Advancements and Future Prospects of Brain-Computer Interfaces Utilizing EEG Technology

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Abstract* — Brain-Computer Interfaces (BCIs) represent a cutting-edge technology that facilitates direct communication between the human brain and external devices, enabling individuals to control devices through neural signals alone. This paper reviews the evolution and current state of EEG-based BCIs, beginning with Hans Berger's pioneering work in electroencephalography (EEG) and progressing through modern applications and methodologies. Key aspects covered include the acquisition of EEG signals, analysis techniques for extracting meaningful data, and the role of machine learning algorithms in signal classification and interpretation. The review identifies challenges such as signal noise and variability, and discusses recent advancements aimed at enhancing BCI accuracy and reliability. Additionally, the paper explores emerging trends in non-invasive BCI technologies, such as EMG, fMRI, and NIRS, highlighting their potential to broaden BCI accessibility and usability across various domains. By synthesizing current research findings and outlining future directions, this review contributes to the ongoing development and adoption of EEG-based BCIs in healthcare, assistive technology, and beyond.

Keywords — Brain-Computer Interfaces, EEG, electroencephalography, machine learning; signal processing, neurotechnology, assistive technology, non-invasive interfaces.

I. INTRODUCTION

The field of Brain–Computer Interfaces (BCIs) traces its origins to Hans Berger, who pioneered the study of electrical activity in the human brain through the development of electroencephalography (EEG). In 1924, Berger achieved a milestone by recording EEG signals directly from the human brain for the first time. Through his analysis of these signals, Berger identified oscillatory brain activity, including the alpha wave (8–12 Hz), which became known as Berger's wave. Initially, Berger used a rudimentary recording device that involved inserting silver wires under patients' scalps. This early method evolved as silver foils attached with rubber bandages replaced the wires. However, initial attempts using a Lippmann capillary electrometer proved disappointing. Success came with more advanced equipment like the Siemens double-coil recording galvanometer, capable of displaying electric voltages as minuscule as one ten-thousandth of a volt. Berger's research focused on correlating changes in EEG wave patterns with various brain disorders, opening up new avenues for studying human brain activity through EEGs. These developments marked a significant advancement in understanding brain functions and laid the foundation for future innovations in the field of neuroscience and BCIs.

There are several types of brain-computer interfaces that are reported. The basic purpose of these devices or types is to intercept the electrical signals that pass between neurons in the brain and translate them to a signal that is sensed by external devices.

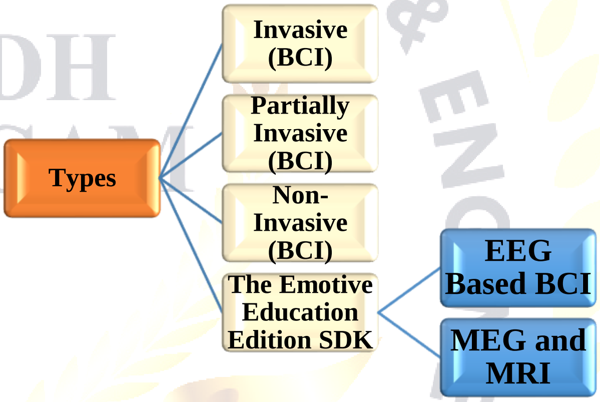

Figure 1 Types of BCI

A. *Brain Computer Interface Structure*

To advance a basic notion of BCI, the insignificant data on brain jobs and conditions is fascinating. This chapter deals with completely different methods of observing the brain with their fundamental differences and advantages.

The electromagnetic pulse generated by neurons allows us to observe the practicality of the brain. Considering some properties of the detected brain signal, it is determined based on the person's activity, that is, whether the person is sleeping or not. Completely different sleep stages have been found to generate different electromagnetic signals. Furthermore, thinking about very different things like emotions, activities or relaxation also signals changes in one way or another. BCI is based on these differences which allow control of the computer.

A brain-computer interface (BCI) could be a means of communication that allows a person to send commands to a device only through brain activity. And that is why they claim that it is the only means of communication for people with certain motor disabilities. The purpose of a BCI is to "read" the user's intention, which is usually done with classifiers that illustrate brain signal readings and translate them into a category from a set of states or intentions.

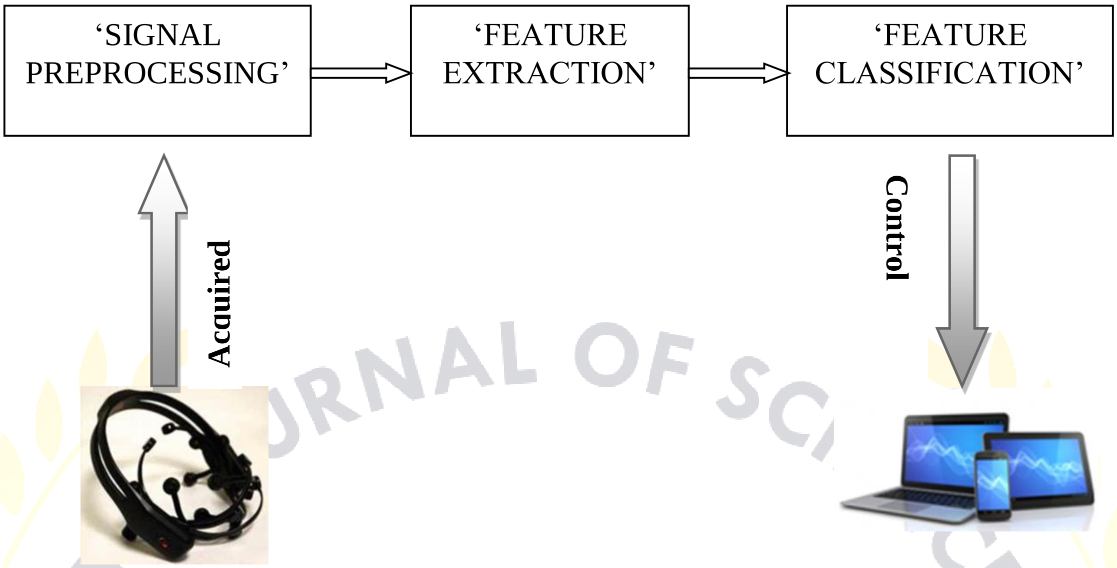

Figure 2 BCI structure

It is especially important for people with ALS, stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophy, and multiple sclerosis. However, considering the EEG-based BCI would allow for faster communication if a person could still use a muscle to correspond. Therefore, the only people who actually benefit from such research are those who suffer from these or similar diseases. BCIs differ in their signal acquisition system, which can be invasive or non-invasive, or in their signal evocation pattern, which can be exogenous or endogenous (how a person is encouraged to generate preferred signals).

Such evoked potentials are fluctuations in voltage dimensions that occur suddenly within the subject or after some (exogenous) event such as a visual stimulus (Event-Related Potential ERP). The universal structure of a BCI system can be seen in Figure 1.3. It can be divided into three parts:

- Signal acquisition, which creates an electronic representation of a subject by recording its signals.
- Signal processing, which modifies data to enable the use of capabilities. After that, he converts it into a demonstration that can be used to operate a gadget. For instance, using a classifier that accepts the attributes as input and outputs a value for each class, which may then be processed or interpreted as a command.
- The algorithm that gives out the commands in the end.

II. Literature Review

Lotte, F., et. al. (2015) [9] Brain-Computer Interfaces (BCIs) are advanced systems designed to translate brain activity patterns into actionable commands for interactive applications, primarily utilizing Electroencephalography (EEG). This article provides a comprehensive overview of EEG-based BCIs, focusing on their engineering aspects. It discusses foundational neuroscience concepts related to brain signal capture and processing, emphasizing signal processing techniques and machine learning algorithms for pattern recognition. The review also highlights challenges such as signal quality and user training, proposing future directions for enhancing BCI performance and usability across diverse applications in healthcare and human-computer interaction.

Rasheed, S. (2021) [10] This review explores the role of machine learning (ML) in Brain-Computer Interfaces (BCIs), covering various studies in the field. It discusses ML techniques for classifying emotions, detecting mental states, and analyzing EEG and event-related potential (ERP) signals in BCI applications. The article provides a comparative analysis of methodologies for feature extraction and classification, aiming to advance the integration of ML in BCI technology and improve application effectiveness.

Rashid, M., et. al. (2020) [11] This article provides an overview of contemporary Brain-Computer Interface (BCI) concepts beyond medical applications. It reviews EEG-based BCI systems, emphasizing electrophysiological control properties, extraction algorithms, and performance assessment. The review identifies current challenges in BCI systems and proposes solutions to enhance their functionality and reliability, showcasing the evolving landscape and potential future directions of BCI research.

Värbu, K. et. al. (2022) [12] Focused on EEG-based BCIs, this systematic review evaluates applications from 2009 to 2019 using the PRISMA model. It categorizes research into clinical and non-clinical domains, highlighting signal processing techniques and equipment used for EEG data collection. The review identifies current challenges and future opportunities in the field, emphasizing the broadening impact of EEG-based BCIs in both medical treatments and enhancing the lives of healthy individuals through collaborative and personal development applications.

Ghumman, M.K., et. al. (2021) [13] This study explores Brain-Computer Interfaces (BCI) as a technology predicting user emotions and facilitating direct brain communication with external devices using EEG. It details EEG-based BCI systems, focusing on signal acquisition, preprocessing, and classification techniques. The research proposes an artifact removal method using Independent Component Analysis (ICA) and feature extraction through Filter Bank Common Spatial Pattern (FBCSP), demonstrating improved classification accuracy with Support Vector Machines (SVM) and other classifiers.

Tang, X., et. al. (2023) [14] Addressing limitations of current BCI technologies, this article explores flexible electronics to develop next-generation Brain-Computer Interfaces. It examines the compatibility of current electronic devices with brain structure and explores flexible, stretchable, and soft electronics in neuroscience and bioelectronic medicine applications. The study discusses design challenges and integration issues, highlighting the potential advantages of flexible hardware in enhancing the effectiveness and usability of BCIs.

Mridha, M.F. et. al. (2015) [15] This comprehensive overview of Brain-Computer Interfaces (BCIs) discusses various applications and technological components, including sensors and algorithms. It highlights the evolution of BCI research and identifies ongoing challenges in the field, emphasizing the need for integrated approaches to improve system performance and user interaction across different applications.

Gonzalez-Astudillo, J., et. al. (2021) [16] Focused on improving Brain-Computer Interface (BCI) effectiveness, this review explores network theory to understand brain activity patterns. It discusses advancements in graph analysis and statistical modeling for interpreting neuroimaging data, aiming to enhance BCI usability and effectiveness by analyzing functional brain connections and their implications for cognitive function and human-machine interaction.

Ramadan, R.A., et. al. (2015) [17] Highlighting the transformative potential of Brain-Computer Interfaces (BCIs), this article emphasizes their role in enabling direct brain-computer communication for applications such as wheelchair control and cognitive simulation. It provides insights into brain anatomy relevant to BCI operation and details hardware and software components essential for constructing and operating effective BCIs, highlighting their impact on enhancing accessibility and advancing AI research.it.

III. Objectives

The aim of this study was to contribute to the expanding field of Brain-Computer Interfaces (BCI) without relying on existing literature. By focusing on the specific modality of electroencephalography (EEG), the objective was to deepen insights into neurophysiological processes that could be harnessed through BCI systems [1-5]. In the progressive development of BCI systems, it became crucial to conceptualize and execute a comprehensive system. A thorough grasp of methods for acquiring EEG data, the characteristics of EEG waveforms, and techniques for signal processing to extract features and classify them was deemed essential prior to embarking on BCI system design and implementation. The key objectives of this project were:

- To study a neurophysiological understanding of the human brain.
- To study electroencephalography as a means of identifying mental activity.
- Provide a comprehensive overview of the EEG-based BCI systems that have been implemented so far.
- Compare the performance of different feature classification methods.
- To discuss the future of BCI technology.

IV. Methodology

This survey aims to categorize different hand and leg movement tasks, outlined in Figure 4.1. The methodology is structured into four main stages. Initially, EEG data is recorded in the first phase. Subsequently, in the second stage, the signal undergoes preprocessing to eliminate unwanted noise and extraneous data. Following noise removal, the third stage involves extracting key features from the EEG signals. Finally, in the fourth stage, the EEG signals are mapped to corresponding movements, specifically 'hand and leg' movements. The flowchart depicted.

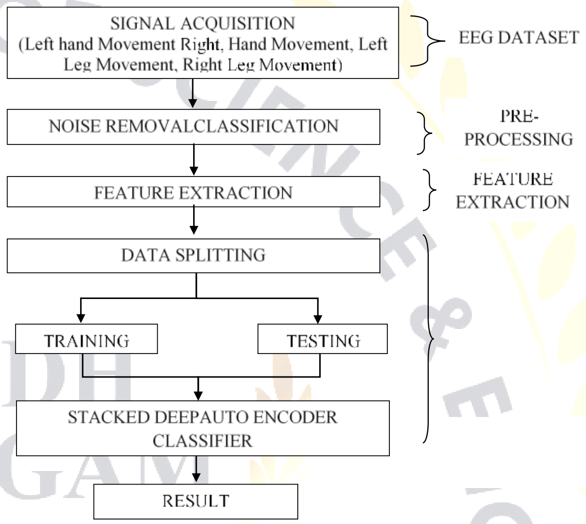

Figure 3 Proposed methodology analysis of EEG signals

A. *Signal Acquisition*

The dataset originates from Project BCI, which is a registered study including right-handed men aged 21 who do not have any known medical issues. With the eyes closed, the EEG is composed of actual, haphazard movements of the right and left hands. An electrode is represented by each line. FP1 FP2 F3 F4 C3 C4 P3 P4 O1 O2 F7 F8 T3 T4 T5 T6 FZ CZ PZ is the electrode order. Using a chain link, the Neuroma EEG device was used to record at 500 Hz. The EEG survey was used as a standard reference for exporting the data. In this nation, power lines run at 50 Hz.

In this research work the following movements are used for the analysis:

1. Three instances of the left hand moving forward
2. Three instances of the left hand moving backward
3. Three instances of the left hand moving forward
4. Three instances of the left hand moving forward
5. A single left leg movement occurrence
6. One movement of the right leg

B. *Pre-processing*

Noise cancellation is necessary since the obtained EEG data is often noisy. In order to eliminate undesired artifacts, the EEG signals were filtered using a Butterworth filter and a band pass filter between 8 and 25 Hz. A predefined frequency band is passed through a band pass filter. Combining a high pass and low pass filter allows for this.

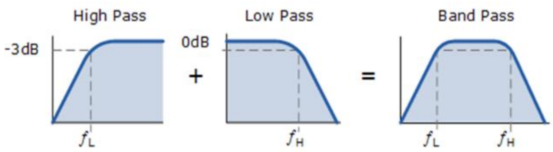

Figure 4 Bandpass Filter

In the typical first order low pass along with high pass filter circuits, the upper corner point (f̃H) and the lower corner frequency limit point (fL) are computed in the same way. Naturally, in order to prevent any interaction between the low-pass and high-pass phases, there must be a suitable distance between the two breakpoints. In addition, the amplifier establishes the circuit's overall voltage gain and offers isolation between the two stages.

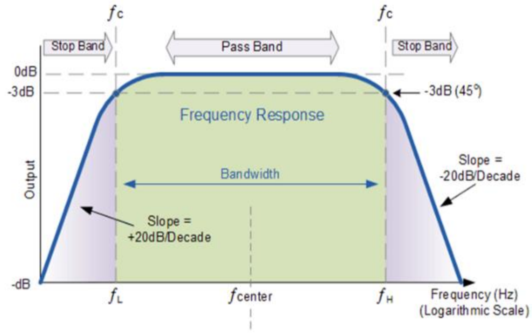

Figure 5 Response of Band Pass Frequency

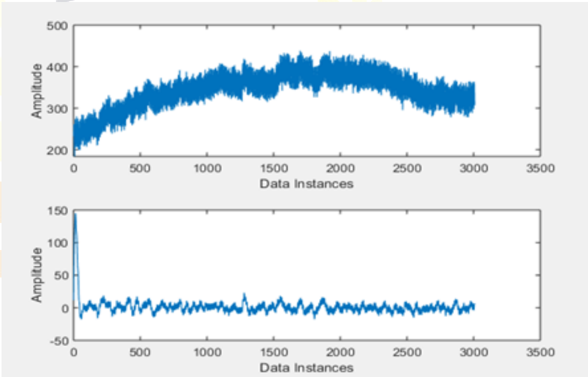

Figure 6 Signal of Left-Hand Movement, Both Original and Filtered

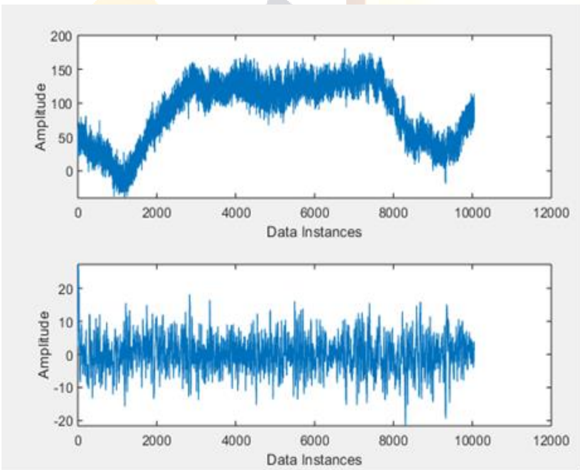

Figure 7 Original and Filtered Left Leg Movement Signal

In addition to having consistent sensitivity to the target frequencies, the perfect electrical filter should totally suppress undesirable frequencies. Reducing the frequency range employed, the number of channels (channel selection), and the number of functions with the help of a band-pass filter directly affects execution time and memory use, which enhances system performance. 4.5 for the dataset on hands and legs.

C. *Feature Extraction*

After denoising the EEG dataset, discrete wavelet transforms (DWTs) are utilized within specific frequency bands. To handle the substantial and intricately detailed EEG input data effectively, condensing it into a concise and informative feature vector is essential. This process, known as feature extraction, focuses on extracting essential signal attributes to shorten the vector length while retaining critical information. The discrete wavelet transform accomplishes this by examining signal properties across various scales using high-pass and low-pass filters. The resulting wavelet coefficients encompass both approximation and detail coefficients, which are pivotal for further analysis and understanding of the signal's characteristics.

- Decompose the signal into N levels using filtering and decimation with DWT to obtain the approximation and detailed coefficients.
- Extract features from the coefficients obtained through DWT.

From these DWTs, valuable information is extracted that serves to streamline the dimensionality of its functionality. Specifically, the analysis yields ten distinct metrics or characteristics, including mean, median, variance, standard deviation, asymmetry, kurtosis, complexity, and mobility, each contributing to a comprehensive understanding and interpretation of the data.

Mean: A set of values' center or focal point is related to its mean. The average is considered for every single sub-band signal.

$$\left(\mathrm{Mean} = \frac{1}{N\sum_{i=1}^{n} Xi}\right) \tag{4.1}$$

Median: The median divides a sample of data or a probability distribution into two equal halves, separating the upper and lower portions. In simpler terms, it can be seen as the midpoint or "average" value of the dataset.

Variance is calculated as the average of the squared differences from the mean

$$(\sigma = (x+a)^n = \textstyle\sum_{i=1}^{n} (X-\mu)^2/N) \tag{4.2}$$

Standard deviation: Standard deviation provides a straightforward measure of the variability within a dataset. It quantifies the root mean square (RMS) deviation of values from the mean.

$$\left(\mathrm{std} = \sqrt{\left(\sum_{i=1}^{n} (Xi - X)^2\right))/N - 1}\right) \tag{4.3}$$

Skewness: Asymmetry refers to the extent of asymmetry in the probability distribution of a real-valued random variable relative to its mean value [15,16]. This measure can be positive, negative, or indefinite.

$$(\mathrm{skewness} = \mathrm{E}[(X - \mu\sigma)^3]) \tag{4.4}$$

Kurtosis: ‘Kurtosis’ quantifies the relative pawedness or ‘flatness of a distribution’ in comparison to the normal distribution:

$$(\text{kurtosis} = \mu 4 / \sigma^4) \quad (4.5)$$

where μ4 represents the fourth moment about the mean and σ is the standard deviation.

Complexity: The 'complexity parameter indicates' the 'variation in frequency'.

$$\text{Complexity} = \text{Mobility}(\frac{dy(t)}{dt})/\text{Mobility}(y(t)) \quad (4.6)$$

Mobility: The 'mobility parameter' indicates the 'mean frequency' or the ratio of the standard deviation of the 'power spectrum'.

$$\left(\text{Mobility} = \sqrt{\text{var}(\frac{dy(t)}{dt})/\text{var}(y(t))}\right) \quad (4.7)$$

An example of all extracted features is presented in Table 4.1.

Table 1 Sample of 'extracted features' from (EEG) signals for hand and leg movement

(Class)	(Left Hand)	(Right Hand)	(Left Leg)	(Left Hand)	(Right Leg)
'Mean'	4735.07	-5320.43	4644.96	-3962.4	3887.815
'Median'	2.192113	1.891534	2.396905	-2.30394	1.948793
'Variance'	4.90E+08	3.83E+08	3.87E+18	3.75E+08	3.76E+08
'Standard Deviation'	19757.77	19556.13	19405.17	29334.16	19367.16
'Skewness'	2.947909	-2.9764	2.116666	-2.95751	2.897447
'Kurtosis'	8.71422	8.73124	8.103585	8.820168	8.612353
'Mobility'	2.41596	2.43423	2.4201	2.45956	2.43797
'Complexity'	2.068747	2.137758	2.146357	2.11742	2.04131

D. *Feature Classification*

After acquiring the characteristics, they are assembled into a vector for practical application. The dataset at hand is initially divided into either a training set or a test set. Once separated, the classifier is employed on the training data to formulate classification rules for each report. Subsequently, the test set is utilized to 'classify the data'. The 'classification utilizes' a 'stacked deep' autoencoder.

E. *Stacked Deep Autoencoder*

A deep 'stacked autoencoder' is formed by combining multiple levels of autoencoders, each consisting of cascaded encoding layers along with a SoftMax classifier. Unlike supervised networks, self-encoding networks do not require labeled data during the learning phase. The fundamental structure of an unsupervised autoencoder 'typically includes' an 'input layer', one or more hidden layers, and an 'output layer'.

Autoencoders serve various purposes such as pre-training and dimensionality reduction, especially when designed with a bottleneck architecture. For example, by stacking more hidden layers, an autoencoder with a single hidden layer can gradually acquire hierarchical representations. This algorithm functions as a feature extraction tool, aiding in the discovery of meaningful data representations that often surpass the original data points in clarity and relevance.

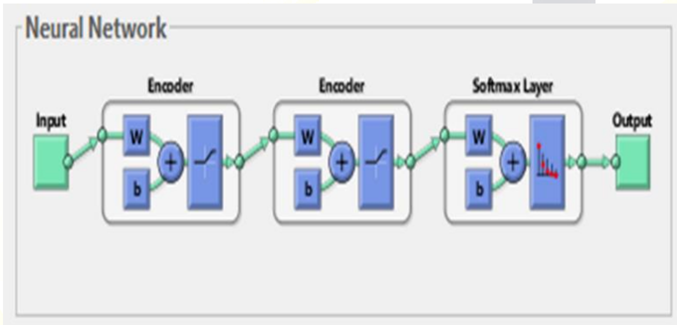

Figure 8 Architecture of Stacked Deep Auto Encoders

The 'deep autoencoder' comprises three layers: an 'input layer, a hidden layer, and an output layer. The input layer receives and processes input values. The computations within the hidden layer are determined by the following formula:

$$\hat{X} = \sum W * X_i + B_i \quad (4.8)$$

'where W is the weight matrix and
X is the input data values from the input layers.
The Bias Matrix is B=

Moreover, the transfer function is computed

$$f(x) = \frac{1}{1 + e^{-y}} \quad (4.9)$$

Where, e=error value

The loss function that needs to be minimized in the stacked deep autoencoder neural network consists of numerous layers of autoencoders. It is expressed as follows:

$$loss_{min} = |X - (W_1\theta(W_2\theta \ldots\ldots\ldots.(W_l(f(x)))))| \quad (4.10)$$

Where W1, W2...Wl is the total autoencoders' weight function.
θ = Autoencoders' decoding function f(x) = function to compute data values at each layer

F. SoftMax classifier

The SoftMax function is widely used in the field of machine learning; it gives each output option a score that is then transformed into a probability utilizing the SoftMax function. Default output level for a classification task with more than two classes is SoftMax.

With this level, which is the most recent, one may forecast a 'discrete probability distribution' between classes.

G. Proposed Algorithm

{left hand movement, right hand movement, left leg movement, and right leg movement} is the output labeled {dataset}.
Step 1: Find feature vector (V) for each instance in D.
Step2: Perform each V
Step 3: Categorization of Data
Step 4: 'Determine the total class label'
Locate the 'True Positive' (TP)
True Negative (TN)
False positives (FP)
False negative (FN)
Step5: Locate the end performance parameters for

H. Confusion Matrix

This unique table arrangement lets you see how well an algorithm performs. Here, the confusion matrix shows how well the suggested method performs. It is clear from the term "confusion" whether two classes are being confused by the system. There are two dimensions to this matrix: actual and planned H. This is a two-row, two-column table used in predictive analytics that shows the quantity of true positives, true negatives, false positives, and false negatives.

TP indicates when a condition is present and FN indicates when a condition is not present.

FP = Identifies the absence of a condition, TN = Doesn't recognize a condition when it doesn't exist

The confusion matrix is used to determine the outcomes of four cells.

The matrix of confusion for hand movement prediction is explained in the following figure 4.7. The training data set is used to evaluate the test set, i.e., H. The actual and expected values are compared.

- When the actual and was expecting motion values coincide, the condition is said to be true positive (TP), or 1.
- When the expected and actual values of the non-movement match, that is, H. 0, the condition becomes true negative (TN).
- When confusion results from a discrepancy between the actual and predicted values of motion and non-motion, such as in B. 1 and 0, the condition is deemed false negative (FN). This is a precarious scenario.
- When confusion emerges and the real and expected values of motion and non-motion do not match, the condition becomes false positive (FP), as in the case of B. 0 and 1. There is uncertainty about this case.

	ACTUAL 1	ACTUAL 0
EXPECTED 1	TP	FN
EXPECTED 0	FP	TN

Figure 9 Confusion Matrix

I. Performance Evaluation Parameters

Accuracy

This metric, which represents the percentage of 'recognition accuracy' for each known test input to the entire amount of trained data, is provided by:

$$(\text{Accuracy} = (\text{TP} + \text{TN})/\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (4.11)$$

Precision

It is defined as the proportion of each class's accurately recognized motions to all classes' properly recognized movements, and it is provided by:

$$(\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}) \quad (4.12)$$

Recall

The number of right answers divided by the total number of results that ought to have been returned is known as recall.

$$(\text{Recall} = \frac{\text{TP}}{(\text{TP+FN})}) \quad (4.13)$$

F-Measure

The precision rate plus recall combined merit is known as the F-Measure. This element was used to assess the implementation's performance in order to determine the system's overall performance in terms of accurate outcomes, or by excluding incorrect recognition observations. The result is provided by:

F-Measure= 2 * [(precision * recall) / (precision + recall)] (4.14)

V. Simulation And Result Analysis

This chapter includes a numerical and analytical explanation of a suggested algorithm for simulated hand and leg movements in order to determine the suggested method's performance.

To assess the effectiveness of the suggested 'algorithm scheme', the suggested algorithm is simulated using the subsequent 'configuration':

Software Prerequisite

'MATLAB'-8.3.0 32/64-bit 'Windows Operating System' Platform
Hardware Prerequisite
2.50GHz Intel Core i5-3210M CPU with 1 GB of RAM
512 Hard Disk

A. *Description of Dataset*

This research uses a dataset from the 'BCI project' for a 21-year-old man's EEG signal, which includes 'left hand, right hand, and leg movement signals', to simulate the suggested methods. The following data were collected for the simulation:

- 'Left hand forward movement'
- 'Left hand backward movement'
- 'Left hand forward movement'
- 'Left hand forward movement'
- 'Left leg movement'
- 'Right leg movement'

B. *Result Analysis*

The performance of several classifiers, including (SVM, KNN, RF), Neural Network, Naïve Bayes, and 'Stacked Deep auto Encoder', is analyzed in order to determine the results. The EEG hand and leg movement dataset is first cleaned in order to assess the performance of these classifiers.

By removing unnecessary noise, the dataset is made clean using the "Butterworth filter." Once more features have been extracted from the cleaned dataset, it is divided into two groups: the training set and the testing set. For more efficient result analysis, the training and testing ratios are divided into 60:40, 70:30, and 80:20 ratios, respectively.

Table 2 Average Performance Assessment with a 60:40 'Training and Testing Split'

Techniques	Accuracy (in %)	Precision (in %)	Recall (in %)
Support Vector Machine	82.542	75.338	53.534
k-Nearest Neighbour	83.904	78.1646	76.476
Random Forest	82.696	64.404	64.404
Neural Network	77.778	44.458	31.648
Naïve Bayes	64.674	58.664	94.186
Stacked DeepAuto Encoder	87.194	83.51	99.966

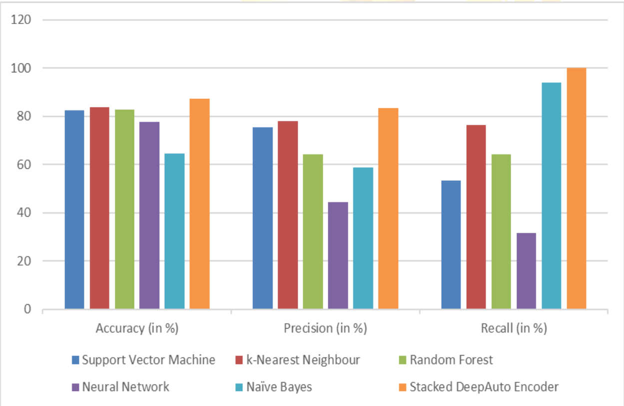

Figure 10 Average Performance Assessment for Training and Testing Ratio of 60:40

The stacked deep autoencoder consistently outperforms other classifiers in terms of performance. This analysis was conducted using five different testing datasets, with average metrics calculated for the 60:40 training and testing ratio dataset. The stacked deep autoencoder achieved approximately 87% accuracy and approximately 83% precision, marking the highest scores among all classifiers evaluated.

Similarly, Table3 displays accuracy results for various classifiers using the 70:30 training and testing ratio dataset. The findings demonstrate that the stacked deep autoencoder consistently achieves superior accuracy across all dataset categories, with performance improving as the training ratio increases. This highlights that increasing the training ratio enhances the classifier's overall accuracy.

Table 3 Average Performance Evaluation for 70:30 Training and Testing Ratio

Techniques	Accuracy (in %)	Precision (in %)	Recall (in %)
Support Vector Machine	83.00522	76.7	54.514
k-Nearest Neighbour	84.97	79.55	73.256
Random Forest	82.748	64.504	64.504

Neural Network	78.462	47	27.884
Naïve Bayes	65.73	59.35	95.156
Stacked DeepAuto Encoder	91.386	88.396	99.96

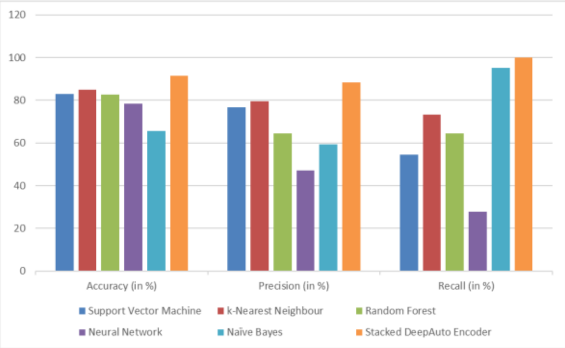

Figure 11 Average Evaluation of Performance for Training provided and Testing Ratio of 70:30

Figure 11 shows the performance evaluation graph comparing the proposed classifier with existing ones, indicating that the stacked deep autoencoder exhibits superior performance. The analysis included testing on five distinct datasets, and the average results were used for the 70:30 ratio dataset. Of all the classifiers tested, the stacked deep automatic encoder had the best accuracy and precision, achieving about 90% and 87%, respectively.

Table 4 Average Performance Evaluation for 80:20 Training and Testing Ratio

Techniques	Accuracy (in %)	Precision (in %)	Recall (in %)
Support Vector Machine	83.056	76.366	54.552
k-Nearest Neighbour	85.054	79.642	73.5
Random Forest	82.678	64.366	64.366
Neural Network	78.81	49.556	34.23
Naïve Bayes	65.434	59.996	95.132
Stacked DeepAuto Encoder	91.446	88.452	99.982

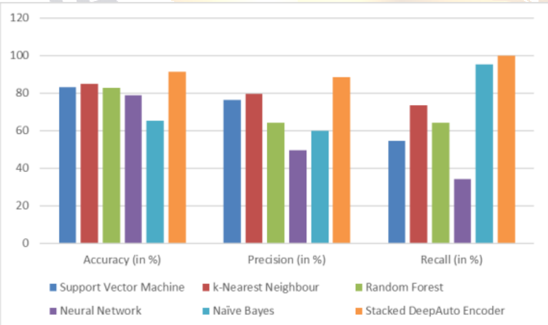

Figure 12 Average Performance Evaluation for 80:20 Training and Testing Ratio

Figure 12 depicts the performance evaluation graph comparing the proposed classifier with existing ones, highlighting the superior performance of the stacked deep autoencoder. The analysis involved testing on five distinct datasets, and the average results from these datasets were considered for the 80:20 ratio dataset. The stacked deep autoencoder achieved approximately 91% accuracy and approximately 87% precision, surpassing all other classifiers in these metrics.

VI. CONCLUSION

EEG-based BCIs have evolved significantly since their inception, driven by advancements in EEG technology, signal processing algorithms, and machine learning techniques. This review has provided a comprehensive overview of the historical development and current landscape of EEG-based BCIs, emphasizing their role in enhancing accessibility and functionality for users with disabilities. The comparative analysis of classification algorithms underscores the potential of advanced methods like Stacked Deep Autoencoder in improving the accuracy and robustness of BCI systems. Looking ahead, ongoing research efforts in non-invasive BCI technologies promise to address current limitations and expand the application scope of BCIs in everyday life. By fostering interdisciplinary collaboration and innovation, EEG-based BCIs are poised to continue transforming human-computer interaction, paving the way for novel applications in healthcare, gaming, and neuro-rehabilitation.

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