Enhancing EEG-Based Brain–Computer Interface Performance: A Review of Machine Learning Algorithms

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Abstract

Brain-computer interface (BCI) systems based on electroencephalography (EEG) are applications that allow human-to-machine communication with intuitive (near-transparent) control, whose neural commands are decoded based on intentional movement. Recent research on the topic of machine learning (ML) has been able to greatly enhance the classification of the EEG-signals associated with the movement of the hands, head movements, and mobility movements of the eyes. The developments allow various utilization across assistive technologies, prosthetic control, and non-verbal communication. EEG, however, is highly non-stationery and noise-sensitive, so advanced preprocessing and optimization methods have to be applied to optimize performance in classification. This paper outlines an in-depth review of some of the most popular ML algorithms, i.e. support vector machines (SVMs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), and optimization methods, i.e., genetic algorithms (GAs), particle swarm optimization (PSO), and transfer learning. We point out existing problems in the processing of EEG signals and suggest directions in the future that will improve the robustness, generalization, and real-time behavior of BCI.

Keywords: BCI; Machine Learning; Deep Learning; EEG; Optimization technique

1. Introduction

Brain-computer interface (BCI) devices offer a channel of communication between the human brain and external equipment and hold substantial post-trial potential for patients with severe motor sequelae. To record the brain signals related to voluntary or imagined motor actions non-invasively, electroencephalography (EEG) is considered the most useful because of its high time resolution and portability. It is possible to decode these signals using branch of machine learning to control robotic limbs, wheelchairs, or virtual applications [1]. EEGs are electrical potentials that are recorded at the scalp and fingers in time. They are usually of low amplitude, and they are usually noise and artifact-contaminated (i.e., ocular and muscular activities). Feature extraction is important in achieving an increased signal-to-noise ratio and includes the use of band power analysis, Common Spatial Patterns

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(CSP), as well as wavelet decomposition. Moreover, the recent advancements in deep learning allow one to run raw EEG data through the model, thereby gaining knowledge of complex spatio-temporal representations. The important role of Artificial Intelligence (AI) in the development of Brain-Computer Interfaces (BCI) is its contribution in classification and interpretation of the EEG signals. The AI systems are used to monitor the neural activity and translate it into usable commands allowing the control of an outside tool like the robotic arm and wheelchair. The models have applications in motion detection, such as hand, eye, and head gestures (e.g., left-right saccades or blinks, nodding or shaking). This is done to enhance the quite low accuracy, speed, and robustness of these applications by various optimizations strategies variably called feature selection algorithms, signal-preprocessing methods, hyperparameter tuning to optimize the performance of machine learning and deep learning models.

2. Related Work

Many studies have been published on improving EEG data analysis using machine learning. These studies focus on classifying and identifying movements of the hands, head, legs, tongue, and eyes, as shown in Table 1.

In [2] the article describes one of the brain-computer interface (BCI) problems, which consists of a difficulty in classifying specific motor imagery electroencephalography (MI-EEG) signals correctly. It implements the Cross Tensor Coupling Decomposition (CTCD) that takes advantage of processing data that has a tensor form to make it more efficient and computationally less demanding. On Dataset 1, the proposed method received an accuracy of 91.75% +/- 3.25, which is a good result. The traditional techniques are concentrated on the average linear correlation; thus, they cannot be effective in the analysis of MI-EEG. Tucker decomposition is applied in the segmentation of the dataset and takes out features to be classified by having a high sensitivity and specificity rate. The paper identifies the necessity of new algorithms to address the few-shot learning and scarce-labeled data. The new model is the Augmented Covariance Networks (ACNs), which focuses on the improvement of nonlinear information representation in MI-EEG signals with a Cohen coefficient of 0.85 +/- 0.07. This technique can demonstrate promising results when compared to traditional ones, such as IVATL-M, FBCCSP, as it allows one to decode quickly and provide feedback in real-time, which helps improve MI-BCI applications. The approach showed better temporal performance than other competitive deep learning models.

In [3] The method that is described in the paper is known as Cross Tensor Coupling Decomposition (CTCD) and can be used to classify motor imagery (MI) tasks as accurately as possible on the basis of electroencephalogram (EEG) signals. CTCD combines tensors within modality feature networks because of intrinsic connections present among modality BFN tensors linked to different MI tasks. Changes in the computational complexity of the method can be an issue when a real-time application is concerned, since the task of decomposing tensors and obtaining features may be demanding. The paper outlines the shortage of measures in the process and analysis of multi-modal feature networks based on EEG data. CTCD rearranges an EEG into a covariance adjacency matrix by computing all the covariances between pairs of EEG channels, which is then utilized in the creation of a complex network model. This method establishes a firm background on the proper ranking of MI-EEG signals, and it helps to further boost computational energy by using the direct mapping approach. Nevertheless, the approach employed in the method might be narrow due to the types of MI tasks and datasets it uses. The findings of the paper enhance comprehension of the BCI issues and legitimize other solutions within its sphere. The scalability of the method to increase collections of data or tasks that are more demanding requires further recognition.

In [4] the paper puts forth two supervised approaches, PSD2DLDA and PCD2DLDA, to enhance the accuracy of classification of EEG signal processing. The methods mentioned are the best alternative to the current unsupervised ones, such as 2DPCA and LPP, showing weaknesses in representing abstract characteristics and the necessity to obtain better classification performance in EEG activities. In general, PSD2DLDA and PCD2DLDA have proven better in many respects than the conventional methods to overcome their weaknesses. The Two-Dimensional Linear Discriminant Analysis (2DLDA) using the L1 norm is susceptible to variants and outliers, and such degrade their performances. The methods proposed have better results in their classification accuracies, especially when the EEG is optimized to 90 dimensions. Another promising feature demonstrated in the study is the effectiveness of the L1-norm and the robustness to noise and outliers over that of the L2-norm. Nevertheless, the discussed procedures continue to have a few limitations when it comes to resolving extreme cases. In the study, Lemma 2 is used to determine the objective function that concerns dimensionality and discrimination of classes. Overall, the presented supervised approaches can contribute to a vast improvement in motor imagery EEG decoding. Such detailed research on the simultaneousness and application of such enhanced procedures is required, with more studies to comprehend their drawbacks in detail.

In [5] the article talks about the issue of decoding the human brain in a non-invasive way, that is, the human brain through improved EEG decoding. It uses a new attention-based Patched Brain Transformer model to decode the EEG, and it performs better relative to the number of parameters. Nevertheless, the research is limited because the training data are scarce and may affect the inductive bias applied by the Transformer. The most relevant problems

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of EEG decoding are noise, scarcity, and temporal-spatial correlations. To increase the size of the training data, data augmentation methods, including Direct Current Shifts, are applied. The idea of the research is to come up with machine learning techniques to enhance the performance of EEG to decode it by adding pre-training and regularizing the models to extend performance and avoid overfitting. Each trained filter gets brain frequencies associated with an increased level of participant concentration, as in the convolutional networks such as EEGNet. The research explains the necessity to examine transferability and scale up pre-training on different classification tasks. The paper shows the comparison of the proposed model with the state-of-the-art models that showed non-trivial complexity in terms of a few parameters and performance. The results indicate that the model can be flexibly trained effectively on disparities of EEG data before training.

In [6] The paper argues that the issue of neural signal interpretation in terms of low signal-to-noise ratio (SNR) limits progress in the field and suggests a hybrid architecture that would allow predicting mental states based on EEGmetric data and should include a four-layered CNN1-D in combination with a GRU. The hybrid models got classification accuracy greater than 99 percent, and the effect of channel selection and data augmentation. As some weak points of EEG-based MI-BCI systems, the paper also touches upon low SNR that is caused by an assortment of artifacts. To tackle the problem of class imbalance in MI EEG data, the SMOTE data augmentation method is applied, including the success rate of five different motor imagery tasks. Nevertheless, the issue with data augmentation is that it is not applicable to the expansion of the sensory motor region noticeably, which will likely have an impact on network performance. This paper highlights the issue of effective feature extraction of raw EEG signals to increase the accuracy of classification. Macro average accuracy of the CNN-GRU and CNN-Bi-GRU models stood at 98.88 percent and 98.93 percent, respectively. The accuracy rates are high after the effectiveness of the proposed models has been tested on the PhysioNet dataset. This suggested solution has the promise of culminating in low-cost EEG-based brain-computer interface systems.

In [7] The proposed Dual-Branch Blocked-Integration Self-Attention Network (DB-BISAN) is an effective solution in terms of classification of EEG motor imagery, addressing the problems of representing the EEG signal as time-frequency dynamics and inter-channel redundancy. The model has a Dual-Branch Feature Extraction Module, which combines the temporal and spatial characteristics, and multi-scale spatio-temporal characteristics in EEG signals are effectively extracted. Nevertheless, the use of small sets of EEG and small sample sizes hinders the efficacy of the model. Single-branch models also lack the multi-branch architecture found in the structures to record dynamic changes that take place in the neural tissues in the motor imagery process. The proposed approach has a Blocked-Integration Self-Attention Mechanism, which is used to point out the key features and diminish redundancy. The paper gives a comparison between DB-BISAN and other state-of-the-art deep learning techniques, stressing its high performance. The result of the experiment indicates that DB-BISAN performs confidently when it comes to motor imagery at a state-of-the-art level. Nevertheless, the effectiveness of this dual-branch structure has not been well tested, and the type-specific efficacy of convolution kernel structures is not deemed to affect performance. It is also mentioned in the paper how CNN and LSTM can be integrated to enhance accuracy in EEG classification.

In [8] the paper shows a collaborative method where five convolutional neural network (CNN) models were used to classify motor imagery with a 79.44 per cent accuracy on the BCI Competition IV 2a data. Credence is given to the issue of model complexity as a key drawback, and the necessity of satisfying solutions as a way of enhancing patient outcomes through brain-computer interfaces (BCIs) in the study. The method suggests wavelet packet decomposition (WPD) as a process of extracting the frequency characteristics that can improve the accuracy of classification in the motor imagery task. Results are not easily interpretable, and the extraction of any reliable control signals out of the brain data that is rather noisy is a rather important challenge. The paper also highlights the necessity of refining the preprocessing technique to alleviate the noise. The use of a band-pass filter in the preprocessing of EEG signals is proposed along with the classification of motor imagery tasks that a BCI system cannot exist without. The results provide a lot of hope that brain-computer interface technologies can serve the needs of people.

In [9] Lightweight Geometric Learning Brain-Computer Interface (LGL-BCI) continues to overcome the deficiency of the existing EEG devices, which are, however, consistent in that they enable the user to perform motor-imagery tasks, but they do not permit the same to be done efficiently. The LGL-BCI reads a personalized geometric Deep Neural Network architecture wherein the EEG channel selection module is deployed to mitigate failures and adapt to variability in EEG signals. The prototype has been 82.54% accurate, which increases the performance outcome of the state-of-the-art to 62.22%. The research also points to the need to come up with better frameworks for the EEG-controlled systems. The LGL-BCI has non-invasive EEG extraction in comparison to invasive procedures such as electrocorticography. The model showed a reduction in parameters, and this means that the model is computationally efficient. The model might, however, experience impaired performance at reduced sampling rates, which affects accuracy. The other source of difficulties explored by the study is that of the EEG motor-imagery trials with amplitude fluctuations and complicated spatial correlations. EEG signals often

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suffer from a low signal-to-noise ratio, which leads to the use of multi-branch CNN modules. The opportunity of geometric deep learning in diverse sensor-based applications is advocated, but the restricted encoding space would restrain futuristic growth. The article recommends cooperation with neurologists to develop a more adequate encoding strategy.

in [10] The paper discusses how machine learning (ML) algorithms, namely, convolutional neural network (CNN) and recurrent neural network (RNN), can be deployed in detecting biomarkers of anxiety disorders and even anticipating therapeutic outcomes. The analysis shows that ML is very effective in recognizing such intricate neural patterns in EEG, especially in anxiety disorders. The ability to analyze and diagnose is, however, thwarted by such challenges as data variability, noise, and model interpretability, among others. The users also have a problem in using brain-computer interfaces (BCIs), with 15-30 percent of them experiencing illiteracy in using BCIs. The experiment proves the necessity of personal and adaptive BCI system training, as repeated training enhances EEG signal classification accuracy. BCIs are also limited by technological factors in their EEG processing. EEG signal quality can be affected by physiological characteristics, which may make the specific placement of the electrode difficult, e.g., dense hair. The extraction of features is used to determine those neural patterns of imagined movements, to which a linear discriminant analysis (LDA) algorithm is applied in order to classify them. It is pointed out in the study that individualized and adaptive EEG analysis techniques will increase the accuracy of signal classification, and the research shows that, in this way, it is important to consider ethical aspects regarding privacy and safety of information.

In [11] this study was set out to design a motor imagery EEG acquisition protocol that would be able to increase the polarization rate of ERD/ERS of elderly users. Nevertheless, the system was prone to EEG noise, which is due to muscle activity and environmental interferences in terms of categorization. It was based on the machine-learning algorithm, namely, Wavelet Package Neural Network that gave the system an 89.23 percent classification accuracy. EEG, VR, and exoskeleton control synchronization presented a problem to the system. The protocol of motor imagery EEG acquisition was created that involves the combination of deep learning and wavelet packet transformation to extract features. The study emphasized the necessity of involving more people as users in the sort of user trials, such as among the elderly and the neurologically impaired population. It was challenging to remove eye movement artifacts because of the lack of electrooculogram (EOG) sensors. The delays in the execution of motor commands impaired user experience and clinical deployment. Some of the Wavelet types that were considered were Coiflets, Symlets, and Daubechies, which were chosen following their property of suitability with EEG signals. Future research is recommended to include clinical trials to determine motor improvement and changes in some markers of neuroplasticity. The optimization of the system and its influence on the polarization of ERD/ERS is questionable, as there was no direct testing with the target population.

In [12] The paper comments upon the EEG research difficulties, the lack of approaches to the EEG analysis standardization, and the complexity of source localization techniques. It applies powerful techniques such as Dipole Fitting, MNE, and Beamforming to EEG analysis, which have recorded a world-level accuracy of 99.15 percent in carrying out tasks of motor imagery. Nonetheless, the small size of the data might influence the generalizability of results. Challenges in single-trial EEG classification encountered because of noise and poor spatial resolution are also reflected in the study. The task of motor classification is carried out using a custom ResNet CNN architecture, with beamforming achieving a 90.83 percent accuracy rate. The following study is concerned with the enhancement of motor task classification based on deep learning and source localization concepts, foreseeing the combination of both deep learning and source localization to facilitate further improvements in the classification accuracy. Nonetheless, beamforming can be affected by DSDs (i.e., inter-subject variability and EEG noise). Methodology involves preprocessing, source localization, and highly featured extraction. The study focuses on the benefits of rapid temporal resolution offered by EEG in real-time monitoring of brain activities, though issues with noise and poor spatial resolution are mentioned to be an obstacle in EEG measurements.

In [13] a research about the brain-computer interfaces (MI-BCIs) based on motor imagery showed a very close relationship between tongue imaginations and MI-BCI flexibility. It was found that the characteristic length of the path and nodal degree in the right hemisphere showed significant correlation with the accuracy of classification, using the data of the healthy 50 subjects. The study also pointed out the relationship between the characteristics of the neural networks and MI-BCIs' adaptability. Four techniques of feature extraction were used, one of which was filter bank CSP (FBCSP). The study indicates that tongue imagination might be used as an indicator of MI-BCI adaptability to clarify the functional network processes underlying motor imagery. In future research, such a clinical population is to be introduced to determine the generalizability of results. The power spectral density was analyzed by employing the multi-taper method, and the conducted experiment showed the correctness of several different modes of classification, which were applied in order to estimate the adaptability of the participants to MI-BCI. A 10-fold cross-validation methodology was undertaken to evaluate the performance of the classifier model.

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In [14] the article introduces a new hybrid deep neural network architecture, namely CLTNet, to classify the motor imagery signal of EEG. The BCI IV 2a and 2b datasets generated 83.02 and 87.11 percent accuracy, respectively. Nevertheless, it still has a scope for enhancement in recognition accuracy of the MI-EEG of LOSO for decoding. To preliminarily extract features, it is based on the convolutional neural network (CNN) and compares with conventional classifiers in recording EEG signals in the motor imagery. The paper also addresses the issues of limited accuracy in recognizing the bounds of cross-subject MI-EEG decoding and talks about the use of different types of classifiers like Support Vector Machines (SVMs), Decision Trees, and Linear Discriminant Analysis (LDA). The S&R module plays a significant role in enhancing the results in modeling, but the more heads are used, the more training and convergence on constrained data becomes convoluted. The training process deploys the Leave-One-Subject-Out (LOSO) approach of evaluation of the models. The paper gives a novel approach to advancing brain-computer interface technology.

In [15] the article is also pioneering in presenting a novel frequency band attention-based temporal convolutional network (FBATCNet) for decoding MI-EEG recordings, hence meeting the demand of calibration-free BCI that has the phenomenology of subject-independent classification. The research presents a tri-class fine motor imagery (FMI) paradigm of upper limb rehabilitation in stroke patients. The model FBATCNet contains temporal convolution, convolution, and frequency band attention blocks. The model had an accurate rate of 84.73% and 66.06% in Datasets 1 and Dataset 2, respectively, showing that more research on the model is required before its application to BCI systems. The paper also reveals the role of the environmental situation in the quality of MI and the clarity of an EEG signal in stroke-related patients. The model applies to a channel attention mechanism that assigns the weights of EEG frequencies, but the removal of FBA and TC blocks led to a considerable loss of classification performance. The study establishes the necessity of efficient unilateral upper limb intervention procedures in stroke victims. The temporal convolution block shown reflects the long-term dependency using spatial features. To show the effectiveness of the use of the model, it is compared to six MI EEG decoding methods.

In [16] the paper proposes a classification model named ORDWT AR, based on an over-complete rational dilation wavelet transform together with an autoregressive model. Model performance with BCI datasets had an average classification accuracy of 99.8%, and the CHB-MIT had an average classification accuracy of 99.7%. Boosted Trees classifier has some extensive training time and optimization issues since it involves the construction of multiple decision trees. The existing models have demonstrated good performance, yet they continue to encounter major challenges in terms of providing sound classification. The research revealed that the weighted k-nearest neighbor's classifier performed better than the other classifiers in classifying the BCI EEG recordings. The selected representation features of EEG signals using an ORDWT-based classifier efficiently extracted representative features, resulting in an increase in classification performance. In the study, feature extraction was employed using wavelet packet decomposition as well as using higher-order statistics. The results show that there were very significant disparities between the performances of the tested classification models. A better particle swarm optimization and neural network is cited in the classification of datasets.

In [17] the paper addressed the issue of wanting to achieve a higher percentage recognition of the classification of the brain-computer interface systems, where images of body movements are depicted, because of the nature of EEG signals. It presents the discussion of preprocessing of the EEG data, which consists of filtering and artifact removal, as well as issues with traditional machine learning techniques. The motor imagery tasks were in the study, and the data were from 109 subjects. Classification was performed using the four traditional machine-learning algorithms, namely LDA, KNN, SVM, and RF. The 14 experiments within the experimental design incorporated different tasks of motor imagery. The article points out the necessity of efficient means of extracting complex characteristics of EEG data. It discusses the corresponding representation of the spatio-temporal features using Gramian Angular Field (GAF) and phase locking value (PLV). The paper also contrasts the drawbacks of existing deep learning models with respect to interpretability as well as feature capture. The non-stationarity and the low signal/noise levels of CNN and LSTM techniques make it difficult to take care of the nonlinear characteristics. GAF and convolutional neural networks (CNN) are applied in combination as feature extraction and classification. This paper has highlighted the necessity of additional research on how to enhance model performance in the brain-computer interfaces related to the motor imagery study. Single-view approaches cannot be used to obtain complex spatio-temporal dynamic features, which disregard spatial location-to-location interactions. The results provide an indication that the use of feature extraction in conjunction with deep learning improves the accuracy of classification.

In [18] the paper proposes a new solution to EEG motor-related task monitoring with minimal preprocessing. Using deep neural networks (DNNs) to detect EEG motor tasks. It implements cooperative learning and deep neural networks based on sub-gestures and neural activity to introduce a new direction of BCI research where physical movement prolongation is correlated to communication across the motor cortex through scalp EEG. The paper points to the necessity of better performance in the classification without too high computational expenses. The given approach will attempt to identify and classify consecutive motions with the help of EEG signals based

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on orthogonal basis functions. The approach indicates reasonably good calibration of the lengthy motor actions in orthogonal functions, with little data. Nevertheless, scaling up larger datasets multiply the computational expenses and training, making their applicability less viable in real-life scenarios. The paper highlights the challenge of using small trains to get good performances and inter-subject variability. EEG preprocessing. With EEG, preprocessing processes are performed to reduce EEG artifacts prior to the application. The validation of the method is carried out on two freely available datasets of EEG motor movement, and the accuracy of the validation is low. The validation of the method is only effective with small datasets; hence, it might not reflect wider situations. Verification of methods is also done using statistical tests, which include the Quade test and the Nemenyi test, among others.

in [19] The article talks about the correct classification of motor imagery (MI) based on electroencephalogram (EEG) signals recorded by a small number of electrodes. MI tasks will be carried out using the Common Spatial Pattern (CSP) method to improve the separability of classes in the form of an average MI classification accuracy of 78.16%. Nonetheless, the applicability of feature selection using central EEG channels is to a certain extent constrained by electrode configuration with fewer or alternative electrodes and spatial distribution. The other problem of illiteracy in BCI, where 15 to 30 percent of users experience problems in using MI-based BCIs, is also discussed in the study. A prediction of EEG signals based on a small set of electrodes by an elastic net regression technique has been achieved, though it showed some difference in performance between individuals. The traditional techniques of using numerous electrodes compromise costs and preparation time. Band-pass filters are used to narrow down on meaningful signal bands in EEG, but the CSP algorithm has the disadvantage that it can only be used to distinguish between two classes. The article underlines that individual BCI models are necessary in order to enhance classification precision in varying subjects. The technique of temporal windowing is also applied in order to modify the data depending on the motor tasks that help to enhance the process of feature extraction. The study also mentions the differences in the quality of the EEG signal and the performance completion of individuals as a serious difficulty. The given approach makes channel selection more efficient, cutting down the level of hardware at the expense of performance.

In [20] the necessity to minimize the calibration time in brain-computer interfaces (BCIs) is examined in the paper. It presents new algorithms of fractal dimensions, which include box counting, DFA, MFDFA, correlation dimension, and introduces a proposal of a new method to classify motor imagery tasks using the fractal dimension measure of EEG signals. The paper thus identifies the problem of BCI illiteracy, in which the user has difficulties in producing a reliable control because of physiological and cognitive causes. Such conventional fractal dimensions include Katz, Petrosian, and Higuchi. Seven feature extraction techniques are applied in the study; these include Katz, Petrosian, Higuchi, box counting, MFDFA, DFA, and correlation dimension. The results point to the fact that fractal dimension characteristics increase the classification reliability of BCIs. The processing needs of suggested practice might restrict its application in online BCI conditions, however. The study also underlines the role of proper identification of imagined intentions that may lead to the successful development of BCI systems. The research involves four types of classifiers, whereas findings indicate that there is a variance in the classification performance of some subjects with regard to BCI illiteracy.

In [21] the foregoing study intends to derive an algorithm for identifying the motion commands in the viewed and imagined commands through EEG signals. It uses the Imperialist Competitive Algorithm (ICA) to detect the best features that lead to the classification of the EEG signals to be used in issuing the robot's commands. Wavelet features are the most effective, and they achieve a high accuracy level in examining and classifying the EEG signal. The paper also uses the Cuckoo Optimization Algorithm (COA) classifier on feature selection. The best characteristics among all channels elicited 96.3 percent precision in the imagined commands and 96.5 percent in expressed commands. The small sample size can, however, act as a limitation to the generalizability of the results. Frontal and parietal lobes were the best EEGs to detect commands, as they attained 91.5 and 86.9 percent, respectively. It can affect the applicability due to the controlled experimental situation that cannot convey real-life conditions. The study outlines the fact that strong methods of feature selection are required to enhance the performance of classification. The ICA algorithm increases exploration and exploitation of features during selection. It is suggested to have a simplified 14-electrode system that is more cost-effective yet with a high level of classification. Local search is one of the optional techniques of refining solutions.

In [22] The ConSwinFormer is an end-to-end network capable of spatio-temporal frequential feature extraction that fuses CNN and Swin Transformer to decode high-dimensional (dimensionality), low signal-to-noise ratio (SNR) EEG signals with motor imagery tasks accurately. The model attained a mean of 83.99 percent accuracy when classifying motor imagery tasks. The limitations of the model include limited datasets, overfitting, and not allowing natural correlations between the electrode channels and distant temporal relations. The ConSwinFormer will have a preprocessing module, a CNN module, a Swin Transformer module, and a classifier module. The study is identified to be in the best interests of improving classification accuracy in MI-BCI applications with a combination of various frequency bands to achieve the best accuracy. The accuracy of the model nosedives at and

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above five-time sampling points. Another method, FBCSP, is mentioned in the study, as its methodology is compared to the study and shows more accurate classification results. This study will be extended in upcoming studies on neuroscience and clinical practice.

In [23] the article discusses a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model of Motor Imagery (MI)-based EEG classification. The model registered an accuracy of 98.38 percent in performing MI-EEG tasks compared to conventional methods. Nevertheless, the model has a limited build on the hyperparameters that may not be adaptive to varying EEG signals, particularly in the case of real-time applications. The traditional methods of classification are less effective in capturing the spatial as well as the temporal characteristics and hence perform sub-optimally. The model exhibited high accuracy, recall, and F1-score (97.87) in all the classes. Small sizes of datasets limit performance by generalizing them to the population, becoming a challenge to experience. In the study, CNN-LSTM is proposed, which provides better classification results, involving signal-processing operations such as Power Spectral Density (PSD) and Common Spatial Pattern (CSP). The robustness of the model is discussed with real-time BCI applications, and nevertheless, the multi-scale feature fusion methods involve tremendous parameter tuning. Future enhancements of the research depend on the diversity of the dataset frameworks and inter-subject adaptation, as stressed in the research.

In [24] paper presents a pipeline for the EEG classification of actual and imagined movements through functional neural networks (FNNs). Application of the FNNs allowed the research to make accuracy gains of 67.99 percent (motor execution, ME) and 58.39 percent (motor imagery, MI). The research, however, does not overlook that it consists of a small number of participants and emphasizes that a larger number of participants should confirm the success of the models. BCI illiteracy affects 15-30% of the population; hence, it restricts usability by a few users. The suggested pipeline encompasses the process of data obtaining, synchronizing, preprocessing, training, and inference in real time. Comparison with EEGNet and SVMs, FNNs achieved higher accuracy in the classification of ME as well as MI tasks. The study also explores the role of gamification in enhancing user engagement through BCI applications. The framework also supports auto-labeling of EEG data in which gesture recognition is used with an inertial measurement unit (IMU). The paper highlights the relevance of modeling AI models for mobile platforms to increase accessibility. The paper relates the performance of FNNs and EEGNet regarding accuracy and processing speed. The study aims to automate the labeling of EEG data, enhancing training efficiency and model performance.

In [25], the authors argue that the issue of properly categorizing motor imagery (MI) EEG signals through deep learning approaches is an essential issue. It presents three deep learning techniques, CNN-LSTM, CNN-Transformer, and EEG-ITNet, on motor imagery detection. The proposed study suggests CNN-LSTM and CNN-Transformer to improve the accuracy of the classification of MI signals. Nonetheless, the sample size of the data collected is insufficient to demonstrate the advantages of those approaches. Data augmentation methods refer to noise injection (NI), the conditional variational autoencoder (cVAE), and conditional GAN with Wasserstein gradient penalty (cWGAN-GP). The greatest result of precision was 79.06 percent on a particular MI dataset when the CNN-LSTM model was utilized. Hand movement classification was not enhanced much by using data augmentation. A CNN-LSTM-type attention inception approach was also mentioned to classify which MI task to focus on. The study population consisted of 29 participants who were healthy individuals aged 21-26 years and 18-23 years in the case of males and females, respectively. cWGAN-GP took a lot of time and energy in the training process as opposed to other methods. Neural dynamics of motor imagery differences in acute stroke patients are also covered in the study, which is poorly comprehended. EEG was recorded when the subjects were doing motor imagery tasks, since it is non-invasive and economical. This research showed an important difference in microstate A and C exercise in the left and the right hands during MI when undergoing acute stroke. The machine learning models involved are the Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). In microstate C, microstates were higher when the right-hand MI occurred, which could be because of an imbalance in gender among stroke sufferers. The goal of the study is to investigate lateralized processes of brain network reorganization with MI tasks. KNN algorithm delivered a mean accuracy of 75.00 per cent in classification, but a larger population and equal proportion of gender should be covered in future research.

In [26], the article examines the neural processes of motor imagery (MI) in acute stroke patients by analyzing the EEG microstates. It records large discrepancies in microstate A and C when performing MI tasks, which implies that, after a stroke, there is a restructuring of the brain networks that influence the motor functions. The research observes that in the case of left-hand MI, microstate A has higher parameters of Duration, Occurrence, and Coverage, and in the case of right-hand MI, microstate C has higher parameters. There is a small sample size and gender imbalance, which is a limitation and might compromise generalizability. Different machine learning models, such as the Linear Discriminant Analysis (LDA) and the K-Nearest Neighbors (KNN), demonstrated an average classification accuracy of 75%. The results highlight the possibility of EEG microstate features to support post-stroke rehabilitation.

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In [27] to analyze the capability of BCI responders in controlling a robotic hand at an individual finger level, the study was conducted. EEG was re-referenced, down sampled, and band-pass filtered to be analyzed. The performance of the system in real-world problems of complexity has not yet been tested, implying a weakness in the real world. It was observed in the experiment that 15-30 percent of the subjects might fail to respond proficiently by using the sensorimotor rhythm BCI paradigm. EEG raw signals were cleaned of artifacts with a method called independent component analysis (ICA). It was noted that the proportion of non-responders towards the BCI paradigm was about 15-30 percent. One of the areas addressed in the paper is the necessity for BCI tasks to be like real-world applications. The Fieldtrip toolbox and MATLAB scripts carried out an analysis of the event-related desynchronization (ERD) in the data. Ongoing robotic feedback has made communication much better and inspired people, which might positively affect the work on the Internet. The study also did not include poor offline performers, such that the generalization of its findings to the general population would be limited. The results imply the necessity of additional study between the BCI-naive sample and poorly performing subjects. The study also indicated great effects of sessions and the model on online performance metrics. In the BCI task, a smoothing strategy was used to improve control outputs.

In [28] study will attempt to decode finger movements and the no mental task case based on the EEG wave using Intrinsic Time-scale Decomposition (ITD) to analyze the same. It suggests a new method of decoding such movements regarding the issue of generalizing classifiers because of small data and the still idle state of the brain. The Ensemble Learning classifier realized the highest degree of accuracy. The study presents a more realistic system for the classification of finger movements through the machine learning technique. Such features as power, mean value, sample entropy, and Hjorth parameters were tested. The experimental results indicated that features using ANOVA-based feature selection in ITD-based features performed much better than the classifiers with respect to determining the finger movement. The other finding that the study points out is the significance of the feature reduction through significance-based statistics in improving the accuracy of classification. We used the classifiers that distinguished various classes of movements based on EEG signals and noticed that they had a moderate, but still significant, performance improvement in the field of classification as complexity grew.

In [29], the multi-modal dataset with EEG and kinematic channels of a Virtual Glove system is offered, and the research is devoted to the definition of neural signals regarding hand movements. To develop a solution that would minimize interference with the identification of movements and increase the accuracy of the classification, the MOVING dataset, including EEG signal samples and the kinematic data on the hand movement activity and the rest movements, was employed. Common average referencing and band-pass filtering were implemented as part of using the MNE library, and the Theta frequency band was found to lie within the aspects that provided the most informative data concerning the classification of movements. The effect of baseline reduction and frequency band analysis in the classification of motor tasks also came under study. EEG data was de-noised using a technique called applying Independent Component Analysis (ICA) to eliminate the artifacts, improving the accuracy of classification of some of the movement comparisons. In the study, there will be a process of accommodating the assistive technologies of people who have their hands immobilized. The overlapping epochs in EEG signals were extracted using data augmentation methods. Classification of movements using EEG data was done using the EEGnetV4 model. Further research will point toward improving the dataset and motor imagery analysis to improve BCI use. It did a train/validation/test split where 60%, 20% and 20% of the data were used in training the neural network.

In [30] the paper addresses machine learning in the context of usefulness in classifying four motor functions in electroencephalogram (EEG) using Common Spatial Patterns (CSP). The WAY-EEG-GAL dataset was used to build five systems, which dealt with the problems of high sensitivity to the quality of the dataset, size, and diversity. The model was the first to apply both time-domain and frequency-domain features and employed the KNN classifier, but small size or noisy datasets might introduce overfitting and generalization. GoogLeNet was taken as a classifier with the transfer of learning to enhance performance. The paper also indicates the necessity of the operation of decent feature extraction procedures and powerful preprocessing to increase the precision of the determinations. The ML-CSP-OVR model that was created by integrating CSP OVR, CWT, and GoogLeNet was used to classify multiclass, and the best result was obtained with 99.73 % of the highest intersubject classification, specifically, the GP-RV pair. Any motor imagery techniques might not be retained well into real movement data because certain individuals have differences. The last model, ML-CSP-OVR, has reached an accuracy of 78.08% with all combined data. Optimal use of CSP depends on how well the frequency applies to the individual participants, which makes it hard to generalize. The proposed model demonstrates great prospects for motor imagery tasks irrespective of the subject.

In [31] this paper is a two-level deep lean strategy to classify motor imagery with Brain-Computer Interfaces (BCIs), Convolutional Neural Networks (CNNs), and Multi-Dimensional Deep Networks (M-DNN). The methodology employs redundancy measurement and the criterion Minimum Redundancy Maximum Relevance (MRMR) criterion to choose features, which are as relevant as possible, and as non-redundant as possible. Motor

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imagery decoding error is to be reduced with this method, which is vital to its applications in brain-computer interfaces and neurorehabilitation. The paper also proposes a hybrid method that uses optimization of War Strategy (WSO) and Chimp Optimization Algorithm (ChOA) to improve channel selection and classification. The approach allows the computation of redundancy and max relevance in selecting features, which enhances the EEG signal classification process. Its results are better in sorting out motor imagery, difficulties in choosing channels as well as classifications, and better face value and accuracy of BCI systems to assist people with motor limitations. The models proposed are more accurate on a wide range of subjects.

In [32] the paper deals with hand movement classification by the EEG signals to control prosthetic hands for amputees. It employs techniques of feature extraction such as fast Fourier transform (FFT), continuous Wavelet Transform (CWT) in the analysis of EEG data. The paper identifies the difficulty behind the extraction of brain commands based on EEG signals, which are associated with a low signal-to-noise ratio (SNR). The extraction of features performs a true classification after denoising. Noise is removed by real-time processing of EEG data on a moving average filter. To enhance the performance of the classification, different feature extraction methods and machine learning functions are used. CWT produces two kinds of features: CWT coefficients and CWT signal spectrum images. The highest accuracy of 88 percent was attained among the machine learning models when FFT features were fed to an XG Boost tool. As proposed in the paper, however, to reach a decent classification accuracy, plenty of denoising and feature extraction is needed. The study will come up with brain-controlled interfaces to be used on patients with ALS, and this may be limited by the need to have a large collection of EEG data to come up with an effective BCI.

In [33] the paper addresses the problem of phase-based connectivity features usage in decoding continuous hand movement using EEG signals. It was discovered that 300 features were ideal in describing hand movement by all the subjects. The paper also revealed the drawbacks of the classical BCI techniques that are based on amplitude characteristics. The study employed brute-force search methodology to arrive at the optimal channel pairs to apply in the extraction of potentially distinguishing features. The witness was that the delta and alpha frequency bands were found to add the most extensive contribution to regression analysis, whereas the low-delta phase characteristics displayed poor results. The theoretical aspect of decoding continuous hand movement with the use of phase-based connectivity was proved in the study.

In [34] A unique algorithm was proposed in the paper that classifies the Cognitive-Motor Imagery activities and achieved an overall 96.02 percent accuracy on the EEG signal. This is achieved by applying the algorithm to an EEG signal where artifacts are removed using a Multi-layer Perceptron Neural Network and computing hand-made statistical time domain and power spectral density features that demonstrated higher classification accuracy. The accuracy of movement prediction within the subjects involved in the study was 94.72%, with nine subjects showing successful classification of movements of the upper limb. Another new methodology represented in the paper involves Independent Components Analysis, aimed at eliminating artifacts and improving performance. A classification algorithm, Support Vector Machine (SVM), was implemented with an F1-score of 68.69%. The SVM strategy was optimized by using the Genetic Algorithm, which yielded an average accuracy of 95%. The paper contrasts with deep learning frameworks, and accuracy, precision, F1-score, and recall are regarded as performance metrics. The analysis of statistical variables was derived by cross-correlation to convert them to cross-correlograms. CNN has been used to process images of attributes converted, and a result of 96.69 percent accuracy has been achieved. The tendency of validation of procedures and the offline-online bridge is brought out in the paper.

In [35] the paper argues about the feature extraction problem in motor imagery Brain-Computer Interface (BCI) systems and concentrates on optimizing spatial filters. It offers a variant of the common spatial patterns (CSP) algorithm referred to as variance characteristic preserving CSP (VPCSP), where a graph theoretic regularization term is added to enhance EEG data feature extraction. In the study, the objective is to reduce the impact of out-of-context points to increase the resiliency of the CSP algorithm. The VPCSP procedure is comparable to the classical CSP algorithm, based on a symmetric positive definite matrix to compute the loss of the abnormalities in projected data, which sustains the local variance attributes. The method records improvement, in terms of increased classification accuracy, by employing sparse sets of spatially occurring patterns in the constraint placed by time to deal with the issue of sparsity. This conventional technique is the source of the objective function of the suggested VPCSP, which implies that the solution can be addressed by generalized eigenvalue problems. Just to confirm the efficiency of the proposed VPCSP, a radial basis function kernel-based support vector machine (SVM) was applied using the open public BCI competition datasets. According to the experimental outcomes, the suggested approach would work significantly better compared to other current methods in terms of classification accuracy. The study draws attention to the importance of efficient classification techniques, mainly the implementation of SVM, to boost small dataset performance in BCI.

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Table 1: Comparative evaluation of the current review research.

Author	year	Method	channels	classes	finding
Su et al.[2]	2025	Cross Tensor Coupling Decomposition (CTCD)	118 channels, 59 channels.	right hand (R) and foot(F) two classes from (left-hand (L), right-hand (R), and foot imagery (F))	average accuracy of 91.75 % ± 3.25 % on Dataset 1 and 85.86 % ± 7.93 % on Dataset 2 cross-subject binary classification experiments, obtained an average accuracy of 93.91 % ± 8.71 % on Dataset 1 and 84.36 % ± 16.63 % on Dataset 2.
Xie et al. [3]	2025	Cross Tensor Coupling Decomposition (CTCD) based on diverse modality BFNs	10 channels.	left hand (L), right hand (R), and foot (F). left-hand, right-hand, and foot imagery	92.09% ± 4.15% and 83.14% ± 8.04% on dataset 1,2.
Lu et al. [4]	2025	two supervised methods, Pairwise Sample Distance Two-Dimensional Linear Discriminant Analysis (PSD2DLDA), and Pairwise Class Mean Distance Two-Dimensional Linear Discriminant Analysis (PCD2DLDA)	14-channel, 59 channels	right or left	77.50±2.77 and 75.47±3.71
Klein et al. [5]	2025	PBT (supervised pre-training) (CNN for feature extraction + Transformer)	22 channels, 3 channels.	Left hand, right hand, both feet, and tongue. left hand, right hand.	BCI Comp. IV2a (4 Classes) 53.96 ± 0.70% BCI Comp. IV2b (2 Classes) 78.13 ± 0.51%
Bouchane et al. [6]	2025	A hybrid model combining a four-layered 1D-CNN and a GRU is proposed for predicting mental states from EEG data. The SMOTE data augmentation.	64-channels.	left fist (LF), right fist (RF), both fists (LRF), and both feet (BF).	The CNN-GRU and CNN-Bi-GRU models achieved macro average accuracies of 98.88% and 98.93%, respectively.
Chen et al. [7]	2025	Dual-Branch Blocked-Integration Self-Attention Network (DB-BISAN) the integration of CNN and LSTM for classification	22 channels, 3 channels.	Left hand, right hand, both feet, and tongue. left hand, right hand.	Classification result BCIIV2a 79.58% Classification result BCIIV2b 87.01%
Mallat et al. [8]	2025	(CNN) models for motor imagery classification Common spatial pattern (CSP) is used for delineating spatial characteristics.	22 electrodes.	left hand, right hand, both feet, and tongue.	79.44% accuracy on the BCI Competition IV 2a dataset.

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Lu et al. [9]	2025	(LGL-BCI) using a customized geometric deep learning architecture	22 electrodes and 3 EOG channels.	left hand, right hand, both feet, and tongue.	LGL-BCI achieved 82.54% accuracy,
Mróz et al. [10]	2025	machine learning (ML) algorithms, particularly convolutional neural networks (CNN) and recurrent neural networks (RNN) classified using a linear discriminant analysis (LDA) anxiety disorders	multi-channel setup	Right hand, left hand	Participant 3: Achieved the highest performance with an average accuracy of 91.58%.
Cataldo et al. [11]	2025	machine learning algorithms, specifically a Wavelet Package Neural Network,	8 channels.	(1) right arm extension, (2) right arm flexion, (3) left arm extension, (4) left arm flexion, or (5) rest.	achieving 89.23% classification accuracy for motor imagery states.
Kaviri et al. [12]	2025	Dipole Fitting, MNE, and Beamforming for EEG analysis. A custom ResNet CNN	22 and 32 channels.	left hand, right hand, both feet, and tongue. six types of reach and grasp tasks	99.15% accuracy For six types of reach and grasp tasks reached 90.83% accuracy.
Gong et al. [13]	2025	accuracy using a Support Vector Machine (SVM) for motion image classification.	60 channels.	six classification results from (Left hand, right hand, both feet, and tongue).	Accuracy varies Lowest participants: ≈55–60% Middle participants: ≈65–75% Highest participants: ≈80–90%
Gu et al. [14]	2025	hybrid deep learning model called CLTNet	22 channels, 3 channels.	Left hand, right hand, both feet, and tongue. left hand, right hand.	accuracy of 83.02% on BCI IV 2 and 87.11% on the BCI IV 2b.
Ma et al. [15]	2025	novel frequency band attention-based temporal convolutional network (FBATCNet) for MI-EEG decoding.	22 channels.	left hand, right, hand, foot, and tongue. elbow flexion, forearm pronation and forearm supination, shoulder flexion.	achieved 84.73% accuracy on Dataset 1 and 66.06% on Dataset 2.
Ghayab et al. [16]	2025	ORDWT_AR, utilizing an over-complete rational dilation wavelet transform combined with an autoregressive model.	118, 64,32 channels.	2,3 and 4 classes right hand, right foot right hand, right foot, generating words left hand, right hand, foot or tongue	accuracy of 99.8% for BCI datasets and 99.7% for the CHB-MIT dataset.

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Lv et al. [17]	2025	LDA, KNN, SVM, and RF are employed for classification. Gramian Angular Field (GAF) and phase locking value (PLV) for spatio-temporal feature representation.	64 channels	4 classes (left fist, right fist, both fists, and both feet motor).	99.73% in binary classification tasks and reaches 83.37% accuracy in four-class classification tasks.
Falcon-Caro et al. [18]	2025	EEGNet and other DNNs have been used for fine hand movement classification.	32 channels, 64 channels.	10 sub-gestures and 5 sub-gestures	EEGNet achieves 62.30% and 78% accuracy, respectively. 2 datasets.
Gómez-Morales et al.[19]	2025	Common Spatial Pattern (CSP) method for EEG signal processing. Elastic Net Regression	22 channels.	Left hand, right hand	accuracy of 78.16% using a signal prediction model with fewer electrodes. Accuracy varied among subjects, ranging from 62.30% to 95.24%, indicating individual differences in performance.
Mohamed et al. [20]	2025	fractal dimension (FD) algorithms, including box-counting, DFA, MFDFA, and correlation dimension. The study employs four classifiers: GSVM, CART, LinearSVM, and SVM with polynomial kernels.	25 channels.	left hand, right hand, both feet, and tongue	achieved 79.2% accuracy.
Ekhlasi et al. [21]	2025	The Imperialist Competitive Algorithm (ICA) was utilized for feature selection. Cuckoo Optimization Algorithm (COA) was also employed for feature selection.	21-channels	8 motion commands	The optimal accuracy 96.3% And 96.5% for expressed commands.
Deng et al. [22]	2025	CNN module, Swin Transformer module.	22 channels.	4-class Motor Imagery classification (Left Hand, Right Hand, Feet, and Tongue).	83.99% classification accuracy on the BCI Competition IV-2a dataset.
Raza et al. [23]	2025	hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) framework.	59 channels.	2 classes (left hand, right hand or foot)	CNN-LSTM classification accuracy 98.38% in MI-EEG tasks, 97.87% across all classes.

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Heim et al. [24]	2025	FNNs and EEGNet	8 channels.	3-class Left Arm (to move the cursor to the left) Right Arm (to move the cursor to the right) No Movement/Rest	FNNs 68.39% accuracy for ME and MI tasks.
Titkanlou et al. [25]	2025	CNN-LSTM, CNN-Transformer, and EEG-ITNet	9 channels out of 21 channels	Hand movements.	The best accuracy achieved was 79.06% using the CNN-LSTM model on a specific MI dataset.
Lv et al. [26]	2025	Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN).	29 channels.	left and right-hand	The research achieved an average classification accuracy of 75.00% using the KNN algorithm.
Ding et al. [27]	2025	EEGNet	128 channels.	2 and 3 classes (fingers movements)	80.56% for two-finger MI tasks and 60.61% for three-finger tasks A uniform screening procedure ensured only subjects with over 70% accuracy in offline tasks were included.
Degirmenci et al.[28]	2024	Ensemble Learning, ANOVA-based feature selection.	19 channels.	Thumb (Class 1), Index finger (Class 2), Middle finger (Class 3), Ring finger (Class 4), and Pinkie finger (Class 5)	55% accuracy.
Mattei et al. [29]	2024	EEGnetV4 model	32-channel	three hand movements—open/close, finger tapping, and wrist rotation—along with a rest period	Highest accuracy 64%.
Kok et al. [30]	2024	ML-CSP-OVR, combined CSP OVR, CWT, and GoogLeNet for multiclass classification.	32 channels.	forward hand movement (FW), grasp (GP), release (RL), and reverse hand movement (RV).	The highest intersubject classification accuracy was 99.73% for the GP-RV pair. The final model, ML-CSP-OVR, achieved 78.08% accuracy using all combined data.
Kumari et al. [31]	2024	hybrid technique that combines the War Strategy Optimization (WSO) and Chimp Optimization Algorithm (ChOA)	EEG channels: 22	(left and right hand) from BCICIV_2a	95.06% accuracy with high precision.

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Altameem et al. [32]	2022	Fourier Transform (FFT) and Continuous Wavelet Transform (CWT). logistic regression, random forest, KNN, and XG Boost, for extracted features	19 EEG channels.	three events: event-1: resting-state, event-2 and event-3: hand motions.	Machine learning models like XG Boost achieved a maximum accuracy of 88% with FFT features.
Hosseini et al. [33]	2022	phase-locking value (PLV) and magnitude-squared coherence (MSC) as connectivity features for decoding hand movements from EEG signals.	63 EEG channels	continuous hand movements four orthogonal directions	The average Pearson correlation coefficients for PLV and MSC features were 0.43 ± 0.03 and 0.42 ± 0.06, respectively.
Kokate et al. [34]	2022	Support Vector Machine (SVM), CNN, ICA	64 EEG channels 10-10	international manner left/right-hand movements	96.69% accuracy, after ICA for 9 subject 94.72%.
Liang et al. [35]	2023	common spatial patterns (CSP) algorithm called variance characteristic preserving CSP (VPCSP)	Channels: 59 EEG + 3 EOG for IV part I, III And Channels: 118 EEG	left hand, for part Iva right hand, and foot imagery	87.88%, 90.07 %, and 76.06 % on public dataset IV part I, III, part Iva.

3. AI Models for EEG Signal Classification

AI models have shown great promise in EEG signal classification by automatically learning complex patterns from the data. These models can be broadly categorized into machine learning and deep learning approaches. As shown in Figure 1. where machine learning algorithms are trained on labeled EEG data to learn the relationship between EEG features and corresponding classes. Common machine learning algorithms used for EEG classification include Support Vector Machines (SVM) which is a powerful classification algorithm that finds the optimal hyperplane to separate different classes in a high-dimensional feature space and has been successfully applied to various EEG classification tasks such as motor imagery classification and seizure detection, K-Nearest Neighbors (KNN) which is a simple yet effective classification algorithm that classifies a new data point based on the majority class of its k-nearest neighbors in the feature space and has been used for EEG-based emotion recognition and sleep stage classification, Random Forest (RF) which is an ensemble learning algorithm that combines multiple decision trees to improve classification accuracy and robustness and has been applied to EEG-based cognitive state monitoring and brain-computer interfaces, and Linear Discriminant Analysis (LDA) which is a dimensionality reduction and classification technique that finds the linear combination of features that best separates different classes and has been widely used for EEG-based motor imagery classification and event-related potential (ERP) analysis. Deep learning models particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have achieved state-of-the-art performance in EEG signal classification because they can automatically learn hierarchical features from raw EEG data eliminating the need for manual feature extraction including Convolutional Neural Networks (CNNs) which are designed to extract spatial features from EEG signals by applying convolutional filters to the data and have been successfully used for various EEG classification tasks such as seizure detection sleep stage classification and motor imagery classification, Recurrent Neural Networks (RNNs) which are designed to process sequential data by maintaining a hidden state that captures information about past inputs specifically Long Short-Term Memory (LSTM) networks that have been used for EEG-based emotion recognition sleep stage classification and language processing, and Hybrid Models combining CNNs and RNNs that can leverage the strengths of both architectures for EEG signal classification where for example a CNN can be used to extract spatial features from EEG data and an RNN can be used to process the temporal sequence of these features [36].

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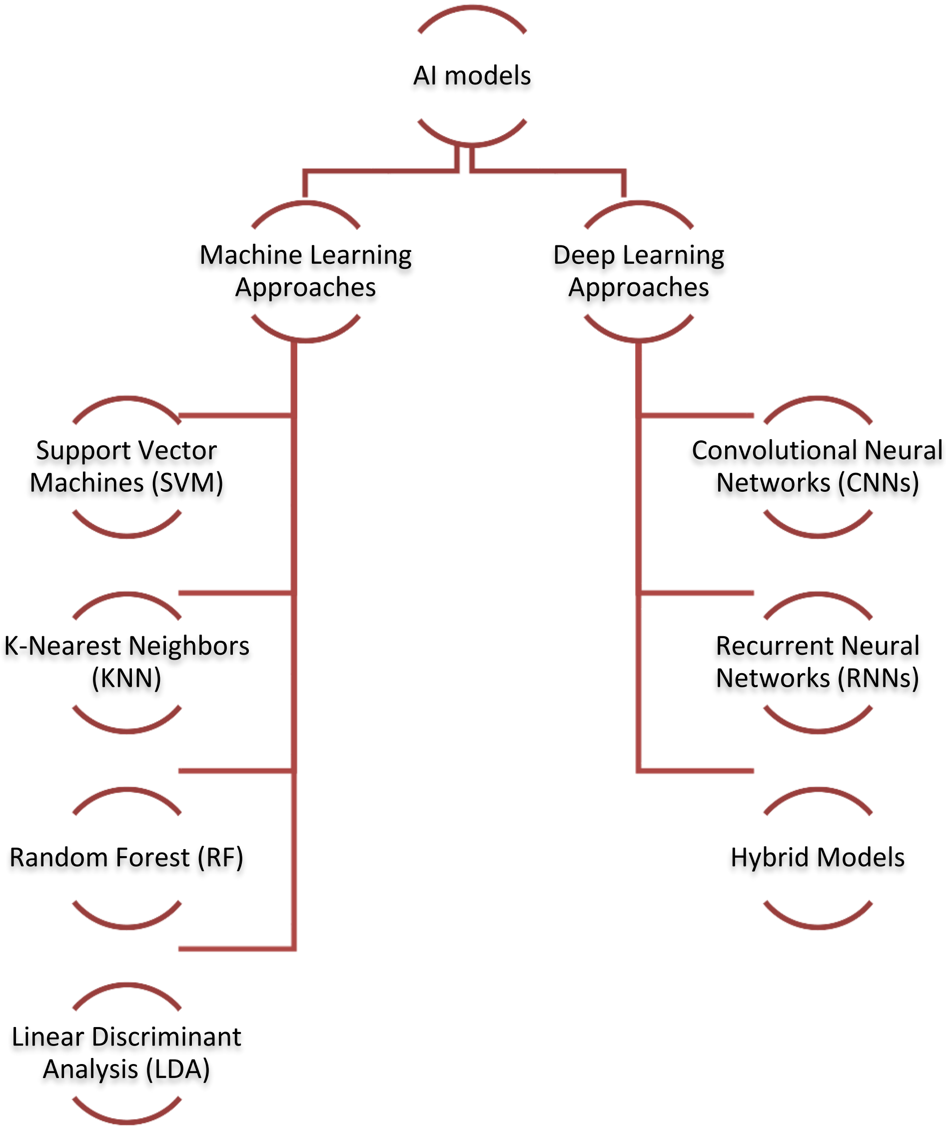

Figure 1. AI Models for EEG Signal Classification

4. Feature Extraction Techniques

Feature extraction is a crucial step in EEG signal classification, as it transforms raw EEG data into a set of meaningful features that can be used by AI models. Common feature extraction techniques are shown in Figure 2. Time-Domain Features: These features capture the statistical properties of EEG signals in the time domain, such as mean, variance, skewness, kurtosis, and amplitude. Frequency-Domain Features: These features capture the spectral content of EEG signals using techniques such as the Fourier transform, the wavelet transforms, and the power spectral density (PSD) estimation. Time-Frequency Features: These features capture the time-varying spectral content of EEG signals using techniques such as short-time Fourier transform (STFT) and wavelet transform. Spatial Features: These features capture the spatial distribution of EEG activity across different electrodes, such as coherence, phase synchronization, and source localization [37].

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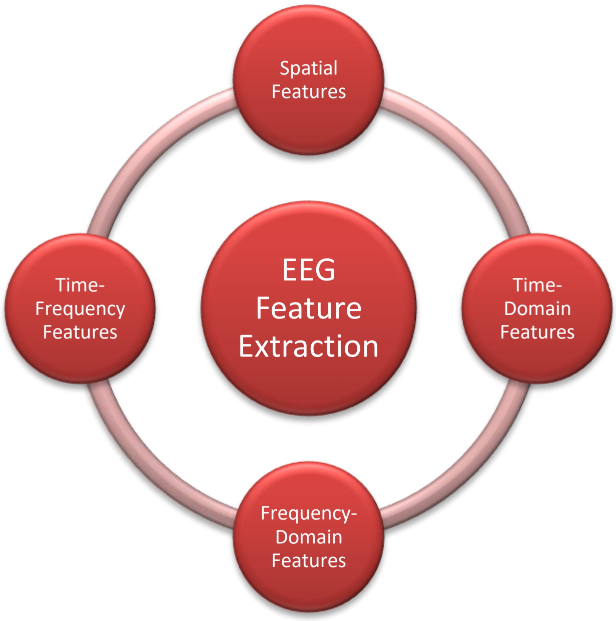

Figure 2. AI Models for EEG Signal Classification.

5. Applications of AI in EEG Signal Classification

AI models have been applied to a wide range of EEG signal classification tasks, as shown in Figure 2. Brain-Computer Interfaces (BCIs): AI models are used to decode user intentions from EEG signals and translate them into control commands for external devices, such as wheelchairs, robotic arms, and communication systems. Seizure Detection: AI models are used to automatically detect seizures from EEG recordings, enabling timely intervention and improving patient outcomes. Sleep Stage Classification: AI models are used to classify sleep stages based on EEG signals, providing valuable information for diagnosing sleep disorders and monitoring sleep quality. Cognitive State Monitoring: AI models are used to monitor cognitive states, such as attention, drowsiness, and workload, based on EEG signals, enabling adaptive systems that can adjust to the user's cognitive state. Emotion Recognition: AI models are used to recognize emotions from EEG signals, enabling affective computing applications such as emotion-aware virtual assistants and personalized entertainment systems [38].

6. Optimization techniques

Electroencephalography (EEG) has been widely used to record electrical activity in the brain, used both in clinical diagnosis, brain-computer interface (BCI), and in cognitive neuroscience; it is a non-invasive technique involving electrodes placed on the skin. Nevertheless, EEG signals are highly non-stationary, high dimensional, and noisy. At each level of the signal-processing pipeline, optimization methods are critical in increasing the accuracy of the process, lowering computational burden, and increasing the level of generalization of EEG-based systems. In this paper, the significant EEG optimization methods will be sorted and documented into five broad segments of signal quality improvement, feature engineering, model optimization, data/electrode management, and adaptation [39]. Methods that were used before feature extraction, and which were aimed at enhancing the clarity of the EEG signal and its appropriateness for further analysis, include pre-processing, which is one of the most basic operations necessary to promote the quality of the EEG signal by eliminating undesired noise and artifacts. Band-pass filters (typically 0.5 40 Hz) can be used to preserve frequencies of interest to the brain, and notch filters can be used to reject 50/60 Hz power line noise. Besides, independent sources in the EEG mixture can be separated and isolated independently using Independent Component Analysis (ICA) in order to eliminate ocular or muscle artifacts. Although Principal Component Analysis (PCA) is mainly a dimensionality reduction method, dominant signal structures can be captured and thereby classified as artifact suppression methods. Good pre-processing is important to guarantee good quality and integrity of the features to be extracted thereafter. Signal Denoising Autoencoders is a solution to signal enhancement in EEG that is deep learning based. These unsupervised neural networks provide an ability to learn how to generate or construct the (clean) signal using the noisy data and learn the key features in the reduced space of the latent variables. SDAEs can be significantly practical in wearable EEG systems

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when multiple wearable side effects may influence real-time data collection by polluting the data and recordings due to environmental and physiological noise. Training the model to be able to exclude the noise in the reconstruction allows the encoder to subsequently provide denoised and robust feature representations to classification procedures. SDAEs, therefore, provide a trainable, adaptive equivalent of fixed filters. Whether it is real-life applications such as neurofeedback, BCI games, or assistive technologies, EEG systems have to interpret and classify signals as fast as possible. Computational efficiency without loss of correctness is also achieved in real-time optimization. Some methods enable it to be performed faster, like the sliding window-based feature extraction, incremental learning algorithms, and lightweight CNNs (e.g., MobileNets). Additionally, quantizing and pruning of the model increases the deployment of the model in edge devices. These measures are necessary to make the EEG systems run under hardware and time restrictions [40]. Such methods handle the input data and sensors with the aim of optimizing the dataset size, quality, and configuration of channels of the EEG, where EEG electrodes do not contribute equally to a particular classification task. By choosing the most pertinent channels, less noise is produced; the computational time and the chance of overfitting are reduced. Techniques, such as Recursive Feature Elimination (RFE), eliminate electrodes of low importance iteratively. Mutual information approaches measure a statistical dependence between EEG signals and target labels. In addition, to locate the best pair of electrodes, metaheuristics such as GA and PSO may be adopted, whereby considerations about exhaustive search are computationally inadmissible. EEG data are usually characterized by inadequate labeled samples. The idea behind data augmentation is to augment the amount and variety of data to make the model robust. Simple ones are noise injections (adding Gaussian noise), time warping, or window slicing (ip-modifying time sequences). New methods such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are able to create realistic artificial EEG signals and hence augment the training data without the need to acquire new data. These methods minimize overfitting and enhance the generalization, especially when dealing with deep learning settings [41]. This group is concerned with mining the most informative and concise characteristics out of EEG signals that would be compatible with high-performance classification, where the process of feature extraction is the translation of the raw EEG signal into numerical features representative of it. The mean, standard deviation, skewness, kurtosis, and Hjorth parameters (activity, mobility, complexity) define the shape and congestion of the waveform in the time domain. In the frequency domain, energy distributions across frequency bands may be described using techniques of the Short-Time Fourier Transform (STFT) and Power Spectral Density (PSD). Hybrid analysis (time-frequency), such as Wavelet Transform (WT) and Empirical Mode Decomposition (EMD), would be appropriate to analyse a non-stationary signal. In addition, measurements of the chaos of the brain signals are taken using non-linear attributes like entropy, fractal dimension, and Lyapunov exponents. The thing is that the aim is to give the most discriminative information to the classifier. Over-fitting may be possible when the feature sets are too large and may lead to learning algorithms running slowly. This can be dealt with by feature selection (or transformation) using dimensionality reduction techniques. Principal Component Analysis (PCA) minimizes the number of dimensions while keeping the maximum variance. Linear Discriminant Analysis (LDA), on the other hand, increases class separability and reduces the dimensions. Powerful refinements of visualization and clustering are possible using modern methods, t-distributed Stochastic Neighbour Embedding (t-SNE) and Uniform Manifold Approximation and Projection (UMAP), which can be applied to high-dimensional time series of EEG data. These methods assist in the process of simplifying learning and improving the performance of a model. Hybrid optimization methods take the complementary advantage of several techniques and integrate them. As an example, a pipeline could consist of first adding PCA to reduce dimensionality and then adding LDA to discriminate between classes. When searching through the space of features or parameter settings of a classifier, it is possible to integrate mutual information-based filtering with metaheuristic search algorithms, e.g., Genetic Algorithms (GA), including Bayesian optimization. Combinations of this sort tend to work better than single-method approaches, both in accuracy and generalizability [42]. These methods ascertain optimal classifier performance after the study has taken place, when intelligent tuning and model design extract features. The classifier is highly sensitive to hyperparameters, or values, such as learning rate, number of neurons, or depth of the tree. Two brute-force search techniques are grid search and random search to traverse the set of hyperparameter combinations. The difference between Bayesian optimization is that, rather than using the non-probabilistic models to approximate the performance of the methods as done in automatic differentiation, it uses probabilistic models and exploits their ability to guide the search, and thus the exploration in improving the search performance by finding better parameter choices. Evolving methods such as Genetic algorithms (GA) and particle swarm optimization (PSO) have been demonstrated to be able to search larger parameter spaces more effectively and so are well suited to difficult problems involving non-differentiable functions. It is desirable to focus on hyperparameter tuning in order to acquire a robust classification. Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformers are examples of deep learning models that are progressively becoming a part of EEG analysis. Nevertheless, such models are unstable and over fit during training. Dropout adjusts the random deactivation of neurons so that training is regularized. Batch normalization facilitates learning stability. Learning rate schedules change the learning rate to train for convergence. Moreover, transfer learning can be applied to load the already trained deep networks on large-scale datasets to smaller and purpose-

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specific EEG datasets. All these tactics enhance the generalization of models and model efficiency [43]. They resolve inter-subject and inter-session variability and augment the learning process when the labels are scarcely available. Transfer learning allows us to reuse trained data on the large EEG dataset in smaller or alternative tasks. Here, intermediate (feature extractor) layers of an already trained model are kept, whereas upper-most (the final) layers are re-trained on the new task. This saves data needs and training time and enhances the generalization of the model. Examples of applications include cross-task EEG classification, recognition of emotion, and cross-domain transfer (e.g., motor imagery to workload detection). Transfer learning has been a significant achievement in low-resource EEG applications. EEG signals are variable both between subjects and between sessions, which is a threat to the coherence of the model. Domain adaptation techniques aim at transforming the distribution of features of various individuals or sessions to a shared space. Transfer Component Analysis (TCA), Correlation Alignment (CORAL), and Riemannian geometry-based classifiers are some of the techniques that solve this problem by enhancing distribution matching and robustness. Such techniques are helpful in deployment in the real world, where it would be unrealistic to retrain on each user or session. Metaheuristic algorithms are optimization methods that are skilled in addressing difficult problems in order to arrive at satisfactory solutions and are described as being derivative-free, stochastic, and having the ability to maintain a balance between exploration and exploitation and their generalization. These algorithms have been inspired by natural phenomena and are broadly divided into evolution-based, swarm intelligence-based, physics-based, and human-related. They provide an effective algorithm to search for huge search spaces that are not exhaustively enumerable. Metaheuristics is also used in the context of Electroencephalography (EEG) signal processing and analysis: feature selection, channel selection, and the tuning of classifier parameters are all optimized. Certain algorithms used are the modified Al-Biruni Earth Radius (MBER) algorithm to select features in classifying eye states, the use of Genetic Algorithms (GAs) to evolve the best feature subsets, Particle Swarm Optimization (PSO) to tune the parameters of classifiers such as Support Vector Machines (SVMs) to perform tasks such as emotion recognition, Ant Colony Optimization (ACO) to select the best EEG channels, and the Whale Optimization Algorithm (WOA) to select the best channels and classify them. EEG optimization via metaheuristic algorithms is often performed in a sequence of steps: data acquisition and preprocessing (which may involve tools such as MNE-Python), signal features (via tools such as NumPy and SciPy), formulation of an archiving criterion to quantify performance, run of the metaheuristic algorithm through startup, cycle, and termination and lastly, analysis and validation of the optimized solution on unseen data. The main issues when applying metaheuristics to EEG optimization are their potentially high computational cost, the necessity to tune the parameters of the metaheuristic algorithm [38,44].

7. Conclusion

The present review provides a detailed analysis of the status of EEG-based Brain-Computer Interface (BCI) systems, with emphasis on the essential role of integrating Machine Learning (ML) and Deep Learning (DL) and on refined optimization strategies. The review of the latest literature shows that the traditional ML algorithms, such as SVM and LDA, are still useful due to their computational efficiency, but the shift towards the Deep Learning architecture, in particular, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and state-of-the-art Transformer-based models is inevitable due to the high dimensionality and non-stationarity of EEG signals. One of the findings of this review is that model architecture is not sufficient to achieve robust performance of BCI. Maximization of classification accuracy is necessary through the application of rigorous optimization algorithms - signal artifact removal, channel selection, metaheuristic hyperparameter optimization (e.g., Particle Swarm Optimization, Genetic Algorithms), etc. The literature supports the fact that hybrid methods that integrate effective feature extraction with deep neural networks always produce the best performance metrics, frequently, better than controlled motor imagery. Nonetheless, with these developments, there are still major challenges. The review presents the ongoing concerns of inter-subject variability, lack of large-scale labelled data, and the phenomenon of BCI illiteracy. Moreover, the computational complexity of sophisticated DL models is a hindrance in the implementation in real-time.

8. Future work

To overcome the gap between laboratory success and practical use, future research should focus on the following areas Transfer Learning and Domain Adaptation: The creation of strong subject-independent models that need the shortest calibration time for new users. Data Augmentation: This paper uses Generative Adversarial Networks (GANs) and synthetic data generation to address the small dataset issue. Explainable AI (XAI): Leaving black box deep learning models to comprehend the neural signature to promote classification that is essential to clinical acceptance. Lightweight Architectures: Minimizing the complexity of the model to achieve real-time processing on low power, portable hardware to allow the daily use in prosthetic control and communication aids.

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