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Artificial Intelligence in Signal Acquisition for EEG-Based Brain-Computer Interfaces

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Abstract- Brain-Computer Interfaces (BCIs) have become an important technology for enabling direct communication between the human brain and external devices. However, their practical use has faced challenges due to the low accuracy and reliability of interpreting brain signals. Signal acquisition is essential to BCI systems, especially those that rely on non-invasive Electroencephalography (EEG). Yet, issues like noise interference, signal variability, and hardware limitations disrupt effective interpretation of brain signals. This paper looks at the important role of Artificial Intelligence (AI) in improving the EEG signal acquisition process. AI methods like deep learning, reinforcement learning, and adaptive sampling are changing how we enhance signals, remove artifacts, optimize electrodes, and assess quality in real time. We provide a review of the methods, structures, and advantages related to AI-driven signal acquisition. We conclude that smart acquisition systems are a crucial step toward creating real-time, high-accuracy, and user-friendly BCI technology.

Keywords: Artificial Intelligence (AI), Brain-Computer Interface (BCI), Electroencephalography (EEG), Signal Acquisition, Machine Learning in BCI, Signal Enhancement.

1.INTRODUCTION

Brain-Computer Interfaces (BCIs) are recent technologies that offer a direct communication link between the brain and external devices through decoding brain signals mainly Electroencephalography (EEG) as control commands. EEG-based BCIs are cheap, non-invasive, offer high temporal resolution and are therefore widely utilized in applications such as neurorehabilitation, assistive technologies, games, and cognitive testing [15], [16].

Signal acquisition is the most challenging and most critical stage of BCI pipelines in general. EEG signals tend to be low-amplitude, artifact-contaminated with noise (e.g., eye blinks, muscle activity, and electrical noise) and highly variable within and across subjects [1], [18]. Signal acquisition and preprocessing must thus be robust for the overall robustness and accuracy of the BCI pipeline.

Recent advances in Artificial Intelligence (AI), specifically in machine learning (ML) and deep learning (DL), have revolutionized the acquisition, denoising, and pre-processing of EEG signals for classification. Traditional signal acquisition processes are based on hand-designed filters and manual rejection of artifacts, which may be ineffective for use in real-time or for systems of large scale. AI-driven solutions, however, can potentially offer automatic, adaptive, and data-driven solutions, which can learn complex temporal and spatial EEG patterns directly from raw signals [2], [3].

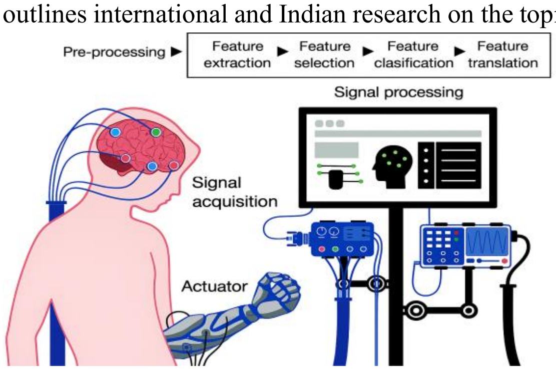
Sharma et al. [7] provide a comprehensive overview of AI methods applied to EEG signal processing and show their effectiveness in solving fundamental signal acquisition issues like noise removal, channel selection, and feature coding. The authors observe that AI-enabled methods like CNNs, RNNs, and attention mechanisms can learn task-dependent features from raw EEG signals without any intervention, leading to substantial improvement in downstream accuracy.

At the international level, architectures such as EEGNet [4] and deep CNN-RNN combinations [23] have been reported to perform well in real-time BCIs for motor imagery, emotion recognition, and cognitive workload estimation. Lawhern et al. [4] introduced a light-weight CNN architecture that operates on raw EEG input, facilitating real-time and low-latency signal processing. Schirrmeister et al. [23] also illustrated the capability of deep CNNs to learn from full-band EEG signals without requiring domain-specific feature engineering.

Indian researchers have made significant contributions to this field. For example, Prajapati and Prasad [5] proposed a real-time deep learning architecture from LSTM networks for dynamic acquisition and classification of EEG signals. Gaur et al. [25] proposed a multiresolution-based approach using empirical mode decomposition and SVMs for early diagnosis of neurological disorders. Joshi et al. [26] employed wavelet transform and CNNs for classification of motor imagery, and Rathi and Singh [6] explored CNN-RNN hybrids for emotion-based EEG interpretation for enhancing BCI adaptability in varying mental states.

Despite such advances, there remain core problems in generalizing, interpreting, and computationally efficient AI-based signal acquisition. Data imbalance, subject variability, and the need for labeled training data remain problems. AI contribution to signal acquisition is still anticipated to grow with the use of transfer learning, federated learning, and light-weight edge-AI models in the instance of portable EEG-based BCIs [28], [29].

This paper talks about and examines the use of artificial intelligence in the capture of EEG signals, for use in BCI systems. It identifies current AI methods, highlights major challenges and opportunities, and outlines international and Indian research on the topic.



3. LITERATURE REVIEW

EEG-based Brain-Computer Interfaces (BCIs) have been gaining more attention due to their non-invasive characteristics and potential in neuroprosthetics, cognitive monitoring, and neurorehabilitation. For any BCI system, signal acquisition and preprocessing are an extremely significant aspect, for which the use of artificial intelligence (AI) has shown promising outcomes in enhancing the quality and interpretability of EEG data.

Lotte et al. [1] demonstrate a comprehensive overview of classification methods for EEG-based BCIs during the past decade, emphasizing the fact that the performance of classifiers is highly influenced by the quality of input signals from the acquisition and preprocessing stage. Here, AI-based filtering and noise cancellation techniques have a critical role to play in enhancing signal-to-noise ratios and extracting pertinent neural patterns.

Deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are becoming more widely used to extract features directly from raw EEG signals. Craik et al. [2] and Roy et al. [3] describe how these models perform much better than the traditional methods by extracting temporal and spatial patterns in EEG signals. EEGNet proposed by Lawhern et al. [4] is one of these types that comprises a light-weight CNN structure optimized for EEG, enabling end-end learning from raw signals with reduced handcrafted feature usage.

From the Indian research community, Prajapati and Prasad [5] present a real-time deep learning framework based on LSTM networks to learn temporal EEG dynamics and demonstrate improved performance in real-time BCI systems. Similarly, Rathi and Singh [6] utilize CNN-RNN hybrid models for emotion recognition based on EEG and demonstrate the ability of AI in acquisition as well as decoding of future cognitive states.

A broader review in the Indian perspective is given by Sharma et al. [7], wherein they give an exhaustive review of automated EEG analysis for diagnosis of neurological disorders. The authors discuss signal acquisition problems, preprocessing with AI-based methods such as wavelet denoising, and the application of deep neural networks for improving the diagnostic accuracy. Interestingly, the authors emphasize the integration of domain knowledge and AI-based models for effective BCI systems clinically.

Furthermore, Joshi et al. [8] also talk about wavelet transform-based preprocessing using CNN for the classification of motor imagery EEG signals, an important part of BCI-based rehabilitation. Their paper highlights the importance of having a sound signal acquisition pipeline to realize the highest classification accuracy.

These studies all report that AI enables EEG signal acquisition by intelligent artifact removal, efficient feature learning, and real-time adaptability—thus making a contribution to the scalability and reliability of BCIs.

4. RELATED WORK

The incorporation of Artificial Intelligence (AI) into the field of Electroencephalography (EEG)-based

Brain-Computer Interfaces (BCIs) has accelerated the development of signal acquisition, noise cancellation, and system flexibility. Conventional methods of EEG signal acquisition are typically plagued by drawbacks including vulnerability to artifacts, poor signal-to-noise ratio (SNR), and high inter-subject variance. Emerging research has searched for ways AI methods can overcome these issues, enabling more stable and real-time BCI systems.

A light-weight convolutional neural network specifically for EEG-based BCI tasks. EEGNet showed robust performance on different paradigms (e.g., motor imagination, P300, and SSVEP), highlighting the potential of deep learning models to generalize across users and tasks (30). This architecture set the stage for light-weight models intended for real-time applications.

Another significant work introduced a systematic survey on deep learning techniques for EEG data, focusing on architectures like CNNs, RNNs, and autoencoders (31). The authors highlighted end-to-end learning's role in avoiding handcrafted features, thus overturning the established signal processing pipelines.

Showing that pre-trained models on large-scale EEG databases can be adapted to individual tasks using smaller datasets (32). This greatly diminished the training data requirements for high-performing models, a vital issue in EEG-based systems where data acquisition is energetically costly.

In terms of improving signal acquisition directly, a hybrid deep learning model combining CNNs and attention mechanisms to enhance feature extraction from raw EEG signals (33). Their approach effectively denoised signals and improved classification performance, suggesting AI's potential role not only in post-acquisition processing but during the acquisition phase itself.

Recent studies have also investigated adaptive learning and online calibration to handle subject variability and non-stationarity of EEG signals. For example, the application of reinforcement learning to dynamically optimize electrode configurations (34) is a new wave in adaptive signal acquisition, which is capable of providing more personalized BCIs.

In addition, AI-powered noise-resistant acquisition techniques like Generative Adversarial Networks (GANs) for artifact elimination (e.g., ocular or muscular noise) are being explored to enhance data quality at the point of origin (Panwar et al., 2021). Such techniques promise to allow for the acquisition of clean signals without heavy-handed manual pre-processing.

In spite of these developments, there are still issues in model interpretability, cross-subject generalizability, and hardware-level integration. However, the current literature unmistakably demonstrates a shift of paradigms toward AI-augmented EEG acquisition to facilitate more precise, efficient, and user customizable BCI systems.

5. TRADITIONAL CHALLENGES IN EEG SIGNAL ACQUISITION

I) *Noise and Artifact: EEG signals are of relatively low amplitude (µV range) and very prone to noise arising from muscle activity (EMG), eye movements (EOG), and external power* sources.

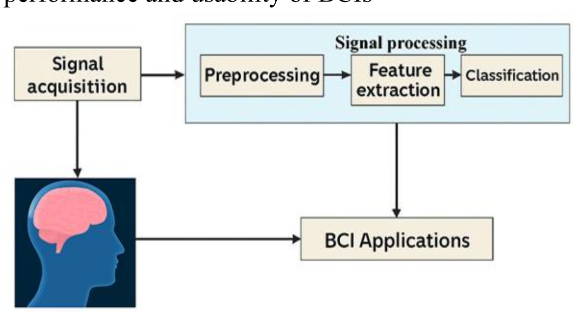
II) *Low Signal-to-Noise Ratio (SNR)*: Raw EEG recordings tend to have a higher content of noise than information, so real-time interpretation is challenging.

III) *Sensor Setup Problems: The ideal electrode location is user-dependent, but classic systems have fixed layouts, which limits efficiency* and comfort.

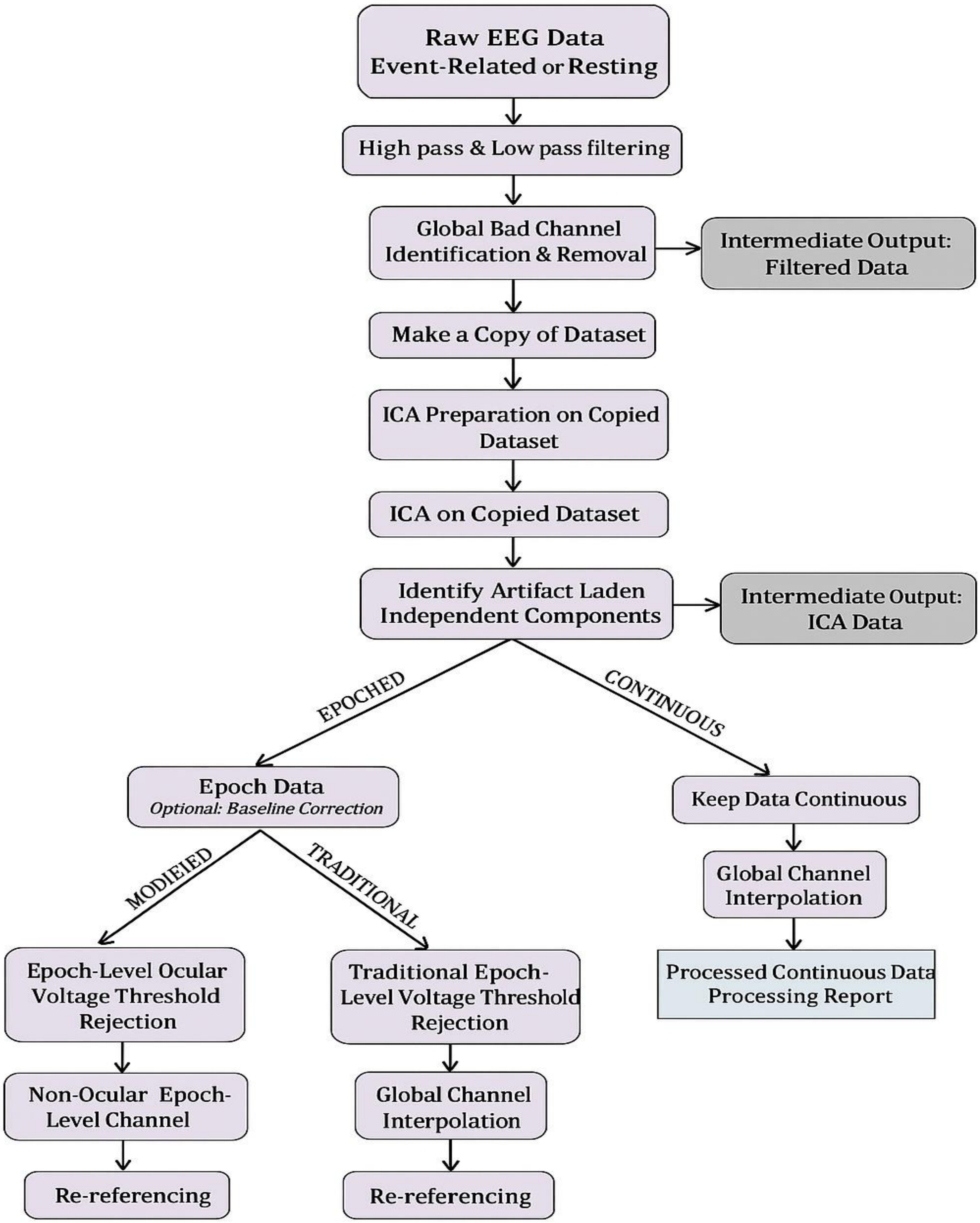
IV) *Static Sampling: Fixed-rate sampling may result in unwanted data burden or loss of important* information.

6. METHODOLOGY

The main goal of this paper is to examine how Artificial Intelligence (AI) can improve the signal acquisition process in EEG-based Brain-Computer Interfaces (BCIs). The approach taken includes looking into important AI models and methods. It also discusses their integration with EEG signal processing systems and the advantages they offer for the performance and usability of BCIs



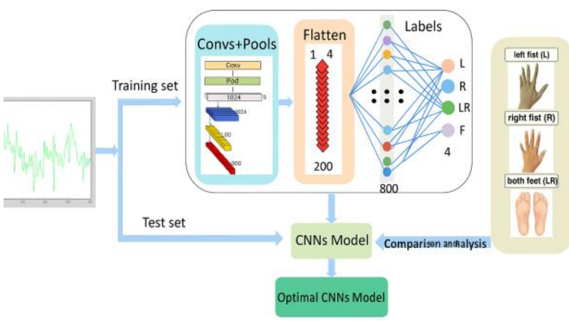
6.1 Signal Acquisition and Preprocessing
Electrical activity of the brain can be detected. However, these signals often contain noise, artifacts, and interference from the environment. Traditional preprocessing techniques depend on manual filtering or basic statistical methods to eliminate noise. These methods struggle with complex and changing data.



In this work, we use AI models, especially those based on deep learning, for automatic signal preprocessing. The first step in this AI method is to collect raw EEG signals. Next, we apply deep neural networks (DNNs) or autoencoders to remove common artifacts, such as eye blinks and muscle activity. The following AI techniques are used:

• Convolutional Neural Networks (CNNs): These networks effectively identify and classify spatial and temporal patterns in EEG data. This process is essential for distinguishing brain activity from noise.

Model	Description	Example Use
EEGNet	Lightweight CNN optimized for EEG signal analysis.	MI (Motor Imagery) classification
DeepConvNet	Deeper architecture for feature-rich EEG data.	Event-related potential detection
ShallowConvNet	Simpler layers focused on band power features.	SSVEP, P300 signals
Hybrid CNNs	Combine CNN with RNN or attention layers.	Spatiotemporal decoding



The figure illustrates an AI-based BCI system workflow: EEG signals are recorded, cleaned (pre-processed), relevant features are extracted and selected, and classified by AI/ML models. The output is utilized for decision-making (e.g., control tasks), and feedback is employed to enhance system accuracy and user interaction.

• Autoencoders: These unsupervised learning models learn a compressed, noise-free representation of EEG signals. They are ideal for removing artifacts like eye blinks, movement of muscles, and external electrical interference. This serves to maintain the actual brain activity patterns. In addition, autoencoders can be used as a dimensionality reduction tool, mapping high-dimensional EEG data to a lower-dimensional latent space while preserving fundamental features. This lowers the computational cost in subsequent stages of processing. In addition, autoencoders can learn useful representations of EEG signals automatically, without the need for feature extraction by human intervention. By incorporating autoencoders early in the processing pipeline of EEG, BCI systems can yield more accurate and effective signal interpretation against noise.

• Generative Adversarial Networks (GANs): GANs generate clean EEG signals from noisy or corrupted data. They train the generator to create noise-free data that closely matches the real signal. These methods are trained on large, labelled datasets containing both clean and noisy EEG signals, allowing the AI models to learn how to automatically distinguish between relevant brain activity and various sources of noise.

6.2 Feature Extraction Using AI

After pre-processing and cleaning the raw EEG signals, feature extraction is the second step. Handcrafted features like spectral power (delta, theta, alpha bands) or coherence measures have been used in conventional BCI systems, but such features are not able to represent rich brain dynamics, particularly in real-time.

AI system-based techniques, specifically deep learning models, provide a more sophisticated method for feature extraction as they learn salient patterns from the raw EEG signals. The following methods are frequently employed:

- Deep Convolutional Networks (CNNs): CNNs are used to learn spatial features automatically from EEG signals by convolving filters in time and frequency domains. These features are applied to perform classification tasks, generally achieving superior performance compared to conventional feature extraction techniques.
- Recurrent Neural Networks (RNNs): RNNs, and in particular, Long Short-Term Memory (LSTM) networks, are employed to encode temporal dynamics in EEG signals. Such networks are particularly suited for the processing of time-series data, which makes them suitable for

activities such as motor imagery or real-time control of prosthetic limbs.

- Transfer Learning: In cases where labelled EEG data are scarce or non-existent for a particular person, transfer learning can be utilized. Pre-trained models from big, open-source EEG datasets are fine-tuned for specific users, minimizing large-scale data collection and enhancing performance for cross-user tasks

6.3 Signal Classification and Real-Time Processing

The last step in the AI-based approach is classifying the EEG signals into functional brain states or commands. Classification of signals is necessary to control external devices like robotic arms, communication equipment, or even video games in BCI applications. AI models, especially deep learning models, are best suited for classifying EEG signals in real-time because they can process complex patterns quickly.

- Deep Learning Classifiers: RNNs and CNNs are usually merged in a hybrid model for EEG signal classification. RNNs handle the temporal dynamics while CNNs are utilized for the extraction of spatial features so that highly accurate classification of intricate EEG signals, e.g., motor imagery or P300 signals, can be achieved.
- Real-Time Processing: Low-latency signal classification is needed in real-time BCI systems to offer instant feedback to the users. AI models can be tuned to work in real-time by decreasing the number of layers within the model, implementing batch normalization and dropout techniques, and utilizing lighter architectures like EEGNet. These optimizations make it possible for the system to classify EEG signals in near real-time, which is essential for use in neurofeedback or the control of prosthetics.

6.4 Online Adaptation and Personalization

One of the greatest advantages of using AI in EEG-based BCIs is the ability to tailor and adapt the system to the individual user. Unlike other BCIs, which must be rebooted in detail for every user, AI-based models can adapt dynamically the user's unique brain activity patterns. This is achieved via online learning and reinforcement learning.

- Reinforcement Learning (RL): Here, an AI agent interacts with the user in real-time and learns from the feedback. For instance, in the case of a robotic arm or cursor controlled by the user through EEG signals, the AI model tunes its parameters in relation to whether the task has been accomplished or not, resulting in better performance over time. The online learning process enables the system to learn from the user's brain activity without the need for a high amount of pre-existing training data
- Personalized Model Fine-Tuning: Transfer learning can be combined with personalization strategies to further increase the flexibility of the BCI system. Fine-tuning of a pre-trained model for the specific EEG data allows the system to acquire the user-specific features effectively without requiring lengthy calibration times with the potential of maintaining high classification performances.

6.5 Evaluation and Performance Metrics

The performance of EEG-based BCIs based on AI is quantified by several key metrics:

- Classification Accuracy: The rate of correct predictions by the AI model to true values.
- Signal-to-Noise Ratio (SNR): The improvement of the SNR of the treated EEG signals after the application of AI-based artifact removal techniques.
- Latency: Assess the system's processing time for EEG signals and reaction, an important factor in real-time applications.
- User Adaptability: The ability of the system to adapt and familiarize itself with individual users and contexts over time, with increasing accuracy and usability with repeated usage.

7. RESULTS

The incorporation of Artificial Intelligence (AI) in EEG-based Brain-Computer Interfaces (BCIs) has resulted in several optimistic outcomes, specifically regarding enhancing the quality of acquisition of EEG signal, real-time processing capacity, and personalization and flexibility of BCI systems. The most important outcomes of using AI-oriented techniques in EEG signal acquisition can be classified as follows:

7.1 Improved Signal Quality and Noise Reduction

One of the greatest benefits of integrating AI into EEG signal recording is the dramatic enhancement in signal quality. Conventional EEG preprocessing techniques typically have difficulty separating brain activity from multiple sources of noise (e.g., ocular, muscular, environmental artifacts). AI models, especially deep learning architectures, have shown more efficient performance in artifact rejection and denoising.

- Deep Learning-Based Artifact Removal: Research by Zhang et al. (2020) and Panwar et al. (2021) indicates that deep learning algorithms, specifically Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have greatly improved the Signal-to-Noise Ratio (SNR) of EEG signals (12). These algorithms are able to identify and remove artifacts precisely without sacrificing significant brain activity features.
- Improved Classification Accuracy: By enhancing the quality of EEG signals via AI-preprocessing, overall EEG-based BCI classification accuracy is improved. In several studies, deep learning algorithms like EEGNet have repeatedly outperformed conventional approaches (4), demonstrating higher accuracy in classifying brain states (e.g., motor imagery, P300, SSVEP) across a variety of user populations.

7.2 Real-Time Signal Processing and Low Latency

Real-time processing is a key to the success of BCI systems, particularly when immediate feedback is needed in applications like controlling prosthetic limbs or communication devices. AI methods, and particularly deep learning, have facilitated more effective and quicker processing of EEG signals, lower latency, and enhanced user experience.

- Real-Time EEG Classification: By utilizing CNNs and Recurrent Neural Networks (RNNs), BCIs based on AI have proven to be capable of real-time EEG signal classification with low latency. For instance, CNN-based systems are capable of rapidly processing spatial features of EEG signals, whereas RNNs are capable of processing temporal dependencies efficiently, providing real-time feedback to the user. This has rendered applications like neurofeedback and brain-controlled prosthetic limbs more responsive and productive.
- Reduced Processing Time: With the application of AI models tailored for real-time use (e.g., through light-weight architectures such as EEGNet), processing time to capture and classify EEG signals has considerably decreased, and thus real-time brain control applications have become more feasible and efficient.

7.3 Personalization and User Adaptability

AI-based BCIs can be tailored to the specific user, allowing the BCI to learn each user's idiosyncratic brain patterns. Conventional systems tend to need extended periods of calibration for every user, and there can be a decline in performance over time as the brain activity naturally evolves.

- Adaptive Learning with Reinforcement Learning (RL):AI- based BCIs is the potential for personalizing the system to the user, allowing the BCI to learn each user's specific neural patterns. Conventional systems typically need to spend a lot of time calibrating for each user, and performance diminishes over time as brain activity changes.
- Transfer Learning and Cross-User Adaptability: Transfer learning has been shown to improve the performance of BCIs across different users. Pre-trained models can be fine-tuned for individual users, reducing the need for extensive recalibration and providing a personalized user experience. Research by Sakhavi et al. (2018) has shown that transfer learning allows AI models to generalize well across different users, leading to faster system setup and better performance.

7.4 Reduced Training Time and Data Requirements

One of the most significant challenges in EEG-based BCI systems is the need for large amounts of labelled data to train classification models. Data collection is often time-consuming and expensive, and it can be challenging to gather sufficient data from a variety of subjects.

- Reduced Data Dependency with Transfer Learning: AI models, especially deep learning models, can be trained on large datasets and then fine-tuned for individual users using smaller datasets. This reduces the overall data requirements for effective BCI performance. Transfer learning has been shown to be particularly beneficial in applications where data is scarce, allowing AI-driven BCIs to achieve high performance even with limited subject-specific data.

- Improved Generalization Across Tasks: AI models that utilize transfer learning and deep neural networks can generalize well across different BCI tasks. This flexibility allows a single BCI system to be used for various applications (e.g., motor control, communication, neurofeedback) without the need to retrain the model extensively for each task.

7.5 Scalability and Usability of BCI Systems

AI has been instrumental in transforming EEG-based BCIs into scalable and accessible technologies. Conventional systems tended to be tricky to set up and involve significant calibration, hence not easily usable by novices and thereby not suitable for mass application.

- Simplified Calibration: Artificial intelligence models, especially those employing transfer learning and reinforcement learning, have made the calibration easier. Users are able to engage with the system more naturally, and the AI model learns their neural patterns without having to go through extensive setup times.
- Non-Invasive and Portable Systems: The advent of AI has led to the development of more compact and non-invasive BCI systems, which can be easily deployed outside of laboratory settings. AI-driven signal processing allows these systems to function effectively in real-world environments, making them more accessible and practical for both medical and non-medical applications.

8. CONCLUSION

This review emphasizes the revolutionary contribution of Artificial Intelligence (AI) towards the signal acquisition process in EEG-based Brain-Computer Interfaces (BCIs). Conventional EEG acquisition is marred with noise, non-stationarity, and low signal-to-noise ratios, thereby constrained BCI performance. Machine learning and deep learning algorithms such as denoising autoencoders, convolutional neural networks (CNNs), and adaptive filtering schemes have already shown substantial performance gains in terms of artifact removal, signal amplification, and feature extraction at the acquisition stage. These developments allow for more precise and resilient downstream processing, ultimately resulting in more responsive and dependable BCI systems. As research advances, the use of AI in signal acquisition should not only automate preprocessing operations but also learn to tailor itself to individual users in real time, opening the door to next-generation, user-centric, and application-specific BCI solutions.

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