A Survey of AI EEG Foundation Model Deep Learning Time Series BCI Neural Networks Brain-Computer Interface and Signal Processing

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Abstract

This survey explores the multidisciplinary integration of artificial intelligence (AI), deep learning, foundation models, and signal processing in the analysis of electroencephalography (EEG) and the development of brain-computer interfaces (BCIs). These technologies have significantly advanced the precision and efficiency of EEG decoding, with frameworks like CTNAS-EEG achieving state-of-the-art performance in Motor Imagery and Emotion tasks. Deep learning techniques have improved the classification and detection of brain signals, enhancing diagnostic tools in neurology. Despite these advancements, challenges remain in achieving reliable performance in real-world BCI applications. The survey emphasizes the need for adaptive methods to optimize BCI design and performance, highlighting significant improvements in EEG classification accuracy through advanced AI techniques. Future research should focus on developing robust algorithms, expanding datasets, and integrating multimodal approaches to enhance emotion recognition systems' reliability and applicability. The survey concludes that continued integration of these technologies is crucial for advancing EEG analysis and BCI development, with potential to improve cognitive enhancement, rehabilitation, and neuroprosthetic technology, ultimately enhancing quality of life for users.

1 Introduction

1.1 Multidisciplinary Field Overview

The domain of brain-computer interfaces (BCIs) represents a significant multidisciplinary convergence of artificial intelligence (AI), deep learning, and signal processing, crucial for interpreting brain signals from electroencephalography (EEG). This integration is vital for transforming EEG data into actionable insights, enhancing human-robot interaction, and improving communication for individuals with disabilities [1].

The use of multimodal pre-training models in AI, while effective, raises challenges related to explainability [2]. BCIs have also progressed in translating emotional states into artistic expressions, showcasing the complexities of human emotions and the need for innovative communication methods [3]. Novel paradigms, such as laryngeal imagery, further illustrate the intersection of neuroscience and technology, particularly for enhancing communication in individuals with severe disabilities [4].

Research continues to advance BCI technology, focusing on the implementation of diverse expressions, emotions, and actions to control devices through brain signals [5]. The incorporation of explainable artificial intelligence (XAI) within BCIs enriches the understanding of the multidisciplinary relationship between AI and BCI technologies [6]. This approach not only enhances BCI capabilities but also serves as an educational resource for newcomers, providing foundational knowledge on EEG's role in human-computer interaction [7].

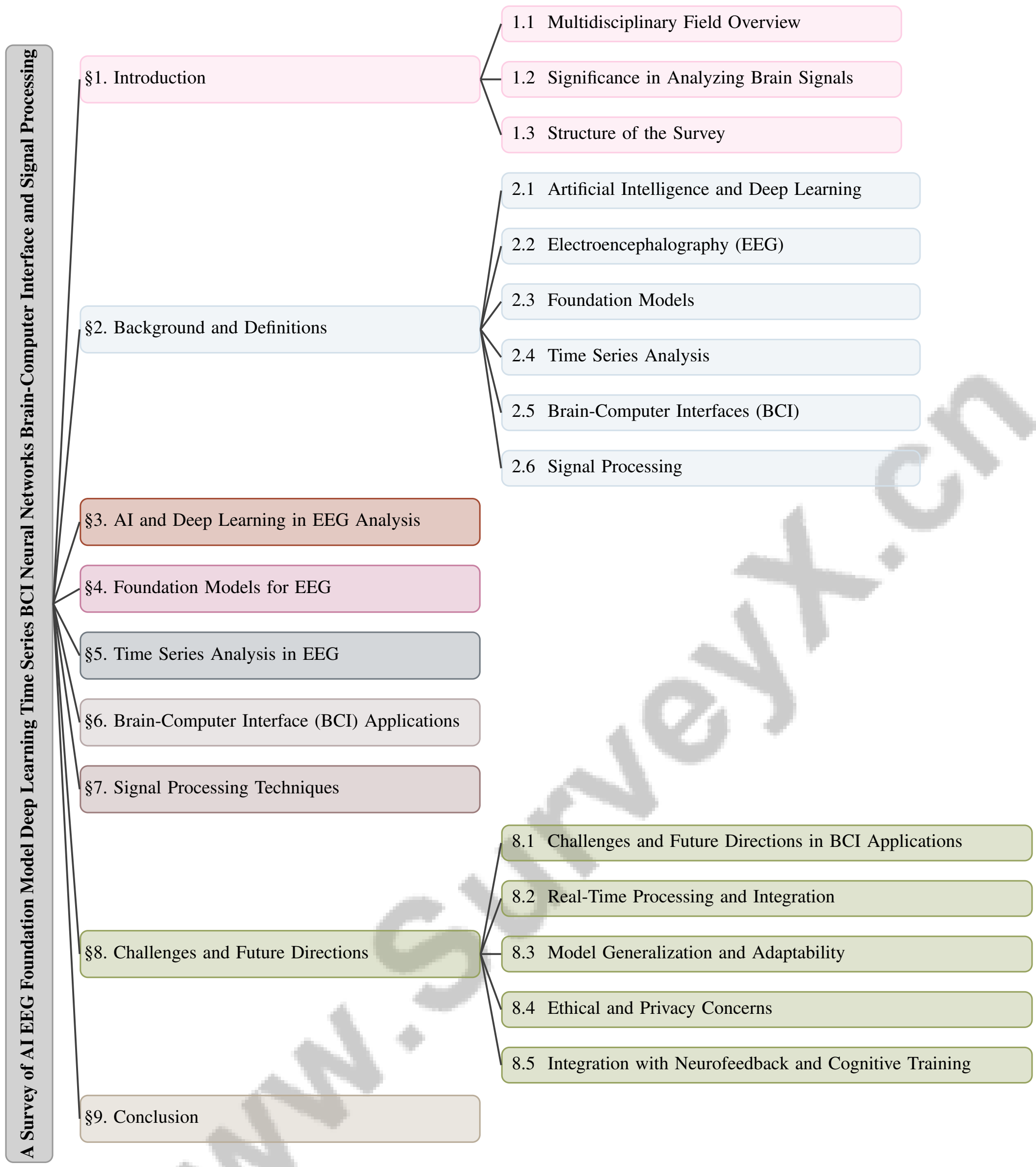


Figure 1: chapter structure

As research progresses, efficient control of complex robotic systems through BCIs remains a focal point, addressing limitations of existing methods and improving human-machine interfaces [8]. The survey highlights the necessity for adaptive BCI systems that cater to user variability, with EEG as a primary measurement tool [9]. This multidisciplinary integration is crucial for the ongoing development of BCIs, ultimately enhancing the quality of life for users. The challenges of EEG data collection and analysis, particularly during the COVID-19 pandemic, further emphasize the importance of integrating consumer-grade devices and machine learning, reflecting the field's multidisciplinary nature [10]. Acknowledging the challenges in utilizing AI in BCI research, there is an increasing focus on promoting human-AI collaboration rather than full autonomy, which enhances BCI effectiveness [11].

1.2 Significance in Analyzing Brain Signals

The integration of artificial intelligence (AI), deep learning, and neural networks into brain signal analysis has significantly advanced brain-computer interfaces (BCIs). Electroencephalography (EEG) offers a non-invasive and cost-effective method for assessing cognitive and affective states, which is essential for human-computer interaction [12]. The application of deep learning techniques in EEG analysis has greatly improved our understanding of human mental states, leading to advancements in real-world applications [13]. These technological innovations are particularly impactful in healthcare, where BCIs present novel interventions for neurological and psychiatric disorders, paving the way for rehabilitation and therapy [14].

In educational contexts, EEG sensors have the potential to monitor and enhance student learning patterns, particularly in STEM fields, thus improving educational outcomes [15]. Despite these advancements, challenges remain in accurately classifying brain activities, necessitating innovative approaches to enhance classification accuracy in BCI systems [16]. Incorporating domain knowledge into model development has shown promise in improving performance in data-scarce scenarios, which is critical for advancing BCI applications [17].

Moreover, BCIs are increasingly utilized in clinical and commercial settings, requiring clear communication of system performance to prevent user frustration and ensure successful adoption, especially for individuals with severe disabilities who depend on BCIs for communication [18]. Privacy protection is also paramount, as EEG signals can disclose sensitive personal information, necessitating robust safeguards for user data [19].

Identifying specific EEG frequency bands that contribute to speech recognition remains an area for further investigation to enhance EEG signal analysis efficacy. The use of deep learning in asynchronous motor imagery-based BCIs has shown promise in classifying transitional imagery signals, which is crucial for real-world applications [8]. Continued development of these technologies is essential for realizing the full potential of BCIs, thereby improving the quality of life for users [9].

The importance of deep learning algorithms in enhancing the assessment of neurological conditions is underscored by their capacity to deepen our understanding of brain signals, as evidenced in recent studies [20]. Additionally, Brain-Artificial Intelligence Interfaces (BAIs) aim to leverage AI to assist individuals with cognitive impairments in communication and control tasks [21]. The translation of Motor Imagery EEG signals into commands using advanced signal processing and deep learning techniques underscores the transformative potential of these technologies in BCI applications [22]. Furthermore, the necessity for accurate and coherent feedback mechanisms for BCI users illustrates the role of AI in enhancing the effectiveness of MI EEG-based BCIs [1]. The significance of these technologies is especially pronounced in assistive devices for individuals with motor disabilities, addressing the limitations of existing BCI systems that primarily function offline, without accommodating real-time interactions that can alter brain activity patterns [23].

1.3 Structure of the Survey

This survey is meticulously structured to provide a comprehensive overview of the multidisciplinary field that includes artificial intelligence (AI), electroencephalography (EEG), foundation models, deep learning, time series analysis, brain-computer interfaces (BCI), neural networks, and signal processing. It begins with an introduction that underscores the importance of these technologies in analyzing and interpreting brain signals. The text explores the multidisciplinary nature of the field, emphasizing the integration of technologies such as machine learning and EEG in brain signal analysis. It discusses the significance of these technologies in enhancing our understanding of cognitive processes, particularly in natural language processing and STEM activities, where EEG data has been shown to improve classification tasks and reveal complex brain mechanisms during cognitive tasks. Additionally, the review aims to empower computer science students by synthesizing recent research on machine learning applications in EEG analysis, fostering a comprehensive understanding of current methodologies and their implications for BCI technology [24, 25, 26].

The subsequent section provides thorough background and definitions of core concepts and technologies, such as AI, EEG, foundation models, and deep learning, explaining their relevance to BCI. This is followed by a discussion on AI and deep learning in EEG analysis, addressing their roles, advancements, and challenges.

The survey further examines the use of foundation models in EEG analysis, discussing their potential benefits and the integration of multimodal and multitask approaches. The analysis of time series in EEG is enhanced by employing advanced machine learning techniques to effectively manage and extract meaningful patterns from complex, high-dimensional EEG data, facilitating improved interpretation and application in clinical settings, particularly for diagnosing neurological conditions and enhancing BCI technologies [27, 25, 28, 29, 26].

Additionally, we review various BCI applications, exploring how BCIs enable communication between the brain and external devices, and highlight advancements in performance and accuracy. The discussion delves into advanced signal processing techniques tailored for analyzing EEG data, addressing specific challenges in feature extraction and presenting innovative solutions to derive meaningful insights from the signals. This includes a comprehensive overview of machine learning algorithms and their application in enhancing the reliability and performance of EEG-based analyses, as well as bridging the knowledge gap between signal processing and machine learning [29, 24, 25, 30].

The survey identifies current challenges and future directions in EEG and BCI research, highlighting critical issues such as the complexity of brain dynamics, psycho-neurophysiological factors, and the need for technology standardization. It explores promising advancements that could significantly enhance BCI capabilities across various applications, including rehabilitation, robotics, and affective computing, facilitating a transition from laboratory settings to practical, everyday use [14, 31, 29]. The conclusion summarizes the key points discussed, emphasizing the importance of integrating AI, deep learning, foundation models, and signal processing in advancing EEG analysis and BCI applications.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Artificial Intelligence and Deep Learning

AI and Deep Learning have revolutionized EEG signal analysis by automating complex pattern extraction and classification, reducing dependence on manual feature engineering [32]. Deep learning effectively handles EEG's high dimensionality and variability by learning nonlinear transformations directly from neural signals [33]. CNNs convert one-dimensional EEG signals into two-dimensional time-frequency representations, aligning with the Signal2Image (S2I) methodology to improve classification accuracy and interpretability [34, 35]. The CTNAS-EEG framework exemplifies AI's role in optimizing neural network architectures for specific EEG tasks [36].

Deep learning methods consistently outperform traditional EEG classification techniques, bridging critical gaps by synthesizing fMRI data from EEG [20, 37]. Techniques like EEG-to-Image Encoding enhance visual classification performance [38]. Federated transfer learning improves EEG classification by enhancing model generalizability and robustness [39]. Despite advancements, challenges in capturing implicit, context-dependent knowledge for BCI research persist [11]. The transition from traditional to advanced deep learning architectures continues to foster innovative BCI applications [1].

2.2 Electroencephalography (EEG)

EEG is a non-invasive tool essential for recording brain electrical activity, providing insights into neural processes and aiding in neurological disorder diagnosis and management [40, 41]. Its real-time monitoring capability is invaluable in smart home and healthcare settings, recognizing multi-person and multi-class brain activities [42]. In BCIs, EEG signals train deep learning models for improved classification accuracy in biomedical diagnostics [35]. EEG data is collected via electrodes on the scalp, processed to enhance classification by leveraging sensor spatial configurations [43]. Effective spatial filtering ensures data accuracy despite noise [44].

EEG advances HCI by decoding imagined speech signals for intuitive interactions [45]. Challenges like calibration and inter-subject variability impact data quality [46]. Nonetheless, EEG remains crucial for non-invasive brain signal acquisition, significantly contributing to clinical applications and BCI development, particularly in translating Motor Imagery (MI) EEG signals into commands [22].

2.3 Foundation Models

Foundation models enhance EEG data analysis by learning universal representations across tasks. Models like EEGFORMER use vector quantization to improve interpretability and performance [47]. Unsupervised pre-training on large EEG datasets allows models like LaBraM to capture intricate patterns for task-specific fine-tuning. Multimodal encoders in foundation models replicate brain-like properties, outperforming unimodal encoders in neural encoding [2]. Advanced data augmentation, as seen in CROP-CAT, addresses data scarcity and model overconfidence, enhancing BCI predictions [48].

Foundation models revolutionize EEG analysis by providing scalable solutions that enhance data interpretability across clinical diagnostics, cognitive research, and BCI development. EEGFormer and GEFM leverage self-supervised learning and graph neural networks to utilize large-scale unlabeled datasets, advancing tasks like seizure detection and wave analysis [47, 49, 50].

2.4 Time Series Analysis

Time series analysis is vital for interpreting EEG data, revealing temporal dynamics and patterns in brain signals. It examines sequential data to identify trends and structures, overcoming challenges posed by EEG's chaotic, non-stationary nature [51]. Recent methods construct matrices of connections from EEG time series, enhancing the analysis of temporal dynamics and functional connectivity [52]. Bridging EEG with fMRI data underscores time series analysis's importance [37].

Integrating time series analysis with deep learning enhances EEG data interpretability and predictive power. Sophisticated signal processing and machine learning algorithms enable effective analysis of EEG's temporal structures, advancing BCIs and optimizing EEG use in clinical and cognitive research settings [53, 29].

2.5 Brain-Computer Interfaces (BCI)

BCIs enable direct brain-to-device communication, benefiting individuals with severe motor impairments by decoding EEG signals into actionable commands [54, 55]. The variability and noise in EEG signals challenge accurate user intention decoding [56]. Advanced representation techniques improve user intention identification in BCI applications [55]. Privacy concerns and limited training samples necessitate robust data handling, with federated transfer learning enhancing BCI performance [39].

BCIs assess cognitive processes and facilitate communication for individuals with cognitive impairments, extending to applications like smart home interactions using P300-based systems [21, 54]. Overcoming signal acquisition and processing challenges remains a focus to expand BCI applications and enrich human-machine interactions [57].

2.6 Signal Processing

Signal processing is crucial for EEG data analysis, focusing on extracting, transforming, and interpreting brain signals. Techniques enhance signal quality and extract meaningful features from raw EEG data, often contaminated by noise [53]. EEG signals' variability and complexity necessitate advanced methods for accurate analysis [58]. Wavelet-based denoising and ICA are common for enhancing signal clarity, especially in translating motor imagery signals [22].

The intersection of signal processing and machine learning addresses complexities in EEG feature extraction and classification [30]. ML algorithms optimize signal processing techniques, improving EEG-based BCI accuracy and reliability [53]. Synthetic EEG data generation methods preserve privacy and reduce reliance on extensive datasets [59].

The EEG4Students protocol exemplifies structured data collection, using consumer-grade devices for efficient EEG data acquisition in remote experiments [10]. It broadens EEG research accessibility, particularly in educational contexts. Signal processing underpins advancements in neuroscience and neuroengineering, enhancing BCI capabilities and neurotechnological applications [5].

In recent years, the field of EEG analysis has witnessed significant advancements, particularly with the integration of artificial intelligence (AI) and deep learning methodologies. These technologies have not only enhanced the accuracy of signal decoding but have also introduced new challenges that necessitate a deeper understanding of the underlying architectures. Figure 2 illustrates the hierarchical categorization of AI and deep learning applications in EEG analysis, detailing key architectures, advancements in signal decoding, challenges faced, and the importance of interpretability and explainability in model development. This comprehensive overview underscores the multifaceted nature of AI applications in this domain and highlights the critical need for ongoing research to address the complexities involved.

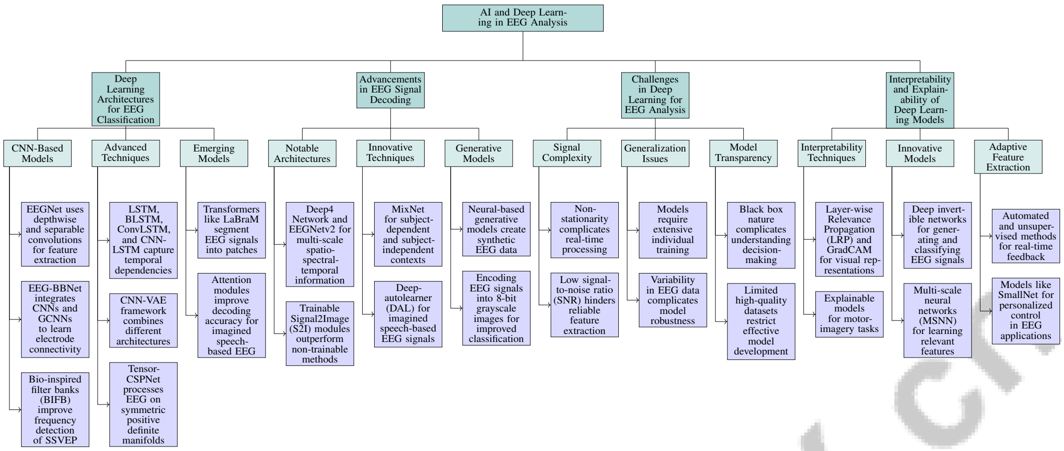


Figure 2: This figure illustrates the hierarchical categorization of AI and deep learning applications in EEG analysis, detailing key architectures, advancements in signal decoding, challenges faced, and the importance of interpretability and explainability in model development.

3 AI and Deep Learning in EEG Analysis

3.1 Deep Learning Architectures for EEG Classification

Deep learning architectures have profoundly impacted EEG classification by effectively managing the complexity and high dimensionality of EEG signals. Convolutional Neural Networks (CNNs) are pivotal, with models like EEGNet using depthwise and separable convolutions to extract features across various BCI paradigms, such as P300, ERN, MRCP, and SMR. EEGNet's compactness ensures robust performance even with limited data, making it a versatile tool for diverse neural signals [38, 60, 61]. These models excel at capturing spatial and temporal EEG patterns, enhancing classification outcomes.

Hybrid models like EEG-BBNet integrate CNNs and graph convolutional networks (GCNNs) to learn electrode connectivity, emphasizing spatial and functional connectivity in EEG analysis. Bio-inspired filter banks (BIFB) improve frequency detection of SSVEP in BCIs by designing filters that account for biological characteristics, outperforming traditional methods like PSDA and CCA [50, 62, 63, 64, 65].

Advanced techniques such as LSTM, BLSTM, ConvLSTM, and CNN-LSTM classifiers further enhance EEG signal classification by capturing temporal dependencies [1]. The CNN-VAE framework exemplifies the potential of combining different neural network architectures to improve EEG classification.

Tensor-CSPNet, a geometric deep learning framework, processes EEG signals on symmetric positive definite manifolds to capture temporospatiofrequency patterns. MixNet enhances motor imagery EEG classification by leveraging spectral-spatial signals through a multi-task learning architecture, MIN2Net, addressing the challenge of identifying discriminative patterns across subjects. MixNet consistently outperforms existing algorithms across benchmark datasets, offering implications for lightweight EEG wearable devices in IoT applications [66, 67, 68, 34].

Transformers are gaining interest for EEG data processing, with models like LaBraM segmenting EEG signals into patches and employing vector-quantized neural spectrum prediction for training [69]. Attention modules in deep learning frameworks improve decoding accuracy for imagined speech-based EEG signals, showcasing the potential of attention mechanisms in enhancing EEG signal interpretation [45].

These advancements significantly enhance EEG-based systems' accuracy and efficiency, facilitating innovative applications in BCIs and related fields. Techniques like self-supervised learning and deep

AI-generated, for reference only.

representation learning create foundation models that improve transfer learning across diverse tasks and individuals, providing interpretable insights into EEG signal patterns. This evolution is crucial for real-world BCI applications, where rapid calibration and adaptability are essential [47, 25, 70, 71, 72].

3.2 Advancements in EEG Signal Decoding

Recent advancements in EEG signal decoding, driven by AI and deep learning, have significantly improved BCI systems' efficiency and precision. Notable developments include the Deep4 Network and EEGNetv2, with EEGNetv2 achieving performance comparable to Deep4, underscoring these architectures' effectiveness in EEG analysis [57]. These models excel in extracting multi-scale spatio-spectral-temporal information, crucial for effective classification across various BCI paradigms.

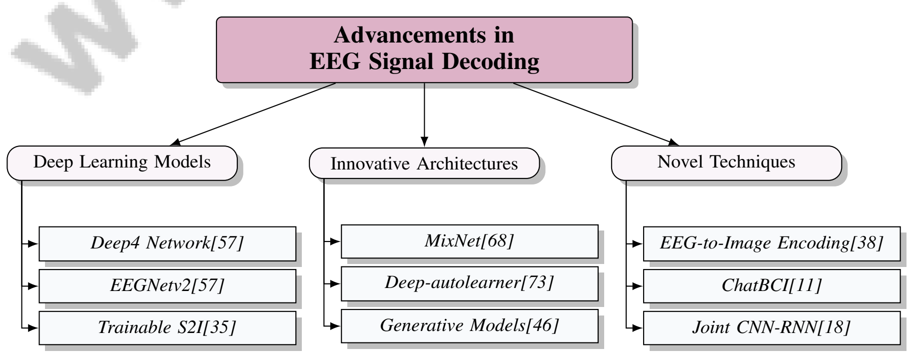
Figure 3 illustrates these recent advancements in EEG signal decoding, highlighting three primary categories: deep learning models, innovative architectures, and novel techniques. Each category includes key developments and methodologies contributing to the field, providing a visual representation of the progress made in this area.

Trainable Signal2Image (S2I) modules, using a one-layer CNN, have outperformed non-trainable methods in EEG classification tasks, demonstrating deep learning's potential to enhance signal interpretation [35]. The Subepoch-wise Feature Encoder (SEFE) advances visual imagery (VI)-based BCI systems, particularly in subject-independent tasks, showing deep learning's adaptability in various EEG applications.

Innovative architectures like MixNet outperform state-of-the-art algorithms in both subject-dependent and subject-independent contexts, indicating their real-world applicability in lightweight and portable EEG devices [68]. The Deep-autolearner (DAL) framework leverages features from overt speech EEG signals to classify imagined speech-based EEG signals, expanding deep learning's applicability in EEG signal decoding [73].

Generative models significantly contribute to EEG signal decoding, with neural-based generative models creating synthetic EEG data to enhance SSVEP classifiers' accuracy and generalization [46]. Encoding EEG signals into 8-bit grayscale images has improved classification accuracy, illustrating the potential of novel data representation techniques [38].

These advancements improve BCI system performance and broaden their applicability across various domains, paving the way for more sophisticated neurotechnological solutions. AI in EEG analysis is exemplified by systems like ChatBCI, facilitating collaboration between human experts and AI technologies. This system combines human oversight with AI autonomy to address complex tasks, enhancing communication capabilities for individuals with cognitive impairments. ChatBCI optimizes BCI development, allowing users to express high-level intentions while AI manages low-level processing details, significantly broadening BCI technologies' accessibility [11, 18, 21].



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3.3 Challenges in Deep Learning for EEG Analysis

Deep learning in EEG analysis faces challenges due to EEG signals' complexity and variability. Non-stationarity complicates real-time processing for effective BCI applications [1]. This non-stationarity, along with EEG data's low signal-to-noise ratio (SNR), hinders reliable feature extraction and accurate classification amid noise and artifacts.

Generalization across different subjects and conditions is a critical issue, as current models often require extensive individual training, limiting broader applicability. Diverse EEG data collection configurations further complicate training models capable of learning from multiple datasets [69]. Variability in EEG data, influenced by recording devices and methodologies, poses additional challenges in developing robust models that generalize well across datasets [39].

The black box nature of deep learning models complicates understanding their decision-making processes, vital for ensuring EEG analysis's reliability and interpretability [38]. Limited high-quality, annotated datasets restrict effective model development, necessitating innovative strategies like data augmentation and transfer learning to enhance robustness and adaptability [1].

Addressing these challenges requires developing sophisticated model architectures and advanced spatial filtering techniques to improve SNR and classification accuracy [44]. Overcoming these obstacles will enable deep learning models to achieve better generalization and performance in EEG analysis, ultimately enhancing BCIs and other neurotechnological applications.

3.4 Interpretability and Explainability of Deep Learning Models

Interpretability and explainability of deep learning models are crucial in EEG applications, providing insights into these complex systems' decision-making processes and fostering trust in their outcomes. Deep learning, particularly CNNs, has shown improved performance over traditional methods, underscoring the need for interpretable models that elucidate underlying mechanisms [74]. Techniques like Layer-wise Relevance Propagation (LRP) and GradCAM convert single-trial decisions of deep neural networks into visual representations, indicating each data point's relevance for classification outcomes and enhancing EEG data analysis interpretability.

Explainable deep learning models for motor-imagery tasks enhance interpretability by providing visual interpretations of decisions, facilitating a better understanding of model functionality and improving trust in predictions [74]. Deep invertible networks for generating and classifying EEG signals address current methods' limitations, offering a novel approach to enhancing model transparency [75].

Multi-scale neural networks (MSNN) in EEG analysis exemplify these models' potential to learn relevant features across multiple scales, enhancing generalization and performance in BCI applications [76]. This capability is crucial for developing models that adapt to diverse EEG data and improve classification accuracy.

Advancements in automated and unsupervised methods for adaptive feature extraction contribute to EEG-based systems' interpretability by enabling real-time feedback and adjustments, enhancing BCI systems' adaptability and effectiveness. Models like SmallNet, which learn optimal features from EEG signals with minimal data, highlight the potential for personalized and adaptive control in EEG applications [23].

Emphasizing interpretability and explainability in EEG applications ensures deep learning models' reliability and accountability, fostering greater confidence among developers and researchers in deploying these technologies [6]. As the field progresses, careful selection and evaluation of interpretation techniques will remain critical for advancing EEG analysis and enhancing BCI capabilities.

4 Foundation Models for EEG

The incorporation of foundation models in EEG analysis presents a complex landscape with significant implications for privacy and security. Given the sensitivity of EEG data, it is crucial to explore potential risks and ethical concerns as these models evolve. The following subsections address key aspects of privacy and security in foundation models, highlighting emerging challenges and innovative strategies.

4.1 Privacy and Security in Foundation Models

Foundation models in EEG analysis pose substantial privacy and security challenges due to the sensitive nature of EEG data. While these models enhance classification by extracting features from raw signals, they risk compromising privacy if not properly managed. The complexity of EEG signals, which include spatial, temporal, and frequency-domain information, necessitates robust security frameworks to protect sensitive data. There is a heightened risk of these models inadvertently disclosing sensitive information through their outputs, which calls for stringent ethical guidelines [21].

In BCIs, privacy threats can be categorized into data-level and model-level concerns. Data-level threats involve unauthorized access to raw EEG data, while model-level threats pertain to information leakage through outputs. Addressing these threats is crucial for maintaining confidentiality, especially in applications involving personal information [36]. The Tensor-CSPNet model addresses these issues by leveraging EEG data's geometric properties to enhance feature extraction and classification in nonstationary conditions [77].

Innovative solutions have emerged, such as the CTNAS-EEG framework, which offers a compatible search space for cross-task searching and customizes network structures for individual subjects [36]. Methods that preserve discriminative information, like those for interpreting imagined speech waves, improve classification while maintaining data security [45]. Models like SmallNet, with their compact design, facilitate real-time adaptations to user preferences, enhancing both privacy and usability [23]. By implementing comprehensive privacy-preserving strategies, researchers can ensure the safe application of foundation models across various domains, including healthcare and human-computer interaction.

4.2 Multi-Task Learning and Clustering Techniques

Multi-task learning and clustering techniques are essential in developing foundation models for EEG analysis, significantly enhancing the interpretability and performance of BCIs. These strategies enable simultaneous training on multiple related tasks, improving generalization across diverse EEG datasets [69]. By leveraging shared representations, multi-task learning facilitates the extraction of common features across tasks, enhancing adaptability to new data [39].

Clustering techniques identify patterns within the high variability and noise of EEG data. By grouping similar data points, these methods simplify EEG signals' complex landscape, aiding in the discovery of meaningful patterns that inform model training [55]. Combining clustering with multi-task learning enhances foundation models' ability to capture EEG signals' diverse nature, leading to more accurate classification outcomes [68].

Recent advancements, such as those in the MixNet framework, demonstrate superior performance in EEG classification by merging classical and deep learning approaches. This hybrid strategy boosts classification accuracy and enhances generalization across subjects and conditions [68]. The integration of clustering with multi-task learning improves the stability and robustness of EEG models, particularly in non-stationary environments [39].

The application of these techniques in foundation models represents a promising avenue for advancing EEG analysis and BCI development. By integrating diverse methodologies from machine learning and domain-specific knowledge, researchers can create models that effectively tackle EEG data complexities. This approach not only enhances model performance but also broadens EEG analysis applicability in real-world contexts, contributing to a growing EEG market [78, 25, 79, 72, 29].

4.3 Multimodal and Multitask Approaches

The integration of multimodal and multitask approaches in foundation models has significantly advanced EEG analysis, enabling comprehensive interpretation of brain signals. These approaches leverage diverse data modalities and tasks to enhance model performance and generalization across EEG applications. The BrainWave framework exemplifies this by integrating diverse neural data types and demonstrating robust performance across tasks [65].

Multimodal approaches process and integrate various data sources, including EEG and fMRI, to improve understanding of cognitive processes and machine learning tasks. These models utilize techniques such as contrastive learning and large-scale pre-training, enabling them to decode visual information and facilitate modality conversion, mimicking human cognition's multimodal nature [2, 24, 50, 65]. This integration captures complementary information that individual modalities may not provide, improving BCI systems' effectiveness.

Multitask learning involves training models on multiple related tasks, enhancing generalization and robustness. This approach facilitates extracting shared features across tasks, enabling models to adapt to new data [70]. Recent surveys categorize existing research into frameworks, underscoring the need for structured approaches to feature extraction in EEG processing [70].

The synergy between multimodal and multitask approaches in foundation models represents a promising direction for EEG analysis. By integrating machine learning methodologies tailored for EEG, researchers can create flexible models that navigate EEG signals' complexities. This approach enhances BCIs' accuracy and opens avenues for innovative applications across fields, contributing to the EEG ecosystem's growth [24, 78, 25, 71, 29].

4.4 Transfer Learning and Universal Representation

Transfer learning and universal representation have emerged as pivotal strategies in EEG data analysis, improving model adaptability and performance across tasks. Transfer learning allows pre-trained models on extensive datasets to extract generalizable features for EEG classification, reducing the need for large labeled datasets [39]. The Federated Transfer Learning (FTL) architecture exemplifies this, enhancing EEG classification accuracy while preserving privacy [39].

Riemannian geometry-based methods effectively handle EEG data's non-Euclidean characteristics, outperforming traditional Euclidean methods [80]. The application of Earth Mover's Distance (EMD) enhances model interpretability by quantifying feature relevance maps aligned with neurophysiological insights [80].

Utilizing autoencoders captures underlying EEG patterns while reducing noise and dimensionality, enhancing classification accuracy [42]. This aligns with the Signal2Image (S2I) approach, which converts EEG signals into image-like representations for improved accuracy [35].

Incorporating transfer learning techniques addresses challenges posed by device heterogeneity, leveraging diverse datasets to improve model robustness [80]. This enhances models' capabilities for person-independent classification, improving EEG analysis applicability in real-world scenarios [18].

The integration of transfer learning and universal representation in EEG analysis signifies a groundbreaking advancement, facilitating sophisticated models navigating EEG data complexities. This approach leverages deep learning techniques to enhance classification accuracy, enabling knowledge transfer across subjects and tasks. Recent studies indicate these methods improve model performance and address data scarcity and EEG signal variability challenges, paving the way for robust BCI applications [71, 81, 82, 83]. This integration enhances EEG signals' interpretability and application across domains, paving the way for innovative applications in neurotechnology and beyond.

5 Time Series Analysis in EEG

5.1 Temporal Dynamics and Predictive Modeling

Temporal dynamics and predictive modeling are pivotal in EEG time series analysis, providing insights into the complex neural patterns of brain activity. Capturing these dynamics enhances BCI systems' decoding accuracy. The EEG-Deformer model exemplifies this by integrating CNNs and Transformers to learn both coarse and fine temporal dynamics, thus improving EEG signal interpretability and classification [84]. This integration is crucial for understanding EEG signals' temporal and spatial characteristics, enhancing sensitivity and specificity in detecting neurological events like seizures [85].

Attention mechanisms within deep neural networks refine predictive modeling by prioritizing significant EEG features, thereby improving classification accuracy [86]. Methods that amalgamate time, frequency, and channel information into novel representations further facilitate effective classification and interpretation of complex EEG data [87]. The combination of temporal convolutional networks (TCNs) and long short-term memory (LSTM) networks exemplifies the capability of sequential models to process temporal information, which is vital for managing EEG's inherent temporal dynamics [54]. This synergy allows for a comprehensive understanding of EEG signal dynamics, critical for advancing non-invasive brain analysis [88].

Advanced preprocessing techniques, including feature extraction and dimensionality reduction, significantly enhance EEG signal classification by focusing on essential patterns and minimizing noise [89]. Integrating temporal dynamics and predictive modeling in EEG time series analysis marks a substantial advancement, fostering the development of more robust and accurate BCI systems. These methodologies deepen our understanding of neural processes and pave the way for innovative applications in cognitive research and neurotechnology.

5.2 Machine Learning and Classification Approaches

Machine learning and classification techniques have significantly propelled EEG time series analysis, establishing robust frameworks for decoding complex neural signals. Transfer learning enables model adaptation from extensive datasets to specific EEG tasks, as demonstrated with BCI Competition IV datasets, where models surpassed traditional techniques, enhancing EEG classification accuracy [81]. Feature learning methods using Denoising Autoencoders estimate spectral power from incomplete EEG data, improving motor imagery task classification and model robustness [90]. Data augmentation techniques, such as Gaussian perturbations in the frequency domain, diversify training datasets, enhancing model generalization and performance [91].

Spatial filtering techniques, including Common Spatial Pattern Regression (CSPR) filters, enhance EEG signal quality for regression tasks, improving the signal-to-noise ratio and enabling accurate regression analyses essential for effective BCI performance [92]. Integrating advanced machine learning and classification approaches into EEG time series analysis underscores their potential to significantly enhance BCIs' accuracy and reliability, paving the way for innovative applications in neurotechnology and cognitive research.

5.3 Preprocessing and Data Augmentation

Preprocessing and data augmentation are vital components in EEG time series analysis, significantly influencing classification outcomes' quality and reliability. Preprocessing involves cleaning and preparing EEG signals, focusing on artifact removal and feature extraction. Techniques like wavelet-synchro-squeezing transform enhance EEG data interpretation by isolating relevant signal components [93]. Transforming EEG signals into images can be beneficial but may introduce challenges such as computational complexity and potential information loss [38].

Feature extraction employs methods like Mutual Information and entropy measures to capture essential EEG characteristics [94]. Data normalization and considerations of training data size and neuron size in Autoencoders optimize classification performance [42]. Data augmentation expands training data, enhancing model robustness. Techniques like frequency domain transformations and Gaussian noise addition increase training sample diversity, though caution is needed to avoid introducing artifacts [95]. Advanced strategies, like the CropCat method, enhance spatial and temporal information in EEG signals, improving model robustness [48].

Integrating sophisticated preprocessing and data augmentation techniques is crucial for advancing EEG analysis, facilitating the development of robust BCI systems. These methodologies enhance EEG data's interpretability and classification accuracy and open new avenues for innovative applications in neurotechnology, including improved BCIs and cognitive task analysis [25, 29, 26, 91].

6 Brain-Computer Interface (BCI) Applications

The exploration of brain-computer interfaces (BCIs) spans a diverse range of applications that leverage the unique capabilities of these technologies to bridge human cognition with machine interaction. Innovations in BCI performance and accuracy are expanding their functionality across various domains, setting the stage for a deeper understanding of their transformative potential in clinical and everyday contexts.

6.1 Enhancements in BCI Performance and Accuracy

Recent advancements in BCI technology, driven by innovative algorithms and architectures, have significantly improved performance and accuracy. Zhang et al. reported classification accuracies of 95.53

EEG-based mechatronic interfaces have benefited from CNN models, outperforming other algorithms in game control, showcasing potential for broader applications in mechatronic systems [96]. Hands-free control systems for infotainment, as demonstrated by Bellotti et al., enhance safety and convenience by allowing brain-based control of car systems [97]. The non-invasive nature of BCIs for controlling drone swarms, highlighted by Jeong et al., offers safer options for managing complex systems using brain signals [98].

Despite these advancements, challenges remain in addressing adversarial perturbations that reduce user scores and information transfer rates (ITRs) [99]. Ongoing research aims to develop robust defenses against such attacks to ensure BCI systems' reliability and security. The integration of explainable artificial intelligence (XAI) techniques into BCI systems addresses the need for transparency in interpreting brain signals, fostering trust among users and stakeholders [14, 6, 31]. Continued innovation drives progress in the field, paving the way for more efficient and effective BCI applications.

6.2 BCI Applications in Rehabilitation and Neuroprosthetics

The integration of BCIs into rehabilitation and neuroprosthetic applications has shown significant potential in improving the quality of life for individuals with motor impairments. BCIs enable direct communication between the brain and external devices, offering innovative solutions for rehabilitation and neuroprosthetic control. EEG signals are leveraged to interpret user intentions, translating them into commands for robotic limbs and assistive devices [100].

Advancements in EEG-based BCI systems focus on classifying specific motor actions, such as handgrip actions, crucial for neurorehabilitation protocols and prosthetic control [101]. BCIs promote motor recovery by providing real-time feedback and facilitating neuroplasticity, particularly for stroke survivors and individuals with spinal cord injuries. Studies show that BCIs, integrated with advanced machine learning algorithms, effectively analyze brain signals for rehabilitation, leading to improved mobility and communication [102, 103].

In neuroprosthetics, BCIs have evolved to include sophisticated sensory feedback systems, enhancing user experience and functionality [104, 31, 105]. By integrating sensory feedback, users achieve more natural interactions with their environment, improving neuroprosthetic devices' effectiveness. Ongoing advancements in signal processing and artificial intelligence enhance BCIs' reliability, paving the way for sophisticated solutions in medical and non-medical contexts [102, 31, 105, 106].

6.3 Human-Robot Interaction and Control

BCIs in human-robot interaction and control systems enhance robotic system capabilities, especially where traditional control methods are impractical. BCIs decode EEG signals to enable direct communication between the brain and robotic devices, benefiting individuals with severe motor impairments [54]. Recent advancements focus on improving the accuracy and responsiveness of human-robot interaction systems, with frameworks like FBCNet enhancing EEG signal decoding for precise robotic control [55].

BCIs extend beyond basic control tasks to include complex interactions, such as controlling robotic swarms, allowing users to manage multiple robots through high-level commands [98]. Integrating BCIs with advanced machine learning techniques improves system adaptability and personalization, providing intuitive interaction experiences [86]. BCIs in telepresence and remote operation scenarios empower users to control robotic systems across challenging environments, enhancing task execution in fields demanding high safety and efficiency [58, 11, 107, 108, 100]. The integration of BCIs in human-robot interaction marks a transformative leap in robotics, enabling individuals to control devices through thought, enhancing human capabilities and quality of life [11, 106, 16].

6.4 Applications in Communication and Cognitive Monitoring

BCIs offer transformative tools in communication and cognitive monitoring, providing solutions for individuals with severe communication impairments and insights into cognitive processes. BCIs decode neural signals into commands, facilitating direct interaction with communication devices, benefiting conditions like ALS or locked-in syndrome [61]. EEGNet, a compact convolutional neural network, demonstrates robust classification across BCI paradigms, generalizing effectively with limited training data [61].

In cognitive monitoring, BCIs assess and track cognitive states, crucial for early intervention in conditions like dementia. Rutkowski et al. proposed methods for home monitoring of cognitive decline, enhancing real-time cognitive change tracking [93]. BCIs enable continuous cognitive monitoring across environments, utilizing advancements in signal processing, machine learning, and wearable devices to assess cognitive states, enhancing productivity and therapeutic interventions [31, 109, 53]. The integration of BCIs in communication and cognitive monitoring enhances interaction through brain activity interpretation while providing cognitive health insights [31, 5, 53]. As research progresses, developing sophisticated BCI systems promises broader applicability across domains.

7 Signal Processing Techniques

Category	Feature	Method
Advanced Signal Processing Techniques	Matrix-Based Analysis Secure Data Processing	ISDM[110] CREE[111]

Table 1: This table provides a summary of advanced signal processing techniques applied to electroencephalography (EEG) data, highlighting methods for matrix-based analysis and secure data processing. The table references specific methodologies, ISDM and CREE, which are instrumental in decoding imagined speech and ensuring data privacy in EEG applications.

The advancement of signal processing methodologies is pivotal for the effective analysis of complex electroencephalography (EEG) data. Table 1 presents a concise summary of advanced signal processing techniques essential for the effective analysis and secure handling of EEG data. Additionally, Table 2 provides a comprehensive comparison of advanced signal processing techniques, feature extraction methods, and transformation approaches crucial for the analysis and secure handling of EEG data. This section delves into state-of-the-art techniques that enhance EEG signal analysis, facilitating innovative applications in neuroscience, particularly focusing on the classification and interpretation of EEG data related to imagined speech and secure data processing.

7.1 Advanced Signal Processing Techniques

Advanced signal processing techniques are crucial for interpreting EEG data, addressing the inherent complexity and variability of brain signals. Utilizing covariance matrices and tangent space projections has notably improved the classification accuracy of imagined speech EEG signals by leveraging the geometric properties of EEG data [110]. Moreover, integrating encryption techniques with neural network models has emerged as a novel approach for secure EEG data processing. By combining homomorphic encryption with advanced neural networks, researchers have developed methods to classify encrypted EEG signals while maintaining data privacy, crucial for privacy-sensitive applications [111].

These methodologies lay the groundwork for more accurate and secure EEG-based systems, facilitating the extraction of meaningful information from brain signals. As research progresses, refining methodologies in Explainable Artificial Intelligence (XAI) for BCIs is essential to enhance system interpretability and effectiveness. Recent studies emphasize the need for a comprehensive framework that balances model accuracy with explainability, promoting effective cognitive state monitoring and expanding BCI applications in healthcare and beyond [6, 53].

7.2 Feature Extraction Techniques

Feature extraction is vital for transforming raw EEG data into meaningful representations for classification and interpretation. This survey introduces a classification taxonomy for feature extraction techniques, aiding in identifying suitable methods for specific applications and enhancing EEG data analysis efficiency [30]. Advanced techniques capture temporal, spectral, and spatial EEG signal characteristics, improving machine learning algorithm performance in BCIs and mental task classification. Methods like multivariate feature selection and time-domain feature extraction provide insights into brain activity dynamics. Frequency-domain techniques, including Fourier and wavelet transforms, reveal patterns associated with cognitive and motor tasks.

Spatial filtering, notably Common Spatial Patterns (CSP), enhances signal-to-noise ratios by focusing on spatially distributed brain activity patterns, crucial for accurate decoding. Deep learning advancements, particularly CNNs, optimize EEG classification performance, demonstrating success in distinguishing mental tasks. Clustering-based multi-task feature learning approaches uncover intrinsic data structures, enhancing decoding accuracy for BCI applications [108, 66, 112, 44].

Techniques like Independent Component Analysis (ICA) and Principal Component Analysis (PCA) separate and reduce EEG data dimensionality, facilitating the extraction of independent and orthogonal components. Combining these with deep learning approaches, such as CNNs, improves classification accuracy and addresses data redundancy and artifact recognition [43, 113, 27, 30, 40].

Integrating feature extraction techniques within the signal processing pipeline is essential for optimizing EEG-based systems, including BCIs. By selecting relevant features that accurately represent EEG signal characteristics, researchers can enhance EEG analyses' interpretability and reliability, deepening understanding of brain activity and opening new avenues for neurotechnology and cognitive research applications [78, 25, 29].

7.3 Transformation and Representation Methods

Transformation and representation methods are critical in processing EEG signals, converting raw data into analyzable forms. Time-frequency transformations, such as the Short-Time Fourier Transform (STFT) and Wavelet Transform, enable simultaneous analysis of temporal and spectral EEG signal characteristics [30]. These techniques decompose EEG signals into time-frequency representations, providing insights into dynamic brain activity changes.

Spatial transformations enhance EEG data interpretability, with methods like ICA and PCA widely used to separate and reduce EEG signal dimensionality, identifying components contributing to neural processes [30]. These techniques extract independent and orthogonal components, crucial for improving EEG classification and interpretation accuracy.

Advanced representation methods, such as Riemannian geometry, capture EEG data's intrinsic properties, enhancing classification performance, particularly in BCI applications [30]. Representing EEG data in Riemannian manifolds allows for better capturing brain signals' variability and complexity, leading to more robust analysis.

Transformation and representation methods are integral to processing EEG signals, enabling meaningful information extraction from complex neural data. As EEG research evolves, ongoing development and refinement of machine learning techniques promise significant enhancements in EEG-based systems' functionality. This advancement promises to improve BCI technologies and opens innovative applications across various fields, including neuroscience, cognitive research, and natural language processing. Leveraging the latest machine learning trends and findings can unlock new potentials for EEG data analysis, leading to improved diagnostic tools, enhanced patient care, and novel insights into human cognition [24, 78, 25, 70, 29].

Feature	Advanced Signal Processing Techniques	Feature Extraction Techniques	Transformation and Representation Methods
Data Handling	Covariance Matrices	Csp, Ica, Pca	Time-frequency Transforms
Classification Technique	Neural Networks	Deep Learning	Riemannian Geometry
Security Feature	Homomorphic Encryption	Not Specified	Not Specified

Table 2: This table provides a comparative analysis of various advanced signal processing methodologies, feature extraction techniques, and transformation methods used in EEG data analysis. It highlights the data handling capabilities, classification techniques, and security features associated with each method, offering insights into their applicability for secure and effective EEG signal processing.

8 Challenges and Future Directions

Addressing the multifaceted challenges in brain-computer interface (BCI) technology is essential for enhancing its applicability and effectiveness. This section explores the specific challenges faced by BCI applications, including signal variability, model interpretability, and security concerns, while outlining prospective research avenues that could advance this dynamic field.

8.1 Challenges and Future Directions in BCI Applications

The advancement of BCIs is contingent on overcoming several critical challenges. A primary issue is the inherent variability and noise in EEG signals, which significantly affect BCI systems' reliability and accuracy. The low signal-to-noise ratio complicates subject-independent classification, often leading to misclassification under intermediate conditions [1]. Interpretability of deep learning models poses another significant hurdle in BCI applications, with ongoing questions about effective utilization of data-driven features and enhancing model transparency [11]. The reliance on large volumes of unlabeled data, as demonstrated in models like LaBraM, limits performance in tasks with constrained data availability. Additionally, the quality of EEG signals and potential misclassification during intention decoding can impede BCI system performance [57].

Security and privacy concerns are paramount in BCI applications due to the sensitive nature of EEG data, which can disclose personal information such as user identity and BCI experience. Given the collaborative nature of BCI systems involving hospitals and universities, the transmission of EEG data and proprietary machine learning models presents significant privacy threats. Researchers have proposed various privacy-preserving strategies, including perturbations to obscure sensitive information while maintaining performance and advanced encryption methods to protect EEG data from unauthorized access [111, 114, 115]. Future research must focus on integrating advanced encryption techniques with neural network models to ensure data security while achieving high classification performance. Additionally, the complexity of BCI tasks hinders the full utilization of EEG data, particularly in intricate scenarios like relation detection.

Future research should prioritize refining data processing techniques, exploring intent-based control methods, and expanding the application range of EEG-based systems. Developing more efficient coding schemes and deeper neural network models is vital for advancing BCI technology. Furthermore, refining objective functions to better correlate with classification performance and exploring additional regularization techniques are crucial for enhancing EEG signal processing [1]. The challenge posed by small EEG datasets remains significant, necessitating structured frameworks for larger dataset collection and more accessible EEG data collection methods. Moreover, scalability of BCI systems to new subjects without additional training is a key area for future exploration. Real-time interactions and neurofeedback exercises utilizing EEG and advanced machine learning techniques present promising research avenues aimed at enhancing cognitive training for individuals with cognitive disorders. These approaches leverage noninvasive BCIs to monitor and analyze brain activity, facilitating personalized cognitive interventions that can improve attention and learning outcomes [116, 28].

Addressing these challenges and pursuing these future directions is essential for advancing BCI technology, which has the potential to transform rehabilitation practices, enhance neuroprosthetic technologies, and improve human-robot interactions. These developments aim to assist individuals with severe motor impairments, leveraging artificial intelligence to decode brain signals for precise and personalized interventions. Integrating brain-inspired AI techniques with advanced BCIs, particularly through closed-loop, intelligent, and miniaturized neural interfaces, promises to deepen our understanding of brain functions and improve operational stability. Such innovations hold the potential to significantly elevate the quality of life for individuals relying on these technologies, facilitating seamless integration into daily life and expanding applications across various fields, including rehabilitation, robotics, and affective computing [14, 106].

8.2 Real-Time Processing and Integration

Real-time processing and integration of BCIs present critical challenges and opportunities for advancing this field. A primary challenge is the efficient handling of inherently noisy and variable EEG data, complicating real-time interpretation. Integrating deep learning architectures has shown promise in addressing these challenges by enhancing the accuracy and speed of EEG signal processing. Future research could explore further enhancements, such as incorporating additional neurophysiological features and optimizing deep learning architectures for improved performance [117].

Developing robust decoding methods based on deep learning is essential for overcoming limitations posed by small EEG datasets, which often hinder real-time BCI system performance. These methods should focus on improving model generalization and adaptability to diverse EEG signals, enhancing applicability in real-world scenarios [118]. Moreover, optimizing models for real-time applications remains a critical area of research, particularly concerning various motor imagery tasks. Investigating model performance across different motor imagery scenarios could yield valuable insights into scalability and effectiveness in real-time settings [119].

Graph-based approaches offer a promising avenue for capturing EEG data's topological features, crucial for improving BCI performance. Future research should enhance the robustness of these models and explore their potential in real-time applications. By leveraging the spatial and temporal dynamics of EEG signals, graph-based models can provide a comprehensive understanding of neural processes, facilitating more accurate and efficient BCI integration [120]. The challenges associated with real-time processing and integration of BCIs necessitate continued research and innovation. Addressing these challenges will unlock the full potential of BCIs, enabling seamless and effective interactions between humans and machines. The integration of cutting-edge computational models and real-time processing techniques is poised to significantly enhance BCI functionality, enabling a wide range of innovative neurotechnology applications. Recent advancements in EEG signal processing, machine learning, and artificial intelligence are particularly promising, facilitating more accurate decoding of brain signals and the development of adaptive systems tailored to individual user needs. As these technologies evolve, breakthroughs are anticipated that will transform both healthcare and everyday applications, providing deeper insights into brain function and enhancing the synergy between humans and machines [71, 106, 53, 121].

8.3 Model Generalization and Adaptability

Model generalization and adaptability are pivotal in EEG and BCI research, ensuring models function effectively across diverse datasets, tasks, and populations. The variability and complexity of EEG signals pose significant challenges to achieving robust generalization, as models must navigate differences in data quality, experimental conditions, and individual brain activity [22]. Ensuring models can generalize across these variations is essential for real-world and clinical applications.

Developing models that can adapt to diverse EEG datasets and tasks is crucial for enhancing BCI systems' flexibility and utility. However, the limited size of training datasets often constrains generalizability, underscoring the need for larger, comprehensive datasets to boost performance. Exploring transfer learning techniques is a promising strategy to enhance adaptability across varying subjects and experimental conditions. By leveraging knowledge from related tasks or subjects, transfer learning mitigates challenges posed by limited high-quality annotated EEG data and inherent brain signal variability, reducing the need for extensive calibration sessions and improving model performance, as evidenced by substantial classification accuracy improvements in various studies. Furthermore, advanced methods like deep transfer learning and self-supervised learning allow for extracting universal representations from EEG data, facilitating robust and interpretable outcomes across diverse tasks [47, 81, 82, 72, 83].

Future research should prioritize enhancing model interpretability and generalizability, particularly concerning varied EEG datasets and clinical applications. The challenges faced by certain methods in generalizing across different EEG datasets due to signal variability highlight the necessity for cross-task neural architectures capable of adapting to diverse EEG scenarios. Integrating prior knowledge into deep neural networks can significantly enhance inter-subject analyses, improving accuracy and interpretability of neural decoding tasks. This approach facilitates meaningful feature extraction from diverse neural signals—such as EEG and fMRI—and enables the application of pretrained models for effective transfer learning across different subjects. Consequently, these advancements increase the applicability of deep learning models in clinical settings, where understanding individual variations in neural activity is crucial for developing personalized interventions and BCIs [7, 122, 81, 71, 33].

Exploring adversarial detection and defense mechanisms is another critical research area, as models must be resilient against adversarial attacks that could undermine performance. Ensuring the reliability and security of EEG-based systems across various applications, particularly in critical areas like BCI communication for disabled individuals, necessitates robust defense strategies. Recent research highlights the vulnerability of EEG-based BCI spellers to adversarial perturbations, which can subtly manipulate the system to produce incorrect outputs, potentially leading to severe consequences such as miscommunication or misdiagnosis. Addressing security concerns is essential to enhance the overall effectiveness and trustworthiness of these technologies [99, 25]. By tackling these challenges, researchers can develop more robust and versatile models that enhance the effectiveness and applicability of BCIs in real-world scenarios.

8.4 Ethical and Privacy Concerns

The rapid advancement of BCI technology necessitates a critical examination of the ethical and privacy implications associated with EEG data use. EEG data is inherently sensitive, revealing intimate details about an individual's cognitive and emotional states, underscoring the need for robust privacy protection measures. The complexity and opacity of AI models used in BCIs contribute to a trust gap among stakeholders, highlighting the necessity for explainable AI approaches that enhance transparency and accountability [74]. Variability in individual subjects' brain signals and the quality of EEG data further complicate ethical considerations, impacting the reliability of BCI applications [74].

Addressing ethical and privacy concerns in EEG and BCI applications requires a multifaceted approach. The Federated Transfer Learning (FTL) method offers a promising solution by enabling effective joint analysis of EEG signals while safeguarding user privacy [39]. This approach facilitates developing adaptive BCI systems that can accommodate individual variability, enhancing the robustness and generalizability of EEG systems [53]. Moreover, integrating security measures is critical, especially given the potential for adversarial perturbations that could compromise BCI system integrity [99].

Future research should focus on enhancing the robustness of EEG systems, exploring transfer learning techniques, and developing adaptive BCI systems that can accommodate individual variability [53]. Additionally, addressing challenges in generalizing results across different subjects and recording methods, particularly with fMRI and fNIRS data, is essential to ensure BCI applications' reliability [33]. By implementing enhanced security measures and fostering a robust ethical framework, the potential of BCIs can be realized while safeguarding user privacy and maintaining public trust.

8.5 Integration with Neurofeedback and Cognitive Training

The integration of EEG and BCIs with neurofeedback and cognitive training represents a significant advancement in cognitive enhancement and therapeutic interventions. Neurofeedback utilizes real-time visualizations of brain activity, derived from EEG and advanced machine learning algorithms, to enhance users' ability to self-regulate their brain functions. This technology enables individuals to consciously modulate their brainwaves, potentially improving cognitive performance and emotional regulation by providing immediate feedback on their neural activity patterns [116, 65, 28, 123]. This process can lead to improvements in attention, relaxation, and overall cognitive performance, making it valuable in clinical and non-clinical settings.

Future research is expected to focus on several key areas to enhance neurofeedback and cognitive training effectiveness and applicability. One area of interest is expanding model applicability to other BCI paradigms and incorporating data augmentation techniques to address data scarcity, thereby improving model robustness and adaptability [86]. Exploring deep convolutional neural networks as benchmarks for different neuroimaging techniques and larger, more diverse datasets could further enhance neurofeedback systems' generalizability and performance [32].

Developing agent modules designed for real-time processing in BCIs is expected to broaden the practical applications of these systems, enabling effective integration of neurofeedback into daily activities. This advancement is crucial for addressing existing challenges in BCI usability, such as the need for improved classification algorithms that accurately capture dynamic interactions of brain networks. By leveraging deep learning techniques and adaptive frameworks, these modules can enhance EEG signal decoding robustness, facilitating a more seamless and intuitive user experience in various real-world contexts [104, 48, 15, 71, 9]. This advancement would expand neurofeedback's reach beyond traditional therapeutic environments, enabling broader access and utility. Additionally, optimizing feature extraction and signal processing techniques remains a priority, particularly for testing BCI systems with patients who have locked-in syndrome.

Integrating automated techniques for incorporating expert knowledge and investigating knowledge-enhanced predictive modeling (KEPM) in fields facing similar data constraints is anticipated to significantly propel advancements in interdisciplinary areas such as signal processing and machine learning, as well as enhance human-AI collaboration frameworks in BCI research and other neurotechnological domains [11, 30]. The potential clinical applications of multimodal approaches in optimizing BCI performance and developing subject-neutral BCI systems using adversarial learning techniques to improve generalizability across different users are promising directions for future research.

Validating synthetic EEG data against real recordings and implementing advanced generative methods in diverse BCI applications is expected to refine and enhance decoding models significantly. This approach addresses challenges associated with data scarcity and variability in real-world EEG signal collection, improving neurofeedback systems' accuracy and generalization. By leveraging synthetic data generated through neural-based models, BCI systems can achieve better performance metrics, such as cross-subject generalization improvements exceeding 35

9 Conclusion

The convergence of artificial intelligence, deep learning, foundation models, and signal processing has revolutionized electroencephalography (EEG) analysis and brain-computer interface (BCI) development. This multidisciplinary synergy has led to substantial advancements in EEG decoding accuracy and efficiency. Innovative frameworks, such as CTNAS-EEG, automate neural architecture design, achieving remarkable performance in Motor Imagery and Emotion tasks. Deep learning has notably enhanced brain signal classification, offering new diagnostic tools in neurology, as evidenced by models like EEG-TCFNet, which achieve high classification accuracy in subject-dependent scenarios.

Despite these achievements, real-world BCI applications still face challenges in reliability. Adaptive methods are essential for optimizing BCI design and performance, addressing literature gaps. Notably, refined EEG classification approaches have outperformed traditional models, highlighting the significance of sensor configuration. The DAL framework exemplifies progress by improving imagined speech EEG decoding through leveraging overt speech features.

Future research should focus on developing robust algorithms, expanding datasets for diverse populations, and integrating multimodal approaches to enhance emotion recognition systems' reliability and applicability. The advancement in interpreting imagined speech waves demonstrates superior classification accuracy, emphasizing the need for neuro-physiologically reliable interpretations in deep learning models. The potential of Brain-Artificial Intelligence Interfaces to improve life quality for individuals with severe cognitive impairments is further underscored by experiments like EEGChat.

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