Classification of Motor Imaginary in EEG using feature Optimization and Machine Learning

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ABSTRACT

Motor image Critical disease diagnosis relies heavily on EEG classification. The complexity of the motor imagery EEG data hindered accurate classification. The motor imagery EEG classification rate is increased using the feature Optimization procedure. A deep neural network-based classifier for motor imagery EEG classification was proposed in this paper. The design deep neural network is a three-layer neural network model that incorporates the teacher learning-based optimization and feature optimization technique. The EEG data's noise and artefacts are reduced by a teacher learning-based optimization technique, which also enhances the input vectors for DNN. The suggested algorithm has been tested on datasets from the third and fourth BCI competitions and has been simulated in MATLAB environments. According to the evaluation's findings, the suggested algorithm compresses the current motor imagery EEG categorization technique quite effectively.

Keywords –**Motor Imagery (MI) EEG, Bayesian Feature Extraction, TLBO, DNN, Wavelet Transform, MATLAB, DWT, Optimization, BCI.**

Date of Submission: July 02, 2023 Date of Acceptance: August 28, 23

I. INTRODUCTION

The effectiveness of the brain-computer interface is greatly influenced by classification accuracy. The effectiveness of the brain-computer interface (BCI) enhances the diagnosis of diseases affecting nerve control, such as brain stroke and ALS. The high dimension and complicated feature's structure is the main issue with motor imagery EEG categorization. The classification rate of the classification algorithm decreases as feature complexity increases. The majority of writers presented feature reduction algorithms such as PCA, LDA, and many more. The lowered motor imagery EEG characteristics improve the machine learning algorithm's classification ratio. Extracting features from motor images. The non-stationary behaviors of the data make EEG categorization a difficult task. A superior approach of feature extraction is provided by transform-based functions as the discrete wavelet transform, SIFT, CSP, and hybrid methods of transform function. However, the huge feature vector dimensions can significantly increase computational complexity, and redundant features will reduce classification accuracy. A motor imagery-based BCI system was subjected to the genetic algorithm to shrink the feature vector and get rid of extraneous characteristics. The genetic algorithm was used to pick feature subsets from the previously described features, and it produced good results. The adaptive regression coefficients, as well as the asymmetric power, spectrum, coherence, and phase-locking values, were recovered from MI EEG.The teacher learning-based algorithm (TLBO)'s global data search for the group search strategy and evolutionary operator settings is a critical component. Due to their generalizability, robustness, and usability, TLBO has been widely utilized for feature selection. However, they are unable to fully utilize local knowledge, and it takes a long time to discover the optimal answer. This research proposed a DNN-based classification technique for the classification of MI-EEG data

II. RELATED WORK

The incremental approach of algorithms development enhances the performance of accuracy of motor imagery EEG classification. in this direction various scholars contribute more as feature optimization, feature selection. Some selected work describe here.

In this [1] author summaries the area and present readers with the most up-to-date research on the subject. The BCI concept is the focus of this article. This also classifies and explains the technique for acquiring brain signals. This also includes an overview of the current BCI equipment. the findings show the latest Brain Computer Interface Survey.

In this [2] author show that there are numerous open issues and research opportunities in the field of HCI for BCI-based games, as most evaluations focused solely on quantitative aspects of the BCI systems. The outcomes of a PRISMA-compliant systematic literature review of consumer-grade BCI-based games were presented in this study.

In this [3] author provide an approachable and up-to-date assessment of EEG-based BCI, with a focus on technical difficulties. Individuals argue BCI programmers, point out present device problems, and provide suggestions. An overview of contemporary BCI equipment is also included. Regardless, it generates a number of potential BCI roadmaps.

In this [4] author proposed Linear fusion, tensor fusion, and path-order polynomial fusion are three fusion approaches. To begin, our data reveal that the hybrid BCI system is more accurate, as expected. Our detection accuracy for a motion imaging test and a mental arithmetic task was 77.53 percent and 90.19 percent, respectively, compared to 74.20 percent and 88.1 percent in previous studies.

In this [5] author Discuss several types of BCI systems, as well as neuro imaging technologies for obtaining brain signals, basic brain activities, and an in-depth look at EEG–based BCI systems for human emotion recognition. Several classification algorithms are available for emotion classifications, but support vector machine classification techniques are the most suggested by various research for analyzing emotions.

In this [6] author devised a framework based on deep convolutional generative adversarial networks for generating artificial EEG to enrich the training set in order to improve the performance of a BCI classifier. researchers created a motor task experiment with diverted and focused attention conditions. Artificial data generation has the potential to save time and money.

In this [7] author describe a new method of controlling drones that uses a P300-based brain-computer interface that can be employed in the military as assistive technology in this study. We want to run swarm drones with only one brain in the near future to improve multitasking abilities. Researchers also intend to provide users the option of sending multiple orders at once rather of just one.

In this [8] author proposed a new deep CNN capable of categorizing time-source maps related to hands' sub-movements (open/close) phase from resting state. EML was also utilized to determine which cortical sources contributed the most to the classification of the motor preparation phase of the hand. As an outcome the recommended approach could be regarded an exciting advancement in BCI applications.

In this [9] author propose the model's training, feature extraction and classification can help obtain the best match. For traditional EEG signal processing systems, the feature extraction and classification procedures are specified independently. DNN has a better probability of improving classification accuracy as an outcome of this.
In this [10] author suggested that transfer learning be used to classify MI signals. The authors used Transfer learning to successfully classify the two-class EEG data. According to the findings, utilizing deep learning instead of standard ANN for BCI applications could be helpful. Even with a minimal amount of data, the transfer learning method can get a greater categorization rate.

III. CLASSIFICATION OF MOTOR IMAGINARY

Motor imagery is a cognitive process in which an individual mentally simulates or rehearses a specific motor action without physically executing it. This mental rehearsal can be used for various purposes, such as skill enhancement, rehabilitation, and brain-computer interface applications. Motor imagery can be classified into different types based on the perspective from which it is analyzed or the specific characteristics being considered. Here are some common classifications of motor imagery:

- **Directionality Classification:**

Kinesthetic Motor Imagery: In this type of motor imagery, individuals mentally simulate the feeling and sensations associated with performing a motor action. They focus on the internal sensations of movement and muscle activation.
Visual Motor Imagery: Here, individuals create mental images of themselves or others performing a motor action. The emphasis is on visualizing the action from an external perspective.

- **Perspective Classification:**

First-Person Perspective (Internal Imagery): In this perspective, individuals imagine themselves performing the action as if looking through their own eyes.
Third-Person Perspective (External Imagery): In this case, individuals imagine watching themselves from an external viewpoint.

- **Temporal Classification:**

Static Motor Imagery: Individuals imagine holding a particular posture or position without any actual movement.
Dynamic Motor Imagery: This involves mentally simulating a complete sequence of movements, capturing the entire action's dynamic nature.

- **Functional Classification:**

Rehabilitative Motor Imagery: Used in physical therapy and rehabilitation to help patients regain motor function after injury or surgery.
Skill Acquisition Motor Imagery: Athletes and performers use this type of imagery to enhance their performance by mentally rehearsing actions and strategies.
Diagnostic Motor Imagery: Used in clinical settings to assess motor-related cognitive functions and identify impairments.

- **Neurocognitive Classification:**

Motor Execution Simulation: Involves simulating the execution of a motor action in the mind.
Motor Planning Simulation: Focuses on mentally preparing and planning a motor action before its execution.

- **Brain-Computer Interface Classification:**

BCI Control Motor Imagery: Used in brain-computer interface systems, where individuals modulate their brain activity during motor imagery to control external devices.
It's important to note that these classifications aren't mutually exclusive, and motor imagery often involves a combination of these aspects. The choice of classification might depend on the specific research or application context.

IV. PROPOSED METHODOLOGY

The proposed algorithm of the motor imagery classification process is in three sections. The first section describes the feature extraction methods of motor imagery EEG data. The second section describes the feature optimization of motor imagery data, and finally, the third section describes the classification algorithm DNN.
A neural network defines the relationship of nonlinear between two variables P and Pi+1 through network function. The process of function defines as
$Pi + 1 = \delta(wpi + b)$ … … … … … … … … (1)
Where δ is activation function and matrix W and b is called model parameters. The variable P and Pi+1 is from of layers. the multilayer neural network argumenta with advance learning called deep neural network. The classification of network defines as y=f(u). the process of network function defines as
P1= δ1(w1u+b1)
P2= δ2(w2p1+b2)….
………
Y= δL(wLpL-1+bL)
Where L is number of layers Process of training of DNN.
The relation of neurons defines the process of EEG data
$Fk{:}Rnx \rightarrow Rnx$, where $xk \in Rnx$
Be the set of EGG data in neurons for the processing. Hypothesis of error estimated by E
$Ej = Hj\ (xj) + vj,\ \forall k \leq j \leq k + A$
where Hj: $Rnx \rightarrow Rny$ is the relation of multilayer input? estimate trained pattern
$xk = F0 \rightarrow k(x0) + \xi k$
3 define learning factor as
$k{+}A$
$x. = arg\min \{\|x - xk\|\ B{-}1 + \sum \|HjFj(x) - yj\|R{-}1\}$
$k\ \ x\ \ k\ \ jk$
Generates the channel of ALS $= \{Fs(x.),\ x.\}$ with $k \in [i.\ M, (i + 1).\ M]$
$k{-}1\ \ k$
Measure i for next step end
Output: $EEGclassifed$

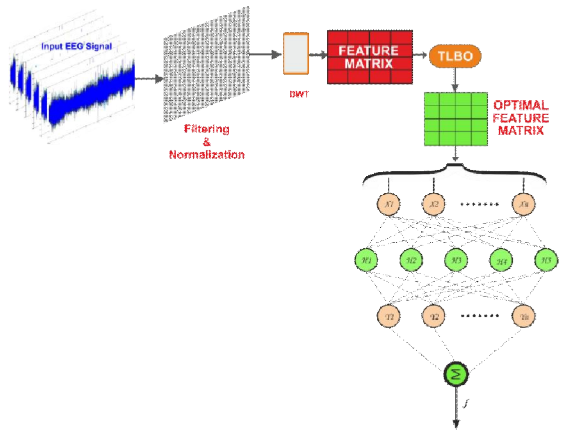


Figure: Process block diagram of EEG signal classification with deep neural network.

V. FEATURE EXTRACTION

Feature extraction is primary phase of EEG classification. The process of extraction applies DWT transform function. The applied DWT transform decomposed the EEG data into three levels. The applied transform methods describe as

$$WTx(a,\tau)\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-\tau}{a}\right)dt \ \ldots\ldots\ldots\ (1)$$

Where a represent scale factor, τrepresent time factor and $\psi(t)$ is a wavelet basis function, including all family of wavelet transform function.

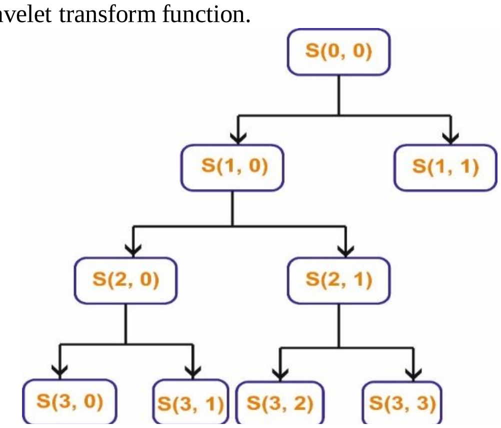


Figure: Describe the process of 3 level decomposition of EEG signals data with DWT transform function.

EEG data signal are non-stationary signals, so DWT are good option for discreet wavelets. The DWT function define as

$$WT_{x(J.k)=\int x(t)\psi j,k(t)dt} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ (2)$$

According to the process of sampling, the maximum frequency of the signal is fs/2. If the signal is decomposed by lower order, the complete frequency signal decomposed into L+1 sub band. The wavelet decomposition layer shown in figure

Volume: 15 Issue: 02 Pages: 5887– 5891 (2023) ISSN: 0975-0290

VI. Feature Optimization

Feature optimization process reduces the artifacts of EEG data and improves the vector processing of EEG data. teacher learning based optimization algorithm applies for the process of feature optimization. The teacher learning based optimization algorithm deals in two section, teacher and students. The students' parts of algorithm process the data and teacher phase optimized the data. the processing of optimization describe here.

- **Algorithm**

process the TLBO optimal data of EEG signals and M is vector of convergence

$$\{x_k \mathrm{I}\ k \in [M.i, M.(i+1)]\}$$

$$x_k = arg\min_x \left\{ \|x - x_k\| P_k^{-1} + \sum_k^{k+p} \left\| H_j M_j, (x) \right\| p_j^{-1} \right\}$$

Generates the channel of ALS $= \{Fs(x_{k-1}),\ x_k\}$ with $k \in [i.M, (i+1).M]$

Measure i for next stepend

Output: $EEGdataclassifed$

VII. Experimental Analysis

To validate the proposed algorithm, simulate in MATLAB tools. For the processing of algorithm use BCI competition III and IV datasets. This dataset contains 200 subjects of ALS penitents. For the evaluation of algorithm measure these parameters.

$$Accuracy = \frac{TotalNo.ofCorrectlyClassifiedInstances}{TotalNo.ofInstances} \times 100$$

$$Precision = \frac{TP}{TP + FP} \times 100$$

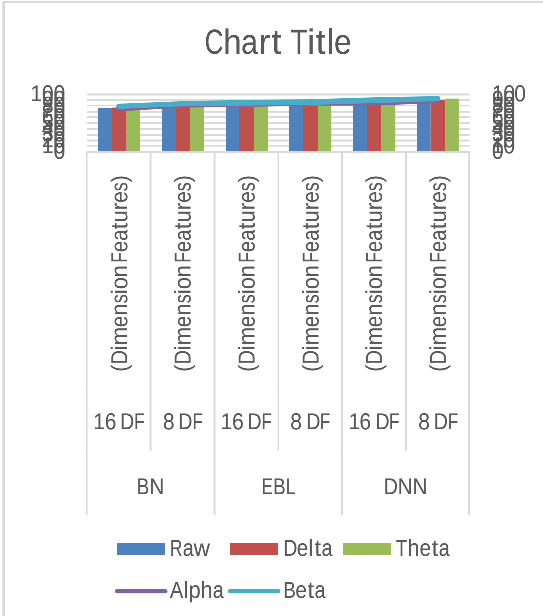
$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

Table 1 summarize the evaluation results of different features bands with BN, EBL and proposed Algorithm

Signal	BN		EBL		DNN	
	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)	16 DF (Dimension Features)	8 DF (Dimension Features)
Raw	75.56	78.67	79.64	82.65	85.45	88.48
Delta	76.44	79.24	80.55	81.34	84.45	90.35
Theta	78.41	83.12	84.08	86.25	87.47	92.47
Alpha	74.63	80.51	82.24	84.78	85.36	89.36
Beta	79.49	83.68	85.31	86.64	89.79	92.79

Comparative analysis of Precision using BN(Bayesian networks), EBL(Ensembled Machine Learning) and DNN(Deep Neural Network) with 16-dimension and 8-dimension features. Here we all five signal bands: raw signal, delta signal, theta signal and beta single of electroencephalogram.



VIII. Conclusion & Results

The serious sickness affecting the human neurological system is brought to light through the brain-computer interface. An intricate network of neurons and analogue signaling mechanisms make up the human nervous system. The brain-computer interface offers a method to monitor brain activity in order to identify sickness using computer vision and machine learning. Motor imagery refers to the BCI's stored information. The motor imagery is non-stationary data that might change across time and frequency. Alpha, beta, gamma, and delta are some of the various signal bands that the terms of frequency in the motor picture are separated into. The major objectives of this paper are the feature extraction of motor imagery EEG data and the categorization of EEG data with human sickness.

The process of feature extraction is complete, and the next phase of motor imagery EEG categorization is featuring selection and optimization. To optimize the different characteristics of the motor imagery EEG data, several heuristic and meta-heuristic functions are studied. The TLBO optimizations methods match the data's pattern and nature.

The DNN technique decreases the BN and EBL bottleneck issue and boosts the classification ratio. The majority of votes cast raises awareness of training data and lowers training error for ALS illness diagnosis.

Volume: 15 Issue: 02 Pages: 5887– 5891 (2023) ISSN: 0975-0290

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Biographies and Photographs

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