A Survey of Brain-Computer Interfaces and EEG Acquisition Devices: Integration, Deep Learning, and AI-Driven Neurotechnology

Abstract

This survey paper explores the integration of brain-computer interfaces (BCIs) and electroencephalography (EEG) devices in medical and everyday applications, emphasizing advancements in deep learning and AI-driven neurotechnology. BCIs and EEGs play a crucial role in enhancing communication and rehabilitation for individuals with disabilities, offering transformative potential across diverse domains. Recent developments in deep learning, particularly convolutional and recurrent neural networks, have significantly improved the accuracy of EEG signal decoding, facilitating more effective user interaction. The paper highlights the application of complex network theory, including Bayesian and graph neural networks, in modeling brain connectivity, enhancing our understanding of neural dynamics. AI-driven techniques have also addressed privacy concerns, ensuring robust data protection while maintaining system performance. Despite these advancements, challenges persist due to the variability of EEG signals and the complexity of neural data. Future research should focus on refining stimulation protocols, enhancing cognitive functions, and developing hybrid BCI systems that integrate multiple modalities to improve signal quality and address adversarial vulnerabilities. The continuous evolution of BCI technology, driven by interdisciplinary collaboration, promises to expand its applicability and enhance human capabilities across various fields. Ethical considerations and regulatory frameworks are essential to ensure responsible deployment and mitigate risks associated with neurotechnology. This survey underscores the importance of ongoing research in unlocking the full potential of BCIs and EEG devices, ultimately advancing our understanding and interaction with the brain through technological and computational innovations.

1 Introduction

1.1 Significance of BCIs and EEG in Medical and Everyday Contexts

Brain-computer interfaces (BCIs) and electroencephalography (EEG) devices are essential in merging cognitive functions with technological advancements, impacting both medical and everyday contexts. EEG, as a non-invasive and cost-effective technique, is crucial for understanding the relationship between cognitive processes and bodily movements [1]. In medical settings, BCIs offer transformative solutions for individuals with severe motor disabilities, facilitating direct communication with external devices and improving quality of life [2]. The non-invasive nature of EEG-based BCIs enhances their appeal, broadening their accessibility [3].

Neurofeedback-based brain-machine interfaces (BMIs) have reinforced their role in cognitive rehabilitation, supporting patients with cognitive deficits. BCIs are also vital for detecting and predicting epileptic seizures, which underscores their medical significance [4]. The classification of distraction levels in pilots via non-invasive BCI technology highlights their potential in enhancing safety by mitigating risks associated with abnormal mental states [5]. With high temporal resolution, EEG has

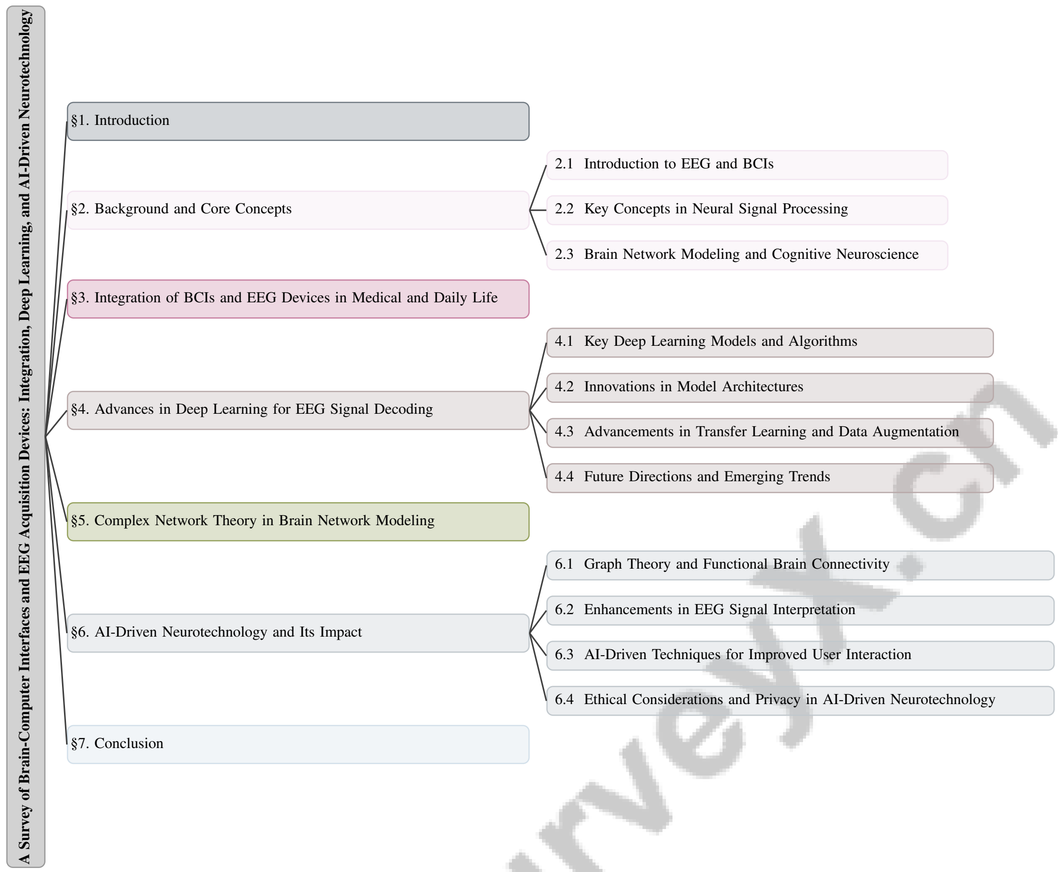

Figure 1: chapter structure

found applications in attention evaluation, particularly in children with attention deficit hyperactivity disorders, exemplifying its utility in various healthcare scenarios. Furthermore, EEG-based BCI systems are pivotal in clinical applications, such as neural prostheses and cognitive workload assessment [6].

In everyday contexts, BCIs extend beyond medical applications, facilitating innovative technology interactions. Their capability to enhance human interactions with the environment is evident in applications like controlling drones and improving computer accessibility for individuals with severe disabilities. The exploration of motor imagery (MI) as a BCI method addresses prior limitations in accuracy and fatigue, thereby enhancing practical applicability in daily activities [1]. Efforts to decode motor-related intentions using EEG-based BCIs highlight the necessity of improving accuracy in classifying motor execution (ME) and MI tasks. Developing personalized BCIs tailored to individual physiological and cognitive differences is vital for maximizing effectiveness [2].

Moreover, BCIs and EEG devices play a crucial role in healthcare applications such as mood detection, where EEG serves as a key method for analyzing brain signals. The challenges posed by noise in EEG signals and the complexity of interpreting brain intentions necessitate advanced AI frameworks to enhance the reliability and accessibility of BCIs [3]. BCIs also improve the Quality-of-Experience (QoE) for users in the Metaverse by optimizing real-time interactions between individuals and objects [4]. These advancements, along with ongoing research into AI integration and brain stimulation technologies, underscore the transformative impact of BCIs and EEG devices in enhancing human interaction and cognitive process understanding across various fields, including medical, educational, and mental health care. The demand for portable, durable, and socially acceptable EEG devices is critical to overcoming traditional system limitations. Furthermore, collaborative brain-computer interfaces (cBCI) that utilize MI tasks among multiple users highlight the significance of BCIs in improving individual performance across contexts [6]. Neuroprosthetic BCIs, which translate neural activity into movements of devices like cursors or robotic arms, further emphasize their medical relevance. The potential applications of EEG-based BCIs in healthcare and daily life continue to expand, offering new opportunities for enhancing human capabilities and interactions [5].

1.2 Role of Advanced Technologies

The integration of advanced technologies, particularly deep learning and artificial intelligence (AI), has profoundly transformed the development and application of brain-computer interfaces (BCIs) and electroencephalography (EEG) devices. These technologies enhance BCI analytical capabilities by improving signal decoding and interpretation accuracy and efficiency. Deep learning methodologies, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been crucial in processing complex neural data, enabling the decoding of motor imagery movements directly from raw EEG signals [3]. The proposed intertwined neural network architecture illustrates machine learning's role in advancing our understanding of brain functions and cognitive processes, showcasing AI's potential to enhance EEG data analysis [2].

Innovations in model architectures have focused on optimizing deep learning models for specific BCI applications. The development of personalized BCIs through user-specific information derived from endogenous EEG paradigms exemplifies advanced technologies' potential to tailor BCI systems to individual users' needs, enhancing adaptability and effectiveness [4]. Personalization is further illustrated by hybrid approaches that combine state-of-the-art BCI technology with adaptable AI algorithms, improving EEG data analysis [2].

AI-driven approaches have expanded BCI applications beyond traditional domains. For instance, hybrid paradigms integrating sensory, motor, vision, and cognition-related encoding have improved BCI classification accuracy. In smart environments, BCIs enable users to control devices through imagined speech tasks, integrating event-related potentials with advanced signal processing techniques [5], highlighting advanced technologies' role in enhancing user interaction with smart home systems.

Implementing flexible and conformal designs in wearable EEG technologies is essential for improving user experience, emphasizing advanced technologies' importance in developing user-friendly BCI systems. Additionally, integrating advanced signal sensing technologies with computational intelligence addresses the complexity of brain functions and the need for high-resolution data acquisition [3]. The proposed FLEEG framework employs a hierarchical personalized Federated Learning approach to enhance BCI performance by addressing device heterogeneity. Moreover, integrating Explainable AI (XAI) techniques with domain knowledge to validate model predictions in EEG applications further underscores advanced technologies' transformative impact on enhancing our understanding and interaction with the brain through technological and computational innovations.

1.3 Structure of the Survey

This survey is meticulously structured to provide a comprehensive examination of brain-computer interfaces (BCIs) and EEG acquisition devices, emphasizing their integration in both medical and everyday contexts. The survey begins with an **Introduction** that underscores the significance of BCIs and EEG devices, highlighting their transformative impact across various domains.

This discussion provides an in-depth exploration of the **Role of Advanced Technologies**, emphasizing how innovations in deep learning and artificial intelligence have fundamentally transformed BCIs and neural decoding methods, enabling significant advancements in understanding human cognition, enhancing neurological diagnostics, and facilitating artistic expression through AI-driven systems [7, 3, 8, 9, 10].

The **Background and Core Concepts** section provides foundational knowledge, elucidating key terms and concepts essential for understanding BCIs and EEG technologies. This section sets the stage for the subsequent exploration of the **Integration of BCIs and EEG Devices in Medical and Daily Life**, where the applications of these technologies in neurorehabilitation, assistive technologies, and cognitive function enhancement are thoroughly discussed.

The survey offers an in-depth examination of the **Advances in Deep Learning for EEG Signal Decoding**, emphasizing recent advancements in decoding techniques, the diverse applications of deep learning in areas such as BCIs, disease detection, and emotion recognition, as well as ongoing challenges and potential future research directions in this rapidly evolving field. It highlights the effectiveness of various deep learning architectures, including CNNs and LSTMs, in enhancing the accuracy and flexibility of EEG signal analysis while addressing the necessity for artifact removal and the integration of pretrained networks for complex decoding tasks [10, 11]. The application of **Complex Network Theory in Brain Network Modeling** is then explored, providing insights into how theoretical frameworks and advanced signal processing techniques contribute to our understanding of brain networks.

The role of AI in advancing neurotechnology is analyzed in **AI-Driven Neurotechnology and Its Impact**, where innovations, potential developments, and ethical considerations are discussed. This section aims to fill knowledge gaps in cognitive neuroscience by reviewing the architecture, data analysis approaches, and recent advancements of real-time fMRI-based BCIs (rtfMRI-BCI) [12].

The survey concludes with a comprehensive **Conclusion** that synthesizes key findings regarding advancements in BCIs and EEG acquisition devices, highlighting their current applications in both medical and non-medical domains, the challenges they face, and the promising future potential for enhancing human-computer interaction through innovative technologies such as machine learning and wearable sensors [13, 14, 15, 16, 17]. This structured approach ensures a thorough understanding of the interdisciplinary field, emphasizing the importance of continued research and development.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Introduction to EEG and BCIs

Electroencephalography (EEG) and brain-computer interfaces (BCIs) are significant advancements in neurotechnology, facilitating direct communication between the brain and external devices. EEG, a non-invasive method, records brain electrical activity via scalp electrodes, offering insights into cognitive and motor functions [4]. Originally used for clinical diagnostics, EEG now extends to personal identification and brain biometrics, integrating into everyday applications [5].

BCIs utilize EEG signals to enable communication and control without physical movement, translating user intentions into commands for AR and multimodal user interfaces (MUI), enhancing interactions in education, healthcare, and home care [5]. However, EEG's non-stationary nature and electromyography artifacts pose challenges in accurate signal decoding, especially in mobile settings [18].

Advancements in signal processing and deep learning have significantly improved BCI accuracy, particularly in decoding complex neural activities like motor imagery (MI) movements [19]. CNNs have been effective in classifying MI tasks, enhancing BCI performance [6]. Despite these advancements, cognitive task classification remains challenging due to EEG data complexity and conventional method limitations. Deep learning models have improved classification accuracy in EEG-based MI tasks [18].

EEG signal variability across individuals and tasks hinders the development of universally applicable BCI systems. Innovative EEG devices measuring EEG, EMG, and ECG signals are being explored for a holistic understanding of neural activities [19]. Additionally, integrating EEG with novel neuroimaging modalities like fNIRS and fMRI has expanded BCI applications [6].

The evolution of EEG and BCI technologies, driven by advancements in signal processing and machine learning, aims to create more intuitive and accessible interfaces, bridging human intention and machine execution and broadening BCI applications in communication and control [18].

2.2 Key Concepts in Neural Signal Processing

Neural signal processing is essential for BCIs, focusing on translating EEG signals into actionable commands. EEG signals' complexity, characterized by low signal-to-noise ratios (SNR) and non-stationarity, presents decoding challenges [20]. Traditional methods like common spatial patterns (CSP) and linear discriminant analysis (LDA) have been instrumental in feature extraction and classification but often fail to capture the temporal dynamics necessary for accuracy [21].

Deep learning has revolutionized neural signal processing, enabling the extraction of intricate features from EEG data autonomously. CNNs excel in spatial feature extraction, while RNNs and LSTMs effectively capture temporal dependencies [22]. However, limited EEG dataset sizes often lead to

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overfitting and poor generalization in deep learning models. Data augmentation techniques, such as the CropCat method, have been developed to generate additional training samples and enhance model predictions [23].

EEG signal variability across subjects and tasks complicates robust neural signal processing algorithm development [24]. Cross-task neural architectures enhance efficiency and consistency by leveraging shared representations across tasks [25]. Additionally, multimodal approaches integrating EEG with other neuroimaging modalities provide a comprehensive understanding of brain dynamics, improving BCI performance [19].

Motor imagery (MI), a crucial BCI paradigm, involves mental simulation of movements, generating EEG patterns similar to actual execution. Advanced neural networks, like NeuroAssist, combining BCI technology with adaptive AI algorithms, decode these complex patterns, capturing spatial and temporal dynamics for accurate predictions [2]. Moreover, meta-algorithms for imitation learning enhance parameter learning by adapting existing algorithms to train BCIs using surrogate intention signals, facilitating effective decoding [26].

Neural signal processing evolves with advancements in machine learning and data augmentation techniques. Integrating deep learning models and innovative strategies to address data scarcity and signal variability is paving the way for more reliable and intuitive BCIs, broadening their applicability across diverse domains [5].

2.3 Brain Network Modeling and Cognitive Neuroscience

The intersection of brain network modeling and cognitive neuroscience is crucial for understanding complex brain function dynamics and cognition. Brain network modeling uses computational techniques to analyze connectivity patterns within the brain, providing insights into neural structures facilitating cognitive processes. These models employ graph theory and complex network analysis to map interactions between brain regions, offering a framework for interpreting the neural basis of cognition and behavior.

In cognitive neuroscience, brain network modeling uncovers neural mechanisms underlying cognitive functions like perception, memory, and decision-making. Advanced techniques, including deep learning architectures, analyze brain activity patterns captured through EEG and fMRI, generating and interpreting brain activity in response to sensory inputs. This approach enhances understanding of cognitive processes involved in language, visual perception, and motor control. Integrating these models with BCI technologies promises to enhance neurological diagnostics and therapeutic interventions while addressing ethical considerations related to cognitive privacy and autonomy [27, 3, 28, 10, 25]. Advanced imaging techniques and computational models explore how brain regions coordinate to execute complex cognitive tasks, enhancing understanding of normal brain function and identifying network disruptions associated with neurological disorders.

Brain network modeling and cognitive neuroscience integration is exemplified by the Human Digital Twin (HDT) concept, creating individualized avatars in the Metaverse. This innovative approach simulates personalized brain networks, facilitating cognitive process studies in virtual environments [29]. The HDT concept highlights the potential of combining advanced computational models with immersive technologies to explore cognitive functions interactively and individually.

As the field advances, the synergy between brain network modeling and cognitive neuroscience expands, driven by improvements in neuroimaging, data analytics, and computational power. This interdisciplinary collaboration enhances understanding of the brain's intricate architecture by integrating insights from neuroscience and artificial intelligence, leading to innovative therapeutic strategies and personalized interventions for cognitive and neurological disorders. Leveraging advanced brain imaging techniques and deep learning models enables researchers to decode neural signals associated with various cognitive processes, paving the way for improved BCIs and more effective treatments for conditions like amyotrophic lateral sclerosis (ALS) and other neurological impairments. This convergence of fields advances knowledge of cognitive mechanisms while addressing ethical considerations regarding privacy and cognitive liberty in technology applications [3, 30, 8, 31].

3 Integration of BCIs and EEG Devices in Medical and Daily Life

The integration of brain-computer interfaces (BCIs) and electroencephalography (EEG) devices has revolutionized both medical care and everyday living, enhancing communication, rehabilitation, and quality of life, especially for individuals with disabilities. As depicted in Figure 2, this figure illustrates the multifaceted applications of BCIs and EEG devices, emphasizing their significant roles in improving communication and interaction, monitoring cognitive and mental health, and addressing critical security and privacy concerns. Such visual representation underscores the transformative impact these technologies have on various aspects of life, further reinforcing their importance in contemporary society.

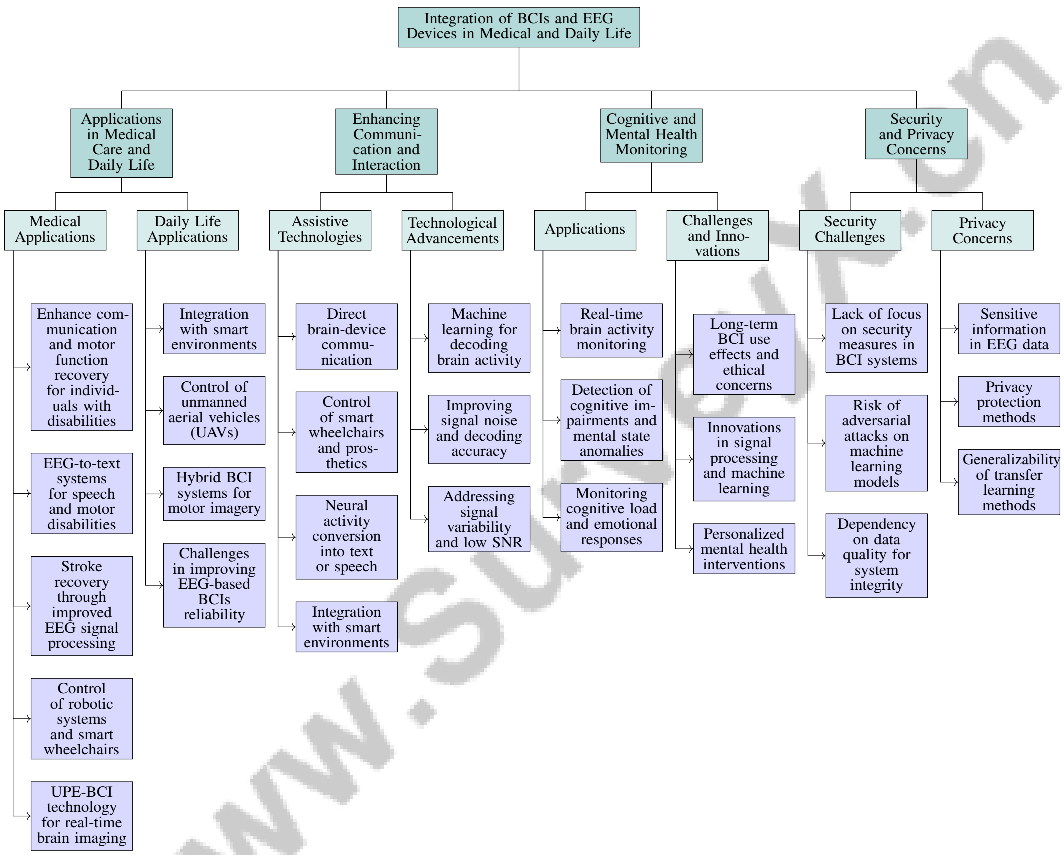

Figure 2: This figure illustrates the integration of BCIs and EEG devices across medical and daily life applications, highlighting their roles in enhancing communication, interaction, cognitive and mental health monitoring, and addressing security and privacy concerns.

3.1 Applications in Medical Care and Daily Life

BCIs and EEG devices have transformed healthcare by enabling individuals with severe disabilities to control external devices through neural signals, thereby enhancing communication and motor function recovery [5]. EEG-to-text systems exemplify advancements in aiding those with speech or motor disabilities. In rehabilitation, BCIs support stroke recovery by improving EEG signal processing and classification, utilizing novel methods like chaotic indices for enhanced medical application effectiveness [6].

BCIs also enable control over robotic systems, allowing users to manipulate robots and smart wheelchairs through thought and eye movements, enhancing mobility and opening new applications in military and disaster response through drone swarm control systems [32, 33, 34]. UPE-BCI technology offers real-time brain imaging advantages, further enhancing medical care and rehabilitation.

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In daily life, BCIs integrate with smart environments, allowing users to control systems by imagining speech related to target objects [5]. The ability to control unmanned aerial vehicles (UAVs) via BCIs highlights their practical application in improving human-machine communication. Hybrid BCI systems with advanced fusion techniques achieve superior classification accuracy in motor imagery, indicating potential for practical use. Despite advancements, improving the reliability of EEG-based BCIs remains challenging due to the low signal-to-noise ratio (SNR) affected by artifacts. Ongoing research aims to overcome these challenges, emphasizing BCIs' transformative potential in enhancing life quality for individuals with disabilities [6].

3.2 Enhancing Communication and Interaction

EEG-based BCIs significantly enhance communication and interaction for individuals with disabilities by facilitating direct brain-device communication, enabling control of assistive technologies like smart wheelchairs and prosthetics [32, 35, 15]. Advances in neuroscience and computational intelligence have improved the efficacy of these systems, translating cognitive intentions into actionable commands, thus promoting autonomy and mobility while addressing security, safety, and privacy challenges.

BCIs also convert neural activity into text or speech, aiding communication for those with speech and motor disabilities. EEG-to-text systems represent a significant technological advancement, utilizing machine learning to decode brain activity into coherent text. Ongoing research addresses challenges such as signal noise and decoding accuracy to enhance system effectiveness and accessibility [36, 16, 37, 38].

BCIs integrated into assistive technologies improve interaction with smart environments, enabling control of smart home systems and robotic devices through imagined speech or thought processes, fostering societal reintegration and reducing isolation [32, 39, 35]. As BCI technology evolves, driven by signal processing and machine learning breakthroughs, it promises significant enhancements in communication and interaction for individuals with disabilities [13, 35, 40, 32, 15]. Addressing signal variability and low SNR is crucial for improving BCI reliability and effectiveness, paving the way for broader adoption in assistive technologies.

3.3 Cognitive and Mental Health Monitoring

BCIs and EEG devices have advanced cognitive and mental health monitoring, offering novel approaches for assessing and enhancing mental well-being. These technologies enable real-time brain activity monitoring, providing insights into cognitive states like attention and emotional health, essential for applications ranging from daily attention tracking to mood detection and cognitive state decoding systems, thus improving clinical interventions and user experiences [41, 42, 16, 43].

BCIs and EEG devices also aid individuals with cognitive impairments by enabling mental state monitoring and anomaly detection in neural activity, supporting early mental health disorder detection and treatment evaluation [14]. Enhanced transitional imagery signal classification is critical for real-time BCI applications, allowing precise cognitive transition and mental state monitoring [44].

Beyond clinical applications, BCIs and EEG devices monitor cognitive load and emotional responses in non-medical domains, including entertainment and personal wellness, underscoring BCIs' versatility in providing real-time mental state feedback [14]. However, challenges regarding long-term BCI use effects, ethical data privacy implications, and user-friendly system development persist [45]. Addressing these concerns is essential for broader BCI adoption in cognitive and mental health monitoring.

As research progresses, integrating BCIs and EEG devices in cognitive and mental health monitoring is expected to evolve significantly. Innovations in signal processing and machine learning will enhance EEG-based BCI capabilities, facilitating real-time cognitive state tracking across various settings. Advanced computational intelligence methods, such as deep learning and transfer learning, will improve monitoring system accuracy and effectiveness, paving the way for personalized mental health interventions [13, 35, 15, 16, 46]. These developments promise enhanced mental health assessment reliability, fostering personalized interventions and improved mental well-being.

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3.4 Security and Privacy Concerns

The integration of BCIs and EEG devices into medical and everyday applications raises significant security and privacy concerns that must be addressed to ensure ethical technology use. A primary challenge in EEG-based BCI systems is the lack of security measure focus, traditionally prioritizing accuracy and speed [47]. As BCIs become more prevalent, the risk of security attacks, including adversarial attacks misleading machine learning models, becomes critical, necessitating robust countermeasures throughout the BCI lifecycle.

Privacy concerns are equally pressing, as EEG data can reveal sensitive user information, including identity and BCI experience [18]. This vulnerability necessitates new privacy protection methods to prevent unauthorized personal information access and misuse. Existing EEG data processing methods often suffer from low accuracy and high time complexity, compromising data security [48].

Moreover, dependency on EEG data quality limits methods like image generation, where poor signal quality can hinder performance [27]. This underscores the importance of high-quality data acquisition and processing to maintain BCI system integrity. Additionally, transfer learning method generalizability across different subjects and tasks remains a challenge, complicating the security landscape [49].

To address these challenges, comprehensive security frameworks and privacy-preserving techniques must be developed. Strategies should include robust methods for detecting and mitigating adversarial attacks on EEG-based BCIs, susceptible to subtle perturbations misinterpreting user intent. Furthermore, these strategies must safeguard sensitive information within EEG data, as system security has been largely overlooked despite their critical role in facilitating communication for individuals with severe disabilities [47, 50]. Addressing security and privacy concerns is crucial for fostering trust and ensuring responsible deployment of these technologies in both medical and everyday contexts.

4 Advances in Deep Learning for EEG Signal Decoding

Category	Feature	Method
Key Deep Learning Models and Algorithms	Feature Extraction Methods Adaptive Learning Techniques Data Privacy Measures	FBCNet[51] NA[2] PPEG[18]
Innovations in Model Architectures	Hybrid and Modular Architectures Feature Enhancement Techniques Efficiency and Adaptation	EInception[52], HDNN[53] RACNN[54], CNN-EEG[55] CNN[56], CNN-MI[57]
Advancements in Transfer Learning and Data Augmentation	Adaptive Techniques Relationship Encoding	SN[58], ACED[23] ECN[19]
Future Directions and Emerging Trends	Real-Time Processing	srMTL[20], NMF[25], 3D-CLMI[1], WE[59]

Table 1: This table provides a comprehensive overview of the methods and innovations in deep learning models and algorithms for EEG signal decoding. It categorizes key advancements in model architectures, transfer learning, data augmentation, and future trends, highlighting the significant contributions of various techniques to the field of brain-computer interfaces. The table serves as a synthesis of current methodologies and emerging directions, underscoring the transformative potential of deep learning in enhancing EEG signal processing.

The integration of deep learning techniques into electroencephalography (EEG) signal decoding has revolutionized the field of brain-computer interfaces (BCIs), providing unprecedented advancements in accuracy and functionality. Table 1 presents a detailed categorization of deep learning methods and innovations that have been pivotal in advancing EEG signal decoding, offering insights into the current state and future directions of the field. Additionally, Table 3 presents a comparative analysis of prominent deep learning models and their innovations, illustrating their impact on EEG signal decoding advancements. This main section explores the significant strides made in applying deep learning methodologies to EEG data, highlighting the transformative impact these technologies have had on decoding neural signals. To begin, we will delve into the key deep learning models and algorithms that have been instrumental in enhancing the performance of EEG signal decoding systems, setting the foundation for subsequent discussions on innovations in model architectures and their implications for future research.

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4.1 Key Deep Learning Models and Algorithms

The integration of deep learning models into electroencephalography (EEG) signal decoding has significantly enhanced the capabilities of brain-computer interfaces (BCIs), offering improved precision and functionality. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are pivotal in capturing the spatial and temporal characteristics inherent in EEG data. CNNs, particularly, have been employed to classify brain states by learning from temporal representations of EEG signals, thereby improving classification performance over traditional methods [4]. The introduction of a 1×1 convolutional block in existing CNN architectures exemplifies enhancements that increase model depth and parameter count, thereby improving classification accuracy [58].

Advanced models such as FBCNet, an end-to-end convolutional neural network, utilize a multi-stage approach to extract spectro-spatial information from EEG data, enhancing subject-specific motor imagery (MI) classification [51]. The 3D-CLMI model integrates 3D CNN for spatial feature extraction and LSTM with attention for temporal feature extraction from MI-EEG signals, showcasing the synergy between spatial and temporal analysis in improving decoding accuracy [1]. Additionally, the use of artificial neural networks (ANNs) with two hidden layers has been effective in classifying attention levels based on EEG signals, further highlighting the significance of deep learning models in EEG signal decoding [20].

Innovative approaches, such as the integration of reinforcement learning into the diffusion model, allow for autonomous optimization of the generative process, significantly improving the fidelity and diversity of synthetic EEG signals [23]. The proposed approach involving information theoretic principles creates a feature transformation learning framework that captures the mutual information between transformed features and class labels, enhancing the robustness of EEG signal decoding [24].

The development of hybrid frameworks, integrating CNNs with metric learning techniques, facilitates effective transfer learning and improves classification performance by creating embeddings of EEG signals [2]. The use of clustering-based multi-task learning frameworks, such as Subclass Relationship Regularized Multi-task Learning (srMTL), optimizes EEG pattern features by leveraging subclass relationships identified through affinity propagation clustering [20].

Despite these advancements, challenges such as the vulnerability of CNN classifiers to adversarial attacks remain prevalent. Addressing these vulnerabilities is essential for developing robust and secure BCI systems [18]. The integration of deep learning with neuroscience insights continues to distinguish these approaches from traditional methods, paving the way for more intuitive and effective BCI applications. The continuous development and evaluation of state-of-the-art deep learning models are pivotal in establishing benchmarks for EEG signal decoding, driving progress in the field and enhancing the capabilities of BCIs [3].

4.2 Innovations in Model Architectures

Recent innovations in model architectures for EEG signal processing have significantly advanced the capabilities of brain-computer interfaces (BCIs), enhancing both accuracy and robustness in decoding neural signals. A notable development is the hybrid deep learning framework that combines convolutional neural networks (CNNs) with long short-term memory (LSTM) networks to classify distraction levels from EEG signals, effectively capturing both spatial and temporal dynamics [53]. This hybrid approach exemplifies the trend towards integrating different neural network architectures to leverage their respective strengths.

The use of shallow CNN architectures has also been recognized for their efficiency in learning spectral-temporal features of EEG signals, outperforming deeper networks and traditional methods in tasks such as mental arithmetic classification [56]. This highlights the potential of streamlined architectures in reducing computational complexity while maintaining high performance.

Inception and residual modules have been employed in the EEG-Inception framework to enhance feature extraction capabilities, coupled with a unique data augmentation technique that mitigates overfitting by increasing dataset size [52]. This innovation addresses the challenge of limited EEG data availability, providing a robust solution for improving model generalization.

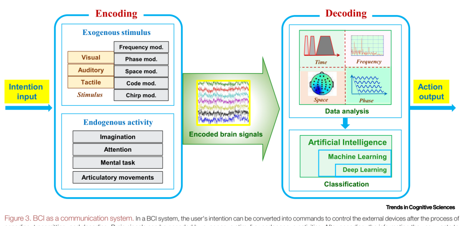
The adaptation of CNN models for real-time applications has been advanced by methods that allow trained models to work effectively with smaller, live data samples, bridging the gap between offline and online EEG analysis [57]. This adaptation is crucial for the practical deployment of BCIs in dynamic environments.

Reinforced Attentive Convolutional Neural Networks (RACNN) introduce a selective attention mechanism and convolutional mapping to process raw EEG signals directly, enhancing the model's ability to focus on relevant features and improve classification accuracy [54]. This approach underscores the importance of attention mechanisms in refining neural signal processing.

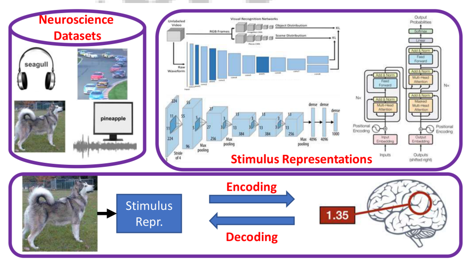
The integration of novel envelope representations of EEG data with CNN architectures has proven effective in learning temporal features, offering a departure from traditional methods and improving the interpretability of neural signals [55]. This innovation highlights the ongoing efforts to refine feature extraction processes in EEG analysis.

Furthermore, the introduction of a siamese network architecture that jointly learns compatibility measures between EEG data and visual features has expanded the potential for multimodal integration, allowing for more effective extraction and utilization of visual information from neural activity [19].

These advancements in model architectures not only enhance the accuracy and reliability of EEG signal decoding but also pave the way for more efficient and scalable BCI systems. As the field of neurotechnology advances, the convergence of innovative architectural designs with sophisticated signal processing techniques is poised to catalyze significant breakthroughs, particularly in the development of brain-computer interfaces (BCIs) that enhance communication and interaction for individuals with neurological disorders. These advancements will leverage high-sensitivity neuron devices and deep learning methodologies to improve the accuracy and adaptability of neural decoding, ultimately leading to a broader range of applications that integrate human capabilities with complex technological systems. [35, 60, 10]



(a) BCI as a Communication System[61]



(b) Neuroscience Datasets and Stimulus Representations in Brain-Computer Interfaces[3]

Figure 3: Examples of Innovations in Model Architectures

As shown in Figure 3, In the realm of brain-computer interfaces (BCIs), the integration of deep learning techniques has led to significant advancements in decoding electroencephalogram (EEG) signals, as illustrated in the examples provided. Figure 1 highlights key innovations in model architectures by showcasing two pivotal components of BCI systems. The first subfigure, "BCI as a Communication System," presents a flowchart that delineates the encoding and decoding processes essential for BCI communication. This process begins with exogenous stimuli, such as visual or auditory inputs, which are encoded to reflect the user's intentions and subsequently converted into brain signals. The second subfigure, "Neuroscience Datasets and Stimulus Representations in Brain-Computer Interfaces," offers a schematic representation of BCI systems, emphasizing the role of diverse neuroscience datasets. This image features various stimuli, including images of seagulls, a car race, and a pineapple, underscoring the range of data utilized in neuroscience research to enhance BCI functionality. Together, these examples underscore the transformative potential of deep learning in refining BCI systems, paving the way for more effective and nuanced communication pathways between the brain and external devices. [**?**]gao2021interface,oota2024deepneuralnetworksbrain)

4.3 Advancements in Transfer Learning and Data Augmentation

Recent advancements in transfer learning and data augmentation have significantly contributed to the enhancement of electroencephalography (EEG) signal decoding, addressing challenges such as inter-subject variability and limited data availability. Transfer learning has emerged as a vital technique, enabling models to leverage knowledge from related tasks to improve performance on new, unseen data. This approach is crucial for reducing calibration time and enhancing decoding accuracy. The proposed deep learning approach effectively reduces the data collection burden per subject and enhances model performance, suggesting significant implications for brain-computer interface (BCI) applications [4].

Innovative frameworks have been developed to account for individual variability in EEG signals. The incorporation of affinity propagation clustering within EEG data uncovers subclasses, allowing for enhanced feature optimization [20]. This method marks a significant advancement in transfer learning for EEG data by maximizing mutual information to enhance the discriminative power of learned representations. Additionally, adaptive training techniques refine models based on user performance during real-time tasks, thereby enhancing user control and interaction [58].

Data augmentation techniques have also seen substantial progress. The method of enhancing EEG signal generation was assessed by comparing classification accuracies of models trained on synthetic data generated by the proposed method against models trained on original datasets, demonstrating the effectiveness of such techniques in improving model robustness and performance [23]. The use of a siamese configuration of deep encoders correlates EEG brain activity with visual features, allowing for enhanced image classification and saliency detection [19].

These advancements collectively contribute to the development of more efficient and accurate BCI systems, expanding their applicability across diverse domains. The ongoing integration of advanced techniques in electroencephalography (EEG) signal processing, such as deep learning models and innovative data augmentation methods, is poised to significantly improve real-time data analysis and decision-making capabilities. This evolution is expected to foster substantial advancements in neurotechnology, particularly in applications like brain-computer interfaces (BCIs), emotion recognition, and disease detection, while addressing existing challenges in accuracy and system constraints. [62, 9, 16, 11]

4.4 Future Directions and Emerging Trends

Method Name	Technological Innovations	Performance Enhancement	Interdisciplinary Collaboration
3D-CLMI[1]	Attention Mechanisms	Transfer Learning	Diverse Scientific Knowledge
srMTL[20]	Affinity Propagation Clustering	Srmtl Algorithm	-
NMF[25]	Matrix Factorization	Learning Rate	Cognitive Systems
WE[59]	Cnn-based Decoding	Data Splitting Strategies	Diverse Scientific Knowledge

Table 2: Overview of recent methodological advancements in EEG signal decoding, highlighting key technological innovations, performance enhancements, and interdisciplinary collaborations. This table summarizes various methods, including 3D-CLMI, srMTL, NMF, and WE, each contributing uniquely to the field of Brain-Computer Interfaces (BCIs).

The future landscape of deep learning for EEG signal decoding is set to be shaped by several emerging trends and research directions. A key area of focus is the development of real-time decoding systems that enhance the usability of BCIs across diverse applications. This involves improving the interpretability of deep learning models and leveraging transfer learning to boost performance across different neural decoding tasks [10]. The integration of channel attention mechanisms, as demonstrated by models like BaseNet, highlights the potential for improved accuracy and adaptability in decoding EEG motor imagery across various datasets [1].

Advancements in information theoretic feature transformations have shown significant improvements in BCI task performance compared to traditional feature selection methods, suggesting a promising direction for enhancing EEG signal processing [24]. Additionally, the development of the srMTL algorithm has demonstrated superior performance in EEG pattern decoding, indicating its potential for advancing BCI applications [20].

Future research should also focus on refining models to incorporate additional physiological predictors and exploring personalized BCI training protocols, which could lead to more tailored and effective BCI systems [25]. The exploration of emerging trends in machine learning and IoT, along with the refinement of BCI technologies for better integration with AR applications, remains a critical area for future exploration [5].

Another important consideration is the need for appropriate data splitting strategies to avoid inflated accuracy in BCI tasks, as high decoding accuracy can sometimes be misleading due to temporal autocorrelations [59]. Addressing these challenges is crucial for ensuring the reliability of BCI systems.

As the field of Brain-Computer Interfaces (BCIs) advances, the ongoing development of deep learning applications for EEG signal decoding—fueled by interdisciplinary collaboration and cutting-edge technological innovations—holds the potential to dramatically improve BCI capabilities. This evolution includes novel techniques such as data augmentation methods that enhance the training of convolutional neural networks (CNNs), enabling better classification of motor imagery EEG signals despite inherent noise and inter-subject variability. Recent studies have demonstrated that these advancements can achieve high classification accuracy, paving the way for more effective neurofeedback and communication systems that translate brain activity into actionable commands [63, 64, 16, 9, 37]. The development of more robust and adaptive machine learning models will be pivotal in achieving these advancements, ensuring that BCIs remain at the forefront of neurotechnology innovation. Table 2 provides a comprehensive summary of recent methods in EEG signal decoding, illustrating the technological innovations and interdisciplinary collaborations that are driving advancements in Brain-Computer Interface (BCI) technologies.

Feature	Key Deep Learning Models and Algorithms	Innovations in Model Architectures	Advancements in Transfer Learning and Data Augmentation
Model Type	Cnns And Rnns	Hybrid Cnn-LSTM	Transfer Learning
Feature Extraction	Spatial And Temporal	Spectral-Temporal	Subclass Optimization
Application Focus	Eeg Classification	Real-time Analysis	Inter-Subject Variability

Table 3: Comparison of key deep learning models and innovations in EEG signal decoding, highlighting model types, feature extraction methods, and application focuses. This table provides insights into the advancements in model architectures and the role of transfer learning and data augmentation in enhancing EEG signal processing.

5 Complex Network Theory in Brain Network Modeling

5.1 Bayesian Networks and Brain Signal Dependencies

Bayesian networks offer a robust framework for modeling dependencies among brain signals, essential for brain-computer interface (BCI) applications. They facilitate the analysis of neural data by modeling causal relationships and integrating prior knowledge. Simple, Gaussian, and Dynamic Bayesian Networks each provide unique benefits for modeling neural interactions [65]. The synergy of Bayesian networks with advanced sensing technologies and signal enhancement techniques has notably improved machine learning algorithms in healthcare [15]. In immersive BCI settings, combining partial directed coherence (PDC) with graph theory offers a comprehensive evaluation of brain connectivity during complex tasks [66], enhancing neural data interpretability.

Bayesian networks excel in decoding motor imagery tasks from electrocorticography (ECoG) signals, surpassing models reliant on hand-crafted features [67]. They also bolster data privacy through homomorphic encryption, enabling operations on encrypted EEG data without decryption, thus safeguarding sensitive information [48]. As neuroimaging technologies progress, Bayesian networks' application in brain signal dependency analysis is expected to grow, particularly in BCIs. The integration of deep learning and traditional signal processing enhances brain signal analysis, leading to innovative applications across diverse fields [68, 69, 16, 9, 65].

5.2 Graph Neural Networks and EEG Data Representation

Graph Neural Networks (GNNs) revolutionize EEG data analysis by utilizing the graph structure of neural connections, improving the understanding of functional brain connectivity by capturing spatial and temporal EEG signal relationships. This approach is vital for accurate BCI system decoding, particularly in motor imagery tasks. Unlike traditional methods that overlook EEG electrodes' topological relationships, GNNs leverage these connections to enhance decoding accuracy, achieving metrics such as 93.06

Integrating graph theory metrics with GNNs provides a comprehensive framework for visualizing brain connectivity. For instance, combining PDC with graph metrics improves functional brain connectivity assessment during motor imagery tasks [66]. By representing EEG signals as graph structures, GNNs address traditional methods' limitations, enhancing BCI decoding accuracy [70, 69, 21, 38, 71].

GNNs' potential extends to real-time BCI systems, enhancing classification performance and enabling dynamic adjustments to brain activity patterns. Recent EEG signal processing and machine learning advancements improve cognitive state interpretation in real-time, facilitating seamless user-device interactions in healthcare and assistive technologies [35, 37, 15]. As GNN research advances, incorporating advanced graph-based techniques is anticipated to drive neurotechnology innovations, refining brain activity decoding related to motor imagery and cognitive tasks, leading to more reliable BCI systems. Combining domain-specific knowledge with explainable AI methods will ensure BCI models' transparency and trustworthiness [35, 72, 31, 46, 25].

5.3 Integration of Traditional and Deep Learning Methods

Integrating traditional methods with deep learning in brain network modeling has significantly advanced BCIs. This hybrid approach combines both paradigms' strengths, enhancing neural signal processing interpretability and performance. Traditional techniques like the common spatial pattern (CSP) algorithm are foundational in EEG feature extraction, while innovations like CCSPNet optimize CSP with dynamic filtering and novel loss functions for improved classification accuracy in real-world applications [73].

Bayesian Networks enhance channel selection and classification, improving computational efficiency and real-time performance, highlighting the potential of combining probabilistic models with deep learning architectures [65]. The integration of chaotic indices with traditional algorithms, such as multilayer perceptrons (MLP) and kernel-based support vector machines (KM-SVM), further demonstrates hybrid approaches' benefits in EEG signal interpretation [74].

Deep learning methods like convolutional neural networks (CNNs) facilitate the extraction of complex, nonlinear mappings from neural data, often outperforming simpler models [10]. The L-CNN method exemplifies this adaptability by computing normalization statistics from new data, enhancing real-time BCI performance [75].

Innovations in signal processing, such as the EMF's flexible decision-making process, have improved accuracy in motor imagery-based BCIs, demonstrating the advantages of integrating traditional methods with advanced machine learning techniques [76]. Additionally, identifying speakers using single-channel EEG through deep learning and traditional techniques highlights hybrid approaches' versatility across various BCI tasks [28].

The continuous evolution of integrated methods promises further advancements in brain network modeling, enhancing BCI effectiveness in diverse domains. By merging traditional methods with deep learning techniques, researchers can develop resilient systems that effectively capture neural dynamics' complexities. This integration not only improves brain function understanding but also enhances BCI technologies, as demonstrated by a joint convolutional recurrent neural network for motor imagery EEG (MI-EEG) classification, achieving a remarkable classification accuracy of 95.53

5.4 Advanced Signal Processing Techniques

Advanced signal processing techniques are crucial for enhancing BCIs by improving neural data interpretation accuracy and reliability. Within complex network theory, these techniques capture intricate brain network dynamics and facilitate effective signal decoding. Despite significant BCI advancements, security vulnerabilities in signal processing components remain underexplored [50], highlighting the need for robust frameworks that ensure user data safety.

Integrating advanced signal processing methods with complex network theory provides a comprehensive approach to modeling brain networks. Techniques like partial directed coherence (PDC) and graph theory metrics assess functional brain connectivity, revealing interactions between brain regions during cognitive tasks. These methods leverage deep learning algorithms and non-invasive signal analysis techniques, such as EEG and fMRI, to visualize and analyze brain network structures, enhancing neural dynamics understanding and facilitating breakthroughs in neurological diagnostics and cognition studies [3, 68, 31].

Machine learning algorithms paired with signal processing techniques have bolstered BCI classification accuracy. Deep learning models, particularly CNNs, facilitate complex feature extraction from EEG data, enhancing neural signal processing robustness. However, security implications must be addressed, as vulnerabilities in signal processing could compromise BCI integrity [77].

Addressing security concerns is crucial for BCI development, necessitating a focus on strengthening signal processing resilience against adversarial attacks. By prioritizing security alongside accuracy and efficiency, researchers can create robust BCI systems that effectively utilize complex network theory while addressing privacy concerns related to sensitive data, such as EEG readings. As BCIs evolve and find applications in medical diagnosis and rehabilitation, implementing privacy-preserving strategies and ensuring secure data transmission becomes essential. This comprehensive approach enhances user trust and mitigates privacy threats, ultimately leading to more reliable and effective BCI solutions [72, 77, 78].

6 AI-Driven Neurotechnology and Its Impact

AI-driven neurotechnology bridges advanced computational methods with the complexities of brain function, emphasizing functional brain connectivity as a cornerstone for understanding neural networks. This section delves into graph theory's application as a fundamental framework to analyze these interactions, crucial for developing brain-computer interfaces (BCIs) where decoding brain signals is imperative for communication and control.

6.1 Graph Theory and Functional Brain Connectivity

Graph theory provides a robust framework for analyzing functional brain connectivity, vital for interpreting complex neural interactions in BCI research. It enhances signal classification accuracy and system performance by facilitating the analysis of EEG signals' temporal, frequency, and spatial characteristics, essential for decoding semantic information from neural data [66]. Integrating graph theory with machine learning has significantly improved neural connectivity modeling, as seen in motor imagery tasks controlling telepresence robots, highlighting immersion's cognitive effects [66]. This integration is crucial for real-time applications requiring low latency [4].

Advancements in AI have refined graph theory's application in understanding brain connectivity, with multimodal approaches showing neural activity's potential to enhance deep learning model performance in tasks like image classification and saliency detection [19]. This synergy promises significant neurotechnology innovations, advancing BCIs and neurological diagnostics by accurately modeling brain networks [3, 31, 69, 10, 25].

6.2 Enhancements in EEG Signal Interpretation

AI techniques have revolutionized EEG signal interpretation, enhancing accuracy and efficiency in decoding neural patterns. Advanced neural network architectures utilizing multiple entropy measures outperform traditional methods, crucial for BCI performance in motor imagery classification [79]. Interpretable deep neural networks, combined with layer-wise relevance propagation, provide insights into neural activity, improving EEG analysis interpretability, especially in clinical settings [21]. The CTNAS-EEG framework customizes EEG signal interpretation, addressing low signal-to-noise ratios and accommodating individual variability [80].

AI-driven techniques also enhance privacy in EEG data, with methods like perturbation reducing classification accuracy of private information while maintaining BCI task performance [18]. As AI evolves, it promises to deepen neural dynamics understanding, expanding BCI applications in medical diagnosis, rehabilitation, and assistive technologies while addressing privacy concerns with robust data protection strategies [37, 78].

6.3 AI-Driven Techniques for Improved User Interaction

AI-driven techniques enhance user interaction with BCIs and EEG devices, improving accessibility and experience. Advanced machine learning algorithms increase classification accuracy and manage complex brain signals, crucial for user interaction [46]. Techniques like TSS-DNN improve speaker identification, while the ACCM model enhances spike sorting accuracy for real-time applications

[28, 81]. Adaptive methods and feature extraction improve classification performance, reducing EEG signal variability and making BCI systems practical. Personalized classifier tuning enhances attentional state decoding accuracy, improving user interaction [62]. Humanoid robots in cBCI methods improve EEG device effectiveness [82].

AI approaches reduce computational demands while maintaining accuracy, suitable for real-time BCI applications [83]. Solutions like BaseNet offer lightweight, effective EEG motor imagery decoding [84]. NeuroKinect exemplifies minimal preprocessing for efficient real-time applications [85]. The FLEEG framework enhances BCI user interaction through collaborative knowledge sharing, showcasing federated learning's potential [86]. Improved interpretability and validation of model predictions address the trust gap in BCI applications [72]. Future research should focus on efficient privacy-preserving algorithms and federated learning to ensure robust data protection, facilitating broader BCI adoption [78].

6.4 Ethical Considerations and Privacy in AI-Driven Neurotechnology

AI integration in neurotechnology, especially BCIs, requires careful examination of ethical and privacy issues due to the sensitivity of data like EEG. While enhancing BCI accuracy and reliability for therapeutic applications, it necessitates attention to proprietary machine learning models and data-sharing practices among institutions [87, 30, 78]. The rapid advancement of AI-driven BCIs raises concerns about data security and privacy, given neural data's vulnerability to unauthorized access and exploitation. Ensuring informed consent and ethical compliance is critical, with guidelines preventing data misuse and ensuring responsible deployment [59].

Innovative methods address privacy without compromising BCI performance, such as generating perturbations to conceal private information [18]. Scalable, privacy-preserving solutions for EEG signal generation advance BCI technologies [23]. BCI design must consider cross-participant limitations, as models may not generalize well across users [1]. Robust methodologies ensure generalizability and reliability [59].

Future research should focus on sophisticated AI models managing neural data intricacies while addressing ethical and privacy concerns. Emphasizing privacy and data security ensures effective, ethically sound BCI systems, enhancing user trust. Integrating BCI with augmented reality and other interaction modes enriches user experience, particularly for individuals with disabilities, highlighting these technologies' potential to improve quality of life [5].

7 Conclusion

The investigation into brain-computer interfaces (BCIs) and electroencephalography (EEG) devices highlights their transformative impact across medical and everyday applications. The incorporation of advanced technologies, notably deep learning and AI, has significantly enhanced the precision and efficiency of EEG signal decoding, facilitating improved user interaction and communication. Frameworks like FBCNet have shown exceptional classification accuracy for motor imagery tasks, demonstrating substantial potential for rehabilitation, particularly in chronic stroke patients. Nevertheless, real-world applications encounter challenges due to EEG signal variability and neural data complexity. The emergence of hybrid BCI systems, integrating EEG with other modalities, offers promise for enhancing signal quality and fortifying deep learning models against adversarial influences.

Future research should focus on refining stimulation protocols, understanding emotional impacts on learning, and exploring cognitive enhancement in healthy individuals. Incorporating session-invariance constraints and adversarial learning frameworks could enhance the generalizability and robustness of feature transformation methods. Emphasizing low-complexity inputs for controlling high-complexity systems underscores the need for continuous innovation in BCI technology. Moreover, the impressive performance of various frameworks in personal identification tasks suggests a need for further exploration in this area.

The conclusion emphasizes the importance of proposed approaches in improving EEG classification accuracy and their potential to autonomously identify brain functional areas associated with specific activities. Personalized BCI applications have shown significant improvements in user experience, underscoring the importance of future research aimed at enhancing intention classification accuracy and integrating user feedback. Personalized BCI models effectively capture individual differences in motor performance, supporting the notion that personalized approaches may yield better rehabilitation outcomes for stroke patients.

As the field progresses, continued research and development are essential to fully realize the potential of BCIs and EEG devices, thereby enhancing human capabilities and interactions across various domains. Future endeavors should also establish ethical standards, regulatory frameworks, and public education to address the risks associated with Neurocapitalism and BCIs. The ongoing integration of AI with EEG analysis is expected to deepen our understanding of neural dynamics and broaden BCIs' applicability, highlighting the potential for interdisciplinary collaboration to advance BCI technology.

References

[1] Shiwei Cheng and Yuejiang Hao. 3d-clmi: A motor imagery eeg classification model via fusion of 3d-cnn and lstm with attention, 2023.

[2] Eeshan G. Dandamudi. Neuroassist: Enhancing cognitive-computer synergy with adaptive ai and advanced neural decoding for efficient eeg signal classification, 2024.

[3] Subba Reddy Oota, Zijiao Chen, Manish Gupta, Raju S. Bapi, Gael Jobard, Frederic Alexandre, and Xavier Hinaut. Deep neural networks and brain alignment: Brain encoding and decoding (survey), 2024.

[4] Chad Mello, Troy Weingart, and Ethan M. Rudd. Cross-subject deep transfer models for evoked potentials in brain-computer interface, 2023.

[5] S. Stirenko, Yu. Gordienko, T. Shemsedinov, O. Alienin, Yu. Kochura, N. Gordienko, A. Rojbi, J. R. López Benito, and E. Artetxe González. User-driven intelligent interface on the basis of multimodal augmented reality and brain-computer interaction for people with functional disabilities, 2017.

[6] Amelia J. Solon, Stephen M. Gordon, Jonathan R. McDaniel, and Vernon J. Lawhern. Collaborative brain-computer interface for human interest detection in complex and dynamic settings, 2018.

[7] Piera Riccio, Kristin Bergaust, Boel Christensen-Scheel, Juan-Carlos De Martin, Maria A. Zuluaga, and Stefano Nichele. Ai-based artistic representation of emotions from eeg signals: a discussion on fairness, inclusion, and aesthetics, 2022.

[8] Jingan Yang and Yang Peng. To root artificial intelligence deeply in basic science for a new generation of ai, 2020.

[9] Xian-Rui Zhang, Meng-Ying Lei, and Yang Li. An amplitudes-perturbation data augmentation method in convolutional neural networks for eeg decoding, 2018.

[10] Jesse A. Livezey and Joshua I. Glaser. Deep learning approaches for neural decoding: from cnns to lstms and spikes to fmri, 2020.

[11] Shu Gong, Kaibo Xing, Andrzej Cichocki, and Junhua Li. Deep learning in eeg: Advance of the last ten-year critical period, 2021.

[12] Yang Wang and Dongrui Wu. Real-time fmri-based brain computer interface: A review, 2018.

[13] Xiaotong Gu, Zehong Cao, Alireza Jolfaei, Peng Xu, Dongrui Wu, Tzyy-Ping Jung, and Chin-Teng Lin. Eeg-based brain-computer interfaces (bcis): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications, 2020.

[14] Kaido Värbu, Naveed Muhammad, and Yar Muhammad. Past, present, and future of eeg-based bci applications. *Sensors*, 22(9):3331, 2022.

[15] Xiaotong Gu, Zehong Cao, Alireza Jolfaei, Peng Xu, Dongrui Wu, Tzyy-Ping Jung, and Chin-Teng Lin. Eeg-based brain-computer interfaces (bcis): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications. *IEEE/ACM transactions on computational biology and bioinformatics*, 18(5):1645–1666, 2021.

[16] Saydul Akbar Murad and Nick Rahimi. Unveiling thoughts: A review of advancements in eeg brain signal decoding into text, 2024.

[17] Bosubabu Sambana and Priyanka Mishra. A survey on brain-computer interaction, 2022.

[18] Lubin Meng, Xue Jiang, Tianwang Jia, and Dongrui Wu. Protecting multiple types of privacy simultaneously in eeg-based brain-computer interfaces, 2024.

[19] Simone Palazzo, Concetto Spampinato, Isaak Kavasidis, Daniela Giordano, Joseph Schmidt, and Mubarak Shah. Decoding brain representations by multimodal learning of neural activity and visual features, 2020.

[20] Yu Zhang, Tao Zhou, Wei Wu, Hua Xie, Hongru Zhu, Guoxu Zhou, and Andrzej Cichocki. Improving eeg decoding via clustering-based multi-task feature learning, 2020.

[21] Irene Sturm, Sebastian Bach, Wojciech Samek, and Klaus-Robert Müller. Interpretable deep neural networks for single-trial eeg classification, 2016.

[22] Lisa-Marie Vortmann, Leonid Schwenke, and Felix Putze. Real or virtual? using brain activity patterns to differentiate attended targets during augmented reality scenarios, 2021.

[23] Yang An, Yuhao Tong, Weikai Wang, and Steven W. Su. Enhancing eeg signal generation through a hybrid approach integrating reinforcement learning and diffusion models, 2024.

[24] Ozan Ozdenizci and Deniz Erdogmus. Information theoretic feature transformation learning for brain interfaces, 2019.

[25] Jennifer Stiso, Marie-Constance Corsi, Jean M. Vettel, Javier O. Garcia, Fabio Pasqualetti, Fabrizio De Vico Fallani, Timothy H. Lucas, and Danielle S. Bassett. Learning in brain-computer interface control evidenced by joint decomposition of brain and behavior, 2019.

[26] Josh Merel, David Carlson, Liam Paninski, and John P. Cunningham. Neuroprosthetic decoder training as imitation learning, 2016.

[27] Eleonora Lopez, Luigi Sigillo, Federica Colonnese, Massimo Panella, and Danilo Comminiello. Guess what i think: Streamlined eeg-to-image generation with latent diffusion models, 2025.

[28] Seo-Hyun Lee, Young-Eun Lee, and Seong-Whan Lee. Voice of your brain: Cognitive representations of imagined speech,overt speech, and speech perception based on eeg, 2021.

[29] Howe Yuan Zhu, Nguyen Quang Hieu, Dinh Thai Hoang, Diep N. Nguyen, and Chin-Teng Lin. A human-centric metaverse enabled by brain-computer interface: A survey, 2023.

[30] Hoda Fares, Margherita Ronchini, Milad Zamani, Hooman Farkhani, and Farshad Moradi. In the realm of hybrid brain: Human brain and ai, 2024.

[31] Yu Wang, Heyang Liu, Yuhao Wang, Chuan Xuan, Yixuan Hou, Sheng Feng, Hongcheng Liu, Yusheng Liao, and Yanfeng Wang. Decoding linguistic representations of human brain, 2024.

[32] Shiva Ghasemi, Denis Gracanin, and Mohammad Azab. Empowering mobility: Brain-computer interface for enhancing wheelchair control for individuals with physical disabilities, 2024.

[33] Aamodh Suresh and Mac Schwager. Brain-swarm interface (bsi): Controlling a swarm of robots with brain and eye signals from an eeg headset, 2016.

[34] Dae-Hyeok Lee, Hyung-Ju Ahn, Ji-Hoon Jeong, and Seong-Whan Lee. Design of an eeg-based drone swarm control system using endogenous bci paradigms, 2020.

[35] Brent J. Lance, Scott E. Kerick, Anthony J. Ries, Kelvin S. Oie, and Kaleb McDowell. Brain computer interface technologies in the coming decades, 2012.

[36] Jung-Sun Lee, Ha-Na Jo, and Seo-Hyun Lee. Towards unified neural decoding of perceived, spoken and imagined speech from eeg signals, 2024.

[37] Xiang Zhang, Lina Yao, Quan Z. Sheng, Salil S. Kanhere, Tao Gu, and Dalin Zhang. Converting your thoughts to texts: Enabling brain typing via deep feature learning of eeg signals, 2017.

[38] Comprehensive review of eeg-to-o.

[39] Michael J Young, David J Lin, and Leigh R Hochberg. Brain–computer interfaces in neurorecovery and neurorehabilitation. In *Seminars in neurology*, volume 41, pages 206–216. Thieme Medical Publishers, Inc., 2021.

[40] Masaru Kuwabara and Ryota Kanai. Stimulation technology for brain and nerves, now and future, 2024.

[41] Subhrangshu Adhikary, Kushal Jain, Biswajit Saha, and Deepraj Chowdhury. Optimized eeg based mood detection with signal processing and deep neural networks for brain-computer interface, 2023.

[42] Pallavi Kaushik, Amir Moye, Marieke van Vugt, and Partha Pratim Roy. Decoding the cognitive states of attention and distraction in a real-life setting using eeg. *Scientific Reports*, 12(1):20649, 2022.

[43] Felix G. Hamza-Lup, Adytia Suri, Ionut E. Iacob, Ioana R. Goldbach, Lateef Rasheed, and Paul N. Borza. Attention patterns detection using brain computer interfaces, 2020.

[44] Patcharin Cheng, Phairot Autthasan, Boriwat Pijarana, Ekapol Chuangsuwanich, and Theerawit Wilaiprasitporn. Towards asynchronous motor imagery-based brain-computer interfaces: a joint training scheme using deep learning, 2018.

[45] Krishna Pai, Rakhee Kallimani, Sridhar Iyer, B. Uma Maheswari, Rajashri Khanai, and Dattaprasad Torse. A survey on brain-computer interface and related applications, 2022.

[46] Saim Rasheed. A review of the role of machine learning techniques towards brain–computer interface applications. *Machine Learning and Knowledge Extraction*, 3(4):835–862, 2021.

[47] Xiao Zhang, Dongrui Wu, Lieyun Ding, Hanbin Luo, Chin-Teng Lin, Tzyy-Ping Jung, and Ricardo Chavarriaga. Tiny noise, big mistakes: Adversarial perturbations induce errors in brain-computer interface spellers, 2020.

[48] Yongshuang Liu, Haiping Huang, Fu Xiao, Reza Malekian, and Wenming Wang. Classification and recognition of encrypted eeg data neural network, 2020.

[49] Kai Zhang, Guanghua Xu, Xiaowei Zheng, Huanzhong Li, Sicong Zhang, Yunhui Yu, and Renghao Liang. Application of transfer learning in eeg decoding based on brain-computer interfaces: a review. *Sensors*, 20(21):6321, 2020.

[50] Lubin Meng, Xue Jiang, Xiaoqing Chen, Wenzhong Liu, Hanbin Luo, and Dongrui Wu. Adversarial filtering based evasion and backdoor attacks to eeg-based brain-computer interfaces, 2024.

[51] Ravikiran Mane, Effie Chew, Karen Chua, Kai Keng Ang, Neethu Robinson, A. P. Vinod, Seong-Whan Lee, and Cuntai Guan. Fbcnet: A multi-view convolutional neural network for brain-computer interface, 2021.

[52] Ce Zhang, Young-Keun Kim, and Azim Eskandarian. Eeg-inception: An accurate and robust end-to-end neural network for eeg-based motor imagery classification, 2021.

[53] Dae-Hyeok Lee, Sung-Jin Kim, and Yeon-Woo Choi. Classification of distraction levels using hybrid deep neural networks from eeg signals, 2022.

[54] Xiang Zhang, Lina Yao, Xianzhi Wang, Wenjie Zhang, Shuai Zhang, and Yunhao Liu. Know your mind: Adaptive brain signal classification with reinforced attentive convolutional neural networks, 2019.

[55] Siavash Sakhavi, Cuntai Guan, and Shuicheng Yan. Learning temporal information for brain-computer interface using convolutional neural networks. *IEEE transactions on neural networks and learning systems*, 29(11):5619–5629, 2018.

[56] Zaineb Ajra, Binbin Xu, Gérard Dray, Jacky Montmain, and Stephane Perrey. Mental arithmetic task classification with convolutional neural network based on spectral-temporal features from eeg, 2022.

[57] Alessandro Gallo and Manh Duong Phung. Classification of eeg motor imagery using deep learning for brain-computer interface systems, 2022.

[58] Pablo Ortega, Cedric Colas, and Aldo Faisal. Compact convolutional neural networks for multi-class, personalised, closed-loop eeg-bci, 2018.

[59] Xiran Xu, Bo Wang, Boda Xiao, Yadong Niu, Yiwen Wang, Xihong Wu, and Jing Chen. Beware of overestimated decoding performance arising from temporal autocorrelations in electroencephalogram signals, 2024.

[60] Yang Wang, Shuangjie Liu, Hao Wang, Yue Zhao, and Xiao-Dong Zhang. Neuron devices: emerging prospects in neural interfaces and recognition. *Microsystems & Nanoengineering*, 8(1):128, 2022.

[61] Xiaorong Gao, Yijun Wang, Xiaogang Chen, and Shangkai Gao. Interface, interaction, and intelligence in generalized brain–computer interfaces. *Trends in cognitive sciences*, 25(8):671–684, 2021.

[62] Maryam Norouzi, Mohammad Zaeri Amirani, Yalda Shahriari, and Reza Abiri. Precision enhancement in sustained visual attention training platforms: Offline eeg signal analysis for classifier fine-tuning, 2024.

[63] Sujit Roy, Anirban Chowdhury, Karl McCreadie, and Girijesh Prasad. Deep learning based inter-subject continuous decoding of motor imagery for practical brain-computer interfaces. *Frontiers in Neuroscience*, 14:918, 2020.

[64] Xiang Zhang, Lina Yao, Xianzhi Wang, Jessica Monaghan, David Mcalpine, and Yu Zhang. A survey on deep learning-based non-invasive brain signals:recent advances and new frontiers, 2020.

[65] Pingsheng Li. Bayesian networks for brain-computer interfaces: A survey, 2022.

[66] Myriam Alanis-Espinosa and David Gutiérrez. On the assesment of functional connectivity in an immersive brain-computer interface during motor imagery, 2019.

[67] Maciej Śliwowski, Matthieu Martin, Antoine Souloumiac, Pierre Blanchart, and Tetiana Aksenova. Deep learning for ecog brain-computer interface: end-to-end vs. hand-crafted features, 2022.

[68] Almabrok Essa and Hari Kotte. Brain signals analysis based deep learning methods: Recent advances in the study of non-invasive brain signals. *arXiv preprint arXiv:2201.04229*, 2021.

[69] Zhongke Gao, Weidong Dang, Xinmin Wang, Xiaolin Hong, Linhua Hou, Kai Ma, and Matjaž Perc. Complex networks and deep learning for eeg signal analysis. *Cognitive Neurodynamics*, 15(3):369–388, 2021.

[70] Jinpei Han, Xiaoxi Wei, and A. Aldo Faisal. Eeg decoding for datasets with heterogenous electrode configurations using transfer learning graph neural networks, 2023.

[71] Yimin Hou, Shuyue Jia, Xiangmin Lun, Ziqian Hao, Yan Shi, Yang Li, Rui Zeng, and Jinglei Lv. Gcns-net: A graph convolutional neural network approach for decoding time-resolved eeg motor imagery signals, 2022.

[72] Param Rajpura and Yogesh Kumar Meena. Towards optimising eeg decoding using post-hoc explanations and domain knowledge, 2024.

[73] Mahbod Nouri, Faraz Moradi, Hafez Ghaemi, and Ali Motie Nasrabadi. Towards real-world bci: Ccspnet, a compact subject-independent motor imagery framework, 2022.

[74] A. Banitalebi, S. K. Setarehdan, and G. A. Hossein-Zadeh. A technique based on chaos for brain computer interfacing, 2018.

[75] Anupam Sharma and Krishna Miyapuram. Evaluating fast adaptability of neural networks for brain-computer interface, 2024.

[76] Javier Fumanal-Idocin, Yu-Kai Wang, Chin-Teng Lin, Javier Fernández, Jose Antonio Sanz, and Humberto Bustince. Motor-imagery-based brain computer interface using signal derivation and aggregation functions, 2021.

[77] Sergio López Bernal, Alberto Huertas Celdrán, Gregorio Martínez Pérez, Michael Taynnan Barros, and Sasitharan Balasubramaniam. Security in brain-computer interfaces: state-of-the-art, opportunities, and future challenges. *ACM Computing Surveys (CSUR)*, 54(1):1–35, 2021.

[78] K. Xia, W. Duch, Y. Sun, K. Xu, W. Fang, H. Luo, Y. Zhang, D. Sang, X. Xu, F-Y Wang, and D. Wu. Privacy-preserving brain-computer interfaces: A systematic review, 2024.

[79] Umang Goenka, Param Patil, Kush Gosalia, and Aaryan Jagetia. Classification of electroencephalograms during mathematical calculations using deep learning, 2022.

[80] Yiqun Duan, Zhen Wang, Yi Li, Jianhang Tang, Yu-Kai Wang, and Chin-Teng Lin. Cross task neural architecture search for eeg signal classifications, 2022.

[81] Lang Qian, Shengjie Zheng, Chunshan Deng, Cheng Yang, and Xiaojian Li. An adaptive contrastive learning model for spike sorting, 2022.

[82] Shiwei Cheng and Jialing Wang. Mi 2 mi: Training dyad with collaborative brain-computer interface and cooperative motor imagery tasks for better bci performance, 2024.

[83] Zhe Sun, Zihao Huang, Feng Duan, and Yu Liu. A novel multimodal approach for hybrid brain-computer interface, 2020.

[84] Martin Wimpff, Leonardo Gizzi, Jan Zerfowski, and Bin Yang. Eeg motor imagery decoding: A framework for comparative analysis with channel attention mechanisms, 2024.

[85] Sidharth Pancholi and Amita Giri. Advancing brain-computer interface system performance in hand trajectory estimation with neurokinect, 2023.

[86] Rui Liu, Yuanyuan Chen, Anran Li, Yi Ding, Han Yu, and Cuntai Guan. Aggregating intrinsic information to enhance bci performance through federated learning, 2023.

[87] Julia Berezutskaya, Anne-Lise Saive, Karim Jerbi, and Marcel van Gerven. How does artificial intelligence contribute to ieeg research?, 2022.

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