A Survey of AI and EEG in Brain-Computer Interfaces

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Abstract

In recent years, the integration of artificial intelligence (AI) and electroencephalography (EEG) in brain-computer interface (BCI) technologies has marked a significant advancement in neurotechnology. This survey paper explores the transformative potential of AI-enhanced BCIs, emphasizing their role in improving quality of life across various domains. AI techniques, particularly deep learning models, have significantly improved the accuracy and robustness of BCIs by enhancing the interpretation of complex neural signals. Innovations such as neural-based models for generating synthetic EEG signals and advanced architectures like EEG-ITNet and ADNN have demonstrated superior classification capabilities, particularly in tasks involving imagined speech and motor imagery. Despite these advancements, challenges such as data variability, signal noise, computational complexity, and ethical considerations remain significant. The survey underscores the need for continuous advancements in AI to transition from perceptual to cognitive intelligence, highlighting the importance of basic theoretical research. Furthermore, the integration of multimodal and generative models has shown promise in enhancing the adaptability and generalization of BCIs across diverse user populations. Addressing these challenges is crucial for the development of more sophisticated and reliable BCI systems. The ongoing research and innovation in AI and EEG integration continue to expand the applicability of BCIs, fostering advancements in human-device interaction and paving the way for more accessible and effective neurotechnology solutions.

1 Introduction

1.1 Scope and Significance of AI and EEG in BCI

The integration of artificial intelligence (AI) and electroencephalography (EEG) in brain-computer interfaces (BCIs) is a transformative advancement in neurotechnology, enabling direct communication between the brain and external devices. This is particularly significant for individuals with motor disabilities, allowing them to control assistive devices through brain activity [1]. AI techniques, especially deep learning and machine learning, have substantially enhanced the accuracy and reliability of emotion recognition systems within EEG-based BCIs, addressing critical performance gaps.

AI's application in BCIs extends beyond communication to include rehabilitation, robotics, and gaming, while adhering to ethical considerations by avoiding invasive procedures [2]. For example, AI improves feedback mechanisms in Motor Imagery (MI) EEG-based BCIs, thereby enhancing user interaction and performance [3]. Additionally, Brain-Artificial Intelligence Interfaces (BAIs) support individuals with cognitive impairments, such as stroke patients, facilitating complex communication even in the absence of intact cognitive function [4].

AI aims to embed itself in fundamental science while fostering brain-inspired platforms, which can catalyze new scientific discoveries and advance BCI development [5]. The integration of AI into

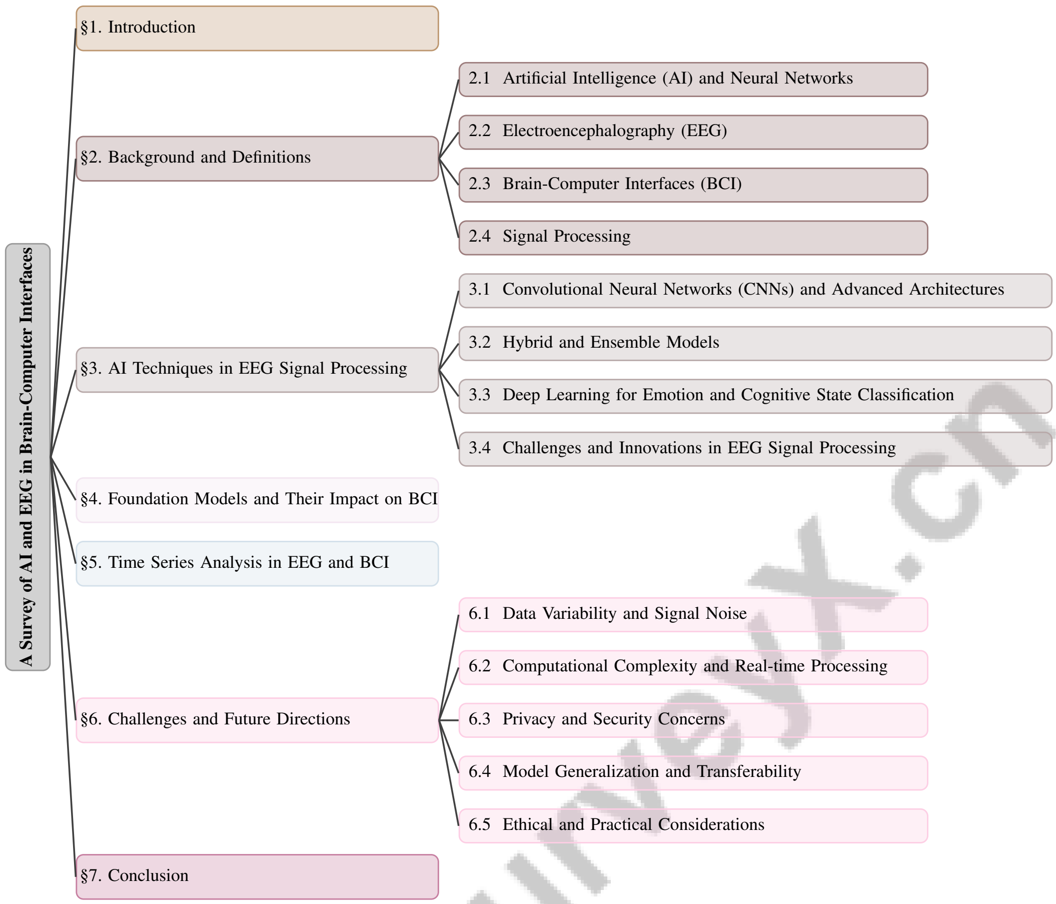

Figure 1: chapter structure

neuroscience and BCI research underscores the importance of human-AI collaboration, rather than full autonomy, in propelling scientific inquiry forward [6].

This survey provides a comprehensive examination of recent advancements in the integration of AI and EEG within BCIs, emphasizing non-invasive techniques. It explores cutting-edge deep learning methodologies, the evolution of EEG signal processing technologies, and their applications in enhancing user interaction and cognitive monitoring, while also addressing the challenges and future directions in this rapidly evolving interdisciplinary field [7, 8, 9, 10]. The survey sets the stage for a thorough investigation of the current landscape and future trajectories of this integration, highlighting both the potential and challenges inherent in BCI technology development.

1.2 Structure of the Survey

This survey is structured to detail the integration of AI and EEG in BCIs, focusing on theoretical and methodological advancements rather than specific applications in areas like healthcare or autonomous vehicles [11]. It begins with an introduction to the significance of AI and EEG in BCI, establishing a foundational context for the discussion. The subsequent background section provides definitions and explanations of key concepts related to AI, EEG, and BCI, elucidating their roles in enhancing BCI systems.

The core of the survey is organized into several sections, each addressing critical aspects of AI and EEG integration. Section 3 focuses on AI techniques in EEG signal processing, particularly the application of deep learning and neural networks to improve BCI applications. Section 4 examines the impact of foundation models on BCI research, emphasizing their adaptability and performance enhancements. Section 5 discusses time series analysis in EEG and BCI, highlighting AI-enhanced methodologies for analyzing EEG data.

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Section 6 offers a comprehensive examination of the challenges and future directions in integrating AI with EEG for BCI applications. It addresses critical issues such as data variability affecting EEG consistency, computational complexity for real-time processing and analysis, and ethical considerations regarding fairness and inclusion in AI decision-making within sensitive contexts. This analysis aims to identify key areas for future research and development in the rapidly evolving BCI landscape [12, 13, 9, 14]. The conclusion summarizes the key points discussed, reinforcing the potential of AI and EEG integration in advancing BCI technologies and the importance of ongoing research.

This structured approach provides a thorough overview of the current state of AI and EEG integration in BCIs, addressing knowledge gaps and exploring various developments within the EEG market ecosystem driven by machine learning [15]. It maintains a clear focus on established benchmarks, concentrating on AI approaches applied to motor imagery (MI) EEG-based BCIs, utilizing publicly available datasets and excluding non-MI related EEG applications [3].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Artificial Intelligence (AI) and Neural Networks

AI encompasses diverse computational strategies, with machine learning (ML) and deep learning (DL) being pivotal in brain-computer interfaces (BCIs) by enhancing the interpretation of complex electroencephalography (EEG) data. These techniques address EEG variability due to factors like drowsiness and fatigue, thereby improving BCI performance [16]. Neural networks, particularly Convolutional Neural Networks (CNNs), are integral to EEG signal processing, effectively managing non-linear relationships and extensive datasets [17]. CNNs excel in mitigating cross-subject variability and enhancing signal quality in motor imagery tasks [3], leveraging generative models to decode brain states from modalities such as magnetoencephalography (MEG) [17]. However, the opaque nature of neural networks necessitates advances in explainable AI (XAI) to build user trust [18].

The absence of a unified model to encapsulate AI systems' intelligence relative to humans complicates their role in BCI [19], compounded by misconceptions about AI consciousness in advanced models like large language models (LLMs) [5]. Despite these challenges, neural networks provide a robust framework for EEG analysis, facilitating cognitive neuroscience advancements through encoding and decoding models that handle naturalistic and multimodal stimuli [20]. The ongoing evolution of AI and neural networks is crucial for advancing BCI systems, contributing to the broader goal of creating machines with human-like intelligence [9].

2.2 Electroencephalography (EEG)

EEG is a key non-invasive method for measuring brain electrical activity, offering critical insights for BCI applications [21]. By capturing neural oscillations through scalp electrodes, EEG facilitates the monitoring and classification of mental states, which is particularly advantageous for individuals with motor disabilities [22]. This capability is essential for BCIs to interpret user intentions, enabling effective interaction with external devices. EEG's applications extend to complex tasks like imagined speech signal interpretation, where methods such as EEG2TEXT improve decoding accuracy for open vocabulary text from EEG data [23], highlighting its potential in aiding communication for users with severe speech impairments.

In clinical settings, EEG is invaluable for diagnosing mental disorders and neurological abnormalities, solidifying its role as a diagnostic tool [21]. Despite challenges like signal noise and low fidelity, EEG remains a cornerstone technology in BCI research due to its non-invasiveness, cost-effectiveness, and portability. These attributes make EEG an appealing choice for various applications, from healthcare to human-computer interaction, thus advancing our understanding of brain functions and enhancing BCI capabilities.

2.3 Brain-Computer Interfaces (BCI)

BCIs are sophisticated systems enabling direct communication between the brain and external devices, bypassing traditional neuromuscular pathways. This technology is transformative for individuals with neurological disorders or motor impairments, allowing interaction with assistive devices through neural activity alone [24]. BCIs have demonstrated significant potential in areas such as rehabilitation, neuroprosthetics, and robotic control, by decoding EEG signals from motor imagery (MI) and speech imagery (SI) to manipulate devices [25].

However, BCIs face challenges like the need for stable and discriminative brain signal patterns, especially in MI tasks requiring extensive training [26]. The classification accuracy of MI EEG signals is often limited by small datasets [27], and device heterogeneity in EEG datasets hampers knowledge sharing, affecting model performance [28]. The difficulty in obtaining high-quality EEG data due to subject and session variance, coupled with lengthy calibration processes, complicates the development of generalizable machine learning models [29].

BCIs also struggle to decode complex actions, such as hand grasping, from EEG signals due to the dynamic nature of brain activity [30]. Traditional BCI systems often fail to interpret implicit brain signals in complex environments, leading to inefficacy in real-world applications [31]. Moreover, reliance on non-intuitive methods, such as visual stimuli or motor imagery, can be slow and confusing for users with motor impairments, reducing overall efficiency [32].

The integration of AI in BCI research emphasizes effective collaboration between human experts and AI systems, particularly given the challenges posed by small datasets and complex signal dynamics [6]. Conventional BCIs often struggle to assist individuals with cognitive impairments, especially those unable to generate language due to conditions like aphasia following a stroke [4]. End-to-end deep neural network approaches have been proposed to overcome the limitations of traditional preprocessing steps in BCI classification tasks, highlighting the necessity for innovative methods [33].

Despite these challenges, BCI technology is advancing with sophisticated neural network models that enhance the efficient processing of complex brain signals. The exploration of brain-to-language decoding techniques underscores the synergy between neuroscience and deep learning, crucial for advancing BCI capabilities. BCIs offer promising communication avenues, particularly for patients with locked-in syndrome (LIS), enabling interaction through non-invasive methods [34]. Continuous advancements aim to enhance the accuracy and reliability of neural signal decoding, improving quality of life for individuals with disabilities and broadening BCI applications [35].

2.4 Signal Processing

Signal processing is vital for analyzing EEG data in BCIs, addressing challenges like high dimensionality, non-stationarity, and low signal-to-noise ratio (SNR) [36]. Variability and noise, exacerbated by non-stationary sources like electromyographic (EMG) activity and eye movements, complicate reliable detection of conscious EEG changes [37]. Advanced preprocessing techniques are essential to filter brain signals, eliminate noise and artifacts, and ensure accurate feature extraction for reliable command prediction [38].

Sophisticated methodologies manage EEG data complexity and variability across subjects and sessions [39]. Techniques such as Common Spatial Patterns (CSP), Time-Resolved CSP (TRCSP), and Filter Bank CSP (FBCSP) enhance feature extraction, while classifiers like K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM) ensure accurate classification [38]. Proper dataset categorization into training, validation, and test sets is crucial for developing robust models [40].

Decentralized data processing frameworks (DDPF) enhance the handling of large datasets by distributing workloads, improving the speed and scalability of EEG data processing [41]. Network-based approaches using graph theory, statistical mechanics, and inferential modeling provide insights into brain networks, contributing to more sophisticated BCI systems [42].

Current methods are often limited by event specificity and reliance on preprocessing, which can introduce biases and are impractical for large datasets [43]. The non-stationarity of EEG signals and the presence of noise, such as ocular artifacts, complicate real-time processing capabilities [3]. The varying formats of EEG data from different devices, including differences in channel numbers, sampling rates, and amplifiers, further complicate data integration [28].

Despite these challenges, advancements in signal processing are crucial for overcoming BCI technology limitations, improving EEG data analysis accuracy, and enhancing BCI applicability in

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complex environments [44]. These developments are integral to optimizing BCI systems for diverse applications, ultimately contributing to efficient and reliable human-device interaction.

3 AI Techniques in EEG Signal Processing

Category	Feature	Method
Convolutional Neural Networks (CNNs) and Advanced Architectures	Sequence and Temporal Analysis	DCRNN[45], CNN-LSTM[46]
	Data Representation Techniques	FBCNet[47]
	Optimization and Efficiency	LNEEG[48]
Deep Learning for Emotion and Cognitive State Classification	Transformer Architectures	E2T[23]
	Attention and Prioritization	ADNN[49]
	EEG Signal Processing	BAI[4], EIE[50]
Challenges and Innovations in EEG Signal Processing	Synthetic Data Generation	SEDG[29]
	Feature Enhancement	LaBraM[51]
	Real-Time Processing	MID[52]

Table 1: This table presents a comprehensive overview of contemporary methods employed in EEG signal processing, categorized into three main areas: Convolutional Neural Networks (CNNs) and Advanced Architectures, Deep Learning for Emotion and Cognitive State Classification, and Challenges and Innovations in EEG Signal Processing. Each category highlights specific features and methodologies that contribute to advancements in brain-computer interface applications, emphasizing the role of AI in enhancing EEG data interpretation and utilization.

Table 3 offers a comprehensive comparison of the AI techniques and methodologies applied in EEG signal processing, categorizing them by their specific features and application domains. Artificial intelligence (AI) techniques have significantly advanced the interpretation and utilization of electroencephalography (EEG) data in brain-computer interface (BCI) applications. Among these, Convolutional Neural Networks (CNNs) stand out for their capability to capture complex spatial and temporal patterns in EEG signals. Table 1 provides a detailed summary of the AI techniques and methodologies used in EEG signal processing, categorized by their application and innovation in the field. **??** illustrates the hierarchical categorization of AI techniques in EEG signal processing, emphasizing CNNs and advanced architectures, hybrid and ensemble models, deep learning for emotion and cognitive state classification, as well as the challenges and innovations in the field. This figure provides a visual representation of each category, detailing specific methodologies and their contributions to enhancing BCI applications. This subsection explores the contributions of CNNs and advanced architectures in EEG data processing, emphasizing their transformative potential in classification accuracy and innovative BCI applications.

3.1 Convolutional Neural Networks (CNNs) and Advanced Architectures

CNNs have become essential in EEG signal processing for BCI applications due to their effectiveness in identifying intricate patterns within EEG data. Their superiority over traditional machine learning methods is well-established, particularly in enhancing classification accuracy. Notable advancements include specialized CNN architectures like FBCNet, which utilizes multi-view data representation and a Variance layer to improve feature extraction for motor imagery classification [47].

Further enhancements in CNN capabilities have emerged through advanced architectures that integrate wavelet-based denoising and Independent Component Analysis (ICA) for preprocessing, followed by CNN and Long Short-Term Memory (LSTM) networks for feature extraction and command translation [46]. These approaches effectively mitigate noise and variance issues in EEG data, thus bolstering BCI application accuracy.

End-to-end deep neural network models, such as E2E-NN, facilitate direct processing of raw EEG data, streamlining human activity recognition [33]. Systems like EEGChat exemplify the application of CNNs in non-invasive conversational interfaces, decoding user intentions from EEG recordings to generate AI-driven responses [4].

The synergy of CNNs with LSTM networks has been explored, where CNNs handle spatial feature extraction while LSTMs manage temporal sequence modeling, enhancing classification performance in EEG-based image feature extraction tasks [50]. Additionally, the Motor Imagery Decoder (MID) employs machine learning to create individualized decoders, utilizing CNNs to predict user intent during motor imagery tasks [52].

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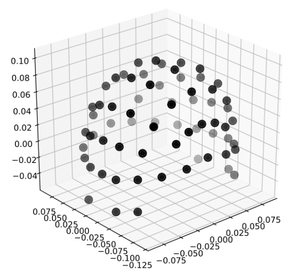
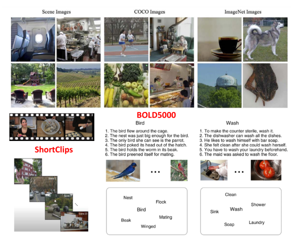
A framework for large-scale evaluation of EEG deep learning architectures reveals significant performance disparities among models, stressing the need for ongoing refinement of CNN-based systems to maintain optimal performance [53].

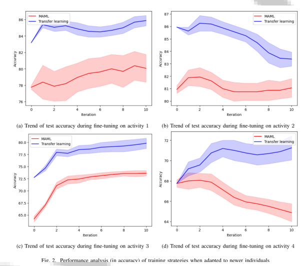
These advancements illustrate the transformative impact of CNNs and advanced architectures in EEG signal processing, paving the way for sophisticated neurotechnology applications. Continued methodological advancements are critical for enhancing human-device interactions, particularly for individuals with paralysis, by improving bidirectional communication between the brain and external devices. The incorporation of Explainable Artificial Intelligence (XAI) techniques into BCI systems is anticipated to facilitate better interpretation of brain signals, enhancing stakeholder understanding of model outcomes. As research progresses in innovative input methods and addresses challenges related to information volume, precision, and invasiveness, the potential applications of BCIs, including brain-to-brain communication, are becoming increasingly promising [54, 55].



(a) A 3D scatter plot with black and gray dots[45]



(b) Scene Images vs. COCO Images vs. ImageNet Images vs. BOLD5000 Short Clips vs. Wash[56]



(c) Performance analysis (in accuracy) of training strategies when adapted to newer individuals[48]

Figure 2: Examples of Convolutional Neural Networks (CNNs) and Advanced Architectures

As illustrated in Figure 2, the integration of AI techniques, particularly CNNs and advanced architectures, has markedly enhanced EEG signal processing capabilities. The first example, a 3D scatter plot, highlights the spatial data distribution and the intricate patterns discernible by CNNs in EEG datasets. The second example contrasts various image datasets, showcasing CNNs' versatility in processing diverse visual inputs and their parallels to EEG signal complexity. Lastly, performance analysis of training strategies reveals the adaptability of CNNs in personalizing models for new individuals, emphasizing their potential in tailored EEG signal interpretation [45, 56, 48].

3.2 Hybrid and Ensemble Models

Hybrid and ensemble models are increasingly vital in enhancing EEG signal interpretation within BCI applications. These models leverage various machine learning algorithms to improve classification accuracy and robustness, effectively addressing the inherent challenges of EEG data, such as variability and noise. The integration of Spiking Neural Networks (SNNs) within hybrid frameworks exemplifies a significant advancement, providing a biologically inspired approach to processing neural data and enhancing the interpretation of complex brain signals [57].

The Knowledge Distillation-based Hybrid Paradigm BCI introduces a hierarchical teacher-student framework that enhances classification of EEG signals, effectively interpreting motor imagery (MI) and speech imagery (SI) data by combining traditional and deep learning techniques [25]. Such hybrid models are crucial for overcoming the limitations of single-model approaches in complex tasks requiring nuanced understanding of brain activity.

Ensemble methods have also gained traction in the BCI domain, combining multiple models to enhance overall system performance and offer robust solutions to EEG data challenges. Bayesian Network models play a key role in high-level applications such as channel selection, classification, and multi-modal integration, improving interpretability and accuracy in BCI systems [44]. These Bayesian frameworks facilitate the incorporation of prior knowledge and uncertainty handling, essential for addressing the stochastic nature of EEG signals.

Data augmentation techniques in both input and feature spaces expand training data diversity, enhancing model generalization and addressing the limitations of small datasets common in EEG research [39].

The continuous development of hybrid and ensemble models is critical for advancing BCI technologies. By integrating various methodologies and harnessing the strengths of multiple algorithms, recent models show significant promise in enhancing EEG signal interpretation and expanding BCI system functionality. This progress is underscored by comprehensive reviews of deep representation learning techniques, emphasizing the growing interest in employing machine learning for EEG analysis through autoencoders and self-supervised learning methods. Establishing specialized benchmarks and datasets remains crucial for developing robust foundation models that effectively tackle challenges in EEG signal decoding [8, 13].

3.3 Deep Learning for Emotion and Cognitive State Classification

Method Name	Methodologies Used	Application Domains	Data Representation
EIE[50]	Cnns, Lstms	Visual Classification	Grayscale Images
ADNN[49]	Adnns	Neural Decoding	Grayscale Images
E2T[23]	Multi-view Transformer	Neural Decoding	Two-dimensional Grayscale
BAI[4]	AI Conversational Agent	Speech Neuroprosthesis	Eeg Data
LaBraM[51]	Transformer Architecture	Emotion Recognition	Channel Patches

Table 2: Overview of various deep learning methodologies and their applications in EEG-based emotion and cognitive state classification. The table details the methods, application domains, and data representations used in recent studies, highlighting the diversity and adaptability of deep learning models in brain-computer interface (BCI) research.

Deep learning applications in classifying emotions and cognitive states from EEG data have significantly advanced BCI capabilities. Table 2 provides a comprehensive summary of the deep learning methods employed for emotion and cognitive state classification using EEG data, illustrating their application domains and data representation techniques. Deep neural networks (DNNs) excel in extracting complex features from high-dimensional, often noisy EEG signals, facilitating accurate emotional and cognitive state classification. These networks utilize a blend of handcrafted features and those generated by deep learning models, enhancing prediction accuracy across applications, including neural decoding of behavior and cognitive states, and improving BCI performance and cognitive neuroscience studies [58, 20, 56].

In emotion recognition, CNNs and LSTMs have proven pivotal, focusing on temporal and spatial patterns in EEG data to improve classification accuracy in tasks involving motor imagery and emotion recognition. The integration of CNNs with LSTMs has been particularly effective in decoding subtle neural signals linked to specific cognitive processes [50]. Attention-based deep neural networks (ADNNs) further enhance classification of imagined speech by prioritizing crucial features while minimizing irrelevant ones, demonstrating deep learning's potential in complex EEG signal interpretation [49].

For cognitive state classification, deep learning models analyze event-related potentials (ERPs) from EEG signals, serving as digital biomarkers for conditions like dementia. The EEG2TEXT method, utilizing EEG pre-training and a multi-view transformer architecture, exemplifies deep learning's robustness in improving brain signal decoding performance into text, facilitating nuanced cognitive state assessments [23]. Additionally, EEGChat allows users to engage in conversations by decoding intentions from EEG data and generating contextually relevant responses using an AI model, highlighting deep learning's versatility in EEG analysis [4].

Innovative methods, such as encoding EEG signals into two-dimensional grayscale images, have adapted EEG data for deep learning, improving classification performance by combining standard image features with EEG data, thereby enhancing interpretability and accuracy in emotion and cognitive state classification [50]. The development of large brain models, inspired by the success of large language models, further illustrates deep learning's potential in advancing EEG analysis [51].

The ongoing exploration of deep learning in EEG-based BCIs highlights its transformative potential in neurotechnology. These advancements not only improve classification accuracy and robustness but also pave the way for novel applications in healthcare, education, and human-computer interaction. Continuous refinement of BCI methodologies positions the field to achieve significant advancements

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in human-device interaction, enhancing quality of life for individuals with paralysis and offering promising applications for healthy individuals. This progress is vital for establishing bidirectional communication between the brain and external environments, addressing challenges related to information volume, precision, and invasiveness. Furthermore, integrating Explainable Artificial Intelligence (XAI) techniques is crucial for enhancing the interpretability of predictive models in BCI applications, ensuring stakeholder understanding and trust in these technologies. As research evolves, these advancements will broaden the utility and accessibility of BCI technologies across diverse domains, paving the way for innovative brain-to-brain communication applications and beyond [54, 55].

3.4 Challenges and Innovations in EEG Signal Processing

Processing EEG signals in BCIs presents inherent challenges due to their non-stationary nature and low signal-to-noise ratio, complicating accurate user intention decoding [52]. Variability across subjects and sessions necessitates robust signal processing techniques to eliminate artifacts and ensure reliable BCI performance [3]. Diverse EEG data collection configurations, including mismatched channels and variable sample lengths, further complicate effective application of existing models [51].

While deep learning models exhibit high performance, they often operate as 'black boxes', posing challenges for reliability and interpretability in BCI applications [18]. Limited neural data availability for training decoders restricts their effectiveness in translating signals into control instructions for external devices [29]. The scarcity of trials in neuroscience datasets and the need for real-time decoding capabilities further complicate robust BCI system development [53].

Recent innovations have addressed these challenges through advanced machine learning techniques and novel methodologies. The application of generative models for dry-EEG data containing SSVEP signals represents a significant yet underexplored innovation in the literature [29]. The FBCNet architecture exemplifies an innovative approach that combines deep learning capabilities with neurophysiological insights, achieving high accuracy even with limited training data [3]. Additionally, the EEG2TEXT method enhances decoding performance through diverse EEG signal learning and spatial modeling of brain regions [33].

Innovative frameworks, such as mixed decision-making and classification approaches, facilitate efficient resource allocation and accurate brain signal classification, enhancing real-time BCI applicability [5]. The development of online EEG data classification systems, enabling real-time control of mechatronic systems, distinguishes these innovations from existing offline methods [3]. Despite these advancements, challenges such as user adaptability and reliable self-paced BCI systems remain significant hurdles, alongside the dependency on BCI device quality and potential noise in brain signal acquisition [52]. Addressing these limitations is crucial for advancing the efficacy and reliability of EEG signal processing in BCIs, paving the way for breakthroughs in human-device interaction.

Feature	Convolutional Neural Networks (CNNs) and Advanced Architectures	Hybrid and Ensemble Models	Deep Learning for Emotion and Cognitive State Classification
Pattern Recognition	Spatial And Temporal	Multi-model Integration	Complex Feature Extraction
Data Processing	Denoising And Feature Extraction	Robust Signal Interpretation	Emotion And Cognitive States
Application Domain	Bci Applications	Enhanced Eeg Interpretation	Healthcare, Education

Table 3: This table provides a comparative analysis of various AI methodologies employed in EEG signal processing, highlighting key features such as pattern recognition, data processing, and application domains. It specifically contrasts Convolutional Neural Networks (CNNs) and advanced architectures, hybrid and ensemble models, and deep learning techniques for emotion and cognitive state classification. The table underscores the distinct capabilities and application areas of each approach, offering insights into their contributions to brain-computer interface (BCI) applications.

4 Foundation Models and Their Impact on BCI

Foundation models have become a focal point in brain-computer interface (BCI) research, offering novel methodologies for neural data interpretation. This section delves into these models' fundamental aspects, exploring their transformative potential in BCI applications. By understanding their principles and functionalities, we can appreciate how foundation models enhance BCI performance and adaptability, with the following subsections detailing their specific roles and implications in this rapidly evolving domain.

4.1 Introduction to Foundation Models in BCI

Foundation models are increasingly recognized for their transformative impact on BCI research, providing a versatile framework for neural data interpretation. LaBraM, a unified foundation model for EEG, exemplifies this potential by learning generic representations through unsupervised pre-training on diverse EEG datasets, thereby improving classification accuracy and interpretability [51]. The integration of large language models in BCI research, as demonstrated by ChatBCI—a Python-based toolbox for collaborative human-AI interaction—highlights the ability of foundation models to streamline knowledge transfer and enhance research efficiency [6]. These integrations allow researchers to better understand complex cognitive functions, advancing BCI capabilities. Theoretical advancements in AI that emulate human learning mechanisms are crucial for BCI technology progression [5]. Foundation models, with their integrative approach, are poised to revolutionize neurotechnology and improve human-device interactions, offering a scalable framework for decoding complex brain signals and facilitating innovative applications.

4.2 Enhancing BCI Performance with Foundation Models

Foundation models have significantly improved BCI performance through sophisticated algorithms that enhance neural data interpretation. EEGNet exemplifies this progress, offering superior generalization across multiple BCI paradigms with fewer parameters, serving as a versatile tool for EEG classification [59]. Advanced architectures like SmallNet and ERA-CNN have enhanced real-time EEG classification accuracy, optimizing feature extraction processes and achieving high performance in motor imagery tasks [1, 60]. Generative models augment BCI performance by synthesizing condition-specific EEG signals, addressing small dataset limitations and enhancing model robustness [61]. Hybrid models combining CNNs and LSTMs capture temporal and spatial EEG patterns, further improving performance [62]. Multi-scale neural networks (MSNN) and the integration of CNNs with RNNs and Autoencoder layers enhance feature extraction and classification accuracy [63, 64]. Innovations, including optogenetics and AI, underscore the importance of interdisciplinary collaboration in advancing BCI capabilities [55]. Foundation models thus provide a scalable framework that enhances BCI performance through advanced learning techniques, cross-domain knowledge transfer, and multimodal integration, crucial for developing sophisticated BCI systems that meet diverse user needs.

4.3 Adaptability and Generalization Across Users

Foundation models in BCIs exhibit significant adaptability and generalization capabilities, crucial for creating systems that effectively serve diverse user populations. This adaptability addresses inherent variability in EEG signals, which can differ due to factors such as age, cognitive state, and neurological conditions [51]. The generalization capabilities of foundation models are enhanced through advanced neural architectures that leverage large-scale datasets and sophisticated algorithms to learn robust EEG representations. For instance, EEGNet's design facilitates generalization across multiple BCI paradigms by employing compact convolutional networks, maintaining high classification accuracy with fewer parameters [59]. Integrating generative models within foundation frameworks further enhances generalization by augmenting training data with synthesized EEG signals, addressing small dataset limitations [61]. Transfer learning and domain adaptation techniques enable knowledge transfer from related tasks or domains, facilitating model adaptation to new users with minimal additional training [51]. These capabilities are crucial for advancing BCI, enabling flexible systems that decode EEG signals across diverse tasks and individuals. Recent studies emphasize their potential to tackle transfer learning challenges and enhance robustness in EEG interpretation, highlighting the need for specialized benchmarks and datasets. The BrainWave foundation model, pretrained on extensive data from thousands of individuals, demonstrates superior adaptability and generalization, achieving zero-shot transfer learning and few-shot classification without fine-tuning, essential for real-world BCI applications [48, 35, 8, 54]. These models promise more inclusive BCI technologies that cater to diverse user needs, enhancing overall user experience and expanding BCI applications.

4.4 Integration of Multimodal and Generative Models

Integrating multimodal and generative models in BCI systems represents a significant advancement in enhancing neural signal processing interpretability and robustness. Multimodal approaches leverage various data modalities, such as EEG, electromyography (EMG), and functional near-infrared spectroscopy (fNIRS), to improve BCI application accuracy and reliability [5]. By integrating diverse data sources, these systems capture a more comprehensive representation of brain activity, enhancing user intention decoding. Generative models, particularly generative adversarial networks (GANs), address challenges related to limited training data and EEG signal variability by synthesizing realistic EEG data that augment existing datasets, facilitating more effective BCI training [61]. The combination of multimodal and generative models enhances BCI adaptability and generalization across users and tasks. For instance, simultaneous analysis of EEG and EMG signals improves motor imagery task classification by providing additional context for interpreting neural activity [51]. Generative models further contribute by creating synthetic data that reflect diverse real-world conditions, thereby improving system robustness. These integrated models facilitate the development of personalized BCIs that adapt to individual users' unique neural signatures, significantly enhancing BCI precision and efficiency. This progress leads to more intuitive human-device interactions, enabling applications such as restoring motor functions in paralyzed individuals and facilitating open vocabulary communication through brain signals. Explainable artificial intelligence (XAI) techniques further support this advancement by addressing brain signal interpretation complexities, ensuring usability across stakeholders [23, 54]. The integration of multimodal and generative models represents a transformative approach to overcoming traditional EEG-based BCI limitations, contributing to the evolution of sophisticated and reliable BCI technologies that address varied user requirements across healthcare, cognitive monitoring, and interactive systems [54, 8, 65, 7, 66].

4.5 Challenges and Future Directions for Foundation Models in BCI

Foundation models in BCI systems face several challenges that must be addressed to enhance efficacy and applicability. A significant issue is the vulnerability of convolutional neural network (CNN) classifiers to adversarial attacks, which can substantially diminish classification accuracy across various models and scenarios. This highlights the urgent need for improved security measures in BCI systems to mitigate such vulnerabilities [67]. Future research should focus on the robustness of foundation models against adversarial attacks, exploring adversarial filtering-based evasion techniques in EEG-based BCI regression problems to enhance overall security [68]. Another challenge involves the adaptability and generalization of foundation models across diverse datasets and neural network architectures. Enhancing query synthesis techniques and investigating their robustness across different architectures could improve model generalization, making them more versatile in BCI applications [69]. The integration of multimodal data sources into foundation models offers both opportunities and challenges. While multimodal approaches enhance BCI interpretability and robustness, future research should explore additional modalities and the explainability of these models using advanced computational neuroscience techniques for more comprehensive BCI systems [70]. Expanding dataset collections and integrating more decoding methods could significantly enhance foundation model capabilities. Systematic hyperparameter optimization for various architectures may also improve performance, providing a more robust BCI framework [53]. Finally, developing bio-inspired AI systems that emulate adaptive and learning capabilities observed in biological organisms represents a promising future research avenue. Such systems could enhance foundation model adaptability and learning efficiency, leading to more sophisticated BCI technologies [71]. Addressing these challenges and exploring future directions is crucial for advancing BCI and realizing the full potential of foundation models in neurotechnology.

5 Time Series Analysis in EEG and BCI

Time series analysis of electroencephalography (EEG) data is integral to deciphering neural dynamics in brain-computer interfaces (BCIs). This section explores methodologies that enhance the interpretability and efficacy of EEG signals, contributing significantly to BCI technology advancements.

5.1 Methods for Time Series Analysis in BCI

Decoding dynamic neural activity patterns from EEG in BCIs demands advanced techniques due to the non-stationary and high-dimensional nature of EEG signals. Machine learning and complex network models are pivotal in effectively decoding user intentions, facilitating applications like emotion recognition [72, 13, 73, 74, 75]. Training models on datasets with varying continuity configurations allows performance assessment under controlled conditions, optimizing configurations for improved accuracy and reliability [76].

Innovations such as the Low-Maintenance Imagined Brain-Computer Interface (LMI-BCI) utilize imagined actions, like humming, to classify EEG signals, enhancing usability for individuals with motor impairments [32]. Integration of machine learning algorithms, including CNNs and RNNs, refines time series analysis by capturing temporal dependencies and spatial patterns, thus improving signal interpretability and enabling real-time analysis across various applications [13, 77, 9, 7, 74].

Continuous innovation in time series analysis is crucial. Refining existing techniques and introducing methodologies like explainable AI and advanced signal processing can significantly enhance BCI performance and usability, broadening applicability in fields such as healthcare and cognitive monitoring [7, 54].

5.2 AI-Enhanced Time Series Analysis

AI techniques in EEG time series analysis have enhanced BCIs' capabilities, particularly in interpreting complex temporal patterns. CNNs and deep learning models excel in feature extraction and classification, improving BCI accuracy and reliability. The CNN-VAE method exemplifies this by processing EEG signals through time, frequency, and channel integration, enhancing classification accuracy [78]. Deep learning approaches applied to minimally processed raw EEG data demonstrate high classification accuracy, suggesting effective raw data utilization [33].

Innovative methods like spiking neural networks enhance decoder performance by generating synthetic neural spike data, improving adaptability and generalization across users and tasks [79]. AI applications extend to practical implementations, such as gaming control, highlighting real-world applicability [80]. Future research should focus on improving data transmission reliability and refining classification models with real-world data [81]. Neural-based generative models also augment limited EEG data, facilitating comprehensive BCI development [29].

5.3 Time-Frequency Analysis and Feature Extraction

Time-frequency analysis and feature extraction are foundational in interpreting EEG signals, decomposing them into frequency components for detailed examination of neural activity. Techniques such as wavelet and short-time Fourier transforms provide a comprehensive EEG representation across time and frequency domains, isolating features critical for accurate BCI control [21, 36, 7].

Feature extraction reduces EEG data dimensionality, improving classification efficiency and accuracy by identifying relevant signal characteristics [47]. Advanced techniques, especially CNNs, capture complex EEG patterns, enhancing classification performance by detecting subtle neural patterns [50]. Integrating time-frequency analysis with advanced feature extraction techniques advances BCI systems, enabling accurate decoding of user intentions and facilitating seamless human-device interaction across applications [73, 13].

5.4 Challenges and Future Directions in Time Series Analysis

Challenges in BCI time series analysis include noise and variability in EEG signals, affecting signal-to-noise ratio (SNR) and performance [82]. Enhancing SNR is vital for accurate neural signal interpretation. Integrating additional signals like P300 and N400 into BCI paradigms can enhance robustness and specificity, offering additional neural markers for sophisticated interpretation [82].

Advancing analytical methods that adapt to EEG data's temporal dynamics is crucial for accurate user intention decoding. Machine learning algorithms, such as deep and reinforcement learning, enhance adaptability and generalization, creating scalable BCI systems for diverse users and environments. Techniques like Model-agnostic meta-learning (MAML) and self-supervised learning (SSL) improve domain adaptation in EEG tasks, essential for real-world applications requiring rapid calibration. Developing GRU-based models facilitates meaningful feature extraction, promoting system generalizability [48, 8, 65].

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6 Challenges and Future Directions

The evolution of brain-computer interfaces (BCIs) entails navigating a complex array of technical, ethical, and theoretical challenges. This section delves into critical issues such as data variability and signal noise, which significantly influence the reliability and efficacy of BCI systems. Addressing these challenges is crucial for advancing neurotechnology solutions.

6.1 Data Variability and Signal Noise

Processing EEG signals for BCI applications is hindered by data variability and signal noise, which lower the signal-to-noise ratio (SNR) and complicate accurate neural interpretation. External factors like eye movements further exacerbate these issues [50]. User and session variability also challenge consistent BCI performance due to inter-individual differences in brain anatomy and physiology [52]. Traditional machine learning algorithms often struggle with real-time interaction adaptation [4].

The reliance on hand-engineered features restricts deep learning models from fully exploiting raw EEG data, adding to variability challenges [53]. Implicit knowledge absent in AI training data further limits scientific discovery [6]. Refining preprocessing techniques to manage noise and variability is vital for enhancing real-time human intervention. Developing adaptive neural network classifiers that account for inter-individual variability is crucial for improving BCI accuracy and reliability [17]. Utilizing multiple datasets can mitigate small sample sizes and data noise, enhancing system reliability [21].

Recent advancements, such as model-agnostic meta-learning (MAML) and layer-normalization techniques, show promise in improving adaptability across tasks and individuals, facilitating quick calibration and real-time performance [48, 13, 56].

6.2 Computational Complexity and Real-time Processing

Integrating AI into BCIs presents challenges in computational complexity and real-time processing. The high dimensionality of EEG features generates substantial computational loads, impacting classification accuracy and responsiveness [83]. Real-time interaction is crucial in applications like gesture recognition and motor imagery tasks [46].

Shallow CNNs offer high classification accuracy with reduced computational demands compared to deeper networks [46], yet integrating multiple aggregation methods and ensuring classifier diversity remains challenging [84]. Traditional methods requiring numerous queries to train substitute models limit real-world application practicality [85]. Additionally, reliance on expensive lab equipment and inadequate real-time processing in current benchmarks exacerbate challenges [80].

Edge AI solutions like the bRIEDGE method aim to optimize real-time processing across devices, yet computational cost and latency challenges persist [86]. Deep transfer learning methods leverage cross-domain knowledge but may require longer prediction times, hindering real-time applicability [33].

Balancing model sophistication and computational efficiency is essential for advancing BCI systems. High-complexity models enhance control capabilities but increase processing demands, potentially hindering real-time performance. Optimizing algorithms to address EEG signal quality variability is crucial for robust functionality in non-invasive settings, advancing BCI technologies across applications from neurorehabilitation to communication aids [87, 13, 54, 88, 82].

6.3 Privacy and Security Concerns

BCI technologies integrated with EEG data present significant privacy and security concerns due to the sensitivity of neural data. The potential for misuse, including unauthorized access to cognitive states, necessitates stringent security measures [89]. Ensuring data integrity and accuracy is crucial for maintaining application reliability and protecting users from privacy breaches [90].

Storage and transmission of EEG data introduce additional security challenges, requiring advanced encryption techniques and secure data handling protocols to protect user information [58, 40, 13, 91]. Robust ethical guidelines and regulatory frameworks must govern the collection, storage, and utilization of neural data to mitigate privacy threats and foster trust and transparency in AI system development [40, 56, 91].

Prioritizing user consent and transparency is essential for informing individuals about data usage and protection. By fostering ethical responsibility and implementing strong security measures, the BCI field can advance while respecting user privacy and building public trust.

6.4 Model Generalization and Transferability

Model generalization and transferability pose significant challenges in BCI applications due to inherent EEG signal variability across subjects and conditions. This variability often results in models that perform well on training data but struggle to generalize to new data [7]. Specific feature extraction techniques further complicate generalization, limiting effectiveness across cognitive tasks or datasets [92].

The lack of transferability, where models trained on one user's data perform poorly on others, underscores the need for robust models accommodating individual differences [60]. Existing benchmarks often overlook EEG signal non-stationarity, leading to performance drops when models are applied to new data [93]. Generative models offer promise in addressing these challenges, yet questions remain regarding their generalizability [61].

Future research should enhance model generalization by exploring new architectures and leveraging advanced machine learning techniques. The LaBraM model, for instance, demonstrates potential for generalizing across multiple tasks by handling diverse configurations and capturing temporal and spatial features [51]. The universal EEG encoder approach reduces the need for task-specific models and manual feature engineering [49].

Addressing model generalization and transferability challenges is crucial for advancing BCI technologies. Developing models that adapt to EEG signal dynamics enhances robustness and applicability, leading to more reliable neurotechnology solutions. Further research is needed to improve generalizability across diverse populations, evidenced by challenges faced by approaches like FBCNet [47].

6.5 Ethical and Practical Considerations

Developing and deploying BCI technologies necessitate evaluating ethical and practical considerations to ensure responsible integration. A primary ethical concern involves the privacy and security of neural data, which is inherently sensitive. Unauthorized access to cognitive information poses significant risks, necessitating robust security measures [5].

Practical considerations include the need for efficient methods to ensure wireless BCI safety and robust AI algorithms for real-time data processing. Enhancing BCI usability, particularly through effective non-invasive methods, remains a research priority. Developing hybrid BCI systems and integrating EEG with other modalities are essential for improving signal quality and addressing deep learning models' vulnerabilities to adversarial attacks.

Addressing ethical and practical considerations is essential for advancing BCIs in a manner that respects user privacy and enhances accessibility. Prioritizing these considerations fosters responsible technology development, aligning with ethical principles and meeting diverse user needs across applications. Future research should focus on enhancing BCI tools' adaptability, improving training data quality, and exploring innovative applications to address neurotechnological challenges [23, 54, 94, 9].

7 Conclusion

The fusion of artificial intelligence (AI) with electroencephalography (EEG) in brain-computer interface (BCI) technologies signifies a groundbreaking shift in neurotechnology, offering substantial improvements in quality of life across various sectors. This survey highlights the transformative capabilities of AI-enhanced BCIs, advocating for continuous advancements in both technological and neuroscientific domains. Notably, neural models, especially in steady-state visual evoked potential

(SSVEP) tasks, exhibit the potential to produce synthetic EEG signals that enhance classification accuracy and generalization.

The deployment of deep neural networks (DNNs) has markedly advanced BCI systems, as evidenced by improved classification accuracies in models such as EEG-ITNet and ADNN for imagined speech-based EEG signals. These advancements underscore the critical role of AI methodologies in enhancing the robustness and effectiveness of BCIs, with innovative approaches like MAP-CNN demonstrating superior predictive performance for continuous muscle movements. Nevertheless, there is an ongoing demand for comprehensive metrics that extend beyond accuracy to evaluate system usability and efficacy.

Additionally, the survey emphasizes the necessity of propelling AI from perceptual to cognitive intelligence, which demands substantial progress in foundational theoretical research. The intricate relationship between activation proximity and categorical similarity in neuropsychological studies adds complexity to the development of sophisticated AI-driven BCIs.

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