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Device Interaction with non-invasive BCI

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Abstract - This review focuses on Non-invasive Brain–Computer Interfaces (BCIs), which are systems designed to establish a direct link between the brain and external devices without the need for physical movement. These EEG-based BCIs are applicable in assistive and interactive contexts. A significant emphasis is on BCI-based spellers, which facilitate communication through brain signals. The review examines three main types: P300, Motor Imagery (MI), and Steady-State Visual Evoked Potentials (SSVEP). P300 spellers utilize event-related potentials for high precision; MI spellers depend on imagined movements but demand extensive training; and SSVEP spellers provide rapid performance using flickering visual stimuli. This review details various EEG signal processing techniques, BCI system architecture, and contemporary classification methods for EEG-based BCI.

***Key Words*:** Electroencephalography (EEG), Brain-Computer Interface, Speller, P300, Motor Imagery (MI), Steady State Visual Evoked Potential (SSVEP)

1.INTRODUCTION

Electroencephalography (EEG) sensors are advanced electronic instruments crafted to record the brain's electrical activity. These devices detect minor variations in electrical current between the skin and sensor electrodes, amplifying and filtering the signals, often employing methods like bandpass filtering to capture the neural activity produced by large neuron groups [14]. The foundational advancements in EEG technology stemmed from early interdisciplinary progress in medicine, physics, and chemistry in the early 1900s. These breakthroughs led to the discovery of the brain's subtle electrical currents and spurred the development of various EEG devices [11]. Human interaction depends on our cognitive and neuromuscular systems for communication through speech and gestures. When these systems are impaired due to conditions such as brainstem stroke, cerebral palsy, and other neurological disorders, individuals may lose muscle control, often resulting in social isolation and emotional distress. To tackle this issue, Brain-Computer Interfaces (BCIs) were created, providing a groundbreaking solution for those with motor impairments. Non-invasive BCIs, especially those based on Electroencephalography (EEG), have become the favored method for monitoring brain activity. EEG sensors detect minute fluctuations in electrical activity on the scalp by measuring the voltage differences between electrodes. The signals are subsequently enhanced and refined, often through methods like bandpass filtering, to capture the neural activity of large groups of neurons. EEG's non-invasive nature offers numerous advantages: it is relatively cost-effective, portable, and simple to set up, while also providing superior time resolution compared to other brain monitoring techniques [14,15]

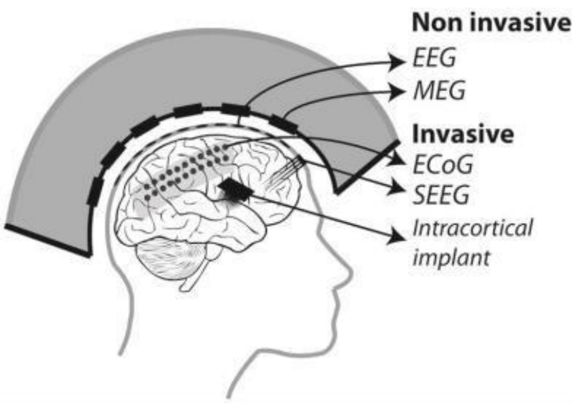

Fig-1.1: Types of Brain Signal Acquisition Methods [29**]**

One of the earliest and most impactful uses of non-invasive BCI technology is the BCI speller. This system allows individuals who are unable to speak to communicate by selecting letters or words using brain signals, representing a major breakthrough in brain-to-computer communication. This advancement in non-invasive BCI technology continues to foster innovative communication methods, providing hope and improving lives of those with severe motor impairments. EEG is widely used non-invasive method. Obtained signals are weaker compared to invasive signals because they must pass through several layers of the head, as shown in Figure 1. EEG

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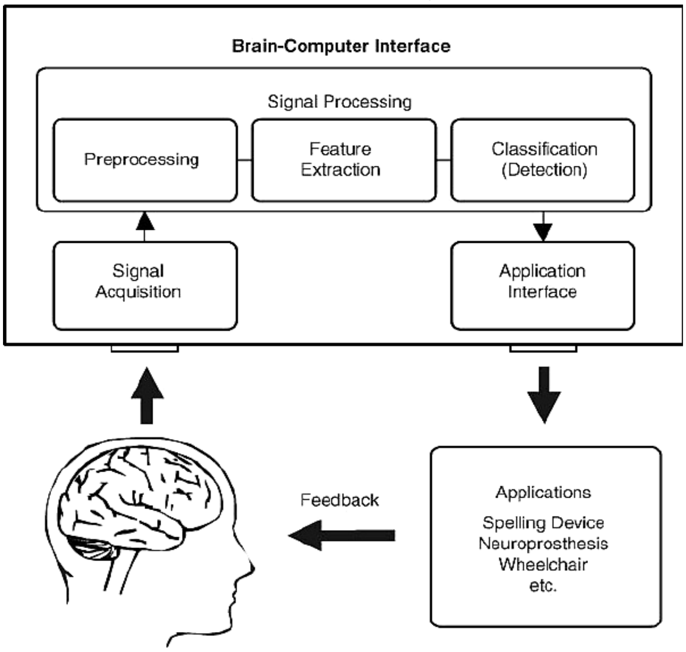
devices are generally divided into wet and dry types. Wet EEG devices connect with the scalp using gel-based or saline solutions to facilitate conductivity, whereas dry EEG devices do not require conductive media. In some instances, conductive solid gel materials, like those used in products such as Enobio, are employed to ensure effective electrode-scalp connectivity. The electrical waveforms generated by neuronal activity in EEG signals provide essential insights into the brain's physiological state and are invaluable for a wide array of applications. These signals are crucial in medical diagnosis, monitoring brain functions, and forming BCI foundations. BCIs are innovative communication systems which converts



the brain's electrical activity into commands, allowing users to control external devices like computer input devices, prosthetic arms, or wheelchairs.

Fig-1.2: Brain Computer Interface [30]

The typical BCI process involves acquiring raw EEG data, preprocessing it to eliminate noise and improve signal quality, extracting relevant features, and finally using classification algorithms to transform these features into actionable commands. Despite their transformative potential in healthcare, assistive technology, gaming, and neurorehabilitation, traditional EEG-based BCIs often require numerous wet electrodes and controlled laboratory environments, limiting their practicality for everyday use. Thus, recent researches have focused on improving the portability and usableness of BCIs. One notable development is the Gaitech BCI platform, which employs a ROS-based system for acquiring EEG signals, integrated with a 10-channel device (Avertus H10C). Besides enhancing the hardware, the research seeks to improve the classification abilities of portable BCI devices, particularly those with a limited number of channels.

The review also explores SSVEP, P300 and MI. A key challenge identified in the review is channel selection, which involves determining the optimal subset of EEG electrodes that most effectively capture relevant cortical activity for specific tasks. By incorporating insights from various neuroimaging modalities, the review aims to create a knowledge-based framework for channel selection that can improve the effectiveness of BCI systems.

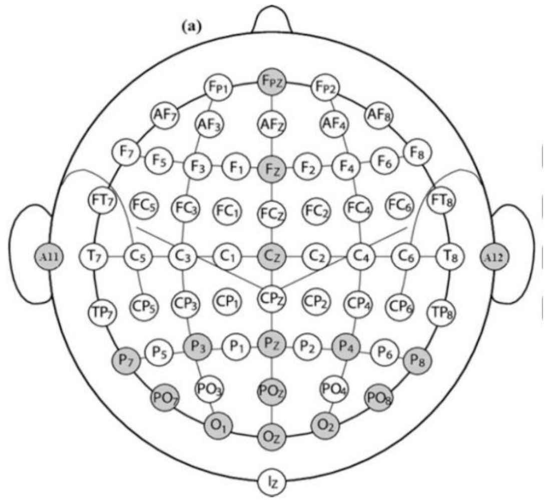


Fig-2.1: The electrode placements based on 10-20 system. [20]

In this comprehensive review, the technological underpinnings of EEG and BCI systems are linked with practical progress, offering a detailed examination of both the hardware advancements and algorithmic methods that drive the creation of state-of-the-art brain-computer interfaces. [11,15]

2. LITERATURE REVIEW

Recent advances in EEG-based BCIs have focused on non-invasive spellers that facilitate efficient communication through distinct paradigms such as P300, motor imagery (MI), and SSVEP. Ma et al. [1] developed a portable EEG signal acquisition system combined with a limited-electrode SSVEP classification network, demonstrating a lightweight yet effective solution for rapid speller applications. This work is complemented by innovations in speller design from Bai et al. [9], who introduced a hybrid P300-SSVEP speller that leverages the complementary strengths of both paradigms.

On the motor imagery front, Zhi et al. [7] proposed a multi-domain convolutional neural network capable of robustly decoding MI signals, addressing common challenges like inter-subject variability and prolonged training requirements. Angelakis et al. [2] provided a comparative analysis of deep learning models for real-time servo motor control using EEG—a study that, while focused on control applications, offers valuable insights into model performance trends that are applicable to MI-based spellers.

In the domain of P300 spellers, Hu et al. [5] presented a subject-independent wearable system incorporating CNNs with metric learning to improve the reliability of P300 detection. This is further enhanced by Aghili and Erfanian [6], who employed a

MINMAX Riemannian geometry scheme integrated with CNN architectures to boost detection accuracy. Additionally, Song et al. [12] introduced an EEG Conformer—an innovative model that adopts transformer techniques to capture long-range dependencies in EEG signals, highlighting a promising direction for future BCI research.

Overall, these studies underscore a clear trend toward the integration of advanced deep learning techniques and hybrid strategies to enhance classification accuracy, robustness, and adaptability across various EEG-based speller paradigms. This convergence of methodologies paves the way for more practical, real-world applications in communication and control interfaces.

3. METHODOLOGY

In EEG classification, the method combines meticulous data acquisition, detailed preprocessing, extensive spectral feature extraction, and sophisticated deep learning models to accurately interpret neural signals. The Fig.2.2 consists a flowchart which portrays the required stages. First, the procedure starts with setting up the EEG acquisition system. To assemble and configure the acquisition system with EEG electrodes, the subject's scalp is initially prepared, and electrodes are positioned following the international 10–20 system, ensuring optimal contact and low impedance using conductive gel. These electrodes are linked to the acquisition system, which amplifies the faint EEG signals and conducts preliminary noise filtering. The processed signals are then connected to the data acquisition board, which includes a high-performance analog-to-digital converter (ADC). The output channels are attached to the correct ADC inputs on the board, ensuring proper grounding and secure connections to preserve signal quality. The ADC settings, such as a sampling rate typically ranging from 250 to 500 Hz, are configured, and the board's wireless communication features are activated to stream the digitized EEG data in real time for further analysis. [1]

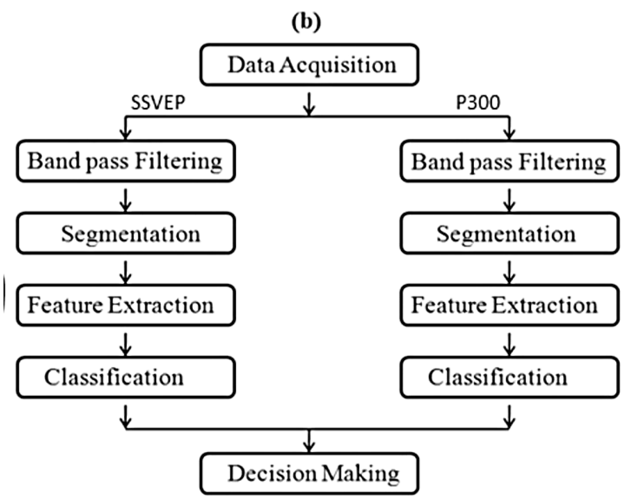


Fig-2.2: Flowchart that portrays preprocessing and classification [20]

After being collected, the raw EEG signals undergo a comprehensive preprocessing procedure, beginning with a 50 Hz notch filter to eliminate powerline interference.This is followed by a fourth-order Butterworth bandpass filter (0.5–50 Hz) to focus on the pertinent brainwave components while reducing noise and artifacts. EEG signals are transformed from the time domain to the frequency domain using Fast Fourier Transforms, which decompose the signal into distinct frequency bands. This spectral analysis allows for the extraction of essential features such as power spectral density (PSD) ratios, peak frequency, spectral centroid, and spectral slope, along with time-domain metrics like Hjorth parameters, Petrosian fractal dimensions, and the Frobenius norm. These features collectively capture both the local oscillatory patterns and the overall spectral characteristics of the EEG data.

By using a CNN-LSTM, the CNN-LSTM network uses convolutional layers extracting spatial features from the EEG data and LSTM layers to capture long-term temporal dependencies, while EEGNet offers a compact and efficient architecture specifically designed for EEG analysis. This combination of thorough preprocessing, comprehensive feature extraction, and advanced deep learning models enables end-to-end EEG decoding, showing significant potential for real-time brain–computer interface applications.

3.1. FEATURE EXTRACTION

The process of feature extraction involves multiple stages that transform preprocessed EEG data into a comprehensive set of distinguishing features. Initially, the cleaned EEG signals are divided into fixed-length segments, typically lasting 2 seconds, to capture temporal dynamics. Spectral analysis is conducted in each segment, using the Fast Fourier Transform (FFT) that breaks down the time-domain signal into its frequency components. From the resulting frequency spectrum, Power

Feature Extraction Technique	***Definition***	***Description***
Time–Frequency Analysis	Analyzes frequency changes over time.	Splits the signal into time windows to capture transient frequency patterns.
High-Order Spectral Analysis	Extracts nonlinear, phase-related features.	Uses higher-order statistics (e.g., bispectrum) to reveal complex signal interactions.
Nonlinear Dynamic Analysis	Measures signal complexity and chaotic behavior.	Uses metrics like Lyapunov exponents and entropy to capture dynamic properties.

Feature Extraction Technique	***Definition***	***Description***
Fourier Transform	Converts a time-domain signal into the frequency domain.	Provides an overall frequency content; best for stationary signals.
Power Spectral Density (PSD)	Quantifies power distribution across frequencies.	Shows energy distribution among frequency bands, aiding band-specific analysis.

Spectral Density (PSD) features are calculated for key EEG bands such as alpha, beta, theta, and delta.

Table -1: Various Feature Extraction Techniques

Beyond band- specific power, additional spectral characteristics are extracted, including the peak frequency (to identify the most prominent frequency), spectral centroid (indicating the "center of mass" of the frequency distribution), and spectral slope (providing insight into how power diminishes with increasing frequency). Together, these metrics form a detailed feature vector that encapsulates both the energy distribution and finer spectral details of the EEG, serving as the basis for effective classification [14].

3.2. PREPROCESSING

An important step before feature extraction and classification is preprocessing. The initial step involves using a 50 Hz notch filter to eliminate powerline interference, which is a frequent contaminant in EEG recordings. Following this, a Butterworth bandpass filter is employed, covering a frequency range of 0.5–50 Hz. This filter is selected for its maximally flat passband response, ensuring minimal distortion of the signal's amplitude while effectively isolating the desired brainwave components. The bandpass filter captures essential low-frequency elements like delta waves and suppresses high-frequency noise, including muscle artifacts and other extraneous signals. Following the filtering step, the signal is transformed into the frequency domain using the FFT, facilitating the detailed spectral analysis required for feature extraction. To further enhance data quality, a Discrete Wavelet Transform (DWT) is employed for artifact removal. DWT is better in providing time-frequency localization, enabling the precise identification and removing of transient artifacts without compromising the integrity of the underlying neural signals. This comprehensive preprocessing pipeline ensures that the EEG data entering the feature extraction stage is both high in quality and free from significant distortions, thereby laying a solid foundation for accurate classification by the subsequent deep learning models.

3.3. SIGNALS

This method relies solely on raw EEG signals, deliberately excluding specialized paradigms like SSVEP, motor imagery, or P300. By concentrating exclusively on the inherent electrical activity recorded by the EEG, this strategy sidesteps the extra complexities and calibration needs linked to these specific paradigms. The focus is on deriving significant spectral features directly from the raw EEG data, ensuring that the developed models can be applied to a range of applications without depending on externally triggered brain responses.

3.4. CLASSIFICATION

The classification phase uses two sophisticated deep learning models: a hybrid CNN-LSTM network and EEGNet. The CNN-LSTM model excels at identifying local spatial patterns across various EEG channels, efficiently extracting high features from the raw data. However, since CNNs mainly capture short-term dependencies, the subsequent LSTM layers are incorporated for checking long-term temporal relations inherent in EEG time series data. This integration allows the model to understand both the spatial and temporal dimensions of the signal. Complementing this method is EEGNet, which employs depthwise and separable convolutions to lessen the number of parameters while still capturing essential features, making it particularly suitable for real-time and low-sample-size scenarios with compact and systematic architecture. Together, these algorithms offer a robust framework for EEG classification, balancing the need for complex feature extraction with computational efficiency. [8,10]

The following table summarizes the average accuracy and representative references for various classification algorithms:

Table -2: ML & DL Algorithms used for classification

Algorithm	***Average Accuracy (%)***	***Representative References***
EEGNet	~89.0	[23]
SVM	~83.0	[21], [24]
Conformer	~87.0	[12]
CNN	~88.0	[5], [6], [7], [25], [26]
CNN-LSTM	~90.0	[3], [2]*

*Although [3] uses a hybrid Bi-directional LSTM–GRU structure rather than a pure CNN-LSTM, and [2] provides a comparative analysis including recurrent models, they are representative of the CNN–recurrent class of algorithms often grouped under the CNN-LSTM umbrella in comparative discussions.

The table describes the average accuracy attained by - CNN-LSTM models achieve the highest average accuracy (~90.0%), followed closely by EEGNet (~89.0%) and CNN-based approaches (~88.0%). Support Vector Machines (SVM) show a lower average accuracy (~83.0%) compared to the deep learning models. The results highlight effectiveness of deep learning techniques in EEG signal classification tasks.

Additionally, the table below outlines recent advancements in EEG classification models along with their reported accuracies. It includes various models used for P300 and SSVEP spellers, as well as for the classification of motor imagery. These models incorporate ensemble-based EEG classification techniques alongside CNN, SVM, and other well-known deep learning algorithms.

Table -3: Recent Advancements of EEG Classification Models

Model / Approach	Paper	Year	Reported Accuracy
FBATCNet	[27]	2025	~90%
Ensemble-Based MI EEG Classifier	[28]	2024	92%
Subject-Independent P300 BCI (CNN + Metric Learning)	[5]	2024	~88%
Hybrid Bi-Directional LSTM-GRU Model	[3]	2024	~90%
Hybrid SSVEP + P300 BCI	[20]	2024	~82%
P300 Speller (MINMAX Riemannian Geometry & CNN)	[6]	2023	~91%
EEG Conformer (Convolutional Transformer)	[12]	2023	~87%
Multi-Domain CNN for Motor Imagery Decoding	[7]	2023	~88%
DeepEnsemble (Ensemble of Deep Learners)	[19]	2023	~90%
Wavelet Transform & SVM for Stress Recognition	[21]	2022	~84%
CNN Approach for EEG Signal Analysis	[25]	2021	~88%
DynamicNet – CNN-Based Cross-Subject Classification	[26]	2021	~87%
EEGNet with Ensemble Learning for Cross-Session SSVEP Classification	[23]	2021	~89%

4. FUTURESCOPE

Although this framework reviews promising outcomes, there are several future research directions to further advance EEG-based BCIs. Machine learning techniques, especially deep learning, have streamlined the EEG signal processing procedure into a complete task; however, they necessitate traditional methods. The complexity of EEG data collection, along with challenges such as noise, non-stationarity, and inter-subject variability, highlights the need for ongoing model enhancement and adaptation. Future research will focus on minimizing data heterogeneity through advanced methods like domain adaptation and federated learning, which enable model training across diverse datasets without compromising data privacy. Additionally, exploring transfer learning and multimodal approaches may open new possibilities, such as enhancing emotion recognition tasks. Addressing these challenges will also involve refining denoising techniques, improving electrode configurations, and enhancing the clarity of deep learning models. Ultimately, the future scope of EEG-based BCI research lies in developing more portable, user-friendly, and personalized systems that can adapt to individual brain activity patterns and meet real-world application demands.

4. CONCLUSION

Recent progress in EEG-based BCI classification marks a notable transition from conventional machine learning methods to advanced deep learning frameworks. Research by Ma et al. [1] and Bai et al. [9] has shown the success of portable systems and hybrid speller designs, respectively, while studies by Hu et al. [5] and Aghili and Erfanian [6] highlight the improved accuracy that can be achieved with sophisticated CNN-based techniques for P300 detection. In the realm of motor imagery, Zhi et al. [7] demonstrate the advantages of multi-domain CNN models in tackling inter-subject variability and enhancing temporal decoding capabilities. Additional research, such as that by Angelakis et al. [2] and Song et al. [12], further indicates that incorporating recurrent components and transformer-based methods can significantly enhance performance by capturing the long-range dependencies present in EEG data. Collectively, these studies suggest a growing consensus: hybrid deep learning models, which can simultaneously exploit spatial and temporal features, outperform traditional methods like SVM. Despite these advancements, challenges related to data heterogeneity, inter-subject variability, and computational requirements persist. Future research should focus on domain adaptation, transfer learning, and federated approaches to make EEG-based BCIs more robust, adaptable, and practical for real-world use. In summary, the shift towards hybrid and deep architectures has greatly advanced EEG classification accuracy, paving the way for next-generation BCIs that promise enhanced usability and wider applicability in both clinical and non-clinical environments.

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