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Applications of Brain Computer Interface for Motor Imagery Using Deep Learning: Review on Recent Trends

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ABSTRACT

Motor Imagery-Brain Computer Interface (MI-BCI) is a very important technology gaining momentum throughout the last decade. This technology enables the linkage of brain activities to computer applications and can give disabled patients who suffer from motor disabilities (e.g., partial paralysis, muscle atrophy, etc.) the ability to interact normally with technologies around them. Currently, the technology is mostly limited to applications within dedicated laboratories and is hardly used in practical settings or in real-life applications. The purpose of this study is to review the latest trends and technologies in the field of MI-BCI, including the major challenges and the state-of-the-art classification techniques. The scope of this review article covers the feature selection algorithms that can help identify the most informative and discriminative features from the recorded brain signals, and the classification techniques that can identify the different types of motor movements.

1. Introduction

Brain computer interface (BCI) [1] is a trending technology that enables the interfacing of human brain with computer systems. This is accomplished by the acquisition of the brain signals using dedicated bio-sensors, which are later processed by a computer system to achieve certain tasks, such as controlling a mouse movement, a wheelchair [2], and so on.

There exist non-invasive and invasive sensors that can be used with BCI [3]. Most of the research focuses on BCI systems using the non-invasive sensors [4] due to the fact that they are safer and easier to set up. Non-invasive BCI technology also has a broader user base, and they do not usually require a dedicated facility to operate (e.g. hospital, lab, etc.,). Another reason which can also be attributed to the widespread use of the non-invasive sensors, is their low prices [5]. However, while non-invasive BCI technologies offer numerous advantages, they also have some downsides when compared to invasive BCIs. The main issues with these non-invasive technologies are their lower signal quality, lower spatial resolution and higher signal interference.

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The main stages of any BCI system consists of

i. Acquiring the signal from the brain using the relevant EEG sensor/headset.
ii. Preprocessing the signal to remove any noises and retain only the desired frequency [6].
iii. Performing application-dependent features selection/extraction.
iv. Classifying the signal according to the application.
v. Carrying out required actions using the classified output. (e.g., motor action).

Figure 1 below illustrates the main stages for most busy eye systems.

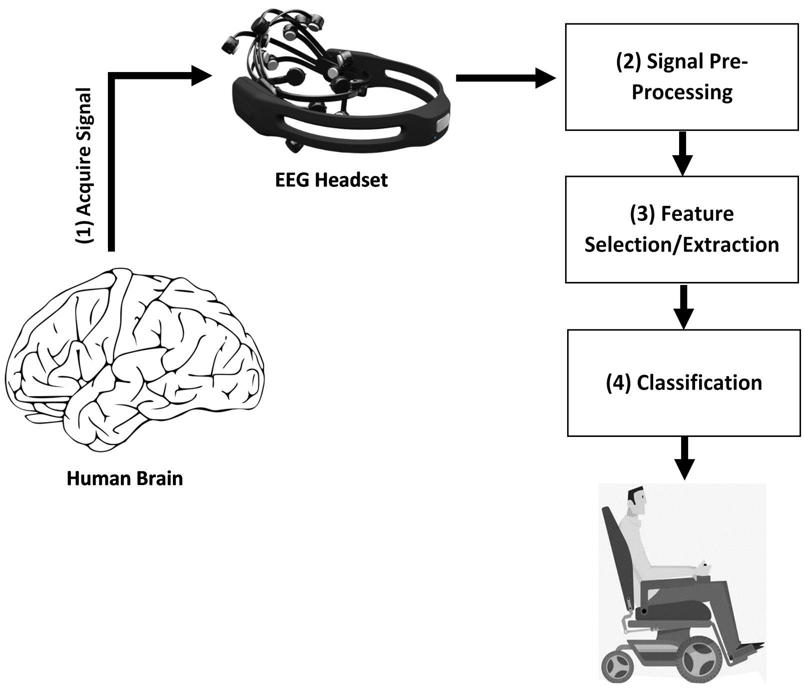

Fig. 1. Main stages of a BCI system

The upcoming section will provide a more in-depth exploration of the latest research pertaining to each stage of BCI systems.

1.1 Acquiring The Signal

In recent times, there has been a rise in the availability of commercially accessible EEG-based headsets in the market [7]. These devices range in price from low-cost options to more costly ones. While some of these devices cater more towards hobbyists rather than scientific or medical communities, their popularity and acceptable error margins [8] have led to their employment in numerous recent studies. The review of EEG headsets presented in this paper encompasses both the inexpensive and the expensive headsets, with a threshold of 1,000 USD separating them. Table 1 lists the widely used commercial devices below the price threshold, and Table 2 lists those above the same threshold.

Table 1
List of commercially available EEG headsets below 1,000 USD

Device Name	Manufacturer	Electrodes #	Method of Adhesion	Sample Rate (Hz)	Resolution	Price (USD)
Muse 2 [9]	IntraXon	4	Dry	256	12	249
Mindwave [10]	Neurosky	1	Dry	512	12	110
Insight 2.0 [11]	Emotiv	5	Semi dry	128	15	499
Epoc+ / Epoc^x [12]	Emotiv	14	Saline-soaked solution, Gel	2048	14	699 (Epoc+) 849 (Epoc^x)
EEG Electrode Cap [13]	OpenBCI	Up to 19	Wet	256	24	499

Most manufacturers provide a set of bundled BCI software tools or platforms [14,15] to help the research community take advantage of their EEG headsets, as well as to serve as a common benchmark. Since BCI is the main target of this review paper, only the headsets that provide such an interface will be covered.

Table 2
List of commercially available EEG headsets above 1,000 USD

Device Name	Manufacturer	Electrodes #	Method of Adhesion	Sample Rate (Hz)	Resolution	Price (USD)
DSI 7 [16]	Wearable Sensing	7	Dry	300	4	19995
DSI 24 [17]	Wearable Sensing	21	Dry	300	8	24800
Quick-20m premium+ [18]	CGX systems	20	Dry	500	24	30700
Active Two [19]	Bio-Semi	Up to 256	Dry / Wet	2,4,8,16 (kHz)	N/A	12000
Gnautilus-pro [20], [21]	Gtec	8, 16, 32	Dry / Wet	1000	8	20000
Eego™ sports [22]	Ant neuro	32, 64, 128	Dry / gel	2000	8	25000+
Epoc flex kit [23]	Emotiv	Up to 32	Saline soaked solution, Gel	1024	14	2099
B Alert X [24]	Advanced brain monitoring	9, 20	Dry	256	16	14950

1.2 Signal Pre-processing

In the realm of Brain-Computer Interface (BCI) signal processing, a new era of enhanced data quality and signal reliability has arrived as a result of recent improvements. For BCIs to be fully utilized in a range of applications, from neurorehabilitation to assistive technology, improvement is essential. In recent years, a number of cutting-edge pre-processing methods have emerged, enabling more reliable and accurate signal analysis. Convolutional neural networks (CNNs) are used as a deep learning-based classification and noise removal method to automatically detect and remove undesired artifacts from EEG and other neuroimaging data [25], as well as to classify them. The effectiveness of this method in improving data quality has been astounding. The incorporation of adaptive signal processing methods, such as blind source separation and adaptive filtering, which adaptively decrease noise and artifacts in real-time, is another significant development [26].

1.3 Feature Extraction and Selection

Recent advancements in Brain-Computer Interface (BCI) technology have highlighted the significance of feature extraction and selection in optimizing the performance of BCI systems. The accuracy and effectiveness of BCIs have been improved by the incorporation of cutting-edge complex approaches that allow the extraction of discriminative information from brain signals. Convolutional neural networks (CNNs) and other machine learning techniques, such as deep learning architectures, have become effective tools for automatic feature extraction, enabling BCIs to detect complex patterns in EEG and fNIRS data. To further reduce dimensionality and improve BCI resilience, feature selection techniques like common spatial pattern (CSP) and genetic algorithms are increasingly used to determine the most pertinent and informative features [27]. These latest advancements highlight the crucial role that the feature extraction and selection techniques play in enhancing BCI capabilities for applications ranging from cognitive enhancement to neuroprosthetics.

1.4 Classification

The classification stage in Brain-Computer Interface (BCI) technology is crucial for turning neural signals into commands or insights that can be put into practice. The accuracy and efficiency of BCI categorization systems have significantly improved in recent years. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two deep learning models, have become well-known for their capacity to recognize intricate patterns in neural data, effectively decoding user intentions or determining cognitive states from EEG, fNIRS, or ECoG signals [28]. These models expand the adaptability of BCIs to accommodate changes in user states or situations, which strengthens their utility in a variety of applications, from neurorehabilitation to gaming and communication [29]. They also improve BCI performance.

The quantity of EEG electrodes impacts the volume of data to be gathered and processed. EEG headsets that possess fewer than 8 electrodes are typically employed for specialized applications such as sleep quality assessment and traditional neuro-feedback. On the other hand, EEG headsets with a higher number of channels are considered high-density devices capable of capturing numerous brain signals. The placement of the electrodes follows the international 10-20 system, which is a widely accepted approach used to define and position scalp electrodes during EEG examinations, polysomnographic sleep studies, or voluntary laboratory research [30].

The main regions of the brain include the pre-frontal (Fp), frontal (F), central (C), temporal (T), parietal (P), and occipital (O) areas. Odd-numbered labels correspond to electrodes placed on the left side, while even-numbered labels indicate electrodes on the right side. Additionally, electrodes positioned above the midline are identified with the letter 'Z'.

EEG signal is measured by getting the voltage difference between the recording electrodes and a reference voltage. Several types of EEG sensors can be placed on the participant's head. Dry electrodes, for instance, do not require the application of any electrolyte substance and can make direct contact with the scalp. One significant advantage is their ease of installation, as they do not necessitate significant preparations, and they eliminate the need for head cleanup afterwards. Their primary limitation lies in the high contact impedance between the sensor and the skin, which necessitates the implementation of enhanced noise and distortion filtering capabilities.

The alternative prominent type of EEG sensors relies on wet electrodes, encompassing semi-dry, saline, and gel-based variants. To improve skin contact and reduce impedance at the electrode-skin interface, an electrolytic substance is applied between the scalp and the electrode. This facilitates enhanced readings and higher performance of the system by reducing sensitivity to noise and other artifacts.

2. Literature Review

In this section, the focus will be on conducting a comprehensive literature review, delving into recent relevant studies, and examining the datasets that have been predominantly utilized in recent research work related to Motor Imagery Brain-Computer Interfaces (MI-BCI). To ensure a systematic review of recent MI-BCI research, we devised a search strategy that combined three primary search terms: 'MI-BCI,' 'EEG' (Electroencephalography), and 'CNN' (Convolutional Neural Network). Recognizing the importance of comprehensive coverage, we also incorporated alternative terms for each of these search categories, connecting them with the logical 'OR' operator. For example, to capture research related to 'EEG,' we included both 'EEG' and 'Electroencephalography' as search terms.

This extensive literature search was executed using the Scopus database, using the following search string: 'MI-BCI' OR 'Motor Imagery Brain Computer Interface' AND 'EEG' OR 'Electroencephalography' AND 'deep neural network' OR 'deep network' OR 'Convolutional Neural Network' OR 'Deep learning' OR 'attention.' Initially, the search yielded a total of 131 research articles. However, to ensure a precise focus on the targeted application of MI-BCI, we meticulously reviewed the titles and abstracts of these articles, following the Preferred Reporting Items for Systematic Review and Meta-analysis (PRISMA) framework, which provides a standardized approach for systematic reviews and meta-analyses, helping us maintain transparency and rigor in our data selection process.

2.1 Limitations

This work is limited to using Brain-Computer Interface (BCI) applications for motor imagery datasets obtained using an EEG headset. All primary papers that use Convolutional Neural Networks for MI-BCI feature extraction, classification, or any other task, and were written in English, were selected. However, since the topic of MI-BCI combined with deep learning is a relatively new discipline, the overall literature that was initially retrieved covered a span of 7 years, starting from year 2017 to year 2023. However, in order to maintain the focus on the most recent advancements in the field, articles published prior to 2020 were left out of this review.

This Systematic Literature Review (SLR) focuses on contemporary research related to MI-BCI employing EEG datasets. Articles that exclusively covered the preparation of new datasets, without any research regarding MI-BCI applications were removed from the selection. Additionally, articles written in languages other than English, were also removed. The same criteria for selecting the research articles were applied to review articles.

2.2 Related Work

The selected publications are detailed in Table 3, which includes information on the article methodology, publication year, source title, and the number of citations for each publication. Figure 2 illustrates the distribution of publications from 2020 to 2023. In the yearly distribution depicted in Figure 2, there is a noticeable sharp increase in literature, with only eight publications in 2021 compared to 16 articles in 2022. Furthermore, as indicated in Figure 3, among the 50 articles, 36 were published in journals, while 14 appeared in conference proceedings. Figure 4 presents the number of manuscripts published by each publisher.

Table 3
Methodology, publication year, source, and the number of citations of the selected publications

No.	Ref.	Methodology	Year	Source Title	Cited By*
1	[31]	CNN	2023	Proceedings of SPIE - The International Society for Optical Engineering	-
2	[32]	Time-Frequency analysis and Deep-Learning.	2023	International Journal of Imaging Systems and Technology	1
3	[33]	Multi-Modal Neural Network.	2023	Journal of Neural Engineering	-
4	[34]	Custom technique and decoding using Bidirectional long short-term memory (BiLSTM) network.	2023	Sensors	1
5	[35]	An Interactive Frequency Convolutional Neural Network (IF-NET).	2023	IEEE Transactions on Neural Systems and Rehabilitation Engineering	1
6	[36]	New EEG classifier based on Riemannian geometry.	2023	Applied Intelligence	-
7	[37]	Multi-branch Fusion CNN (MF-CNN).	2023	Frontiers in Neuroscience	-
8	[38]	Parallel-Fusion Algorithm, Mult-scale CNN and LSTM.	2023	Proceedings of SPIE - The International Society for Optical Engineering	-
9	[39]	CNN	2023	Sensors	-
10	[40]	Deep-ConvNet	2023	Journal of Neural Engineering	1
11	[41]	Subject-Separation Network (SNN).	2023	Brain Sciences	1
12	[42]	Deep-Ensemble: Multi-layer perceptron (ML), vision transformer and CNN.	2023	Digest of Technical Papers - IEEE International Conference on Consumer Electronics	1
13	[43]	Time segments and Frequency bands CSP using Genetic Algorithm (TSFBCSP-GA).	2023	Biomedical Signal Processing and Control	1
14	[44]	2D-CNN and LSTM	2023	Biomedical Signal Processing and Control	1
15	[45]	Multi-scale time frequency-CNN (MTFB-CNN)	2023	Biomedical Signal Processing and Control	3
16	[46]	Review of various Conventional and Deep-learning methods.	2023	Journal of Neuroscience Methods	3
17	[47]	Multi-branch spectral-temporal convolutional neural network with channel attention and LightGBM model (MBSTCNN-ECA-LightGBM)	2023	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2
18	[48]	CNN	2022	Proceedings - 2022 International Conference on Computing, Electronics and Communications Engineering. iCCECE 2022	-
19	[49]	Deep-Learning Support Vector Machine (DL-SVM)	2022	Lecture Notes in Electrical Engineering	-
20	[50]	Wavelet Packets CNN	2022	Proceedings - 2022 4th International Conference on Applied Machine Learning, ICAML 2022	-
21	[51]	A Feature-Level Graph Embedding Method (EEG_GENet)	2022	Biocybernetics and Biomedical Engineering	3
22	[52]	2 class Filter Bank Convolution Neural Network (2Con-FBCNet)	2022	Medicine in Novel Technology and Devices	2
23	[53]	Filter Bank and Convolution Network (ConvNet)	2022	ACM International Conference Proceeding Series	3

24	[54]	Active Inference Neural Network (EEG-ARNN)	2022	IEEE Transactions on Industrial Informatics	6
25	[55]	Deep Adversarial Domain Adaptation With Few-Shot (Deep-ADA)	2022	IEEE Access	5
26	[56]	Deep Convolution Generative Adversarial Network.	2022	International Journal of Neural Systems	9
27	[57]	Tensor-based frequency feature combination (TFFC).	2022	Communications in Computer and Information Science	8
28	[58]	multiscale time-frequency with OVR-SVM	2022	Computers in Biology and Medicine	10
29	[59]	CSP and LDA for feature selection, and CNN for classification.	2022	PLoS ONE	14
30	[60]	Tensor-based frequency feature combination (TFFC)	2022	IEEE Transactions on Neural Systems and Rehabilitation Engineering	20
31	[61]	CNN-LSTM	2022	Biomedical Signal Processing and Control	27
32	[62]	Multi-scale CNN	2022	Biomedical Signal Processing and Control	46
33	[63]	DeepConv Neural Network	2022	Engineering Applications of Artificial Intelligence	48
34	[64]	Filter bank Wasserstein adversarial domain adaptation framework (FBWADA)	2021	Proceedings of the International Joint Conference on Neural Networks	1
35	[65]	Ensemble empirical mode Decomposition (EEMD) and Filterbank common spatial pattern (FBCSP)	2021	International Conference on Information Networking	3
36	[66]	Time-Incremental End-to-End Shared Neural Network with Attention-Based Feature Fusion.	2021	Computational Intelligence and Neuroscience	5
37	[67]	DNN with Subdomain adaptation	2021	Medical Engineering and Physics	7
38	[68]	Multi-domain CNN	2021	Sensors	6
39	[69]	CNN	2021	Journal of Neural Engineering	12
40	[70]	Sparse Spectro-Temporal Decomposition and Deep learning.	2021	IEEE Transactions on Automation Science and Engineering	24
41	[71]	Novel DNN based on EEGNet	2021	IEEE Access	44
42	[72]	CSP	2020	8th International Winter Conference on Brain-Computer Interface, BCI 2020	6
43	[73]	SVM	2020	IEEE Transactions on Neural Systems and Rehabilitation Engineering	10
44	[74]	Fisher's linear discriminant analysis (FLDA)	2020	Electronics (Switzerland)	10
45	[75]	Feature Similarity-Based Weighted Ensemble Learning (Sessionnet)	2020	IEEE Access	11
46	[76]	Fusion CNN	2020	Brain-Computer Interfaces	14
47	[77]	Deep Metric Learning	2020	IEEE Access	21
48	[78]	CSP	2020	Behavioural Brain Research	24
49	[79]	A MultiView CNN with Novel Variance Layer.	2020	Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS	32
50	[80]	EEGNet-based technique.	2020	IEEE Medical Measurements and Applications, MeMeA 2020 - Conference Proceedings	47

* Citations based on Scopus database

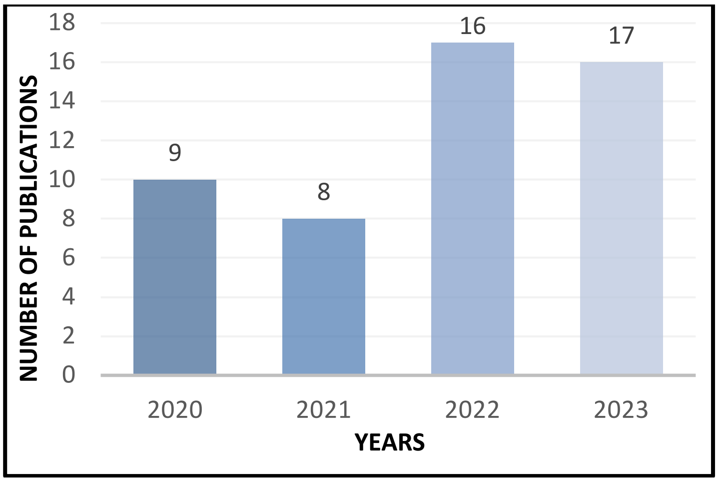

Fig. 2. Number of publications per year

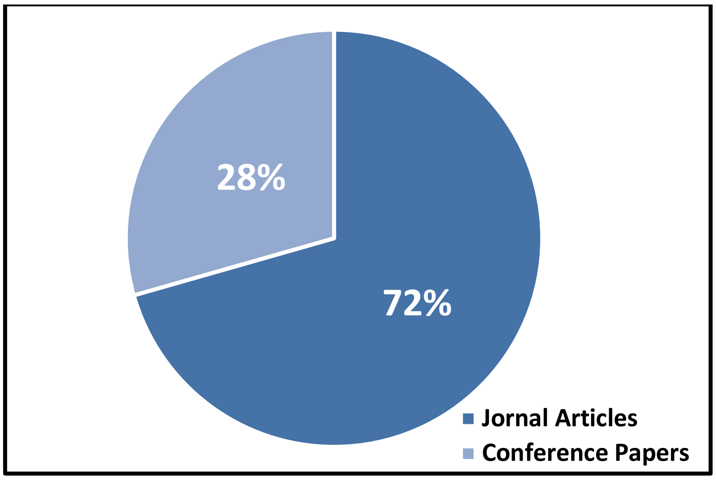

Fig. 3. Ratio of conference and journal publications

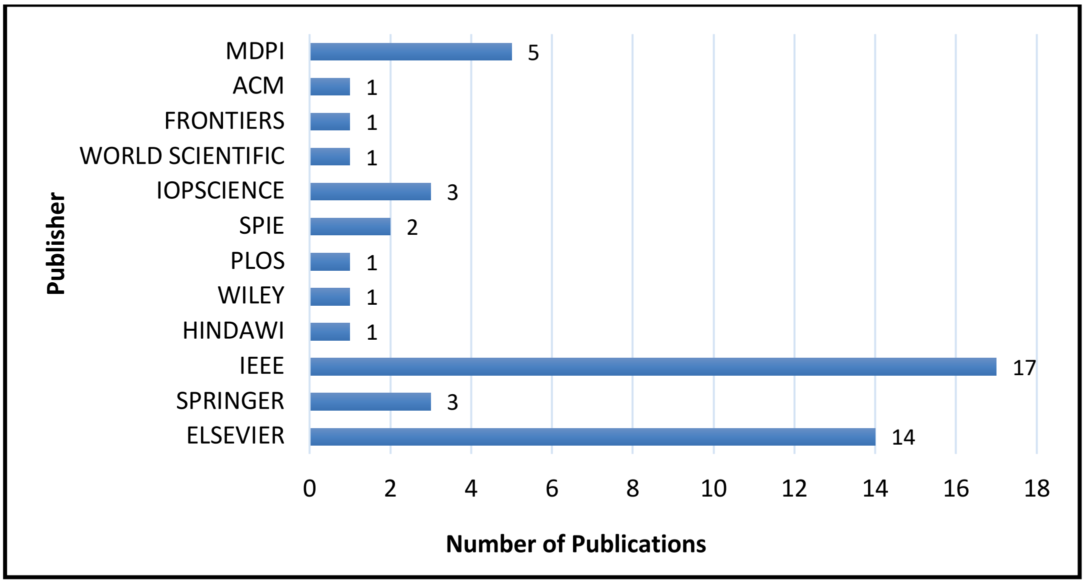

Fig. 4. Number of publications per publisher

A detailed explanation of the most cited articles within the covered literature is covered below. The next paragraphs will delve deeper into the methodology employed, the used dataset, as well as the results, potential shortcomings, and advantages of the techniques applied.

Li *et al.,* [61] proposed an EEG classification algorithm that combines multilevel spatial-temporal features based on CNN and LSTM to overcome the shortcomings of traditional machine learning algorithms. The superiority of the proposed method stems from using parallel structure and fusion features. By employing the CNN-LSTM parallel structure, both networks can simultaneously extract features from the input signal, thereby incorporating abundant original features in both temporal and spatial dimensions. In contrast, the serial structure that relies on CNN features as input for LSTM can only extract features layer by layer, leading to the loss of certain features during this process and ultimately resulting in a decreased accuracy. The authors used the four classes of BCI Competition IV-2a dataset, which consists of (left, right, tongue, and feet). The results showed that the fusion of features demonstrated stronger separability and higher classification accuracy compared to using a single feature. The results have shown a Kappa value and average accuracy 0.8245 and 87.68%, respectively.

Roy *et al.,* [62] introduced a novel technique aimed at enhancing the classification of MI-BCI. The technique uses a multi-scale convolutional neural network (MS-CNN) to address the challenge of inter-subject variability in EEG data classification. By extracting two highly distinguishable features from non-overlapping frequency bands of EEG signals at multiple scales, the technique overcomes this issue. To further enhance accuracy and performance, user-specific features are incorporated into the CNN classifier, and various data augmentation techniques are employed to improve the model's robustness. The outcomes show that the suggested MS-CNN is successful, obtaining a remarkable Cohen's kappa-coefficient of 0.92 and an average classification accuracy of 93.74% on the dataset of BCI competition IV-2b. These results surpass those of baseline and state-of-the-art models, indicating the algorithm's ability to overcome limitations in existing CNN-based EEG-MI classification models and significantly improve classification accuracy. The findings provide a solid foundation for the development of efficient and reliable real-time human-robot interaction systems.

To address the most common challenges of Deep learning (DL)-based MI-BCI classification, such as inter-subject variability, complex properties, and low signal-to-noise ratio (SNR). Roy *et al.,* [63] conducted a study based on a transfer learning (TL)-based multi-scale feature fused CNN (MSFFCNN) that captures distinctive features from different non-overlapping frequency bands of EEG signals at different convolutional scales for multi-class MI classification. Notably, the study introduced four model variants to account for inter-subject variability, including subject-independent and subject-adaptive classification models with different adaptation configurations. These configurations leverage the full learning capacity of the classifier, fine-tuning extensively trained models, and exploring a wide range of learning rates and degrees of adaptation. The performance of the MSFFNN model has been evaluated on the BCI competition IV-2a dataset which contains EEG data from 9 patients with 4 different classes. The proposed model achieved an average classification accuracy of 94.06% (±0.70%) and a kappa value of 0.88, surpassing several baseline and state-of-the-art EEG-based MI classification models while using fewer training samples. The research demonstrates an effective and efficient transfer learning-based framework for robust MI-BCI systems, providing a foundation for high-performance applications in this domain.

Sun *et al.,* [70] proposed a two-stage classification framework for accurately classifying motor imagery (MI) signals using EEG data. The first stage of the framework involves employing sparse spectro-temporal decomposition. This technique was chosen to address the challenge of capturing both spectral and temporal information in the EEG signals. By decomposing the signals into sparse representations, it allows for the extraction of relevant features that enhance the separability between different MI tasks. The second stage of the framework uses deep learning techniques, specifically convolutional neural networks (CNNs), to learn and classify the extracted features. The combination of sparse spectro-temporal decomposition and deep learning enables the proposed method to effectively capture discriminative features from the EEG data and automate the classification process. The results demonstrate that SSD-SE-CNN provides a 12.9% improvement with respect to BP-SVM and a 2.2% improvement with respect to CNN-SAE using the BCI Competition IV-2b dataset.

While deep learning-based Motor Imagery (MI) BCI systems have exhibited enhanced accuracy compared to traditional algorithms, the interpretability of these models remains a challenge. In an effort to address this, Deng *et al.,* [71] conducted a study based on EEGNet, a popular deep learning model, and performed a comparison with the conventional Filter-Bank Common Spatial Pattern (FBCSP) algorithm. Then, the study proposed improvements to EEGNet by establishing a connection between its 1-D convolution and a specialized Discrete Wavelet Transform (DWT), as well as relating its depth-wise convolution to the Common Spatial Pattern (CSP) algorithm. To boost performance, the researchers applied the Temporary Constrained Sparse Group Lasso (TCSGL) algorithm to EEGNet, resulting in the proposed model, TSGL-EEGNet. Evaluations were carried out using the BCI Competition IV-2a and BCI Competition III 3a datasets, which involve 4-class MI tasks. The findings revealed that TSGL-EEGNet achieved notably higher average classification accuracy (78.96% with kappa 0.7194) compared to EEGNet, C2CM, MB3DCNN, SS-MEMDBF, and FBCSP, particularly for subjects with low sensitivity. Similarly, on the BCI Competition III 3a dataset, TSGL-EEGNet outperformed EEGNet*,* attaining an average classification accuracy of 85.30% (kappa 0.8040). Moreover, the researchers employed average-validation and stacking techniques to further enhance model performance, resulting in accuracy rates of 81.34% and 88.89%, with kappas of 0.7511 and 0.8519 on the BCI Competition IV-2a and BCI Competition III 3a datasets, respectively. The study also utilized Grad-CAM to visually depict the frequency and spatial features learned by the neural network.

Alwasiti *et al.,* [77] proposed a triplet network to classify MI-EEG signals. The proposed method used the Stockwell transform to convert the datasets from the time domain to the frequency domain, representing the EEG power for a specific frequency range plotted over time. The dataset used in their study was collected from 64 EEG channels of 109 subjects. The proposed goal was to classify the MI-EEG signals and assign them to one of three labels: left, right, or rest. The classification using the Stockwell transform demonstrated higher performance compared to DML with Short-Term Fourier Transform (0.647% vs. 0.431%).

Mane *et al.,* [79] proposed a multi-view CNN with a novel variance layer for classifying MI-BCI actions. The system, called FBCNet, starts by creating a multi-view data layout using a band-pass filter that categorizes EEG into multiple frequency bands. Then, for each view, spatially discriminative patterns are learned using CNN layers. Finally, a fully connected layer divides the collected features into various MI classes by classifying the temporal information using a new variance layer. The performance of FBCNet was evaluated on a publicly available dataset obtained from Korea University, which includes two classes (left vs. right hand movements). The results demonstrated that FBCNet achieved a 6.7% higher accuracy compared to other state-of-the-art deep learning techniques, while using less than 1% of the learning parameters.

Wang *et al.,* [80] presented a precise and robust embedded system for Motor Imagery-based Brain-Computer Interfaces (MI-BCI). Their suggested model, which is based on EEGNet, was created mainly to satisfy the memory and processing needs of low-power microcontroller units (MCUs), such as the ARM Cortex-M family. To further reduce memory usage without compromising accuracy, the authors employed various techniques including temporal down-sampling, channel selection, and narrowing of the classification window. Evaluating their system on the Physionet EEG Motor Movement/Imagery dataset, the standard EEGNet achieved impressive classification accuracies of 82.43%, 75.07%, and 65.07% for 2, 3, and 4-class MI tasks in global validation, outperforming state-of-the-art convolutional neural networks (CNNs) by margins of 2.05%, 5.25%, and 6.49% respectively. The proposed framework successfully achieved significant reductions in memory footprint, with a minimal accuracy loss of 0.31% and memory reduction of 7.6×, as well as a small accuracy loss of 2.51% with a memory reduction of 15×. Deploying the scaled models on a commercial Cortex-M4F MCU yielded inference times of 101 ms and energy consumption of 4.28 mJ per inference for the smallest model, while a Cortex-M7 achieved an inference time of 44 ms and energy consumption of 18.1 mJ per inference for the medium-sized model. These results demonstrated the potential for fully autonomous, wearable, and accurate low-power BCI systems.

2.3 Data Sets

A notable observation is that the majority of recent studies have relied on secondary datasets obtained from the BCI competition archive. Alternatively, some researchers have opted to generate their own primary datasets for use in their original experiments.

The latest data set used in the BCI competitions was created in 2008, employing outdated devices and a limited number of samples. The largest participation in any of the BCI competition data sets involved nine subjects, while certain data sets, such as BCI competition II, dataset 3, comprised only one subject. In terms of the number of samples, the largest study was conducted by Karácsony *et al*., [81], using the PhysioNet EEG data set with approximately 109 individuals over a four-year period. It is worth noting that while this study was conducted in 2019, the data set itself was generated between the years 2000 and 2004.

The trend of processing EEG data for the advancement of BCI systems, notably in Motor Imagery tasks, is crippled by the absence of modern, diverse and big data sets. Such data set was actually created by Kaya *et al.,* [82] and published in Scientific Data journal by Nature Research in 2018. They released the largest publicly available data set based on EEG signals for BCI applications. Their data set contained 60 hours of EEG signal recordings, and over 60,000 motor imagery data, based on 4 different interactions. Table 4 presents the data sets commonly used in MI-BCI research.

Table 4
Data sets commonly used in MI-BCI

Dataset	Year	Type	Number of subjects
BCI Comp. IV: IIa	2008	EEG-MI	9
BCI Comp. III: IIIa	2004	EEG-MI	3
BCI Comp. II (aka 2003): III	2003	EEG-MI	1
BCI Comp. IV: IIb	2008	EEG-MI	9
BCI Comp. III: IVa	2004	EEG-MI	5
High Gamma Dataset (HGD)	2017	EEG-MI	14
Technische Univsersitat Berlin dataset 1	2016	Brain Cognitive using EEG and fNIRS	26
Technische Univsersitat Berlin dataset 2	2017	EEG-MI	29
NIRSCOUT and NIRX Medical Technologies dataset	2020	fNIRS-MI	10
PhysioNet EEG dataset	2000 – 2004	EEG-MI	109
OpenBMI	2021	EEG-MI	36
Meng dataset	2019	EEG-MI	42
Stieger dataset	2021	EEG-MI	42
Kaya dataset	2018	EEG-MI	13

3. Methodology and Discussion

3.1 Various Deep Learning Techniques for MI-BCI

As already mentioned, EEG data is widely used in MI-BCI classification research. It records the brain's electrical signals through electrodes placed on the scalp. Before EEG signals can be used, they are first subjected to various pre-processing techniques to enhance their quality and extract relevant information. These techniques include filtering methods such as band-pass and notch filters to remove unwanted frequencies and eliminate noise. Artifact removal techniques are applied to address sources of interference like eye blinks and muscle artifacts. Additionally, signal normalization is performed to improve the signal-to-noise ratio and facilitate accurate feature extraction.

Feature extraction is a critical step in MI-BCI classification, involving the extraction of discriminative information from pre-processed EEG signals. As demonstrated in the related work section, various techniques are employed, such as time-domain analysis, frequency-domain analysis (e.g., Fourier Transform), time-frequency analysis (e.g., wavelet transform), and spatial filtering methods (e.g., Common Spatial Patterns). These techniques aim to capture relevant features that can distinguish between different motor imagery classes.

Machine learning algorithms are commonly employed to classify the extracted features into different classes. Some of these techniques according to the literature are rule-based methods, including Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN), as well as traditional machine learning algorithms such as Random Forests and Naive Bayes.

Deep learning techniques have shown incredible capabilities in classification tasks due to their ability to handle complex patterns and large amounts of data. Some of the most important techniques covered by the literature are

i. Stacked Autoencoders (SAEs): which are unsupervised deep learning models used for feature learning and dimensionality reduction.
ii. Deep Belief Networks (DBNs): which are probabilistic generative models capable of capturing complex representations of the input data.
iii. Recurrent Neural Networks (RNNs): neural networks that can model sequential data by using recurrent connections. In the context of MI-BCI classification, RNNs are suitable for capturing temporal dependencies in EEG signals, making them effective for analyzing time-varying patterns during motor imagery.
iv. Convolutional Neural Networks (CNNs): designed to analyze grid-like data, such as images or time-frequency representations. In MI-BCI classification, CNNs can be applied to EEG signals or spectrograms to automatically extract spatial and temporal features.
v. Three-dimensional Convolutional Neural Networks (3D CNNs): extend the CNN architecture to analyze volumetric data, such as spatiotemporal EEG data. These networks capture both spatial and temporal dependencies simultaneously, making them suitable for MI-BCI classification tasks where 3D information is relevant.
vi. Attention CNNs: incorporate attention mechanisms into CNN architectures. These mechanisms allow the model to selectively focus on informative regions or features in the input data, enhancing the discrimination between different motor imagery classes.

Figure 5 below shows the knowledge mapping for MI-BCI based on the literature review.

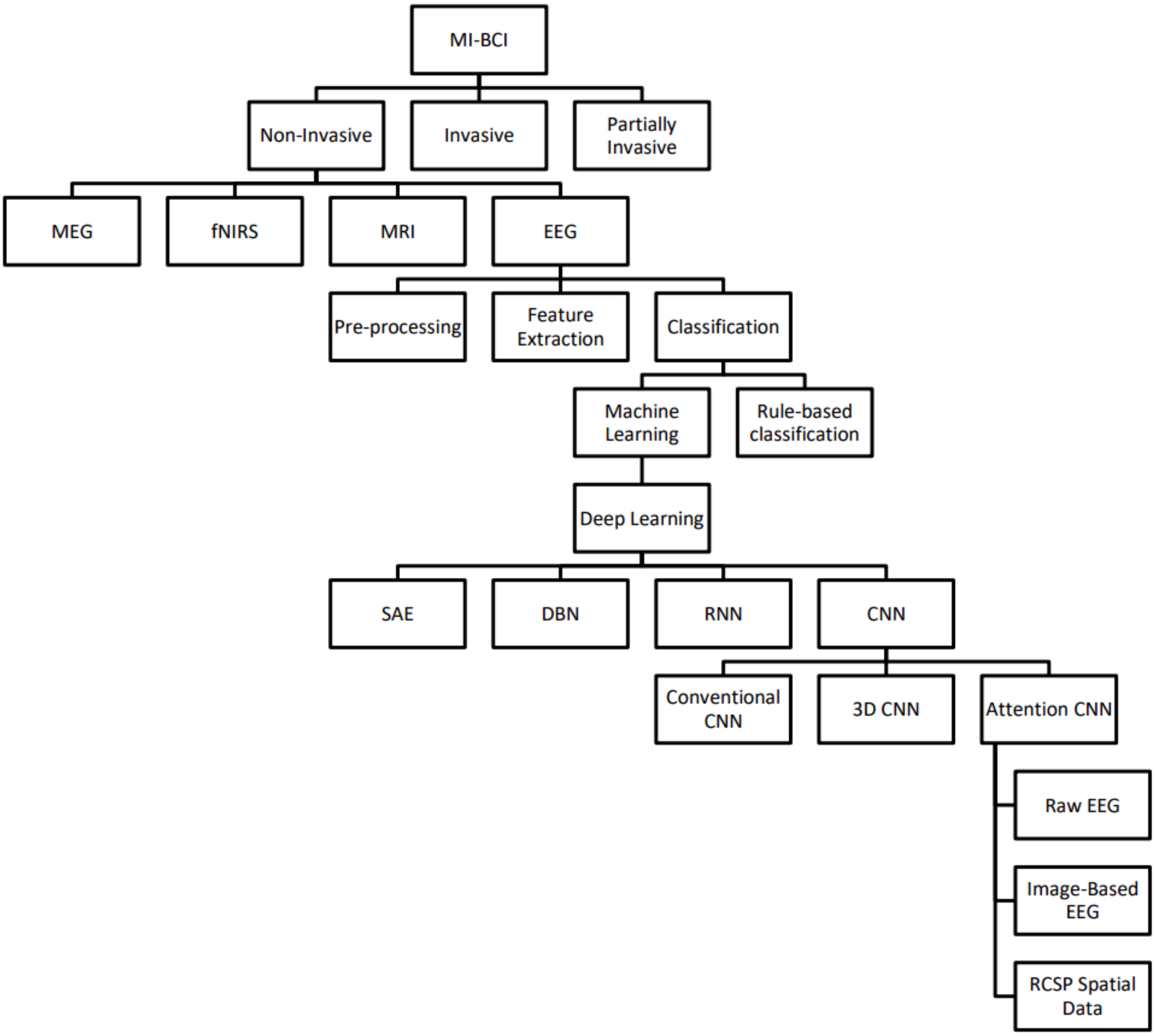

Fig. 5. Knowledge mapping for MI-BCI

CNNs in general show superior performance when compared to other deep learning techniques. Incorporating attention or self-attention mechanisms within CNN can significantly help with applications related to MI-BCI applications. The next sub-section highlights the shortcomings of using conventional CNNs and how self-attention technique can help overcome these issues.

3.2 Challenges of Using CNN for MI-BCI Applications

CNNs are considered as a powerful type of deep learning models, which are primarily designed for applications that deal with matrix (aka., grid) data. However, most of the research that has been covered in this review article showed that CNNs were often used for classification of MI-BCI classes without an explicit features selection technique. In this case, CNN can have certain disadvantages.

For instance, CNNs tend to produce a huge number of feature maps in their hidden layers, and if these features are not explicitly filtered or selected, they can lead to very high-dimensional feature representation. This negatively affects the computational performance and memory usage, and it will lead to longer training times.

Another major disadvantage of using CNNs in such a way is the lack of feature interpretability. CNNs are often treated as a black-box due to their complex structures, and therefore, it is very challenging to understand which features in the original input affect the CNN prediction. As such, it will be quite challenging to assert the link between the MI-BCI output and the relevant segments of the EEG signal.

According to the comprehensive review done by Khademi *et al.,*[46] in 2023 that explored the challenges in the field of MI-BCI, deep learning techniques have shown acceptable performance in handling complicated and dynamic neural signals. However, they reached the conclusion that separate models need to be trained for each subject due to individual differences in EEG signals. Another major finding was that training deep learning models, such as CNN, on limited data can lead to over-fitting because of the large number of parameters. Furthermore, they recommended the usage of unsupervised models since real-life BCI applications lack class labels.

The self-attention mechanism can be a valuable technique in addressing the aforementioned challenges. It allows the model to focus on the different important parts of the EEG signal, effectively learning personalized patterns from each individual person. Also, given the enough computational resources are available, it can capture very long-range dependencies from the input which helps the model understand the complicated relation between different EEG channels.

Compared to other techniques, self-attention is known to be data-efficient which means that it can extract important information from small datasets, which is the case for MI-BCI datasets, where the average number of subjects varies from 8 to 13 (e.g., BCI Competition datasets and HGD).

The self-attention mechanism can also be applied in an unsupervised learning setting, which is very crucial for MI-BCI applications where the class labels are missing (e.g., real-life applications). Finally, the self-attention can mitigate overfitting problems, even when the deep learning model is dealing with millions of parameters, as it allows the model to tend exclusively to important information, while suppressing the irrelevant noisy information.

4. Results

Based on recent trends, the self-Attention Convolutional Neural Network (CNN) technique holds significant importance in MI-BCI classification research. It stands out as one of the most important techniques due to several reasons. Firstly, self-attention mechanisms in CNNs enhance discrimination by selectively focusing on informative regions or features in the input data. This selective attention improves classification accuracy and enables the capture of subtle patterns. Additionally, attention CNNs provide interpretable results by highlighting the regions of interest contributing most to the classification decision. This is valuable in understanding the underlying neural processes in motor imagery and facilitating the development of targeted interventions. Furthermore, attention CNNs adaptively handle inter-subject and intra-subject variability in motor imagery tasks. They robustly focus on relevant features and regions, enhancing model performance across different individuals and sessions. Self-attention CNNs also excel in processing high-dimensional data, such as multi-channel EEG recordings or time-frequency representations. They learn discriminative features at multiple spatial and temporal scales, capturing complex patterns and dependencies within the data.

Generally, Self-attention mechanism is one of the very prominent sub-types of attention mechanisms, due to its ability to capture long-range dependencies, adaptively weight input elements, handle variable-length sequences, provide interpretability, and integrate with other deep learning techniques.

Given an input sequence of length *N*, denoted as $X = [x_1, x_2, \ldots, x_N]$, where x_i represents the i^{th} element of the sequence, the self-attention mechanism computes attention weights and generates context-aware representations.

First, the input sequence *X* is transformed into three types of embeddings: query embeddings (*Q*), key embeddings (*K*), and value embeddings (*V*). These embeddings are linear transformations of the input sequence and are computed as

$$Q = X \times WQ \quad (1)$$
$$K = X \times WK \quad (2)$$
$$V = X \times WV \quad (3)$$

where WQ, WK, and WV are learnable weight matrices.

Next, the self-attention mechanism computes similarity scores between the query and key embeddings to capture the relationships between elements in the sequence. The similarity scores are obtained by taking the dot product between the query and key embeddings

$$S = Q\,.K^T \quad (4)$$

where *S* is a matrix of shape (N, N), where each element $S_{i,j}$ represents the similarity score between the i^{th} and j^{-th} elements of the input sequence. K^T is the transposed matrix *K*.

The similarity scores are then scaled by the square root of the dimension of the key embeddings and passed through a *softmax* function to obtain attention weights

$$A = softmax(\frac{S}{\sqrt{dk}}) \quad (5)$$

where *dk* represents the dimensionality of the key embeddings, and *A* is a matrix of shape (N, N), where each element $A_{i,j}$ represents the attention weight between the i^{th} and j^{th} elements.

Finally, the attention weights are used to compute the context-aware representations of the input sequence by taking a weighted sum of the value embeddings

$$C = A \times V \quad (6)$$

where *C* is a matrix of shape (N, d), where *d* represents the dimensionality of the value embeddings. Each row in C represents the context-aware representation of the corresponding element in the input sequence.

As can be inferred, the self-attention mechanism allows each element in the sequence to attend to other elements based on their importance, as determined by the attention weights. This way, it captures the relationships and dependencies between different elements, enabling the model to focus on the most relevant information during processing.

In context of MI-BCI, the self-attention mechanism enables capturing long-range dependencies in temporal sequences. Since brain signals are recorded over time, it is crucial to model and understand the temporal dynamics and relationships between different time steps. Therefore, the self-attention mechanism allows the model to attend to relevant time steps and weigh their importance, facilitating the identification of critical patterns and correlations in the brain signals. It is also capable of handling variable-length sequences. In MI-BCI analysis, the duration of motor imagery tasks can vary among individuals and sessions, therefore, traditional approaches like fixed-size windows may not be optimal for capturing the entire temporal context. On the other hand, self-attention can adaptively attend to different time steps, regardless of their length, providing flexibility in analyzing variable-length sequences commonly encountered in MI-BCI. Another major advantage of using self-attention mechanism is its inherent ability to handle both local and global information. Local attention focuses on capturing fine details within a specific temporal context, while global attention considers broader patterns and dependencies across the entire EEG sequence. This ability to capture both local and global information is very beneficial for MI-BCI analysis, where local temporal patterns (e.g., specific patterns preceding or following motor imagery) as well as global temporal dynamics (e.g., overall trends or changes during a whole session) are relevant for accurate classification.

In summary, while attention mechanisms generally refer to mechanisms that selectively focus on relevant information, self-attention is a specific type of attention mechanism that focuses on establishing relationships within the same input sequence. Combined with temporal EEG data, self-attention is particularly useful for capturing long-range dependencies and modeling complex relationships in tasks such as MI-BCI classification.

5. Conclusion

The objective of this review article is to evaluate the different deep learning techniques used for the classification of MI-BCI applications, notably CNNs. The aim is to discover what are the current limitations of the existing techniques and how they can be mitigated.

In this comprehensive review article, a detailed overview of the diverse range of technologies employed for acquiring EEG signals was provided, encompassing both wet and dry EEG sensors/headsets. The article not only presented a thorough examination of the most popular EEG headsets available during the time of the study but also delved into recent advancements in research concerning the critical tasks of feature selection and classification of EEG signals, specifically focusing on their application in Motor Imagery-Based Brain-Computer Interface (MI-BCI) systems.

Within the context of MI-BCI applications, the article shed light on the formidable challenges faced by these technologies, such as signal artifacts, noise interference, and the need for accurate and efficient feature extraction methods. To overcome these challenges, the article explored the potential of various machine learning techniques, showcasing how they can be harnessed to effectively address the aforementioned issues and improve the overall performance of MI-BCI systems.

To validate and benchmark these techniques, the review also extensively covered the datasets most commonly employed in the field. These included renowned resources such as the collective BCI competition datasets, which offer standardized and rigorously evaluated data for benchmarking purposes, as well as well-known repositories like PhysioNET and EEGnet, which provide access to a diverse range of EEG recordings from different experimental settings and populations.

A comparison with the findings of a recent review article was also conducted, and in this review paper, the self-attention mechanism was proposed to tackle the current challenges. Self-attention mechanism, particularly the self-attention mechanism when combined with temporal EEG signals. This innovative approach showcased immense potential in enhancing the accuracy and efficiency of feature selection and classification in MI-BCI applications. By leveraging the self-attention mechanism's ability to capture long-range dependencies and temporal dynamics, researchers can effectively exploit the rich temporal information present in EEG signals, enabling more precise identification of discriminative patterns and yielding improved performance in MI-BCI systems.

Through this in-depth exploration of technologies, challenges, machine learning techniques, datasets, and the emerging role of attention mechanisms, this review article offers valuable insights into the field of EEG signal acquisition and analysis, while also pointing towards exciting directions for future research in the pursuit of more advanced and efficient MI-BCI systems.

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