EEG-Based Brain–Computer Interface: Fundamentals, Methods, Applications, and Challenges

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***Abstract*—The electroencephalogram (EEG)-based brain–computer interface (BCI) is important for Internet of Things (IoT) applications. EEG data can be used to control IoT devices for applications such as smart home automation or healthcare monitoring. EEG-based BCI systems are crucial for recognizing human brain thoughts and analyzing neurological diseases, enabling thought visualization, and improving accessibility for people with disabilities. With the rapid development of machine learning, including deep learning technologies, as well as the emergence of wearable and hybrid BCI systems, this field has progressed rapidly. Researchers have conducted extensive experiments to improve the accuracy of the system. This article provides a comprehensive review of BCI based on EEG, highlighting the fundamental principles of EEG signals, common acquisition devices, feature extraction techniques, and classification models, with a particular focus on the latest advances in deep learning. We also summarize available datasets and discuss the latest applications of EEG-based BCI in human–computer interaction (HCI) and neurological diseases. Finally, we highlight the main findings and explore future directions, offering researchers deeper insight to foster further progress in this field.**

***Index Terms*—Brain–computer interface (BCI), deep learning, electroencephalogram (EEG), feature extraction, Internet of Things (IoT), neurological diseases.**

NOMENCLATURE

ALS	Amyotrophic lateral sclerosis.
ADHD	Attention deficit hyperactivity disorder.
AE	Autoencoders.
BCI	Brain–computer interface.
CNN	Convolutional neural network.
CSP	Common spatial pattern.
CWT	Continuous wavelet transform.
EC	Emotion classification.
ECoG	Electrocorticography.
EEG	Electroencephalogram.
ErrP	Error-related potential.
FBCSPs	Filter bank CSPs.
fMRI	functional magnetic tesonance imaging.
fNIRS	functional near-infrared spectroscopy.
FT	Fourier transform.
FFT	Fast FT.
GAN	Generative adversarial network.
GCN	Graph convolutional network.
GNN	Graph neural network.
HCI	Human–computer interaction.
ICA	Independent component analysis.
IoT	Internet of Things.
KNN	K-nearest neighbors.
LDA	Linear discriminant analysis.
LSTM	Long short-term memory.
MEG	Magnetoencephalography.
MI	Motor imagery.
P300	P300 event-related potential.
PET	Positron emission tomography.
RF	Random forest.
PSD	Power spectral density.
RNN	Recurrent neural network.
RNNs	Recurrent neural networks.
SBL	Sparse Bayesian learning.
SCP	Slow cortical potential.
SR	Speech recognition.
SNN	Spiking neural networks.
SSA	Singular spectrum analysis.
SSAEP	Steady-state auditory evoked potential.
SSSEP	Steady-state somatosensory evoked potential.
SSVEP	Steady-state visual evoked potential.
STFT	Short-time FT.
SVM	Support vector machine.
WT	Wavelet transform.

Received 15 July 2025; revised 25 August 2025; accepted 21 October 2025. Date of publication 23 October 2025; date of current version 8 December 2025. *(Corresponding author: Mohammed A. A. Al-qaness.)*

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Digital Object Identifier 10.1109/JIOT.2025.3625060

I. INTRODUCTION

BCI is a complete system composed of both hardware and software. The hardware part includes signal acquisition, signal amplification, data transmission, and control devices, which are mainly responsible for the acquisition and transmission of brain signals. The software part covers signal preprocessing, feature extraction, classification, decoding,

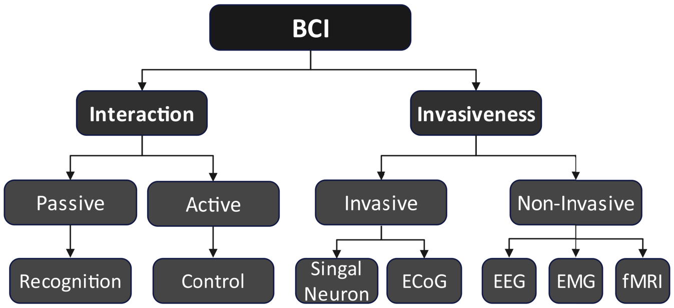


Fig. 1. Classification of types of BCI.

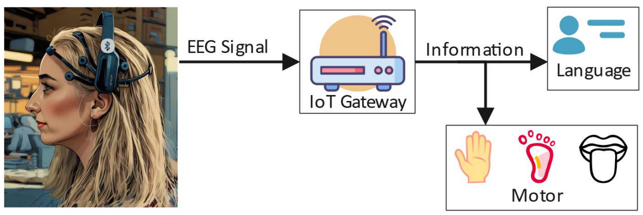


Fig. 2. EEG-based BCI system in IoT environments.

feedback mechanisms, and user interfaces, mainly for data processing, decoding, and user interaction. The emergence of BCI provides a direct communication pathway between the human brain and external electronic devices, making it an important interdisciplinary field between engineering [1] and neuroscience [2]. Only through the collaboration of hardware and software can the ultimate goal of a BCI system be achieved—recognizing brain states through brain activity [3], interacting with devices [4], even communicating and interacting with digital environments [5], and others [6], [7], [8], [9].

With the rapid development of the IoT, BCI systems can achieve seamless connectivity with a wide range of smart devices through wireless networks. For instance, electroencephalogram (EEG) signals acquired by BCI systems can be transmitted to the cloud via IoT platforms for remote processing [10], [11], or applied in intelligent healthcare [12], [13], and rehabilitation scenarios [14].

According to Lebedev and Nicolelis [15], BCI can be classified into two types: passive BCI and active BCI. Passive BCI assesses brain states, such as emotion, attention, or fatigue, by monitoring brain activity without directly controlling external devices. Active BCI, on the other hand, allows users to control devices like prosthetics or wheelchairs using their brain activity. Furthermore, invasive BCI [4] involves surgically implanting devices into the brain or its surface, offering high signal-to-noise ratios but facing risks such as postsurgery complications and long-term control challenges, which limit their development. Noninvasive BCI is the most common method for extracting brain signals, including fNIRS, EEG, PET, fMRI, and MEG. As shown in Fig. 1, each technique has certain advantages and disadvantages, and the best choice depends on the specific project requirements. The integration of IoT not only enhances the efficiency and flexibility of data transmission in BCI systems but also opens new possibilities for applications in telemedicine, smart rehabilitation, and intelligent living, as illustrated in Fig. 2.

Recently, due to the inability to capture brain signals and effectively decode thought signals, BCI research has not attracted many researchers. Brain activity studies were limited to exploring brain functions in clinical and laboratory settings. Meanwhile, signal decoding technologies and devices were either unavailable or very expensive, resulting in only a small number of research groups engaging in this area. However, with the development of science and technology, research in the BCI field has undergone significant changes over the past two decades, with major updates in key hardware and the emergence of large datasets, which have driven BCI system research. So far, EEG [16], [17], ECoG [18], and single-neuron recordings [19] appear to be the three effective methods for BCI systems. These methods provide good control channels and communication environments using relatively inexpensive devices. Among them, EEG is the most widely used in BCI systems because of its noninvasive nature, requiring only external electrodes placed on the scalp. EEG is a safer option than other techniques involving invasive procedures, such as ECoG or intracortical recordings. Its noninvasive nature also makes it reusable, making it ideal for long-term monitoring and rehabilitation applications. Furthermore, EEG allows for real-time monitoring of brain activity, as BCI systems depend on quickly detecting and interpreting brain signals for direct communication or control with external devices. This real-time capability makes EEG especially useful for applications that require immediate responses, such as controlling assistive devices. Although acquiring EEG datasets is costly and time-consuming, they hold significant value. A single publicly available dataset can serve as the foundation for many different research projects, leading to broader scientific studies.

BCI systems can use specific EEG patterns to decode user intent. Song et al. [20] presented a compact convolutional transformer, namely EEG Conformer, which, by combining convolutional modules and self-attention mechanisms, is able to extract both local and global features within an overall framework, improving EEG signal decoding, predicting EEG signal categories, and achieving advanced performance on three public datasets. Wang et al. [21] proposed a new approach called SBL for end-to-end Spatiotemporal-filtering-based single-trial EEG classification for decoding noninvasive EEG signals. The algorithm integrates spatial and temporal filters with a classifier into a linear matrix regression model. It optimizes it within the SBL framework, thereby achieving end-to-end EEG decoding.

As the accuracy of EEG signal recognition continues to improve, BCI systems are increasingly being adopted across diverse domains such as human–computer interaction, rehabilitation medicine, industrial applications, and virtual reality. In robotics, for instance, wearable exoskeletons rely on decoding MI signals to ensure safe and intuitive human–machine collaboration [22]. In healthcare, BCIs have been applied to aid stroke and paralysis patients in motor function recovery through prosthetic control and rehabilitation training [23], [24], [25], while lightweight deep learning frameworks have also been developed to classify psychological activities using

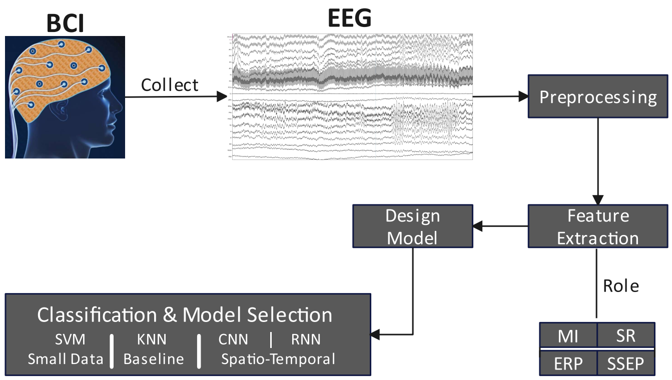


Fig. 3. Basic process of EEG signals.

separable CNNs enhanced with attention mechanisms [8]. Moreover, advanced BCI methods can support spinal cord injury patients in regaining movement capabilities [26], or assist individuals with severe speech and motor impairments, such as those with ALS, in communicating via EEG-based spelling systems [27]. Beyond medical applications, EEG plays a critical role in monitoring brain activity during anesthesia to prevent intraoperative awareness [28], and in entertainment settings, it has been employed to evaluate player skill levels and analyze neural responses during gaming tasks [29], [30].

The widespread application of BCI systems across various fields has increased efficiency and made life more convenient for people. With numerous research articles concluding that capturing brain signals through sensors is becoming increasingly common, this technology has significantly driven the development and progress of brain–machine interface science. EEG-based BCI is a key trend for future development. As illustrated in Fig. 3, EEG-based BCI can be broken down into five steps: signal acquisition, data preprocessing, feature extraction, model training, and classification.

A. Scope and Objectives of the Article

The studies included in this review were primarily collected through keyword-based searches related to EEG-based BCIs. Relevant studies from the past seven years were selected by searching several academic databases using combinations of keywords such as "EEG-based BCI + speed recognition," "MI," "P300," "SSVEP," "human–computer interactionHCI," "neurological diseases," and other related terms.

This review provides an in-depth analysis of the state-of-the-art techniques and methods in EEG-based BCI, including signal processing (such as denoising and feature extraction) and classification models, covering both traditional machine learning and deep learning approaches. Moreover, we compile and summarize currently accessible datasets and models, offering valuable resources to support further exploration in this field. In addition, the article discusses the wide range of application scenarios for EEG-based BCIs across various domains.

Furthermore, this article identifies and discusses key challenges currently faced in the field. Based on these challenges, it proposes potential future research directions, aiming to provide essential insights and guidance for the continued advancement of BCI technology.

B. Comparison to Previous Studies

In the literature, several review papers have been published in recent years. Many of them have focused on classification strategies from different perspectives. Table I compares recent review works, highlighting the main themes and limitations of each. In contrast, this article specifically emphasizes classification methods tailored for EEG-based BCIs.

The main contributions of this article can be summarized as follows.

1) A detailed exploration of advanced technologies and methodologies employed in EEG-based BCI systems, including signal processing techniques and classification algorithms. In addition, we catalog publicly available datasets and tools, offering valuable resources for researchers to support innovation and further development in this field.
2) An investigation into the diverse application scenarios of EEG-based BCI across various domains, with particular emphasis on their significant impact in enhancing HCI and medical rehabilitation.
3) The identification and comprehensive discussion of key challenges faced by EEG-based BCI, along with proposed future research directions aimed at addressing these challenges and promoting continued progress in the field.

C. Structure of the Article

To provide readers with an intuitive understanding of the current state of development of EEG-based BCIs and to address the existing challenges and future directions in HCI and medical diagnosis, this article reviews and summarizes recent research achievements. The overall framework is shown in Fig. 4. Section II highlights the fundamental knowledge and background. Section III explores the signal acquisition, preprocessing, feature extraction, and classification methods of EEG signals. Section IV presents common open-source datasets. Section V reviews the current applications of EEG signals. Section VI discusses the challenges EEG signals face in practical applications and outlines future directions, followed by the conclusion in Section VII.

II. Role of Electroencephalogram in BCI

EEG control signals can also be understood as decoding neurophysiological signals to allow the BCI to interpret human thoughts. These signals encompass a variety of types, including SCPs, P300 event-related potentials, MI, SR, ERRPs, SSVEPs, SSAEPs, and SSSEPs. Among these, MI, P300, SR, and SSVEP are more commonly utilized. Therefore, we discuss these in this article.

TABLE I
COMPARISON TO SOME OF THE EXISTING REVIEW PAPERS

Ref./ Year	Focus of the paper	Limitations
[31] 2021	-Four Applications of Transfer Learning in EEG Signal Analysis.	-Has not discussed EEG datasets -Not sufficiently address the issue of negative transfer
[32] 2022	-Use ML techniques and DL approaches to classify EEG-based BCI.	-Insufficient discussion on other EEG paradigms. -Lack in-depth discussion on emerging technologies.
[33] 2023	-Explore the latest developments in BCI and motor control for rehabilitation.	-Effectiveness of the preprocessing techniques has not been explored thoroughly. -Has not discussed EEG datasets.
[34] 2024	-The application of different GNN architectures in EEG classification was compared.	- No systematic comparison with other variant graph attention networks and graph transformers.
[35]	Non-Invasive Brain-Computer Interface Control of External Devices: Clinical, Rehabilitation, and Algorithmic Aspects	No comparative analysis of advantages across various algorithms
[36] 2025	MI Signal Decoding Techniques, Deep Learning Algorithms, Clinical/Device Applications	Limited to literature from 2017–2023, without quantitative exclusion of non-EEG modalities
Our	-Collecting devices -Feature extraction -Classification models -Public datasets -Current applications -Challenges and future trends	

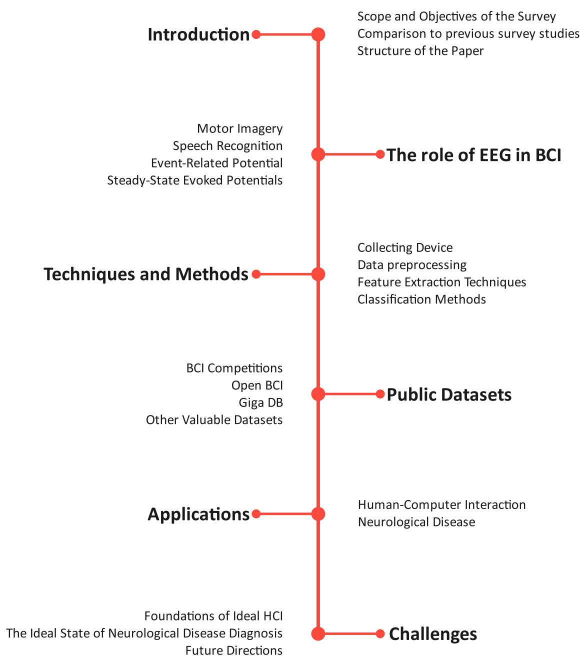


Fig. 4. Framework of the article structure.

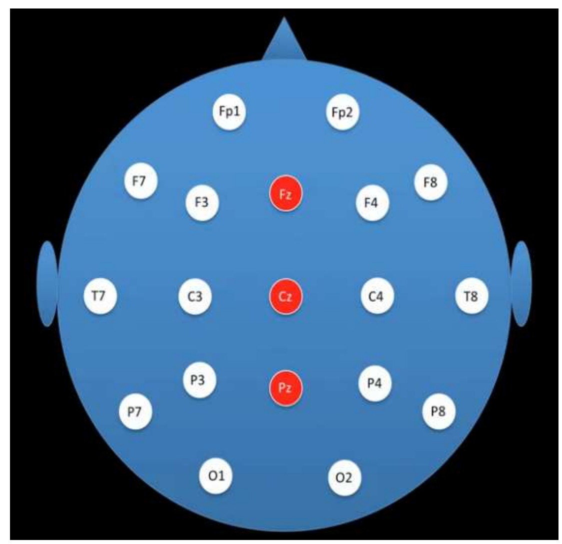


Fig. 5. Electrodes positions. F: Frontal, C: Central, and P: Parietal, T: Temporal, O: Occipital.

A. Motor Imagery

MI [37] is a cognitive process where one imagines the movement of a body part without actually moving that part. It can alter the neural patterns in the primary sensory–motor areas, closely resembling actual movement execution. BCI decodes MI tasks from EEG and aligns them with specific scalp regions. MI is most strongly influenced by the alpha and beta frequencies of EEG. As experience with EEG recording increases, the 10–20 systems [38], depicted in Fig. 5, are recommended as the standard electrode placement layout. The movement imagery for the right hand originates from the C3 region of the brain, for the left hand from the C4 region [39], and for foot movement imagery from Cz [40]. Therefore, the BCI system can modulate the movement of these body parts through imagination.

B. Speech Recognition

SR [41] refers to imagining a sentence in the brain without actually speaking it, and then converting the physiological signals into natural language. During experiments, it was found that the reading phase activated brain regions linked to language processing, such as the left temporal lobe and the inferior frontal gyrus [42]. These regions are also engaged during the imagined speech, exhibiting similar neural representations. Therefore, this traditional paradigm demonstrates a key advantage in signal processing. By constructing deep learning models, semantic information from the EEG can be output as the semantic categories of sentences corresponding to imagined speech.

C. Event-Related Potential (ERP)

ERP is a noninvasive neurophysiological technique recorded through EEG to study the brain's real-time response to specific stimuli or cognitive events [43], [44]. It involves repeatedly presenting the same type of stimulus (such as visual, auditory, or motor tasks) and time-locking and averaging the EEG signals to extract stable brain components associated with the event. The core advantage of ERP lies in its millisecond-level temporal resolution, which allows precise tracking of dynamic changes in cognitive processes. For example, N170 [45] reflects face recognition, mismatch negativity (MMN) [46] characterizes auditory deviation detection, error-related negativity (ERN) [47] is associated with error monitoring, and P3 [48] involves attention resource allocation and decision-making. These components, separated by different wave techniques to isolate overlapping neural activity, serve as crucial tools for revealing complex brain functions such as perception, memory, language, and motor control.

D. Steady-State Evoked Potentials

Steady-state evoked potentials (SSEPs) are induced by stable frequency oscillatory stimuli [49]. SSEP can be classified into SSVEP, SSAEP, and SSSEP, based on the type of stimulus (visual, auditory, and somatosensory).

SSVEP-based BCI is triggered by visual stimuli of constant frequency [50]. When a user fixates on a visual stimulus flickering at a fixed frequency (usually between 3.5 and 75 Hz), his EEG signal will produce synchronous oscillations at the stimulus frequency or its harmonics. This characteristic makes SSVEP an efficient information transfer paradigm in BCI. For example, in BCI spellers, targets flickering at different frequencies can be decoded as the user's selected commands, allowing for high information transfer rates.

SSAEPs are neural electrical responses induced by repetitive acoustic stimuli [51], which can be recorded using EEG. These responses are characterized by steady-state analysis that captures neural responses in the auditory pathway that are synchronized with the stimulus frequency.

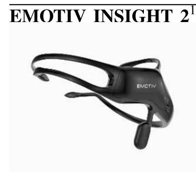
SSSEPs are steady-state EEG signals induced by applying specific frequency tactile stimuli (such as vibration) to the somatosensory system (e.g., fingertips) [52]. By exploiting the "resonance" characteristics of the human sensory system, the somatosensory area is continuously stimulated within a specific frequency range of 17–35 Hz, generating stable periodic responses in the EEG. The advantage of SSSEP is that it does not rely on the visual system or voluntary eye movement control, making it suitable for patients with visual impairments. By extracting signal features using a phase-locked amplifier and combining them with LDA, subjects can actively modulate the SSSEP amplitude through attention, enabling binary classification control in BCIs. SSSEP provides a novel control strategy for BCIs based on the somatosensory channel.

III. Techniques and Methods

A. EEG Collecting Device

To understand the thoughts of Homo sapiens, few places are more suitable than the brain itself. There are many ways to detect changes in brain activity, but none are as direct as

TABLE II
Typical EEG Signal Acquisition Equipment

Device	Communication	Channels
EMOTIV MN8[1] 	BT5	2
Muse S Headband[2] 	BT4.2 & USB	4
EMOTIV INSIGHT 2[1] 	BT5.2 & USB-C	5
EMOTIV EPOCX[1] 	BT5 & USB	14
EMOTIV FLEX 2[1] 	BT5 & USB-C	32
NE Enobio Dx[3] 	Wi-Fi & USB	8,20,32
NeuroScan Grael[4] 	MDR80	32,64,128,256

EEG. Therefore, stable and accurate EEG signal acquisition is the foundation of noninvasive BCI technology.

Table II summarizes common EEG acquisition devices. Typically, EEG systems process 8 to 64 channels, ECoG systems process 32 to 192 channels, and single-unit recordings may handle 100 to 300 channels [53].

When using acquisition devices, the first consideration is the number of channels. More channels generally mean more data, which is usually a good thing, but it is not always

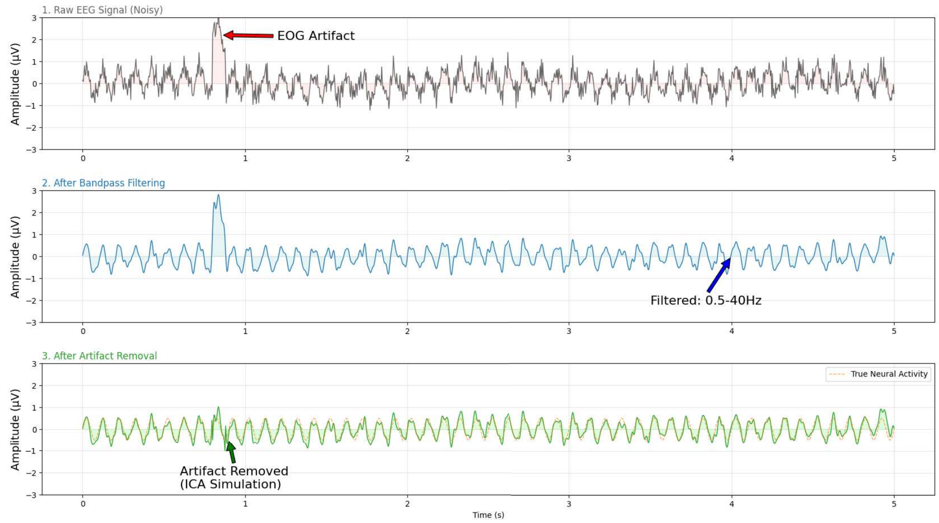


Fig. 6. EEG preprocessing: filtering and artifact removal.

necessary. Additionally, according to the Nyquist theorem, for any signal to be detected, a sampling rate of at least twice the frequency of the signal is needed. To detect the fastest characteristic signals with EEG, a sampling rate of 128 Hz is usually sufficient. Faster sampling rates generate more detailed data, so, when conditions allow, it is better to have more data rather than less. Furthermore, amplifiers are typically the most expensive part of EEG equipment. They are needed to amplify the signals recorded from the electrodes, making the data visible and analyzable. This is one of the key aspects of EEG equipment that ensures data quality.

B. Data Preprocessing

To provide more precise and more accurate data inputs for subsequent analysis and modeling, preprocessing is a key step in ensuring the reliability and accuracy of the results. Raw signals often contain noise, artifacts, and other unwanted components, which can interfere with the accuracy of the analysis. Therefore, the primary goal of preprocessing is to remove or reduce these interferences, allowing the valuable signals to stand out and ensuring that the data is suitable for later analysis or classification tasks as shown in Fig. 6.

EEG signals are inevitably contaminated by physiological artifacts such as blinking, eye movements, and muscle activity [54]. To address these challenges, various signal processing and pattern recognition techniques have been developed to extract meaningful information from noisy recordings. Classical approaches include filtering and ICA for artifact removal [55], while more advanced strategies leverage machine learning, such as variational AEs (VAEs) for denoising [56]. Signal transformation techniques also play a crucial role in feature extraction: WT enables capturing time-domain characteristics across multiple frequency bands [57], whereas FT converts signals into the frequency domain to examine power distribution [58]. Furthermore, event-related analysis segments EEG data around task-specific stimuli to reveal neural dynamics before and after the event [59].

Dimensionality reduction techniques such as LDA and principal component analysis (PCA) are often employed to reduce the complexity of signal features, thereby lowering computational costs and eliminating redundant information. A widely used spatial feature extraction method is CSPs [60], which can derive the most discriminative spatial projections from multichannel EEG signals and have been extensively applied in BCI research. In recent years, various improved algorithms have been proposed to enhance their generalization ability and robustness. For example, Cherloo et al. [61] introduced the ensemble regularized common spatial spectral patterns (Ensemble RCSSPs), which integrate ensemble learning and regularization strategies to reduce the risk of overfitting, outperforming traditional CSP and other variants. Meanwhile, FBCSP and its deep learning extensions have also been widely adopted. Mammone et al. [62] proposed the AE-FBCSP, which combines filter banks with a deep AE framework to extract discriminative spatial features from high-density EEG for MI decoding.

Beyond CSP-based methods, other approaches have been developed to address diverse EEG decoding tasks. For instance, Deng et al. [63] proposed the cross-subject dual-domain fusion network (CSDuDoFN), which integrates task-related component analysis (TRCA) and task-discriminant component analysis (TDCA), and has been applied to one-shot SSVEP (O-S SSVEP) classification for data augmentation. Ieracitano et al. [64] introduced the CWT, which enables the extraction of time–frequency features for the automatic classification of Alzheimer's disease (AD), mild cognitive impairment (MCI), and healthy controls. Anuragi et al. [65] proposed the FBSE-EWT framework, which leverages enhanced time–frequency representations and has demonstrated strong performance in seizure detection. ICA remains one of the most widely used independent-source separation technique for removing EEG artifacts. Bigdely-Shamloet al. [66] proposed the PREP pipeline, which, after data resampling, provides a standardized preprocessing framework to eliminate

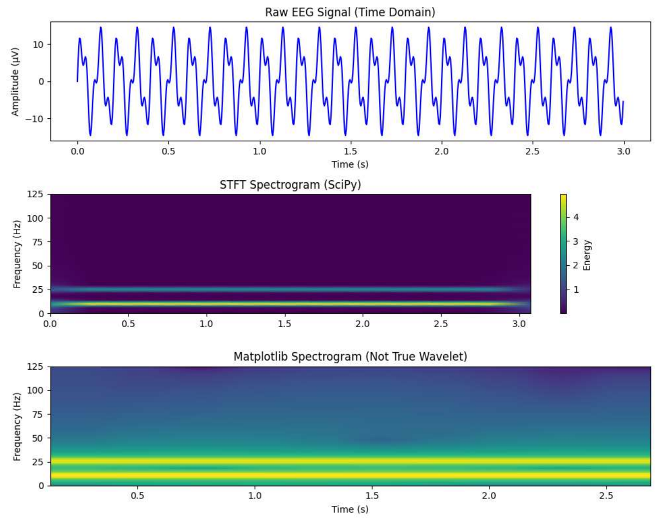


Fig. 7. Feature extraction: raw signal and spectral representation.

line noise, robustly rereference signals to an estimated average reference, and automatically detect and interpolate bad channels. By leveraging these representative feature extraction and preprocessing techniques, EEG decoding performance can be significantly improved in both BCI and clinical applications.

C. Feature Extraction Techniques

Due to the complexity and nonstationarity of EEG signals, directly applying them for automatic feature learning may lead to suboptimal performance. Therefore, appropriate feature extraction is necessary, as show in Fig. 7. Traditional EEG signal analysis typically involves three main stages: first, extracting feature information from the raw signals; second, selecting and retaining task-relevant features; and third, classifying the selected feature set by constructing a classifier. In the feature extraction process, besides the classical frequency band power and time-domain features, recent studies have explored other types of features, such as connectivity features of brain networks and higher-order statistical features [67], [68]. Moreover, several studies have combined different types of features to extract more information. For instance, Cai et al. [69] presented a feature extraction method depending on window Kullback–Leibler divergence (WKLD) and discrete wavelet analysis. Additionally, a triple-stream skipped feature extraction module, combined with a dual-parallel attention transformer network leveraging both EEG and fMRI modalities, was developed to enhance seizure detection accuracy [70].

In feature selection, besides using filter [71] methods to eliminate irrelevant features, wrapper [72] methods and ranking algorithms were also developed to optimize the selection of feature subsets. During the feature classification stage, efficient methods such as deep learning and Riemannian geometry were used to boost classifier performance, enhancing classification accuracy from multiple dimensions [73], [74]. Notably, some algorithms, such as neural networks and embedded methods, can perform joint optimization during feature extraction and classification [75]. In most traditional approaches, it is usually assumed that the training and test data share the same distribution, but this assumption is often difficult to hold in practical applications. This distribution bias makes the difference between training data and real-world data significant, leading to high costs in model reconstruction and data retrieval, which in turn limits the broad application and deployment of algorithms [76]. Recently, methods such as global redundancy minimization in orthogonal regression have been proposed to effectively assess the dependencies between all EEG features from a global perspective, selecting a discriminative and nonredundant EEG feature subset for emotion recognition [77].

A comparative summary of representative feature extraction methods is presented in Table III. Each method reflects different emphases in feature design. For example, CSP and FBCSP primarily rely on spatial filtering, while FFT, STFT, and CWT focus on frequency or time–frequency transformations. CNN-based models, when combined with such transformations, significantly outperform classical methods on Dataset 2b. This highlights the critical role of informative and discriminative feature representations in boosting classification performance for nonstationary EEG signals.

TABLE III

Comparative Analysis of Feature Extraction Methods

Feature Extraction	Average (%)	
	BCI IV 2a [78]	BCI IV 2b [79]
CSP [80]	50.30	52.00
FBCSP[80]	56.90	59.90
CSP-CNN [81]	-	79.9
FFT-CNN [81]	-	79.6
STFT-CNN [81]	-	81.9
CWT-CNN [81]	-	84.1

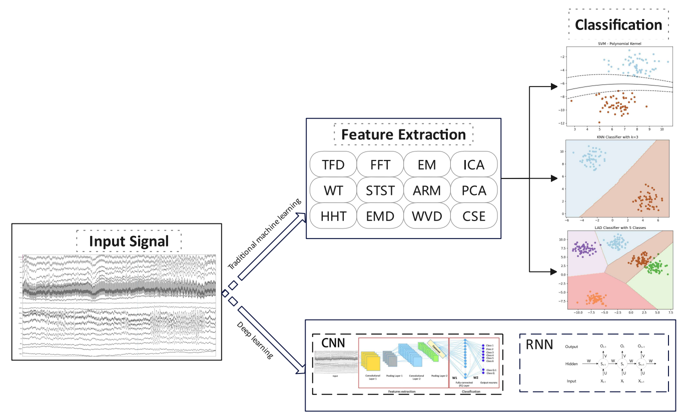


Fig. 8. Specific processes of machine learning and deep learning.

D. Classification Methods

Based on the features extracted from EEG signals, different classifiers can be employed to classify MI, P300, and SSVEP signals. Over the years, researchers have proposed various classification methods, such as SVM, KNNs, RF, and LDA, each demonstrating its own advantages and applicability in different fields and applications. The specific steps of the classification process are in Fig. 8. Compared to traditional machine learning methods, deep learning significantly enhances model generalization by learning multilevel abstract representations of data through multilayer network models. When using feature-based classifiers such as LDA and SVM, manual feature extraction is required. In contrast, deep learning models adopt an end-to-end learning approach, automatically learning meaningful features from raw data and directly performing classification or mapping the data into continuous output sequences. This characteristic has led to deep learning gaining widespread attention and achieving significant success in applications such as EEG signal recognition. In what follows, we introduce commonly used classifiers in machine learning, such as SVM and KNN, as well as popular deep learning architectures like CNNs and RNNs.

1) SVM: SVM is a traditional machine learning method widely used for binary classification tasks, and it still plays a crucial role in BCI research. SVM is effective in handling small sample data, exhibits good generalization ability, and can solve nonlinear classification problems. However, since EEG signals are complex, nonperiodic time series data, their data structure differs significantly from traditional linear data, making the selection of an appropriate kernel function and penalty parameter (C) challenging in practical applications. If not chosen correctly, these parameters can significantly reduce the model's classification accuracy. Using particle swarm optimization (PSO) to select the optimal kernel and penalty parameters has been shown to improve classification accuracy compared to traditional SVM methods [82].

2) KNN: KNN algorithm is a classification and regression method based on distance metrics. It predicts the class or value of a new sample by calculating the distances between the sample and each training sample, selecting the k closest neighbors, and using their labels to make the prediction. KNN is a nonparametric method, meaning it does not assume any specific distribution of the data, making it very effective for handling complex data in some cases. Its simplicity makes it suitable for classification tasks in smaller feature spaces [83] and can also be used for regression tasks [84].

3) CNN: CNNs are widely recognized in fields like computer vision and SR, and have demonstrated strong potential in BCI and EEG signal processing. In EEG signal analysis, CNNs not only effectively extract the spatiotemporal features of EEG data, but also play a crucial role in BCI applications, driving the development and application of EEG feature extraction techniques [85]. CNNs construct deep network architectures by stacking multiple convolutional layers, pooling layers, and other components. The introduction of batch normalization and residual blocks has significantly alleviated the model degradation problem in deep neural networks. These advancements enable deep networks to scale from dozens to hundreds or even thousands of layers, greatly improving model performance and generalization ability, making CNNs suitable for various datasets and tasks [86].

In EEG signal processing, CNNs have become the dominant deep learning architecture, widely applied to tasks such as MI, ERP, P300, and SSVEP. Despite their strong capability in feature learning and pattern recognition, CNNs are prone to overfitting in small-sample scenarios, which can compromise classification accuracy. To address the challenges posed by individual variability and data scarcity in EEG-based BCIs, several end-to-end deep learning frameworks have been proposed. Autthasan et al. [87] introduced MIN2Net, which integrates deep metric learning into a multitask AE to simultaneously learn compact and discriminative latent representations while performing classification, yielding significant improvements in cross-subject performance. Liu et al. [88] proposed FBMSNet, which employs a filter bank to construct multiview spectral representations, combined with multiscale convolutions and spatial filtering to extract discriminative features, and further incorporates joint supervision of cross-entropy and center loss to maximize interclass separability and intraclass compactness. More recently, to further alleviate cross-subject variability and overfitting risks, Autthasan et al. [89] subsequently proposed MixNet, which integrates spectral–spatial feature extraction via FBCSP with the multitask architecture of MIN2Net, and introduces an adaptive gradient blending mechanism to dynamically regulate the learning pace of multiple tasks while mitigating overfitting. Experimental results demonstrated that these methods significantly outperform existing algorithms across multiple public datasets, with particularly strong performance in low-density EEG classification tasks, thereby opening new avenues for lightweight and portable BCI applications as well as IoT-based wearable devices.

The powerful feature learning capabilities of CNNs have enabled state-of-the-art performance in EEG recognition tasks. With the continuous optimization of network architectures and the integration of multitask learning and adaptive mechanisms, CNNs have achieved further improvements in both accuracy and generalization, providing strong support for the rapid advancement of EEG analysis and BCI technologies.

4) RNN: RNNs are deep learning models specifically designed for processing sequential data. Unlike traditional feedforward neural networks, RNNs have an internal state (memory) that allows them to use this state to process input sequences, thereby maintaining memory of previous inputs. This makes RNNs particularly well-suited for applications that require context and data sequence understanding, such as natural language processing (NLP), SR, and time series forecasting. The design of RNNs enables them to learn temporal dependencies in sequences, meaning the current output is influenced by previous inputs.

Although RNNs have significant potential, they faced challenges in practical applications due to the vanishing gradient problem. To address this issue, LSTM networks were introduced [90], enabling RNNs to effectively learn long-term dependencies. Additionally, gated recurrent unit (GRU) [91] offers a simplified version of LSTM, while still maintaining strong performance. With the advancement of these techniques, RNN architectures have been widely applied across various fields and continue to push deep learning models toward more complex tasks. For instance, Roy et al. [92], Idrees et al. [93], and Mao et al. [94] proposed ChronoNet, designed to efficiently process EEG data, particularly for diagnosing brain-related diseases (such as epilepsy) and detecting abnormal brain activity.

5) AEs: AEs [95] are unsupervised learning methods that extract key features from data by adjusting the hidden layer weights to make the input and output as close as possible, similar to PCA. However, traditional AEs tend to simply copy the input vector to the output during training, leading to poor model performance, especially when the distribution of training and test samples is inconsistent. In EEG signal processing, due to the high dimensionality and correlations between dimensions, traditional AEs struggle to effectively extract features.

CNNs overcome this challenge by using local perception (receptive fields) and parameter sharing to extract local features from EEG signals. Through convolution and downsampling, CNNs reduce feature dimensionality while preserving key features, thus improving model performance. To address the limitations of traditional AEs, Wen and Zhang [96] proposed the AE-CDNN model, which combines CNN and AE techniques. This model iteratively extracts features through convolution kernels and downsampling, ultimately reducing the number of features and optimizing feature learning for EEG signals.

6) Other Valuable Models: The success of Transformers [116] in the field of NLP can be attributed to their superior ability to handle long-range dependencies, offering significant advantages over traditional CNNs and RNNs. This capability to process long-range dependencies is equally crucial for the analysis of EEG signals, as EEG signals have clear time-series characteristics. The EEG Conformer, proposed by Song et al. [20], combined Transformers with CNNs to capture global dependencies in the time domain. This approach has demonstrated exceptional performance in EEG decoding tasks, effectively enhancing the accuracy of EEG signal recognition. Xie et al. [117] presented a deep learning framework that includes five models, combining Transformer models with CNNs, and achieved high accuracy in MI classification tasks.

Lawhern et al. [85] presented EEGNet, a compact CNN. Following this, other researchers integrated well-established frameworks in their respective fields, proposing models that achieve high accuracy in specific domains. Song et al. [118] presented a practical end-to-end framework called LSDD-EEGNet for EEG-based depression detection. Deng et al. [100] developed the advanced TSGL-EEGNet model for MI-based BCIs. Schneider et al. [119] suggested the Q-EEGNet model, a high-energy-efficiency 8-bit quantized parallel implementation of EEGNet for marginal MI BCIs. Huang et al. [97] presented an EEG classification network using the Hilbert–Huang transform (HHT), known as separable EEGNet (S-EEGNet), and a separable CNN with bilinear interpolation. Ghosh et al. [120] presented deep oscillatory neural networks (DONNs) and oscillatory CNNs (OCNN), which integrate Hopf oscillators to capture the oscillatory nature of EEG signals, offering a biologically plausible and efficient approach for EEG classification tasks. These models achieved competitive accuracy with fewer parameters. Wu et al. [121] presented a multimodal learning model for EEG and eye movement signals, consisting of offset-reconstruction convolution, eye-movement convolution, and multimodal channel attention dense modules. This model simultaneously records EEG and eye movement signals for image classification and target localization.

It is worth noting that whether models are trained in a subject-dependent or subject-independent manner is crucial, as this distinction directly affects the generalization capability and practical applicability of EEG-based BCIs. Subject-dependent schemes, where training and testing are performed on data from the same individual, often yield higher accuracy due to reduced intersubject variability. However, such approaches have limited practical value, since models may fail when exposed to unseen subjects. In contrast, subject-independent training schemes, though typically associated with lower accuracy, are more challenging yet essential for real-world deployment, as they evaluate the robustness of algorithms under cross-subject conditions. This distinction is particularly relevant in applications such as affective computing, MI, and clinical diagnostics, where reliable performance across diverse populations is critical. Therefore, the choice between subject-dependent and subject-independent training not only influences reported performance metrics but also determines the translational potential of the proposed methods. Table IV presents examples of some of the classification methods used in recent years.

IV. Public Datasets

Public datasets provide standardized benchmarks for evaluating the performance of models and algorithms, making it possible to compare different methods under the same experimental conditions, thus ensuring the comparability and consistency of evaluation results. Moreover, public datasets significantly enhance the reproducibility and transparency of research, allowing other researchers to conduct validation experiments based on the same data, which strengthens the reliability and scientific rigor of the studies. These datasets typically cover a diverse range of tasks and scenarios, supporting comprehensive assessments of a model's generalization ability across various conditions.

Public datasets are usually collected and annotated by authoritative organizations or professional teams, effectively reducing the data collection costs for researchers, accelerating scientific progress, and promoting deep collaboration and technology transfer between academia and industry in Table V. Through open sharing platforms, researchers can more easily exchange knowledge and innovate, further advancing breakthroughs in the field.

A. BCI Competitions

The BCI Competitions [123] aim to provide the scientific community with high-quality neuroscience data, attracting scientists and scholars from diverse backgrounds and nationalities, including both senior experts and students. Participants drive advancements in the field by evaluating the performance of algorithms across various BCI tasks. The core goal of all competitions is to challenge new paradigms, handle complex data, and foster innovation and development in BCI research.

BCI Competition III [122] includes multiple datasets focusing on brain signal classification and decoding, covering

TABLE IV
EXAMPLES OF CLASSIFICATION MODELS USED IN RECENT YEARS

Ref./Year	Method	Dataset	Task	Training Schemes	Accuracy
[97] 2020	Separable-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	77.9%
		DEAP	EC-Valence (2 classes)	Subject-independent	89.91%
			EC-Arousal (2 classes)	Subject-independent	88.31%
[98] 2020	Regularized-GNN	SEED	ER (3 classes)	Subject-dependent	94.24%
				Subject-independent	79.37%
		SEED-IV	ER (4 classes)	Subject-dependent	85.3%
				Subject-independent	73.84%
[99] 2020	Temporal-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	77.35%
[100] 2021	TCSGL-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	78.96%
		BCI III IIIa	MI (4 classes)	Subject-independent	85.30%
[101] 2021	Temporal-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	83.73%
		HGD	MI (4 classes)	Subject-independent	94.41%
[102] 2022	Temporal-CNN	PhysioNet	MI (4 classes)	Subject-dependent	93.06%
				Subject-independent	88.57%
		High Gamma	MI (4 classes)	Subject-dependent	96.24%
				Subject-independent	80.89%
[103] 2022	Temporal-CNN	BCI IV IIa	MI (4 classes)	Subject-dependent	78.74%
				Subject-independent	69.64%
		OpenBMI	MI (2 classes)	Subject-dependent	71.91%
				Subject-independent	73.52%
[104] 2023	IF-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	78.21%
		OpenBMI	MI (2 classes)	Subject-dependent	71.22% ± 18.85%
				Subject-independent	71.23% ± 16.05%
[105] 2023	2D-LSTM-CNN	BCI IV IIb	MI (2 classes)	Subject-independent	75.40%
[106] 2023	Attention-CNN	BCI IV IIa	MI (4 classes)	Subject-dependent	86.87%
				Subject-independent	79.39%
		BCI IV IIb	MI (2 classes)	Subject-dependent	87.26%
				Subject-independent	87.81%
		OpenBMI	MI (2 classes)	Subject-dependent	87.26%
				Subject-independent	65.26%
[107] 2024	Conditional-GAN	BCI IV IIa	MI (4 classes)	Subject-independent	74.2%
		BCI III IVa	MI (2 classes)	Subject-independent	89.8%
[108] 2024	No-Filter-EEG-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	81.05%
			MI (2 classes)	Subject-independent	93.56%
		BCI III IIb	MI (2 classes)	Subject-independent	88.40%
[109] 2024	Transformer-GCN	Physionet	MI (4 classes)	Subject-independent	97.43%
[110] 2024	Domain Generalization	BCI IV IIa	MI (4 classes)	Subject-independent	81.79%
		BCI IV IIb	MI (2 classes)	Subject-independent	87.12%
		OpenBMI	MI (2 classes)	Subject-dependent	78.37%
				Subject-independent	76.94%
[111] 2025	Transformer-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	83.22%
		BCI IV IIb	MI (2 classes)	Subject-independent	89.70%
		HGD	MI (4 classes)	Subject-independent	95.89%
[112] 2025	Attention-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	84.73%
[113] 2025	Multi-model Struct	EEG-fNIRS	MI (2 classes)	Subject-independent	92.20%
			GT (2 classes)	Subject-independent	85.30%
[114] 2025	Attention-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	81.17%
		BCI IV IIb	MI (2 classes)	Subject-independent	89.83%
		HGD	MI (4 classes)	Subject-independent	95.49%
[115] 2025	Sinc-Attention-CNN	BCI IV IIa	MI (4 classes)	Subject-independent	80.21%
		BCI IV IIb	MI (2 classes)	Subject-independent	84.02%
		OpenBMI	MI (2 classes)	Subject-independent	72.70%

MI: Motor Imagery, EC: Emotion Classification, GT: Gripping Tasks, GAN: Generative Adversarial Network, GCN: Graph Convolutional Network, GNN: Graph Neural Network, LSTM: Long Short-Term Memory.

various subtasks such as MI and P300 speller tasks. These datasets are applicable to both within-subject and cross-subject scenarios. For instance, Dataset IVb is used for MI classification tasks, specifically focusing on uncued classifier applications.

BCI Competition IV [123] expands on this by including several subdatasets targeting MI, speller tasks, and brain signal decoding. For example, Dataset 1 deals with continuous EEG signal classification, distinguishing MI from resting states. Dataset 2 focuses on EEG signal classification affected by eye movement artifacts, with tasks related to MI in different body parts. Dataset 3 involves classifying wrist movement directions from MEG signals. Dataset 4 requires fine spatial resolution for ECoG signal classification, specifically targeting flexion and extension movements of the five fingers.

B. OpenBCI Datasets

OpenBCI provides a series of EEG datasets generated using its hardware, including both raw EEG signals and processed data. These datasets are publicly available and related to EEG and BCI research, aiming to provide resources for researchers to develop and evaluate BCI algorithms. The datasets cover a variety of experimental tasks, EEG signal types, and application scenarios, making them suitable for different research needs, such as MI, brain signal decoding,

TABLE V
AVAILABLE PUBLIC DATASETS FOR EEG

Name	Dataset	Classes	Subjects	Trials	Channels	Download
BCI Competitons III	II (P300 speller paradigm) [122]	36	2	100	64	https://www.bbci.de/competition
	IIIa (MI, multi-class)	4	3	60	60	
	IIIb (MI with non-stationarity problem)	2	3	60	2 bipolar	
	IVa (MI, small training sets)	2	2	280	118	
	IVb (MI, uncued classifier application)	2	1	210	118	
	IVc (MI, time-invariance problem)	2	1	210	118	
	V (Mental imagery, multi-class)	3	3	-	32	
BCI Competitons IV	I (MI, uncued classifier application) [123]	2	7	-	64	https://www.bbci.de/competition
	IIa (MI)	4	9	288	22	
	IIb (MI)	2	9	160	3 bipolar	
GigaDB	MI (EEG-MI dataset) [124]	2	52	100 / 120	64	https://gigadb.org/dataset
	OpenBMI [125]	2	54	200	62	https://gigadb.org/dataset
	SSVEP (Binocular swap exp.) [126]	40	35	200	9	https://gigadb.org/dataset
	SSVEP (Binocular vision exp.)	40	35	200	9	
	SSVEP (Checkerboard arrangement exp.)	40	35	200	9	
SEED	IV (Emotion Recognition) [127]	4	15	24	62	https://bcmi.sjtu.edu.cn
	V (Emotion Recognition) [128]	5	20	24	62	
	VII (Emotion Recognition) [129]	7	20	20	62	

and attention monitoring. OpenBCI also boasts a large and active user community, where members share datasets related to mental state classification, MI, and other BCI tasks, further fostering collaboration and innovation in the field of BCI.

C. GIGA DB

GIGA DB is an open academic platform specifically designed for storing and sharing large-scale biological datasets [126]. It provides researchers worldwide with a high-quality environment for data storage, management, and sharing, supporting the upload and access of various data types. GIGA DB aims to promote the open sharing and reuse of scientific data, fostering innovation and collaboration within the research community. Researchers can access and analyze large datasets from different experiments and projects through the platform, accelerating scientific discoveries and enhancing the transparency and reproducibility of research.

D. Other Valuable Datasets

Zhang et al. [41] proposed the Chinese Imagined Speech Corpus (Chisco), which contains high-density EEG recordings of imagined speech from healthy adults, with over 20 000 sentences. Each participant's EEG data exceeds 900 min, making it the largest individual neural language decoding dataset to date. The stimuli used in the experiment include more than 6000 daily phrases spanning 39 semantic categories, covering almost all facets of everyday language.

Miltiadous et al. [130] introduced a dataset containing conventional EEG data, which includes scalp EEG recordings from AD, frontotemporal dementia, and healthy subjects. The dataset consists of 36 Alzheimer's, 23 cases of frontotemporal dementia, and 29 age-matched healthy individuals, along with the Mini-Mental State Examination (MMSE) scores for each participant. The EEG signals were captured using a monopolar montage. The dataset is provided in the standard BIDS format, including both raw and preprocessed EEG data. During preprocessing, common denoising techniques, including artifact subspace reconstruction and ICA, were applied.

V. APPLICATIONS

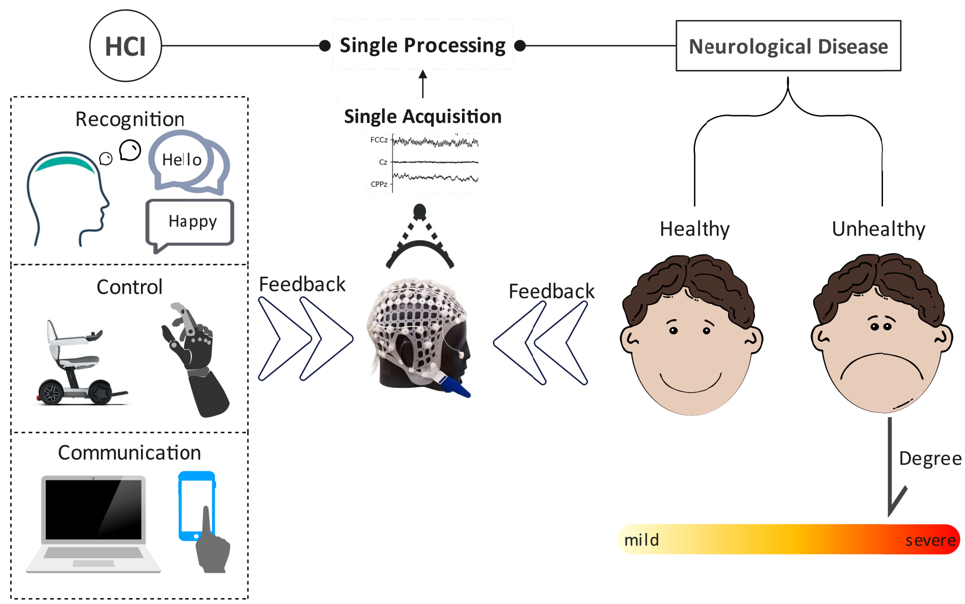
EEG plays a vital role in both HCI and neurological disease diagnosis. In HCI, brain signals are commonly employed in areas such as SR [131], rehabilitation [132], emotion detection [133], and user experience evaluation [134]. In neurological disease diagnosis, EEG has become an important tool for doctors and researchers in diagnosing brain function disorders, including conditions like epilepsy [135], [136], cerebral palsy [137], schizophrenia [138], [139], AD [140], and MCI [141].

A. Human–Computer Interaction

HCI [142] is an interdisciplinary research field that explores the design and application of computer technology, particularly the interaction between users and computers. Initially, HCI focused primarily on the design of computer systems and user operations. However, with the continuous advancement of information technology, the scope of HCI research has expanded to encompass nearly all forms of technological devices and platforms, including smartphones, virtual reality, IoT devices, and other embedded systems. The applications of HCI are illustrated in Fig. 9(a). The goal of HCI is to enhance the usability, ease of use, and user experience of technology, enabling technology to better serve human needs and behaviors.

SR allows latent speech to be expressed as explicit speech, assisting individuals with special needs. Das et al. [143] presented a new method to enhance the automatic SR (ASR) system by suggesting a multimodal framework that integrates EEG and speech input. This provides a potential solution for facilitating communication among individuals with speech disorders and highlights the synergistic potential of integrating EEG signals with speech data.

Emotion recognition technology reveals emotions that are intentionally concealed, helping people better understand emotional changes and environmental influences. Xu et al. [144] presented a novel emotion recognition method using SNNs called Emo-EEGSpikeConvNet (EESCN). This model not only improves the performance of EEG-based emotion recognition but also offers faster operation speeds and lower memory consumption.



(a) (b)

Fig. 9. Application fields of (a) HCI and (b) ND.

For patients with muscle and motor system impairments, EEG provides a new solution for assisting in rehabilitation. Su et al. [145] found that in MI tasks, stroke patients showed reorganization in both the contralateral and ipsilateral motor regions of the brain, providing strong evidence for neuroplasticity and offering a new perspective for rehabilitation treatment.

B. Neurological Disease

The spatial patterns and dynamic characteristics of the brain play an essential role in diagnosing neurological diseases, uncovering the complex relationships between brain functions and structure [146]. Through imaging techniques, researchers are able to observe the time-varying fluctuations in brain networks and connectivity, which reflect the brain's adaptability over time. Each individual's brain structure is unique, influencing the spatial distribution of neural activity, which in turn is reflected in EEG patterns. The nonlinear dynamics of the brain and cross-regional coordination of activity are critical for the generation of thoughts and behaviors. Spatial domain analysis is considered a core tool for understanding brain function and the changes caused by neurological diseases, helping to deepen our understanding of the complexities of these disorders [147].

To diagnose spatial pattern changes caused by neurological diseases, advanced imaging technologies, such as EEG and MRI, provide complementary perspectives. EEG is capable of recording abnormal electrical activities, such as seizures, which aid in locating the affected areas and analyzing their impact on brain function. MRI, on the other hand, reveals the brain's anatomical structure and activity, supporting the diagnosis by analyzing changes in brain connectivity patterns. Fig. 9(b) shows the applications in neurological diseases. For example, EEG coherence analysis is applied to accurately differentiate AD from multi-infarct dementia [148]. In general, both EEG and MRI play essential roles in the assessment of neurological diseases [149]. The spatial, topological, and dynamic data can enhance our understanding of the underlying mechanisms of diseases and improve clinical diagnosis and treatment approaches.

VI. Challenges

We reviewed various applications of EEG signals in machine learning. Based on the experiences from these applications, the following briefly outlines the challenges faced in future EEG signal analysis research. A structured overview of these challenges, along with representative solutions and prospective directions, is presented in Table VI.

A. Foundations of Ideal HCI

To achieve near-error-free HCI applications, EEG is a commonly used physiological signal, and an ideal signal processing method is essential. This not only sets high requirements for dataset creation but also presents strict challenges for the data preprocessing process. With the rapid development of the IoT, the acquisition, processing, and transmission of EEG signals increasingly depend on the computing power and intelligence of edge devices. In real-time BCI systems, in particular, the efficiency and accuracy of preprocessing directly impact system responsiveness and user experience.

1) Artifact Removal: ICA [150] effectively removes artifacts from EEG recordings through independent-source separation techniques. It can accurately isolate and eliminate contamination caused by human factors, and compared to regression analysis and PCA, ICA performs better. ICA can

TABLE VI
SUMMARY OF IDEAL EEG SIGNAL PROCESSING AND APPLICATION SCENARIOS

Aspect	Key Challenges	Representative Methods	Requirements
Ideal Human-Machine Interaction	- Non-stationary, noisy EEG signals requiring real-time processing. - Preprocessing efficiency and accuracy impact system responsiveness. - Limited computing resources on IoT and edge devices.	- **Artifact Removal**: ICA [150], SSA+ICA+SWT hybrid [151]. - **Feature Extraction**: CSP, RCSP [153], CNN-based deep learning. - **Classification**: Deep neural networks [154], lightweight models [20].	- Develop lightweight, adaptive artifact removal methods for edge devices. - Balance accuracy and computational cost. - Improve generalization across EEG paradigms and platforms.
Ideal Neurological Disease Diagnosis	- Subject variability and disease stage complicate EEG patterns. - Real-time interpretation and automation needed clinically.	- **Epilepsy Detection**: 13-layer CNN by Acharya et al. [155]. - **Alzheimer's**: Spectral and nonlinear analyses revealing reduced coherence, complexity [156]. - **REM-NREM Regulation**: Brainstem flip-flop model [157].	- Develop adaptive, patient-specific algorithms. - Enhance real-time analysis and clinical interpretability. - Use multimodal data (EEG + imaging) to improve accuracy.
Future Directions	- Need fine-grained, personalized, multimodal strategies. - Challenges in data heterogeneity, standardization, sharing. - Real-time, efficient, reliable EEG acquisition and transmission in resource-limited IoT environments.	- **Cross-disciplinary collaboration**: Neuroscience, engineering, computing, medicine. - **Multimodal fusion**: EEG combined with fMRI, PET, CT, eye-tracking, ECG, EMG. - **Personalized processing**: Subject-specific models and features. - **Integration with IoT**: Lightweight algorithms and protocols for wearable EEG devices connected to cloud/edge platforms, enabling continuous monitoring and personalized intervention.	- Build standardized, sharable EEG databases. - Develop interpretable, integrative AI models. - Enable wearable BCI and health monitoring in daily life. - Develop lightweight algorithms and protocols suitable for IoT-constrained environments to support brain health monitoring, early warning, and personalized interventions.

also be employed to analyze brain signals associated with physiological activities such as blinking. However, while ICA performs well in multichannel EEG signal processing, it still faces challenges in single-channel EEG applications. To address this, Noorbasha and Sudha [151] combined SSA with ICA, along with stationary WT (SWT), to improve artifact separation performance. Although hybrid approaches improve accuracy, their high computational cost limits their applicability in resource-constrained settings. As EEG systems increasingly adopt edge-computing architectures under the IoT paradigm, artifact removal methods must meet stricter requirements for real-time performance, efficiency, and low power consumption. This calls for lightweight and reliable algorithms tailored to edge devices. Moreover, due to the diverse characteristics of artifact types, more adaptive and generalizable methods are essential for robust EEG preprocessing across varied platforms and scenarios.

2) Feature Extraction in BCI: The CSP is one of the most well-known feature extraction methods in the BCI field [152], and its efficiency and wide application have been well established. However, CSP is highly sensitive to noise, which can lead to overfitting problems. To address this, Lotte and Guan [153] presented a regularized CSP (RCSP) method, providing a theoretical framework for improving CSP. Despite this, selecting the best technique for specific EEG signal modalities remains a challenge.

3) Deep Learning in EEG Classification: Many studies have been presented using deep learning methods for classification in tasks such as language recognition, MI, P300, and SSVEP. The CNN model has been the most frequently reported in the literature. However, how to strike a balance between classification accuracy and computational efficiency—especially on resource-constrained IoT devices—remains a major challenge when designing models suitable for real-time applications and rapid calibration.

B. Ideal State of Neurological Disease Diagnosis

EEG is commonly used as an auxiliary signal in detecting and diagnosing neurological diseases. In the detection process, accuracy is crucial, especially when automatic detection is achieved, as it can significantly improve diagnostic efficiency. Acharya et al. [155] presented a 13-layer deep CNN algorithm for detecting different categories of normal, preictal, and epileptic seizures. AD is the most prevalent neurodegenerative disorder, characterized by cognitive decline, intellectual impairment, and behavioral abnormalities. Jeong [156] found that, through conventional spectral analysis and nonlinear dynamic approaches, the EEG of AD patients exhibited slower average frequencies, reduced activity complexity, and decreased coherence between cortical regions, providing evidence for the early diagnosis of AD. Similarly, Lim et al. [158] introduced Cogoland, a lightweight BCI gaming system integrating EEG headbands and real-time feedback, which enables personalized attention training for children with ADHD. This innovation illustrates how EEG can extend beyond passive diagnosis to active regulation, establishing a technological chain from diagnosis to intervention. Furthermore, Huang et al. [159] proposed a single-channel wearable BCI system for efficient attention modulation, offering a lightweight, cost-effective closed-loop solution that accelerates the transition of BCI technologies from laboratory settings to daily life applications.

Despite these advances, EEG in the diagnosis of neurological diseases becomes more complex due to individual differences, the different stages of the disease, and other influencing factors, necessitating the development of more precise algorithms. Additionally, real-time processing and automated analysis of EEG signals are critical for clinical applications, but the current models still need further optimization in terms of real-time performance and adaptability.

In this context, the integration of EEG-based diagnostic systems with IoT infrastructures has opened new opportunities for remote and continuous healthcare monitoring. Wearable EEG devices, connected via IoT networks, enable the real-time transmission and analysis of neural data on edge servers or cloud platforms. This not only facilitates early detection of abnormal brain activity in daily life environments but also reduces the burden on clinical personnel. However, achieving high diagnostic accuracy in resource-constrained edge environments demands lightweight, low-latency, and energy-efficient signal processing algorithms.

Finally, interdisciplinary collaboration and the combination of multimodal data provide opportunities to improve diagnostic accuracy. However, research in this area still faces challenges related to data sharing, privacy protection, and standardization across devices and platforms.

C. Future Directions

The future development of EEG technology relies heavily on interdisciplinary collaboration across fields such as neuroscience, engineering, computer science, and clinical medicine. By integrating these disciplines, more precise EEG data acquisition, processing, and analysis can be achieved, which in turn drives the development of cutting-edge technologies such as BCI, neurofeedback, and EEG signal decoding. With the rapid advancement of lightweight deep learning models, recent studies have demonstrated their great potential in IoT environments. For instance, Autthasan et al. proposed MixNet [89], which leverages spectral–spatial features and multitask learning to enhance MI classification. Remarkably, MixNet achieves outstanding performance even under low-density EEG montages, offering promising applications for portable and wearable EEG devices. Similarly, Chaisaen et al. [160] introduced AlphaGrad, an adaptive loss blending strategy that automatically balances multiple loss functions for MI-based EEG classification. This method delivers substantial improvements in subject-independent tasks and demonstrates strong adaptability across various BCI paradigms. These innovations highlight the feasibility of designing models with low latency and computational efficiency, making them particularly well-suited for embedded or wearable systems in real-time BCI applications [161].

In terms of datasets, single EEG data alone is insufficient to fully reveal the brain's complex activity patterns. Future advancements may involve multimodal data fusion, integrating EEG with other neuroimaging techniques (such as fMRI, PET, and CT) and physiological signals (such as eye movement, electrocardiograms, and electromyograms) for comprehensive analysis. This will provide more comprehensive information for the early diagnosis of neurological diseases, thereby improving diagnostic accuracy and reliability. At the same time, future research will focus more on personalized signal processing and feature extraction, aiming to achieve more accurate neurological disease diagnosis and treatment.

Future advancements in EEG-based BCI development can prioritize the following areas.

1) *Interdisciplinary Collaboration:* EEG technology will rely on collaboration across fields such as neuroscience, computer science, engineering, and clinical medicine to enhance the accuracy of EEG data acquisition and analysis and to promote the development of cutting-edge technologies like BCI.
2) *Multimodal Data Fusion:* In the future, EEG will be combined with neuroimaging techniques such as fMRI, PET, and CT for multimodal data analysis, improving the accuracy of early diagnosis of neurological diseases.
3) *Personalized Signal Processing:* Future research will focus on personalized EEG signal processing and feature extraction to provide more precise diagnosis and treatment for different patients with neurological diseases.
4) *Integration With IoT:* In the future, continuous, remote, and real-time monitoring of EEG signals will be realized through wearable and implantable devices connected to cloud or edge computing platforms. Lightweight and energy-efficient algorithms and communication protocols suitable for resource-constrained IoT environments will be developed to ensure reliable processing and transmission of EEG data, promoting brain health monitoring, early warning of neurological events, and personalized interventions.

VII. Conclusion

This review primarily discussed the basic principles of EEG-based BCIs and their current applications, focusing on EEG data acquisition, preprocessing, and feature extraction methods. Regarding classification methods, with the significant increase in computational power, traditional machine learning methods have gradually transitioned to deep learning architectures, laying both the theoretical and practical foundation for decoding EEG signals and improving BCI system performance. Additionally, this article briefly introduces several public datasets that provide valuable data support for BCI research and applications. With continuous technological advancements and the ongoing efforts of researchers, BCI technology is progressing toward higher precision and efficiency, providing a solid foundation for realizing ideal HCI models and accurate neurological disease diagnosis in the future. Breakthrough developments have illuminated the current advancements in BCIs and painted a promising blueprint for future BCI progress.

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