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Study on Brain Computer Interface for disabled people with communication disorders

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***Abstract*— For people with serious physical disabilities who lack the means of conventional communication or who are no longer able to communicate, a Brain Computer Interface (BCI) is a good and advantageous option. The goal of this research is to help people with severe muscular disorders like amyotrophic lateral sclerosis (ALS), stroke-related paralysis, locked in syndrome, tetraplegia, and myasthenia gravis regain their ability to communicate. It is true that BCI can be used for a broad range of activities, not just neurofeedback, the recovery of motor function in paralyzed patients, enabling interactions with locked patients, and improving sensory processing. This review article discusses various methods and approaches for neural correlations of attempted or simulated speech that may help people with severe communication disorders regain communication and enhance their quality of life.**

***Index Terms*—Brain Computer Interface, Electroencephalography, Imagined speech, Neurosky Mindwave sensor**

I. INTRODUCTION

In this current tendency, the emerging technology known as BCI is gaining a lot of popularity. This pattern reveals that more researchers are becoming involved in BCI study. Previously, BCI study got its start in 1970 at the University of California. The first human neuro prosthetic devices that can replace malfunctioning neurons were discovered in the middle of 1990s. The first brain computer interface device was implanted into a human in 1998, which was a significant advancement in the area of brain mapping. Jonathan Wolpaw and researchers from the Wadsworth-Center of the New York State Department of Health put forth a study report in December 2004 that indicates BCI's ability to control computers. In this research, subjects wore a cap with electrodes so that electroencephalography (EEG) signals from their motor cortex, a part of the cerebral cortex that is involved in planning and controlling movements, could be recorded. Features were extracted from those signals and then transformed into outputs that replace, restore, enhance, supplement, or better human functions.

A Brain Computer Interface is a component of hardware that enables people to interact with technology by sending electrical signals from their brains. Through neural correlations of attempted or envisioned speech, BCI would enable real-time communication, which could possibly restore communication and enhance the quality of life for patients who are confined or who have severe communication disorders. Imagined speech is a form of first-person narration in which actors perform speaking in its entirety without using any articulatory movements. Imagined speech can naturally function as the most intuitive process of brain communication because verbal communication through speech is the most universal form of communication between humans.

The BCI is frequently utilized to treat many of the disabilities that disabled people experience. NeuroSky MindWave sensor is used to acquire brain signals and then the signals are interfaced. Individuals with severe physical and speech disabilities will have access options owing to BCI, avoiding the need for other interfaces. BCI systems are an innovative augmentative and alternative communication (AAC) tool when used for conversation.

II. LITERATURE REVIEW

According to Victor Martinez-Cagigal et al. [1], the design, construction, and testing of an asynchronous P300 BCI system for managing social media platforms on mobile devices such as smartphones and tablets includes both motor-able and healthy users. The system is watching the patient's EEG output while an RCP (Row Col Paradigm) matrix flashes its rows and columns, opportunities were promoted by P300 on the user's head. The final Android smartphone interprets the selected instructions after receiving them via Bluetooth in real-time, then provides the user with visual feedback. The system was tested using 18 motor-disabled subjects (MDS) and 10 controlled subjects (CS). During the evaluation, this included a single evaluation session and two calibration sessions. Users had to do six distinct activities that were graded according to their level of difficulty. In both the quantitative and qualitative evaluations, the average accuracy for CS and MDS was respectively 92.3% and 80.6%. The accuracy results have been proven to be considerably different from those reported in trials with comparable designs but lower performance levels. This study's accuracy results and those published in comparable research that achieved lesser performances showed significant disparities. It is thus shown that the P300 based BCI connecting system is an acceptable replacement for motor disabled users, enabling them to fulfil their regular communication prerequisites.

The statement highlighted by Fatemeh Fahimi et al.[2], that deep learning (DL) techniques and their applications that are in several fields, including imagine speech, vision, and BCI systems. DL networks are capable of processing large amounts of electroencephalogram (EEG) data based on time series for classifying tasks. However, EEG classification methods may face challenges such as information loss and difficulties while knowledge transformation between subjects. Moreover, the research of what a DL network learns can be a challenge. To address these challenges, the statement proposes that deep convolutional neural network (CNN) framework is classifying EEG into attentive state and non-attentive mental states. This framework can have applications in various domains such as game based BCI, and neurorehabilitation. The limitations of conventional classification techniques can be overcome, and better accuracy can be attained, by using a deep CNN for EEG classification. Furthermore, the proposed framework can be used in various BCI applications, including cognitive BCI, which uses EEG signals to control devices, game-based BCI, which uses EEG signals to play games, and neuro-rehabilitation, which aims to restore neural function after injury or disease. Overall, the proposed framework shows promise in addressing the challenges in classification of EEG and has potential applications in various BCI systems. The authors Sujay Narayana et al. [3], have suggested simple signal processing methods to interpret unprocessed EEG data as opposed to signals obtained from an EEG headset. To show controlling various devices and applications, they combined EEG and EMG signals. Additionally, a technique for differentiating between neutral states (relaxed state, not working) and attentive states (person in attentive state, meditating state) was suggested for identifying mental tasks. The authors show a BCI-based wheelchair locking and unlocking system that also allows for movement control. The method described here employs a single electrode electroencephalography (EEG) headgear from NeuroSky called the MindWave Mobile, which can be paired with any Bluetooth-capable device. The electromyography (EMG) patterns caused by eye blinks and jaw muscle action are extracted from the raw data from the headset using an android smartphone. A wheelchair's mobility can be controlled in all directions using these patterns. The wheelchair is equipped with a biometric security system that locks and unlocks it by deriving data from the raw EEG output about various brain waves. Only the user is aware of the password in this system, which can manage the security of the wheelchair and operate it. The password is created using brain waves.

The authors Pramit Saha et al. [4], describes a deep neural network architecture that is novel and hierarchical that utilizes a parallel spatial-temporal convolutional neural networks (CNNs) and deep autoencoder used for imagined speech EEG data for predicting phonological and speech tokens. The paper makes several contributions, including a method where a cross-covariance matrix is used for embedding high dimensional EEG data into that captures joint variability of electrodes. This matrix is then used to successfully classify phonological attributes into six categories and to identify speech tokens based on the predicted categories. The paper suggests that underlying articulatory movements represent speech tokens. This finding is significant, as it provides evidence that imagined speech may be decoded from EEG data using machine learning algorithms as shown figure1. Overall, the paper provides a promising approach to decoding imagined speech from EEG data, which could have important implications for improving communication and assistive technologies for individuals with speech impairments. The proposed method could also provide insights into the neural mechanisms underlying speech production and perception. The author Seo-Hyun Lee et al. [5], suggests that the cognitive approaches that can be used to communicate user intentions and instructions directly and support brain communication include imagined speech and visual imagery. The paper also suggests that both paradigms can be used in multiclass decoding and that performance can be improved with neural processing and optimal features usage. According to the paper, both the paradigms share some features in common, especially their properties, which can contribute to a comprehensive understanding of both the paradigms. Overall, the paper suggests the mentioned methods have significant potential for improving brain communication and that further research is needed to fully explore their properties and potential applications. It also implies that understanding the class dependency of the effective and functional connectivity can aid in selecting efficient classes for decoding. Also, investigating these paradigms' features indicates a major role in improving effectiveness, potentially leading to the ability to "read the mind" in the future.

The author Sahar Sadeghi et al. [6], compares two different methods of estimating information transfer rate (ITR) the bit rate in a BCI. The definition of Wolpaw's and the formula which is proposed both aim to estimate the amount of information that can be transmitted from the brain to computer via a BCI system. Wolpaw's definition is based on N and P parameters, which represent the number of bits used to represent a signal and the probability of correctly classifying the signal, respectively. The formula estimates the bit rate as N times P. However, this definition does not consider the probability of occurrence of each symbol in the signal. On the other hand, the proposed formula considers the probability that symbols occur in the signal to calculate bitrate. Specifically, the frequency rate of each symbol is considered as its occurrence probability. This results in a more accurate estimation of the bit rate and ITR. Based on comparing the graphs corresponding to these two definitions, it seems that the graph overestimates the bitrate to that proposed. This is because the Wolpaw's definition does not consider the symbol occurrence probability, which can lead to inaccurate estimations of bit rate. The graph proposed, on other hand, provides more accuracy on the ITR by decreasing the estimated error. In conclusion, compared to Wolpaw's definition, the suggested formula that considers the probability of symbols yields a more precise estimation of the bit rate and ITR in a BCI system.

The authors Rahul Agrawal et al. [7], have developed a system that will likely enable the people who are disabled to communicate with the others more readily or to tell carers of their basic needs. Additionally, the technique used to address the issue of speaking impairment in people with brain injuries, epilepsy, issues in sleep, Alzheimer's, Parkinson's, ALS, paralysis, cerebral palsy, etc. In this work, brain activity that serves as the patient's primary means of communication with the outside world is recorded using an EEG-based brain state signal measurement technique. An electroencephalogram is a non-muscular channel that the brain computer interface, which records electrical activity for the brain to examine EEG data, provides between the human brain and a computer system. Then, using Time-Frequency approaches (T-F) like the fast Fourier transform and short time Fourier transform, these signals are divided into smaller signal segments. Both methods serve as extraction strategies before the data is trained and Support Vector Machine (SVM) are used to classify the data. The performance metrics accuracy, precision, sensitivity, and specificity are computed based on the values of the evaluation metrics, and the overall system accuracy is 92%. Patients can use the four categorized signals as communication messages to help with the issue of speech impairment in disabled people. The authors Xun Wu et al. [8], examines the strength, coefficient of clustering and eigen vector centrality properties of three EEG functional connectivity networks and suggests a novel emotion-relevant subnetwork which is a critical selection algorithm. based on the publicly available datasets such as SEED, SEED-V and DEAP,Ddiscrimination capacity of connectivity features of EEG in identification of emotion is assessed. Based on single-channel analysis of the raw data, the strength feature outperforms the state-of-the-art differential entropy feature and gets the best categorization performance. The findings of the experiment show that all emotions like happiness, sadness, fear have their own functional connectivity patterns. Additionally, using deep-canonical correlation analysis, the features like physical signals and movements of eyes were used to build a multimodal emotion detection model. The SEED dataset has classification accuracy of 95.08 6.42%, SEED-V has classification accuracy of 84.51 5.11%, and the DEAP dataset has classification accuracy of 85.34 2.90% and 86.61 3.76% for arousal and mood, respectively. The outcomes show how eye movement data and EEG functional connectivity network features have complementary representational qualities. It also illustrates the patterns of functional connectivity in the brain associated with emotions and the possibility of using networks of brain.

According to the study, the authors Vikrant Doma et al. [9], identified the brain regions that store information pertaining to various emotions and understand how neurophysiological systems might cause an individual to experience emotion. Linear-Discriminant Analysis, Decision Trees, Logistic Regression, Naïve Bayes classifier and K Nearest Neighbors Algorithm methods all bring meaning with accuracy within 55 and 75% and a F1 measure between 70 and 86% because of using the basic machine learning techniques. KNN classification for "Liking" produced the best results, while other classification methods did not outperform one another. K Nearest Neighbors, Decision trees, Support Vector Machine, Logistic Regression, and Linear Discriminant Analysis, are the classification algorithms in descending order of maximum accuracy attained. As the analytical details about the streams and the raw streams data showed that the rear left hemisphere of the brain was active, dimensional reduction was performed along with the division of the data of 60s chunks, that is divided into four 15s chunks to get the best selection features, improving accuracy. Spark also worked well for splitting out the burden associated with tweaking hyperparameters. Without sacrificing F1 or accuracy, the trials might be expanded to include other emotions. The study reveals that traditional machine learning algorithms produce decent results and can pinpoint details about significant epoch channels that oversee regulating emotional states. The authors Seo-Hyun Lee et al. [10], suggests imagined speech and visual imagery could start the results applied in the natural communication for paralyzed patients to communicate with the outside world by simply thinking of the emergency that user wants to convey. It can also be applied in the contemporary epoch for communication purposes. The patient's intention can be directly delivered to their close ones that helps in interaction with the external environment. This approach can be more efficient than the system that works on entering by letter called conventional speller systems. These BCI intuitive communication systems can further implemented in the modern technology using sound devices, that is these devices are enabled to speak out the imagination of user's thought that the actual words and that can be delivered. The authors Li Wang et al. [11], extracts time series frequency features of EEG signals and also by conventional. This study uses Deep Neural Network (DNN) for extraction of frequency features. parallel and series structures are integrated to achieve the desired results. Convolutional Neural Network (CNN) is used in extracting different frequencies and spatial features, Characteristics is extracted using Long Short Term Memory(LSTM). The best matching can be achieved during model training through feature extraction and classification. The series topology can outperform conventional techniques and alternative DNN architectures in terms of generalized performance.The authors Firgan Feradov et al. [12], for audio visual stimuli as the reference-matrix, EEG activity based on the artificial monitoring of dislike reactions is the main emphasis of this research. Authors specifically examine the discriminative ability of the EEG features calculated by either segmenting the signals of EEG or not on the task of dislike detection. They performed a comparative analysis using 18 variations that are mentioned above EEG features that span various frequency bands, employ many techniques of energy decomposition, and have various spectral resolutions. The authors used SVM classifiers the radial-basis-function (RBF) kernel trained using the Sequential Minimal Optimization (SMO) technique, as well as the Naïve Bayes classifier (NB), Classification and regression trees (CART), k Nearest Neighbors (kNN), and kNN classifiers, for this purpose. On frequently used DEAP dataset, the experimental assessment was carried out. For the top performing mix of preprocessing, EEG features, and classifier, categorization accuracy of up to 98.6% was seen. The DFT based features are unable to capture information about the activity during the time that the entire signal features. Contrarily, the DWT based features are capable of temporal localization, which is reflected in the significantly better detection accuracy. The authors Feng Li et al. [13], suggests the transfer learning of cross subject can be done offline in P300 speller paradigm can be accomplished using the method of transfer learning, which is suggested in this paper, it is combination of Riemannian Geometry classifier (RGC) and XDAWN spatial filter. The components of P300 in the unprocessed signal are improved, and the size of the signal is decreased, using the given spatial filter. Then, to make the data from various subjects comparable, the Symmetric Positive Definite (SPD) of affine transformation of covariance matrix derived from the filtration of signal is carried out using the as the reference-matrix Riemannian Geometry Mean (RGM). In order to acquire the outcomes of transfer learning experiments, the RGC is used in the end. When there are few training data sets available, this method has the ability to reduce or remove the calibration step. The authors Rachael I Cano et al. [14], suggests the calculating the states can enhance human and computer interaction and advance the treatment of severely disabled individuals. Many procedures, such as Fast Fourier Transform, short Time Fourier Transform, and Welch's-power methodology for estimating of spectral density methodology, can be used to compute spectral density and band powers. Frontal EEG asymmetry has been proposed as moderator and modulator of affective states. Most commonly, frontal alpha asymmetry is employed as an indicator of depression vs mental wellness. It can also be employed to categorize affective states, though. The power of the band is best for classifying arousal, theta band power for classifying valence, and theta and ratio of beta-1 for classifying dominance, according to research results. This study demonstrates that balanced accuracy has a number of benefits, including the fact that it doesn't include a "preferred class" hence it and comparison is done across class, that the bounds can be estimated using established notations, that it is simple to extend to classes which are huge in numbers, and that it consistently has the 1/k chance performance for novice classifiers. In this paper, the authors Wilson Junior et al. [15], proposed a BCI based smart house device to assist amyotrophic lateral sclerosis patients. The suggested program, which enables the operation of inexpensive sensors, was created for Android smartphones. Based on these data, the author may speculate that ALS Help application may be a device that allows ALS patients to do daily tasks independently. Positive findings were obtained with ten participants. Additionally, the use of the program was endorsed by 80% of these participants. These outcomes attest to the application's effectiveness and performance. To verify our findings, we must repeat the exercise with individuals with ALS in a real-world residential setting. In this article Gao X et al. [16], provides a short history of BCI development and a synopsis of current BCI technology using an I3 model of evolution. The model depicts how, as science and technology advanced, the relationship between the brain and machine has grown closer and their interchange of information has progressed from sense and sensation to cognition, enabling seamless communication and cognitive cooperation. Future advancements in BCI, an interdisciplinary study area, are dependent on advances in engineering and neurobiology. The foundation for the success of BCIs in the future, from a neuroscience viewpoint, is an understanding of how the brain functions and how it works. Applications for multimodal and extensive ultra-high speed, neural recording wireless broadband signal transmission, and cloud platforms hyper data processing power are the future directions for technological advancement. BCI technology is still in its youth overall, despite significant advancements in the recent past. The bulk of BCI systems in use today have only undergone limited experimental testing and have a long way to go before they are applied in actual situations. BCIs must become more dependable and accessible so that both fit and disabled people can use them on a regular basis.

The authors Li Q et al. [17], employed important methods for emotion detection is the deep sparse autoencoder network (DSAE), which is also used to decompose EEG signals and extract channel correlation. By selecting the right number of SEA layers, this method improved the effectiveness of feature extraction and the precision of sentiment classification. then a hybrid CNN and LSTM network modelled for learning and processing the dependency of EEG time series characteristics to enhance accuracy. These experiments proved to achieve higher accuracy in given tasks on DEAP dataset that is for recognition of sentiment and arousal. Though these experiments were not done on real-world scenarios these were based on extraction of frequencies during mental tasks. All the temporal-spatial-frequency features were extracted from EEG signals using DNN. Parallel and series structures were obtained by integrating LSTM and CNN. Convolutional Neural Network (CNN) is used in extracting different frequencies and spatial features, characteristics are extracted using Long Short Term Memory (LSTM). The best matching can be achieved during model training through feature extraction and classification. The series topology can outperform conventional techniques and alternative DNN architectures in terms of generalization performance. The authors S Lee et al. [18], utilized the V1, V2, and V3 based C-c CNN system to extract the characteristics of the vast system, and the accuracy of the classification for nine emotions was 93.7%. Consequently, the underlying assumption of the study's investigations was that every emotion exhibited is distinct and recognizable. The inability to describe the qualities of the output and the requirement that we swiftly recognize emotions for the application of emotion recognition were the study's shortcomings. The number of training intervals needed to implement and compare to other models it is lower than the traditional CNN models after using B N layers, this model had to extract the data features three times there are middle, bottom, top layer, which limited running efficiency a preprogrammed Python Editor. Using the recommended approach for the classification of online emotions to gain network weights which is suitable can reduce the time required to train initialization weights significantly. The researchers Dai J et al. [19], have carried out experiments to gather EEG data on both visual imagery and visual perception. With the aid of the visual imagery paradigm, this article explored the degree of flexibility and potential intuitiveness of BCI. For the experiment, three categories with three classes each were taken into consideration. EEG time series data can be transformed into several formats and classified using different classifiers for permissible formats. Many methods have been tried to classify visual imagery. Mean accuracy of 24.02% for nine class and 57.59% for three category classification was observed in this experiment. It was found that the MultiRocket classifier performed the best, indicating that some of the images were visually similar. It was proven that the categories shared some visual characteristics, and the three-category classification might be a little more accurate. The choice of visual pictures should be made carefully as it can influence and enhance classification performance. In this study Arjun Chikkankod et al. [20], has used EEG data which was collected continuously from 32 people while they watched music video snippets selected to elicit various emotions in viewers, hence imposing various mental states, to examine the best latent space dimension. The sliding window method was employed., were produced, Every EEG band is mapped by five topographic ones for each window in frequency domain (alpha, beta, delta, theta, and gamma). This study expands the body of knowledge by creating an architectural pipeline for maintaining crucial EEG features while discarding redundant EEG data, defining its boundaries, and demonstrating its applicability in ecological contexts. This study will be expanded in future research to strengthen its conclusions.

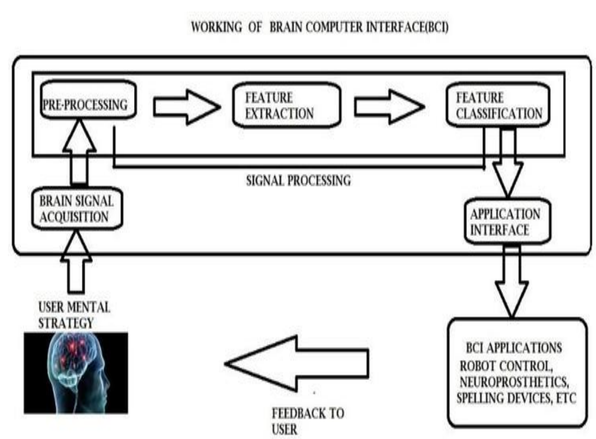

Figure 1: Working of BCI

II. LITERATURE SUMMARY

Sl. No	Citation	Year	Methodology/Algorithms used	Remarks
1.	Martínez- Víctor Cagigal, Santamaría-Eduardo Vázquez, Gomez-Javier Pilar, & Hornero Roberto.	2018	Row-Col Paradigm (RCP) is used to enable coding user intention. Signal acquisition, Signal processing, Application & Evaluation procedure	Providing audio feedback to the user and P300 based BCI system has been devised, created, and evaluated including both motor disabled and healthy individuals to operate social networking programmes on tablets or smartphones.
2.	Fatemeh- Fahimi & Zhuo-Zhang & Boon- Goh & Tih- Shih Lee & Kai- Ang & Cunta- Guan	2018	Deep CNN is used for minimizing the computational-load and preserving the information.	The least amount of the raw EEG processing is produced as the input to reduce the burden on computing and preserve the information. The major causes of information loss and processing costs- pre-feature extraction and/or converting the EEG to images- should both be avoided.
3.	Sujay Narayana, Ranga Rao Venkatesha Prasad, Kevin Warmerdam.	2019	EEG pattern recognition: Blink detection, Jaw tension detection	There is a biometric identification system provided for security features of the wheelchair by acquiring information on various brainwaves from the unprocessed EEG signal.
4.	Saha, Pramit, Muhammad Abdul-Mageed, and Sidney Fels	2019	Convolutional Neural is used for the Feature extraction and the Network-Long Short Term Memory is used for classification	Convolutional Neural is used for the Feature extraction and the Network Long Short Term Memory is used for classification and using this more accuracy can be acquired.
5.	Seo Hyun Lee, Lee Minji, Hoon Ji Jeong, Seong Lee Whan	2019	1. Cyber-Physical Systems is used for feature extraction 2. RLDA is used for classification.	Convolutional Neural is used for the Feature extraction and the Network Long Short Term Memory is used for classification and using this more accuracy can be acquired.
6.	Sahar Sadeghi, Ali Maleki.	2019	Diffusion Convolution Récurrent Neural Network is used for analysis and the extraction of features.	Convolutional Neural is used for the Feature extraction and the preprocessed information is not used which leads to computational loss.
7.	Rahul Agrawal, & Preeti Bajaj.	2020	1.Feature extraction: fast Fourier transform, short time Fourier transform 2.Support vector machine classifier	Hardware can be designed to extract the entire information of the brain, which is to be processed, determine the thoughts in the brain.
8.	Wu Xun, Long-Wei Zheng, & Lu Bao-Liang.	2020	Diffusion Convolution Recurrent Neural Network is used for analysis model	Reveals the functional connectivity patterns in the brain connected with emotions and the possibility of using brain networks with fewer electrodes in BCI systems.
9.	Vikrant Doma & Matin Pirouz.	2020	Naive Bayes, Decision Trees, Logistic regression Classic machine leaning techniques of Support vector machine, K Nearest Neighbors Algorithm and Linear Discriminant Analysis is used	The machine learning algorithms achieved identify information and reliable results about important channels that are responsible for Accuracy in speech detection and the emotional states.
10.	Seo Hyun Lee, Lee Minji, Hoon Ji Jeong, Seong Lee Whan	2020	Diffusion Convolution Récurrent Neural Network.	Convolutional Neural is used for Feature extraction and Network-Long Short Term Memory is used for classification and using this more accuracy can be acquired in visual imaginary.
11.	Wang Li, Huang Weijian, Yang Zhao, Zhang Chun.	2020	Deep neural networks are used for pre-processing.	LSTM and CNN are proposed to extract frequency. The classification algorithms and feature extraction are set independently

				of the traditional EEG signal-processing algorithms.
12.	Feradov Firgan, Mporas Iosif and Ganchev Todor.	2020	Power Spectral Density, Logarithmic Energy and Linear Frequency Cepstral Coefficients are used for feature extraction	The EEG features from a minimal frame allow for a significant size reduction of data, demand in memory, and complexity in computation, which would make these a viable trade-off choice.
13.	Li Feng, Xia Yi, Wang Fei, Zhang Dengyong, Li Xiaoyu and He Fan	2020	XDAWN spatial filter, Riemannian Geometry Classifier, and affine transformation of SDP Covariance Matrix	The creation of a BCI transfer learning method that is more reliable. Prospects are high for the Riemannian Geometry related transfer learning method.
14.	Cano I Rachael, Dhuyvetter J Katie, and E David	2020	Fast Fourier Transform, Short Time Fourier Transform, or Welch's power spectral density	In balanced accuracy a "preferred class" does not exist, so it is comparable between groups. With basic classifiers, balanced accuracy always performs at 1/k chance and is insensitive to class bias.
15.	G. Wilson Júnior de Oliveira, M. Oliveira Juliana de, Munoz Roberto & Albuquerque V.H.C.	2020	MindWave integration with Arduino microcontroller. A L S Help integration with Arduino micro-controller	BCI system is based on Io-HT. Used as assistant to assist patients with ALS task performing which are predefined for personal digital brainwave sensor.
16.	Xiaorong -Gao, Yijun Wang, Xiaogang-Chen, Xiaogang-Gao	2021	Cortical surface stimulus (uses electrodes that is placed on surface of brain), Intra Cortical Microstimulation (ICMS)	A decoder usually has three procedures: signal pre-processing, extraction feature, and pattern-classification.
17.	Li Qi, Liu Yunqing, Shang Yujie , Zhang Qiong and Yan Fei	2022	The DSAE method is used to derive signals without noise. Information which is relevant in EEG signal using LSTM techniques	Improve recognition accuracy. It is essential to validate the viability of the techniques in real life scenarios.
18.	Dai Jinxiao, Xi Xugang, Li Ge, & Wang Ting.	2022	Convolutional neural network structure is used for signal acquisition.	To establish shorten the training period for initialization weights and appropriate initial network weights. online categorization of emotions and input raw EEG cannot convey positional connection.
19.	Sunghan Lee,Sehyeon Jang,Sung Chan Jun	2022	Multirocket classification is used for classification, Event-Related Spectral Perturbation (ERSP), MobileNet V2 as classifier.	Signal preprocessing, feature extraction, and pattern classification make up the typical decoder.
20.	Chikkankod Arjun & Longo Luca	2022	The study of Structural Similarity Index Measure (SSIM), study of Mean Squared Error (MSE) and the normalized version (NRMSE), as well as the Peak Signal relates Noise Ratio (PSNR).	Development of intuitive BCI paradigms have not considered the features of EEG data's that is a functional connection. The functional connectivity of time series data such as EEG is a distinctive characteristic.

IV. CONCLUSION

In conclusion, brain-computer interfaces have shown promising results in enabling severely impaired paralyzed patients to communicate their basic needs through brain signals. These patients have considerable limitations in their ability to control voluntary muscles, but with the help of BCI systems, they can communicate effectively with the external world. The direct sharing of data between the brain and external devices is made possible through BCI systems. One promising application of BCI systems is in the generation of voice output, which can be controlled by the user's attention levels. To create a unique footprint, user-based or modules can be developed, and innovative technology can be used to make iterations simple and feasible. Overall, BCI systems hold great potential in improving the quality of life for severely impaired paralyzed patients and have the ability to change the way we communicate and interact with technology. As technology continues to evolve, BCI systems are likely to become even more advanced, offering greater opportunities for patients to communicate and control their environment through their thoughts and brain signals.

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