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Enhance the Classification Methods for Neurological Signals in Motor Imagery BCI Systems

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Abstract: Brain-Computer Interfaces (BCIs) are pioneering advancements in medical, neurological, and rehabilitation fields by merging insights from various disciplines. Motor Imagery (MI) is particularly promising for enhancing mobility in individuals with impairments. This study offers a comprehensive review of signal processing methods and electroencephalography (EEG) techniques used in MI-based BCI training. It encompasses the full process from EEG signal acquisition to preprocessing, feature extraction, and classification. Integrating machine learning (ML) and deep learning (DL) techniques significantly improves the accuracy and efficiency of BCI motor imagery signal classification, facilitating real-time neurofeedback applications. A crucial element of MI-BCIs is detecting Sensorimotor Rhythms (SMR) during motor imagery tasks, which indicate changes in brain activity linked to movement intentions. To tackle challenges related to low-resolution EEG signals, this research introduces a standardized MI-BCI reporting format. Additionally, novel algorithms for feature extraction and classification are proposed based on data from 10 participants performing four distinct MI tasks using scalp electrodes. The study also assesses the hardware and signal processing capabilities required for MI-BCI data collection, highlighting current technological limitations and opportunities for enhancement. In conclusion, the study anticipates continued advancements in EEG-BCI research, emphasizing the potential of these technologies to revolutionize clinical practices and improve the quality of life for individuals with neurological conditions.

Keywords: *Brain-Computer Interface (BCI), Electroencephalography (EEG), Motor Imagery (MI), Electrocorticography (ECoG), Signal, Deep learning (DL), Feature extraction, Wavelet packet decomposition (WPD), Sensorimotor Rhythms (SMR), Machine Learning (ML), feature extraction, low-resolution.*

1. Introduction

BCIs have showed considerable potential in conveying communication between the brain and computers or other devices without using of traditional input channels such as devices or displays. To collect brain waves, EEG and other intrusive technologies are utilized, which are essentially distracting and difficult. For the development of a reliable and successful BCI device, modern digital signal processing technologies are critical [2]. With the unique qualities of MI-based BCI, categorizing EEG signals is extremely difficult. The first challenge is low signal-to-noise ratio (SNR). Because scalp electrodes are designed to collect the median activity of multiple brain cells, EEG-based BCI devices have a low SNR [3]. People with severe and persistent physical disabilities are among the more than 200 million people worldwide who have major functional limits. People with significant physical disabilities may require ongoing assistance and care if they difficulty with fundamental actions such as walking, grasping, and maintaining bodily level [4]. Because of its ability to read and analyse brain signals, BCI equipment is a vital medical tool for improving the freedom and mobility of people with disabilities throughout their lives. Because of its low cost, greater temporal accuracy, and lack of invasiveness, EEG is a popular signal gathering approach in BCI devices. BCI models, such as the MI-EEG-based BCI, that convert unique emotional perceptions of behavior.BCI technology collects brain signals using a range of non-invasive and invasive technologies, including magnetoencephalography, (EEG) electroencephalograph electrocorticography (ECoG), and MRI [5]. MI-BCIs, which are based on changes in Sensor Motor Rhythms during mental movements, are among the most extensively used EEG methodologies. A nonstationary EEG signal is a challenge that must be addressed if successful MI-EEG categorization systems are to be developed; this means that signals from the same individual will continue to change dramatically and sporadically between trials. Most current models of EEG signals include the unreasonable assumption that the propagation of assigned information is time-invariant and thus could be meaningful in an irregular historical background [6]. Because EEG information is frequently acquired across a set of geographically separated electrode channels, MI-EEG classification algorithms face an extra barrier in overcoming the possibility of multiple channels of communication signals. Because task-related information is not consistently distributed in length and channel size, the models suffer in a variety of multi-channel contexts [7]. The research [8] focused on advancements in MI-BCI-based robots. A BCI is

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one means of communicating internal brain activity to the outside world. MI-based BCIs are heavily used in rehabilitation robots, nursing bed robots, wheelchair robots, autonomous aerial vehicles, and other applications. The study [9] gave a short summary of EEG-based BCI machine learning and deep learning approaches. To control physical things, the BCI system uses algorithmic detection of cognitive processes. Deep separation convolutional neural networks (DSCNNs) and Extreme Learning Machines (ELMs) were used in the study [10] to improve the identification rate of patients' motor intention. The study [11] proposed a novel method for detecting MI-EEG data by employing conditional empirical mode decomposition and a DMSCNN. BCIs rely heavily on the proper categorization of EEG data. The paper [12] described an interactive head-worn brain-computer connection based on neuro feedback for increasing MI practice. The efficacy of solo and combined visual and vibrotactile input was investigated. The research [13] determined that the efficacy of an EEG MI-BCI is strongly dependent on the operational frequency range of the EEG for EEG identification of MI. MI-BCIs are an established way for connecting the human brain with digital technologies. Due to its origins in sophisticated and non-linear artificial neural networks, the study [14] examined the most significant recent breakthroughs in Artificial Intelligence, with applicability to neurology, neurological imaging, machine vision, and automation. The study [15] proposed a novel EEG Classification system that uses CNN in a semi-supervised sorting scenario. Deep learning, minimal categorization, and controlled learning are a few examples of well-known machine learning algorithms, the success of which is largely dependent on the data used for training. The study [16] used multidimensional EEG data graph-theoretic frameworks to create MI categorization algorithms. MI sequences are frequently used in computerized brain structures to run external devices without engaging the body's musculoskeletal system. The paper [17] reported EEG_GENet, a one-of-a-kind network constructed by combining EEG Net with a graph-based encoding approach that operates at the characteristic levels. MI-EEG signals, on the other hand, are multi electrode and include topological knowledge, whereas picture or language information does not. The study [18] provides a thorough examination of the topic of artificial intelligence-enhanced human EEG analysis. An emerging research topic is human EEG evaluation supported by artificial intelligence (AI) technologies. Using previously tagged MI-EEG information, the research [19] proposed a unique transferred learning technique that may increase classification precision for a restricted sample of classed EEG signals. The study [20] involved sparsely expressing data using a specified or acquired language and then categorizing it based on the amount of leftover mistake. According to recent research, a learnt dictionary outperforms one with an established lexicon.

2.Litnature Review

2023 Fengge Bao, Weiheng Liu, and collaborators [21] This literature review delves into the area of motor imagination (MI) BCIs and its critical role in extracting relevant characteristics from electroencephalogram (EEG) signals when researching Brain-Computer Interfaces (BCIs). It investigates a variety of strategies in four distinct domains: time-based, frequency-based, time-frequency analysis, and spatial-based methods. Furthermore, it compares their practical applications in depth, acting as a helpful point of reference for the direction of future study in this field. Weiheng Liu, Fengge Bao Liu, and colleagues (2022) [22] The Motor Imagery-based Brain-Computer Interface (MI-BCI) has piqued the interest of researchers due to its simple and effective method to recovering motor capability in people with physical limitations. This review study looks at the different categorization approaches used in MI-BCI systems. Machine learning, the Nave Bayes classifier, Support Vector Machines, Linear Discriminant Analysis, Sparse Auto encoder, Convolutional Neural Networks, and Recurrent Neural Networks are among the approaches used. The study investigates not only their accuracy but also their classification speed and data requirements, giving useful insights for practitioners and scholars in the field.

M. S. Ali and colleagues (2023) [23] The deep convolutional EfficientNetB0 model is used in this study to grasp the complexities of electroencephalogram (EEG) signals using the BCI competition IV dataset 2b. The technology uses the Short-Time Fourier Transform (STFT) algorithm to extract relevant features from EEG signals, addressing concerns with deep convolutional neural networks (DCNN) classification accuracy. The results show that the model outperforms existing state-of-the-art DCNN models in feature extraction and classification of two-class motor imagery.

S. Ghafari and E. Azizi et al. (2022) [24] In recent years, Brain-Computer Interfaces (BCIs) have garnered increasing interest, with a particular focus on Motor Imagery (MI)-BCI systems. While various techniques have been proposed for the extraction of EEG signal characteristics, this study introduces a novel approach that combines deep learning through Convolutional Neural Networks with the discrete wavelet transform. The findings demonstrate the superiority of this method over traditional approaches, offering valuable support for real-time motor imagery classification and decision-making.

S. Siuly, Y. Li, and colleagues (2012) [25] This paper describes a hybrid approach for improving the classification accuracy of motor imagery (MI) data in the context of brain-computer interfaces (BCIs). The approach includes a cross-correlation-based feature extraction mechanism and a Least Square Support Vector Machine (LS-SVM) for recognising two-class MI signals. The method's performance is evaluated by running it on BCI Competition III datasets IVa and IVb and comparing it to eight contemporary algorithms. The LS-SVM classifier outperforms the most current eight reported approaches, yielding a remarkable 7.40% improvement in classification accuracy.

C. E. Hernández-González et al. (2017) [26] This study outlines an experiment involving the classification of EEG signals utilizing discrete wavelet transform and MODWT techniques. The outcome of this experiment yielded an impressive average accuracy of 98.81% within the support vector machine classification system, showcasing its efficacy for BCI applications.

N. Rathipriya et al. (2013) [27] This paper introduces a hybrid algorithm aimed at enhancing the classification accuracy of Motor Imagery (MI) in electrocorticography (ECoG) for Brain-Computer Interface (BCI) systems. The proposed classifier employs features extracted via the cross-correlation method and is rigorously evaluated through a 10-fold cross-validation procedure. A comparative analysis with existing systems is conducted to tackle unresolved challenges within the realm of BCI methodologies.

Tian-jian Luo and colleagues (2013) [28] The goal of this study is to address the issues of low recognition accuracy and robustness in Motor Imagery-based Brain-Computer Interfaces (MI-BCI). It addresses these challenges by exploiting common spatial pattern features collected from EEG data and implementing a novel feature selection genetic technique. To improve efficiency, the parallel genetic algorithm is implemented within a Map Reduce framework. Comparative investigations show that the MRPGA design achieves a remarkable average recognition accuracy, with faster classification accuracies.

Rongnian Tang et al. (2021) [29] This research aims to enhance the classification of motor imagery by leveraging the frequency and spatial information present in electroencephalography signals. To achieve this, the study introduces an upper triangle filter bank and an auto encoder neural network, tailored to amplify frequency information and extract spatial features from sub-bands. Experimental assessments illustrate the effectiveness of this approach, demonstrating improved discriminative features and superior classification performance when compared to alternative algorithms."

Mohammad Mahdi Togha et al. (2021) [30] This investigation introduces an innovative approach that amalgamates local activities estimation (LAE) with common spatial pattern (CSP) within EEG-based motor imagery Brain-Computer Interfaces (BCIs). LAE-CSP leverages both regularized CSP and LAE spatial filters, effectively reducing data dimensionality while extracting features through fast Fourier transform. The study conducted evaluations using three distinct sets of motor imagery data from BCI competition III and IV, revealing that LAE-CSP outperformed all tested methods, achieving an impressive average accuracy rate of nearly 80%.

Yu Zhang and colleagues (2015) [31] The Sparse Filter Band Common Spatial Pattern (SFBCSP) is introduced in this paper as a novel strategy to improving feature extraction for motor imagery (MI) in Brain-Computer Interface (BCI) applications. SFBCSP entails estimating CSP features from various signals acquired from EEG data, selecting suitable filter bands via sparse regression, and implementing a MI classification support vector machine (SVM). The experimental results show that SFBCSP improves MI classification performance significantly when compared to alternative techniques, indicating its potential as a tool to progress MI-based BCI systems.

Raj deep Chatterjee et al. (2019) [32] The Brain-Computer Interface (BCI) serves as an interface between the human brain and computer systems, offering a means to replace or enhance the nervous system by translating brain signals into control instructions. Among various signal recording methods, Electroencephalography (EEG) is widely adopted due to its advantages, including fine spatial and temporal resolution, cost-effectiveness, and portability. This chapter delves into the analysis of ensemble learning strategies for classifying motor imagery EEG signals, specifically comparing bagging and boosting techniques to identify the most appropriate composition for this specific application.

Zhihua Wang et al. (2019) [33] This research introduces a hybrid Brain-Computer Interface (BCI) paradigm designed for gaming through the utilization of electroencephalogram (EEG) signals. It integrates two distinct modalities, motor imagery, and steady-state visually evoked potentials, employing the game Tetris as the controlled object. The BCI games are designed using the 'dwell time' approach and fusion rules. The study effectively showcases the viability of this paradigm, offering individuals with disabilities the opportunity to enjoy brain-controlled games, which can potentially enhance their overall happiness and quality of life.

Kaishuo Zhang et al. (2019) [34] Deep learning serves as a potent tool in the development of Brain-Computer Interface (BCI) systems. However, its effectiveness is often constrained by the scarcity of subject-specific data. In response to this challenge, this paper introduces five strategies aimed at adapting a Convolutional Neural Network (CNN)-based electroencephalography-BCI system for decoding hand motor imagery. These schemes lead to enhanced model performance when evaluated on target subjects, resulting in an average accuracy of 84.19% for two-class motor imagery and a statistically noteworthy enhancement in the classification process.

Table 1. Literature Review Performance of Problem Formulations

Reference	Authors	Methods	Research Gaps	Limitations	Challenges
[35]	Xu, B., Zhang, L., Song, A., Wu, C., Li, W., Zhang, D., et al. (2018).	Feature extraction using wavelet transform-based input, followed by a 2-Layer convolutional neural network	Incorporating deep learning in BCI systems.	Reduced calculation complexity, faster training.	Scaling the method for larger datasets.
[36]	Yan et al. (2017)	Extreme multi-kernel learning machine	Limited exploration of different kernel functions and multi-kernel learning strategies.	MKELM is a relatively simple algorithm, but it may not be as effective as more complex deep learning methods for EEG classification. MKELM may be sensitive to the hyper parameters of the kernel functions.	Developing more effective multi-kernel learning strategies for EEG classification. Comparing MKELM with other state-of-the-art deep learning methods for EEG classification. Developing methods to make MKELM more robust to hyper parameter selection.
[37]	Wang et al. (2022)	Rested-state EEG in the alpha rhythm predicted motor imagery-based BCI performance.	Predicting a user's MI capacity in BCI experiments is difficult.	The study only investigated a small sample size of 105 subjects.	Replicating the findings in a larger and more diverse sample.
[38]	Gu et al. (2021)	Current literature on EEG signal detection and computational intelligence in BCI applications	The past five years in brief.	The survey focused on studies published in the past five years. The survey did not include a comprehensive evaluation of the different technologies and approaches discussed.	Covering EEG-based BCI research in detail.

[39]	X. Gu, et al. (2021)	Deep learning methods for BCI	Limited availability of BCI datasets High-dimensional, chaotic, nonstationary brain signals.	Deep learning methods computationally expensive and require big datasets to train Hyper parameter selection can affect deep learning models.	deep learning approaches for noise-resistant and nonstationary brain signals Developing deep learning approaches that are efficient and can be used on real-time EEG data Conducting clinical trials to evaluate the efficacy of deep learning-based BCIs for different applications
[40]	X. Wang et al.(2022)	Combined feature extraction using wavelet packet transform, quick ensemble empirical mode decomposition, local mean decomposition, phase space reconstruction, and common spatial pattern.	Limited effectiveness of CSP for extracting EEG features from fewer channels	The study only evaluated the proposed method on two datasets.	Developing more robust and efficient feature extraction methods for EEG signals with fewer channels.
[41]	Wang et al. (2020)	Combination of conditional empirical mode decomposition (CEMD) with one-dimensional multi-scale convolutional neural network (1DMSCNN) for MI EEG signal categorization.	Limited effectiveness of existing methods for EEG signals classification, especially for online recognition	The study only evaluated the proposed method on two datasets.	Developing more robust and efficient methods for EEG signals classification, especially for online recognition.
[42]	Wang et al. (2019)	CSP-R-MF multi frequency band EEG channel option.	Traditional channel selection approaches cannot extract useful EEG characteristics.	The study only evaluated the proposed method on two datasets.	Developing more robust and efficient channel selection methods for

			from different frequency bands		multi frequency band EEG.
[43]	Roy et al. (2022)	ORICA-CSP with A-SVM classifier feature extraction method.	Existing CSP-based methods are sensitive to artifacts and non-stationary uncertainty, and absence frequency domain data and need several input channels.	The study only evaluated the proposed method on one dataset.	Developing more robust and efficient feature extraction methods for EEG-based online and real-time BCIs.
[44]	Bhandari & Tomar et al .(2020)	Feature extraction flexible analytic wavelet transform (FAWT) and ensemble learning-based classification KNN subspace classifier	Existing methods Motor imagery (MI) classification using EEG data is inaccurate and unreliable.	The study only evaluated the proposed method on a binary classification task (right hand vs. right foot MI).	Developing more resilient and efficient multi-class MI feature extraction and classification methods.
[45]	Sharma et al.2021	UIHBCI model for motor execution (ME) classification using Deep Belief Network (DBN).	Limited accuracy and robustness of existing BCI systems for ME classification	The study only evaluated the proposed method on a small dataset of 9 subjects.	Developing more robust and efficient BCI systems for ME classification, especially for user-independent applications.
[46]	Huang et al. (2021)	Multi-layer temporal pyramid pooling helps classify motor imagery EEG.	Limited ability of existing deep learning to capture key EEG signal features	The study only evaluated the suggested approach for one dataset.	Creating more reliable and efficient deep learning approaches for EEG categorization, especially motor imagery Classifying EEG.
[47]	Alzahab et al.(2021)	Review on hybrid deep learning (hDL)-based brain-computer interfaces (BCIs)	Limited understanding of the trends and challenges in hDL-based BCI research	The study is limited to a review of papers published between 2015 and 2020.	Developing more comprehensive and up-to-date reviews of hDL-based BCI research.
		Deep transfer CNN framework based on VGG-16	Deep learning for MI EEG signals classification face	The study only evaluated the proposed method	Developing more robust and efficient deep

[48]	Lu et al.(2019)	for EEG signal classification.	two challenges: (1) the need for a large amount of labelled data, and (2) the high time and computational cost of training from scratch.	on a single dataset.	learning methods for MI EEG signal classification, especially methods that can be trained on limited amounts of unlabelled data.
[49]	Tan et al.(2021)	Critical review of recent achievements in deep learning for computer vision (CV)	Limited understanding of the latest emerging techniques and applications of deep learning in CV	The study is focused on CV and does not cover other speech recognition and natural language processing are deep learning domains..	Developing more comprehensive and up-to-date reviews of deep learning research.
[50]	Zhang et al. (2022)	Multilayer residual convolutional neural network (CNN) with gradient-class activation mapping (Grad-CAM) for brain-computer interface (BCI) classification	Existing BCI models are often trained and tested on a single subject, which limits their generalization to unknown participants.	The study only evaluated the proposed method on a single dataset.	Developing more robust and generalizable BCI models, especially models that can be trained on limited amounts of data from multiple subjects.
[51]	Kumar et al. (2022)	MI-BCI classification using modified Binary grey wolf optimization (MBGWO) feature selection	Existing MI-BCI classification feature selection approaches are computationally expensive and may not remove duplicated and irrelevant information.	The study only evaluated the proposed method on two subjects and a single dataset.	Developing more robust and efficient feature selection methods for MI-BCI classification, especially methods that can be used with limited amounts of data.
[52]	Singh et al. (2023)	Pearson correlation coefficient (PCC)-based channel selection and wavelet packet decomposition	Existing channel selection and feature extraction methods for MI classification are often not robust to non-stationary EEG data.	The study only evaluated the proposed method on a single dataset and two classification algorithms.	Developing more robust and generalizable channel selection and feature extraction methods for MI

		(WPD) for BCI motor imagery (MI) classification.			classification, especially methods that can be used with limited amounts of data and that are robust to non-stationary EEG data.
[53]	Wang et al. (2022)	Multi-domain feature extraction, iterative EEG source localization for channel selection, and particle swarm optimization-based SVM for lower limb motor imagery (MI) classification.	Lower-limb MI is harder and less studied than upper-limb MI. Not all channel selection and feature extraction strategies for MI classification work for lower limb MI..	The study only tested the approach with one dataset and classification algorithm (SVM).).	Developing more robust and generalizable channel selection and feature extraction methods for lower limb MI classification, especially methods that can be used with limited amounts of data.
[54]	Patil et al. (2021)	Frequency centric statistical discrete wavelet transform (SDWT) based features with harmony search algorithm for motor imagery (MI) classification	Existing feature selection methods for MI classification are often not able to effectively select the most informative features.	The study only tested the proposed strategy using a single dataset and classification algorithm (weighted KNN).	Developing more robust and generalizable feature selection methods for MI classification, especially methods that can be used with limited amounts of data.
[55]	Yu et al. (2021)	TSGL-EEGNet: A deep learning model for motor imagery classification with improved interpretability	Existing deep learning models for MI classification are hard to interpret, making it hard to comprehend why they forecast.	The study only evaluated the proposed method on two datasets and one classification algorithm (SVM)).	Developing more interpretable deep learning models for MI classification.

3. Background Information

In this portion of the survey, we provide a summary of the MI EEG-Based BCIs. We provide a rundown of what we know about BCIs, EEG signals, wearable technology, and MI.

EEG Signal Collection:

Electroencephalography (also known as EEG) has been around for more than a century. In 1929, German physician Hans Berger was the first person to record electrical brain activity using something called an electroencephalogram (EEG) [56]. A key component of BCI systems is brain oscillation measurement. EEG-BCI systems record brain activity during tasks. Many invasive and non-invasive brain signal acquisition methods have been studied [57]. Invasive approaches require neurosurgery to implant electrodes in or on the brain. In contrast, non-invasive brain activity monitoring uses external sensors [58].

Here, we'll discuss non-invasive EEG technology. Electroencephalography uses sensors or electrodes in a cap to record brain EEG [59]. This brain signal recording technology has advantages over others, making it commercially viable. It is portable, user-friendly, and affordable. EEG recordings also provide high temporal resolution [60]. EEG has lesser spatial resolution and SNR than other methods. EEG spatial resolution and SNR enhancement solutions have been proposed to address these constraints. Some studies recommend 256 electrodes [61]. The publically available 10-20 international electrode positioning scheme is extensively used [62]. Figure 2 shows the space between sensors, usually 10% or 20% of skull diameter [63,64]. set to 10% or 20% of the diameter of the skull [63,64].

EEG frequency bands

Different frequency bands/rhythms of the EEG signal are responsive to neocortical behaviour.

Delta: EEG's slowest variable frequency component is 0.5-4Hz. In new-borns under one-year-old, it dominates. Drowsiness and deep sleep used to have slower, synchronized frequencies in healthy adults.

Theta: Slow-wave theta rhythm (4-8Hz) is normal in children. It manifests in children and adults during drowsiness and spikes when trying to suppress a response or activity, as witnessed during meditation.

***Alpha*:** 8-16Hz is the alpha or mu rhythm. It increases with eyes closed, relaxation, and mental activity (alertness).

Beta: Active mental states are associated with the beta rhythm (13-30Hz). Healthy adults' alert, awake, conscious rhythm helps cognitive processing. The high-frequency EEG gamma rhythm (30-60 Hz) enhances attention, learning, perception, and working memory. EEG signals are excited by motor activities, memory tasks, and sensory stimuli.

Applications of electroencephalography (EEG):

Electroencephalography (EEG) has a variety of applications. Electroencephalography, sometimes known as EEG, is a technology that does not require any kind of invasive procedure, is relatively inexpensive, and can be carried around easily. It is relevant in a wide range of settings, including therapeutic, scientific, and business settings, among others.

Table -2. EEG signals vary per band [65].

Name of the Band	Frequency in Hz	Original Source	Cognitive Function
Delta (δ)	0.5 to 4	Brain centre, parietals	Linking sleep with developmental stages
Theta (θ)	4 to 8	The frontal, spatially, and parietal lobes	Identification of feelings, utmost concentration, and a strong sense of scent
Alpha (α)	8 to13	The cortex responsible for visual perception	Detecting eye-closed relaxation and drowsiness
Beta (β)	13 to 30	To the motor lobe	The use of muscles
Gamma (γ)	30 to 100	Somatosensory cortex (cortex)	Learning, concentration, recollection, and the capacity for visual perception

Clinical applications

Diagnosis of brain disorders: EEG can be used to diagnosis brain illnesses include Alzheimer's, autism, brain tumors, depression, epilepsy, Parkinson's, sleep difficulties, and mental disorders.

Monitoring brain function: EEG can be used to monitor brain function during surgery, anaesthesia, and other medical procedures.

Neuro feedback: EEG can be used for neuro feedback therapy, which involves training individuals to control their brain activity to improve cognitive function and reduce symptoms of various disorders.

Research applications:

Cognitive neuroscience: EEG studies attention, memory, learning, decision-making, and emotion.

Brain-computer interfaces (BCIs): EEG may be used to create brain-computer interfaces (BCIs) that let people control external equipment with their brain signals. BCIs can help disabled persons live better.

Commercial applications:

- ***Neuro marketing:*** EEG is used to study consumer behavior and preferences.
- ***Gaming:*** EEG is used to develop video games that are controlled by brain signals.
- **Education:** EEG is used to develop educational tools that adapt

Motor cells:

Motor cells are the foundation of the brain's signal generating and transmission systems. Motor neurons are CNS neurons that control downstream targets. Two types of motor neurons:

Upper Motor Neurons (UMN):

- UMN are located in the cerebral cortex, which is the outermost layer of the brain.
- They play a crucial role in the initiation and planning of voluntary muscle movements.
- UMN send signals to lower motor neurons to execute specific motor tasks.

Lower Motor Neurons (LMN):

- LMN are located in the spinal cord and the peripheral nervous system.
- They receive signals from upper motor neurons and are responsible for directly controlling muscle movements.
- LMN transmit the commands for muscle contraction and movement, leading to the execution of specific motor activities.

Motor neurons are notably the longest type of cells in the human body and are essential for the communication of movement commands from the brain to the muscles, allowing us to perform a wide range of physical actions.

3.1 A Summary of the MI EEG-Based BCIs

First, describe the manner in which a standard signal-processing channel for MI-EEG data is normally configured. Second, look into the challenges that inevitably occur when employing MI EEG data, as well as the MI explanation. Third, BCIs make use of EEG data. It also discusses some of the most significant technological challenges that researchers encounter, such as dealing with a vast volume of multidimensional EEG data, determining whether to use averaged or single-trial results, and deciding on a pre-processing technique. MI is often employed in BCI systems due to its inherent discriminating features and low signal gathering costs. Furthermore, information acquired from MIs can enhance therapy for stroke recovery [66]..

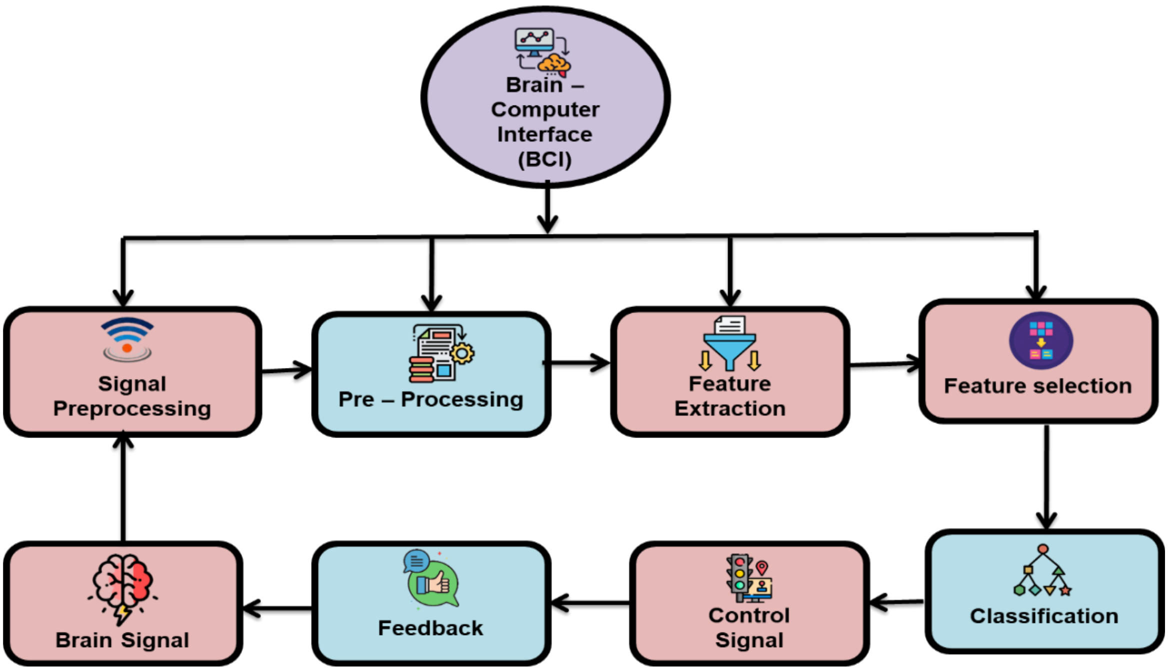

Fig 1: A schematic showing the many methods for feature selection, extracting features, and classifying data utilized in MI EEG-based BCIs

However, because EEG signals are unstable, several treatment and classification approaches struggle with precise categorization when applied to MI data, making analysis of MI data problematic. Furthermore, despite the fact that data from time series enhances categorization precision, many categories ignore it. The development of BCIs for post-stroke rehabilitation or therapy is hindered further by the fact that brain injury patients' MI signals differ significantly from healthy controls. A combination of sensitive instruments and the availability of items for the general public help to identify improvements in EEG equipment promptly. This data is a fantastic starting point for evaluating various wearable devices. A study of the neurophysiological auto mechanics underlying EEG signal generation, followed by a focus on the cutting-edge hardware and software utilised in EEG-based BCIs. This distinct approach is divided into four sections: pre-processing, feature selection, feature extraction, classification, and classification accuracy. Figure 1 depicts the feature extraction algorithms that performed the best across all classes

Table -3. Recent work on EEG-BCI systems.

Reference	Research objective	Feature extraction methods	Method of classification	Accuracy
[67]	Right-left hand	DWT and EMD	SVM	95.10%
[68]	Right – left hand and foot	CSP	SVM	76.34%
[69]	Right – left hand and foot	CSP SVM 96.02%	SVM	96.02%
[70]	Tongue, right-left hands and feet DWT CNN 96.21%	DWT	CNN	96.21%
[71]	To develop a BCI module for opening, closing, pronation, and supination of the right hand using EEG signals	Pearson correlation and wavelet packet decomposition	Support vector machine (SVM)	91.66% for opening-closing, 90.33% for pronation, and 89.75% for supination
[72]	To develop a BCI module for lower limb MI classification	Iterative EEG source localization and multi-domain feature extraction	Particle swarm optimization based SVM (PSO-SVM)	88.43% for lower limb MI classification (including opening-closing, pronation, and supination)

3.1.1 Signal processing

The applications of EEG-based brain-controlled emerging computational intelligence mobility equipment are discussed, and this examination emphasizes the harmless technologies around which such uses depend. There is a wide range of EEG data-collecting equipment in terms of price, channel count, rate of sampling, technique for joining electrodes, and time needed to get the headphones ready [73]. The results of this investigation indicate that invasive or non-invasive signal gathering techniques, which are the most often used EEG equipment in MI-based brain-controlled intelligence applications, can be applied to BCI. For example, invasive methods such as electrocardiograms and single-neuron observations provide better signal quality than non-invasive methods. An example of a non-invasive method is EEG. Before being used by a computer programme, signals are processed and amplified to boost their power.

Table 4. Performance of Pre-processing signals

S. No.	Technique	Characteristics
1	Common average reference (CAR) [74]	Increases signal-to-noise ratio (SNR), suitable for recordings with significant background noise.
2	Independent component analysis (ICA) [75]	Computationally efficient, delivers good performance, especially for large datasets; may not be suitable for

		certain issues, requires additional computational effort for decomposition.
3	Surface Laplacians (SL) [76]	Robust against artifacts and noise, sensitive to spline patterns and artifacts, can produce noise in areas not covered by sensors or electrodes.
4	Principal component analysis (PCA) [77]	Reduces dimensionality and often performs better than ICA.
5	Common Spatial Pattern (CSP) [78]	Yields superior results for EEG-Motor Imagery (MI) data but requires a larger number of electrodes (typically >64).
6	Adaptive Filter [79]	Achieves optimal performance with inputs having overlapping spectra, and necessitates one or two reference signals.
7	Digital Filter [80]	Effectively eliminates noise, but requires knowledge of multiple frequencies.

3.1.2 Pre-processing

Several approaches have been proposed in the literature to reduce the impact of background noise on EEG readings. Band pass filters are the most common type of filter [81]. To gather the signal at the desired frequency, additional study and experimentation are needed to determine the best and optimum filter settings.

3.1.3 Feature Extraction

The conventional specialized pattern, which operates in the technical signals domain, is the most used technique to extract characteristics from brain signals [82]. The process of feature extraction, in which raw data is transformed into a simplified, understandable representation of fundamental qualities or features, is a critical step in data analysis and pattern identification.

Table 5. performance of the Feature Extraction o EEG-Bci

Approaches	Advantages	Drawbacks	Domain
Autoregressive Model (AR) [83]	Good spectral estimations, superior frequency resolution for short segments.	Model validity depends on AR coefficient selection, slow, not suitable for real-time analysis.	Time
Fast Fourier Transform (FFT) [84]	Effective for stationary signal analysis, suitable for narrowband signals like sine waves.	Inadequate for nonstationary EEG signals, high noise sensitivity.	Frequency
Common Spatial Pattern (CSP) [85]	Suitable for multichannel data, provides good results for chaotic signals.	Requires many electrodes for optimal results, assumption of Gaussian distribution may not always hold for EEG data.	Spatial
Short-time Fourier Transform (STFT) [86]	Provides frequency information at each time point.	Less effective for non-stationary signals due to fixed temporal resolution.	Time and frequency
Wavelet Transform (WT) [87]	Well-suited for analysing transient and abrupt signal changes (non-stationary).	Selection of appropriate mother wavelet is crucial.	Time and frequency
Empirical mode decomposition (EMD) [88]	Suitable for nonstationary and nonlinear signal processing.	Prone to mode mixing and sensitivity to noise.	Time and frequency

3.1.4 Feature Selection

The goal of feature selection in certain BCIs is to decrease computation time and increase accuracy by selecting the most discriminant characteristics from a given feature set to be supplied to the classifier. Selecting relevant elements that directly affect brain signal classification is a crucial use of feature selection [89]. However, the feature selection approach was only used in some investigations. Future research will inevitably need to address this issue to find the most effective approach to feature selection suitable for signal processing for multi and dual-class MI tasks.

3.1.5 Classification

The goal is to deploy a generic classification in the MI-based BCI that utilizes the effective VR system. However, investigators may use regressive and ensemble categorization techniques in the future [90]. For a BCI to be practical, the consumer's brain activity patterns must be recognized, characteristics extracted, and classified with as much precision as possible. This categorization phase translates the user's intent into signals that may control an output device. Methods of classification found in the research such as Power Spectral Density (PSD), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Light Gradient Boosting Machine (LGBM)and One-Versus-The-Rest Filter-Bank Typical Spatial Pattern (OVR-FBCSP), Figure 2 demonstrated the accuracy of various classifiers in making classifications.

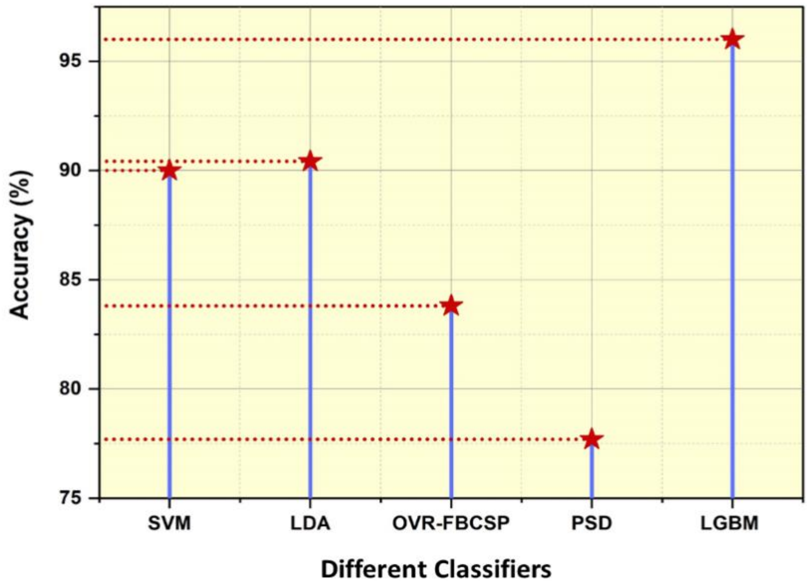

Figure 2: Classification accuracy using several classifiers

3.1.6 Frequency

First of all, this band is crucial since it contains the alpha and beta bands, two essential parts of the MI signal. According to the intricacy of brain signals, Individual differences in α and β band frequency have been demonstrated. Hence, further research is needed to determine the best frequency range. The present a novel kind of feedback that integrates the frequency, time, and several channels of data. Short-time Fourier transform (STFT) methods, EEG time series are transformed towards a two-dimensional imagery. From each MI EEG documenting, we retrieved 2-second EEG signals [91]. The electrical brain waves were captured at a rate of 250 Hz, which means that for every 2 s of data, there are 500 samples. The time series was then subjected to the STFFT.

3.1.7 Evaluation of Classification

In the MI-based BCI for the EEG design, classification accuracies were maintained between 50% and 100%. Since this classification accuracy is concerned with human safety when used in the actual world, it still has limits. Consequently, additional resources should be allocated to this study area to deploy a powerful MI-based BCI

system in augmented and EEG, Virtual Reality (VR), and the natural world for control and rehabilitation.

3.1.8 BCI Feedback

In order to give a preliminary evaluation of the examined publications, a summary of the potential functions and output varieties that exist for advanced MI-BCI tools based on EEG data is specified the sections that follow. In addition, it appears that MI is frequently employed to control external devices, notably recuperation. As a result, the motions of wheelchairs, robots, drones, exoskeletons, and prostheses are commonly used as feedback. Visual input on a screen or through VR devices is one possibility. In addition, users' MI abilities may be modulated through feedback [92]. For instance, focus on developing a BCI system that improves usability and training effectiveness by including discontinuous and ongoing input.

The findings demonstrate that constant feedback effectively enhances imaging capability and reduces controlling duration. Table 6 summarizes the various approaches taken in the literature; further explanation is provided.

Table 6: Recognizing Patterns

Reference	Pre-processing	Feature Extraction	Feature Selection	Frequency	Classification	Evaluation
[93]	Band pass filters	Discrete Wavelet Transform (DWT)	principal component analysis (PCA)	7–30 Hz	SVM	90%
[94]	Butterworth band pass filter	Common Spatial Pattern (CSP)	Particle Swarm Optimization (PSO)		LDA	90.42%
[95]	Band pass filter	Phase Locking Value (PLV)	multi-kernel relevant vector machine (MK-RVM)	0.5–100 Hz	OVR-FBCSP	83.81%
[96]	Butterworth band pass-filters	Common Spatial Patterns (CSP)	Frequency-domain features (FDF)	250 Hz	PSD	77.7%
[97]	Notch Filtering (NF)	Directed Transfer Function (DTF)	Decision Tree (DT)	160 Hz	LGBM	96%

3.2. Number of Channels Used in EEG

Several channels used for EEG-employed research shows discussed cover a comprehensive variety. 163 EEG channels to differentiate between elbow and shoulder torque intentions using EEG. Overall, only 5% of research employed over a hundred EEG channels, suggesting this amount of EEG channel density is rather infrequent. Sixty-four percent of these investigations use between one and twenty EEG channels, with one-tenth of those using between eleven and twenty. Eleven investigations have been completed with 61-70 EEG channels.

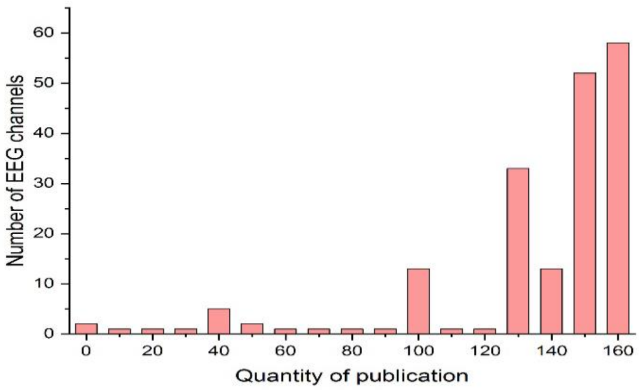

Fig 3: Quantity of publications EEG channels

This means there have been a significant amount of research investigations that employ 21-40 EEG channels. The number of electrodes used to acquire EEG data can range from 1 to 256, with the middle 50% of research employing 9 to 61 electrodes [98]. Conventional wisdom using increasing the number of channels is not feasible for research outcomes, and instead, what matters most is pinpointing the precise placement of a smaller number of electrodes. According to that paper, expanding the total amount of EEG channels beyond 22 does not provide a similar benefit, even though there is a large improvement in sensitivity and specificity while raising the number of sensors. Table 7 and Figure 3 summarize the research addressing the total number of EEG channels.

Table 7 Channels in the EEG based on the number of publications

Quantity of publication	Number of EEG channels
0	2
10	1
20	1
30	1
40	5
50	2
60	1
70	1
80	1
90	1
100	13
110	1
120	1
130	33
140	13
150	52
160	58

3.3 Motor Imagery (MI)

MI refers to a mental rehearsal of a physical motion. In MI, an individual appears to utilize motor representation, the subconscious process of actively planning and imagining motion; imagination may also be done from the first or third person. There should be an internal sense that the individual is carrying out the projected action and an exterior sense that they are observing personally act for the initial instance. In addition, multiple studies have discovered that the brain's motor system is activated in the same regions, whether one is making the movement in question or simply visualizing the organization [99]. Due to individual variation, however, MI is a skill that must be evaluated before it can be used in research or learned. In particular, in the realm of MI-based BCIs, appropriate BCI management is generally attained when the patient can accomplish at least 70% of the needed tasks effectively, which might take considerable time.

3.3.1Architecture of MI

The primary parts are the EEG, Filtration and Normalization, Feature Extraction, and Classification Unit. The suggested architecture for MI categorization is depicted in Figure4.

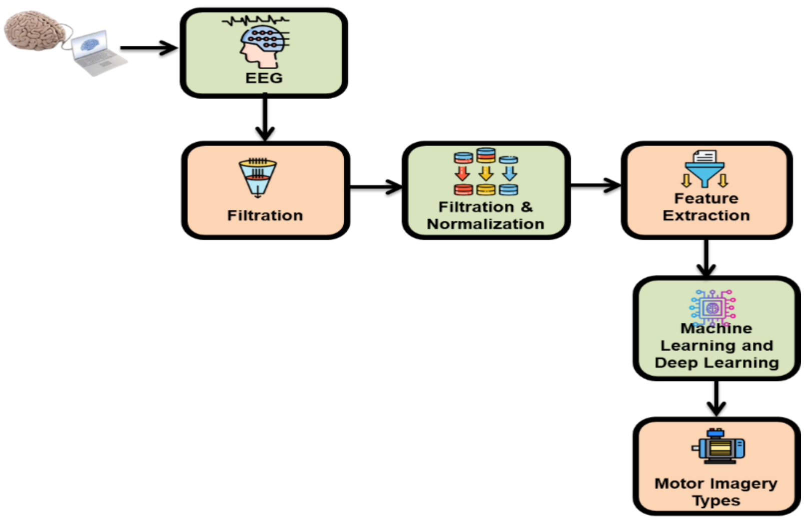

Fig 4: MI categorization

3.3.1.1Filtration and Normalization Unit

This section removes Noise and artifacts from the EEG data using filtering and normalizing.

- ***Normalization:*** The normalization procedure unit receives the filtrated information from the filtering device and adjusts its frequency and amplitude. The filtering input signal's magnitude and frequency are normalized in this device using an s-transformation approach. This normalizing method lessens the impact of noise in the background on the EEG signal.

- ***Filtration:*** The raw EEG data is separated into alpha and beta frequency bands employing filtering. Due to an insufficient signal-to-noise ratio, removing noise from the transmitted signal is challenging. The EEG data from the left and right channels are normalized. The goal is to conjure up mental images of yourself moving your left and right hands and feet [36]. In this section using Butterworth band pass filter and using 118 EEG channels for further alterative functions.
- ***Feature extraction:*** The bi-spectrum may be retrieved with the use of this device. Several hybrid features, SLA and FOSM, are retrieved using the bi-spectrum for both channels and bands of frequencies [100]. Since they constitute a vector with eight dimensions. A categorization component accepts this vector of information and processes it higher.
- ***Classification:*** Hybrid characteristics are used in the process of classification for EEG data. The input signals may be partitioned into four categories using a machine-learning classification. A grid-based search is performed to determine the significance of the regularity variable and the kernel parameter γ. Grid searching yields a set of c and γ having an optimal identification rate from a series of c and γ that expand rapidly. The smallest γ and associated value from the set of outcomes are selected to prevent the classification algorithm from being overfitting. Different type of classifier using in machine learning and deep learning technique [101]. Table 8 and Figure 5 shows the Accuracy of long short-term memory (LSTM), SVM, k nearest neighbors (KNN), Dynamically Weighted Ensemble Classification (DWEC), and Multi-Channel Deep Belief Network (MCDBN) in subject classification.

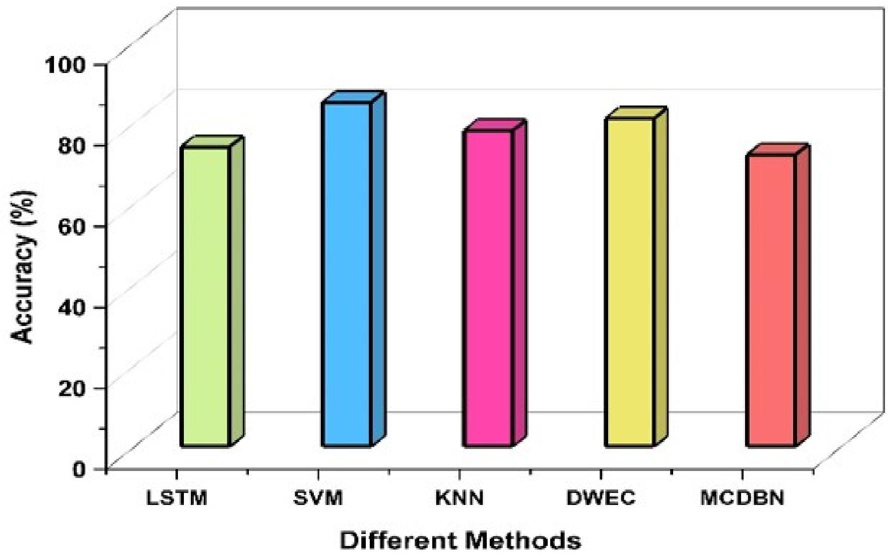

Fig 5: Accuracy for Machine Learning and Deep Learning Methods based on MI

Table 8: Different Methods in MI

Different Methods	Accuracy (%)
LSTM [102]	74
SVM [102]	85
KNN [102]	78
DWEC [102]	81
MCDBN [102]	72

4. Statistical Analysis

These digital assets have been selected for their capacity to accommodate interdisciplinary research by housing several papers that may be used to address questions from a research perspective, electronic devices, and various medical contrasting perspectives. These documents conducted a Boolean analysis employing subject-specific keywords BCI, EEG, and MI. Publications returned by other search engines and papers previously maintained in the confidential archives of the various research organizations were also reviewed in Google Scholar to glean additional details. The concluding batch of evaluated papers will include the latest interaction for accuracy. Table 9 shows the data gathered about MI-BCI and EEG machines. Figure 6 shows the number of channels used in EEG in various methods.

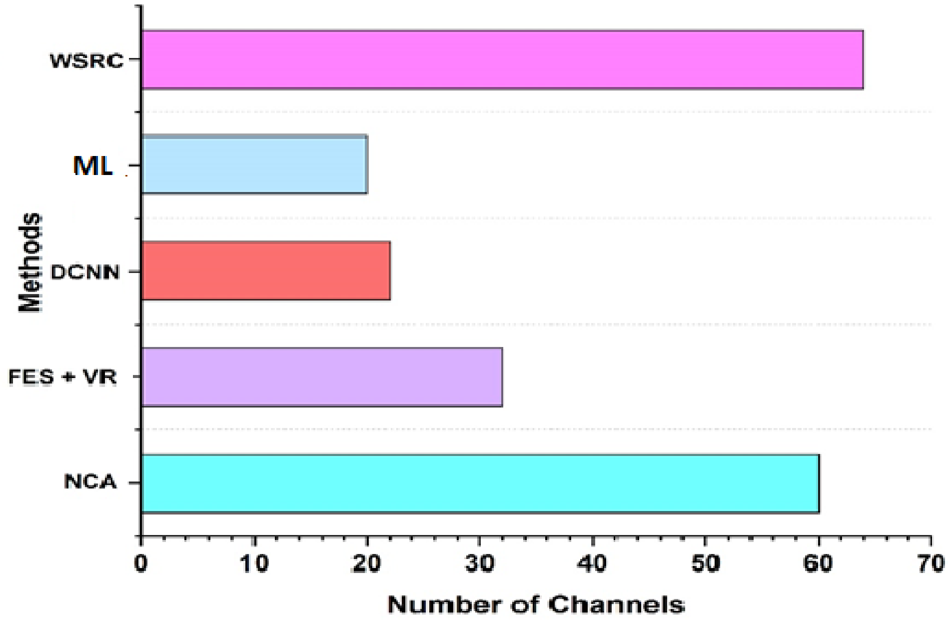

Fig 6: Number of Channels and different Methods

Table 9

Current Technology for Amount of channels in an EEG and data gathering, limitations, result for MI- BCI, EEG

Reference	Methods	Dataset	Drawbacks	Outcomes of the Study	Number of channels used in EEG device
[103]	Methodology for Guided Study Utilizing Neighbouring Component Analysis (NCA)	Band pass filtering at frequencies ranging from one to 50 Hz and a filter with a notch were added to the database to ensure electrical line distortion would be suppressed.	Due to the specificity of brain actions, choosing a collection of broad frequency ranges for various individuals leads to a low classification rate.	The suggested method's classification accuracy and kappa coefficient were higher than conventional approaches. The findings imply that the suggested approach may be used to develop an MI BCI device with improved performance.	60 channels
	The research proposes an improved MI-BCI that utilizes	EEG data are processed using the sliding window approach to raise the number used for training specimens and enhance classification effectiveness. EEG signals initially appeared in a frame with a duration of	Despite FES and VR technologies demonstrating progress in improving neurological rehabilitation and customer service, the combination of MI-BCIs is still being maximized. The study focuses	The outcomes of the study demonstrated that using the FES+VR framework substantially enhanced classification effectiveness. Additionally, the motor brain was more intensely activated employing the FES+VR framework compared to the situation employing the VR	32 channels

[104]	Functional Electrical Stimulation (FES) and VR.	512 sampling indications, followed by moving down the duration plane at an interval of 256 sampling points.	on strategies effectively combining FES and VR into the MI-BCI architecture.	model, particularly on channels C3 and Cz.	
[105]	Deep convolution neural networks (DCNN) entirety relationship section, they added an adaptation component.	The Seong-Whan Lee group from South Korea provided the Giga DB database, encompassing three experimental methods: time-related potential, MI, and steady-state visual evoked potential. The Ministry of Health's information collection included 54 people in good health.	The major issue of EEG data is nonstationary, which is extremely simple to be influenced by the person's emotional condition and the surrounding environment.	The investigation above showed that the suggested approach performed better regarding categorization across sessions in the MI system.	22 channels
[106]	Machine Learning and Deep Learning	To maximize a specific positive reinforcement operation, it has been suggested that the framework directly gathers data from the environment.	The restriction may lead to decreased specific geographical data, making it harder to identify precise locations for brain activity.	To solve complex challenges in engineering and medicine, researchers have turned to machine learning (ML) and deep learning (DL) techniques, which open the door to a wide variety of bioinspired programming tactics.	20 channels
[107]	Weighted Sparse Representation -Based Classification (WSRC)	Data from five healthy volunteers who performed right-hand and right-foot MI tasks throughout each trial was recorded using EEG.	It demonstrates that the SRC technique, which depends solely on linear information, cannot classify data that lacks localization.	Compared to the SRC method, the WSRC method provides higher-quality results in accuracy and time. Therefore, it doesn't matter how many training signals they provide WSRC; it performs successfully with all subjects.	64 channels

4.1 Brain-Computer Interfaces (BCI) and Motor Imagery (MI)

The collection and examination of physiological data in various sectors has benefited greatly from the rapid advancements in brain technology in recent years. In medicine, specifically, they enabled progress in diagnosing and treating neurological illnesses. BCIs emerged from this context and have developed into online mental-machine communication technologies that enable control of equipment or activities through monitoring and analysis of brain activity [108]. The information collection modules process the BCI technique's inputs, including amplifying and digitizing physiological signals. This information is then sent into an information processing module, transforming the signal into instructions for an external system. It has been shown that visual, auditory, and sensory inputs may alter brain surges; this phenomenon is known as the stimulation from outside experiments. The Event-Related and Steady-State vision-motivated perspectives are two paradigms that fit this description. Certain elements in ERPs can be used to determine the waveform's form. The P300 is an element of the event-related potential (ERP) that correlates with an elevated signal deviation and results in a peak beginning at 300 milliseconds when an original stimulus is presented. From neuro rehabilitation and avoiding illnesses to the precise detection of diseases and diagnostics, medical applications are the original inspiration for EEG-based BCI devices [109]. For instance, they are used to detect and avoid epileptic seizures, and methods are being created to improve the efficiency in their recognition and forecasting and the location of the centre of seizures. In neuro rehabilitation, BCI devices aid individuals with motor limitations, such as those left behind by a stroke. In particular, MI-BCI tactics, including operational electrical excitement, mechanical support, and hybrid virtually reality-based simulations, demonstrate promise as practical tools for following a stroke rehabilitation therapy. Tumors, seizure disorders, sleep problems, dyslexia, and brain inflammation due to conditions like influenza can all be detected using a BCI [110]. BCIs have numerous more potential uses outside medicine and neurological recovery. For instance, EEG data is used in the advertising industry to measure the impact of commercials on viewers' attention and accuracy. Additional information about the amount that individuals remember and how their learning might be tailored to their needs has emerged from studies of cognitive processes in the learning environment. Instead of relying solely on rote memory, this approach may help pupils strengthen their abilities in practical applications. Qualifications like adaptable consideration, decision-making, innovation mentality, multidisciplinary methods, and computational competencies might also flourish in the classroom.

4.1.1 Non-Biomedical Areas

BCIs may be most known for their use in the medical field, but they are increasingly showing up in other sectors besides healthcare. BCIs are being used to improve non-biomedical areas of interaction between humans and machines and solve problems in other sectors. Figure 7 shows the BCIs have benefited several fields.

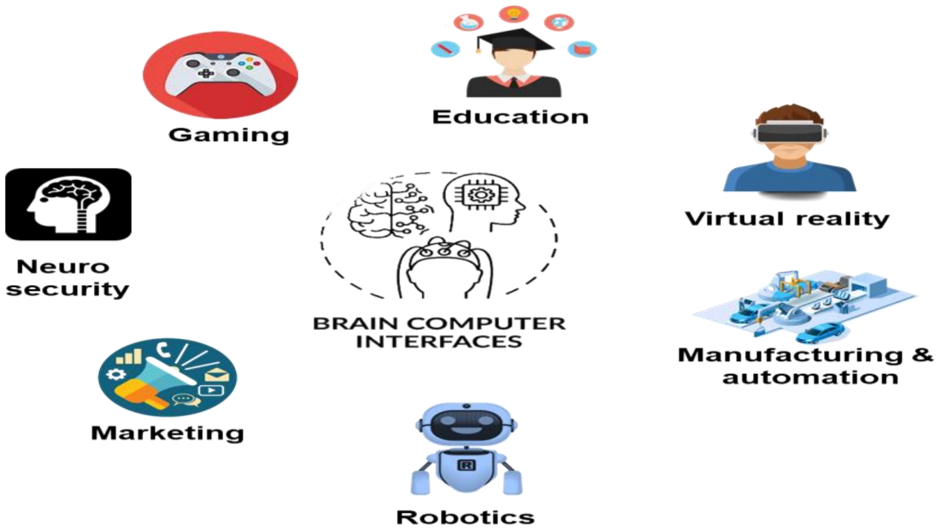

Fig 7: BCI supports multiple study areas

- **Gaming**

Brain-computer interfaces are utilized to make games more realistic. The ability to direct in-game actions with mental imagery or brain signals opens up exciting new possibilities for interactive play. The BCI and video games focused solely on BCI, with no other forms of interaction being investigated. It's easy to see how individuals might be nervous about such solutions, given their effectiveness is very sensitive to factors like ambient noise and the activity level of the system's end users. The BCI system's ability to meet user demands and create an effortless connection is a major problem [111]. While some BCI interface models might be draining and time-consuming for individuals, games depend heavily on player participation, controlling simplicity, and stimulating and difficult gameplay features. It has consequences for BCI study participant recruitment and making BCI use more pleasant. Not only do games span a wide variety of categories, but they also feature a staggering array of play techniques.

- **Education**

BCI are investigated for their potential to customize course materials to each student's unique skills, interests, and motivations. Creating unique educational opportunities has been shown to boost memory and understanding [112]. By giving immediate feedback on a learner's pattern of speech and interaction, BCIs can help students of a foreign language refine their pronunciation and language. BCI can aid in the development of individualized study plans. The system may adapt the activities, resources, and difficulties it presents to each user to best suit their current level of knowledge and skill acquisition.

- **Brain-Driven Robotics**

Applications for BCI-enabled robotic systems include disaster response, search and rescue, and exploration of hazardous environments. Robots can be controlled in real-time by humans through brain impulses [113]. Using BCIs can improve the efficiency and security of building and tearing down structures. Humans may operate demolition robots and construction machines to do complex tasks in confined areas.

- **Neuro security**

BCIs can be used in safe monitoring and systems for authentication. Unidentified individuals would find it extremely hard to access restricted places or information if users were verified based on their distinctive neurological patterns. Incorporating BCIs into cryptographic systems paves the way for key generation and decoding based on brain processes [114]. This strengthens encryption by a significant amount. The importance of preserving BCI and brain information may be spread by creating programs for instruction and efforts to educate.

- **Marketing**

The term BCI can be used interchangeably with BCI industry" to describe the current state of this industry.

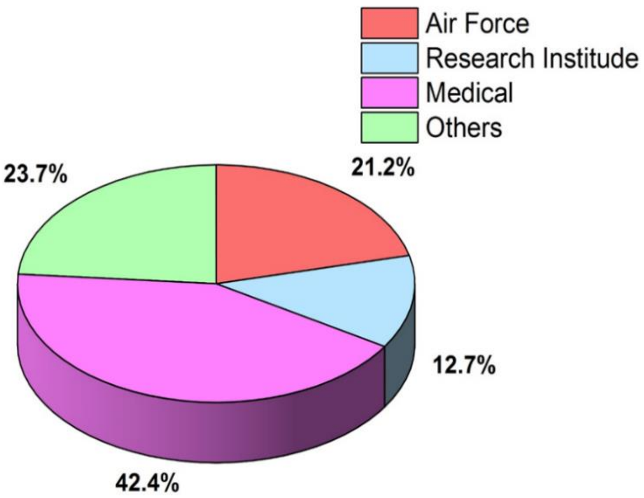

Fig 8. Marketing strength for BCI

Connecting the brain to external technology such a robot the area or a computer is the purpose of the BCI is all concerning. BCI, using the most cutting-edge commercially available technology, allow researchers to collect and analyses neural signals from linked external equipment, shedding light on a wide range of problems with development. In the field of medicine, for instance, the use of the BCI, such as EEG, has grown and allowed for operation of devices via the brain. This is made possible by the merging of hardware as well as software advancements, which contributed to better features and enhanced communication between humans and machines [115]. It helps people with neurodegenerative disorders overcome speech and movement difficulties and interact with others more effectively. Due to the rising prevalence of chronic conditions like brain disorders, the worldwide market for BCI is expected to expand at a faster rate in the medical sector than in any other consumer industry in Figure 8 and Table 10. The efficiency of the established therapy contributes to the expansion of the industry for BCI. BCIs can be used to enhance therapies by providing further insight into the functioning of the brain.

Table 10 Marketing Sector in many Consumer

Marketing Fields	Value (%)
Air Force	21.2
Research Institute	12.7
Others	23.7
Medical	42.4

- **Manufacturing and Automation**

Employees' mental health on the factory floor may be tracked with BCIs. An alarm can be given to the worker, or the operation can be temporarily halted if the system detects exhaustion or preoccupation. In dangerous settings, such as building sites or disaster recovery zones, BCIs provide remote control of robots and machines [116]. BCIs can be used to develop lifelike simulated environments for emergency response education in sectors where physical harm is possible. Numerous artificial auxiliary systems and assistive gadgets have been developed with relevant industrial processes to enhance people's daily lives in various contexts.

- **Virtual Reality**

Artists utilize VR to create fully realized worlds and experiences that users may explore using head-mounted displays. To further assess the contribution of brain dynamics to the driving task, we implemented an event-related lane-departure controlling experiment in VR. Participants in the VR driving paradigm were instructed to remain inside the constructed environment and to keep the imaginary transport in the middle of the designated driving zone at all times [117]. The simulated transportation would deviate from the channel's centreline due to random lane disturbance occurrences.

4.1.2 BCI Transfer Location

BCIs have the potential to facilitate the inter-domain transmission of both discriminatory and unchanging pieces of information. The amount of overlap among both domains serves as a criterion for deciding what pieces of data should be exchanged. If each domain is exceptionally comparable and the data set is limited, discriminatory data needs to be transferred; positioned details are required to create greater stability processes when the data set has minimal frequent encounters between the origin and destination categories. Covariate shifting is closely associated with adaptation to domains, the most common challenge BCIs face. The conceptual objectives and operational duties may be distinct yet interconnected in the BCI realm, where EEG data are gathered to examine participants. Using mental subtracting or MI to evaluate an electronic movement is an example of an emotional assignment [118]. In contrast, the equipment movement, or the outcome of the equipment action coming from ERPs, is an example of an operative function. The mentioned instances of transferable learning in BCIs are exceptions; in a perfect world, a BCI system shouldn't require a specific EEG headset for measurement, allowing the user to freely replace or update their headset as needed. This should pave the way for more BCIs to be used in practical settings. It's a tall order to accomplish this objective, though. Earlier information from identical consumers can be used to save time during the calibration process for the new EEG headset.

4.1.3 Challenges

The difficulties associated with BCI applications can be broken down into technological and user-related categories. The following groups: problems with discovery and development, problems with production, problems with the procedure for testing, problems with BCI usage, and concerns about ethics. The present dependability of the BCI system in typical loud surroundings is the biggest obstacle. The barrier impacts technical and nonmedical uses, although nonmedical uses away from a laboratory setting are more vulnerable. The implications for fields outside of healthcare are also substantial, given the greater accessibility and potential population of users of EEG-based BCI technologies outside of medicine compared to their clinical counterparts. Challenges in the medical field include a poor ability to recognize mental orders, issues with the dependability of signals-gathering devices, and a difficult training procedure [119]. Developing BCI

applications that work for every individual is more challenging since everyone's brain signals are qualitatively different. To create BCI applications that don't depend on a particular subject, developers must first design high-performance person-independent classification techniques capable of overcoming person-dependent situations in which instruction and collections are generated from an identical individual.

4.2 Application of EEG-BCI

Daily usage of EEG-based BCI applications requires careful attention to several factors, the most crucial of which is user security. In a connected BCI, the individual using it can send commands during specific allotted blocks of time, and the transmission of those instructions via the consumer to the equipment is specified. Individuals may prefer delayed BCI software if they can provide commands to the device whenever they want to the employee. Whether it comes to safeguarding the user's privacy, determining whether the user truly intended to provide a request, along with whether the person got distracted by other ideas, is crucial when dealing with delayed devices. Due to this, brain switch technology will have to be refined so that users may mentally disengage from their gadgets while they aren't actively using anything. Recent, more practical techniques of collecting EEG data open up even more potential uses for BCIs based on this technology. The long-term effectiveness of EEG-based BCI equipment can be improved by collecting data from parts of the brain where hair doesn't grow. It has also been demonstrated that measuring EEG in certain circumstances merely around the middle of the ear may prove adequate, which might facilitate the implementation of EEG-based BCI technologies. If MI-BCIs are to find widespread usage and benefit, they must be usable by people with a wide variety of abilities, including those with profound motor impairments. The following demands the creation of user interfaces with a low learning curve and high efficiency [120]. The development process should be guided by user-cantered design concepts, which consider the user's needs, preferences, and abilities to make the final product as useful and enjoyable as possible. Neuroimaging technology, such as EEG, and invasive procedures are frequently used in MI-BCIs. Hence, strict safety protocols are required to protect users' brain health. Safety is also an important factor to consider with MI-BCIs because of their potential for real-time control of physical objects or interactions in virtual worlds.

To enhance the precision and performance of EEG-based applications of BCI, it is being proposed that composite BCI structures, which integrate BCI devices into a different BCI or different types of interactions, be created. Instead of relying just on EEG to collect biologically relevant signals, we may also make utilization of additional technologies, examples including Functional Magnetic Resonance Imaging (fMRI), to bolster the information' intensity and quality. Heart rate or vision movement are two further examples of such physiological indicators [128]. FNIRS has been getting a lot of press lately since of its appealing list of benefits, which include being non-invasive, cheap, safe for users, and portable. Emissions from fNIRS vary greatly from any participant, and they are unreliable from one test to the following. EEG-BCI techniques have an enormous opportunity but are not in the medical sector due to many prospective clients. Increased interest in EEG-based BCI technologies outside the healthcare sector is possible as the technology improves, costs decrease, and user convenience rises. These innovations have enormous promise in healthcare, communication, and human-machine interaction, not just for those with movement limitations. Many people's lives will be improved as research and development work toward making MI-BCIs more widely available, flexible, and efficient. Overall, signal processing strategies in MI-BCIs and emerging computational intelligence work together to provide effective and user-friendly BCIs that allow people with motor limitations to operate external devices and improve their quality of life. The future of assistive technology and HCI is bright thanks to these rapidly developing technologies.

Table11. EEG-BCI of the Advantages and Disadvantages

Classifiers Type	Advantages	Disadvantages
SVM [121] Linear classifiers	Faster and more effective with fewer samples. Suitable for regression and classification. Can handle nonlinear data.	SVM algorithms are sophisticated, and choosing the right kernel function is difficult.
ANN [122]	Can handle multiple tasks simultaneously. Offers flexibility in structure and provides accurate results.	Large neural networks take longer to process.
LDA [123]	Features are reduced to reduce variance. Features are assumed to be normal.	Data Dimensionality: LDA may not handle high-dimensional EEG data efficiently and can lead to overfitting.
k-NN [124] Nonlinear classifiers	An easy way to learn and save time.	Select the number of neighbours 'k' independently..
MD [125]	Commonly used in classification and clustering algorithms.	Performance can significantly decrease in the presence of noise.
NBC [126]	Method for non-linear problems using probabilities. Lacking outlier bias. Assumes each attribute has the same statistical importance..	limited Signal Depth: EEG signals may not access deeper brain regions or subcortical structures.
HMM [127]	Built on robust statistics and rapid learning approaches for raw sequence data without losing accuracy.	Depending on each condition and seen object.

4. 3. Discussion

The number of obstacles preventing the advancement of EEG-BCI usage would have to be solved in future research. Recognizing these factors helps in identifying potential fixes or other approaches. They benefit greatly from highlighting the various potential applications of their work and exchanging suggestions about the most effective way to use these possibilities [129]. The open discussion of novel concepts and promising directions for additional study facilitates the proliferation of EEG-BCI applications.

5. EEG MI-BCI System Challenges

Brain-Based Motor Imagery their potential uses in different industries have drawn attention to computer interfaces.

However, some fundamental obstacles must be overcome to maximize their potential:

5.1. Signal Variability

- *Inter-Subject Variability:* EEG signals can vary greatly between individuals. What works good for one individual may not work for another. A universal MI-BCI system for varied users is difficult to develop.
- *Intra-Subject Variability:* Even within the same individual, EEG signals can change due to factors like fatigue, attention, and emotional state. The system must adapt to these variations.

5.2. Signal Quality

Eye blinks, muscle contractions, and ambient noise can distort EEG data. Accurate MI-BCI operation requires clean and reliable signals. It is essential to develop advanced signal processing techniques for artefact removal and noise reduction**.**

5.3. Calibration and Adaptation

MI-BCI systems often require a calibration phase where users perform motor imagery tasks. This calibration can be time-consuming and may lead to user fatigue. Developing adaptive MI-BCI systems that reduce the need for frequent recalibration is essential. These systems should be capable of self-adjustment based on the user's current mental state.

5.4. Information Transfer Rate (ITR)

While MI-BCIs offer valuable control signals, the achievable Information Transfer Rate (ITR) is often limited. This limitation can affect the speed and efficiency of interactions, particularly for applications requiring rapid and precise control. Enhancing ITR is a significant research challenge. This involves improving the accuracy of decoding algorithms and the number of distinguishable mental tasks.

5.5. User Training and Fatigue

Training users to accurately perform motor imagery tasks can be demanding. The challenge is to design training protocols that are efficient, engaging, and minimize user fatigue.

5.6. Real-time Processing

Achieving real-time processing and feedback is crucial for many MI-BCI applications, such as neurofeedback and real-time control. It remains a technical challenge to ensure low-latency processing. Real-time processing requires optimizing algorithms for speed and efficiency, which can be resource-intensive.

5.7. Mental Workload

Prolonged use of MI-BCIs can impose a significant mental workload on users. The challenge is to design systems that balance effective control with mental effort. High mental workload can reduce user acceptance and usability.

5.8. Hybrid BCIs

Integrating MI-BCIs with other BCI modalities, such as P300 or SSVEP, presents challenges related to signal fusion and decoding algorithms. Combining multiple BCI modalities for more versatile and robust control adds complexity to the system.

5.9. Ethical and Privacy Concerns

As MI-BCIs become more widespread, ethical concerns regarding mind-reading technologies and privacy issues must be addressed. It's crucial to establish ethical guidelines and data privacy protections, especially in applications like neuro feedback and communication.

5.10. Clinical Validation and Certification

For medical and therapeutic applications, ensuring the clinical effectiveness, safety, and regulatory compliance of MI-BCI systems is a complex challenge. Clinical validation studies and regulatory approvals are necessary but time-consuming processes. Addressing these challenges will be pivotal in advancing EEG-based Motor Imagery-BCI systems, making them more practical, efficient, and user-friendly for a broad range of applications, from assistive technology to neuro rehabilitation. Creating an appropriate Brain-Computer Interface (BCI) system using Motor Imagery (MI) brain impulses involves a number of obstacles, both in terms of usability and technological elements. The signal-to-noise ratios of EEGs are notably poor, especially in real-world settings. While many signal processing techniques have shown to be useful in EEG-based MI-BCI systems, some unresolved concerns and obstacles continue to pique the interest of academics.

6. Conclusion

MI-BCI devices enable individuals with disabilities to interact with their environment using brain signals, significantly enhancing their quality of life. These systems allow users to control external devices and applications with their thoughts, fostering greater independence. This study explores MI-BCI EEG signal processing, including acquisition, pre-processing, feature extraction, and classification. While methods like Wavelet Transform (WT), Empirical Mode Decomposition (EMD), and Common Spatial Patterns (CSP) show promise, Wavelet Packet Transform (WPT) is the most effective for MI-EEG signal feature extraction, improving classification accuracy. Wavelet Packet Decomposition (WPD) coefficients are particularly useful for identifying non-stationary and time-varying MI-EEG signals. The research also examines motor imagery and various machine learning and deep learning methods for EEG paradigm identification. Linear Discriminant Analysis (LDA) is an efficient BCI classifier for short training datasets, yet there is a need for methods that can learn quickly without compromising accuracy. This analysis highlights the importance of robust classifiers capable of managing the complex, high-dimensional nature of EEG data. A significant contribution of this work is the establishment of a new reporting standard for MI-BCI experiments, addressing EEG signal resolution issues. Despite progress, challenges such as low Information Transfer Rate (ITR) persist. Future research should focus on enhancing ITR for practical applications, aiming to reduce training time while maintaining effectiveness.

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Data Availability

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No Data Availability

Author Contribution

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Conflict of interest statement

I (we) certify that there is no conflict of interest with any financial organization regarding the material discussed in the manuscript.

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