., Grandjean, D., & Pun, T. (2006). Emotion assessment: Arousal evaluation using EEG's and peripheral physiological signals. IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(4), 586-594. doi:10.1109/TPAMI.2006.80

[54] Miranda, E. R., Magee, W. L., & Wilson, J. J. (2005). EEG-based approaches to the emotional content of music and speech. In B. Whitman & I. Hargreaves (Eds.), Proceedings of the 7th International Conference on Music Perception and Cognition (pp. 657-660).

[55] Puthankattil Subha, D., & Joseph, P. K. S. (2010). An efficient method for artifact removal in EEG signals using adaptive filters in EMD domain. Computer Methods and Programs in Biomedicine, 99(3), 256-264.

[56] Krol, L. R., Pawlowski, M., & Wróbel, A. (2020). Limitations and Challenges of EEG-Based Brain–Computer Interface. In Advanced Brain-Computer Interface Research (pp. 27-47). IntechOpen. doi:10.5772/intechopen.91229

[57] Sutrisno Ibrahim, Ridha Djemal, Abdullah Alsuwailem, Electroencephalography (EEG) signal processing for epilepsy and autism spectrum disorder diagnosis, Biocybernetics and Biomedical Engineering, Volume 38, Issue 1, 2018

[58] Alhalaseh, R.; Alasasfeh, S. Machine-Learning-Based Emotion Recognition System Using EEG Signals. Computers 2020, 9, 95. https://doi.org/10.3390/computers9040095

[59] Gu, Weiqing & Yang, Bohan & Chang, Ryan. (2022). Machine Learning-based EEG Applications and Markets. 10.48550/arXiv.2208.05144.

[60] Trambaiolli, Lucas & Cassani, Raymundo & Biazoli, Claudinei & Cravo, Andre & Sato, João & Falk, Tiago. (2018). Resting-Awake EEG Amplitude Modulation can Predict Performance of an fNIRS-Based Neurofeedback Task. 10.1109/SMC.2018.00199.

[61] Türk, Ömer & Ozerdem, Mehmet. (2019). Epilepsy Detection by Using Scalogram Based Convolutional Neural Network from EEG Signals. Brain Sciences. 9. 115. 10.3390/brainsci9050115.

[62] "The introductory guide to EEG (electroencephalography)," EMOTIV,21- Mar-2023.[Online]Available: https://www.emotiv.com/eeg-guide/. [Accessed: 17-Apr-2023].

LIST OF PUBLICATIONS

[1] B. Mishra and M. Kumar, “Review of Methods for Analysis and Classification of EEG Signal and its Applications “accepted at 5th IEEE International Conference on Advances in Computing, Communication Control and Networking (ICAC3N-23).

Acceptance Notification 5th IEEE ICAC3N-23 & Registration: Paper ID 708

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Microsoft CMT <email@msr-cmt.org>
to Bhavesh

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Dear Bhavesh Mishra,
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Greetings from ICAC3N-23 ...!!!

Congratulations....!!!!!

On behalf of the 5th ICAC3N-23 Program Committee, we are delighted to inform you that the submission of "Paper ID- 708 " titled " Review of Methods for Analysis and Classification of EEG Signal and its Applications " has been accepted for presentation and further publication with IEEE at the ICAC3N- 23 subject to incorporate the reviewers and editors comments in your final paper. All accepted papers will be submitted for inclusion into IEEE Xplore subject to meeting IEEE Xplore's scope and quality requirements.

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The formatting of paper is not proper. Formatting must be strictly as per template.
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Add a comparison table in literature review section with the work already done in this filed.
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