MIND MAPPERS: AN IN-DEPTH EXPLORATION OF BCI DATASETS, STRATEGIES, AND ANALYTICAL FRAMEWORKS

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Abstract: *This study determines the complexity of Brain-Computer Interface (BCI) research through an examination of the methods, data sets, and analytical techniques used in this innovative area. The paper offers a thorough analysis of a BCI data set, illuminating its distinctive qualities and suggestions for future examination in the area of neuroscience. The philosophy area intends to further develop straightforwardness and consistency in BCI research by giving a thorough explanation of the design of the study, data gathering, and preprocessing methods used. Moreover, the analysis part reveals new information extracted from the data processing, highlighting the importance of strong methods in machine learning and statistical analysis. A more modern comprehension of cerebrum designs and their relationship to outside data sources or engine purposes is made possible by the integration of sophisticated analytical methods.*

Keywords: *BCI, EEG, GUI, MNE, MEG, EOG, EMG, EXG1, ICA, PCA.*

I. INTRODUCTION

The electrical activity of the brain causes noise pollution, which makes it difficult to extract meaningful information from EEG scans. Beyond the skull, the electrical fields of the brain are weakened, making physical barriers challenging to surmount.

We still don't have a system that can reliably interpret imagined EEG speech for practical application, even after more than ten years of focused research. Researchers are finding better sets of prompts with highly discriminable EEG signatures, developing more sophisticated machine learning algorithms, and examining the effect of language on the signatures in an effort to improve the decoding process.

II. RESEARCH ISSUE

Is it currently feasible to design a non-invasive, therapeutically effective BCI system that takes ethics, money, and the economy into account?

Till date, the closest a research has reached our research problem is thinking and planning a framework and mechanism for making a non-invasive BCI technology. Ethical and economics criteria have not yet fit the framework in the expected space and hence, its production, public availability and usage has not been procured for the common man in the market.

Technological advancements like electroencephalography (EEG) headsets have simplified brain signal interaction between users and computers/other devices, eliminating the need for invasive treatments.

Studies have looked into the use of BCIs in cognitive improvement therapies, communication support for those with locked-in syndrome, and rehabilitation. Patients with neurological illnesses may see an improvement in quality of life as a result of these applications.

But since BCIs gather private neural data, it's critical to secure the protection and safety of this data. To secure neuronal data from misuse and unwanted access, researchers are creating encryption techniques and protocols.

Hence, it feels proud to be said aloud that while the research problem has been touched and being investigated at a great rate today, it carries with it a lot more potential than what meets the eye and clouds the brain.

III. WORKFLOW

Ten sound right-given people, half a dozen males and the same number of females, with a mean age of 34 (standard deviation = a decade), no neurological, outer muscle, or mental issues, and no discourse or hearing weaknesses chipped in for the review and gave composed informed assent. All subjects took part in about two hours of recording, none of whom had ever used a BCI. Under the aliases "Person A" through "Person J," participants in this study can be identified; they are Native Americans from various locations who speak various languages. Complete participant data is included in the table below.

Due to the existence and identification of noise artifacts, outside impediments, and saturation effects, the data from additional individuals was not included in the trial or workflow.

Table 1.1: Participant Information

Participant	Gender	Age	Dominance	Native
Person A	M	56	Right	English
B	F	50	Right	Hindi
C	M	34	Right	Hindi
D	M	24	Right	English
E	F	30	Right	English
F	F	29	Right	Hindi
G	M	26	Right	Urdu
H	F	28	Right	Urdu
I	M	35	Right	English
J	M	31	Right	English

IV. MECHANISM

The review was led in an electrically safeguarded climate. The members were situated serenely before a PC screen that showed the visual signs. The participant became familiar with the room arrangement and the experimental protocol while all aspects of the analysis were made sense of and the outside anodes and EEG head cap were fitted. The arrangement cycle requires roughly 45 minutes.

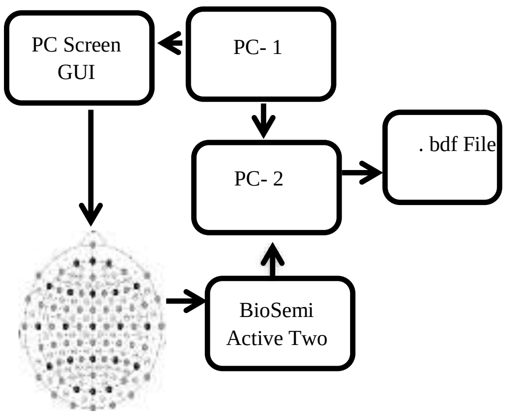

Fig. 3.1 The experiment's main setup.

V. CONFIGURATION

Two PCs that weren't in the acquisition room were PC1 and PC2. As the stimulation process is being carried out, PC1 alerts PC2 to each cue that is provided. PC2 uses the information that PC1 supplied to annotate the events after receiving the EEG data through the acquisition device (sample). The creation along with saving of a. bdf file marks the conclusion of the recording.

The protocol of stimulation was developed using a device Psychtoolbox-347 which is ran in MatLab48 on the PC1 machine shown in Figure 3.1. Through the Graphic User Interface, the procedure provided the participants with visual signals (GUI). The background of the screen was light grey to prevent glare and eye strain. In this manner, an MNE module that works in conjunction with numerous other Python packages is also heavily utilized [1].

Preprocessing, source estimates, time-frequency analysis, statistical evaluation, and several methods to estimate functional linkages between dispersed brain regions are just a few of the many analysis tools and workflows that this software package provides. Its capacity to extract cortically-constrained minimum-norm present estimations from M/EEG data gives rise to its name.

Each member partook in a solitary recording day that contained three successive meetings, as shown in Fig. 3.2. To prevent boredom and fatigue, a self-selected intermission (inter-session break) was offered in between sessions. Every session started with a baseline recording lasting fifteen seconds, during which the individual was told to unwind and remain still as much as possible. There were five runs of stimulation in each session.

The three factors- verbal speech, inner speech, and visualized conditions (explained in Section BCI Interaction Conditions) all match these runs. The condition was displayed on the screen for three seconds at the start of each run. In every example, the runs were as follows: two inner speeches, two pronounced speeches, and two visualized conditions. Every run was separated by an inter-run, which lasted one minute.

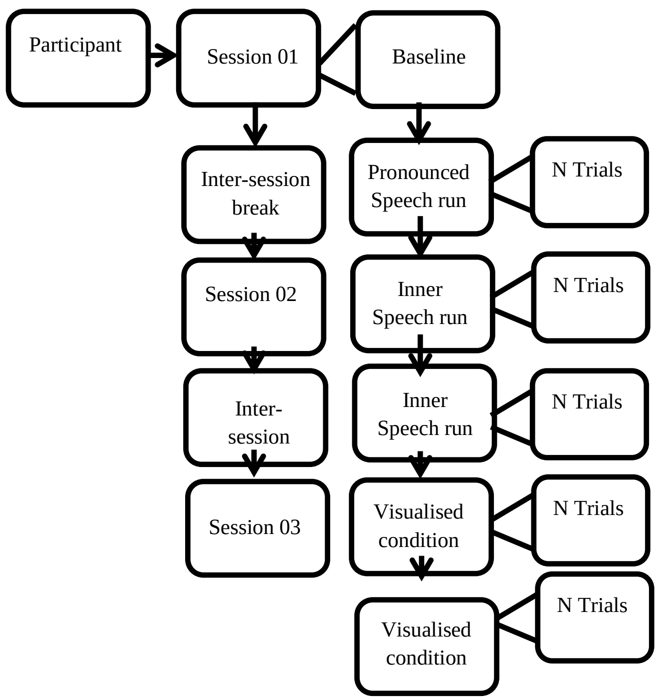

Fig. 3.2: The schedule for each participant's day of recording

The phrases "up," "down," "right," and "left" were carefully chosen for the courses with reference to an application of natural BCI control. The trial's class (word) was chosen at random. During the first and second sessions, every participant finished 200 trials. However, due to exhaustion and willingness, not every participant completed the third session's trial count remained the same.

Figure 3.3 displays the relative and cumulative times as well as the composition of each trial. Every trial began with a 0.5 s concentration gap at time t = 0 s. The participant was advised that a fresh visual cue would appear soon. The subject was told not to flicker until the preliminary was finished and to keep in touch with the white circle that showed up in the center of the screen. The cue interval started at time t = 0.5 seconds. A white triangle with four points was visible: left, right, down, and up. The direction in which the cue pointed was suitable for every class. After 0.5 s, or at t = 1 s, the triangle-shaped symbol vanished from the screen, flagging the beginning of the activity span. The members were told to begin the proposed task when the viewable signals disappeared and the monitor showed only the white circle. The white circle turned blue at t = 3.5 s, which is 2.5 s after the action period ended, and the relax interval began. At this time, the subject was advised to stop working on the task, but not to blink until the blue circle had vanished. The blue circle vanished at t = 4.5 s, marking the end of the experiment. In between trials, a variable-length rest period of 1.5 to 2 seconds was given.

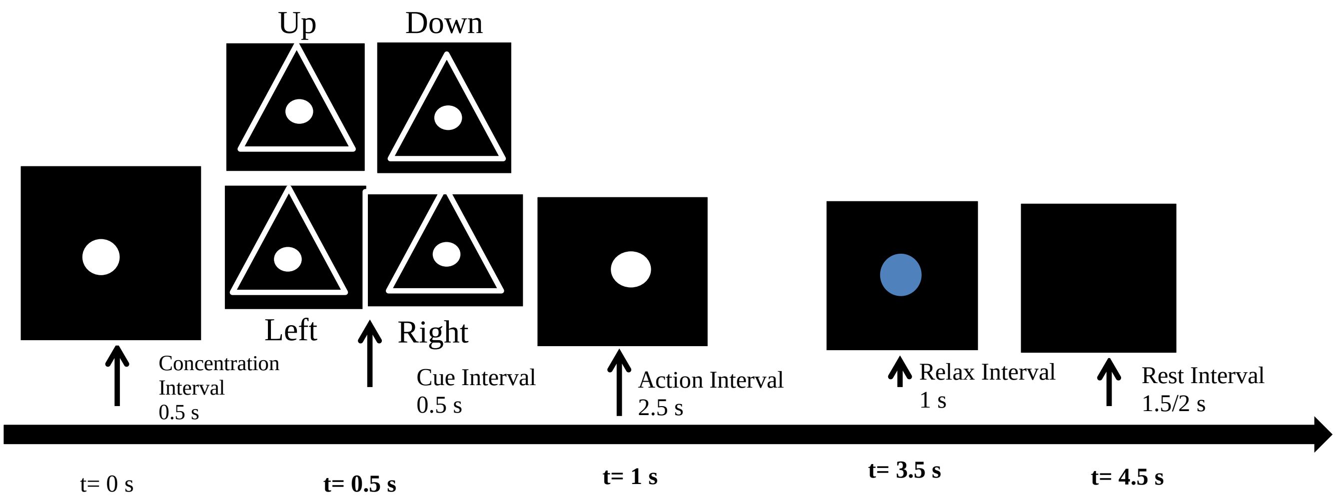

Fig. 3.3: Trial workflow: The top arrow plots the participant's screen at each time interval. The arrow is plotted above and below for relative and global time.

Each participant's attentiveness was measured by running the imagined condition after a concentration control was sporadically inserted to an inner discourse. After a few randomly selected trials, the control task involved asking the participant what orientation the previous class demonstrated. The candidate has to choose the movement using the keyboard's arrow keys. The process continued as long as the candidate any of the four arrow keys, and there was no time limit on answering these questions. The correctness of the response to the question was indicated visually [1].

VI. DATA ACQUISITION

A BioSemi ActiveTwo high-resolution biopotential equipment which is a measuring device, used to collect data for electroencephalography (EEG), electrooculography (EOG), and electromyography (EMG). 128 active EEG channels and 8 external active EOG/EMG channels with a 1024 Hz sampling rate and 24-bit resolution were used for data collection. Standard EEG head helmets with pre-fixed electrode locations are also available from BioSemi in a range of sizes.

To determine the appropriate size cap, a tape measure was used to measure each participant's head circumference. A conductive SIGNAGEL® gel was used to fill the void in between the scalp and electrodes after every EEG electrode was inserted into the cap at its proper location.

Utilizing a flat active electrode consisting of the same conductive gel and secured with a detachable adhesive disk, signals in the EOG/EMG channels were recorded. External electrodes are called to by the designations "EXG1" through "EXG8". The electrodes EXG1 and EXG2, which are located at the left and right lobes of both ears, respectively, functioned as no-neural activity reference channels. To record horizontal eye movement, electrodes EXG3 and EXG4 were positioned above the candidates's left and right temples. Vertical eye movements, mostly blinks, were to be recorded by electrodes EXG5 and EXG6.

The right eye was positioned with one electrode above and the other below. Finally, both the superior and inferior right orbicularis oris were covered with electrodes EXG7 and EXG8. The electrodes were made to record oral movements during spoken speech in order to make sure that there were no mouth movements while trials of inner speech or visualizing condition runs.

The recording software, ActiView, was also developed by BioSemi. It gives a medium of examining the impedance of the electrode and the general caliber of the arriving information. Every electrode's impedance was verified to make sure it was less than 40 Ω before any recording session was started. A digital 208 Hz low-pass filter was utilized while the acquisition phase and no high-pass filter was used.

Following the recording of every session, PC2 stored and generated a.bdf file. This file contains the labeled events, the eight exterior channels, and the 128 EEG channels that are continuously recorded.

VII. BCI INTERACTION CONDITIONS

The main goals of the dataset's production were to decode and comprehend the mechanics of making inner speech and to examine how the dataset might be applied to BCI applications. As mentioned in the Section above, the neural network's numerous intricate connections play a role in the development of inner speech. Three circumstances were offered to the subjects to complete the experiment: spoken speech, inner speech, and imagined speech. Finding the main sources of activation and examining their connections was the aim.

A. Inner Speech

The dataset's principal condition, inner speech, seeks to detect brain activity in the brain linked to a subject's thought process about a certain phrase. During the inner speech runs, each participant was instructed to repeat the matching word until the white circle turned blue, allowing them to picture themselves speaking to the computer directly. Each participant understood why it was so crucial to disregard the articulation motions. Every participant was also told not to move their mouth or tongue and to remain as still as possible. No rhythm signal was provided to promote spontaneous imagining.

B. Pronounced Speech

While the imagined speech paradigm is typically linked to motor activity, inner speech can also depict motor activity. The purpose of the condition of pronounced speech was to identify motor areas involved in pronunciation that matched those active during the condition of the inner speech. Each participant in the apparent speech runs was instructed to loudly speak the word many times in sync with each visual cue, creating the illusion that they were directly directing the computer. As in the inner speech runs, there was no sign of rhythm.

C. Visualized Condition

Given that specific words have an important visual and spatial component, the visible condition was proposed. Finding any behavior that resembled inner speech production was the aim. Notably, the occipital and parietal regions of the brain are the primary brain regions associated in spatial cognition. Furthermore, it has been shown that spatial attention significantly affects the amplitude of the SSVP. Participants in the visualized condition runs were instructed to concentrate on mentally dragging the circle at the middle of the screen in the direction indicated through the visual cue.

VIII. HANDLING OF DATA

To assist the organization of continuous raw data to a more useable and manageable dataset, a transformation technique was provided. The code and raw data for this processing, done primarily with the help of the MNE library in Python, are publicly available, allowing interested readers to alter the processing configuration to their specifications readily.

A. Loading of raw data

A feature was created that enables the raw data for a specific participant and session to be loaded quickly. The whole EEG and external electrode signals and the annotated events are recorded in the raw data. bdf file.

B. Verifying and adjusting event

Verifying that the events in the signals were correctly tagged was the first step in the signal-processing process. An approach for repair was suggested once missing tags were found. The method finds and finishes the event sequences. Following the adjustment, all events aligned those sent from PC1, and no tags were missing.

C. Reassessing

Since BioSemi is referred to as a "reference-free" acquisition system—that is, every channel records the standard mode (CM) voltage—a re-reference mode is necessary. This process was produced using a specific MNE re-reference function utilizing channels EXG1 and EXG2. The former function makes a virtual channel that is deducted from all other acquired channels by averaging EXG1 and EXG2. In addition to removing the CM voltage, this step also lessens body potential drifts and line noise (50 Hz)

D. Digital Screening

An impulse response filter with a zero-phase bandpass was used to process the data using the relevant MNE function. A lower bound of 0.5 Hz and an upper bound of 100 Hz were specified. In order to enable new users to filter the data in the bands of their choice, the broadband filter attempts to preserve the data as raw as possible. A 50 Hz frequency filter notch was also employed.

E. Decimation and epoching

A resulting sampling rate of 254 Hz was obtained by decimating the data four times. Following that, the only signals from the continuously recorded data that were kept were the 4.5 s duration signals, which matched the window of time between the starting of the concentration measurement interval and the end of the relaxation period. A final tensor with size [trials × channels × samples] was constructed by stacking each trial's matrices of dimension [channels × samples].

F. ICA

A common and broadly utilized a strategy of dazzle source division for killing artifacts from EEG signals is Autonomous Components Investigation (ICA)52,53,54. ICA preparing was constrained to the EEG channels for our dataset, with the MNE execution of the infomax ICA-55. There was no utilize of Central Component Investigation (PCA), and 128 sources were famous. Sources related with flicker, look, and mouth development that were missed amid the remaking of the EEG signals were found by means of different relations with the EXG channels in arrange to get a last dataset.

G. Correction of ad hoc tags

Following the first session, participant person 3 stated that he only completed three imagined condition runs and one inner voice run because of a misinterpretation. The condition tag was changed as needed. To counterbalance the unequal number of trials by condition, the same individual completed three inner speech runs, in session 3 and in the same session, one visualized condition.

H. Data Files

The OpenNeuro repository can access all data files, along with the raw recordings. All the files are housed in a primary folder named "Inner Speech Dataset," named and organized according to the BIDS recommendations for EEG data extension. Ten subfolders for each participant make up the final dataset folder. Each subfolder contains the raw session data. Five files—EEG data, baseline data, data from external electrodes, data from events, and a report file—were acquired following the suggested procedure and are contained in an additional folder.

I. Raw data

The raw data file consists of the continuous recording of the whole session for all 136 channels. The average length of the tapes is 1554 seconds. The.bdf file constitutes of the EEG/EXG data and the annotated events in addition to additional information on the recording sample rate, channel names, and recording filters. The tags delivered by PC1 are synced with the recorded signals in the raw events, which are retrieved from the raw data file. Table 5.2 shows the ID, description, and code for each occurrence. At the start of the recording and various times during specific sessions, a spurious event with ID 65536 emerged. Its origin is unknown. This event was eliminated during the processing stage known as "Events Check" since it has no connection to any submitted tags. The three-column matrix that holds the raw events has the event ID in the third column, the trigger information in the second, and the first we had the time stamp information.

Table 5.2: The number and meanings of raw data event tags

Event ID	Description
1	Beginning of protocol
12	Ending of protocol
13	Beginning of baseline
14	Ending of baseline
15	Beginning of run
16	Ending of run
17	Cognitive control - question posing
21	Beginning of pronounced speech run
22	Beginning of inner speech run
23	Beginning of Visualized condition run.
31	“Up” trial - start of cue interval
32	“Down” trial - the start of cue interval
33	“Right” trial - start of cue interval
34	“Left” trial - start of cue interval

42	Starting of concentration interval
44	Starting of action interval
45	Starting of relaxation interval
46	Starting of rest interval
51	Starting of inter runs rests interval.
61	Response to cognitive control: “Up.”
62	Response to cognitive control: “Down.”
63	Response to cognitive control: “Right.”
64	Response to cognitive control: “Left.”

J. EEG data

After processing, as previously mentioned, the collected data for every participant and session is in every EEG data file and saved in the.fif format. Each file constitutes an MNE Epoched object containing the EEG data for every trial in the relevant session. The related tensor data has a [Trials × 128 × 1154] dimension. Each participant in a session received a different number of trials, as detailed in the "Data Acquisition" Section. One hundred twenty-eight channels were utilized for recording, and 1154 samples total—each representing 4.5 seconds of signal capture at a final sampling rate of 256 Hz. Table 3.3 displays the distribution of the 2236 inner speech trials, 2276 visualization condition trials, and 1128 pronounced speech trials collected.

K. Data from external electrodes

All of the EXG data files, with the exception of the ICA processing, contain the data that the external electrodes collected after the appropriate processing was applied. They were kept in the format of.fif. The dimension of the related data tensor is [Trials × 8 × 1154]. In this case, the count of EXG and EEG data trials are similar, the count of external electrodes employed were 8, and the count of sampled 4.5-second signal recordings at a final sampling rate of 256 Hz is 1154.

Table 3.4 Events data conditions and tag meaning

Sample	**Trial’s class**	**Trials’ Condition**	**Trials’ session**
Sample at which the event occurred (Numbered beginning at n = 0, corresponding to the starting of the recording)	0 = “UP”	0 = Pronounced Speech	1 = session 1
	1 = “DOWN”	1 = Inner Speech	2 = Session 2
	2 = “RIGHT”	2 = Visualized Condition	3 = session 3
	3 = “LEFT”		

L. Event information

Every event data file (in .dat format) has a four-column matrix with one trial per row. After renumbering classes 31, 32, 33, and 34 as 0, 1, 2, and 3 and removing the trigger column (the second column of the raw events), the first two columns were recovered from the natural events. Lastly, the condition and session number are represented by the final two columns, respectively. Table 3.4 illustrates the events data file's final structure.

Baseline information

A data tensor of dimension [1 × 136 × 3841] is present in every file of the baseline data (in the.fif format). In this case, 1 denotes the single baseline that was recorded throughout each session, 136 represents the complete number of EEG + EXG channels (128 + 8), and 3841 is the number of signal recording seconds (15) multiplied by the sampling rate resulted in the end (256 Hz). Visual inspection revealed that Participant sub-03's recorded baseline from session three and Participant sub-08's recorded baseline from session 2 were significantly polluted.

M. Report

General participant information and specific session processing results are included in the report (in.pkl format). In Table 3.5, its structure is shown.

Table 3.5 Report file fields.

Listed Field	**Content**
Age	Participant's Age
Self-declared gender	Participants' self-declared gender: 'F' for female, 'M' for male.
Recording_time	The length of the complete session recording is in seconds.
Ans_R	Number of times the participant correctly answered the cognitive control questions.
Ans_W	Number of times the participant incorrectly answered the cognitive control questions.
EMG_trials	Position of the contaminated trials.
Power_EXG7	Mean power for channel EXG7 of the contaminated trials. Array with the same dimension as EMG_trials.
Power_EXG8	Mean power for channel EXG8 of the contaminated trials. Array with the same dimension as EMG_trials.
Baseline_EXG7_mean	Mean power for channel EXG7 in the Baseline.
Baseline_EXG8_mean	Mean power for channel EXG8 in the Baseline.

Baseline_EXG7_std	The standard deviation of the power for channel EXG7 in the Baseline.
Baseline_EXG8_std	The standard deviation of the power for channel EXG8 in the Baseline.

N. Paying attention

The inner voice and the imagined condition runs were used to gauge the participant's level of attentiveness. Its purpose was to keep track of how focused they were on the assigned task. The evaluation's findings demonstrated that participants completed the job after making a few mistakes (Table 3.6; mean = 0.5, standard deviation 0.622). Participant A and Participant J reported that during the first two questions of session 1, they inadvertently hit the keyboard. In addition, participant A said that following the first session, they thought there were too many questions. As a result, fewer questions were asked of the following participants to keep them from growing weary.

IX. LIMITATIONS AND REMARKS

Regarding the dataset's limitations, it's crucial to note that, unlike in any other endogenous BCI paradigm, participants were asked to imagine their voices and not concentrate on their muscular activity. However, this does not ensure that their mental activity is accurate. Furthermore, the participants' inexperience with BCI probably prevented them from distinguishing between various speech components. In the same vein, it is essential to note that, despite every participant getting the exact instructions, each person may have interpreted them and then carried out different mental activities. It's also crucial to note that insufficient data substantiates the idea that inner speech and imagined speech produce other brain processes. Furthermore, it's unclear whether recognizable traits could be recorded with the current electroencephalography technology, even if they could. Nevertheless, since the user does not have to concentrate on the articulatory motions, inner speech is undoubtedly a better organic method of conducting a BCI.

Even though there's a chance that the pronounced speech trials were tainted by muscle movement, simulating the raw EEG data and the recordings of EMG can help with the creation and evaluation of EMG de-noising techniques. If the participant is not provided with rhythmic cues to complement their natural pace, the timing of their speech and imagination may change from trial to trial. This is likely to happen since it is unrealistic to memorize or focus on a single word at a time. But this issue would come up in any real-world BCI application. If during the trials the participants changed their pace, further research is needed to determine whether this phenomenon could have an impact on the decoding performance. It is important to note that the references to relevant studies regarding their implemented paradigms only represent an initial attempt at classification; more research is required. This is mainly because the requested acts are not often described in great depth, and those publications do not always consider the distinction between imagined and interior speech.

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S.No	Researcher	Focus	Findings	Knowledge Gap Areas
1.	D. Pawar and S. Dhage, 2020	Vowels and syllables have received the majority of attention in the current EEG signal-based covert speech classification research. The writers examined the accuracy of English vowels /a/ and /u/ in speech imagery BCI. The EEG signals of the syllables /ba/ and /ku/ were investigated for speech imagery classification in another study.	The paper focused on classification of EEG-based covert speech signals of whole words into many classes. According to experimental findings, the most popular classifiers in BCI are outperformed by the Daubechies-dwt based features kernel ELM in terms of classification accuracy and computing efficiency. The results clearly show that for the chosen BCI users, kernel ELM can be used to classify EEG-based covert speech signals.	The authors conducted a unique and well-established experiment and found well-observed results. However, a secondary phase focusing on a larger set of words and vocabulary would be helpful to understand the methodology and process even better.

S.No	Researcher	Focus	Findings	Knowledge Gap Areas
			According to our research, information gathered from language processing regions is adequate for differentiating between hidden voice signals.	
2.	M. Rashid et al., 2020	Reviewing EEG-based BCI systems in terms of the various brain control signals, feature extraction techniques, classification algorithms, and assessment metrics employed are the article's goals. Additionally, this article provides a succinct summary of EEG-based BCI systems so that the reader or readers can choose the best approach for a particular BCI system.	This study presents the relevant research gaps that need to be investigated further. It is noteworthy that important challenges related to applications of EEG-based BCI systems are enumerated, along with suggestions for potential remedies. Additionally, this review offers a more thorough overview that readers can easily understand to identify the gaps in the body of knowledge, unlike other published review articles about EEG-based BCI systems that were specific in nature, especially with regard to either its particular applications or part of the methodology employed (e.g., feature extraction, signal processing, and classification, among others).	The authors have well-defined understanding and relevance of the limitations of the research and the EEG-based BCI methodologies such as commercialization, contemporary techniques, accessibility etc. Each limitation is well-defined and explained, however, explaining a trend and perhaps a chart showing the trends of challenges would help better the comprehensiveness of the study.
3.	Peksa, J., & Mamchur, D	It examines the state of the art in research	The paper highlights a few major issues that	Overall, the paper defines all possible

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	2022	on the use of BCI for educational, medical, and other objectives, along with possible uses for this technology in the future	still need to be resolved before widespread adoption may take place. The paper offers a valuable perspective on the direction of advancement and innovation in the field of BCI technology by offering a current evaluation of the state-of-the-art	techniques for the processing of brain signals and the different applications of the BCI Technology.
4.	Yiyuan Han 02 Mar 2022	The focus of the paper was the application of UCD to respond to the users' needs while using BCI, both in studies with healthy non-end-users and end-users in clinical environments. The paper also highlighted electrophysiological signal features that can be extracted from EEG, functional connectivity.	The paper discusses the application of user-centered design (UCD) and electrophysiology-based online user state adaptation in brain-computer interfaces (BCIs) to optimize BCI performance. It highlights the utility of UCD for end-users and its potential in early-stage BCI development, as well as explores the integration of various BCI user state adaptation methods for BCI optimization	Detailed explanation about the types of BCI and the security risks associated with them and their components would have provided a greater insight on what type of BCI is to be looked forward to and what more technological progresses are to be done and devised.
5.	Davis, Kaylee R. 2022	The article explains how BCI can open a new realm of possibilities for future advancements for the common public to use.	BCI tech and its tools have immense potential to redefine existing medical treatments and can warn or provide prior information	The author could have provided a brief comparison on Invasive and Non-invasive technology to provide a clear understanding of the categories.

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		It can be used for assisting patients with neurodegenerative diseases and neuromuscular injuries.	regarding the abnormality. Ethical issues regarding this technology have been described in detail and their potential solutions such as ethical testing, encryption technologie, privacy security and robot control can help control these issues.	The article could have also briefed about the various devices and system interfaces that BCI would use to make readers understand the public use of this technology.
6.	Mane et al., 2022	focuses on how cutting-edge BCI systems have been used to enhance the quality of life for stroke victims. It also covers current developments, obstacles, and potential future research areas in this field. Additionally, it presents the physiological underpinnings of BCI-stimulated brain healing mechanisms and focuses on rehabilitative BCIs. The most current developments in BCI systems for motor rehabilitation are then discussed. A review of the far less studied subject of BCI-	2014 saw improvements in the patient's expressive speech after ten sessions of neurofeedback training aimed at raising the beta/theta band power ratio at the C3 EEG electrode, according to a study by Mroczkowska et al. The authors noted improvements in understanding syntactically complicated phrases, faster and more accurate word retrieval, less phonemic paraphasias, and enhanced speech fluency. Additionally, neurofeedback training to raise the relative alpha	As identified int epaper itself, work has been done to demonstrate the viability and usefulness of real-time control and communication based on BCI. But, more research on these methods in the stroke population is necessary, especially for those who have severely severe paralysis and cognitive deficits. Also the paper does not provide detailed insights on the applications of this technology in BrainGate and Neuralink- such prominent technological innovations.

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		mediated poststroke cognition and speech rehabilitation follows this. Finally, we examine the most recent developments in assistive brain injury (BCI) systems for stroke patients.	power in the brain's occipital area shown marginal gains in verbal fluency, sentence completion, image and color identification, and naming.	
7.	Subasi, 2022	demonstrated that motor imagining (MI) is a helpful cognitive strategy for improving motor abilities and for the rehabilitation of movement disorders. BCI technique, which offers real-time feedback on the subject's mental attempts, can increase the effectiveness of MI training. The use of artificial intelligence (AI) techniques is crucial for identifying alterations in brain activity and translating them into the proper control signals.	concentrate on using scalp-derived brain impulses to operate assistive technology. Furthermore, the AI, feature extraction, dimension reduction, and signal denoising algorithms used for EEG-based BCI are assessed. Utilizing EEG signals, Bagging and Adaboost to classify MI tasks for BCI. increases the accuracy of MI recognition by using a wavelet packet decomposition feature extraction technique. The suggested method uses ensemble approaches to classify brain signals associated to MI.	A detailed description to help non-computer researchers to understand AI and ML techniques would be of great use to them for better understanding complex codes and algorithms.
8.	Y. Han, et al., 2022	The two-hour workshop titled "Optimizing BCI performance by	This paper discusses the following subjects: (1) UCD measurements and motivational	

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		integrating information on the user's internal state" that was held during the 8th International BCI Meeting in 2021 is the foundation for this study.	considerations for fundamental study design; (2) BCI as AT: UCD in a clinical context; (3) data and metrics for consciousness detection; and (4) developing a classification model with integrative EEG features.	
9.	Baraka Maiseli 04 August 2023	In this study, insights have been given on the perspective of the brain–computer interface. an observation was made that the existing challenges in brain–computer interface have received little attention	Notwithstanding the promising capabilities and merits of BCI, a significant number of challenges and threats have not been adequately addressed. While BCI opens up new possibilities for human well-being, its practical applications still need extensive research, including several clinical studies. If the current hazards and problems are not adequately addressed, the technology might not be prepared for society to use.	The gap in addressing the challenges and capabilities that BCI offers, including development of BCI-Internet and BCI-CBI communication devices. Another gap is the number of participants in the clinical trials is low and undiversifed, which makes generalization of the results questionable. Also, there has been no universally acceptable standards for measuring the accuracy of BCI applications, and we will attempt to narrow this research gap.
10.	Li et al., 2023	Through the use of knowledge maps, this study thoroughly and aesthetically presents the wealth and depth of literature resources	This study uses bibliometric techniques to thoroughly and methodically review the pertinent literature that has been published over	As recognized in the paper itself, omission of other databases and sources can lead to a limited knowledge area on the topic at hand,

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		on BCI technology in stroke research. This helps academics better grasp the field's advancements and future possibilities, which encourages more research.	the last ten years on BCI technology in stroke research. The study provides an intuitive depiction of the knowledge structure and developmental trajectory in this topic from several angles by displaying knowledge maps. The results show that BCI technology has drawn a lot of interest and more researchers to the field of stroke research, which has led to a prolific output of research accomplishments and encouraged the field's rapid expansion.	hence exploration and in-depth research from other certified resources can further enhance the studies and provide a comprehensive result and knowledge maps intended in the study.
11.	Canny et al., 2023	We evaluate whether FES (functional electrical stimulation) technology can improve current BCI communication strategies for those who are locked in. We go over studies on FES applied to body and facial muscles, examine work on assistive communication technology for locked-in individuals, including non-implantable and	The restoration of arm and hand motions has been the main focus of research on stroke patients utilizing non-implantable BCI in conjunction with transcutaneous FES systems. Larger clinical trials corroborated the initial case report results, which demonstrated improvements in upper limb motor function with BCI-controlled FES compared to FES-only therapy. Even though fewer studies have	In total LIS, with non-implantable BCIs, slow cortical potentials, P300 and sensorimotor rhythms paradigms may not be able to produce consistent and reliable BCI control

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		implantable BCIs, and summarize current advancements on merging FES with BCI. Lastly, we go over the potential, difficulties, and probable future paths of putting BCI-FES systems into practice to help people who are locked in regain their ability to communicate.	employed these BCI-FES systems for the rehabilitation of lower limb motor function following a stroke, their results demonstrate that these systems increase motor function and are more successful than FES-only therapy. When using combined BCI-FES technology for spinal cord injury rehabilitation, users expressed a favorable opinion of the perceived efficacy of the technology. They especially valued the technology's ability to improve their relationship with loved ones and their apparent active role in the experience (watching their hand move). This is consistent with previous research on user priorities for BCI, which found that people with spinal cord injuries preferred connecting a BCI with FES to a BCI that controlled a computer, wheelchair, or robotic arm.	

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12.	Karikari & Koshechkin, 2023	examined the developments and potential uses of BCI technology in a variety of contexts, as well as publications discussing the creation of fresh methods, enhanced hardware, or new algorithms.	To increase the long-term durability and biocompatibility of neural implants, researchers are investigating novel materials and designs. Research on non-invasive BCIs, such those that use EEG, is still quite popular. Along with developing new signal processing methods to extract additional information from brain signals, efforts are being undertaken to enhance the accuracy and dependability of non-invasive brain-computer interfaces (BCIs). In order to enhance their functionality and enable increasingly complicated activities, BCIs are incorporating machine learning and artificial intelligence approaches.	There are a number of obstacles associated with implementing AI in BCIs, including the requirement for substantial training data sets, interpretability issues, and privacy and security worries. In order to clear the path for further developments in this area, researchers are attempting to solve these issues and enhance the functionality and performance of AI-BCI systems.
13.	Ramadan & Altamimi, 2024	thorough literature analysis to look at the uses of Brain-Computer Interface (BCI) technology in medical diagnostics and rehabilitation. The objective is to fulfill the needs for	In BCI rehabilitation, where users' brain activity is tracked and real-time feedback is provided, constant monitoring and feedback are extremely helpful. Users can modify their	A brief comparison about the big data algorithms and interfaces that can be implied, would have provided a comprehensive study about how and what filters are required in a

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		improved accuracy, usefulness, and accessibility of the applied BCI techniques.	performance and skill acquisition during tasks thanks to the feedback, which encourages skill development during tasks. Neuronal signals are recorded and analyzed as part of the monitoring process to decipher users' mental commands pertaining to their motor intents. Additionally, the input may come in the form of tactile, aural, or visual cues. These feedbacks and monitorings also support the rehabilitation processes.	system which would be designed for the motor impaired humans and those which require external assistance needs.
14.	Komeilipoor, 2024	altering our perception of, approach to, and understanding of healthcare. The future in which brain-computer interfaces (BCIs) are key to the development of a more sophisticated, compassionate, and inclusive healthcare ecosystem is being shaped by the harmonious union of human neuroscience and technical innovation.	devices and disabilities of hearing, cognitive processes and therapies, diagnosis of a neurological condition, management of chronic pain BCIs that aim to manage chronic pain by modulating brain pain receptors through closed-loop neurostimulation.	

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15.	T, 2024	The main focus of the author here is the influence of BCIs in almost all domains of the day-to-day human life. Mostly utilized in the medical domain, BCI Technology can help patients and affected individuals with rehabilitation, physical abnormalities and restricted movements in impaired individuals.	Applications of the BCI technology were explained in details keeping the medical area and gaming world in mind. This serves as a crucial resource for those patients suffering from locked-in syndrome as BCI applications shall help convert thoughts into brain signals and waves. BCI also offers enhanced productivity, personal growth, and optimal mental performance. The authors also list various challenges and limitations related to BCI such as signal processing and security, hardware restrictions etc.	The authors do intend to provide a future perspective for the technology and its applications but a further insight on solutions for issues related to privacy and security of the signals received and the data being collected. Also, the author has not provided much insight on the ethical aspect of the technology.