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A Survey on Machine Learning Methods for Brain–Computer Interface Applications: Techniques, Challenges, and Future Directions

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***Abstract*—A Brain Computer Interface (BCI) turns information from the brain into commands that a computer can understand, so a person can talk to an outside object directly through their brain activity. An EEG-based class of BCI systems is the subject of this paper's research. Specifically, ERP, DL, and ML for processing and classifying signals. Using EEG for signal extraction, preprocessing, feature extraction, classification, and user interface development in BCI pipeline because it is less invasive than other approaches. Reliable BCI signal classifier development requires EEG signals to be non-stationary, extremely noisy, and highly derivative. In order to improve non-invasive EEG classification, machine learning algorithms including linear discriminative analysis and support vector machine classifiers have been developed. Conversely, deep learning methods like transformers, long short-term memory autoencoders, and convolutional neural networks have enabled BCI systems for healthcare rehabilitation, human interface, brain monitoring, and assistive devices.**

Keywords*—Brain–Computer Interface (BCI), EEG, Machine Learning, Deep Learning, Signal Processing, EEG Classification, ERP, CNN, LSTM, Healthcare Applications, Rehabilitation, Assistive Technology.,

I. Introduction

Healthcare assistive technologies that facilitate communication, rehabilitation, patient monitoring, and independent living are urgently needed due to the rising incidence of neurological illnesses, stroke, spinal cord injuries, and severe motor impairments. The brain-computer interface (BCI) is a new piece of technology that might revolutionize human-computer interaction. By converting brain impulses into commands, BCIs enable users to control electronic equipment. Neurogadgets, which are used to control robotic systems, moving objects and interactive applications, are increasingly used for entertainment purposes. More significantly, these technologies are being created to help people who have serious disabilities, such as paralysis, to do their daily activities and communicate with the world [1]. BCIs are typically unidirectional or bidirectional, depending on the direction of communication. Bidirectional BCIs allow the brain to operate an external device by sending and receiving signals, whereas unidirectional BCIs can only read or write brain signals.

Direct brain-to-device communication is made possible by electroencephalogram (EEG) technology, which measures electrical activity in the brain and converts it into signals that a device understands. This is the basis of BCI systems, which employ neural impulses for control and interaction in HCI, assistive technology, and rehabilitation applications [2].

These brain signals are, however, mostly non-linear, noisy, and inter-record-session and inter-individual variables. Thus, the accurate analysis of these signals by traditional signal processing methods is still a great challenge[3][4]. Therefore, the use of Machine Learning (ML) has become an essential part of modern BCIs, which helps to extract features, recognize patterns and classify complex brain signals automatically [5]. Besides ML, other Deep Learning (DL) techniques, such as more flexibility, robustness and real-time decoding capabilities, have also further improved the performance of the systems. As a result, BCIs have found increasing utility in fields like as motor imagery, emotion identification, cognitive monitoring, and assistive technologies for those with profound disabilities [6].

Major BCI paradigms, such as motor imagery, event-related potentials, emotion recognition, and their usage in healthcare, rehabilitation, assistive communication and human–computer interaction are the focus of this survey [7][8]. Modern ML and DL techniques are focused on to improve the accuracy, resilience, and flexibility of BCI systems in non-stationary and noisy environments. For this purpose, a systematic classification of the existing research, methodologies and techniques was provided at various stages of the BCI pipeline in this paper, and current challenges and further research directions for ML-based BCI applications were discussed [9].

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A. Structured of the paper

The rest of the paper is structured: Basics of brain-computer interfaces are covered in Section II. Section III discusses ML techniques for EEG-based BCIs, while Section IV reviews conventional ML and DL models. Section V highlights major BCI applications, Section VI surveys related literature, and Section VII concludes the paper with future research directions.

II. Fundamentals of Brain–Computer Interface

Feature extraction, categorisation, pre-processing, and signal capturing are all components of the BCI system. One of the most popular non-invasive methods in BCI is EEG, which has risen in popularity because to its portability, low cost, and high temporal resolution. Raw EEG signals are prone to noise and other unwanted components, which is why EEG preprocessing includes techniques like notch filtering, PCA, and CAR. Later, EEG feature extraction is performed with PCA, ICA, FFT, wavelet transform, and AR methods.

A. Types of Brain Signals

BCI technologies record neural activity using many forms of brain signals. The major techniques for brain signal acquisition currently used are Electroencephalography (EEG), Electrocorticography (ECoG), and Magnetoencephalography (MEG).

1) Electroencephalography (EEG)

The method of taking a reading of a person's brainwaves by attaching electrodes to their scalp. EEG has widespread applications in BCI systems because it is easy to carry and relatively inexpensive. Despite this, EEG signals are generally quite faint and highly susceptible to interference from noise and artifacts. Electrodes, signal amplifiers, analogue-to-digital converters, and a recording medium are the standard components of an electroencephalogram (EEG) system. The electroencephalogram (EEG) can be broadly classified into five distinct frequency bands: theta, beta, alpha, and gamma.

2) Electrocorticography (ECoG)

The device uses electrodes put on the brain's surface to measure electrical activity. Instead of relying on artefacts like blinks and eye movements, ECoG spectra provide better spatial and temporal resolution, larger amplitudes, and more reliability. Despite its usefulness, this recording technique is highly invasive and poses serious health concerns due to the craniotomy required to install an electrode grid.

3) Magnetoencephalography (MEG)

This method allows one to see the magnetic activity of the brain as a result of neuronal currents without causing any harm. Because of its neurological roots, it shares many similarities with EEG but provides higher spatial and temporal resolution, is more sensitive to main currents, and is otherwise extremely similar. Unfortunately, MEG systems are not practical for use in BCI applications because to their high cost, size, and requirement for a magnetically shielded environment.

4) Functional Near-Infrared Spectroscopy (fNIRS)

Brain activity monitoring using fNIRS is quite a popular method as it is non-invasive, gives good spatial resolution, is portable, and is affordable. That's why it can be applied to BCI. Yet, the temporal resolution of fNIRS is inferior to EEG because the measurement of brain activity is done indirectly by monitoring blood-flow changes [10].

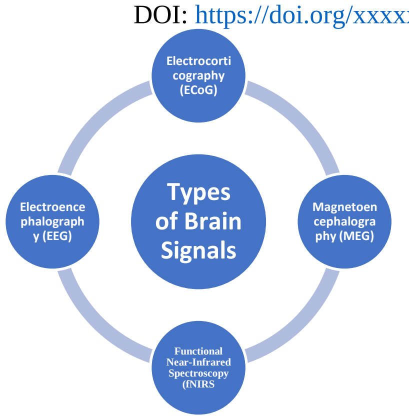

Fig. 1. Type of Brain Signals

B. EEG Signal Preprocessing Techniques in BCI Systems

Preprocessing an EEG signal can help brain-computer interface (BCI) systems eliminate artefacts and noise including eye movements, muscle activity, and outside interference. Improving the signal quality by filtering, artefact removal, and signal normalization is essential for feature extraction and classification in BCI applications.

1) Noise and Artifact Sources in EEG Signals

The EEG signals are rather weak and non-stationary, making them incredibly vulnerable to artefacts and noise. They are common sources, such as EOG, EMG, ECG, power line interference, which affect signal quality and BCI performance. For modern BCI systems, it is crucial to effectively detect and remove artifacts to ensure trustworthy EEG analysis.

2) Filtering Techniques for EEG Signal Enhancement

EEG preprocessing also employs many filtering methods to denoise and enhance the signal quality. Notch filters eliminate 50/60 Hz power-line interference, whereas band-pass filters incorporate the gamma, theta, alpha, and beta frequency bands—essential for brain activity. An enhanced SNR, preserved meaningful information in the neural network, and enhanced performance of the subsequent BCI processing stage are all outcomes of the filtering strategies.

3) Artifact Removal Methods

EEG signals are separated from unwanted noise to enhance the quality of the data by using artifact removal techniques. ICA recognizes artifacts such as eye blinking and muscle movement, PCA reduces noise (dimensionality), and CAR improves spatial resolution by averaging electrode signals. These methods improve the accuracy of EEG signals and make BCIs more dependable.

4) Signal Enhancement and Normalization Techniques

Once the artifacts have been removed, the EEG data needs to be normalized and smoothed to standardize the data and minimize variability between channels and subjects [11]. BCI systems benefit from these methods because they improve signal consistency, feature quality, and classification reliability.

III. Machine Learning in BCI Systems

BCI systems can do more by using ML to improve their features by extracting and sorting noisy EEG and ERP data. This makes them more useful for motor imagery, emotion recognition, mental state analysis, and rehabilitation [12].

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A. Data Acquisition

Artifacts can be reduced during data acquisition by requiring a subject to maintain central fixation and blink at the end of trials (though this may not be feasible in naturalistic experimental designs). Electro-oculographic (EOG) measurements can be easily used to monitor blinks and eye movements. It is recommended that the ECG electrodes be positioned on the chest (including their leads) for optimal cardiovascular recording. Also, having a cool, comfortable laboratory is another way to reduce sweat gland activity [13].

1) Classification of Signal Acquisition Technologies in BCI

The level of invasiveness and the placement of the recording sensors are the most typical ways of categorizing BCI signal acquisition technologies. In the past, they usually were divided into non-invasive and invasive methods. More specific types of classification are those that are non-intrusive, semi-intrusive and intrusive, and non-invasive, embedded and intracranial technologies. With recent developments in the design of electrodes and the methods of implanting them these categories have also been extended and the requirement for flexible and broad classification schemes has grown.

2) EEG Signal Acquisition Systems

The EEG acquisition system consists of an EEG signal controller and feedback, an ADC, preprocessing circuits, and EEG electrodes. The EEG acquisition system should provide highly accurate measurements and low noise, with the highest priority on user safety and comfort.

3) EEG Electrode Types

The quality of the EEG signal is greatly affected by the EEG electrodes, which are an essential component of EEG acquisition systems. Emblems that are both non-invasive and invasive in nature can be placed using these. Electrodes can be either non-invasive, worn on the scalp, or invasive, implanted directly into brain tissue, allowing for more precise signal capture [14]. Common types include non-invasive electrodes shaped like micro-needles or fingers and invasive ones like thin-film or straight-beam electrodes.

B. Feature Extraction in EEG-Based BCI Systems:

The In an EEG-based BCI system, feature extraction methods can be based on wavelet transforms, CSP approaches, or ANN methods:

- **Temporal features EEG signal analysis BCI:** The study of the EEG's behaviour in the time domain is known as temporal feature analysis, and it is a key component of EEG-based BCI. It records whether or not certain brain rhythms are present and distinguishes between typical and non-typical waveforms in the signal.
- **EEG Spectral Features BCI:** Recent attempts have attempted to use trained spectrum filters, CWTs, or Short-Time FTTs to incorporate the spectral information. Time–frequency analysis has been shown to be effective for modeling discriminative MI features, as in the SincNet and Spectral CNN models.
- **EEG Time–Frequency Analysis in BCI:** In brain-computer interfaces, EEG time-frequency analysis is used to examine the strength and direction of EEG oscillations at specific frequencies. It offers a finer depiction of brain activity than the conventional ERP analysis [15].

IV. Conventional Machine Learning Techniques In BCI

Three main processes are involved in traditional BCI systems: signal acquisition, preprocessing, and feature extraction and classification. It is common practice to employ shallow classifiers like SVM, LDA, and RF for EEG signal categorization due to their efficient computation and ease of interpretation.

A. Traditional Machine Learning Classifiers for BCI:

Several processes are involved in the signal acquisition process in BCI systems, including preprocessing, feature extraction, and classification. Due to the accuracy, efficiency, and effectiveness of traditional classifiers, LDA, SVM, and RF on small datasets, they are very popular and support applications like neuroprosthetics, emotion recognition, and assistive devices [16].

- **Linear Discriminant Analysis (LDA):** Tactile BCI experimentation has also demonstrated that LDA is typically the technique chosen for classifying stimuli in this type of system because LDA includes a feature-reduction process in addition to its use as a classifying method consequently, LDA obtains a set of features for use in classifying stimuli, which best defines the boundary between the stimulus classes.
- **Random Forest (RF) Classifier:** RFs are considered a superior approach to ensemble learning for supervised ML. The final classification is obtained by aggregating the outputs of numerous DTs that are constructed during training. By integrating the judgements of separate trees, RFs can lessen the possibility of overfitting and improve generalisation, which is their main advantage.
- **Support Vector Machine (SVM):** The SVM is a type of supervised learning model that builds an optimised hyperplane using statistical theories of learning. This hyperplane allows for a lot of space between classes and isolates them as much as possible. The data was transformed from one dimensionality to another using kernel functions. The kernel functions allow for classification problems when there is non-linear separability of the data [17].

B. Deep Learning Models for BCI

DL methods automatically categorise EEG waves and extract features in brain-computer interface systems. To extract local features from EEG data, several approaches use CNNs; to capture global relationships, they use Transformers. Such a hybrid architecture is very efficient in analyzing intricate, non-linear EEG patterns. This is mostly the case in motor imagery-based BCI applications.

- **Long Short-Term Memory (LSTM) Networks:** LSTM outperforms traditional RNNs and FNNs when it comes to time-series forecasting and classification issues because it captures the long-term temporal dependencies in the sequences.
- **Autoencoder-Based Model:** Autoencoder-based models, such as sparse stacked GRU-based, and deep denoising auto-encoders, are capable of cleaning EEG artifacts and unveiling features, yet their purely deterministic nature might lead to a greater risk of overfitting [18].

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- **Transformer Architectures:** Recent emotion recognition studies use transformers, graph neural networks, contrastive learning, attention mechanisms, and hybrid DL models to capture spatial–temporal patterns and enhance the accuracy of emotion recognition and its cross-subject generalization on EEG signals.

V. Applications of Brain–Computer Interface Systems

A BCI technology translates electrical impulses from the brain into actionable commands, allowing the human brain to have two-way conversations with everyday objects. BCIs can be used for various purposes including hand movement decoding, emotional state identification, communication and typing systems, rehabilitation, and neuroproteins, which Really bolster the healthcare and assistive technology sectors.

A. Medical and Healthcare Applications

BCIs based on electroencephalogram (EEG) data have found extensive application in areas such as communication, epilepsy, neurodegenerative diseases, emotion identification, and rehabilitation. That they can play a crucial role in healthcare is well demonstrated here [19][20]. A hybrid BCI that uses EEG data can improve the system's functionality and open up new medical uses for the technology [21]:

- **Neurorehabilitation Systems:** BCI-VR systems are gaining popularity in the neurorehabilitation field, where they provide immersive and interactive feedback to assist motor recovery and rehabilitation training for stroke and brain-injured patients.
- **Epilepsy Detection and Monitoring:** Epilepsy is a brain disorder affecting many people across the globe. It is caused by irregular neurologic activity in the brain [22]. BCI technology has made considerable advancements in epileptic seizure diagnosis, detection and even prediction.
- **Stroke and Paralysis Recovery:** Rehabilitation after a stroke or paralysis can be facilitated with systems that utilize BCI and functional electrical stimulation. These systems decode motor intention from EEG data and provide feedback through robotic devices, FES, and virtual reality systems.
- **Neuroprosthetic Control:** One of the most important healthcare technologies utilizing BCIs is the neuroprosthesis [23]. These systems convert signals from the brain into the commands needed by a prosthetic or robotic limb, or assistive device. Direct brain-to-device connection is made possible by neuroprosthetics, which can aid individuals with severe motor impairments in regaining functional movement, enhancing their independence, and living a better life.
- **Emotion Recognition and Mental Health Monitoring:** The brain activity patterns of emotion states (stress, anxiety, depression, happiness, relaxation) can be identified and classified using EEG based BCI system [24]. In mental health, they are being used for early detection of mental health issues, emotional evaluation, stress reduction, and providing tailored mental health care. Recent developments in AI and ML have improved the accuracy and reliability of emotion identification systems, expanding their potential.

B. Communication and Assistive Technologies

BCI systems can help people with severe motor disabilities talk to each other without having to use their bodies to send instructions. BCI, such as EEG spellers and speech systems, enable direct interaction with devices using the brain. In recent years, advancements in artificial intelligence and deep learning have made these assistive communication systems more practical, faster, and more accurate.

1) EEG-based Spelling and Typing Systems (BCI Spellers):

BCI speller systems First and foremost harness P300 and SSVEP brain signals, enabling people with severe motor impairments to interact and express their thoughts via virtual keyboards. These methods are now much faster and more accurate thanks to ML and DL.

2) Speech Decoding & Assistive Communication Systems:

BCIs target speech decoding and assistive communication systems to reconstruct or classify imagined speech based on EEG, ECoG or intracortical signals. They employ DL algorithms, like CNNs and RNNs, to analyze the brain's language-related signals and translate them into either text or synthetic speech [25]. Once more, integration with AI-powered forecasting text enhances interaction efficiency, making it more rapidly, natural, and effective for those with speech impairments.

VI. Literature Review

This section provides a survey of recent research on ML-based Brain-Computer Interface (BCI) applications. It focuses on advances in EEG processing, DL, generative AI, hardware acceleration, and new research problems.

Jiang et al. (2026) Delves into DL techniques for MI-EEG decoding in a systematic manner, focusing on fusion across various model architectures, subject populations, and data paradigms. Examining public, patient-specific, and clinical datasets, it draws attention to the constraints of generalisability and evolution of models developed for healthy subjects, the decline in performance when applied to EEG data from patients, and the necessity of population-adaptive frameworks [26].

S. Wang et al. (2026) Provides a systematic analysis of the convergence of generative AI and BCI systems, highlighting generative and discriminative brain decoding. Data augmentation and optimised hardware design highlight expanded uses in medical rehabilitation, industrial systems, and consumer electronics, while improved BCI data is also addressed [27].

V. P. Balam (2025), Describes in detail the many approaches of EEG sub-band extraction that have been developed for use in BCI applications. It uses quantitative and qualitative analysis to assess wavelet transforms, FFTs, STFTs, FIR/IIR filters, and their usefulness for automated EEG signal classification [28].

Xie and Oniga (2024) The paper breaks down EEG signal characteristics into five groups and then talks about the hardware solutions that go along with each one; it covers hardware acceleration for wearable EEG devices. Research on effective CNN optimization methods for processing EEG signals is also included [29].

Suganthi et al. (2023) This study uses pre-drawn facial components and a CNN algorithm to accurately classify images for BCI-based image selection. The facial regions are identified using the processed EEG signals, and the resulting facial structure is compared to an existing criminal database for matching [30].

Singh et al. (2023) proposes a framework for synthesizing images from EEG-recorded brain activity using small-size EEG datasets. It employs contrastive learning for EEG feature extraction and a conditional GAN with a modified loss function to generate 128 × 128 images from imagined objects and English characters [31].

Table I summarizes recent studies on ML-based BCI applications, highlighting their research focus, advantages, limitations, and future research recommendations

TABLE I. SUMMARY OF STUDY ON BRAIN–COMPUTER INTERFACE APPLICATIONS USING MACHINE LEARNING METHODS

Authors	Study Focus	Advantages	Limitations	Recommendations
Jiang et al. (2026)	Deep learning approaches for MI-EEG decoding	Comprehensive analysis of fusion strategies and datasets	Limited generalization across subject populations	Develop adaptive and generalized MI-EEG models for diverse users.
S. Wang et al. (2026)	Integration of generative AI with BCI systems	Improved brain decoding, data augmentation, and broader BCI applications	Challenges in model complexity, scalability, and practical implementation	Develop efficient and scalable generative AI frameworks for real-time BCI applications.
Balam (2025)	EEG preprocessing and sub-band extraction techniques	Comprehensive evaluation of preprocessing methods	No unified preprocessing framework for all BCI tasks	Develop standardized and adaptive EEG preprocessing techniques.
Xie and Oniga (2024)	Hardware acceleration for wearable EEG devices	Efficient CNN optimization and hardware solutions	Resource constraints and implementation complexity	Design lightweight and energy-efficient hardware architectures.
Suganthi et al. (2023)	CNN-based facial image classification using EEG	Improved image classification and facial matching	Limited application scope and database dependency	Enhance robustness using larger datasets and generalized BCI models.
Singh et al. (2023)	EEG-based image synthesis using conditional GAN	Generates images from EEG features with small datasets	Limited image quality and dataset scalability	Improve image resolution and model performance using larger EEG datasets.

VII. CONCLUSION AND FUTURE WORK

ML and DL have been the primary areas of focus for BCI systems when it comes to analysing EEG signals. In addition to outlining the many stages of a BCI pipeline—including signal collecting, preprocessing, feature extraction, and classification—the authors provided examples of the most significant BCI uses in field, including healthcare rehabilitation, assistive technology, and human-computer interaction. This research discusses that through ML and DL, BCI systems can achieve a remarkable increase in performance over classical methods. But existing challenges that make it difficult for BCI implementations to be used in real-world environments, include noisy EEG signals, high inter-subject variability, a lack of large datasets, and computationally expensive requirements. Future work should include more sophisticated, lightweight, and generalized models with improved cross-subject performance. Also, hybrid DL models, like transformers and graph-based models, should be widely studied. In addition, future work should focus on more real-time, low-cost BCI systems and greater dataset diversity

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