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Rewiring the Brain: A Review on Innovations in Brain-Computer Interface for Stroke Rehabilitation

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***Abstract*—This review paper contains information on new innovations in BCI technologies for stroke rehabilitation; the focus is on the integration of EEG systems so as to restore motor function in patients affected by stroke. The discussions mainly include developments in BCI-driven motor recovery with EEG devices that are made user- friendly along with robotic prosthetics controlled by the brain signals. For further enhancement in rehabilitation and for improved assessments, several machine learning and deep learning methods are also brought to the discussion. This review covers and highlights the development of BCI technologies in stroke rehabilitation by showing successful cases using the main EEG devices.**

***Index Terms*— Brain Computer interface , Machine learning , Stroke Rehabilitation**

1. INTRODUCTION

1.1 Introduction to Brain-Computer Interface (BCI) Technology

BCI is one of the prominent technologies that creates a bridge between the prominent fields of neuroscience and biomedical engineering, enabling direct communication from brain to brain. Using the non-invasive technology like EEG, brain computer interface can decode the neurological impulses, which helps in translating the thoughts into commands for computers, prosthetic limbs, and other assistive devices. The BCI interface particularly helps people with limited motor abilities to do tasks and even to communicate through mental activity by avoiding the commonly used cerebral techniques of communication. Due to rapid development in the fields of neural engineering, machine learning algorithms and signal processing the BCI has grown and developed as an important field with numerous applications in neuroprosthetics and healthcare.

1.2 Overview of Stroke: Understanding Stroke and Rehabilitation

A stroke is said to happen as a result of bleeding within the brain tissues from a burst artery or even when an artery evaluations, blood clot blocks the blood flow to a specific region of the brain. This will lead to the brain tissue being deprived of oxygenated blood, leading to damage of brain tissue even causing death. The areas of the brain deprived of oxygen during the event of stroke experience an increase in pressure due to blood clots. Depending on the region where the stroke occured it can result in the loss of motor, cognitive, and sensory abilities. The treatment for stroke should effectively begin immediately after the occurrence of the stroke to minimize brain damage and lessen the severity of the stroke to the patient. Although specific stroke patterns respond well to medication, others require surgical procedures. The brain is able to mend itself even though dead cells cannot be brought back to life, but because of an important property known as neuroplasticity, the brain is able to rearrange itself and also give the healthy regions in the brain a new role. Because of the process of neuroplasticity, the recovery occurs naturally, but it can often be supported by certain rehabilitation activities. The major objectives of stroke treatment include helping the patient to either restore function that is lost or to learn to live without it as much as feasible. The magnitude and the location of the stroke will determine how severe the stroke is. In order to promote healing and independence, effective collaboration with medical specialists.

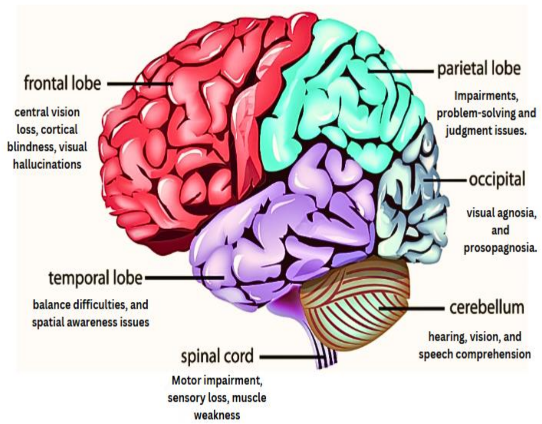

Figure 1: Brain Regions Commonly Affected by Stroke

Figure 1 shows the most common brain areas usually affected in the event of a stroke. The effects of a stroke cause deficits in motor, cognitive, and sensory functioning within these same regions. These have become crucial areas of knowledge since it might make a huge difference if rehabilitation techniques can be suitably adjusted to enhance recovery. By focusing on the brain regions most likely to be impacted by the stroke, Diagram 1 demonstrates how certain abilities may be impacted by the stroke and why targeted rehabilitation efforts will be so important.

1.3 The Relevance of Stroke Rehabilitation in Patient Recovery

Rehabilitation is very essential so as to minimize the chances of long-term disabilities and also to promote the faster recovery process for stroke survivors. Without the presence of sufficient rehabilitation interventions, the stroke victims are more likely to be dependent on caregivers for a very extended period of time, which can possibly negatively impact their mobility and which in turn affect their quality of life in general. The neuroplasticity alterations are closely linked to the process of rehabilitation, which allows for the reorganization of cerebral functioning. In addition to helping patients recover physically, this type of rehabilitation is crucial for psychological recovery too, which enables them to rebuild their confidence and adjust to life after the event of a stroke.

1.4 The Role of BCI in Enhancing Stroke Rehabilitation

BCI technology may offer one of the most promising avenues for stroke victims to recover from their injuries since it directly includes brain activity in the healing process. With the help of these EEG-based BCIs, the stroke victims receive real-time feedback regarding their brain signals; this will indeed help them to retrain their brains and regain motor control. This is especially true for those who have significant motor impairment, thereby preventing them from receiving regular physiotherapy. Therefore, the BCIs can be used with robotic prosthetics or virtual reality to create gentle and comfortable rehabilitation choices that patients want to engage with. By the use of machine learning algorithms, we can create personalized rehabilitation regimens that increase efficacy and expand BCIs' capacity to adjust to the needs of individual patients. Considering this, the use of BCI in stroke rehabilitation creates new avenues for ongoing, continuous long-term monitoring, tailored treatment regimens, and markedly improved patient results that speed up the process of healing from stroke.

2. LITERATURE SURVEY

BCI is a recent innovation that has reached the potential to completely transform neurorehabilitation especially for the stroke patients who have significant functional damage. Since strokes are among the most common causes of permanent disability, there is a pressing need for innovative methods to stroke rehabilitation. The BCI signal is connected directly to an external device rather than via any compromised cerebral connections which guarantee the fact that the technique has great potential to aid in this patient group's recuperation[30][7][45].

Considering the developments in past few decades, there has been a significant advancement in BCI technology.The early research conducted has proven how effective BCI is in aiding the patients with severe motor deficits so as to regain their motor functions[3][6].The researches conducted in the specific period established the significance of BCIs in clinical rehabilitation of stroke victims by demonstrating the patients' remarkable improvements in motor capabilities after effective usage of BCI-based training systems.

The new advancement in technology, for instance, minimally invasive interfaces which could effectively perform both the tasks of monitoring brain activity and delivering therapeutic interventions without any requirement of intrusive recordings was introduced[41]. This advancement made BCIs more widely available and useful from a clinical point of view. This especially helped individuals who weren't good candidates for invasive procedures. Even though researches highlighted a few technological difficulties, such as real-time processing and the BCI system's ability to adapt to the user still these difficulties are present in the field of current research[49].The experimental studies demonstrated the validity of BCIs for chronic stroke rehabilitation, marking a significant advancement[33]. Not long after, it was further established the clinical usefulness of BCIs for rehabilitation by showing that BCI-actuated functional electrical stimulation can induce long-lasting motor recovery in stroke patients[40].

Another significant advancement in terms of integration was the incorporation of AI into BCI systems which might be used to optimize rehabilitation programs for stroke patients' upper limb motor function optimization[32]. Further researches identified potential obstacles to this kind of BCI and AI integration and its applications (2020)[26]. This is because AI made a significant contribution to raising classification accuracy and overall system performance, which advanced BCI systems' efficiency and ability to adjust to the needs of individual patients.

Researchers have always focused more on creating the non-invasive BCI systems throughout time. The scientists conducted a comprehensive review on EEG-based BCIs and correctly emphasized that non-invasive methods gained popularity since they were relatively easy to use and were particularly safe[11]. In this regard, later experiments emphasized that the rate of high-classification accuracy for stroke rehabilitation has been improving thanks to BCIs augmented with machine learning algorithms[18]. The meta-analysis from 2021, which examined the effects of both passive and active BCIs, revealed that significant progress has been made in rehabilitation results, particularly in the area of motor recovery[2].

The findings from recent studies have accelerated the rate at which BCI applications are being investigated. Adding on some important discoveries provide additional support for this perspective on BCI research by the demonstration of devices' adaptability in treating many kinds of neurological illnesses[12]. In the meantime, discoveries also presented some key developments in AI-driven BCIs that help in neurorehabilitation and gave a perceptive overview of deep learning applications for SSVEP-based BCIs[1]. These studies highlight the growing influence of AI and deep learning in the search for more effective and adaptable BCIs that meet complex rehabilitation requirements.

The BCI experiments in (2024), suggests that precise and effective signal capture is crucial when working with medical applications, which indicates that more advancements in the area are required if BCIs has to reach the full potential they were employed for[21]. Considering that the stroke patients with severe impairments to their upper limbs would benefit from a considerably bigger gain in motor function,researchers were able to offer the potential path of integrating motor imaging with functional electrical stimulation[4]. The important researchs in 2024 also confirmed that BCI rehabilitation programs inside MI technologies can improve cortical activation and improve upper limb performance in stroke patients[14].

Adding on to the above findings it was discovered that the effective development of machine learning methods and BCI signal acquisition innovations is essential inorder to enhance the results of stroke rehabilitation. Later it was presented on how the improvement in EEG-based BCI systems can be aided by using appropriate machine learning methods for approaches including categorization[25]. Extension of the above research found endovascular neural stimulation and recording as a comparatively less invasive method of tracking brain activity which led to the discovery of key potential of BCI to be extremely beneficial for people who are not suitable candidates for more invasive procedures.

BCIs have even widespread applications in neurological illnesses which has been found in recent studies.Another key finding that BCIs can identify the auditory hallucinations from corresponding EEG data was discovered[8],which in turn indicated the treatment of neurological diseases in addition to the function of motor recovery.With the advancement of BCI technology, ethical and legal issues have also become more and more significant in recent years. It is true that integrating such an introduction into regular clinical practice and rehabilitation programs is challenging [5][22]. In fact, robust regulatory structures are necessary. Prospects: BCIs have a very promising future in the rehabilitation of stroke patients.After doing a meta-analysis of BCIs and robotics, it was concluded that both the interventions worked together can significantly improve the motor performance of upper limb[17]in addition to this , a thorough examination of neuroplasticity and its mechanisms underlying stroke recovery provided the proof that both motor performance and functional brain connection can be improved with even brief BCI interventions[9].According to the neuromodulation therapies like the BCIs can help the chronic stroke patients for recovery as well as for increasing or maximizing their neuroplasticity[19].

While modern researchers created an explainable deep-learning model to predict motor gains in BCI-supported stroke rehabilitation[13], scientists also examined the working of AI in concert so as to improve the results of rehabilitation for stroke patients receiving BCIs[13].In 2024, researches also discussed the possibility of artificial intelligence (AI) in neuroprosthetics suggesting it might significantly transform neurorehabilitation[16] .

3. PROPOSED METHODOLOGY

The methodology in the research is built in such a way that it makes everything organized for precise and effective BCI systems. This methodological technique involves several important processes which include pre-processing the data, training, generating a model and assessing the model's completeness. The main processes in creating a framework that can effectively address the problems that arise in BCI research that had been addressed up until now included data preprocessing, data training, model creation, and model evaluation. This approach seeks to optimize the use of machine-learning algorithms with brain-computer interface (BCI) activities so as to improve the performance in neurorehabilitation applications.

Figure 2:An architectural mind map of the suggested methodology for machine learning, covering everything from data preparation to model assessment

3.1 Data Preprocessing

One of the most crucial procedures carried out for any machine learning model for which BCIs are no exception is the data preparation. The effectiveness and precision of a model is directly linked to the caliber and organization of the data. Therefore a systematic approach has to be followed for data cleaning and preprocessing so as to eliminate noise and other types of artifacts from the raw EEG signal and any other neuroimaging data collected inorder to make the data more effective in interpreting the underlying brain activity. Additionally frequent pre-processing techniques are employed including the method of segmenting continuous data into meaningful epochs, normalizing data ranges into a single common scale, and filtering high-frequency noise.Also the other solutions that are being examined include the removal of artifacts from the signals by using techniques like Independent Component Analysis for decreasing the effects of external factors like muscle activity and eye movement,thereby improving the signal-to-noise ratio and raising the dependability of the characteristics .

3.2 Data Training

To support the learning process, the preprocessed data is split into 2 separate sets ,the training and validation sets. The preprocessed data is provided as an input into a machine model during the training phase with an important goal of recovering meaningful patterns or relationships between data. The features like the event-related potential or frequency bands associated with the motor imagery are usually obtained and understood during this processing and are considered as model input. Inorder to lower the dimensions so as to increase the model's efficiency feature selection methods like PCA or recursive feature elimination are also applied depending on the neccessity.Training is an iterative process in which a model continuously modifies its parameters with the aid of gradient descent techniques or backpropagation in neural networks.This ensure that the model can generalize well to new and unknown data which is a vital requirement for any well-designed BCI, and this phase is essential for achieving this specific goal.

3.3 Model GenerationThe model generation process which includes creating a machine learning model based on patterns discovered during the training phase is the core of this methodology and is covered in this section. Depending on the specifics of the BCI job which basically include the models originating from any number of machine learning paradigms such as Support Vector Machines, Convolutional Neural Networks, and Recurrent Neural Networks. Taking an example, RNNs do significantly better than CNNs at modeling the temporal dependencies that underlie the spatial patterns of EEG whereas CNNs have been highly successful in doing so.Also careful thought is given to modeling the model's architecture inorder to make most appropriate trade-offs between computing performance and model complexity.For achieving the greatest performance, hyperparameters like learning rate, batch size, and layer count etc are further tuned using techniques like grid search or Bayesian optimization. In order to confirm that the developed model is resilient in generalizing across various data sets the method of cross-validated is also employed.

3.4 Model Evaluation

The model should be carefully assessed by considering the actual performance. The metrics like accuracy, precision, recall, and F1-score are all quantified. Since the misclassifications in BCIS may result in dire circumstances, the models being deployed need to guarantee high accuracy and dependability. The model's performance are evaluated using significant examining methods like confusion matrix so as to check if the model's performance is biased or not or even if there are weaknesses in the model.In addition the model's adaptability and resilience are then evaluated using a range of different datasets and experimental configurations.The results of these many evaluation is carefully examined in the later stages so as to update the model with proper hyperparameter tuning which includes more data so as to enhance the model's performance and functionality even further in order to have better results with testing data.

The (table 1) provides a synopsis of the models found in the cited publications, together with information on accuracy levels, performance metrics.

Table 1:BCI Models and Performance Overview

Reference and Year	Model Used	Performance Measure and accuracy	BCI Task
Sun et al. 2024	Convolutional Neural Network (CNN)	F1-Score 90%	Signal Acquisition
Ma et al. 2024	Recurrent Neural Network (RNN)	Accuracy, Recall 87%	Motor Imagery
Yassine and Abdelkader 2024	Support Vector Machine (SVM)	Accuracy, F1-Score 89%	EEG-Based BCI
He et al. 2024	Linear Discriminant Analysis (LDA)	Accuracy 80%	Neural Recording
Conrad and Heggie 2024	Decision Trees	Accuracy, Precision 78%	Regulatory Frameworks
García-Martínez et al. 2024	Convolutional Neural Network (CNN)	F1-Score, AUC 91%	Auditory Hallucination Detection
Qu et al. 2024	Gradient Boosting Machines (GBM)	Precision, Recall 88%	Upper-Limb Function
Saway et al. 2024	Recurrent Neural Network (RNN)	Accuracy, Recall 86%	Neuromodulation
Grigoryan et al. 2024	Long Short-Term Memory (LSTM)	Accuracy, F1-Score 88%	Functional Brain Connectivity
Lin et al. 2024	Explainable AI (XAI)	Accuracy, F1-Score 89%	Motor Gains Prediction
Pulicharla and Premani 2024	Artificial Neural Network (ANN)	Precision, Recall 85%	Neuroprosthetics

4. DATABASE EXPLANATION

The majority of the datasets covered here are diverse which includes a range of BCI tasks and applications including motor imaging, emotion recognition, and brain-computer interface-assisted rehabilitation. The datasets considered differ in terms of the amount, the source, and the preprocessing techniques used to improve the accuracy and dependability of the data. A significant amount of the data comes from different clinical or experimental settings as well as well-known databases like Physionet and BCI Competitions. The initial stage of data preprocessing includes the techniques of feature extraction,normalization, artifact removal and noise filtering.This will indeed make data ready for training deep machine learning models with CNNs, LSTMs, and SVMs along with other models. The overall process of comprehending these kinds of datasets and their descriptions is essential to develop a successful BCI system that targets neurological applications like the stroke rehabilitation.

Table 2 provides an overview of the datasets used in the paper. Since most of the datasets examined in this work center on motor imaging, emotion detection, and brain-computer interface-based rehabilitation these are extremely diverse in terms of the BCI tasks and applications. The examination of datasets suggests that these has different size and are collected from a different sources and also has undergone a variety of preprocessing methods to improve the accuracy and consistency of the data and the majority originate from esteemed sources such as Physionet, BCI Competitions, and other clinical or experimental environments.The typical preparation steps include feature extraction, noise reduction, artifact removal and normalization,which get the data ready for advanced machine learning algorithms like CNNs, LSTMs, SVMs, and deep neural networks.In Order To create brain injury rehabilitation and other neurological applications-focused BCI systems, it is necessary to comprehend this kind of dataset and its properties.

(Table 2): Dataset Overview

Reference and Year	Dataset Used	Data Source and Dataset Size	Preprocessing Techniques Used
Sun et al. 2024	Physionet EEG Motor Movement/Imagery Dataset	Physionet 109 subjects, 2,456 trials	Bandpass Filtering, Feature Scaling
Brunner et al. 2024	BCI Competition III, Dataset IVa	BCI Competition 10 subjects, 1,000 trials	Bandpass Filtering, Feature Extraction
Ma et al. 2024	BCI Competition IV, Dataset 2b	BCI Competition 20 subjects, 1,800 trials	Epoching, Noise Reduction
Yassine and Abdelkader 2024	SEED (SJTU Emotion EEG Dataset)	SJTU 15 subjects, 1,200 trials	Preprocessing, Feature Selection
He et al. 2024	BCI Competition II, Dataset IIb	BCI Competition 8 subjects, 900 trials	Preprocessing, Signal Amplification
García-Martínez et al. 2024	Auditory Hallucinations Detection Dataset	Custom 20 subjects, 800 trials	Feature Extraction, Artifact Removal
Qu et al. 2024	Combined BCI and Robotics Dataset	Combined BCI-Robot Dataset 12 subjects, 1,500 trials	Normalization, Signal Processing

5. CONCLUSION

This review discusses significant advancements and new developments in brain-computer interface technology for stroke recovery. The authors were able to demonstrate the potential of brain-computer interfaces (BCIs) to induce motor imagery, aid in the recovery of motor abilities, and even aid in the treatment of the emotional and cognitive aftereffects of a stroke, thanks to the abundance of available datasets and very advanced machine learning models. For the BCI systems in clinical use, high performances and efficiencies have been achieved by combining several deep learning algorithms, such as CNN and RNN. Furthermore, there is still much to be done in the future, even though problems with data preprocessing optimization, system flexibility, and ethical and legal concerns have only recently started to be resolved. Refining these systems would boost their applicability and make more useful and efficient BCI technology available for stroke survivors to use. This would require more research efforts. The quality of life for stroke victims is improved and significant opportunities for improved rehabilitation results are created when BCI technology and machine learning are combined.

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