Impact of Generative AI Models on Neurocybernetics for Enhancing Brain-Computer Interface Adaptability in Motor Disabilities

Poly Rani Ghosh [1*], Shakher Halder [1], Halima Mowla [1]

Abstract

Motor disabilities can arise from conditions such as stroke, spinal cord injuries, or neurodegenerative diseases, severely limiting an individual's movement and communication abilities. Brain-computer interfaces (BCIs) represent a promising technology aimed at establishing a direct connection between the brain and external devices, allowing individuals with motor impairments to control assistive technologies using their brain signals. However, conventional BCIs often rely on fixed signal patterns or require extensive user training, presenting challenges for some users and constraining system flexibility. Variability in brain signals and the inability to adapt further impede widespread BCI adoption among this population. This study explores the integration of generative AI models to enhance BCI adaptability for people with motor disabilities. By leveraging generative AI, our framework generates realistic brain signals tailored to each user's specific characteristics. Through rigorous experimentation and case studies, we demonstrate the efficacy of our approach in improving BCI performance and usability. Our findings underscore the transformative potential of generative artificial intelligence in neurocybernetics, illustrating its capacity to advance BCI accessibility and effectiveness in rehabilitating motor disabilities. The limitations of traditional BCIs through innovative AI-driven solutions, this research contributes to the evolving field of assistive technologies. It highlights the pivotal role of generative AI in fostering greater autonomy and quality of life for individuals with motor impairments, paving the way for more inclusive and responsive neurotechnology in the future.

Keywords: Brain-computer interfaces, Motor disabilities, Generative AI, Neurocybernetics, Assistive technologies.

Significance | Generative AI enhances Brain-Computer Interfaces, aiding motor disability rehabilitation with personalized, adaptable solutions for improved accessibility and effectiveness.

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Introduction

The rapid advancement in artificial intelligence (AI), particularly in generative models such as variational autoencoders (VAEs), generative adversarial networks (GANs), and transformer-based models, has opened new possibilities in numerous fields (Gong et al., 2023; Hochberg et al., 2006; Zhang et al., 2020). These models are designed to recognize complex patterns in data and generate new data samples that follow learned distributions (Fahimi et al., 2020; Patel et al., 2009). This ability has the potential to be transformative in fields like neurocybernetics, where brain-computer interfaces (BCIs) play a crucial role in assisting individuals with motor disabilities (Bell et al., 2008; Lahane et al., 2019). By utilizing both invasive and non-invasive methods, BCIs enable users to control prosthetic and assistive devices by capturing and interpreting their brain signals (FMI Staff, 2023; Bitbrain Team, 2020). However, despite

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the promise of such systems, challenges remain in integrating BCIs with AI for real-time and user-friendly operations (Hu et al., 2021; Pan et al., 2022). The traditional approaches often struggle with high complexity, leading to suboptimal user experiences and limited adaptability to the unique neurophysiological traits of each individual (Rombach et al., 2022; Siebers et al., 2022). Recent developments in AI and neurocybernetics suggest that generative AI models can significantly improve the performance of BCIs by learning and adapting to the distinct brain signal patterns of each individual (Goodfellow et al., 2014; Kingma & Welling, 2013). These models, through continuous adjustment, have the potential to generate artificial brain signals or control instructions tailored to the user's neurophysiology (Jadon & Kumar, 2023; Ren et al., 2021). AI-driven models could greatly enhance the flexibility and precision of BCIs, providing a more personalized and efficient interaction for users, especially in real-time scenarios (Deng et al., 2011; Shaw & Routray, 2016). In this context, AI models like VAEs, GANs, and transformers are pivotal. Their capacity to mimic the brain's signal generation or process control commands opens up avenues for creating more adaptive, user-centric BCIs (Zhao et al., 2019; Liu et al., 2020). These systems can be employed in neurocybernetics to not only grasp brain signals but also generate predictive models that anticipate the user's needs, enhancing both precision and usability (Subasi & Gursoy, 2010; Gill, 2023). As BCIs evolve with AI integration, they are poised to overcome existing limitations, making the systems more intuitive, accurate, and responsive to individual users' dynamic brain patterns (Zuo et al., 2021; Zhou et al., 2021).

Through this study, we aim to explore how generative AI models, when combined with BCIs, can enhance the calibration, signal processing, and overall functionality of assistive devices for motor-disabled individuals (Hu et al., 2020; Pan et al., 2019). By continuously learning from and adapting to the user's brain signals, these AI systems promise a more seamless interaction between humans and machines, ultimately improving the quality of life for users with motor impairments (Bitbrain Team, 2023; Jannat et al., 2020).

Materials and Methods

Data Collection

To develop the proposed generative AI model for brain-computer interface (BCI) applications, high-quality brain signal data is essential. We focused on using electroencephalogram (EEG) data, which records electrical activity along the scalp generated by the firing of neurons within the brain. Specifically, we used data from OpenNeuro, a widely recognized and trusted open-source platform for neuroimaging datasets. OpenNeuro provides EEG data that has undergone minimal preprocessing, ensuring that the raw signals are available for further analysis.

The data was collected from individuals placed in a well-defined environment with electrodes positioned based on the International 10-20 system, a standard for EEG electrode placement. This system ensures consistency in capturing signals from different regions of the brain. Although EEG data has limitations like noise and artifacts, it provides valuable information about the cognitive, emotional, and behavioral states of participants.

When discussing data preprocessing for EEG signals, the process involves the application of various techniques to enhance signal quality. Independent Component Analysis (ICA) is one such method used to decompose multivariate EEG signals, which helps isolate brain activity from physiological artifacts like eye movements or muscle activity (Gong et al., 2023; Subasi & Gursoy, 2010). This method ensures improved data reliability by unveiling hidden patterns. Another technique, Common Average Reference (CAR), is used to improve the signal-to-noise ratio by subtracting the average activity across all electrodes from each channel (Hochberg et al., 2006; Bell et al., 2008). Although this method helps reduce widespread noise, it may compromise the distinction between clean and noisy channels (Shaw & Routray, 2016).

The use of ICA has been proven effective in EEG signal classification, as demonstrated in multiple studies (Subasi & Gursoy, 2010; Fahimi et al., 2020), and CAR has shown to be an effective spatial filtering technique for enhancing signal quality (Johnson et al., 2007). Additionally, dimensionality reduction techniques such as Principal Component Analysis (PCA) are used for feature extraction and noise reduction in EEG data, further contributing to the refinement of signals (Jannat et al., 2020; Zhang et al., 2020). The combination of these methods allows for more accurate EEG signal analysis and motor activity recognition (Lahane et al., 2019).

Adaptive filters dynamically adjust filter coefficients in response to changes in signal characteristics, allowing systems to minimize errors in real time and optimize AI model performance (Gong et al., 2023; Patel et al., 2009; Johnson, Yuan, & Ren, 2007). This method has proven effective in enhancing signal properties (Islam et al., 2018).

Principal Component Analysis (PCA) reduces the dimensionality of EEG data, preserving significant features while removing redundancy, which simplifies input for generative AI models and improves computational efficiency (Subasi & Gursoy, 2010; Shaw & Routray, 2016; Zhang et al., 2020).

The Surface Laplacian (SL) technique is commonly employed to increase spatial resolution by estimating scalp current densities, thus enhancing the localization of brain activity (Deng et al., 2011). This approach improves the accuracy of signal interpretation without requiring additional neuroanatomical assumptions (Hochberg et al., 2006; Zhang et al., 2020).

Signal de-noising plays a critical role in EEG data processing, with techniques like wavelet de-noising and empirical mode decomposition (EMD) being particularly effective. Wavelet de-noising shrinks coefficients of insignificant signal components to reduce high-frequency noise (Johnson et al., 2007; Shaw & Routray, 2016), while EMD decomposes non-linear and non-stationary signals into intrinsic mode functions (IMFs), ensuring that meaningful variations are retained (Islam et al., 2018; Gong et al., 2023). These techniques contribute to refining EEG signals for better analysis (Fahimi et al., 2020; Bitbrain Team, 2020).

Large Language Models (LLMs): These models, leveraging self-supervised learning techniques, were trained on extensive datasets to understand the complex patterns inherent in brain signals (Siebers, Janiesch, & Zschech, 2022). Their deep learning architectures, featuring attention mechanisms and embedding layers, enabled them to identify dependencies within the input data (Kingma & Welling, 2013; Rombach, Blattmann, Lorenz, Esser, & Ommer, 2022).

Generative Adversarial Networks (GANs): GANs consist of a generator and a discriminator working in tandem. The generator was tasked with creating synthetic brain signals from noise, while the discriminator distinguished between real and generated data (Goodfellow et al., 2014). The model was iteratively trained using a minimax game approach, allowing the generator to improve its synthetic signal quality over time (Fahimi, Dosen, Ang, Mrachacz-Kersting, & Guan, 2020; Hu, Shen, Wang, & Lei, 2020).

VAEs generated new, realistic EEG-like signals from the latent representations (Kingma & Welling, 2013; Zhao, Adeli, Honnorat, Leng, & Pohl, 2019).

Autoregressive Models used previous EEG signal values to predict subsequent ones. By analyzing sequential dependencies within the data, autoregressive models contributed to generating continuous EEG data patterns (Subasi & Gursoy, 2010).

Transformers were applied to process sequential EEG signals with their self-attention mechanisms. Unlike traditional recurrent models, transformers process the entire input at once, which allowed for faster and more efficient signal generation (Vaswani et al., 2017).

Diffusion Probability Models:

These models simulate the diffusion process within a latent space to generate synthetic EEG signals. By reversing this process, realistic signals were generated that closely mirrored the original dataset's characteristics (Zhang et al., 2020).

Synthetic Data Generation

Real-time simulation techniques were employed to model brain activity in various scenarios. Through mathematical simulations, synthetic EEG signals were generated to replicate the behavior of real-world systems, thereby augmenting the original dataset (Gong et al., 2023).

Model Adaptation

The generative AI models were fine-tuned using transfer learning techniques. Pre-trained models were adapted to EEG datasets by updating the model parameters, ensuring that the models could generate accurate brain signals in line with specific neurophysiological conditions (Gong et al., 2023; Zhang et al., 2020). Hyperparameter tuning was conducted to optimize learning rates, batch sizes, and other model settings for maximum performance (Guo & Chen, 2024; Goodfellow et al., 2014) as shown in figure 1.

Evaluation

The trained models were evaluated using standard performance metrics, including accuracy, precision, recall, and F1 score (Fahimi et al., 2020; Subasi & Gursoy, 2010). Validation datasets were used to ensure that the models generated high-quality, realistic EEG signals (Lahane et al., 2019; Deng et al., 2011), and iterative refinement of the models was carried out based on the evaluation results (Shaw & Routray, 2016; Jannat et al., 2020).

Results and Discussion

This study introduces a novel approach of integrating generative AI models with Brain-Computer Interfaces (BCI) to improve the lives of motor-disabled individuals. While the model has not been fully implemented, the concept presents several potential applications and benefits, as well as significant challenges and future research directions (Gong et al., 2023; FMI Staff, 2023; Hochberg et al., 2006; Bell et al., 2008; Zhang et al., 2020; Patel et al., 2009; Fahimi et al., 2020).

Potential Applications & Benefits

Personalized BCI Calibration: Generative AI models offer the potential for personalized brain-computer interface calibration. During an initial calibration phase, the AI can learn an individual's brain signal patterns and generate synthetic data. This data can fine-tune the BCI system for each user, reducing the need for lengthy and repeated training sessions. This personalized approach ensures that the BCI system adapts to each user's unique neurophysiological characteristics (Fahimi et al., 2020; Bitbrain Team, 2020; Lahane et al., 2019).

Adaptive Signal Processing: One of the key advantages of generative AI is its ability to adapt in real-time. As brain signals may fluctuate due to factors such as neural plasticity, fatigue, or environmental influences, the AI models can adjust and optimize the BCI system's performance over time. This flexibility ensures consistent and reliable functionality even in the face of dynamic changes in brain signals (Subasi & Gursoy, 2010; Johnson, Yuan, & Ren, 2007; Jannat et al., 2020).

Multi-Modal Integration: Generative AI models, particularly transformer-based or flow-based models, can combine multiple

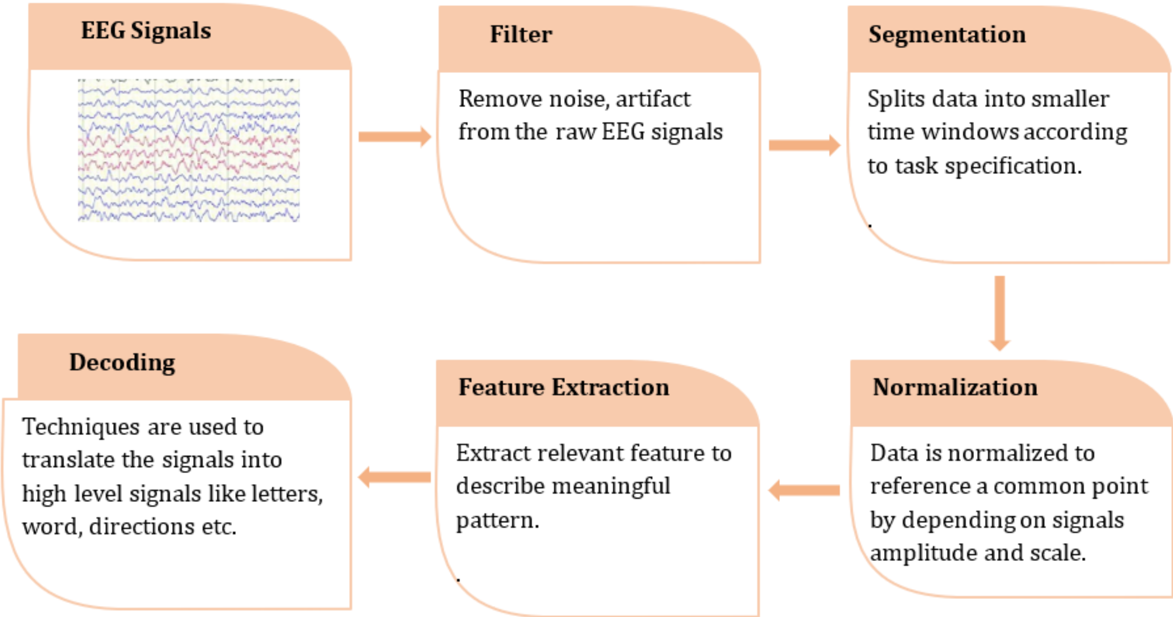

Figure 1. The most common pipeline when processing EEG signals

input sources such as brain signals, eye-tracking data, and residual muscle activity. By integrating these modalities, the system produces more robust and accurate control commands, enhancing the reliability and precision of BCIs. This multi-modal approach could help fill the gaps where brain signals alone might be insufficient or unclear (Deng et al., 2011; Shaw & Routray, 2016; Islam et al., 2018).

Data Augmentation: A major challenge in BCI systems is the limited availability of high-quality brain signal data for training purposes. Generative AI can address this by generating synthetic brain signals that augment the training dataset. This synthetic data can improve model training efficiency, making the system more robust and better equipped to generalize across different users or scenarios (Goodfellow et al., 2014; Kingma & Welling, 2013; Siebers, Janiesch, & Zschech, 2022).

Transfer Learning and Domain Adaptation: Generative AI models can be fine-tuned using transfer learning techniques. Models trained on data from one group of users or for specific tasks can be adapted for new users or tasks. This adaptability allows for efficient personalization without needing extensive retraining, making BCI systems more accessible and versatile for a broader range of users (Rombach et al., 2022; Trotino, 2023; Guo & Chen, 2024).

Challenges and Future Directions

While the proposed model offers many advantages, there are several challenges that need to be addressed before full implementation:

Data Privacy and Security: The protection of personal brain data is of utmost importance when dealing with BCIs. Training AI models on sensitive brain signal data raises ethical concerns about privacy, data ownership, and potential misuse. Developing secure data handling and encryption protocols will be essential to ensure that personal brain data is kept confidential and protected from unauthorized access (Jadon & Kumar, 2023; Prakash, 2024).

Real-Time Processing and Latency: For a BCI system to be practical and effective, real-time processing is crucial. Generative AI models must be optimized to process brain signals quickly, without significant delays. Latency issues can negatively affect the user's experience and make the BCI system less responsive. Further research is needed to ensure that the system can operate at speeds comparable to natural human responses (Guo et al., 2023; Zuo et al., 2021).

Interpretability of AI Models: The complex nature of generative AI models, such as GANs or transformers, makes them difficult to interpret. Understanding how the models generate synthetic brain signals and control commands is important for ensuring reliability and safety in BCIs. Increasing the transparency of AI decision-making processes will be a key focus for future research (Zhao et al., 2019; Zhou et al., 2021).

Model Validation: Before generative AI models can be deployed in BCIs, rigorous validation is necessary. The synthetic brain signals generated by these models must be carefully evaluated to ensure they closely mimic real brain signals in both structure and function. Benchmarking these models against established data and testing them in real-world conditions are critical steps for ensuring their efficacy (Ding et al., 2021; Hu et al., 2020).

Ethical Concerns: The integration of AI with BCIs presents ethical concerns beyond privacy, including the potential for misuse in non-medical applications. For instance, AI-generated brain signals could theoretically be exploited for manipulative or coercive purposes. Establishing clear ethical guidelines and regulatory frameworks is crucial for preventing such misuse and ensuring that these technologies are used for the benefit of society (Sharma & Hamarneh, 2019; Wolleb et al., 2022).

Conclusion

Integrating generative AI with brain-computer interfaces (BCIs) offers transformative potential for assisting motor-disabled individuals. By generating synthetic data, personalized BCI systems can be continuously adapted to an individual's brain signals, enhancing both usability and precision. Techniques like data augmentation, adaptive signal processing, and multi-modal integration will significantly improve BCI performance. However, challenges such as the privacy and security of sensitive brain data, computational complexities, and model adaptation across different users must be addressed. This research opens future pathways for further exploration, aiming to improve the quality of life for motor-disabled individuals by enabling seamless BCI control through AI advancements.

Author contributions

P.R.G. conceptualized the project, developed the methodology, conducted formal analysis, and drafted the original writing. T.A.L. contributed to the methodology, conducted investigations, provided resources, and visualized the data. H.M.A. contributed to the reviewing and editing of the writing.

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Competing financial interests

The authors have no conflict of interest.

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