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SURVEY

A Survey of EEG and Machine Learning-Based Methods for Neural Rehabilitation

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ABSTRACT One approach to therapy and training for the restoration of damaged muscles and motor systems is rehabilitation. EEG-assisted Brain-Computer Interface (BCI) may assist in restoring or enhancing 'lost motor abilities in the brain. Assisted by brain activity, BCI offers simple-to-use technology aids and robotic prosthetics. This systematic literature review aims to explore the latest developments in BCI and motor control for rehabilitation. Additionally, we have explored typical EEG apparatuses that are available for BCI-driven rehabilitative purposes. Furthermore, a comparison of significant studies in rehabilitation assessment using machine learning techniques has been summarized. The results of this study may influence policymakers' decisions regarding the use of EEG equipment, particularly wireless devices, to implement BCI technology. Moreover, the literature review results offer suggestions for further study and new research areas. We plan to identify the additional characteristics of each EEG equipment and determine which one is most suited for each industry by measuring the user experience based on various devices in future research.

INDEX TERMS Brain–computer interface (BCI), EEG, electrocorticography, electroencephalogram.

I. INTRODUCTION

Rehabilitation is an approach to therapy and training aimed at restoring damaged muscles and motor systems. A developing area of neurotechnology is the brain-computer interface (BCI). BCI applications have found usage in diverse areas by helping individuals suffering from neuromuscular problems like stroke, diseases in the spinal cord, Amyotrophic Lateral Sclerosis (ALS), and injuries in the spinal cord to improve their quality of life. Modern prosthetic technology, aid, and rehabilitation may be replaced by a system that combines neurology, robotics, machine learning, and BCI. BCI may also aid in restoring or enhancing the brain's lost motor abilities. Assisted by brain activity, BCI offers simple-to-use technology aids and robotic prosthetics. BCI converts user-triggered brain activity into the control output of suitable equipment to carry out any predetermined action [1]. Technology for rehabilitation relies on more sophisticated neurophysiologically inspired designs that help in operant conditioning and recovery. For instance, a robot-guided system may help the movement of an injured limb based on the operand's neuromotor activity [2]. BCI facilitates neuromodulation and augmentation in neuromotor outcomes for stroke survivors [3].

BCI applications are primarily intended to aid those with significant motor impairments in daily life. Several BCI-enabled devices have been designed to support human activities and rehabilitation [4]. Moreover, numerous investigations have vouched for BCI to aid those with severe disabilities like paralysis. BCI offers direct communication between the brain and technology, which may help restore the capabilities of a disabled person suffering from musculoskeletal diseases. The distinction between invasive and non-invasive techniques for observing brain activity depends on where the electrodes are placed. In procedures involving invasive operations, neurosurgery is performed in which one or more BCI units are used for direct electrode implantation in the cavity of the brain to monitor the brain region [5].

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The signals generated here are of excellent quality, but this procedure has a substantially detrimental effect since it causes the brain's scar tissue to increase [6]. Electrocorticograph (ECoG) which directly records brain activity from the brain surface, illustrates an invasive technique [7].

An alternative non-invasive electroencephalogram is more accurate, less expensive, yet uncomfortable than the invasive approach [4]. For instance, an EEG uses electrodes on the scalp to track and record brain electrical activity in the form of waves. These wave signals are sent to a computing system based on the obtained patterns in the generated waves. The three main signal-capturing techniques used in the EEG primary paradigm are motor imagery (MI), P300, and steady-state visual evoked potential (SSVEP) [8]. These three paradigms offer different potentials and approaches. In the P300, a high positive peak is observed in the generated EEG waves after about 300ms of a stimuli-inducing task involving tasks related to a human event, if the person is intensely focused on a task.

On the other hand, motor imagery is focused on the psychological mechanism to any movements which do not involve any muscle activity [9]. BCI can visualize specific actions, like holding an object, and the brain directs the order towards the controlling device that controls these movements. Some strategies were presented to help patients regain impaired motor control [10]. The first technique involves teaching patients to generate more motor brain impulses, while the second involves teaching patients to activate tools that enhance motor performance. Even though people with acquired motor deficits frequently show issues with motor connections, the EEG approach reveals incredible gains and ongoing alterations. An evaluation of 16 patients affected by chronic stroke who used a brain-computer interface for feedback related to arm and hand orthotics was first published in [11]. Persons with physical disabilities are enabled by assistive technology in different situations, such as moving, playing, and conversing like regular people. The tension that caregivers experience when considering people with impairments can be lessened by this technology [11], [12], [13].

Although the use of EEG signals has only been partially investigated thus far, it is abundantly evident from the literature that these methods provide essential and supplementary data regarding several neuromotor assessment-related topics [14]. Various research studies have demonstrated that the use of such technologies enables a more efficient understanding of disorders affecting the central nervous systems that result in motor impairments, especially from a neuromotor perspective. The EEG provides detailed insights that help customize and modify therapy by providing doctors with pertinent information on motor organization. This topic has been investigated using EEG [15] in separate investigations, and it is in a setting that is progressing toward resource reduction, cost containment, and rehabilitation efficiency [16].

In light of the previously mentioned considerations, this systematic literature review seeks to review all available papers on a topic that has not been thoroughly explored. EEG is required to guide rehabilitation and study physio-pathological motor function. Further, there is a need to discuss state-of-the-art techniques and foreseeable patterns and directions for using EEG as a successful measure for neural rehabilitation. Adaptive technology is a generic term to describe improved versions of currently available technologies that provide additional features and interaction opportunities to assist individuals in carrying out particular tasks [17].

The primary objective of the literature review is to locate pertinent material using BCI technology that can support rehabilitation. The rest of this manuscript is structured as follows; the subsequent section elaborates on the adopted methodology. Further, the findings from the systematic review were then compiled to conclude the findings. A discussion was presented, conclusions were established based on the results, and new research areas were suggested to maximize the impact of the outcome. As shown in Table 1, several survey articles relevant to BCI for brain rehabilitation have been recently proposed.

II. ROLE OF EEG AND COMPUTER VISION TECHNIQUES FOR NEURAL REHABILITATION

This section examines how these technologies are used to help individuals recover and improve their neural functions after suffering from neurological conditions or sickness.

- Brain-computer interfaces (BCIs) based on EEG allow people to control external equipment with their brain signals. EEG signals are used in motor imagery exercises to aid with motor function rehabilitation [11], [12], [75], [76], [78]. EEG-guided tasks targeting memory, attention, and other cognitive processes are used in cognitive rehabilitation. Real-time EEG data is employed in feedback systems [18], [21] to alter and personalize rehabilitation methods.
- Motion tracking and gesture recognition are used to evaluate and enhance motor function and coordination. Systems that use virtual reality (VR) and augmented reality (AR) create immersive and interactive rehabilitation environments [23], [27], [31]. Visual feedback devices that provide real-time visual cues to patients direct their movements and activities. Gaze tracking and eye movement analysis can help with vision rehabilitation and correct coulometer problems [36], [47], [51].
- Users can operate virtual environments or prosthetic equipment using a combination of brain signals and visual cues in hybrid EEG-computer vision systems [18], [32], [36].
- Multimodal feedback mechanisms involve the use of both EEG and visual data to provide real-time coaching and modification during rehabilitation exercises. Neurofeedback and visual feedback research and development aim at improving brain plasticity and recovery outcomes [44], [56], [59], [67]. The summary of various EED driven BCI technologies for rehabilitation is shown in table 2.

TABLE 1. Comparison of this survey with existing survey.

Ref	Year	Type of article	Devices	Objective	Description
[57]	2022	Survey	EEG, EMG	This review analyzed 55 articles from scientific databases after rigorous scrutiny of 213 articles.	Analyzing EEG/EMG signals simultaneously is relatively rare since each signal is analyzed using gold-standard techniques in their respective fields
[58]	2021	Survey	EEG	In total, 238 papers met the inclusion criteria.	Different adaptive, and rehabilitation BCI were identified.
[59]	2023	Survey	EEG	Described how BCI and brain-controlled robotics have improved rehabilitation and assistance of upper and lower limb motor functions.	BCI-controlled robotics are becoming more widely used in clinical settings, but there are challenges preventing their widespread use. This article discusses the upcoming trends in BCI-controlled robotics to expand its intervention capabilities and to overcome existing challenges.
[60]	2020	Survey	Mi-EEG	In this study, DL-based approaches have been used in MI-EEG classification research for the last decade and they must be systematically reviewed.	A summary of MI-EEG applications, an intensive exploration of public MI-EEG datasets, and a visual representation of the performance obtained for each dataset are presented in this work.
[61]	2022	Review	EEG, EMG	A study was conducted to investigate electromyography (EMG) and electroencephalography (EEG) as possible control input signals to exoskeletons.	Compare two methods for controlling exoskeletons with a brain-machine interface.
[62]	2019	Review	EEG	For the rehabilitation of upper limb stroke patients, electroencephalogram (EEG)-based Neurofeedback has been used based on 14 studies	According to the findings of this research, Neurofeedback training was superior to conventional therapy in terms of effectiveness, and it was much more beneficial when used in conjunction with EEG.
[63]	2021	Experimental	EEG, EMG	The authors presented a brand-new method for real-time movement prediction utilising physiological data that is based on field programmable gate arrays (FPGA).	Twelve healthy volunteers in total participate in an offline study and an online study to evaluate the system. Demonstrated that it offers good computing performance and considerably less power usage than a typical PC.
[64]	2021	Review	EMG	The authors focused on EMG signals to highlight applications in the context of rehabilitation. Instead of focusing on how sensors and biological applications are employed in business, this review examined how they are used in literature.	This study focused on sensors and systems for physical rehabilitation and health monitoring, as well as the identification of the main commercial sensor types currently utilised in biomedical applications. The study looked at work that has been done between 2016 to present.
Our survey		Systematic literature review	BCI with neural rehabilitation	A total number of 80 articles were extracted through search string. The search string has been made in research process.	This survey's goal is to give a comprehensive and systematic assessment of current research at the interface of electroencephalography (EEG) and machine learning in the context of neurological rehabilitation.

III. BACKGROUND

BCIs are based on neuroplasticity principles, which refer to the brain's ability to reorganize it by creating new neural connections. Because this reorganization might occur as a result of neurological traumas or disorders [21], [22], [27], [29], [31], [47], [53], BCIs provide a viable option for brain rehabilitation. Machine learning is also critical in improving the capabilities and efficacy of BCIs for brain rehabilitation:

- Machine learning methods such as support vector machines (SVMs), deep neural networks (DNNs), and random forests are used to recognize patterns in brain signals that correspond to certain motor or cognitive objectives [43], [58], [62], [74].
- Machine learning allows BCIs to adapt to changes in a user's brain signals over time. Adaptive models constantly adjust their parameters in response to new data, resulting in increased accuracy and robustness [53], [56], [59], [60].
- Machine learning enables tailored rehabilitative interventions. Models can be trained to recognize a user's distinct brain patterns and alter rehabilitation methods as needed [7], [11], [19], [41], [47], [79].

TABLE 2. Summary of EEG-Driven BCI technologies used for rehabilitation.

Application Domain	Deployment	Use case
Addiction disorders	Real-time detection of cravings to provide live feedback to patients with addictions.	Eating disorders [5], obesity [8], [11], drug addiction [12], [15], [16], alcohol addiction [19], [21], [22]
Assistive technology	To help the rehabilitation of persons with physical disabilities.	Upper and lower extremities [7], [8], [11], persons with tetra- or quadriplegia [13], [18], [19], motor nerve control locked-in patients [11], [12], [13], [15], [61], [62], [36], [64]
Diagnosis	To assist diagnosis through neurophysiological markers.	Locked-in state, mild cognitive impairment [51], [52], [53], [55], vegetative state/coma [63], [65],[66]
Testing and observing	To instantly recognize and categorize different brain states.	Acute trauma [18], [19], [34], [39], Alzheimer's disease [23], [37], Parkinson's disease [36], [41], [52]
Prevention	To slow down neurodegeneration through neurofeedback.	Alzheimer's disease [23], [37], [41], mild cognitive impairment in elderly persons [51], [52], [65], [67]
Therapy	To initiate or accelerate brain plasticity in damaged or disordered cortical networks by providing neurofeedback.	ADHD [41], [53], autism [15], [18], epilepsy [11], [21], [39], cortical stroke [21], [37], [39], [49], Alzheimer's disease [23], [37], [41], schizophrenia [21], [37], [53], [56], depression [59], [63], [65], [66], psychopathy [56], [58], [70]
Wellness	To trigger mental performance or emotional well-being. This is also known as cognitive enhancement.	All users

- Machine learning algorithms process brain impulses in real-time, providing consumers with rapid feedback. BCIs combined with machine learning can produce closed-loop systems that respond in real-time to a user's brain signals [13], [21], [29], [46], [53], [63]. A BCI-controlled robotic arm, for example, can adapt its movements based on the user's motor intentions, increasing motor relearning.
- Using a user's brain signals, machine learning can forecast the likelihood of effective rehabilitation outcomes. This data assists clinicians in personalizing interventions for the best possible outcomes [53], [57], [64], [69], [71].
- Using machine learning techniques, BCIs may fuse data from several modalities, such as EEG, fMRI, and kinematic data, to provide a more comprehensive picture of brain activity and rehabilitation progress [23], [29], [53], [69].

The combination of BCIs and machine learning technologies has the potential to completely transform neurological rehabilitation by providing more accurate, adaptable, and personalized therapies. These technologies hold promise for people suffering from stroke, spinal cord injuries, traumatic brain injuries, and neurodegenerative disorders, with the goal of restoring lost functions and improving their quality of life.

IV. RESEARCH PROCESS

This section details the chosen methodological approach for carrying out a systematic review of literature [13]. In light of the research questions mentioned earlier, the pertinent literature from 2010 to 2023 has been examined for this survey. Various scientific databases such as IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, Taylor & Francis Online, and Wiley Online Library were searched to obtain scientific material, using keywords like Electroencephalography + rehabilitation, EEG + rehabilitation, EEG + Brain Computer Interface, Electroencephalography + BCI, EEG + BCI + rehabilitation, BCI + Motor control, BCI + rehabilitation. The obtained material underwent screening, validation, and inclusion. The exclusion before screening involved the removal of articles that occurred multiple times or were published in languages other than English. The information conveyed by the article's title, abstract, and conclusion was used to decide on the relevancy of the article for the survey. A coherent library was built with the help of Mendeley, in which articles were aggregated, filtered, and excluded.

The relevant articles that were chosen were rigorously evaluated and included in the study. The Mendeley reference management technology was used to create a consistent reference library. The collected papers were collated, categorized, and systematically organized inside this library depending on their thematic importance. To refine the collection, filtering procedures were used to ensure that publications were suitably organized based on their focus on EEG-based neurological rehabilitation. This methodological technique ensures the survey's completeness and validity, allowing for a thorough examination of the current literature. The survey captures a comprehensive overview of advancements in EEG-based brain rehabilitation throughout the selected timeframe by accessing a variety of sources and employing targeted search phrases.

The research focuses on individuals using prosthetic arms, gait exoskeletons, and state-of-the-art stroke rehabilitation for Lower/Upper extremities (UE/LE). In this study, we place particular emphasis on recent technological advancements in BCI robotics that have the potential to be used in therapeutic settings. Research trends include the adoption of decoding tools such as artificial neural networks using deep learning, portable and personal robot-wear such as soft robotics, the development and testing of procedures investigating the use of brain-computer interfaces for stimulation and the effectiveness of various feedback modalities, and the development of brain-computer systems that can handle heterogeneous data, augmented with inputs that are not directly related to the brain. Finally, the problems with existing BCI systems and rehabilitation robotics are discussed, along with potential future study routes. The following subsection elaborates on

TABLE 3. Research questions and its motivation.

RQ	Description	Motivation
RQ1	What are the most current innovations and patterns in the integration of Brain-Computer Interfaces (BCIs) with various applications?	To provide an overview of the field's current state of research and to identify major developments in the application of BCIs.
RQ2	What types of neural rehabilitation activities are addressed by EEG and machine learning and deep learning?	It focuses on categorizing the many rehabilitation tasks that have been targeted utilizing EEG and machine learning methodologies, such as motor recovery, cognitive rehabilitation, communication restoration, and so on.
RQ3	What are the most prevalent EEG signal processing techniques used in neural rehabilitation research?	To investigate EEG signal processing approaches such as preprocessing, feature extraction, dimensionality reduction, and noise reduction strategies.
RQ4	What machine learning and deep learning methods have been used for EEG-based neural rehabilitation?	To investigate the machine learning algorithms used in the context of brain rehabilitation for analyzing EEG data, such as classification, regression, clustering, and reinforcement learning techniques.
RQ5	What performance indicators are utilized to assess the efficacy of EEG-based neural rehabilitation methods?	This question focuses on the quantitative and qualitative evaluation measures used to analyze the success and impact of various EEG and machine learning-based rehabilitation treatments.
RQ6	What are the present research limits and gaps in EEG-based neural rehabilitation utilizing machine learning and deep learning methods?	This topic aims to bring out areas in which further study is needed, as well as the limitations and obstacles that present methodologies and studies confront.
RQ7	What are the possible possibilities towards creating trends in neurological rehabilitation research based on EEG?	To investigate potential advancement paths, such as advance technology, interdisciplinary collaborations, and undiscovered application areas.
RQ8	What is the current state of research in machine learning-based EEG-based neural rehabilitation?	To overview the available extracted studies and identify the important trends, strategies, and approaches in the discipline.

the use of fundamentals of EEG-driven neurotechnology used for rehabilitation. Based on the keywords, the search string has been generated to extract the relevant studies which have been used for survey purposes. The search string is:

(''EEG'' OR ''electroencephalography'') AND (''machine learning'' OR ''computational intelligence'') AND (''neural rehabilitation'' OR ''neurorehabilitation'') AND (''survey'' OR ''review'' OR ''systematic review'' OR ''literature survey'') AND (''methods'' OR ''approaches'' OR ''techniques'').

Throughout the search string, a total number of 80 articles have been identified through ScienceDirect, SpringerLink, IEEE Xplore, ACM digital library and Scopus search databases. Several research questions have been built based on extracted studies. The research questions (RQ) along with motivation have been presented in table 3.

A. SAMPLE VIEW OF RESEARCH QUESTION IN DATA EXTRACTION MODE

The EEG method uses the skull to track the brain's electrical activity. EEG is used to diagnose conditions that cause seizures and metabolic, viral, or inflammatory conditions that alter brain activity. EEGs can be used to confirm brain death, assess sleep problems, and track brain activity in patients who have lost consciousness or are entirely sedated. This risk-free, painless test can be carried out in a testing facility, a hospital, or a controlled environment. The subject typically lies in a chair or bed during the exam. Several cup-shaped electrodes are placed on the scalp using a unique conducting material. The electrodes are connected to wires, often called leads, that transmit the brain's electrical signals to a machine. External stimuli may be used during an EEG recording session, including loud noises, bright or flashing lights, or even specific medicines. People can be instructed to alter their breathing patterns or to open and close their eyes. An EEG device or computer records and analyzes changes in brain wave patterns. Typically, an EEG test lasts about one hour while an EEG during sleep is necessary for testing disorders and takes several hours. Additionally, researchers [56] propose a unique method for distinguishing between EEG signals from alcoholics and healthy controls that includes phase space dynamic and geometrical properties. Geometrical features are also extracted from the phase space representation of the EEG signals, representing the underlying structures and complexity.

The experimental findings shows that the suggested method provides the best classification performance for the twenty-three features chosen by Henry gas solubility optimization using feedforward neural network (FFNN), with 99.16% accuracy, 100% sensitivity, and 98.36% specificity. A summary of the BCI sample view through machine learning and deep learning is presented in table 4.

B. NEUROTECHNOLOGY BASED ON EEG

Any technology that communicates with the neurological system is referred to as neurotechnology. Monitoring brain activity is one of the critical components of many neurotechnological advancements. EEG monitoring enables us to measure various brain waves, also referred to as neural oscillations. Brain control of various devices is one of the most well-known and widely publicized uses of EEG-based neurotechnology. Examples include keyboards for individuals with locked-in syndrome [5] and controls for

TABLE 4. Usage of BCI in machine learning/deep learning.

EEG usage in BCI	Description
EEG Data Acquisition	Collection of EEG signals using electrodes
EEG Preprocessing	Filtering, noise reduction, artifact removal
Feature Extraction	Extracting relevant features from EEG data
Classification Algorithm	ML/DL algorithms (e.g., SVM, CNN, LSTM)
Training and Testing	Training on labeled data, testing on new data
Performance Evaluation	Metrics like accuracy, precision, recall
Adaptive BCI Systems	Adjusting models based on user responses
Cognitive State Classification	Identifying mental states (e.g., attention)
Motor Imagery Control	Controlling devices via imagined movements

wheelchairs, drones, or robots [18], [19]. One remarkable aspect of neurotechnology is its ability to alter our neural circuits' function by using the nervous system's plasticity. This indicates that the results will last for a while after using neurotechnology for a specific amount of time. Typically, this is carried out by monitoring brain waves and delivering tailored stimulation according to specific activity patterns decoded by the brain. We commonly refer to this as closed-loop or brain state-dependent feedback. Electro/magnetic stimulators, robotic exoskeletons, and visual and auditory stimuli are some standard methods used to excite the nervous system and produce such changes.

V. RESULTS AND DISCUSSIONS

A. WHAT ARE THE MOST CURRENT INNOVATIONS AND PATTERNS IN THE INTEGRATION OF BRAIN-COMPUTER INTERFACES (BCIS) WITH VARIOUS APPLICATIONS?

There are several applications that are integrated with BCI along with EEG integration as shown below.

1) BCI-ROBOTICS FOR REHABILITATING MOTOR PARADIGM

Millions of people worldwide live with motor disabilities brought on by spinal cord injuries or strokes. Many of them cannot execute simple tasks like picking up a glass or walking, and typical rehabilitation techniques frequently fall short in helping patients regain their crippled functionality of motor nerves.

The foundation of neurotechnology-based rehabilitation of motor functionality is that the interdependent relationship between the electrical activity of the human brain when motion is attempted and the sensory feedback from outside the central nervous system enables restoration of the sensory circuits in motor nerve connections fosters recovery of motor circuitry [20]. This indicates that after using the technology for some time, the patient's motor function will improve due to the training's facilitation of restructuring their brain and/or motor pathways.

One of the most extensively investigated application areas of non-invasive brain-computer interfaces utilizing EEG signals is motor rehabilitation. They usually function by recognizing when a patient is making an effort to move (e.g., by sensing the attempt of movement from EEG) and then assisting the sensed movement either with the aid of a prosthetic limb [21], [22] or by electrically stimulating the muscles [23], [24].

A prominent area where BCI solutions can be deployed for applications involving clinical procedures is post-stroke UE motor therapy because of the severe motor deficits brought on by stroke and how they affect the survivor's quality of life. The ground-breaking study in this area, published more than ten years ago, used magnetoencephalography as data input for their (MEG)-BCI-controlled hand orthosis for stroke rehabilitation [25]. Even though the participants could not experience a meaningful therapeutic benefit, it was found that they attained control over orthosis by learning to alter the mu rhythm amplitude. Using numerous brain-computer interfaces non-invasively in conjunction with input provided by a robot or orthosis was then documented.

The role of brain-computer interfaces in UE stroke rehabilitation has been studied and methodically analyzed in studies [26]. It was revealed in the study [27] that chronic stroke patients may train their fingers to extend using a BCI and a finger-individualized orthosis. The findings show that finger extension ability and functional outcomes were both improved in the participants with more robust sensorimotor rhythm (SMR) modulation. BCI-robotics can incorporate rehabilitation of both coarse and delicate hand movements. The previous BCI research employed heavy, hard-bodied robots that are frequently expensive, have intricate controls, and have a limited range of motion [28].

Soft robots are a kind of wearable, lightweight robots with flexibly mounted actuators. It has been shown that using soft robots increases the effectiveness of hand rehabilitation [29]. Consequently, by combining soft robotics with brain-computer interfaces, a nonrestrictive, intuitive, and real-life movement can be added to the feedback mechanism. Using a soft robotic glove controlled by EEG-BCI and task-specific visual feedback, a stroke rehabilitation system was described in the article [30] as pilot research in this area. The research revealed improvements as proof of a phenomenon known as a kinesthetic illusion in the test individuals. For the relationship between observed activity in motor circuitry and natural motor recovery, a substantial number of human clinical studies and neurological data are required to support these conclusions.

A somewhat new BCI application is post-stroke LE rehabilitation. An effective BCI design includes robot control in real-time and closed-loop accurate deciphering of kinesthetic walking intention and visuals by the BCI (or exoskeleton). The performance of LE decoding, which has not yet been perfected, severely restricts the former while increasing safety issues in the latter. A few research studies have shown that it is possible to use BCI to decode lower limb joint kinematics and kinetics while in motion. In experiments [31], EEG was captured when the individual practiced walking with a robot. Moderate LE joint kinematics deciphering accuracy based on offline analyses was observed in research [31], [32].

TABLE 5. Non-invasive EEG apparatuses are used for assistive, adaptive, and rehabilitative purposes.

Brand	Model	Wired	Wireless	Number of channels	Additional sensors supported	Intended Use
Advanced Brain Monitoring	B-Alert® X10	×	✓	9 channels	✓	Neuromarketi+G2:G41ng, BCI, identify biomarkers
	B-Alert X24	×	✓	20 channels	✓	
BIOPAC Systems Inc.	EEG100C	✓	×	16 channels	×	Epilepsy, tumor pathology, sleep studies, evoked responses,
						Cognition studies.
ANT Neuro	eegosports	×	✓	64 channels	✓	BCI, neurofeedback
						Neurorehabilitation, neurogaming
Biosemi	ActiveTwo ×	✓	×	16-256 channels	✓	Electrophysiology research
Brain Products	actiCAP system	✓	×	8-256 channels	✓	Neuroscience
	ACTi- Hamp	✓	×		✓	Neurofeedback
	Brain -Amp	✓	×		✓	Neurophysiological
	Brain -Vision	✓	×		✓	
	V-amp	×	✓		✓	
	MOVE system	×	✓		✓	
Cognionics Inc.	HD-72 EEG	×	✓	64 channels	✓	Neurofeedback,
	Quick-20	×	✓	21 channels		Neurodiagnostic
CompumedicsNeuroscan	Grael	✓	×	Up to 256 channels	✓	Clinical
	Nu-Amps	✓	×		✓	Neuro-diagnostics,
	Syn-Amps	✓	×		✓	research
Emotiv	Emotiv EPOC	×	✓	5-14 channels	✓	Research, personal use
	Emotiv Insight	×	✓		✓	
g. Tec	g.BSamp	✓	×	Up to 256 channels	✓	BCI, neuroscience, neurotechnology
	g.Hiamp	✓	×		✓	
	g.USBamp	✓	×		✓	
	g.MOBIlab+®	×	✓		✓	
	g.Nautilus	×	✓		✓	
	Unicorn Hybrid Black	×	✓		✓	
Neuroelectric	Enobio 8	×	✓	8-32 channels	✓	Neuroscience, BCI, neurogaming,
	Enobio 32	×	✓		✓	Neurofeedback
	StarSim 8	×	✓		✓	
	StarSim R32	×	✓		✓	
NeuroBioLab	NBL640	✓	×	24 channels	×	Neurobiofeedback
OpenBCI	OpenBCI 32bit	×	✓	4-21 channels	✓	BCI, biosensing, neurofeedback
	Open BCI Cyton	×	✓		✓	
	OpenBCI Ganglion	×	✓		✓	
	Ultracortex BCI	×	✓		✓	

TABLE 5. ***(Continued.)*** **Non-invasive EEG apparatuses are used for assistive, adaptive, and rehabilitative purposes.**

Narosky	Brainwave	×	✓	Single channel	✓	BCI, neurogaming, neurofeedback,
	Mind Flex	×	✓		✓	Neuroscience, meditation
	Mind Wave	×	✓		✓	
	ThinkGearAM (TGAM)	×	✓		✓	
Medical Computer Systems	NVX52	✓	×	48 channels	✓	Research

Following the gait training, functional ambulation capacity, functional connectivity, and sensorimotor plasticity all showed a substantial increase, according to a connectivity analysis in the study [33]. A study [34] has also looked into the modulations in sensorimotor rhythms and motion-related brain potentials connected to gait decoding performance. The spectral and temporal dynamics of the neuronal encoding of gait patterns are also controversial, as recently examined [35]. This makes the consistent and accurate decoding of gait using non-invasive brain data an arduous task. As a result, no studies have been completed that demonstrate the success of BCI-robotics in treating LE stroke. However, recent information on BCI gait decoder technology advancements promise high accuracy and the possibility of continuous gait decoding.

Multiple EEG-based gait decoding techniques were recently rigorously compared to develop a viable online decoding system [36]. A variety of Machine Learning (ML) approaches are used to analyze EEG signals and analyze the effectiveness of Brain-Computer Interface (BCI) technologies for neural rehabilitation [35], [42], [47], [63]. These techniques are critical for decoding brain activity, comprehending cognitive processes, and enabling effective BCI-based rehabilitation solutions. EEG data is prepared for analysis using preprocessing procedures such as artifact removal [52] and feature extraction. Support Vector Machines [45], Random Forests [47], and deep learning architectures such as Convolutional Neural Networks [36], [38], [45] and Recurrent Neural Networks decode brain signals and allow for precise classification of cognitive states or motor intentions. In BCI applications, feature selection and dimensionality reduction strategies improve model performance [32], while domain adaptation and transfer learning handle inter-subject variability. Adaptive BCI paradigms, such as P300-based [52], motor imagery, and SSVEP-based BCIs [15], [67] provide a variety of neurorehabilitation techniques. By giving users with feedback for adaptive control, reinforcement learning can improve BCI systems. Cross-validation [68] and online assessment approaches are used to examine the generalization and real-time performance of BCI models. The study [56] extracts the graphical features from dynamic and geometric properties of EEG data. The geometric features [69] have been fed to a feed forward neural network (FFNN) model for the classification of alcoholic and healthy control factors [70]. For precision control of BCI-based exoskeletons employing versions of recurrent neural networks (RNN) based on offline benchmarking and comparing approaches spanning various linear decoders as well as RNN. It is also important to point out that a deep neural network based on LSTM was also employed in the recent experiment, which focused on healthy volunteers to accomplish reliable gait reconstruction [37] assessed in both offline and online scenarios.

2) BCI-ROBOTICS FOR MOTOR ASSISTANCE

The brain-computer interface (BCI) is a turning point device that expressly [62] uses cognitive function for interaction with external devices without the use of motors. Although BCI based on motor imaging has proven efficacy in stroke patient treatment, their usage in clinical practice has been limited due to poor performance, non-flexible properties, and extensive training periods. It has been demonstrated that BCI can provide neurological regulation of a robotic arm and exoskeleton of the lower limb using invasive intracortical recordings. The first case study describing invasive-BCI use to enable continual voluntary regulation over a robotic arm having multiple joints by an individual suffering from tetraplegia can be found in [38]. Additional research has documented tetraplegic patients' stroke-related paralysis using neuroprosthetic control of a prosthetic arm [39], [40]. The article [41] thoroughly evaluated the use of BCI as a communication, control, and rehabilitation tool in paralysis. Since then, interest has risen in developing non-invasive BCI to manage more freedom robotic arms for potential motor assistance and rehabilitation.

In contrast, traditional non-invasive BCIs exclusively use bidirectional as well as unidirectional control over motor circuitry. Some recent experiments have shown high-dimension continual motor control using the unique decoding algorithms and control methodologies to work effectively with a poor signal-to-noise ratio of non-invasive data. Healthy volunteers [42], paralyzed patients [43], [44], and quadriplegics [43], [44] have all been used in studies.

A closed-loop prosthetics monitoring via BCI was described in papers [43] [44] using EEG and MEG, respectively. Recently, it was demonstrated [42], [45] how to precisely combine two sequential low-dimensional controllers to operate a robotic arm with numerous degrees of freedom. Movement-related cortical potentials in the low frequency-time domain were used in the study [46] to show the simulation of brain-computer interface control of a virtual robot online.

In addition to traditional collaborative tasks performed by BCI robots, getting control of the robotic arm simultaneously with the arm of the individual was described as an alternative [47]. Researchers developed a BCI-controlled robot control framework that produced a continual trajectory of robot movement out of the discontinuous BCI signals. The outcomes of the experiments conducted on healthy participants suggest that BCI-based robotic control systems are a more efficient and realistic way to operate robotic devices.

A robotic arm in a 3D environment is controlled by BCI [48], powered by machine learning. Machine learning using a multi-directional convolution neural network and a bidirectional LSTM network was reported in the study. With the mentioned advancements in technology, BCIs developed non-invasively, can manage a robotic assistance device continuously and expertly.

The author describes [59] a unique method for Motor Imagery (MI) classification in Brain-Computer Interface (BCI) systems that employ two-dimensional modelling in empirical wavelet transform (EWT). Using EWT, a data-driven time-frequency analysis method, the authors presented a new technique for extracting features from MI EEG signals. The spatial and temporal dynamics of EEG signals during motor imagining tasks are captured using this method. A novel method for classifying Motor Imagery (MI) in Brain-Computer Interface (BCI) systems based on multivariate variation mode decomposition (MVMD) has been employed [60]. By decomposing the data into intrinsic mode functions, the approach tries to extract discriminative features from MI EEG signals. MVMD enables multivariate analysis by taking into account the interdependencies across EEG channels during motor imagery tasks. The study [61] assesses the efficacy of this technique in decoding MI EEG patterns, with the goal of improving the accuracy and reliability of BCI devices. Machine learning classifiers are used to classify the retrieved features into several MI classes. The results provide promising results, demonstrating that the multivariate empirical wavelet transform paradigm improves the resilience of MI decoding in BCIs. Using empirical Fourier decomposition (EFD) and enhanced EFD (IEFD) approaches, the study [63] provides a unique automated computerized framework for proficient detection of motor and mental imagery (MeI) EEG activities. Specifically, MSPCA is used to denoising EEG data initially, and then EFD is used to divide nonstationary EEG into successive modes, while the IEFD criterion is provided for a single noticeable mode selection. Finally, the features in the time and frequency domains are retrieved and categorized using a feedforward neural network (FFNN) classifier.

3) USING EEG-BASED NEUROTECHNOLOGY TO ENHANCE AND REHAB COGNITIVE FUNCTION

The enhancement of cognitive ability can be helpful for individuals, irrespective of whether they have any brain-related neural disorder. However, improving motor function is explicitly focused on patients with movement impairment. Some mental and psychological illnesses, such as depressive disorders, attention-deficit disorders, mood disorders, and addictive disorders, can benefit from cognitive rehabilitation based on neurotechnology. A person with a healthy brain would also be open to cognitive advancement (e.g., in memory or attention). Studies in neuroscience have pinpointed distinct brain activity markers linked to cognitive function, such as parieto-occipital alpha activity [49]. The goal of neurofeedback approaches is to help users self-regulate such markers to improve their behavior.

These strategies establish a causal relationship (operant conditioning) between patterns in the brain and positive or negative feedback, driving brain alterations. Techniques like neurofeedback or EEG biofeedback have been suggested to aid cognitive improvement in various populations. For instance, [50] studied healthy volunteers, patients with depression, and children with ADHD using Elevvo, a cognitive training tool created by Bit brain [51].

4) THE USE OF EEG-BASED NEUROTECHNOLOGY TO IMPROVE MEMORY DURING SLEEP

Sleeping takes up about a third of our lives. During sleep, our bodies enter a state where control over behavior and awareness ceases to exist. During the period of sleep, the human body does several tasks necessary for maintaining our vital systems. Because some of these processes occur in the brain, improving them via neurotechnology may enhance certain of our abilities. One crucial process when you sleep is consolidating recently acquired memories [52]. Since it is now possible to observe someone's EEG while they sleep, numerous studies have examined the precise brain correlates of memory processing and consolidation. Real-time identification of the correlations can be used to change the occurrence, increase the effectiveness, and give brain state-dependent stimulation. Two well-researched neurotech-based methods were studied to enhance the consolidation of new memories. By delivering auditory or electrical stimulation in time with one of the slow-wave oscillation trains linked to information processing while you sleep, your memory will operate better [53], [54]. When properly timed with the appearance of sleep spindles, reactivating previously learned events has been found to promote their consolidation [55]. Table 2 offers a summary of EEG-driven BCI technologies to assist various types of rehabilitation.

5) NON-INVASIVE EEG-BCI APPARATUS DESIGNS

According to the studied literature, G. Tec, Compumedics Neuroscan, and Brain Products were the most popular EEG brands used by the research community. G. Tec's wired EEG equipment was mentioned in 41 research articles, with 26 articles mentioning Compumedics Neuroscan and 15 articles mentioning Brain Products. Biosemi revealed itself as the fourth most popular wired equipment brand, with eight study papers mentioning it. Among 42 research articles, a total of 40 studies have been work on Emotiv's wireless technology. Notably, Brain Products and G. Tec were among the few brands that offered both wired and wireless EEG equipment, while other brands provided a combination of wired and wireless BCI-based technologies. Wireless models are a developing method, but wired solutions continue to be the traditional answer. Table 3 summarizes the different non-invasive wired and wireless EEG equipment that could be used for rehabilitation and BCI.

B. WHAT TYPES OF NEURAL REHABILITATION ACTIVITIES ARE ADDRESSED BY EEG, MACHINE LEARNING AND DEEP LEARNING?

Here are some types of neural rehabilitation activities that can be addressed using EEG.

- *Motor Rehabilitation:* EEG signals captured during motor imagery tasks (e.g., imagining limb movements) can be decoded using machine learning algorithms to control external devices, such as robotic exoskeletons [13], [17] or prosthetics, assisting individuals with motor impairments. EEG-based real-time feedback systems can guide users to perform specific motor tasks or exercises, aiding in motor skill relearning and neuroplasticity [21], [23], [47], [51].
- *Cognitive Rehabilitation:* EEG signals can be used to measure and enhance attention and concentration levels through Neurofeedback techniques [8], [11], [13], [14]. Machine learning can be applied to adapt training protocols based on individual cognitive states. EEG and deep learning can help design personalized memory training tasks by analyzing neural patterns associated with memory recall and encoding [7], [8], [13], [14].
- *Neuropsychiatric Rehabilitation:* EEG can be utilized to provide biofeedback for stress and anxiety management. Machine learning can identify stress-related patterns and trigger relaxation interventions [10], [16], [19], [20]. EEG-based Neurofeedback can help individuals with ADHD improve focus and attention control by rewarding desired brain activity patterns.
- *Gait Rehabilitation:* EEG and machine learning can be integrated with motion capture systems to analyze gait patterns and provide real-time feedback during walking exercises [13], [14], [17], [73].
- *Visual and Auditory Rehabilitation:* EEG-based protocols combined with machine learning can be used to design visual and auditory training tasks for individuals with impaired sensory perception [23], [26], [27].
- *Multimodal Rehabilitation:* Combining EEG with other technologies such as functional near-infrared spectroscopy or virtual reality can create multimodal rehabilitation approaches that target a wider range of neural functions [37], [38], [47], [51], [53].

The flexibility and adaptability of these technologies offer promising ways to enhance rehabilitation outcomes and improve quality of life for people with neurological disorders.

C. WHAT ARE THE MOST PREVALENT EEG SIGNAL PROCESSING TECHNIQUES USED IN NEURAL REHABILITATION RESEARCH?

In neural rehabilitation research, various EEG (electroencephalography) signal processing techniques are used to analyze, interpret, and extract meaningful information from EEG data.

- *Filtering:* EEG signals are often contaminated with noise and artifacts. Filtering techniques such as high pass, low pass and notch filters [18], [26] are used to remove unwanted frequency components and improve signal quality.
- *Artifact removal:* Techniques such as Independent Component Analysis (ICA) and Principal Component Analysis (PCA) are used to separate and remove artifacts such as eye blinks, muscle activity and electrocardiogram (ECG) interference [28], [29], [31].
- *Time Domain Features:* Features such as mean amplitude, root mean square value, and signal variance are extracted to capture the temporal characteristics of EEG signals [47], [48], [51], [53].
- *Frequency domain properties:* Power spectral density, spectral entropy, and band power ratios provide insight into the frequency distribution of brain activity [11], [17], [18].
- *Time-frequency characteristics:* Techniques such as the wavelet transform and the short-time Fourier transform reveal how the characteristics of the EEG signal vary in time and frequency [23], [57], [61].
- *Functional connectivity:* Measures such as coherence, phase synchronization, and mutual information assess the functional relationships between different brain regions [51], [52], [54].
- *Graph theory analysis:* EEG data can be represented as networks, and graph theory metrics reveal organizational and communication patterns in the brain [64], [69].
- *Pattern recognition and motor imagery:* EEG signals captured during motor imagery tasks are processed to recognize specific patterns associated with imagined movements. These patterns can be used to control external devices [59], [60], [65], [72].

D. WHAT MACHINE LEARNING AND DEEP LEARNING METHODS HAVE BEEN USED FOR EEG-BASED NEURAL REHABILITATION?

In the context of EEG-based neural rehabilitation, various machine learning and deep learning methods have been applied to analyze EEG data and develop interventions aimed at enhancing neural function and facilitating recovery.

- *Machine learning techniques:* SVMs have been used for tasks such as motor image classification, which uses EEG signals to distinguish between different motor tasks or targets. These methods are used to classify EEG patterns associated with specific cognitive states, motor goals, or rehabilitation tasks. LSTMs are popular for time series data such as EEG and are used for tasks such as learning motor sequences and predicting cognitive states. k-NN algorithms have been used in EEG data for tasks such as identifying brain activity patterns related to cognitive performance and mental states.

- *Deep learning techniques:* In this section, we look at the various DL architectures used in BCI-EEG categorization studies. DL models are classified into four types based on their role [30]: discriminative, representative, generative, and hybrid DL models.
  - Discriminative models: Discriminative models are DL architectures that can learn different features from input signals using nonlinear transformations and classify them into pre-defined classes using probabilistic prediction. As a result, these techniques can be employed for feature extraction as well as categorization. CNN, RNNs (and their variants, GRU and LSTM), MLP, and ELM are examples of discriminative models [12], [16], [31], [37], [39], [43], [47], [51]. A CNN is a typical deep learning model that specializes in extracting local and spatial patterns. The CNN design is made up of a series of neural networks arranged in a specific order, each with a different size layer that performs a specific task. The deeper layers learn high-level features while the earlier layers learn low-level features. Convolutional layers (for feature extraction) [31], [36], pooling layers (for feature dimensionality reduction), and fully connected (FC) layers (for classification) are the three building blocks that make up CNNs. A convolutional layer is an important component of the CNN architecture for feature extraction. A pooling layer does conventional down sampling to reduce network processing. The pooling layer's output feature maps are typically flattened layers.
  - Representative models: Representative DL models are DL architectures that specialize in unsupervised feature extraction and can be utilized for a variety of applications such as clustering and classification. Deep AEs (D-AEs), deep RBMs (D-RBMs) [31], and DBN are examples of DL models. An autoencoders (AE) is a form of representative artificial neural network that uses efficient data coding to learn features unsupervised. AE is made up of three major components: an encoder, a code, and a decoder [51]. The encoder compresses the input into a latent-space representation called the code, which is subsequently utilized to reconstruct the input by the decoder.
  - Generative models: Typically, generative DL models are used to supplement and improve training data. GAN and VAE are the most often used generative DL models. Several researchers in this study used non-DL data augmentation procedures, including noise addition [11], sliding window [8], and amplitude perturbation [13], to enhance the quantity of training data. Two of the research evaluated [64], [67] used GAN and VAE networks for DL-based data augmentation. These studies found that utilizing GAN models for MI data augmentation considerably improved classification performance.
- *Hybrid DL models:* Hybrid deep learning models combine two or more deep learning models into a single network. In addition to the solo deep learning models discussed above, researchers have attempted to integrate several deep learning networks, with promising results for MI classification tasks [7], [63]. This analysis identifies five types of combinations: two discriminative models (for example, CNN/LSTM [56], [63], [68], [11], [17], [18], CNN/GRU [59], and CNN/MLP [55]), representative model combined with a discriminative model (e.g., CNN/SAE [60], [68]), generative model combined with a discriminative model (e.g., CNN/GAN [64], [68], and CNN/VAE [69]), discriminative model followed by SGAN.

E. WHAT PERFORMANCE INDICATORS ARE UTILIZED TO ASSESS THE EFFICACY OF EEG-BASED NEURAL REHABILITATION METHODS?

Here are some common performance indicators used to evaluate the effectiveness of EEG-based neural rehabilitation methods:

- *Classification accuracy:* In tasks such as motor imagery classification or cognitive state detection, classification accuracy measures how well an EEG-based model can distinguish between different classes or states [11], [13], [17], [21], [26], [27], [32], [47], [48].
- *Receiver operating characteristic (ROC) curve and area under the curve (AUC):* ROC curves and AUC values are used to evaluate the trade-off between sensitivity and specificity in classification tasks [26], [29], [33], [54].
- *Mean Squared Error (MSE) or Root Mean Squared Error (RMSE):* This metric measures the difference between the predicted and actual values, often used in regression functions to measure the accuracy of the prediction [13], [43], [46], [53], [63].
- *R-squared (R2) or coefficient of determination:* R2 measures the amount of variation in the dependent variable that can be predicted from the independent variables. It shows how well the regression model fits the data [56], [57], [59], [61].
- *Real-time performance metrics:* For real-time applications, metrics such as response latency, response time, and overall system latency are evaluated [55], [59], [60], [61], [63], [65].

F. WHAT ARE THE CURRENT RESEARCH LIMITATIONS AND GAPS IN EEG-BASED NEURAL REHABILITATION UTILIZING MACHINE LEARNING AND DEEP LEARNING METHODS?

There are many gaps that are identified in the study. The identified gaps include:

- Noise and artifacts in EEG data might impair the accuracy of machine learning and deep learning models. To achieve trustworthy and consistent results, researchers must address concerns such as data quality, pre-processing methodologies [15], [18], [43], [44], and standardization of data gathering protocols.
- Because of the difficulties in obtaining high-quality EEG data from patient populations, many EEG-based brain rehabilitation research have small sample sizes. This can result in model overfitting and poor generalizability [18], [23], [24], [27]. To create robust models, additional efforts are needed to collect larger and more diverse information.
- Monitoring progress in neural rehabilitation is frequently required. However, longitudinal EEG datasets that capture changes in brain activity while patients undertake rehabilitation are scarce. Long-term research is critical for determining the efficacy of various interventions and tailoring treatments accordingly [51], [59], [63], [74].
- Deep learning algorithms excel at learning patterns from data, but their black-box structure makes interpreting results difficult. To get a deeper knowledge of the underlying neurophysiologic mechanisms connected to brain rehabilitation, there is a need for research that integrates deep learning approaches with neuroscientific insights [15], [16], [17], [19], [26], [31]. As machine learning models get increasingly complicated, physicians and researchers must ensure that the judgments made by these models can be explained and evaluated. Creating tools to provide insights into why a model makes a particular decision can improve its clinical value [51], [53], [59], [64].
- Offline analysis is highlighted in several EEG-based brain rehabilitation techniques. Due to processing limits and the necessity for rapid and accurate reactions, real-time applications [31], [32], [49], [59], in which EEG data is analyzed and acted upon in real-time, are harder data for rehabilitation poses ethical problems about patient consent, data ownership, and privacy. These issues must be addressed carefully to guarantee that patients' rights are honored.
- While EEG-based neurological rehabilitation research is progressing, there may be a gap between academic research and clinical implementation [57], [61], [64], [66].

G. WHAT ARE THE POSSIBLE POSSIBILITIES TOWARDS CREATING TRENDS IN NEUROLOGICAL REHABILITATION RESEARCH BASED ON EEG?

Developing trends in EEG-based neurological rehabilitation research entails finding prospective directions that can affect the field's future. Here are some potential trends in EEG-based neurological rehabilitation research that could influence future research:

- *Multimodal Approaches:* By combining EEG data with additional modalities such as fMRI, fNIRS (functional near-infrared spectroscopy), or behavioral data, researchers [13], [17], [19], [20], [43], [49] can gain a more comprehensive understanding of brain activity and improve the efficacy of rehabilitation methods. Integrating numerous data sources could result in more personalized and targeted treatments.
- *Closed-Loop Systems (CLS):* The potential for developing closed-loop systems that alter rehabilitation interventions in real-time based on EEG input is enormous. These devices can optimize the rehabilitation process by automatically adjusting stimulation parameters or feedback mechanisms based on the patient's real-time brain activity.
- *Neurofeedback and Brain-Computer Interfaces (BCIs):* Real-time Neurofeedback and BCIs use EEG signals to allow patients to operate external equipment directly using their brain activity [19], [21], [27]. This method can improve motor or cognitive training while also promoting neuroplasticity by strengthening brain networks. EEG can be used to interpret motor intentions and aid in the control of prosthetic devices like exoskeletons. Advances in decoding motor orders from EEG data have the potential to revolutionize rehabilitation for those with motor disabilities.
- *Adaptive Learning Algorithms:* Using adaptive machine learning algorithms, rehabilitation treatments can be customized to each patient's development and needs. These algorithms [43], [49], [63], [65], [66], [79] can analyze EEG data in real time and change the complexity or character of training exercises as needed.
- *Brain connection Analysis:* Using EEG data to investigate functional and structural brain connection patterns can reveal how different brain regions interact throughout rehabilitation. This knowledge can be used to guide the development of focused therapies [80].
- *Individualized Biomarkers:* Identifying EEG biomarkers that correlate with various neurological diseases and rehabilitation outcomes might help patients be differentiated and treated more effectively. Personalized therapies based on these biomarkers have the potential to improve rehabilitation success [81].
- *Real-World Applications and Telehealth:* Research focusing on deploying EEG-based rehabilitation

interventions outside of clinical settings, such as at home or via Telehealth platforms, can enhance patient compliance and increase access.

H. WHAT IS THE CURRENT STATE OF RESEARCH IN MACHINE LEARNING-BASED EEG-BASED NEURAL REHABILITATION?

Machine learning algorithms were used on EEG data for motor rehabilitation, with the goal of interpreting motor intents and giving real-time feedback to control prosthetic devices or exoskeletons. These treatments are intended to restore motor function in people who had lost it due to a stroke.

- *Cognitive Rehabilitation:* Using EEG data, researchers used machine learning to create personalized cognitive rehabilitation programmers [13], [17], [18], [43]. In neurodegenerative illnesses, these interventions targeted issues such as attention deficiencies, memory impairments, and cognitive decline.
- *Neurofeedback and BCI:* Using machine learning algorithms, real-time Neurofeedback systems were developed, in which individuals receive instant feedback regarding their brain activity [6], [31], [33], [37], [56], [79]. By allowing users to adjust their brain activity patterns, these systems attempted to improve neuroplasticity and cognitive skills.
- *BCI Biomarkers:* Machine learning algorithms were used to find predictive biomarkers from EEG data, which indicated the likelihood of effective rehabilitation outcomes. This enabled personalized treatment planning and more precise intervention targeting [21], [36], [46], [61], [71].
- *Closed-Loop Rehabilitation:* Researchers were looking towards closed-loop devices that might change rehabilitation protocols in real time depending on EEG feedback [49], [53], [56], [77]. These technologies optimized the rehabilitation process by adapting training parameters to the user's continuous brain activity.
- Generalization of transfer learning models: Researchers were focused on increasing the generalization of machine learning models trained on one dataset to other datasets or individuals [14], [21], [27], [53]. To address the heterogeneity in EEG data across different patients and circumstances, transfer learning techniques were being researched.

Table 5 presents a summary of various non-invasive EEG apparatuses that are used for assistive, adaptive, and rehabilitative purposes.

VI. DISCUSSIONS AND CONCLUSION

The field of BCI research shows promise in clinical applications and neurophysiologic evidence for BCI-induced neuroplastic adjustments. However, conclusive clinical investigations demonstrating the effectiveness of BCI interventions are limited, hindering its integration into accepted clinical procedures.

BCI systems vary in design characteristics, and priming the brain before intervention has been shown to improve functional outcomes in rehabilitation. Combining BCI-based robotic solutions with other approaches like BCI-neuromuscular electrical stimulation has demonstrated favorable impacts. BCI-controlled soft robots have potential for effective stroke rehabilitation.

BCIs and rehabilitation can help individuals become more independent, benefiting both those with cognitive issues and physical impairments. EEG equipment can be utilized by healthy individuals and those with disabilities in various daily life situations.

To create non-invasive BCI applications, researchers should consider market needs and focus on end-user products. Wireless devices offer convenience and feasibility for long-term usage and outdoor applications. Ensuring data integrity and user experience assessments are essential for the adoption in BCI technology in various industries.

Additionally, for a positive impact, intensive strategies involve combining BCI-based robotic solutions with other approaches, such as BCI-neuromuscular electrical stimulation [15]. According to user satisfaction and usability assessments [34], soft robots are reportedly appropriate in rehabilitation applications for people with neurological disabilities. Both those with cognitive issues and those with physical impairments can benefit from assistive technology.

Overall, the EEG channel serves as a guide for adapting the technology to various levels of limitations and impairments. Furthermore, the BCI system [57] utilizes Binary Particle Swarm Optimization (PSO) and geometrical features collected from the Signal Order Difference Profile (SODP) form. This method shows promise in accurately diagnosing depression from EEG data, which could help with depression diagnosis and management. To generate Poincaré plots [58] using EEG data, the Discrete Wavelet Transform (DWT) can extract graphical features. The proposed technique shows promising results in reliably recognizing seizure occurrences by analyzing these aspects. The experimental results show that study has important implications for seizure detection and may help improve the diagnosis and treatment of epilepsy and other seizure-related illnesses.

To create non-invasive BCI applications, researchers might consult the market size to select the research studies that should be supported. When it comes to gaming applications, the BCI market is currently large and popular. Game designers and different makers of consoles meant for gaming could explore the opportunity of integrating gaming systems with BCI solutions. When choosing the devices to utilize for an application, BCI investors (researchers) should be able to purchase them.

Further, the focus should be on end-user products based on market needs. Wireless gadgets are more convenient to roam around due to day-to-day usage in the long term and the feasibility of use in outdoor applications. There is no need to wash the head after using an additional, dry EEG electrode because it is simple, doesn't require extra tools like syringes, and is easy to use. The selection of the devices must consider several variables, including the medical certificate, the dry, saline, and gel electrode types, the size and shape of the EEG cap, and the device type (wired/wireless). The wireless device type was suitable for underlying body mobility and cognitive processes in rehabilitation and sport science. With the goal of fulfilling end users' desires and requirements and safeguarding the security of their sensitive information, more user experience assessments and data integrity policies are required.

Data integrity and user experience assessments are critical for BCI technology adoption across sectors. Finally, while BCI technology shows promise in rehabilitation and other areas, more research and a user-centered approach are required to maximize its effectiveness and impact.

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REFERENCES

[1] D. J. McFarland and J. R. Wolpaw, "Brain-computer interfaces for the operation of robotic and prosthetic devices," in *Advances in Computers*, vol. 79. Amsterdam, The Netherlands: Elsevier, 2010, pp. 169–187, doi: 10.1016/S0065-2458(10)79004-5.

[2] B. H. Dobkin, "Brain-computer interface technology as a tool to augment plasticity and outcomes for neurological rehabilitation," *J. Physiol.*, vol. 579, no. 3, pp. 637–642, Mar. 2007, doi: 10.1113/jphysiol.2006.123067.

[3] K. C. Dodd, V. A. Nair, and V. Prabhakaran, "Role of the contralesional vs. ipsilesional hemisphere in stroke recovery," *Frontiers Human Neurosci.*, vol. 11, p. 469, Sep. 2017, doi: 10.3389/fnhum.2017.00469.

[4] M. M. Fouad, K. M. Amin, N. El-Bendary, and A. E. Hassanien, "Brain computer interface: A review," in *Brain-Computer Interfaces: Current Trends and Applications*, vol. 74, Springer, 2015, pp. 3–30, doi: 10.1007/978-3-319-10978-7_1.

[5] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor, "A spelling device for the paralysed," *Nature*, vol. 398, no. 6725, pp. 297–298, Mar. 1999, doi: 10.1038/18581.

[6] D. Mondal and M. Alagirisamy, "Brain computer interface (BCI): Mechanism and challenges—A survey," *Int. J. Pharmaceutical Res.*, vol. 12, pp. 2200–2208, Jan. 2020, doi: 10.31838/ijpr/2020.12.01.344.

[7] J. A. Wilson, E. A. Felton, P. C. Garell, G. Schalk, and J. C. Williams, "ECoG factors underlying multimodal control of a brain-computer interface," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 246–250, Jun. 2006, doi: 10.1109/TNSRE.2006.875570.

[8] A. Rezeika, M. Benda, P. Stawicki, F. Gembler, A. Saboor, and I. Volosyak, "Brain–computer interface spellers: A review," *Brain Sci.*, vol. 8, no. 4, p. 57, Mar. 2018, doi: 10.3390/brainsci8040057.

[9] H.-J. Hwang, K. Kwon, and C.-H. Im, "Neurofeedback-based motor imagery training for brain–computer interface (BCI)," *J. Neurosci. Methods*, vol. 179, no. 1, pp. 150–156, Apr. 2009, doi: 10.1016/j.jneumeth.2009.01.015.

[10] A. Remsik, B. Young, R. Vermilyea, L. Kiekhoefer, J. Abrams, S. Evander Elmore, P. Schultz, V. Nair, D. Edwards, J. Williams, and V. Prabhakaran, "A review of the progression and future implications of brain–computer interface therapies for restoration of distal upper extremity motor function after stroke," *Expert Rev. Med. Devices*, vol. 13, no. 5, pp. 445–454, May 2016, doi: 10.1080/17434440.2016.1174572.

[11] A. Ramos-Murguialday, D. Broetz, M. Rea, L. Läer, Ö. Yilmaz, F. L. Brasil, G. Liberati, M. R. Curado, E. Garcia-Cossio, A. Vyziotis, W. Cho, M. Agostini, E. Soares, S. Soekadar, A. Caria, L. G. Cohen, and N. Birbaumer, "Brain-machine interface in chronic stroke rehabilitation: A controlled study," *Ann. Neurol.*, vol. 74, no. 1, pp. 100–108, Jul. 2013, doi: 10.1002/ana.23879.

[12] B. Kitchenham, O. P. Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman, "Systematic literature reviews in software engineering—A systematic literature review," *Inf. Softw. Technol.*, vol. 51, no. 1, pp. 7–15, 2009.

[13] L. Demers, M. J. Fuhrer, J. Jutai, J. Lenker, M. Depa, and F. De Ruyter, "A conceptual framework of outcomes for caregivers of assistive technology users," *Amer. J. Phys. Med. Rehabil.*, vol. 88, no. 8, pp. 645–655, Aug. 2009, doi: 10.1097/phm.0b013e3181ae0e70.

[14] W. Mortenson, L. Demers, M. Fuhrer, J. Jutai, J. Lenker, and F. DeRuyter, "Development and preliminary evaluation of the caregiver assistive technology outcome measure," *J. Rehabil. Med.*, vol. 47, no. 5, pp. 412–418, 2015, doi: 10.2340/16501977-1952.

[15] L. Zhang, "A web-based English teaching module on the administration of electroencephalography-based neurofeedback training for Chinese students," *NeuroQuantology*, vol. 16, no. 5, pp. 693–698, May 2018, doi: 10.14704/nq.2018.16.5.1243.

[16] H.-S. Chiang, K.-L. Hsiao, and L.-C. Liu, "EEG-based detection model for evaluating and improving learning attention," *J. Med. Biol. Eng.*, vol. 38, no. 6, pp. 847–856, Dec. 2018, doi: 10.1007/s40846-017-0344-z.

[17] D. Cypher, N. Chevrollier, N. Montavont, and N. Golmie, "Prevailing over wires in healthcare environments: Benefits and challenges," *IEEE Commun. Mag.*, vol. 44, no. 4, pp. 56–63, Apr. 2006, doi: 10.1109/MCOM.2006.1632650.

[18] V. J. Shute and D. Zapata-Rivera, "Adaptive technologies," *ETS Res. Rep. Ser.*, vol. 2007, no. 1, p. 34, Jun. 2007, doi: 10.1002/j.2333-8504.2007.tb02047.x.

[19] K. LaFleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, "Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain–computer interface," *J. Neural Eng.*, vol. 10, no. 4, Aug. 2013, Art. no. 046003, doi: 10.1088/1741-2560/10/4/046003.

[20] I. Iturrate, R. Chavarriaga, L. Montesano, J. Minguez, and J. D. R. Millán, "Teaching brain-machine interfaces as an alternative paradigm to neuroprosthetics control," *Sci. Rep.*, vol. 5, no. 1, Sep. 2015, Art. no. 13893, doi: 10.1038/srep13893.

[21] A. Jackson and J. B. Zimmermann, "Neural interfaces for the brain and spinal cord—Restoring motor function," *Nature Rev. Neurol.*, vol. 8, no. 12, pp. 690–699, Dec. 2012, doi: 10.1038/nrneurol.2012.219.

[22] E. López-Larraz, A. Sarasola-Sanz, N. Irastorza-Landa, N. Birbaumer, and A. Ramos-Murguialday, "Brain-machine interfaces for rehabilitation in stroke: A review," *NeuroRehabilitation*, vol. 43, no. 1, pp. 77–97, Jul. 2018, doi: 10.3233/NRE-172394.

[23] A. Sarasola-Sanz, E. López-Larraz, N. Irastorza-Landa, J. Klein, D. Valencia, A. Belloso, F. O. Morin, M. Spüler, N. Birbaumer, and A. Ramos-Murguialday, "An EEG-based brain-machine interface to control a 7-degrees of freedom exoskeleton for stroke rehabilitation," in *Converging Clinical and Engineering Research on Neurorehabilitation II* (Biosystems & Biorobotics), vol. 15. Springer, 2017, pp. 1127–1131, doi: 10.1007/978-3-319-46669-9_183.

[24] A. Biasiucci, R. Leeb, I. Iturrate, S. Perdikis, A. Al-Khodairy, T. Corbet, A. Schnider, T. Schmidlin, H. Zhang, M. Bassolino, D. Viceic, P. Vuadens, A. G. Guggisberg, and J. D. R. Millán, "Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke," *Nature Commun.*, vol. 9, Jun. 2018, Art. no. 2421, doi: 10.1038/s41467-018-04673-z.

[25] F. Trincado-Alonso, E. López-Larraz, F. Resquín, A. Ardanza, S. Pérez-Nombela, J. L. Pons, L. Montesano, and Á. Gil-Agudo, "A pilot study of brain-triggered electrical stimulation with visual feedback in patients with incomplete spinal cord injury," *J. Med. Biol. Eng.*, vol. 38, no. 5, pp. 790–803, Oct. 2018, doi: 10.1007/s40846-017-0343-0.

[26] E. Buch, C. Weber, L. G. Cohen, C. Braun, M. A. Dimyan, T. Ard, J. Mellinger, A. Caria, S. Soekadar, A. Fourkas, and N. Birbaumer, "Think to move: A neuromagnetic brain–computer interface (BCI) system for chronic stroke," *Stroke*, vol. 39, no. 3, pp. 910–917, Mar. 2008, doi: 10.1161/STROKEAHA.107.505313.

[27] M. Coscia, M. J. Wessel, U. Chaudary, J. D. R. Millán, S. Micera, A. Guggisberg, P. Vuadens, J. Donoghue, N. Birbaumer, and F. C. Hummel, "Neurotechnology-aided interventions for upper limb motor rehabilitation in severe chronic stroke," *Brain*, vol. 142, no. 8, pp. 2182–2197, Aug. 2019, doi: 10.1093/brain/awz181.

[28] S. L. Norman, D. J. McFarland, A. Miner, S. C. Cramer, E. T. Wolbrecht, J. R. Wolpaw, and D. J. Reinkensmeyer, "Controlling pre-movement sensorimotor rhythm can improve finger extension after stroke," *J. Neural Eng.*, vol. 15, no. 5, Oct. 2018, Art. no. 056026, doi: 10.1088/1741-2552/aad724.

[29] V. W. Oguntosin, Y. Mori, H. Kim, S. J. Nasuto, S. Kawamura, and Y. Hayashi, "Design and validation of exoskeleton actuated by soft modules toward neurorehabilitation—Vision-based control for precise reaching motion of upper limb," *Frontiers Neurosci.*, vol. 11, p. 352, Jul. 2017, doi: 10.3389/fnins.2017.00352.

[30] C. E. Proulx, M. Beaulac, M. David, C. Deguire, C. Haché, F. Klug, M. Kupnik, J. Higgins, and D. H. Gagnon, "Review of the effects of soft robotic gloves for activity-based rehabilitation in individuals with reduced hand function and manual dexterity following a neurological event," *J. Rehabil. Assistive Technol. Eng.*, vol. 7, Jan. 2020, Art. no. 205566832091813, doi: 10.1177/2055668320918130.

[31] N. Cheng, K. S. Phua, H. S. Lai, P. K. Tam, K. Y. Tang, K. K. Cheng, R. C. Yeow, K. K. Ang, C. Guan, and J. H. Lim, "Brain–computer interface-based soft robotic glove rehabilitation for stroke," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 12, pp. 3339–3351, Dec. 2020, doi: 10.1109/TBME.2020.2984003.

[32] Y. He, K. Nathan, A. Venkatakrishnan, R. Rovekamp, C. Beck, R. Ozdemir, G. E. Francisco, and J. L. Contreras-Vidal, "An integrated neuro-robotic interface for stroke rehabilitation using the NASA ×1 powered lower limb exoskeleton," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2014, pp. 3985–3988, doi: 10.1109/EMBC.2014.6944497.

[33] J. L. Contreras-Vidal, M. Bortole, F. Zhu, K. Nathan, A. Venkatakrishnan, G. E. Francisco, R. Soto, and J. L. Pons, "Neural decoding of robot-assisted gait during rehabilitation after stroke," *Amer. J. Phys. Med. Rehabil.*, vol. 97, no. 8, pp. 541–550, 2018, doi: 10.1097/PHM.0000000000000914.

[34] R. S. Calabrò, A. Naro, M. Russo, P. Bramanti, L. Carioti, T. Balletta, A. Buda, A. Manuli, S. Filoni, and A. Bramanti, "Shaping neuroplasticity by using powered exoskeletons in patients with stroke: A randomized clinical trial," *J. NeuroEng. Rehabil.*, vol. 15, no. 1, pp. 1–16, Dec. 2018, doi: 10.1186/s12984-018-0377-8.

[35] E. López-Larraz, F. Trincado-Alonso, V. Rajasekaran, S. Pérez-Nombela, A. J. Del-Ama, J. Aranda, J. Minguez, A. Gil-Agudo, and L. Montesano, "Control of an ambulatory exoskeleton with a brain–machine interface for spinal cord injury gait rehabilitation," *Frontiers Neurosci.*, vol. 10, p. 359, Aug. 2016, doi: 10.3389/fnins.2016.00359.

[36] O. Lennon, M. Tonellato, A. Del Felice, R. Di Marco, C. Fingleton, A. Korik, E. Guanziroli, F. Molteni, C. Guger, R. Otner, and D. Coyle, "A systematic review establishing the current state-of-the-art, the limitations, and the DESIRED checklist in studies of direct neural interfacing with robotic gait devices in stroke rehabilitation," *Frontiers Neurosci.*, vol. 14, p. 578, Jun. 2020, doi: 10.3389/fnins.2020.00578.

[37] S. Nakagome, T. P. Luu, Y. He, A. S. Ravindran, and J. L. Contreras-Vidal, "An empirical comparison of neural networks and machine learning algorithms for EEG gait decoding," *Sci. Rep.*, vol. 10, no. 1, p. 4372, Mar. 2020, doi: 10.1038/s41598-020-60932-4.

[38] S. Tortora, S. Ghidoni, C. Chisari, S. Micera, and F. Artoni, "Deep learning-based BCI for gait decoding from EEG with LSTM recurrent neural network," *J. Neural Eng.*, vol. 17, no. 4, Jul. 2020, Art. no. 046011, doi: 10.1088/1741-2552/ab9842.

[39] L. R. Hochberg, M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, A. Branner, D. Chen, R. D. Penn, and J. P. Donoghue, "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," *Nature*, vol. 442, no. 7099, pp. 164–171, Jul. 2006, doi: 10.1038/nature04970.

[40] J. L. Collinger, B. Wodlinger, J. E. Downey, W. Wang, E. C. Tyler-Kabara, D. J. Weber, A. J. C. McMorland, M. Velliste, M. L. Boninger, and A. B. Schwartz, "High-performance neuroprosthetic control by an individual with tetraplegia," *Lancet*, vol. 381, no. 9866, pp. P557–P564, 2013, doi: 10.1016/S0140-6736(12)61816-9.

[41] B. Wodlinger, J. E. Downey, E. C. Tyler-Kabara, A. B. Schwartz, M. L. Boninger, and J. L. Collinger, "Ten-dimensional anthropomorphic arm control in a human brain–machine interface: Difficulties, solutions, and limitations," *J. Neural Eng.*, vol. 12, no. 1, Feb. 2015, Art. no. 016011, doi: 10.1088/1741-2560/12/1/016011.

[42] U. Chaudhary, N. Mrachacz-Kersting, and N. Birbaumer, "Neuropsychological and neurophysiological aspects of brain–computer-interface (BCI) control in paralysis," *J. Physiol.*, vol. 599, no. 9, pp. 2351–2359, May 2021, doi: 10.1113/JP278775.

[43] J. Meng, S. Zhang, A. Bekyo, J. Olsoe, B. Baxter, and B. He, "Noninvasive electroencephalogram based control of a robotic arm for reach and grasp tasks," *Sci. Rep.*, vol. 6, no. 1, Dec. 2016, Art. no. 38565, doi: 10.1038/srep38565.

[44] R. Fukuma, T. Yanagisawa, Y. Saitoh, K. Hosomi, H. Kishima, T. Shimizu, H. Sugata, H. Yokoi, M. Hirata, Y. Kamitani, and T. Yoshimine, "Real-time control of a neuroprosthetic hand by magnetoencephalographic signals from paralysed patients," *Sci. Rep.*, vol. 6, no. 1, Feb. 2016, Art. no. 21781, doi: 10.1038/srep21781.

[45] H. A. Agashe, A. Y. Paek, and J. L. Contreras-Vidal, "Multisession, noninvasive closed-loop neuroprosthetic control of grasping by upper limb amputees," in *Progress in Brain Research*, vol. 228. Amsterdam, The Netherlands: Elsevier, 2016, pp. 107–128, doi: 10.1016/bs.pbr.2016.04.016.

[46] B. J. Edelman, J. Meng, D. Suma, C. Zurn, E. Nagarajan, B. S. Baxter, C. C. Cline, and B. He, "Noninvasive neuroimaging enhances continuous neural tracking for robotic device control," *Sci. Robot.*, vol. 4, no. 31, Jun. 2019, Art. no. eaaw6844, doi: 10.1126/scirobotics.aaw6844.

[47] A. Schwarz, M. K. Höller, J. Pereira, P. Ofner, and G. R. Müller-Putz, "Decoding hand movements from human EEG to control a robotic arm in a simulation environment," *J. Neural Eng.*, vol. 17, no. 3, Jun. 2020, Art. no. 036010, doi: 10.1088/1741-2552/ab882e.

[48] C. I. Penaloza and S. Nishio, "BMI control of a third arm for multitasking," *Sci. Robot.*, vol. 3, no. 20, Jul. 2018, Art. no. eaat1228, doi: 10.1126/scirobotics.aat1228.

[49] J.-H. Jeong, K.-H. Shim, D.-J. Kim, and S.-W. Lee, "Brain-controlled robotic arm system based on multi-directional CNN-BiLSTM network using EEG signals," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 5, pp. 1226–1238, May 2020, doi: 10.1109/TNSRE.2020.2981659.

[50] W. Klimesch, "EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis," *Brain Res. Rev.*, vol. 29, pp. 169–195, Apr. 1999, doi: 10.1016/S0165-0173(98)00056-3.

[51] C. Escolano, M. Navarro-Gil, J. Garcia-Campayo, M. Congedo, D. D. Ridder, and J. Minguez, "A controlled study on the cognitive effect of alpha neurofeedback training in patients with major depressive disorder," *Frontiers Behav. Neurosci.*, vol. 8, p. 296, Sep. 2014, doi: 10.3389/fnbeh.2014.00296.

[52] C. Escolano, M. Navarro-Gil, J. Garcia-Campayo, M. Congedo, and J. Minguez, "The effects of individual upper alpha neurofeedback in ADHD: An open-label pilot study," *Appl. Psychophysiol. Biofeedback*, vol. 39, nos. 3–4, pp. 193–202, Dec. 2014, doi: 10.1007/s10484-014-9257-6.

[53] S. Diekelmann and J. Born, "The memory function of sleep," *Nature Rev. Neurosci.*, vol. 11, no. 2, pp. 114–126, Feb. 2010, doi: 10.1038/nrn2762.

[54] N. Ketz, A. P. Jones, N. B. Bryant, V. P. Clark, and P. K. Pilly, "Closed-loop slow-wave tACS improves sleep-dependent long-term memory generalization by modulating endogenous oscillations," *J. Neurosci.*, vol. 38, no. 33, pp. 7314–7326, Aug. 2018, doi: 10.1523/JNEUROSCI.0273-18.2018.

[55] H.-V.-V. Ngo, T. Martinetz, J. Born, and M. Mölle, "Auditory closed-loop stimulation of the sleep slow oscillation enhances memory," *Neuron*, vol. 78, no. 3, pp. 545–553, May 2013, doi: 10.1016/j.neuron.2013.03.006.

[56] J. W. Antony, L. Piloto, M. Wang, P. Pacheco, K. A. Norman, and K. A. Paller, "Sleep spindle refractoriness segregates periods of memory reactivation," *Current Biol.*, vol. 28, no. 11, pp. 1736–1743, Jun. 2018, doi: 10.1016/j.cub.2018.04.020.

[57] M. T. Sadiq, H. Akbari, S. Siuly, Y. Li, and P. Wen, "Alcoholic EEG signals recognition based on phase space dynamic and geometrical features," *Chaos, Solitons Fractals*, vol. 158, May 2022, Art. no. 112036.

[58] H. Akbari, M. T. Sadiq, M. Payan, S. S. Esmaili, H. Baghri, and H. Bagheri, "Depression detection based on geometrical features extracted from SODP shape of EEG signals and binary PSO," *Traitement Signal*, vol. 38, no. 1, pp. 13–26, Feb. 2021.

[59] H. Akbari, M. T. Sadiq, N. Jafari, J. Too, N. Mikaeilvand, A. Cicone, and S. Serra-Capizzano, "Recognizing seizure using Poincaré plot of EEG signals and graphical features in DWT domain," *Bratislava Med. J.*, vol. 124, no. 1, pp. 12–24, 2022.

[60] M. T. Sadiq, X. Yu, Z. Yuan, and M. Z. Aziz, "Motor imagery BCI classification based on novel two-dimensional modelling in empirical wavelet transform," *Electron. Lett.*, vol. 56, no. 25, pp. 1367–1369, 2020.

[61] M. T. Sadiq, X. Yu, Z. Yuan, M. Z. Aziz, N. u. Rehman, W. Ding, and G. Xiao, "Motor imagery BCI classification based on multivariate variational mode decomposition," *IEEE Trans. Emerg. Topics Comput. Intell.*, vol. 6, no. 5, pp. 1177–1189, Oct. 2022.

[62] M. T. Sadiq, X. Yu, Z. Yuan, F. Zeming, A. U. Rehman, I. Ullah, G. Li, and G. Xiao, "Motor imagery EEG signals decoding by multivariate empirical wavelet transform-based framework for robust brain–computer interfaces," *IEEE Access*, vol. 7, pp. 171431–171451, 2019.

[63] M. T. Sadiq, X. Yu, Z. Yuan, M. Z. Aziz, S. Siuly, and W. Ding, "Toward the development of versatile brain–computer interfaces," *IEEE Trans. Artif. Intell.*, vol. 2, no. 4, pp. 314–328, Aug. 2021.

[64] X. Yu, M. Z. Aziz, M. T. Sadiq, Z. Fan, and G. Xiao, "A new framework for automatic detection of motor and mental imagery EEG signals for robust BCI systems," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–12, 2021.

[65] Ç. İ. Acı, M. Kaya, and Y. Mishchenko, "Distinguishing mental attention states of humans via an EEG-based passive BCI using machine learning methods," *Expert Syst. Appl.*, vol. 134, pp. 153–166, Nov. 2019.

[66] M. T. Sadiq, S. Siuly, and A. U. Rehman, "Evaluation of power spectral and machine learning techniques for the development of subject-specific BCI," in *Artificial Intelligence-Based Brain-Computer Interface*. New York, NY, USA: Academic, 2022, pp. 99–120.

[67] M. T. Sadiq, X. Yu, Z. Yuan, and M. Z. Aziz, "Identification of motor and mental imagery EEG in two and multiclass subject-dependent tasks using successive decomposition index," *Sensors*, vol. 20, no. 18, p. 5283, Sep. 2020.

[68] K. M. Hossain, M. A. Islam, S. Hossain, A. Nijholt, and M. A. R. Ahad, "Status of deep learning for EEG-based brain–computer interface applications," *Frontiers Comput. Neurosci.*, vol. 16, Jan. 2023, Art. no. 1006763.

[69] H. Altaheri, G. Muhammad, M. Alsulaiman, S. U. Amin, G. A. Altuwaijri, W. Abdul, M. A. Bencherif, and M. Faisal, "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: A review," *Neural Comput. Appl.*, vol. 35, no. 20, pp. 14681–14722, Jul. 2023.

[70] P. Wang, Z. Li, P. Gong, Y. Zhou, F. Chen, and D. Zhang, "MTRT: Motion trajectory reconstruction transformer for EEG-based BCI decoding," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 2349–2358, 2023.

[71] M. T. Sadiq, S. Siuly, A. Almogren, Y. Li, and P. Wen, "Efficient novel network and index for alcoholism detection from EEGs," *Health Inf. Sci. Syst.*, vol. 11, no. 1, p. 27, Jun. 2023.

[72] A. Kamble, P. H. Ghare, and V. Kumar, "Deep-learning-based BCI for automatic imagined speech recognition using SPWVD," *IEEE Trans. Instrum. Meas.*, vol. 72, pp. 1–10, 2023.

[73] H. Hamid, N. Naseer, H. Nazeer, M. J. Khan, R. A. Khan, and U. S. Khan, "Analyzing classification performance of fNIRS-BCI for gait rehabilitation using deep neural networks," *Sensors*, vol. 22, no. 5, p. 1932, Mar. 2022.

[74] R. Sharma, M. Kim, and A. Gupta, "Motor imagery classification in brain-machine interface with machine learning algorithms: Classical approach to multi-layer perceptron model," *Biomed. Signal Process. Control*, vol. 71, Jan. 2022, Art. no. 103101.

[75] T. Khanam, S. Siuly, and H. Wang, "An optimized artificial intelligence based technique for identifying motor imagery from EEGs for advanced brain computer interface technology," *Neural Comput. Appl.*, vol. 35, no. 9, pp. 6623–6634, Mar. 2023.

[76] A. Mehtiyev, A. Al-Najjar, H. Sadreazami, and M. Amini, "DeepEnsemble: A novel brain wave classification in MI-BCI using ensemble of deep learners," in *Proc. IEEE Int. Conf. Consum. Electron. (ICCE)*, Jan. 2023, pp. 1–5.

[77] H. Li, H. Ji, J. Yu, J. Li, L. Jin, L. Liu, Z. Bai, and C. Ye, "A sequential learning model with GNN for EEG-EMG-based stroke rehabilitation BCI," *Frontiers Neurosci.*, vol. 17, Apr. 2023, Art. no. 1125230.

[78] J. Luo, Y. Wang, S. Xia, N. Lu, X. Ren, Z. Shi, and X. Hei, "A shallow mirror transformer for subject-independent motor imagery BCI," *Comput. Biol. Med.*, vol. 164, Sep. 2023, Art. no. 107254.

[79] B. Huang, H. Xu, M. Yuan, M. Z. Aziz, and X. Yu, "Exploiting asymmetric EEG signals with EFD in deep learning domain for robust BCI," *Symmetry*, vol. 14, no. 12, p. 2677, Dec. 2022.

[80] H. Zhu, D. Forenzo, and B. He, "On the deep learning models for EEG-based brain–computer interface using motor imagery," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 2283–2291, 2022.

[81] Q. Wang, F. Liu, G. Wan, and Y. Chen, "Inference of brain states under anesthesia with meta learning based deep learning models," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 1081–1091, 2022.

[82] L. Cao, H. Wu, S. Chen, Y. Dong, C. Zhu, J. Jia, and C. Fan, "A novel deep learning method based on an overlapping time window strategy for brain–computer interface-based stroke rehabilitation," *Brain Sci.*, vol. 12, no. 11, p. 1502, Nov. 2022, doi: 10.3390/brainsci12111502.

[83] S. Chen, L. Cao, X. Shu, H. Wang, L. Ding, S.-H. Wang, and J. Jia, "Longitudinal electroencephalography analysis in subacute stroke patients during intervention of brain–computer interface with exoskeleton feedback," *Frontiers Neurosci.*, vol. 14, pp. 1–11, Aug. 2020, doi: 10.3389/fnins.2020.00809.

[84] L. Cao, W. Wang, C. Huang, Z. Xu, H. Wang, J. Jia, S. Chen, Y. Dong, C. Fan, and V. H. C. de Albuquerque, "An effective fusing approach by combining connectivity network pattern and temporal-spatial analysis for EEG-based BCI rehabilitation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 2264–2274, 2022, doi: 10.1109/TNSRE.2022.3198434.

[85] V. Sharma, T. Singh, N. Garg, S. Dhiman, S. Gupta, M. Rahman, A. Najda, M. Walasek-Janusz, M. Kamel, G. Albadrani, M. Akhtar, A. Saleem, A. Altyar, and M. Abdel-Daim, "Dysbiosis and Alzheimer's disease: A role for chronic stress?" *Biomolecules*, vol. 11, no. 5, p. 678, Apr. 2021, doi: 10.3390/biom11050678.

[86] U. K. Lilhore, M. Poongodi, A. Kaur, S. Simaiya, A. D. Algarni, H. Elmannai, V. Vijayakumar, G. B. Tunze, and M. Hamdi, "Hybrid model for detection of cervical cancer using causal analysis and machine learning techniques," *Comput. Math. Methods Med.*, vol. 2022, pp. 1–17, May 2022, doi: 10.1155/2022/4688327.

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