*Trends in Machine Learning Applications for EEG-based Brain-Computer Interfaces*

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*Abstract*—Brain Computer Interfaces have gained traction for their revolutionary applications in biotechnology. Brain Computer Interfaces have applications in motor rehabilitation such as prosthetic limbs, voice decoding, visual prosthetics, and more. This report explores machine learning applications on brain computer interfaces based on EEG data.

Keywords—machine learning, artificial neural networks, machine learning, neural networks, linear regression, support vector machine, rehabilitation, spiking neural networks, artificial intelligence

# Introduction (*Heading 1*)

Brain Computer Interfaces are incredibly powerful systems that connect the brain with computers [1]. In the 1970s, Research into BCI devices began, but research in humans has taken off since 1990. There is a special interest in the usage of these devices for their role in the treatment of diseases and disorders including tetraplegia, ALS, epilepsy, and more [11].

Brain-computer interfaces have made revolutionary strides in rehabilitative technologies for individuals with motor or speech deficits. In particular, strides have been made in neuro-prosthetics, visual prosthetics and speech decoders, such as Nicolas Card’s ALS decoder [9].

There are a variety of methods to collect information that is brain activity – including non-invasive (fMRI, MEG, EEG) and invasive methods – including close-loop brain computer interfaces or brain machine interfaces such as some devices that assist those with motor or speech deficits. Electroencephalogram, or EEG, data is a commonly used measure of brain activity in the context of BCI [11]. For the scope of this review, studies that use EEG data will be selected. Electroencephalogram, or EEG, data measures the electrical activity of neurons. Neurons communicate using electrical activity and this information can be collected by using small, metal discs called electrodes placed on the scalp [24].

In general, EEG data collected from the brain may be noisy or have many features [24]. To apply machine learning techniques, first the data must be preprocessed. Preprocessing can involve a variety of steps including filtering and signal processing. Next, feature extraction/selection typically takes place and the information is sent to some type of decoder [23].

# Selection criteria

The aim of this report is to provide a cursory overview of the applications of machine learning on BCI, indicating interesting approaches to BCI decoders with EEG data. There are a multitude of brain-computer interfaces for a variety of applications. To perform this literature review, search queries used were “EEG-based BCI” and “Artificial intelligence” or “BCI machine learning techniques” or “BCI algorithms” on a variety of search engines such as google, google scholar, Pubmed, etc. Papers were then selected based on the type of data (EEG: either motor imagery or specific applications such as disease versus non disease state (for instance healthy control versus epileptic fit)). Additionally, due to the complexity of this topic, some papers were found in cited literature reviews.

# METHODS

A literature review from 2022 shows a bar plot that indicates some common classifiers used for feature extraction in EEG-based machine learning for brain-computer interface dynamic device control. There are several methods that teams have used to implement and train BCIs [5].

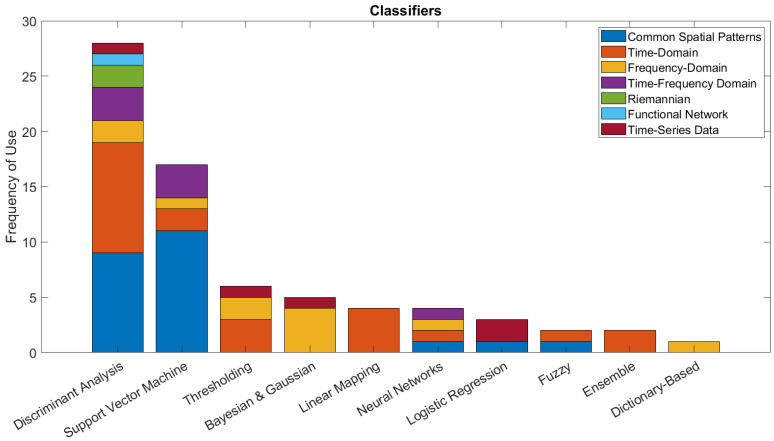


Figure 1. Figure 1 was taken from **Padfield et al’s work** which indicates trends in machine learning classification methods for EEG based BCI dynamic device control [5]. In other words, this chart breaks down trends in machine learning applications for implanted brain computer interfaces in the context of motor control [5]. This highlights the mere sample of the diversity in methods used in BCI research.

## Artificial Neural Networks (ANN)

A powerful tool for Brain-Computer Interfaces is the artificial neural network which can decode and interpret brain signals. This tool has been recently popularized. As many BCI devices have complex and non-linear data, more traditional methods of machine learning had limitations. However, ANNs can learn information and excel with some spatial or temporal relationships. This means an ANN is well suited for tasks like motor imagery classification (MI), event-related potential (ERP) detection [22].

Motor Imagery is when the participant imagines initiating and undertaking a movement without execution of the movement. This process yields neural activity that creates spiking patterns in the EEG data. These signals fall within the mu (8–12 Hz) and beta (13–30 Hz) frequency bands when data is collected over the motor cortex region. Neural signals such as the spiking data from EEGs is noisy and non-static and varies a great deal from subject to subject. These drawbacks have spurred the desire for improvements in the signal processing and classification methods, such as Artificial Neural Networks (ANNs), Spiking Neural Networks (SNNs), and Convolutional Neural Networks (CNNs), for accurate detection.

Event-Related Potentials (ERPs) are brain signals in direct response to specific sensory, motor, or cognitive events, making them closely tied to the timing of those stimuli. A particularly well-known ERP component in BCIs is the P300 potential, which manifests as a positive peak in EEG recordings approximately 300 milliseconds after a rare or significant stimulus. ERPs are frequently employed in systems like spellers and attention-driven BCIs, where users concentrate on specific targets, producing reliable patterns that can be interpreted to decode their intentions. Unlike motor imagery (MI), ERPs are more straightforward to identify and classify, as their temporal patterns are highly consistent and exhibit a stronger signal-to-noise ratio. However, these systems depend on external stimuli to trigger responses, which can limit their adaptability compared to the more self-driven nature of MI-based BCIs.

Artificial neural networks (ANNs) are made up of interconnected layers of nodes, or neurons, that process data by passing information between layers [23]. Each node takes in weighted inputs, applies an activation function, and forwards the result to the next layer. By recognizing patterns in data, ANNs are highly effective for tasks such as classification, regression, and pattern recognition. Their layered structure—consisting of input, hidden, and output layers—allows them to capture hierarchical features, making them particularly useful for analyzing complex, high-dimensional data like images, time series, and signals. Training ANNs involves optimizing the network’s weights through iterative processes using techniques like backpropagation and gradient descent to minimize errors. These networks are widely used in fields such as image processing, speech recognition, natural language processing, and medical diagnostics. Although ANNs can require substantial computational power and large datasets, improvements in hardware and optimization strategies have enhanced their efficiency, scalability, and overall performance [22, 23].

In **2017, Yaacoub et al.** conducted an investigation with Artificial Neural Networks (ANNs) in combination with Genetic Algorithms (GA) for classifying motor imagery (MI) EEG signals to distinguish between left- and right-hand movements [22]. They utilized the Graz Dataset III from the 2003 BCI Competition, which contains EEG recordings from C3, C4, and Cz electrodes at a sampling frequency of 128 Hz. To prepare the data, the team applied a finite impulse response (FIR) bandpass filter within the 0.5–30 Hz range, effectively isolating motor imagery-related frequency bands, including the Mu band (8–12.5 Hz) and beta band (13–30 Hz). The feature extraction process incorporated spectral, temporal, and statistical methods, resulting in a highly detailed feature vector containing 12,336 features per EEG sample. Due to the incredibly high number of dimensions, the team applied a unique approach in implementing the genetic algorithm, or GA. GA encodes the features into a binary chromosome – representing either the inclusion or the exclusion of a specific feature. The fitness function, defined by the classification accuracy of the ANN, enabled the selection of an optimized feature subset, boosting both computational efficiency and the model's applicability for real-time use.

The ANN utilized in this study consisted of a single hidden layer with seven neurons and employed a data split of 70% for training, 15% for validation, and 15% for testing. The hybrid approach integrating ANNs and GA-driven feature selection demonstrated remarkable improvements in classification accuracy and computational efficiency. Results show that the proposed hybrid approach combining ANNs with GA-based feature selection achieves significant improvements in both classification accuracy and computational efficiency. When using the full feature set of 12,336 features, the ANN achieves a classification accuracy of 90.5% on the test data. Cross-validation further validates these results, with K-fold testing yielding accuracies of 91.43% (K=5) and 92.86% (K=7). Feature vector by 99.5%, retaining only 0.5% of the original features. Despite this significant reduction, the classification accuracy improves to 92.2%. The convergence analysis of the GA reveals that the algorithm reaches an optimal solution after approximately 15 generations, achieving a maximum fitness of 95% during cross-validation.

## Spiking Neural Networks (SNN)

Spiking Neural Networks (SNNs) are bio-inspired networks that seek to emulate the brain’s neuron firing system. Neurons in the brain communicate with one another, and can process discrete, time driven events. There is a spiking pattern in the brain. Unlike traditional artificial neural networks, SNNs incorporate these spikes using some sort of temporal dynamics. Thus, they can encode events and efficiently process time-dependent signals like EEG data [1, 19].

Spiking Neural Networks (SNNs) have demonstrated significant potential for real-time brain activity decoding, particularly in applications such as motor imagery and event detection. Their capability to manage the non-linear and dynamic characteristics of brain signals, coupled with energy-efficient computation on neuromorphic hardware, positions them as an excellent choice for portable and embedded Brain-Computer Interface (BCI) systems [1]. SNNs also utilize mechanisms like Spike-Timing Dependent Plasticity (STDP), which allows adaptive performance improvements and provides a biologically inspired and scalable approach for future BCI advancements. These networks operate based on a spike-driven paradigm, where activation occurs only upon receiving or transmitting spikes, highlighting their ability to achieve low latency and enhanced computational efficiency [1].

In 2017, one of the first attempts at using a Spiking Neural Network for decoding MI from EEG occurred with the work **of Tayed et al [19].** This team ran their SNN model on SpiNNaker hardware. The paper introduces a method for decoding Motor Imagery (MI) movements (specifically left-hand versus right-hand movements) from EEG signals using a Spiking Neural Network (SNN) implemented on SpiNNaker neuromorphic hardware. Data was preprocessed, signals were filtered in the 8–30 Hz frequency range, focusing on the alpha and beta bands, which are closely associated with motor-related brain activity. Band Power (BP) features were extracted using 72 overlapping frequency bands. Principal Component Analysis (PCA) was applied to reduce the dataset to 10 features. These features were then used as inputs to the SNN classifier. For baseline comparison, a Support Vector Machine (SVM) classifier was also tested using the same feature set, achieving an accuracy of 77.49% [19].

The Spiking Neural Network (SNN) mimics the three-layer structure of the insect olfactory system: input layer encodes EEG features into spike trains, which are then processed in the decorrelation layer, inhibitory neurons reduce correlation between inputs, organized into functional groups called “glomeruli”, association layer implements mechanism to classify the motor imagery tasks into left or right-hand movements. The network uses Leaky Integrate-and-Fire (LIF) neurons with exponential synapse models to simulate biological spiking activity [19].

The team found an accuracy of 75% for MI tasks, which was lower than the 77.49% achieved by the SVM baseline but the SNNs are energy-efficient and scalable real-time computation. While the SNN with the LIF model shows competitive accuracy there are alternatives which may be advantageous including Spike-Timing Dependent Plasticity (STDP) [19]. This study was one of the first to demonstrate the advantages of using an SNN based network. Although the accuracy is slightly lower than conventional SVM-based methods, the advantages of SNNs, such as energy efficiency and biological inspiration, make them promising for real-time, scalable BCI systems. Future work will focus on improving learning mechanisms, expanding the model’s complexity, and integrating feedback for closed-loop neuro-prosthetic applications.

These bio-inspired neural networks have been used in a variety of applications, including for decoding EEG signals for BCI. They help to reduce the energy burden needed to train models and retain accuracy. Using Intel’s Loihi processor, a team used SNN’s for BCI feature extraction and training of EEG data. **Kumar et al published their findings in 2022** in which they showed that their model extracted spatiotemporal features from EEG data using specialized layers. SNNs are unique in the algorithm they use for training. This team used a LIF, or leaky integrate and fire model which is modeled after the way a neuron fires (the equation is derived from the original work of Hodgkin and Huxley). In summary, running their models on the neuromorphic hardware from Intel, they found remarkable results which are comparable to other deep neural network methods. The accuracy was as follows: 81.93% (SNN) vs. 79.81% (3D-CNN); (Four-Class): 79.95% (SNN) vs. 82.00% (3D-CNN) using a Motor Imagery and Movement task EEG dataset.

One of the most remarkable things about SNNs, that the team also reported on was that their SNN on Loihi consumed 95% less energy per inference compared to DNNs on Jetson TX2. Additionally, the team breaks down how their SNN outputs might be correlated with low-frequency oscillations (e.g., delta band), consistent with prior studies of motor-related brain activity.

The integration of Spiking Neural Networks (SNNs) into Brain-Computer Interfaces (BCIs) represents a significant step forward in the field, building upon decades of research aimed at improving the accuracy, efficiency, and scalability of brain signal decoding. Inspired by biological processes, SNNs leverage temporal dynamics and event-driven computation, enabling them to process the non-linear and non-stationary nature of EEG signals with remarkable energy efficiency. Early studies, such as the work of Tayed et al. in 2017, demonstrated the feasibility of using SNNs for motor imagery (MI) classification, achieving competitive results compared to traditional Support Vector Machines (SVMs) while highlighting the advantages of neuromorphic hardware like SpiNNaker. Subsequent advancements, such as Kumar et al.'s 2022 study using Intel's Loihi processor, further showcased the potential of SNNs for feature extraction and classification, achieving accuracies comparable to deep neural networks (DNNs) while consuming up to 95% less energy per inference.

The historical progression of BCIs has seen a shift from simpler linear classifiers to energy-intensive deep learning models, and now toward SNNs, which bridge the gap between biological inspiration and computational efficiency. As research continues, future trends will focus on refining SNN architectures with mechanisms like Spike-Timing Dependent Plasticity (STDP), expanding the complexity of tasks beyond binary classification, and integrating feedback for closed-loop neuroprosthetic systems. The use of neuromorphic hardware, coupled with advancements in bio-inspired learning algorithms, holds the promise of real-time, portable, and scalable BCIs. This trajectory reflects a growing emphasis on sustainable and energy-efficient solutions, which are essential for practical, long-term deployment of BCIs in both clinical and everyday applications.

## Convolutional Neural Networks (CNN)

CNNs are very good at identifying both spatial and temporal patterns in data and are thus apt to extract features across EEG channels and frequency bands.

In **2020, Lee et al** conducted a study to evaluate the use of CNN for EEG signal analysis. This team used EEG signals and preprocessed the data by filtering re-referencing, and segmenting EEG signals [17]. They then input a CNN model is trained on data from all subjects except the one being tested via leave-one-out-cross-validation. This helps train the model on subsets of the data, ensuring that the model is trained more generally. They set up the data so that the data from the subject that was being tested was left out and all the remaining data was the train data [17]. The authors proposed a hybrid system where the CNN provides initial labels to train a subject-specific linear classifier (SWDLA) during live sessions and this was found to ultimately improve the subject’s performance as data became available [17]. The results from this study were that the hybrid system combining zero-trained CNN and SWLDA achieved 92.98% accuracy, similar to within-trained methods (94.28%); However, the zero-trained CNN achieved 89.22% accuracy, comparable to the conventional SWLDA method with calibration (94.28%) and SWLDA without training performed poorly (69.80%) [17].

In a 2020 study by **Kwon et al,** EEG BCI data was trained on a CNN [16]. Some BCIs which were more traditional need subject-specific calibration. This can take time to do and is temporally expensive. This paper is novel in its approach to eliminating this calibration burden where a framework is implemented that can generalize across many different users [16]. The authors created a motor imagery (MI)-based EEG database consisting of 54 subjects and 21,600 trials. The team then trained a CNN on the spectral–spatial inputs to extract features and classify motor imagery motion (left vs right-hand movements) [16].

The neural network integrates leave-one-subject-out cross-validation (LOSO-CV) strategy and achieved significantly higher classification accuracy compared to both subject-independent and subject-dependent methods. The reported multiple classification accuracies for the designed methodologies: pooled Fused Model: 67.37%, MR-FBCSP: 68.59%, Proposed CNN: 74.15%, CSP: 68.57%, CSSP: 69.68%, FBCSP: 70.59%, BSSFO: 71.02%.

The study demonstrates the effectiveness of a subject-independent BCI framework using deep convolutional neural networks (CNNs). Their CNN model outperforms conventional subject-independent and subject-dependent BCI calibration methodologies. This research paves the way for practical calibration-free BCIs that are more generalizable across subjects [16].

Convolutional Neural Networks (CNNs) are highly effective for processing EEG data due to their structured architecture, which includes convolutional layers for extracting features, activation layers, pooling layers, and fully connected layers. These components enable CNNs to capture intricate spatial and temporal patterns within EEG signals efficiently. For instance, Zhu et al. utilized a CNN model enhanced with common spatial pattern (CSP) for feature extraction, achieving a classification accuracy of 73.00%. However, the study's reliance on a small sample size underscored the necessity for larger datasets to enhance the model's generalizability and robustness [24].

CNNs have also shown promise in P300-based speller systems. In a study by **Lee et al.,** a CNN was trained on EEG data from 55 healthy participants engaged in a conventional P300 speller task [17]. The model employed a zero-training framework, achieving an accuracy of 85.00%, which surpassed calibration-based methods that achieved 82.00%. This research highlighted the importance of diverse and extensive training datasets in boosting model accuracy. Nonetheless, the presence of low-amplitude signals slightly hindered classification performance, emphasizing the need for improved preprocessing techniques to address these challenges effectively.

## Recurrent Neural Networks (RNN)

There has been a great deal of models developed using recurrent neural networks and long short-term memory because these models handle EEG signals especially well. While RNNs are noteworthy in the context of BCI work, they were not incorporated as part of this review. In recent work, RNNs and CNNs are often part of hybrid models in an attempt to improve feature extraction, especially for EEG-data based BCIs. Khademi et al performs a literature review to explore common challenges with RNN implementation in BCI [24].

## K-Means (unsupervised learning) and Artificial Neural Network to train a Multilayer Perceptron Unit: sources found but section needs to be finished

In 2011, **Orhan et al** explored k-means clustering and Multilayer Perceptron Neural Networks for EEG data in the context of epilepsy, a disease know nto cause seizures and effects approximately 1% of the global population [13]. The method of their investigation was to explore a hybrid model combining k-Means clustering and a Multilayer Perceptron Neural Network (MLPNN) for classification. First they had to preprocess their data and EEG signals were decomposed into frequency sub-bands using DWT (good for dynamic and not static signals). Unsupervised machine learning was used as the waveform coefficients were clustered via implementation of the k-Means learning algorithm. K-Means grouped the coefficients into clusters without prior knowledge of their distribution before probability clusters were calculated for the various EEG segments based on the clustered wavelet coefficients. Thus, the dimensionality of the feature space was reduced.

Subsequently, the probability distributions were pushed into a multilayer perceptron neural network. Speaking broadly, the model architecture is as follows: feedforward neural network with an input, hidden, and output layer. Training was done using a backpropagation algorithm optimized with the Levenberg-Marquardt method for faster convergence and reduced overfitting [13]. Levenberg-Marquardt (LM) algorithm is an optimization method that combines gradient descent and the Gauss-Newton method so it can handle non-linear least squares problems and is often used in training neural networks, particularly in applications like Multilayer Perceptron Neural Networks (MLPNNs).

The results from training the model yielded very high levels of accuracy [13]. The results from this study are as follows:

Experiment 1: Differentiated between healthy and seizure states with a classification accuracy of 99.6%.

Experiment 2: Distinguished healthy subjects (eyes open) from seizure states with 100% accuracy.

Experiment 3: Identified healthy subjects and all epilepsy states (seizure-free and seizure) with an accuracy of 98.8%.

Experiment 4: Differentiated healthy, seizure-free, and seizure states, achieving 95.6% accuracy.

Experiment 5: Classified healthy, seizure-free, and seizure states from specific brain regions, with an accuracy of 96.67%.

The hybrid model outperformed previous BCI classification methods, including standalone MLPNNs and other neural network-based classifiers. This study highlights the effectiveness of combining k-Means clustering and MLPNNs for EEG signal classification. By leveraging the strengths of unsupervised learning for feature extraction and supervised learning for classification, the proposed model achieved high accuracy in distinguishing between healthy versus epileptic states.

## Support Vector Machines for Feature Extraction

Support Vector Machines (SVMs), a class of supervised machine learning algorithms are used primarily for binary classification and regression tasks [26]. SVMS have been extensively used in the context of EEG-based Brain-Computer Interfaces (BCIs) [6]. An example of this application in the field was a study by Bhattacharyya et al in 2017, where SVM served as the classification method for a robotic arm (or a motor) BCI device. Motor imagination (MI) involves the thought process and neural signal underpinning movement [6]. In this study, MI signals were converted into robotic arm commands and EEG data was collected and then preprocessed using: spatial filtering techniques like Common Average Referencing (CAR), band-pass filtering for motor related signal at (8-12 Hz) and beta (16-24 Hz) bands, and then. wavelet transforms were applied to extract features. Following feature extraction and preprocessing, correlation-based feature selection (CFS reduced the dimensionality of the data. Then, an SVM classifier used a one-against-one strategy. These data consisted of multiple classes: no movement, clockwise, and counterclockwise motion of the robotic arm. The SVM classifiers reported an **accuracy of over 83% across participants for MI decoding tasks**. In this report, SVM was computationally efficient and had a high degree of precision.

In related research, **Ferrez et al. [7]** further demonstrated the value of SVMs for motor imagery and error-related potential detection. Their study achieved an online recognition rate of 84.7% for correct trials and 78.8% for erroneous trials. Without ErrP integration, the BCI error rate remained at 30%; however, integrating ErrP detection reduced the error rate to 7%, effectively improving the system's performance and multiplying the bit rate by a factor of three.

Recent advancements have also explored hybrid approaches combining SVMs with other classifiers to improve performance. For instance, Padfield et al. (2020) demonstrated that ensemble learning, integrating SVMs, random forests (RF), and artificial neural networks (ANNs), achieved higher sensitivity and reliability for a BCI-controlled wheelchair system. By adopting a hierarchical classification approach and leveraging certainty thresholds, their ensemble method achieved a sensitivity of 85%, outperforming individual classifiers (65%, 76%, and 79% for ANN, SVM, and RF, respectively). This hybridization highlights the growing trend of combining SVMs with other machine learning methods to enhance BCI performance, particularly in multi-class and real-time applications.

In summary, SVMs continue to play a critical role in EEG-based BCI research, demonstrating their adaptability for both motor imagery decoding and error detection. Their computational efficiency, accuracy, and ability to handle multi-class classification problems make them well-suited for complex neurotechnology applications. Moving forward, integrating SVMs with hybrid models and exploring advanced feature extraction techniques will likely further improve their performance in real-time BCI systems.

# Discussion

## The findings presented in this review highlight the significant advancements in brain-computer interfaces (BCIs) achieved through the integration of artificial intelligence (AI) and machine learning (ML). As many of the selected papers have demonstrated, there are unique challenges in BCI applications. For example, neural data is spiky, noisy, and can be challenging to work with. Poor signal quality or spectral artifacts such as eye blinks, muscle movements, and external interference lead to less than optimal data. Further, it is difficult to train models that can automatically differentiate between noise and useful signals especially in real-time. This is very computationally expensive. It is also challenging to have the participant deal with training demands for data collection and for classification. While calibration-free systems and reduced-time calibration have shown promise, they still result in lower accuracy for motor imagery (MI) tasks compared to event-related potentials (ERP).

Some models have been shown to be especially effective, such as neural network-based approaches (accuracy above 95%). However, they are computationally intensive, making real-time implementation difficult, especially in portable or embedded systems. At this point in time, there is also a lack of standard approach and lack of publicly available, high-quality, and large-scale datasets for alternative techniques like fNIRS, MEG, EEG, fMRI which further complicates standardization and research into BCIs,

1. **Future Directions**

To address these challenges, future research could focus on multimodal BCIs or hybrid training models. Multimodal **BC**Is could combine EEG with other modalities like fNIRS, MEG, or fMRI can provide complementary brain activity patterns, enhancing signal quality and classification accuracy. Hybrid BCIs hold the potential to extract richer features and improve robustness.

Future research should also focus on high quality signal filtering and detection so these  
AI- and ML-based methods will select high-quality signals and improving accuracy while reducing computational burden.

Approaches like transfer learning (TL) for SVM and CNN models can also improve real-time performance with minimal training. available, large-scale datasets that include both physiological and pathological recordings will be critical. Such datasets should reflect real-world conditions and include standardized evaluation criteria for AI/ML methods.

# Conclusion

AI and ML-based algorithms have demonstrated promise in the processing, analysis, and interpretation of brain signals for BCI applications. Techniques such as ANNs, CNNs, SVMs, and SNNs have advanced noise suppression, classification accuracy, and calibration efficiency. Some hybrid approaches have proven to improve the classification accuracy as well. However, challenges persist, including signal quality, computational complexity, and inter-subject variability, particularly in real-time applications for disabled subjects.

Future research must prioritize hybrid BCIs, automated signal selection, and real-time optimization while addressing dataset limitations through standardized protocols. By addressing these limitations and furthering the improvement of existing algorithms and methods, many bioengineering applications can be met.

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# References

1. J. He *et al.*, “The development of Spiking Neural Network: A Review,” *2021 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pp. 385–390, Dec. 2022, doi: 10.1109/robio55434.2022.10012028.
2. N. Pawan and R. Dhiman, “Machine learning techniques for electroencephalogram based brain-computer interface: A systematic literature review,” *Measurement Sensors*, vol. 28, p. 100823, Jun. 2023, doi: 10.1016/j.measen.2023.100823.
3. S. R. Sreeja, J. Rabha, K. Y. Nagarjuna, D. Samanta, P. Mitra, and M. Sarma, “Motor Imagery EEG signal processing and classification using Machine learning approach,” *IEEE*, Oct. 2017, doi: 10.1109/ictcs.2017.15.
4. C. Mühl, B. Allison, A. Nijholt, and G. Chanel, “A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges,” *Brain-Computer Interfaces*, vol. 1, no. 2, pp. 66–84, Apr. 2014, doi: 10.1080/2326263x.2014.912881.
5. N. Padfield, K. Camilleri, T. Camilleri, S. Fabri, and M. Bugeja, “A comprehensive review of endogenous EEG-Based BCIs for dynamic device control,” *Sensors*, vol. 22, no. 15, p. 5802, Aug. 2022, doi: 10.3390/s22155802.
6. S. Bhattacharyya, A. Konar, and D. N. Tibarewala, “Motor imagery and error related potential induced position control of a robotic arm,” *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 4, pp. 639–650, Jan. 2017, doi: 10.1109/jas.2017.7510616.
7. P. W. Ferrez and J. Del R Millán, “Simultaneous Real-Time Detection of Motor Imagery and Error-Related Potentials for Improved BCI Accuracy,” *ResearchGate*, pp. 197–202, Jan. 2008, [Online]. Available: https://infoscience.epfl.ch/record/145986/files/ferrez\_graz\_2008.pdf?version=1
8. S. EgyptianInformaticsJournal, A. Atia, and Mostafa, “Braincomputer interfacing:Applications andChallenges,” *EgyptianInformaticsJournal*, vol. 16, pp. 213–230, 2015, doi: 10.1016/j.eij.2015.06.002.
9. N. S. Card *et al.*, “An accurate and rapidly calibrating speech neuroprosthesis,” *New England Journal of Medicine*, vol. 391, no. 7, pp. 609–618, Aug. 2024, doi: 10.1056/nejmoa2314132.
10. K. Barnova *et al.*, “Implementation of artificial intelligence and machine learning-based methods in brain–computer interaction,” *Computers in Biology and Medicine*, vol. 163, p. 107135, Jun. 2023, doi: 10.1016/j.compbiomed.2023.107135.
11. A. Kawala-Sterniuk *et al.*, “Summary of over Fifty Years with Brain-Computer Interfaces—A Review,” *Brain Sciences*, vol. 11, no. 1, p. 43, Jan. 2021, doi: 10.3390/brainsci11010043.
12. A. K. Maddirala and K. C. Veluvolu, “Eye-blink artifact removal from single channel EEG with k-means and SSA,” *Scientific Reports*, vol. 11, no. 1, May 2021, doi: 10.1038/s41598-021-90437-7.
13. U. Orhan, M. Hekim, and M. Ozer, “EEG signals classification using the K-means clustering and a multilayer perceptron neural network model,” *Expert Systems With Applications*, vol. 38, no. 10, pp. 13475–13481, May 2011, doi: 10.1016/j.eswa.2011.04.149.
14. K. Barnova *et al.*, “Implementation of artificial intelligence and machine learning-based methods in brain–computer interaction,” *Computers in Biology and Medicine*, vol. 163, p. 107135, Jun. 2023, doi: 10.1016/j.compbiomed.2023.107135.
15. Z. Tan *et al.*, “Neural machine translation: A review of methods, resources, and tools,” *AI Open*, vol. 1, pp. 5–21, Jan. 2020, doi: 10.1016/j.aiopen.2020.11.001.
16. O.-Y. Kwon, M.-H. Lee, C. Guan, and S.-W. Lee, “Subject-Independent Brain–Computer interfaces based on deep convolutional neural networks,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 10, pp. 3839–3852, Nov. 2019, doi: 10.1109/tnnls.2019.2946869.
17. J. Lee, K. Won, M. Kwon, S. C. Jun, and M. Ahn, “CNN with large data achieves true Zero-Training in online P300 Brain-Computer interface,” *IEEE Access*, vol. 8, pp. 74385–74400, Jan. 2020, doi: 10.1109/access.2020.2988057.
18. Z. Tayeb, E. Ercelik, and J. Conradt, “Decoding of motor imagery movements from EEG signals using SpiNNaker Neuromorphic hardware,” *IEEE*, pp. 263–266, May 2017, doi: 10.1109/ner.2017.8008341.
19. N. Kumar, G. Tang, R. Yoo, and K. Michmizos, “Decoding EEG With Spiking Neural Networks on Neuromorphic Hardware,” *Transactions on Machine Learning Research*, 2022.
20. N. A. Alzahab *et al.*, “Hybrid Deep Learning (HDL)-Based Brain-Computer Interface (BCI) Systems: A Systematic review,” *Brain Sciences*, vol. 11, no. 1, p. 75, Jan. 2021, doi: 10.3390/brainsci11010075.
21. C. Yaacoub, G. Mhanna, and S. Rihana, “A Genetic-Based feature selection approach in the identification of Left/Right hand motor imagery for a Brain-Computer interface,” *Brain Sciences*, vol. 7, no. 1, p. 12, Jan. 2017, doi: 10.3390/brainsci7010012.
22. K. Barnova *et al.*, “Implementation of artificial intelligence and machine learning-based methods in brain–computer interaction,” *Computers in Biology and Medicine*, vol. 163, p. 107135, Jun. 2023, doi: 10.1016/j.compbiomed.2023.107135.
23. **“EEG (electroencephalogram) - Mayo Clinic.” https://www.mayoclinic.org/tests-procedures/eeg/about/pac-20393875**
24. H. Li, M. Ding, R. Zhang, and C. Xiu, “Motor imagery EEG classification algorithm based on CNN-LSTM feature fusion network,” *Biomedical Signal Processing and Control*, vol. 72, p. 103342, Nov. 2021, doi: 10.1016/j.bspc.2021.103342.
25. Z. Khademi, F. Ebrahimi, and H. M. Kordy, “A review of critical challenges in MI-BCI: From conventional to deep learning methods,” *Journal of Neuroscience Methods*, vol. 383, p. 109736, Oct. 2022, doi: 10.1016/j.jneumeth.2022.109736.
26. A. Joby, “Unsupervised Learning: How machines learn on their own.” https://learn.g2.com/unsupervised-learning