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Research Article

A Review on: EEG-Based Brain-Computer Interfaces for Imagined Speech Classification

Pravin V. Dhole[1]*, Deepali G Chaudhary[2], Vijay D. Dhangar[3], Sulochana D. Shejul[4], Dr. Bharti W. Gawali (Senior Professor)[5]

[1]*Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar-431004 (MS), India, Email: pravindhole07@gmail.com
[2]Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar-431004 (MS), India, Email: deepalichaudhary51@gmail.com
[3]Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar-431004 (MS), India, Email: csit.vdd@bamu.ac.in
[4]Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar-431004 (MS), India, Email: shejul.sulochana1106@gmail.com
[5]Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar-431004 (MS), India, Email: drbhartirokade@gmail.com

***Corresponding Author:** Pravin V. Dhole
*Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar-431004 (MS), India, Email: pravindhole07@gmail.com

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ABSTRACT

In the field of medical science, particularly in neuroscience, recent studies have focused heavily on combining artificial intelligence with electroencephalography (EEG) for brain–computer interfaces (BCI). This area has become a crucial domain for research because of its potential to understand brain activity and develop new technologies to interpret brain signals for various applications. The goal of Brain-Computer Interfaces (BCIs) is to help people with speaking disabilities communicate. BCIs connect the brain to a computer, allowing individuals to control devices or communicate based on their thoughts. Brain signals are usually measured using an EEG. EEG signals constantly change and are unique to each person, varying in frequency. This study aimed to explore the potential of electroencephalogram (EEG) signals in classifying imagined speech data, with a focus on understanding the brain's response to speech-related activities and its application in BCI. This study highlights the importance of feature extraction techniques, including time-domain, frequency-domain, and time-frequency domain analyses, in enhancing the classification of EEG-based imagined speech data and covering EEG signal processing and classification, including data acquisition, pre-processing, feature extraction, and classification. Linear classifiers, such as support vector machines and logistic regression, are employed alongside neural networks, particularly convolutional neural networks (CNNs) and artificial neural networks (ANNs), to analyze and classify EEG data associated with imagined speech and applications of EEG. Research indicates that EEG data used for analyzing brain activity are complex and can be gathered via different techniques using different devices. Multiple steps, such as preprocessing, feature extraction, and classification, may be necessary based on the signal collection method and study objectives.

Keywords: Electroencephalography (EEG), electrocorticography (ECoG), Brain-Computer Interface (BCI), Imagined Speech, Signal Processing, EEG Signal Classification, Machine Learning, Deep Learning.

1. Introduction:

A brain-computer interface (BCI) is a bidirectional communication between the brain and external devices. It acquires, analyzes, and translates brain signals into electric signals to take specific actions as desired by brain waves. Different brain waves, such as Delta, Theta, Alpha, Beta, and Gamma waves, have unique frequencies and amplitudes. These waves specify the different stages of the human mind. These brain waves or signals are acquired using sensors placed on or within the scalp. The concept of using brain signals to control artificial arms began in 1971(Nirenberg, Hanley et al. 1971, Wolpaw, Birbaumer et al. 2002, Punsawad, Ngamrussameewong et al. 2016). Studying the brain has become important to better understand life because of advances in medical technology and our increasing knowledge about how the brain works(Fan, Fang et al. 2020). Scientists have been researching the complexity of the brain since the mid-1900s, and recently, it has become a popular area for more research(Lane, Ryan et al. 2015). The study of electrical activity in the brain is a major focus in brain science.

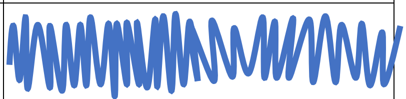
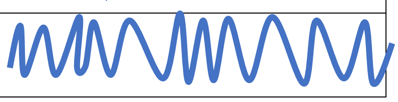
Speech is an important part of everyday life. This is how we connect with other people. However, sometimes things like mental disorders, diseases, accidents, or even hurting one's voice can make it hard to speak. This can make life difficult and sometimes lead to feelings of being alone(Shah, Alzubaidi et al. 2022). EEG and speech are closely related in two important respects. The first benefit of EEG is its insight into how the brain understands the spoken language. Researchers have uncovered the brain's processes for decoding sounds, understanding language, and even anticipating words by monitoring electrical activity. The implications of this information for areas such as cognitive science and language acquisition are significant. Furthermore, EEG-based speech creation is a relatively new area of study that investigates the potential for manipulating or even producing speech using brain signals. This might be a way for those who have trouble speaking to communicate; it entails reading the mental patterns of speech and turning them into words. There has been a lot of work in these fields, but obtaining EEG-based speech processing and creation to work reliably and accurately for practical uses is still a problem (Abdulghani, Walters et al. 2023, Puffay, Accou et al. 2023).

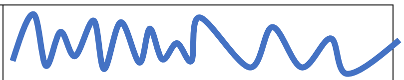
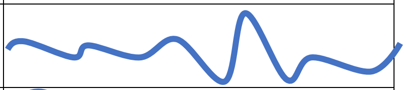
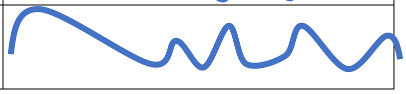
BCIs are helpful to individuals who struggle to speak or are paralyzed. These systems allow users to communicate quickly with their environments. BCIs are computer systems that can identify and interpret brain signals. These signals are then converted into commands that control the output device, allowing the user to perform specific actions. BCI systems are used in various ways such as communication tools and controlling gadgets. Originally designed for severely impaired individuals, these systems are now also used by healthy people for communication and everyday assistance in their lives(Mohanchandra and Saha 2016). The brain is a complex system composed of billions of nerve cells, called neurons. It exhibits complex patterns in both space and time.

Brain signals can be acquired through invasive (implanted electrodes), noninvasive (scalp electrodes), or semi-invasive (partially implanted electrodes) methods (Mudgal, Sharma et al. 2020, Chaddad, Wu et al. 2023). The invasive method involves placing sensors inside the skull to track brain activity, giving high-quality results, but posing a risk of scar tissue. It is helpful for paralyzed patients to control devices such as artificial arms. Noninvasive methods use sensors placed on the scalp to read brain signals without surgery. It is simple, inexpensive, and portable; however, it does not capture brain signals because of skull interference. This technique is prone to noise and has weaker signal quality. Semi-invasive approaches include inserting electrodes partly inside the skull, which provides a higher signal quality than non-invasive methods without being completely intrusive. They are employed in specific medical treatments and research, although they require surgery and pose considerable risk.

EEG is a non-invasive method for recording electrical activity signals in the brain. This is done using electrodes placed on the scalp, which has a small amplitude; hence, it is measured in microvolts (mV). Studying how the brain's electrical signals function is a major focus in brain science (da Silva 2013). This is why scientists pay close attention to electroencephalograms (EEG), which help them understand the brain in many different areas of research (Da Silva 2023, Saibene, Caglioni et al. 2023). These brain signals, like small messengers, contain a wealth of information that researchers use to learn more about how our brains function in different situations, such as when talking, thinking, or imagining things. EEG is a safe and non-invasive brain imaging method that uses electrodes on the scalp to capture the electrical activity of the brain. This technology helps researchers understand how the brain works by analyzing these signals. It provides crucial insights into brain functions, helps identify different brain conditions, and explores how we perceive things, focus, remember, etc.. EEG has become popular because it is safe, does not require surgery, and allows for comfortable study of brain activity. Moreover, EEG signals can be combined with other imaging techniques, such as MRI, fNIRS, and PET, to obtain a clearer image of how the brain functions and its structure (Chaddad, Wu et al. 2023).

Table 1: Frequency bands of EEG signals

Frequency Band	Frequency (Hz)	Amplitude (μv))	Brain States	Signals
Gamma (γ)	> 35 Hz	< 5	Associated Concentration, Problem-Solving, Consciousness, Cognitive Processing.	
Beta (β)	12-35 Hz	5-30	Associated Anxiety-dominant, active, external attention, relaxed.	

Alpha (α)	**8-12 Hz**	**30-50**	**Associated with Very Relaxed, passive attention.**	
Theta (θ)	**4-8 Hz**	**>20**	**Associated Deeply Relaxed, inward-focused**	
Delta (δ)	**0.5-4 Hz**	**>20-200**	**Associated Sleep**	

EEG signals were categorized into five types of waves (alpha, beta, gamma, theta, and delta) based on their frequency. Table 2 shows the frequencies obtained from human EEG wave categorization. Gamma (γ) waves are the fastest brain waves, with a frequency of more than 35 Hz. They had the lowest amplitude of all brain waves at less than 5 microvolts (µv). Gamma waves are associated with concentration, problem-solving, consciousness, cognitive processing, and sleep. Gamma waves are thought to play an important role in binding, the process of integrating information from different parts of the brain to create a unified percept. It is also involved in attention, memory, and language processing (Benitez, Toscano et al. 2016).
The beta (β) wave is the second fastest of the five main types of brainwaves. This is associated with a state of alertness and focused attention. Beta waves are also involved in information processing, problem solving, and decision-making. There are two main types of beta waves: low-beta waves (12-20 Hz) and high-beta waves (21-35 Hz). Low-beta waves are associated with a state of relaxed alertness, whereas high-beta waves are associated with a state of intense focus and concentration. Beta waves can be increased by activities that require focus and attention, such as studying, working or driving. They can also be increased by stimulants, such as caffeine or nicotine. Beta waves are generally considered good. They indicated that their brains were alert and engaged. However, excessive beta activity can also lead to anxiety, stress, and insomnia (Lan, Müller-Putz et al. 2016).
Alpha (α) waves are brain signals occurring between beta and theta waves, with a frequency of 8 to 12 Hz with an amplitude ranging from 30 to 50 µv. Alpha waves are known as relaxed waves because they are dominant when a person is awake, but not focused on anything in particular. These are also associated with creativity, daydreaming, and mindfulness. Alpha waves can be increased by meditation, yoga, and spending time in nature (Lan, Müller-Putz et al. 2016).
Theta (θ) waves have a frequency of 4-8 Hz and amplitude greater than 20 µv. They are associated with deeply relaxed and inward-focused states. Theta waves are thought to play a role in a variety of cognitive processes, including learning and memory, and are active during REM sleep, which is important for consolidating memories. They are also active during deep meditation, which enhances learning and memory. Creativity and problem solving: Theta waves are associated with daydreaming and imagination, which can be important for creative problem solving. Emotional processing: Theta waves are active during emotional states such as love and compassion. They may also play a role in regulating emotions and promoting emotional well-being (Madoš, Ádám et al. 2016).

1.1 Component of EEG Signal Analysis

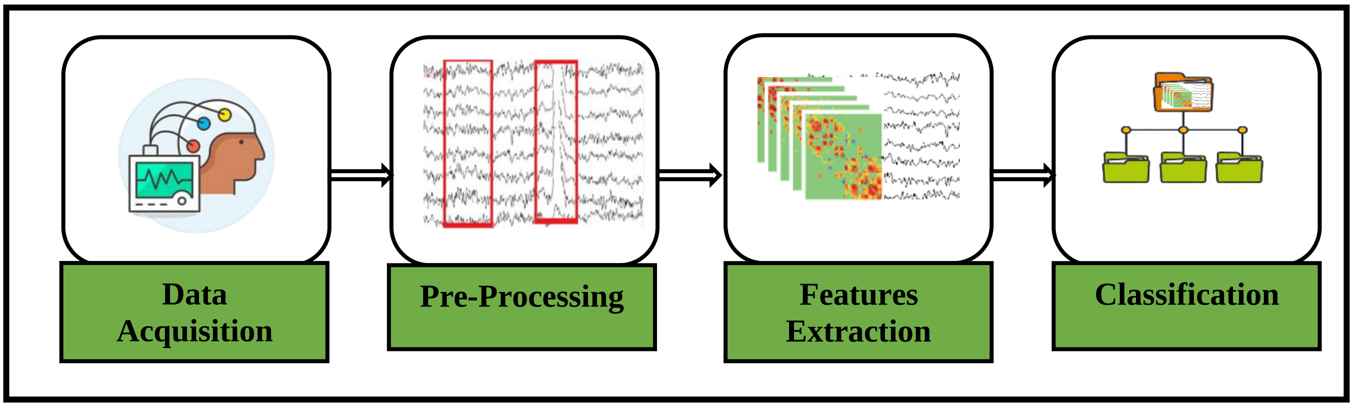


Figure 1:EEG Signal Analysis Steps

The type of brain wave that is more active depends on what we are doing, thinking, or feeling at a given time. To understand these brain signals, we first need to study EEG signals. Figure 1 shows the four steps involved in analyzing EEG signals.

1.1.1 Data Acquisition:

EEG data acquisition is the process of capturing these electrical signals and converting them into a digital format that can be analyzed by computers. The data acquisition process was divided into five steps: electrode placement, signal amplification, Filtering, Digitization, Data storage, and transmission (Li, Cheng et al. 2021).

1.1.2 Pre-Processing:

During pre-processing, the collected data underwent several steps to enhance its quality. This includes references to linked mastoid channels, applying a band-pass filter (0.5 - 50 Hz) to focus on specific frequency ranges, interpolating removed channels, reconstructing artifact subspaces, down-sampling to 250 Hz for efficiency, removing noisy or flat channels, and extracting the power spectral density to understand the frequency distribution of the signals(Clerc 2016, Kim 2018, Vajravelu, Jamil et al. 2021). When we study EEG data, we begin by using various preprocessing methods. One method is to use filters, which help us focus on important parts of the data to remove unwanted noise. For example, a Bessel filter smooths the data without distortion. The bandpass filter allows only certain frequencies to Pass through, helping us isolate specific parts of the signal. A large Butterworth filter eliminates the background noise. We also have a Chebyshev filter that helps separate the frequency bands. These filters are similar tools in a toolbox, each serving a different purpose to help us understand EEG data preprocessing and analysis.

1.1.3 Features Extraction

Two processes are involved in the recognition of EEG signals: feature extraction and signal classification based on the features that were extracted. The time-domain, frequency, and time-frequency domain are the most used feature extraction techniques for EEG (Mudgal, Sharma et al. 2020).

Time-domain feature extraction techniques analyze temporal changes in EEG data. It observes information such as the intensity of the signals at various times. By analyzing the ups and downs in EEG signals, these techniques assist in our understanding of the changes in brain activity over time. Taking the characteristics and important aspects from EEG data, each feature its special properties. Hjorth Features emphasize movement, motion, and complexity, while providing simplicity, quickness, and application to fixed signals. Statistical features, such as Mean, Standard Deviation, Variance, Skewness, Kurtosis, and Signal Energy, are simple to use and appropriate for both stationary and non-stationary data. Although it might take some time, the Fractal Dimension assesses the self-similarity and complexity of the signals. The Kalman Filter assesses states and signal uncertainty and is perfect for localizing EEG sources. The particle Filter uses particles and weights to provide scalability and non-deterministic state estimation while being computationally costly (Mudgal, Sharma et al. 2020).

Frequency domain features are very important in EEG-based brain-computer interfaces because they reflect the various frequency components of brain activity. The Discrete Fourier Transform (DFT) and Fast Fourier Transform (FFT) are two techniques widely used for this purpose. DFT separates the EEG signal into discrete frequencies, providing information about its intensity and phase; however, FFT is faster, making it suitable for real-time BCI applications. The FFT is a mathematical algorithm that converts a signal from its original (time) domain into a frequency-domain representation. By applying FFT to EEG data, we can identify the power spectral density of different frequency bands such as delta, theta, alpha, beta, and gamma. Each frequency band is related to a specific brain state and function. The different frequency bands in EEG signals correspond to different cognitive processes and brain activities. For example, delta and theta waves are often observed in deep sleep. The waves are associated with memory processes, alpha waves are associated with relaxation and meditation, beta waves are associated with active thinking and concentration, and gamma waves are involved in higher cognitive functions (Klimesch 1999, Niedermeyer and da Silva 2005, Başar 2012, Sanei and Chambers 2013).

Time-frequency features are very popular and widespread methods for studying BCI with EEG signals because they collect information that changes at any particular time and frequency. It includes methods such as the autoregressive model, short-time Fourier transform (STFT), Continuous Wavelet Transform (CWT), and Discrete Wavelet Transform (DWT)(Mudgal, Sharma et al. 2020). The STFT offers a windowed technique for examining the frequency of EEG signals over a brief period of time, demonstrating how the frequency spectrum changes over time. The CWT analyses the data at various scales using simple waveforms (waves) that may be extended and amplified. helpful in identifying brief, localized patterns of activity in EEG data. DWT is used in real-time BCI applications because it is computationally effective and breaks down the signal into time-frequency components for examination. The autoregressive model predicts the EEG signal values from past events to forecast future values. It is helpful in identifying abnormalities and stimulating brain function.

1.1.4 Classification

Several techniques have been used to classify imagined speech data. These are linear classifiers and neural networks (Lotte, Congedo et al. 2007). Linear classifiers, such as support vector machines, are a part of statistical learning theory and are capable of addressing issues related to limited sample sizes, nonlinear correlations, and multiple categories. This classification aims to create an ideal hyperplane that serves as the decision boundary to distinguish between various classes by maximizing the margin between them. It is effective and easy to understand, but may face challenges with complex patterns of data (Ma, Ding et al. 2016). Another technique is the logistic regression. This technique allows linear regression to be used for classification (Guerrero, Parada et al. 2021). It serves as a bridge between linear regression and classification approaches, offering valuable statistical insights and forecasts continuous variables, while classification categorizes data points into specified groups. It is useful for tasks that require forecasting continuous values and sorting data into classes.

For the purpose of classifying EEG data associated with imagined speech, neural networks are highly effective techniques. By modeling the anatomy of the human brain, these techniques acquire the ability to identify intricate patterns and connections present in the EEG signal. Neural networks can enhance their capability to classify imagined speech for applications such as brain-computer interfaces and cognitive state analysis through the utilization of labeled EEG data for training purposes. Convolutional neural networks (CNNs) are a popular form of neural network used for a variety of applications. They are influenced by the visual cortex of the human brain and are composed of layers that analyze various elements of the incoming data. The layers include of convolutional layers, pooling layers, and fully linked layers. The convolutional layer collects features from the input, the pooling layer decreases feature dimensionality, and the fully connected layer classifies based on these features. CNNs are often used for evaluating bio-signals because to their ability to replicate important characteristics of the brain's visual cortex, such identifying patterns in a localized manner and being indifferent to the precise placement of objects (Park and Lee 2023). Artificial neural network (ANN) can be utilized to evaluate and identify EEG rhythms associated with motor imagery (Sheela sobana Rani, Pravinth Raja et al. 2022) . Long Short-Term Memory (LSTM) networks excellent in classifying EEG data due to their ability to comprehend temporal changes in brain activity, so understand the sequential data in EEG signals LSTM network can be used. LSTM is a technique derived from RNN that exhibits superior performance in handling long-term memory (Hochreiter and Schmidhuber 1997, Kim and Choi 2020, Yang, Huang et al. 2020).
Table 2 represents a comprehensive overview of the main phases involved in processing EEG signals classification. It explains the complex process of analyzing EEG signals and its practical applications in the real world.

Table 2: EEG Signal Processing and Classification Overview

Stage	**Sub-Stage**	**Operation**	**Application**	**Example and Reference**
Data Acquisition	Electrode Placement	Position electrodes on the scalp.	EEG-based Brain-Computer Interfaces	Controlling a computer cursor with thoughts (Wolpaw, McFarland et al. 1991).
	Signal Amplification	Boost weak brain signals using a differential amplifier.	Neurofeedback, Brain-Computer Interfaces	Monitoring and improving attention levels (Larsen 2011, Qin, Zhang et al. 2023).
	Filtering, Digitization	Apply a high-pass filter and convert analog signals to digital.	Clinical Diagnosis, Research	Diagnosing epilepsy through EEG recordings (Imtiaz, Iranmanesh et al. 2019, Khosla, Khandnor et al. 2020, Clarke, Karoly et al. 2021, Qaisar 2023).
	Data Storage and Transmission	Store and send digitized EEG data.	Telemedicine, Remote Monitoring	Remote monitoring of patients' brain activity(Singh and Bansal 2014, Li, Cheng et al. 2021).
Pre-Processing	Reference to Linked Mastoid Channels	Align data with linked mastoid reference channels.	Cognitive Research, ERP Analysis	Studying neural reactions to certain events (Trujillo, Stanfield et al. 2017, Molina, Tardón et al. 2024)
	Band Pass Filtering (0.5 - 50 Hz)	Filter signals to include frequencies between 0.5 and 50 Hz.	Sleep Studies, Cognitive Tasks	Analyzing sleep patterns and cognitive processes (Khosla, Khandnor et al. 2020, Huang, Zhang et al. 2021).
	Interpolation of Removed Channels	Fill in gaps left by removed channels.	EEG Data Reconstruction	Enhancing data integrity for accurate analysis (Kim 2018, Bahador, Jokelainen et al. 2021, Vajravelu 2021).
	Artifact Subspace Reconstruction	Reconstruct data to mitigate artifacts.	Artifact Removal	Reducing artifacts caused by eye blinks or movement (Chang, Hsu et al. 2019).
	Down-Sample to 250 Hz	Reduce data rate for efficient processing.	Real-Time Processing	Enhancing the real-time performance of EEG systems (Mayeli, Zotev et al. 2016).

	Remove Noisy or Flat Channels	Eliminate channels with excessive noise or no variation.	Quality Improvement	Improving the quality of recorded EEG signals (Bigdely-Shamlo, Mullen et al. 2015, Pedroni, Bahreini et al. 2019).
	Extract Power Spectral Density	Derive frequency domain information.	Cognitive State Assessment	Assessing cognitive workload or stress levels (Ong, Saidatul et al. 2018, Reddy and Pachori 2024).
Features Extraction	Time Domain Features	Mean, Median, Variance, Standard Deviation, Skewness, Kurtosis	Pattern Recognition, Mental State Analysis	Recognizing specific mental states based on EEG patterns (Stancin, Cifrek et al. 2021, Wang and Wang 2021).
	Frequency Domain Features	Delta, Theta, Alpha, Beta, Gamma.	Neurofeedback, Cognitive Load Estimation	Measuring and observing the brain's reaction to inputs (Stancin, Cifrek et al. 2021, Makkar and Bisen 2023, Singh and Krishnan 2023).
	Time-Frequency Domain Features	Wavelet Transform (WT), Spectrogram, Short-Time Fourier Transform, fast Fourier transform (FFT)	Motor Imagery, BCI Systems	Enhancing Brain-Computer Interface (BCI) performance (Al-Fahoum and Al-Fraihat 2014).
Classification	Frequency-Based Approach	Classify based on signal frequencies.	Motor Imagery, BCI Systems	Controlling external devices through imagined movements (Wahdow, Alnaanah et al. 2023).
	Time-Frequency Analysis	Analyze changes over time and frequency.	Cognitive Load Estimation	Real-time assessment of mental workload (Morales and Bowers 2022).
	Spatial Approach	Focus on the spatial distribution of signals.	Brain Mapping, Neuroimaging	Understanding brain activity in specific regions (Miao, Hu et al. 2020).
	Event-Related Potentials (ERP)	Classify based on responses to stimuli.	Neuroscience, Cognitive Research	Investigating brain responses during cognitive tasks (Kuncheva and Rodríguez 2013, Sabeti, Boostani et al. 2020).
	Wavelet Transform	Simultaneously analyze time and frequency domains.	Sleep Analysis, Signal Decomposition	Decomposing signals for detailed sleep stage analysis (Hazarika, Chen et al. 1997, Jareda, Sharma et al. 2019).
	Deep Learning-Based Approach	Utilize neural networks for classification.	Automated Diagnosis, Pattern Recognition	Enhancing accuracy in automated EEG diagnosis (Sarmiento, Villamizar et al. 2021, Tibrewal, Leeuwis et al. 2022, Abdulghani, Walters et al. 2023).
	Source Localization Approach	Determine the spatial origin of signals.	Neuroimaging, Brain Mapping	Identifying brain regions involved in specific tasks (Wentrup, Gramann et al. 2005, Eom 2023).
	Cognitive State-Based Approach	Classify based on cognitive states.	Human-Computer Interaction, BCI Systems	Adapting interfaces based on user cognitive states (Chakladar, Roy et al. 2021).

2. Application of EEG

Table 3 provides a summary of the practical use of brain signals in daily activities. The exploration encompasses several domains like as healthcare, gaming, and communication, demonstrating how humans can take control over items, express their thoughts clearly and effectively, and even enhance their state of well-being via the power of their cognition. Each row provides a concise description of the application's purpose, functionality, and unique advantages. However, one must also take notice of the challenges that arise from these technologies, such as their accuracy and accessibility. Furthermore, there are several advancements still to be made in the field of brain-computer interfacing. The potential for remarkable progress is always increasing.

Table 3: Applications of EEG technology integrated into Brain-Computer Interfaces

Category	Application	Description	Benefits	Challenges
Healthcare	Artificial Control: Arms, legs, hands(Beyrouthy, Al Kork et al. 2016, Teng, Xu et al. 2018, Gao, Luo et al. 2019)	Allows individuals who have had limbs lost to operate their artificial limbs using their thoughts.	Restores independence and functionality.	Accuracy, reliability, and affordability.
	Assistive Technologies: Wheelchairs, communication devices (Punsawad, Ngamrussameewong et al. 2016, Tariq, Trivailo et al. 2018)	Allows persons with motor disabilities to manipulate equipment using their mental capacities.	Increases independence and communication ability.	Signal clarity and user training.
	Neurofeedback: ADHD, anxiety, pain management(Moyosola, Alexandru et al. 2019)	Provides training to individuals in order to help them control their brain activity for therapeutic reasons.	Non-invasive treatment option with potential for long-term benefits.	Requires consistent use and individual tailoring.
Gaming & Entertainment	Brain-Computer Interfaces (BCI) Games: Thought-controlled gameplay(da Silva Ferreira 2017)	Builds unique forms of gaming using brainwave patterns.	A fun and engaging way to explore BCI technology.	Technical limitations and limited game variety.
Communication & Control	Text composition: Typing, spelling correction(Van der Weel and Van der Meer 2024)	Facilitates direct communication via the conversion of thoughts into written text for those with restricted physical movement.	Faster and more natural communication.	Accuracy and speed of text generation.
	Smart Home Control: Lights, appliances(Nafea, Abdul-Kadir et al. 2018, Kim, Kim et al. 2019)	Facilitates the manipulation of intelligent home equipment via the use of brain signals, without the need for manual interaction.	Increases convenience and accessibility.	User training and potential security risks.
	Imagined Speech Classification(Lee, Lee et al. 2021, Abdulghani, Walters et al. 2023, Hossain, Das et al. 2023)	Facilitates communications by converting mental patterns of speech into written text or instructions.	Offers alternative communication for individuals with speech impairments or in noisy environments.	Accuracy, decoding complexity, and ethical considerations.
Research & Development	Brain-Computer Interfaces Research: Understanding brain function(He, Yuan et al. 2020, Ramsey 2020)	Offers significant knowledge on the interface between the brain and computer systems, as well as the control of neurological processes.	Advances BCI technology and its potential applications.	Ethical considerations and data privacy concerns.
	Cognitive Enhancement: Attention, memory, focus(Sethi, Dabas et al. 2018, Zhang and Gruber 2019)	Examines the possibility of enhancing cognitive function via BCI intervention.	It could offer benefits for learning, productivity, and well-being.	Early stage of development and potential safety concerns.

3. Literature Review:

The understanding of imagined speech classification and recognition in different languages is enhanced in these studies. The most important studies are examined and classified based on the technique used for gathering brain signals.

3.1 Electrocorticographic (ECoG): Electrocorticography or ECoG is the method of recording and analyzing the electrical signals in the brain by directly placing electrodes on the cerebral cortex or the outermost layer of the brain (Wyler 1987).

The analysis the function of high-gamma brain activity in monitoring the regular patterns of musical rhythms throughout both the process of perceiving them and imagining them Herff Steffen A. et al 2020. The study examines the correlation between high-gamma brain activity and the rhythmic patterns of music by analyzing electrocorticographic (ECoG) recordings from human participants. The findings suggest a strong link between high-gamma autocorrelations in auditory and frontal regions and the autocorrelations of musical rhythms, especially in the right prefrontal cortex. This indicates that individuals are actively engaging in the cognitive processing of rhythm structure throughout both the perceptual and imagining processes. the study provides important knowledge on the neurological processes involved in perceiving and imagining rhythm. It highlights the importance of high-gamma brain activity in auditory processing (Herff, Herff et al. 2020).

Proix Timothee et al. in 2022 explore the capacity to decipher imagined speech by analyzing brain activity recorded using ECoG in individuals diagnosed with epilepsy. Prior studies have shown advancements in deciphering explicit speech, however decoding imagined speech presents difficulties owing to the presence of feeble and inconsistent brain signals. The ECoG data collected from a sample of 13 patients who engaged in both overt and imagined speaking activities. They discovered the presence of low-frequency power and the interaction between different frequency ranges are crucial for accurately deciphering imagined speech. The studies consisted of word repetition tasks when participants mentally simulated the perception and articulation of certain words. The research used a hypothesis-driven methodology, specifically investigating the interaction between low-frequency brain oscillations and their cross-frequency coupling in the perception of speech. Although there were variations in the way tasks were designed in different experiments, the findings demonstrated encouraging prospects for deciphering imagined speech using ECoG signals. This study makes a significant contribution to the development of brain-computer interfaces (BCIs) for those who have severe difficulties in producing speech (Proix, Delgado Saa et al. 2022).

Meng Kevin et al 2023 explore the study on the capacity of brain-computer interfaces (BCIs) to restore communication skills in individuals who are paralyzed and unable to talk. The research sought to create artificial speech sounds by analyzing brain activity recorded from the cortical surface using intracranial electrode arrays temporarily implanted in 10 patients with epilepsy. Two subjects, whose precentral gyrus was covered by electrodes, were able to make fake speech sounds effective while doing overt and mimed word reading tasks. The artificial sound was assessed using both objective measures, comparing them to speech recordings, and subjective evaluations conducted by human listeners. In forced-choice tasks, about one-third of the sounds were accurately recognized. However the attempt to create fake speech sounds while participants imagined speaking was unsuccessful. However, the study of neural features identified possible activation patterns in some parts of the brain, including the postcentral gyrus and superior temporal gyrus, throughout the process of imagining speech (Meng, Goodarzy et al. 2023).

In the past brain-computer interfaces (BCIs) have depended on spelling methods that are dependent on the abilities induced by stimulation, which may be burdensome. Nevertheless, the initial study conducted by Herff et al. (2011) showcased the potential of generating speech directly from brain signals obtained using electrocorticography (ECoG) in real time. They recreated audio magnitude spectrograms by analyzing the brain activity over time and then produced corresponding audio waves. This work represents a notable advancement in synthesizing speech from imagined speech, demonstrating promising associations between the original and recreated signals, despite the use audibly uttered speech for modeling (Herff, Johnson et al. 2016).

Overall studying Electrocorticography (ECoG) as a means of understanding and decoding a range of cognitive functions associated with speech perception, imagination and synthesis Herff Steffen A. et al. (2020) provided evidence that the cognitive processes associated with rhythm sense by demonstrating the significance of high-gamma brain activity in the perception and visualization of musical rhythms. Proix Timothee et al (2022) study on the use of ECoG signals for imagined speech decoding revealed the significance of cross-frequency coupling and low-frequency power for precise speech decoding. Meng Kevin et al. (2023) investigation on the recovery of communication abilities in paralyzed people highlighted the possibility of ECoG-based BCIs in producing fake speech sounds by examining brain activity captured by intracranial electrode arrays. Ultimately, real-time speech production from ECoG data was achieved in the Herff et al. (2011) work, which represents a breakthrough in the direct synthesis of speech from brain activity. All things considered, these studies demonstrate the creative use of ECoG technology to understand and control speech-related cognitive processes, providing encouraging information for the advancement of brain-computer interfaces and neuroprosthetic devices.

3.2 EEG for Imagined Speech:

An interesting new field of study is the investigation of imagined speech using Brain-Computer Interface (BCI) and Electroencephalography (EEG) technologies. We explore the current research on the topic of imagined speech recognition and classification using EEG data in this literature review. Classification of imagined speech with BCI technology has already been the subject of various studies. These including recognize Wang et al. (2013) studied Chinese characters(Wang, Liu et al. 2013), Matsumoto and Hori (2014) studied Japanese vowels (Matsumoto and Hori 2014), Paul et al. (2018) concentrated on Hindi vowels (Paul, Jaswal et al. 2018), Agarwal

& Kumar (2022) studied English words(Agarwal and Kumar 2022). Bengali vowels have been studied by Ghosh et al. (2023) (Ghosh, Sinha et al. 2023), and Bengali numbers and vowels were included in the research by Arman Hossain et al. (2023) (Hossain, Das et al. 2023).
In a study by Wang et al. (2013) tried a new idea in Brain-Computer Interface (BCI) technology. Instead of using movements, they asked eight Chinese people to think about different Chinese characters. They used EEG signals to detect these thoughts and a method called Common Spatial Patterns (CSP) to analyze the EEG data. Then, they used a Support Vector Machine (SVM) to process the data. The results showed that the method was good at telling if someone was thinking about one character with accuracy ranging from 73.65% to 95.76%. It opens up a possible application for Brain-Computer Interface (BCI) systems, suggesting the integration of speech and motor imagery to expand the range of uses.
Matsumoto and Hori et al (2014) studied the ability of people to generate speech via their thoughts, even in the presence of significant communication difficulties. The researchers collaborated with a group of five individuals who engaged in the mental process of picturing Japanese vowels (/a/, /i/, /u/, /e/, and /o/). During this task, the researchers recorded the participants' brain activity using scalp electrodes. By using CSP filtering, adaptive collection (AC), and relevance vector machines with a Gaussian kernel (RVM-G), researchers discovered that RVM-G exhibited slightly superior performance compared to SVM-G, obtaining an accuracy rate of 79%. However RVM-G exhibited a higher demand for computational resources and had difficulties when dealing with a limited number of training instances. This underscores the promise of RVM-G in enhancing silent speech recognition, while also acknowledging its limits in terms of insufficient data and slower processing speed (Matsumoto and Hori 2014).

In a study conducted in 2018, Paul et al used Brain-Computer Interface (BCI) technology to assist those who have difficulties in verbal communication. The participant's attention was directed towards three Hindi vowels that they contemplated silently. By using EEG to monitor cerebral impulses, a computer algorithm deciphered these cognitive processes and transformed them into spoken utterances or directives, thus enhancing the efficacy of communication. Their highest achievement yielded a 70.74% accuracy in discerning unsaid sentiments. Brain-computer interface (BCI) technology has great promise in enhancing the quality of life for those with communication difficulties. The research included eight individuals engaging in quiet contemplation of three distinct Hindi vowels. The EEG data was acquired and examined using a linear support vector machine to detect the specific vowel associated with the individual's thoughts (Paul, Jaswal et al. 2018).

In 2022, Agarwal and Kumar et al developed a brain-computer interface (BCI) by using 32-channel EEG equipment. Their objective was to analyze the cognitive process of imagining speech for certain English words and phrases. The study had a sample size of 13 individuals. Their attention was directed towards certain terms such as SOS, stop, medicine, restroom and the phrase come here. They used a deep learning technique known as the Long Short-Term Memory (LSTM) network to examine seven EEG frequency bands across nine significant brain areas. Their findings demonstrated a remarkable accuracy of 73.56%, exceeding that of previous methodologies. The researchers discovered that the alpha EEG band had exceptional efficacy in identifying imagined speech. The LSTM (long short-term memory networks) model demonstrated superior accuracy and faster prediction time in comparison to other models such as CNN, highlighting the efficacy of deep learning networks (Agarwal and Kumar 2022).
Ghosh et al. (2023) used electroencephalography (EEG) data to discern and classify mentally seen Bengali vowels. An "activity map" (AM) was generated using EEG data to visualize the temporal dynamics of brain activity. The EEG signals of the subjects were recorded as they contemplated Bengali vowels. The AM quantified neural activity across several frequency ranges. A Convolutional Neural Network (CNN) was used to assess the AM, resulting in an accuracy of 68.9%. This approach exhibited superior performance compared to other methods, demonstrating the potential for the identification of imagined speech using EEG data (Ghosh, Sinha et al. 2023).

Arman Hossain et al (2023) explored the use of a non-invasive brain-computer interface (BCI) in the recognition of imagined Bengali speech. The use of a 14-channel electroencephalography (EEG) headset to capture EEG signals while engaging in mental imagery of Bengali vowels and numerals. Four statistical variables, including standard deviation, root mean squares, sum of values, and energy, were derived from the EEG data. A classification procedure was conducted to distinguish between vowels and digits. The random forest classification approach yielded an accuracy of 84.28% at the coarse level and 76.13% at the fine level, which is the highest degree of accuracy achievable. The findings indicate that a Brain-Computer Interface (BCI) system can accurately differentiate Bengali vowels and digits based on Electroencephalogram (EEG) data. This highlights the potential of BCI as a beneficial tool for those with speech impairments who are in search of alternate means of communication. This study establishes the foundation for possible systems enabling users to communicate via imagined speech (Hossain, Das et al. 2023).

Luis Alfredo Moctezuma et al. studied brain signals to identify imagined Spanish words to create a real-time classification system. They used the Discrete Wavelet Transform technique in Python using the sci-kit-learn module to analyze EEG data from 27 participants who were picturing five Spanish words. Their toolkit demonstrated significant accuracies of around 77% for speech classification, 78% for differentiating speech from stillness, and 98% for subject identification. The method's effectiveness stemmed from its capability to extract characteristics from EEG data and categorize them using random forest techniques. This work highlights the possibility of using EEG-based imagined speech categorization to assist communication in nonverbal persons. Future research will focus on improving the system for practical use by minimizing noise and improving signal detection (Moctezuma and Molinas Cabrera 2018).

Maurice Rekrut et al. work explores Semantic Silent Speech Brain-Computer Interfaces (BCIs), which are essential for interpreting imagined speech from brain signals. It tackles a major problem with conventional BCIs: their restricted capacity to identify words. This project intends to significantly enhance word recognition skills by introducing Semantic Silent Speech BCIs that use semantic category categorization. The research attains impressive accuracy rates, reaching up to 95% for individual respondents, by rigorously evaluating five semantic categories using multiple methodologies. The combination of Common Spatial Pattern feature extraction with Support Vector Machine classification shows potential but only partially meets real-world application needs. This work provides useful insights for improving Semantic Silent Speech Brain-Computer Interfaces, although facing obstacles in maintaining consistency across different participants. It highlights the significance of customized techniques for each person, derived from thorough training sessions (Rekrut, Sharma et al. 2021).

B. Dekker et al. compiled the DAIS database, which comprises crucial speech and neural data from twenty Dutch speakers. These individuals were recorded as they both envisioned and spoke in response to fifteen distinct Dutch prompts. ResNet-50, a specialized model, was employed to analyze the brain signals captured in the EEG recordings. With a 70.6% accuracy rate, this model could distinguish whether the subject was at rest, envisioning speech, or speaking aloud. The researchers employed 64 electrodes to capture brain activity and a high-quality microphone to capture spoken words. Each participant completed 20 sets of 15 trials during which they were observed as their brain activity varied between reading, imagining, and speaking the stimuli. The data was cleansed of any errors and subsequently partitioned into distinct segments in preparation for analysis. Brain activity exhibited distinct variations when the subject was at rest, envisioning speech, or speaking aloud. This indicates that while imagining communication, the brain is extremely active. The results of their experiments demonstrated that brain signals generated during imagined speech are distinct from those generated while at rest or speaking aloud. Utilizing this database to investigate how the brain functions during speech and imagination can lead to the development of more effective technologies, such as silent speech interfaces (Dekker, Schouten et al. 2023).

The B. Min et al.(Min, Kim et al. 2016) machine learning classifiers SVM with RBF kernel and ELM (Extreme Learning Machine) with various kernels were used to classify the imagined speech data of EEG signals of vowels such as a, e, i, o, and u. Vowel EEG data was collected from five participants utilizing a 64-channel EEG equipment over the course of five sessions, with 10 trials lasting three seconds for each vowel. The single-trial EEG data of imagined vowels was divided into thirty segments in order to extract the characteristics from the data. The segmented EEG data was used to extract the following features: skewness, variance, mean, and standard deviation. The author employed the sparse regression model to make the feature vectors smaller.

Wayan Pio Pratama et al. used two datasets from the MBD (MindBigData) platform: one from an EMOTIV EPOC+ EEG device with fourteen channels and another from a MUSE headband with four electrodes to train a KNN classifier to detect EEG signals representing digits 0–9 (Pratama, Kesiman et al. 2021). Principal Component Analysis (PCA) and the frequency band technique (delta, theta, alpha, beta, and gamma bands) were used to extract features. Features including spectral entropy, power ratio, and power spectrum were calculated for each band and given into the classifier. The classifier's accuracy was 9% with the EMOTIV dataset and 31% with the MUSE dataset. With the EMOTIV dataset, the classifier achieved 12.5% accuracy using PCA, whereas with the MUSE dataset, it achieved 24.8% accuracy.

Table 3: EEG-Based Imagined Speech Classification Studies

Authors Year	**Study Focus**	**Languages**	**Methodology**	**Technique Used**	**Findings**	**Limitations**
Wang et al. 2013 (Wang, Liu et al. 2013)	Discrimination of Chinese characters via EEG imagery	Chinese characters	EEG signals recorded - Common Spatial Patterns (CSP) applied for feature extraction - Support Vector Machine (SVM) used for classification	Common Spatial Patterns (CSP) with SVM	Achieved accuracy ranging from 73.65% to 95.76% in distinguishing characters	Limited sample size; Generalization to broader character sets not tested

Matsumoto & Hori 2014 (Matsumoto and Hori 2014)	Identification of English vowels during speech imagery	Japanese vowels	EEG signals recorded - Relevance Vector Machines with Gaussian kernel (RVM-G) - SVM with Gaussian kernel (SVM-G) used for classification	Relevance Vector Machines (RVM-G), SVM	Successful identification of Japanese vowels with RVM-G slightly outperforming SVM	Challenges in decoding imagined speech due to variability in brain signals
Paul et al. 2018 (Paul, Jaswal et al. 2018)	Recognition of Hindi vowels through EEG-based imagery	Hindi vowels	EEG signals recorded - Linear Support Vector Machine (SVM) applied for classification.	Linear Support Vector Machine (SVM)	Attained accuracy in identifying Hindi vowels	Limited to Hindi language; Performance may vary with other languages
Agarwal & Kumar 2022 (Agarwal and Kumar 2022)	Decoding English words from EEG signals during imagery	English words	EEG signals are recorded using a 32-channel EEG device Long Short-Term Memory (LSTM) network utilized for classification	Long Short-Term Memory (LSTM) Network	Demonstrated promising accuracy in recognizing English words from EEG data	Performance influenced by quality of EEG signals; Limited to specific English words and phrases
Ghosh et al. 2023 (Ghosh, Sinha et al. 2023)	Classifying imagined Bengali vowels using EEG signals	Bengali vowels	EEG signals recorded - Convolutional Neural Network (CNN) employed for classification	Convolutional Neural Network (CNN)	Achieved high accuracy in distinguishing Bengali vowels from EEG signals	Limited to Bengali language; Potential challenges in generalizing to other languages
Arman Hossain et al. 2023 (Hossain, Das et al. 2023)	Recognition of Bengali vowels and numbers from EEG data	Bengali vowels, numbers	EEG signals recorded using a 14-channel EEG headset - Random Forest classification utilized for differentiation between vowels and numbers	Random Forest	Obtained notable accuracy in distinguishing Bengali vowels and numbers from EEG data	Relatively small sample size; Further validation needed for real-world applications
Stephanie Martin et al 2016 (Martin, Brunner et al. 2016)	Classify individual words during imagined speech	English	High gamma (70–150 Hz) time features with SVM model	Support Vector Machine (SVM)	Classification accuracy of 88% was achieved for individual words during imagined speech	Lower classification accuracy compared to listening and overt speech conditions
Brigham & Vijaya Kumar (2010) (Brigham and Kumar 2010)	Imagined syllable classification	-	EEG signals were recorded while imagining /ba/ and /ku/ syllables	Auto-Regression (AR) coefficients	Classification accuracy varied between 56% to 88%. Further enhanced to 99.76% for subject identification.	Limited sample size, specific focus on syllable classification
Yoshimura et al. (2016) (Yoshimura, Nishimoto et al. 2016)	Decoding vowels from imagined articulation	Japanese vowels /a/ and /i/	EEG signals from imagining Japanese vowels	Sparse Logistic Regression (SLR)	Higher classification accuracy was achieved due to EEG cortical currents.	Limited to Japanese vowels, small sample size
Rojas & Ramos et al (2016) (Rojas, Ramos et al. 2016)	Identification of Spanish vowels using imagined speech	Spanish	EEG signals from imagined Spanish vowels	Symbolic Aggregate Approximation (SAX), Support Vector Machines (SVM)	Achieved an accuracy of 85.29% in classifying two Spanish vowels	Specific to Spanish vowels, limited stimuli

Gonzalez-Castaneda et al. (2017) (González-Castañeda, Torres-García et al. 2017)	Enhanced classification of unspoken words using sonification and textification	Spanish	EEG signals during imagined speech of Spanish words	Discrete Wavelet Transform (DWT), Sonification, Textification, SVM, Naïve Bayes, Random Forest	High classification accuracy with sonification and textification methods compared to original EEG signal.	Limited to Spanish words, potential bias introduced by sonification/textification
Nguyen et al. (2017) (Nguyen, Karavas et al. 2017)	Suitability of speech imagery for BCI	-	EEG signals during speech imagery	Riemannian manifold features, Relevant Vector Machine (RVM)	Classification accuracy of 70% for vowels and 95% for words.	Specific to BCI applications, limited evaluation metrics

The literature and table 3 are showing existed study on EEG-based imagined speech classification mostly concentrates on English, Spanish, Dutch, Bengali, Chinese, Japanese, and Hindi. Still, there is a clear study gap when it comes to Marathi and how imagined text is classified. Future research on imagined text classifications in Marathi seems promising, considering the language's cultural and linguistic importance. We can create classification models particularly for Marathi language processing by taking EEG data from people when they envision speaking or reading Marathi words, phrases, or sentences. In order to accommodate the linguistic peculiarities of Marathi, this may include modifying established techniques like Common Spatial Patterns (CSP), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and others. Furthermore, studying the neurological correlates of Marathi imagined text may help create brain-computer interface (BCI) systems that are more inclusive and culturally appropriate. All things considered, researching imagined text classification in Marathi has the potential to advance neurotechnology more broadly and improve communication tools for Marathi-speaking communities.

4. Discussion

EEG signal analysis highlights the interdisciplinary method used to interpret brain signals for many purposes, especially in brain-computer interfaces (BCIs). The procedure starts with data gathering, in which brain electrical impulses are collected and refined to improve precision. The following phases include extracting features that identify significant characteristics and classifying them to understand these characteristics, using techniques that vary from frequency analysis to deep learning. The information shown in Table 2 highlights the wide range of uses of EEG-based BCIs in healthcare, gaming, communication, and research. Although these technologies have the potential for advantages including enhanced communication and cognitive improvement, problems like accuracy, user training, and ethical concerns must be resolved for general acceptance and dependability. EEG-based approaches show flexibility and potential in deciphering imagined speech and recognizing cognitive processes. EEG is a non-invasive technique for measuring brain activity, making it widely available and appropriate for many uses. EEG studies show significant progress in classifying imagined speech while being prone to noise and artifacts. Several techniques include Common Spatial Patterns (CSP), Support Vector Machine (SVM), Relevance Vector Machines (RVM), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) have great accuracy in identifying imagined speech. EEG-based Brain-Computer Interfaces (BCIs) are used in healthcare, gaming, communication, and research fields, demonstrating the significant impact of using brain signals to control devices, improve communication, and investigate cognitive processes. Advancements in signal processing and machine learning methods are improving EEG's capabilities, making it a vital instrument for neurotechnological progress.

5. Conclusion

In conclusion, this research shows how combining artificial intelligence with EEG can be really helpful for Brain-Computer Interfaces (BCI) and understanding how we imagine speech. It's important because it helps us develop new ways for people to communicate and interact using just their thoughts. BCI, which use EEG technology can be super useful in different areas like healthcare, communication, gaming and boosting brain functions. The complexity of EEG data and the importance of multiple steps in the analysis process including data acquisition, pre-processing, feature extraction, and classification are explored in detail. Throughout the study our focuses on feature extraction techniques, including time-domain, frequency-domain, and time-frequency domain analysis, have been highlighted for enhancing the classification of EEG-based imagined speech data. Linear classifiers, such as support vector machines and logistic regression, have been employed alongside neural networks, particularly convolutional neural networks (CNN) and artificial neural networks (ANN), to effectively analyze and classify EEG data associated with imagined speech. We found that machine learning and deep learning algorithms may potentially classify EEG signals with good precision. The study described our understanding of the use of BCI and EEG technologies for the classification and understanding of imagined speech. It shows how working together across different fields and coming up with new ideas can help people with speech problems have a better life. As we keep studying and improving these technologies, there's a lot of hope that they can make a big difference in how people communicate and think, making it easier for them to express themselves and interact with the world.

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