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Research Article

A Comprehensive Review of Modern EEG Signal Processing for Emotional and Stress Detection: From Data to Insight

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ABSTRACT

Using the brain's thoughts to communicate with the outside world is known as brain-computer interface. Electroencephalography (EEG) has emerged as a powerful non-invasive method for understanding brain activity and developing applications in neurology, medicine, and human-computer interaction.

Robust signal processing techniques, which convert raw EEG data into meaningful insights, are crucial to the effectiveness of EEG-based systems. This paper aimed to discuss the various approaches that need to be adjusted for each stage of brain signal processing, with a number of approaches and experimental results reported and compared in previous surveys. The advantages and disadvantages of each method, such as signal capture, signal augmentation, feature extraction, and signal classification, are easily and clearly interpreted in this work.

Keywords: Signal Processing, Feature Extraction, EEG signals, machine learning. Brain Computer-Interface.

I. INTRODUCTION

Recent years have seen significant advancements in the field of brain-computer interfaces, or BCIs, driven by the growing need for technology that enables direct communication between the brain and external devices. These systems are based on the analysis of electroencephalography (EEG) signals, which are a non-invasive way to record brain activity. Among the various areas where EEG-based BCIs have opened up new possibilities are neuro-rehabilitation, assistive technology, gaming, and cognitive status monitoring.[1]

EEG signals are a desirable modality for BCI systems because of their high temporal resolution, affordability, and simplicity of acquisition. However, analysing and interpreting EEG data can be extremely difficult due to their complex nature, which is impacted by noise, artifacts, and inter-subject variability. Four-phase processing pipelines are necessary for efficient EEG signal analysis. They are Signal Acquisition, Signal Pre-Processing, Computer Interaction, and Signal Classification [1,3].

In recent years, the application of state-of-the-art computer techniques like machine learning and deep learning has revolutionized EEG signal analysis.. By improving the capacity to decode brain activity, these methods have made BCIs more precise and dependable. The range of these systems has also been increased by the creation of hybrid BCIs, which combine electromyography (EMG) and other modalities like near-infrared spectroscopy (NIRS).

An extensive review of EEG signal analysis techniques in relation to BCIs is given in this paper. We thoroughly examine feature extraction techniques for gathering pertinent data, classification strategies for decoding brain states, and pre-processing techniques for removing artifacts.

II. SIGNAL ACQUISITION

Brain signals must first be obtained in order to understand brain function and develop neuro-technological applications such as Brain-Computer Interfaces (BCIs). Because they don't involve surgery, non-invasive techniques are very useful because they're safer and easier to employ for clinical and research settings. Among the most popular techniques are functional magnetic resonance imaging (fMRI), near-infrared spectroscopy (NIRS), electroencephalography (EEG), and magnetoencephalography (MEG).[1]

A. EEG

One of the earliest non-invasive techniques for obtaining brain signals is EEG. The first person to capture electrical activity from the human brain was Hans Berger, a German doctor, who invented it in 1924. Modern EEG study began when Berger's work led to the discovery of alpha waves, also known as Berger waves. In order to capture signals on paper, early analog EEG equipment used ink tracers. The 20th century's shift to digital systems made it possible for more accuracy, real-time analysis, and portability.[2] Nowadays, EEG is frequently utilized in clinical and research settings, especially for Brain-Computer Interface (BCI) applications and the diagnosis of sleep disorders and epilepsy.

B. fMRI

Building on Magnetic Resonance Imaging (MRI) technology, which was initially presented in the 1970s, functional magnetic resonance imaging (fMRI) was created in the early 1990s and is now a routine tool for mapping brain function and researching neurological diseases.. Researchers were able to visualize brain activity in response to cognitive and sensory tasks thanks to the discovery of the Blood-Oxygen-Level Dependent (BOLD) contrast mechanism by Seiji Ogawa and his colleagues. Over time, fMRI expanded to include functional connectivity analysis, real-time imaging, and sophisticated statistical modelling.[2]

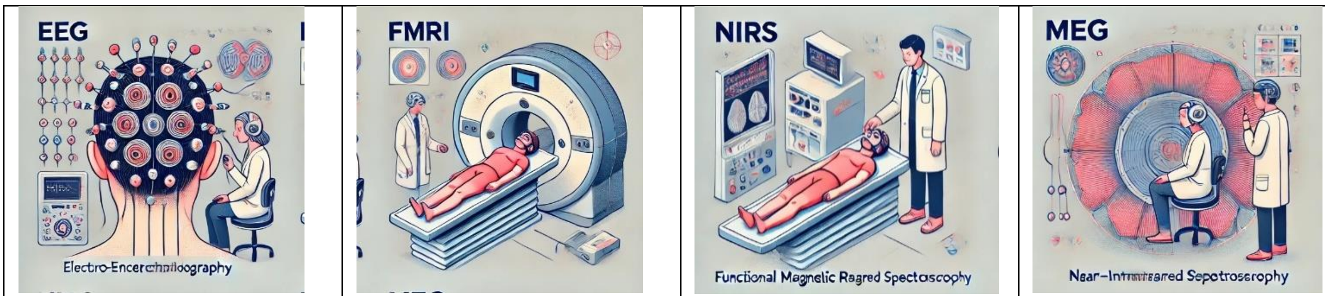
C. NIRS

The development of optical imaging technologies in the late 1970s and early 1980s led to the emergence of NIRS. In order to evaluate brain oxygenation and hemodynamic responses, researchers such as Maki et al. created the first functional NIRS system in the early 1990s.

Due to their wearability and portability, modern NIRS devices enable the investigation of brain activity in realistic environments. From portable neuroimaging in sports and cognitive research to new-born brain monitoring, there are many uses.[2]

D. MEG

David Cohen gave the first demonstration of MEG at the Massachusetts Institute of Technology (MIT) in 1968. MEG became viable for practical usage in the 1970s with the invention of very sensitive Superconducting Quantum Interference Devices (SQUIDs). MEG systems have advanced over time, providing excellent temporal and spatial resolution. MEG is still a potent technique for functional brain mapping, especially in epilepsy surgery and cognitive neuroscience, despite its high cost and requirement for specialist facilities.



A. EEG	B. fMRI	C. NRIS	D. MEG

Fig.1: Techniques for acquiring signals

TABLE I: Comparing Signal Acquisition Techniques for Non-Invasive BCI Systems

Technologies	**Underlying physical activity**	**Electrode placemen t**	**Key advantage**	**Key disadvantage**
EEG (electroencephalog ram)	Synchronoss neuronal Activities (potential)	Scalp contact (usually cap)	Non-invasive, portability High temporal resolution, Low cost	Low spatial resolution, Susceptible to noise and artifacts
MEG (electromyogram)	Synchronous Neuronal activities	Remote (eg. helmet)	Non-invasive, High spatial and temporal resolution, Direct measure of neural activity	Non-portability, Very expensive, Requires shielded environment,
MRI (Magnetic resonance imaging)	Increased blood flow at cortical lobes	Remote (eg. helmet)	Non-invasive, non-contact, Very high spatial resolution, Detailed brain mapping	Non-portability, temporal resolution, Very expensive , Requires a strong magnetic field
ECoG (electrocardiogram)	Local field potential	Intracranial, cortical	Signal quality,	Surgery requirement,
NIRS	Changes in blood oxygenation levels (hemodynamic response)		Portable and affordable compared to fMRI, Non-invasive, Suitable for long-term use	Limited penetration depth, Slower temporal resolution

Conventional EEG signal analysis consists of a framework that includes acquiring the EEG signal, extracting characteristics, and categorizing them. A system that can hold different emotions must be created in order to determine whether or not a person is stressed. The process of identifying stress may then start. This traditional EEG signal processing framework consists of the following steps: Data collection and band

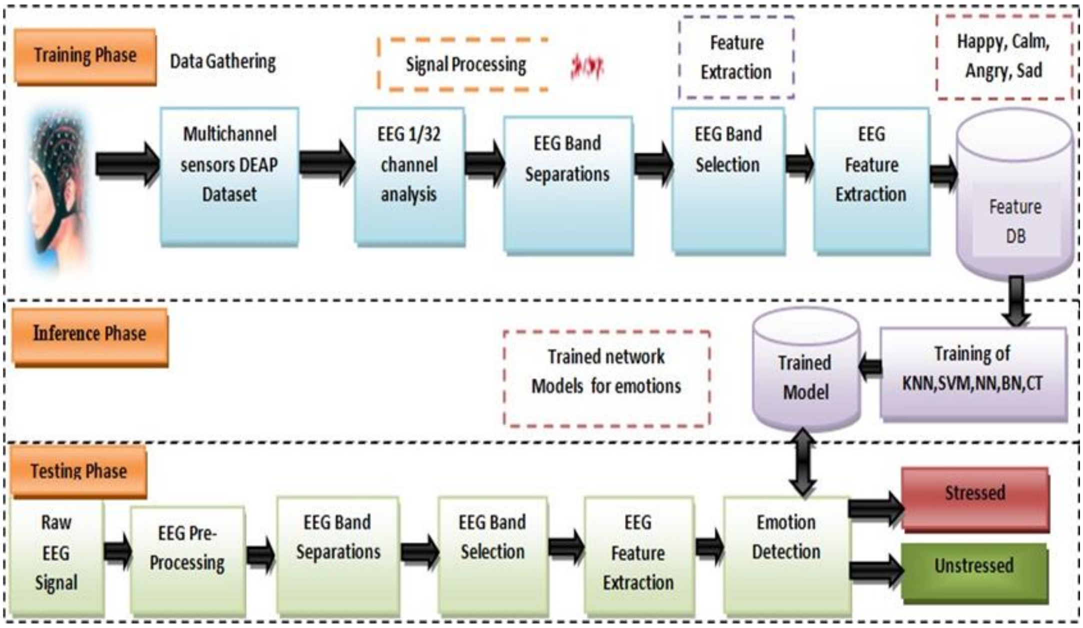


Figure 2 : The Developed framework for stress detection system using EEG signals.

separation, Selecting bands, extracting features, detecting emotions, and recognizing stress

Figure 2 illustrates a method for identifying whether an individual is stressed or unstressed that consists of multiple steps: emotion detection, EEG band selection, EEG feature extraction, pre-processing, and EEG band separation.

III. DATA GATHERING

The continuous, systematic process of gathering, analyzing, and interpreting different kinds of information from many sources is known as data collecting. Data collecting is typically carried out for research purposes in order to gain a comprehensive understanding of a topic of interest and to serve as the basis for decision-making. It makes it possible for healthcare systems to create patient-centered viewpoints, customize treatments, improve treatment methods, enhance doctor-patient contact, and enhance health results. EEG is a broad range of non-invasive data collection and processing methods used in industry to evaluate a system, part, or component's inherent characteristics.[3,4]

EEG employing the person's stressed and unstressed states is one method that has been proven to be both practical and dependable. Pre-processing, band separation, band selection, feature extraction, and emotion recognition are all included in this technique. The EEG data is captured at a frequency of 512 Hz. This dataset uses the pre-processed EEG data that was filtered (4 to 45 Hz) and down-sampled (128 Hz). The 32 electrodes are arranged according to the global 10-20 system: Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4, and O2.[4]

Table II : Data Gathering & Band Selection

Index	Type	Domain	Notations of the extracted features
1-128	Statistical Measures	Time domain	Mean, variance, zero-crossing rate and approximate Entropy of 32 EEG channels (4features*32channels)
129-288	Power features	Frequency domain	AveragePSDintheta(4-8Hz),slow-alpha(8-10HZ),alpha(8-12HZ),Beta(12-30HZ)andgamma(30-45Hz)bandsforall EEG Channels(5power * 32channels)

289-344	Power Difference	Frequency domain	Average PSD difference for 14 EEG channels in the theta, alpha, beta, and gamma bands pairings of 14 channel pairs with a power difference from right to left scalp
345-664	HHS Features	Time-Frequency domain	Average Values of squared amplitude and instantaneous frequency of HHS based time frequency representationindelta(1-4Hz),theta(4-8Hz),alpha(8-12HZ),Beta(12-30HZ)andgamma(30-45 Hz)bands for all EEG Channels (5 power *32channels)

EEG Features

However, determining emotions from EEG data is not easy. This massive mechanical imbalance makes it difficult to establish robust, long-lasting electrode-neural tissue connections. A NeuroSky Mind wave headset, which uses a single electrode to capture the EEG signal, will be used to gather the data.[5]There are a lot of noise sources that might be present during this process, including muscle activity and any surrounding electrical gadgets. These noise signals are mostly filtered by the ear clip, which acts as a ground or reference. Videos and physiological recordings of the front of the face are included in the dataset for emotion analysis, which uses EEG, physiological, and video inputs. Using a range of datasets, we can evaluate the suggested architecture's performance and demonstrate its versatility. Dataset for Emotion Analysis of Physiological Signals (DEAP). In a laboratory setting, the DEAP recorded electroencephalogram (EEG) readings from thirty-two volunteers. The 32 EEG electrodes record the EEG data at a sampling frequency of 128 for 63 seconds, or 8064 samples. Neuroscan and similar real-time EEG datasets can be loaded into the EEGLAB. Our dataset of physiological recordings and frontal face movies, along with the signal processing capabilities of MATLAB, allows us to capture the desired conclusion.[6,7]

IV. SIGNAL PRE-PROCESSING (SIGNAL ENHANCEMENT)

Pre-processing is the next step after brain signal collection to make the data cleaner and more accurate for analysis. This procedure is known as signal augmentation or signal pre-processing. When brain signals are first collected, they are frequently mingled with other kinds of undesired disruptions, which are referred to as noise or artifacts.[8] Typical kinds of artifacts include the following:

• Eye Blinks and Eye Movements (EOG): These can disrupt the brain signal and are brought on by shifts in eye position or blinks.

• Heartbeats (ECG): Particularly in EEG recordings, the electrical impulses from the heart and the brain may overlap.

• Muscular Movements: Unwanted electrical signals can also be produced by muscular movements.[8]

CAR stands for Common Average Referencing. This technique averages the signals from each electrode and subtracts the average from each electrode to reduce noise. This method removes noise by subtracting the common activity from the area of interest. The shared activity could be the noise in the EEG data [16]. Reference approaches are used to improve the Signal-to-Noise Ratio (SNR). Low SNR in EEG signals is the result of artifacts. The CAR technique produces noise-free signals by removing the mean of all electrodes from all electrodes.

According to the findings in [17], CAR performs better than all referencing techniques and has the highest classification accuracy. Finite sample density and inadequate head coverage of EEG electrode arrays make calculating the averages in reference techniques challenging [18].

Surface Laplacian (SL): This method uses the difference between adjacent electrodes to calculate the signal, improving its spatial resolution. The current density entering or leaving the scalp through the skull is estimated by the Surface Laplacian of the skull. It does not require any information on volume conduction; it merely takes into account the volume conductor's external shape [19]. It is possible to effectively remove eye movements while acquiring the signal.

Visual examination is required for big artifacts that range from 50μV to >50μV, and gradients of activities are derived by taking into account the artifacts' morphology [20]. A useful foundation for theoretical investigations is provided by the Hjorth technique. SL resolves the electrode reference issue and is resistant to artifacts produced in exposed areas by the electrode cap [21]. The EEG data may be seen with great spatial resolution using SL. The selection of spline parameters during spline interpolation has an impact on SL [18].

Independent Component Analysis (ICA): Makeig et al. [11] introduced ICA to EEG for the first time, and it successfully divides the artifacts from the EEG signals into different components according to the data's properties without relying on the reference channels. The ICA artifact reduction process also preserves the data in the frontal data, each channel data, and the recorded trails [12]. By separating mixed signals into distinct sources, ICA helps distinguish brain signals from artifacts such as heartbeats or eye blinks.

The multi-channel EEG data is broken down into spatially fixed and temporally independent components using the ICA technique. It is efficient in terms of computing. When the amount of data to be decomposed is enormous, ICA performs well [13]. More calculations are needed for ICA to break down signals [12] [14]. Nearly 20 different ICA algorithm types are supported by EEGLAB; the most popular ones are Infomax, fixed point ICA, and Joint Approximate Decomposition of Eigen matrices (JADE) [15].

Common Spatial Patterns (CSP): This technique highlights the differences between different brain states, such as active and quiet, which facilitates signal interpretation. CSP is a dimensionality reduction technique that aims to identify the spatial patterns in EEG data that best differentiate between two classes of brain activity. It functions by identifying spatial filters that minimize the EEG signal in one class while maximizing its variance (or power) in another. In essence, CSP assists in identifying the most instructive characteristics that distinguish various activities or mental states (e.g., picturing traveling left vs right).

Principal Component Analysis (PCA): PCA reduces data complexity while preserving crucial information by spotting patterns in the signals.. Karl Pearson created PCA in 1901, and Harold Hotelling independently refined it in 1930 [22]. The correlated vectors are converted into linearly uncorrelated vectors via the PCA. The term "Principal Components" refers to these uncorrelated vectors [22][23].

This is a traditional second-order statistical approach. It is dependent upon the covariance matrix's decomposition. PCA aids in feature dimension reduction. PCA will be used to rank according to the signal attributes' variability. This rating aids in data categorization. The best classification results are obtained when PCA is used in a BCI system [24]. Though it is not as good as ICA, the PCA is still good [25].

A mathematical method called Singular Value Decomposition (SVD) breaks down complex data into simpler components to aid in noise detection and removal.

CSSP, or Common Spatio-Spatial Patterns: By combining temporal and spatial features, this advanced method improves signal separation. CSP, which Koles introduced, can detect abnormal EEG activity [26]. In order to maximize class discrimination, CSP converts the EEG input into a variance matrix [27].

CSP uses spatial filtering and spatial information to identify patterns in EEG. CSP does not require a priori selection of subject-specific frequency bands or expertise with these bands, but it does require the use of many electrodes. Artifacts and electrode placements can affect it [27] [28]. The electrode positions must stay constant during the training process in order to record the same signals. The improved precision could become obsolete due to the change in electrode positions [29].

Adaptive Filtering: Depending on the unique features of the signals under analysis, adaptive filters can alter the signal's qualities. Using filters to reduce noise eliminates both noise and crucial information. Filters will eliminate the signal of interest if the noise and signal overlap. The adaptive filters are able to solve this issue. The issue of signals and interferences with overlapping spectra can be effectively resolved by adaptive interference cancellation. By using the least mean square technique (LMS), EEG signal artifacts can be successfully removed. The LMS technique is used for mean square error optimization [29].

In order to remove artifacts from ECG data, a new adaptive filter method known as the Recursive Least-Squares (RLS) algorithm was released in [30]. It has been shown to remove artifacts and significantly increase the signal-to-noise ratio (SNR).

Table III compares the processing, benefits, and drawbacks of the most used signal pre-processing techniques.

Because of their efficacy and wide range of applications in brain signal processing, SL, PCA ICA, CAR, CSP, and adaptive filtering are the most often used of them.. By using these methods, you can make sure that the data you're dealing with is as precise and clean as possible for subsequent analysis, such determining stress levels or emotions.

TABLE III: COMPARISON OF SIGNAL ENHANCEMENT METHODS

Sr No	Method	Advantages	Disadvantages
1	ICA	It is computationally efficient, performs well with vast amounts of data, and breaks down signals into spatially fixed and temporally independent components.	Not applicable in specific situations, More calculations are needed for decomposition.
2	CAR	Performs better than any reference approach. Produces higher SNR	Incomplete head covering and a finite sample density make computing averages difficult.
3	SL	strong against artifacts produced in areas where the electrode cap is not present. It resolves the issue of electrode reference.	the ability to detect artifacts and spline patterns
4	PCA	aids in the feature dimensions' decrease Data will be categorized with the aid of ranking.	Not as good as ICA.
5	CSP	Needs no prior selection of sub-specific bands or familiarity with them.	Numerous electrodes must be used. Classification accuracy may be impacted by an electrode location change.
6	Adaptive Filtering	Effective for signals and artifacts with overlapping spectrum nature; Capable of adjusting the signal characteristics in accordance with the signals being examined	High Computational Complexity, Slow Convergence

V. FEATURE EXTRACTION

The next stage is to extract significant characteristics from the EEG signals after they have been pre-processed and cleared of noise and artifacts. Feature extraction is crucial for transforming the raw EEG data into a more readable format for further analysis, such as classifying or recognizing specific brain states like stress or emotions. Depending on the signal's characteristics and the intended use, there are a number of methods for obtaining features from EEG data, each with unique advantages.[12]

Typical Techniques for Feature Extraction:

1. **Parameters for adaptive auto-regression (AAR):**A time series may be described using the Auto-Regressive (AR) model by looking at its historical values. It makes the assumption that the signal's present value is a linear mixture of its earlier values plus some noise. This model is altered by adaptive AR (AAR), which makes it more sensitive to non-stationary signals (those that fluctuate over time) by modifying the parameters in response to the signal's changes over time.[13]The basic AR model is extended by bilinear AAR and multivariate AAR to address more complicated situations with numerous signals or non-linear relationships.
2. A signal is converted from the time domain to the frequency domain using the second technique, the Fast Fourier Transform (FFT). Examining the signal's frequency components is useful. In EEG signals, specific frequency bands (delta, theta, alpha, beta, and gamma) are associated with particular mental states. Since FFT aids in identifying the power distribution of specific frequency bands, it can be used to identify states

such as relaxation or concentration. The energy at different frequencies, or power spectral density, is one property that may be extracted using FFT.[14]

3. Principle Component Analysis (PCA): PCA is a technique for reducing dimensionality that transforms data into a different coordinate system. The fundamental components, or axes, are the directions that show the most fluctuation in the data. In order to simplify the signal while preserving the essential features for classification, PCA can be applied to EEG data processing. Reducing noise and focusing on the key trends in the data is helpful.[13]
4. Independent Component Analysis (ICA), which separates a multivariate signal into independent components, is the fourth technique. In the context of EEG, it may distinguish between brain activity and artifacts such as heartbeats, muscle contractions, and eye movements. ICA is highly useful when dealing with mixed signals that come from multiple sources. By isolating these sources, ICA improves the quality of the features that are recovered.[13]
5. Wavelet Transform (WT): This method divides a signal into its component elements at various frequency and time intervals. Because WT functions in both time and frequency, as opposed to the frequency domain of the Fourier Transform, it is ideal for analyzing non-stationary signals that might fluctuate over time, such as EEG. [14] Both temporal and frequency-based information may be extracted because to WT's time-frequency representation of the data. It's especially helpful for identifying fleeting occurrences or characteristics that change over time.
6. Wavelet Packet breakdown (WPD): A more comprehensive breakdown of the data is provided by WPD, an extension of the wavelet transform that iteratively splits the signal into many frequency bands. In the context of EEG signals, this approach provides improved frequency and temporal resolution, enabling more accurate feature extraction, particularly when finer details are needed for classification.[15]
7. Genetic Algorithms (GA): Natural evolution serves as the inspiration for these optimization strategies. They can be applied to optimize feature extraction settings or choose the most pertinent characteristics. The best feature selection for EEG analysis can be found using GA, which will streamline the process and enhance the performance of classification algorithms.[15]

In Table IV various feature extraction methods are compared and their advantages, disadvantages are presented.

TABLE IV: COMPARISON OF FEATURE EXTRACTION METHODS

Method	**Description**	**Strengths**	**Weaknesses**
Adaptive Auto-Regressive (AAR)	A time-series modelling method that can adjust to shifting signal dynamics by using historical signal values to forecast future values.	Outstanding for time-dependent features and adaptable enough to non-stationary inputs.	Noise sensitivity is possible; careful parameter adjustment is necessary.
Fast Fourier Transform (FFT)	Converts a signal from the time domain to the frequency domain to reveal information about its frequency components.	Widely utilized for spectral characteristics, it is easy to use and effective for frequency analysis.	Only fixed signals are captured; neither time-varying nor transitory properties are captured.

Principal Component Analysis (PCA)	A technique for reducing dimensionality that finds the data's major components, or directions, with greatest variation.	Emphasizes important patterns, decreases complexity, and increases computing efficiency.	If too many components are eliminated, information is lost; linear relationships are assumed.
Independent Component Analysis (ICA)	Breaks down a signal into discrete parts in order to distinguish between different sources (e.g., brain activity from artifacts).	Efficient at separating brain impulses from noises such as muscle contractions and eye blinks.	Demands meticulous component selection and pre-processing; computationally demanding.
Wavelet Transform (WT)	Divides the signal into its frequency and time components to provide a time-frequency representation of the data.	Both temporal and frequency properties are captured, making it appropriate for non-stationary signals.	Performance is impacted by the choice of wavelet function, which is computationally more difficult than FFT.
Wavelet Packet Decomposition (WPD)	A WT extension in which the signal is well resolved in both time and frequency by breaking it down into several frequency bands.	Offers a more thorough decomposition than WT, with superior temporal and frequency resolution.	More computationally costly than WT; the amount of decomposition must be carefully chosen.
Genetic Algorithms (GA)	An optimization technique for choosing the best features or adjusting extraction settings that draws inspiration from natural development.	Able to handle complicated situations with flexibility and improve model parameters and feature selection.	Might be computationally costly and necessitates meticulous parameter adjustment. .

VI. EEG SIGNAL CLASSIFICATION

Following the extraction of the signals' properties, the EEG signals are next classified into multiple categories or classes. It is possible to distinguish specific mental states or activities, such as tension, relaxation, or different motor imagery tasks, by classifying the brain activity based on the parameters that were obtained.[15]

Classifiers Most Frequently Used in BCI Design:

Because they work well with EEG data, linear classifiers and nonlinear Bayesian classifiers are most frequently utilized in Brain-Computer Interface (BCI) systems: When the data is straightforward and can be divided linearly, linear classifiers are frequently chosen. Nonlinear Bayesian Classifiers are helpful when working with more complex data where the relationship between features and classes cannot be captured linearly. LDA and SVM (with linear kernels) are popular choices in BCI applications because they provide a good balance between computational efficiency and classification accuracy.[16] When there is ambiguity in the data, these classifiers—like Gaussian Mixture Models or Naive Bayes—are useful, which makes them ideal for deciphering ambiguous or noisy EEG signals.

A. ***ANN:***

An enormous number of linked components, known as neurons, make up ANNs, which are nonlinear classifiers. Each ANN neuron may carry out basic computing operations and mimics a real neuron. With three layers—the input layer, the hidden layer, and the output layer—the Multi-Layer Perceptron Neural Network (MLPNN) is the most often used neural network. MLPNN's advantages are its quick operation, simplicity in implementation, and low training set requirements. The number of inputs indicates how many characteristics were chosen, while the number of outputs indicates how many classes were created. The complexity of an ANN is determined by the number of neurons in its hidden layer. The complexity of the buried layer increases with the number of neurons; categorization errors occur when there are fewer neurons. In the concealed layer, no particular standard was established for this choice. The number of neurons must be determined by trial and error [17] .

B. ***NBC:***

Nonlinear decision boundaries are produced by NBCs. Because they are generative in nature, they can reject uncertain samples more successfully than discriminative classifiers. Bayesian classifiers assign a feature vector to the class with the highest probability. Bayes' rule is used to determine a feature vector's a posteriori probability. A dynamic, nonlinear Bayesian classifier is the Hidden Markov Model. This classifier works well for classifying time series. They are less prevalent than NNs and Linear Classifiers in the field of BCI applications [18].

c. NNC:

NNCs use a class's closest neighbors to choose which feature vector to give to it. If the feature vector comes from the training set, the classifier is known as a k-Nearest Neighbor (k-NN) classifier. A non-parametric method called k-NN predicts object values or class memberships by using the k-closest training samples in the feature space. The test sample is labeled using the majority label of its k-nearest neighbors from the training set. k-NN is transparent, simple to build, debug, and very easy to understand [19].

In Table V, comparison of various signal classification methods was given.

TABLEV: COMPARISON OF SIGNAL CLASSIFICATION METHODS

Sr No	**Method**	**Advantages**	**Disadvantages**
1	LDA	It requires less computing power. It is easy to use and yields outstanding results.	When the discriminating function is in the variance of the characteristics rather than the mean, it fails. It might not maintain the intricate structures for non-Gaussian distributions
2	SVM	It offers good generality. It outperforms other linear classifiers.	Possesses a high level of computational complexity.
3	ANN	Simplicity of usage and application. It is robust in nature and involves straightforward calculations. There are minimal criteria for the training set.	Challenging to construct. The number of neurons in the buried layer affects performance.
4	NBC	To estimate parameters, a minimal quantity of training data is needed. The complete covariance matrix does not need to be calculated; only the variance of the class variables has to be.	Fails to generate an accurate assessment of the class probabilities.
5	k-NN	Very easy to comprehend; Simple to implement and troubleshoot.	If the training set is huge, there will be poor runtime performance. Perceptive of superfluous and unnecessary features. Other classification approaches outperform them on challenging classification problems

VII. CONCLUSION

This study presents a clear depiction of the different signal processing techniques employed at each level of BCI signal processing. The survey's findings provide a means of choosing the necessary signal processing techniques.

Additionally, it describes the following stages of EEG/BCI data processing and talks about inappropriate methods: 1) Acquisition of Signals 2) Signal Strengthening 3) Identifying features and 4) Classifying signals. This information might help determine the most effective way to carry out pertinent studies. The aforementioned techniques are now being implemented using a hybrid methodology.

Researchers have created models for thought-based games, object animation, and human emotion recognition using a variety of processing techniques. It is possible to design innovative and effective techniques that combine several features to consistently get superior results if one has sufficient understanding about them. These new methods may drive to a new era of BCI applications including the thought based operating system, finding the intensity of human emotion, detecting the gender of human based on thoughts, automation of house hold appliances

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