Overview of Current Trends in Machine Learning Approaches for EEG-Based Brain Computer Interface Applications

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Abstract
The potential of the human brain to communicate and interact with the environment is promoted by advances in neuroscience and computer science, making brain-computer interface (BCI) top interdisciplinary study. Addition-ally, with recent developments in machine learning (ML), electroencephalogram (EEG)-based BCIs for AI are gaining popularity. This review article offers a look at recent research on brain-computer interfaces (BCIs) and how the technology of machine learning (ML) is used in BCIs. It highlights the role that ML has had in the execution of various BCI tasks and examines the various research methodologies used in this area. Additionally, it discusses ML techniques for detecting mental states, classifying mental tasks, classifying emotions, classifying electroencephalogram (EEG) signals, classifying event-related potential (ERP) signals, classifying motor picture data, and classifying limb movements. This paper aids readers in learning about recent advances in BCI and ML as well as upcoming discoveries required to enhance and create better BCI applications.

Keywords
Brain-Computer Interfaces, Electroencephalography, Classification, Machine Learning

1. Introduction

A brain-computer interface is a method that captures and interprets a person's brain signals in order to carry out a desired actuation. However, one of the most used techniques for BCI applications is EEG [1, 2]. BCI offers the chance to create a brand-new kind of brain-controlled communication technology. Applications can be found in many different domains, such as biometrics [41], education [42], entertainment [43], gaming [44], and communications [39]. Those who have motor impairment greatly benefit from this sort of mechanism [3]. Applications like brain-controlled limbs, chairs, speech systems, etc. may all be created utilizing a brain-computer interface, for instance. A humanoid robot interfaced with using this communication system opens up various opportunities to mimic human movements. In terms

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of both physical appearance and the range of motions it is capable of, a humanoid robot [4,5] mimics the human body. A few methods for obtaining brain signals include electrocorticography (ECoG), near-infrared spectroscopy (NIRS), and electroencephalography (EEG). The detection and analysis of EEG is referred to as electroencephalography where electroencephalogram (electro = electrical, encephalo = brain, gram = record). The EEG is a recording of electrical impulses produced by brain cells. Electroencephalograms (EEGs) can be recorded using electrodes insert-ed on the scalp or directly through the cortex, which is known as an electrocorticogram. Local field potentials are electric fields generated by the cortex. EEG is monitored in reaction to an external or internal stimulation, referred to as event-related potential (ERP), as well as in the absence of any stimulus, referred to as spontaneous EEG [6]. EEG has long been regarded as a crucial technique in clinical neurology. Bioelectric potentials are generated by the electrochemical action of excitable cells found in neurological, muscular, or glandular tissue [7]. Rabbit and monkey brain bioelectric potentials were initially seen in the 1870s by English physiologist Richard Caton, whereas the human EEG was originally identified in 1924 by German psychiatrist Hans Berger. Berger believed that during his terrible accident, he was in contact with his sister via mental telepathy hundreds of kilometers distant [8]. Voltages are produced by the brain's neuronal activity in response to outside circum-stances, events, or stimuli. By examining EEG rhythms, it is possible to use the shift in neural activities for clinical diagnosis. EEGs have frequencies between 0.5 and 40 Hz and an amplitude between 10 and 200V [9]. EEG has been used to identify the following five rhythms: beta (13–30 Hz), alpha (8–13 Hz), theta (4–8 Hz), and gamma (over 30 Hz) as in Table 1 are presented.

Table 1
Five different brain waves' characteristics

Brain wave	Scope	Amplitude	Brain states
Delta (δ)	0.5–4	Higher	Dreamless deep sleep, deepest meditation
Theta (θ)	4–8	High	Drowsiness, dreaming, inward-focused
Alpha (α)	8–12	Medium	Very relaxed, alert, positive attention
Beta (β)	13–35	Low	Active, anxiety dominant, attentive, judgment, relaxed
Gamma (γ)	>35	Lower	Concentration, integrated thoughts

A Brain-Computer Interface (BCI) system consists of four primary components: signal acquisition, preprocessing and feature extraction, classification, and feedback or output, as depicted in Fig. 1. Signal acquisition utilizes diverse methods, such as invasive, semi-invasive, and non-invasive techniques, to capture brain signals. Invasive and semi-invasive methods involve placing devices directly into the brain or skull, whereas non-invasive methods place devices on the scalp. After acquisition, signals undergo preprocessing and feature extraction, where tasks like noise reduction and artifact correction are performed to improve signal quality. The classification stage identifies relevant information in the signal, extracting distinct features and organizing them into a vector.

This extraction process is challenging yet crucial due to concerns about signal overlap and distortion. Feature data size is typically reduced to facilitate input into machine learning algorithms, simplifying complexity without losing significant information. Effective selection of discriminative features is essential for accurate pattern recognition, enabling precise interpretation of user intentions. Machine learning algorithms guide the output device, allowing users to perform various tasks by translating brain signals into actionable commands. Due to its advantages, several studies support the benefits of EEG (e.g. accessibility, etc.). Here, [34] uses EEG data to present a thorough overview of the most recent biometric identification systems based on deep learning and machine learning. With a focus on machine learning methods, this review aims to present recent work and examine the latest findings in the field of EEG-based brain-computer interfaces. In addition, this review provides readers with a comprehensive overview of this evolving topic by summarizing the key components and final conclusions of several studies rather than reading each one separately.

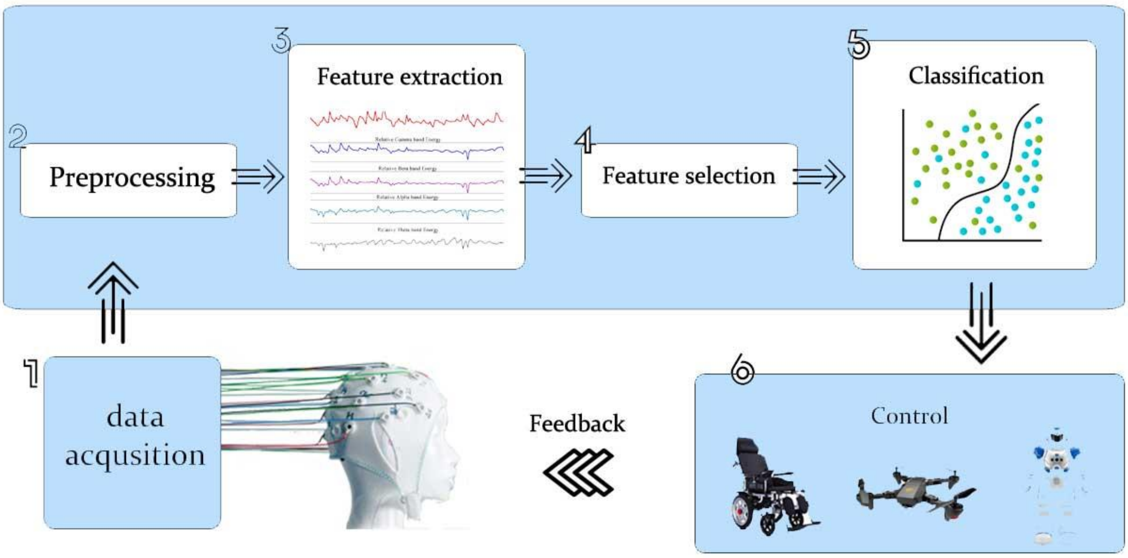

Figure 1: The typical framework of a BCI system.

2. Methods: Machine Learning Algorithms

The ability to perform well in terms of accuracy in classification is one of the primary needs for classifiers in BCI systems [10]. Consider the situation of a patient who uses a wheelchair that is controlled by a BCI. Imagine if they could steer the BCI wheelchair with their thoughts, moving it left, right, forward, or backward. Therefore, the BCI system must be able to accurately analyse the brain impulses and classify the movement as "move to the left" when they believe the wheelchair should move to the left. These classification algorithms' task is to distinguish between many categories (in the example given above, left, right, forward, and backward) using a variety of features (for example, brain signals) as input. In order for the classification algorithm to effectively distinguish between a variety of classes, it is crucial to properly select characteristics when carrying out this activity [11]. The employment of various classifiers to convert features collected from brain signals into control commands can be used to describe the function of classification [12, 13]. Simple linear classifiers and complicated nonlinear classifiers are also included in this group. Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees (DT), K-means and Neural Networks are a few examples of frequently used classifiers. Below is a detailed discussion of these classifiers.

2.1. Support Vector Machine

Support Vector Machine (SVM) is a classical and most important technique for categorizing different data points. This approach classifies data points, also called sup-port vectors. The support vector's hyperplane is created using the kernel function. Radial, radial-integral, polynomial, and linear kernel functions are only a few of the several types of kernel functions. A hyperplane is a plane that passes through the centers of the data points. Its job is to generate the proper separation classes for the given data set. The area bounded by the hyperplane will have the largest margin. The support vectors of subgroups +1 and -1 are closest to the dividing hyperplane and the edge of the slab. The margin can be fully expanded by using the right methods for identifying support vectors [14, 15].

2.2. K-Nearest Neighbors

KNN is an easy algorithm for supervised machine learning that can be used to ad-dress classification and regression issues. It makes use of a database with data points divided into various classes, and the method attempts to classify a sample data point that is sent to it as a classification issue. KNN is referred to as non-parametric since it makes no assumptions about the distribution of the underlying data. The following are KNN's benefits: It is an easy strategy to use. The model's construction is inexpensive. It is a very adaptable classification technique that works well for classes with several modes of communication. Records have various classification labels. It may occasionally be the most effective approach. Classifying unclassified records is relatively expensive, which is one of KNN's drawbacks. It needs the calculation of the k-nearest neighbors' distance. The size of the training set increases as the method becomes more computationally intensive. Accuracy will decrease when there are too many distracting or irrelevant elements. It computes distance across k neighbors since it is a slow learner. It preserves all of the training data without making any generalizations about it. Large data sets are handled, which results in costly calculations. Greater dimensionality in the data will lead to a drop-in region accuracy [16].

2.3. Decision Trees

Decision Trees (DT) are trees that classify instances by sorting them based on feature values. Each node in a decision tree represents a feature in an instance to be classified, and each branch represents a value that the node can assume. Instances are classified starting at the root node and sorted based on their feature values [17]. Decision tree learning, used in data mining and machine learning, uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value. More descriptive names for such tree models are classification trees or regression trees [18]. Decision tree classifiers usually employ post-pruning techniques that evaluate the performance of decision trees, as they are pruned by using a validation set. Any node can be removed and assigned the most common class of the training instances that are sorted to it [17].

2.4. K-means

K-means is one of the easiest unsupervised learning algorithms, according to [19] and [20], that resolves the well-known clustering problem. The process uses a predetermined number of clusters (let's suppose k clusters) defined a priori to categorize a given data set. When labeled data is not available, the K-Means technique is used [21]. A general technique for turning imprecise rules of thumb into extremely precise prediction rules. A boosting technique may provably generate a single classifier with extremely high accuracy, say, 99%, given a "weak" learning process that can regularly identify classifiers ("rules of thumb") at least somewhat better than random, say, accuracy of 55% [22].

2.5. Neural Networks

Neural Networks (NN) that may, despite the fact that typically each network only performs one, perform many regression and/or classification tasks at once. Therefore, in the great majority of cases, the network will have an only one output variable, albeit in the case of many-state classification issues, this may represent a number of units of output (the post-processing stage taking care of the mappings from output units to output variables).Three key elements, including network architecture, the weight of each input link, and the input and activation functions of the unit, determine the performance of an artificial neural network (ANN). Since the first two factors cannot be changed, the behavior of the ANN is determined by the weights' present values. Instances from the training set are regularly presented to the net after the weights of the to-be-trained net are first set to values that are random. The value inputs for an instance are set up on the input units, and the net's output is compared to the instance's desired output. The net's output values are then slightly modified in a way that would bring those values closer to the values that are the intended output. A network may be taught using a variety of techniques [23].

3. Results and Discussion

Clinical diagnostic and brain-computer interface applications frequently require automated removal of artifacts since EEG is nearly always polluted with various artifacts while capturing brain signal activity. EEG artifact elimination serves as the primary analytical method in digital signal processing and visual evaluation. To overcome this, *K.Yasoda et al.* [26] introduced a novel wavelet ICA (WICA) approach employing a fuzzy kernel support vector machine (FKSVM) to automatically remove and categorize EEG traces. Manual removal of the artifact is quite time-consuming. Without explicitly introducing the cutoff value, the suggested technique offers an effective and reliable system for utilizing automatic categorization and computing artifacts from the EEG signal. Additionally, WICA and FKSVM work together well to eliminate target artifacts. Additionally, they provide model building techniques that leverage training and testing of FKSVM data to categorize artifacts of the EEG signal. These properties include mean, standard deviation, variance, kurtosis, and extent.

Through the use of the analytical elastic wavelet transform (FAWT) technology, *Shalu Chaudhary et al.* [27] in their work suggested a unique method for categorizing various MI tasks based on EEG data. Where time-moment-based characteristics are retrieved from the subdomains of the FAWT's analysis of the EEG data. To lessen the classifier's bias, they used feature normalization. Several classifiers employed the FAWT-based features as inputs. The best and most potent classifier for differentiating between right-handed (RH) and right-footed (RF) MI tasks was subsequently created using the Subspace K-Nearest Neighbor (KNN) classifier based on group learning approach. The KNN classifier based on clustering approach produced the highest performance parameters when they evaluated the subscale (SB) features on several classifiers. The best parameterized results for the fourth SB were 99.33% accuracy, 99% sensitivity, 99.6% specificity, F1-Score 0.9925, and 0.9865 kappa value. The KNN subspace classifier produced substantial results for other subscales as well. They concluded that their proposed work investigated the use of FAWT-based features for identifying EEG data for RH and RF MI tasks. Their suggested study also showed the efficiency of using several classifiers to categorize MI work-loads. When compared to the most recent approaches, their proposed method per-formed better.

In the field of identifying epileptic seizures by classifying EEG signals into two types of seizures and convulsion is a difficult problem since it distinguishes epileptic seizure and epileptic seizure states. In the paper of [29] several machine learning-based algorithms for investigating and interpreting EEG data for correct categorization have been provided in earlier publications. However, because EEG signals are nonlinear and non-static, collecting accurate information about these dynamic bio-logical signals is difficult. To solve this issue, *Aayesha et al.* concentrated their efforts on extracting the most recognized and recognizable aspects of regulated EEG recordings in order to build a strategy for epileptic seizure identification that employs both classical and fuzzy-based machine learning techniques. The proposed framework divides unknown EEG signal segments into interictal and interictal categories. They tested the model on two standard datasets, the Boone and Children's Hospital Boston-MIT (CHB-MIT) datasets. The findings revealed that K-Nearest Neighbor (KNN) and Fuzzy Rough Nearest Neighbor (FRNN) had the greatest classification accuracies in both scenarios, with better sensitivity and specificity ratios.

In their work, *Abhijit Bhattacharyya et al.* [30] developed a unique multi-level method for calculating spectral and temporal entropy from a multichannel electro-encephalogram (EEG) data. This makes it easy to distinguish between three types of human emotions: positive, neutral, and negative. The suggested method is based on the use of the experimental wave transforms based on Fourier-Bessels expansion (FBSE-EWT). They enhance the current FBSE-EWT approach to calculate spectral Shannon and entropy for multichannel signals and multivariate fringe Hilbert spectra (MHMS) based on FBSE-EWT. K-NN stands for K-nearest neighbor. Multivariate FBSE-EWT breaks down multichannel EEG data into small sub band signals. The process of adaptive multivariability in the spectrum domain is dependent on the selection of the sub band signals' consecutive instantaneous amplitude and frequency functions. They calculated the multiscale K-NN entropy in the time domain from cumulatively accumulated multidimensional subscale signals, on the other hand. For sentiment classification, the acquired spectral and temporal entropy features were smoothed and input into a sparse random forest (ARF) classifier structure based on an autoencoder. The suggested method was evaluated using multichannel EEG signals from a publicly accessible database (SJTU EEG Emotion Dataset (SEED)). Inputs to their suggested system were bivariate EEG signals from separate pairs of channels with distinct spatial placements above the scalp. Their total classification accuracy of 94.4% demonstrates that the suggested method is effective for categorizing human emotions. They also used the DREAMER emotion EEG public database to

validate the approach. The approach outperformed the most recently examined methods in these datasets.
Also, *Anupam Garg et al.* [31] in their work they proposed a model that calibrates music mood and human emotion using machine learning methodologies. The pro-posed model is divided into three phases: (a) predicting song mood using audio cues, (b) predicting human emotion using physiological indicators such as EEG, GSR, ECG, and Pulse Detector, and (c) mapping between music mood and human emotion and categorizing them in real time. Extensive studies were conducted on various musical temper and human emotion data to extract influencing elements, train, test, and evaluate performance.
In the research of *Roy Lee et al.* [32] their overarching goal was to offer a novel group learning technique for subject-independent EEG-based emotion identification based on MOPSO. In contrast to traditional group learning on classification tasks, their technique used group learning abilities to regression problems. They also developed a group operator m that employs a continuous value to indicate the absolute confidence of input data belonging to a specific class, with a value ranging from -1 to 1. They solved the classification problem by using the group operator and regression techniques. MOPSO is a swarm intelligence method that can swiftly find each sub-model's coefficient while avoiding the local optimal solution. The model selection procedure was established in order to find the best base model. SVM, NB, and KNN were chosen as the best baseline models based on the studies, and they are the most often used classifiers for emotion recognition. To address the issue of model instability and low classification accuracy for a single model, they merged MOPSO and classical classification methods to create the MOSNK approach. To describe the linear and nonlinear properties of the EEG signals, they extracted and merged 13 different types of linear and nonlinear features. To better maintain the temporal properties of the EEG signals, a sliding time frame is used. They then ran LOSOCV tests on two SEED and DEAP datasets. The experimental findings revealed that their model was far more accurate than the individual models. Furthermore, the MOSNK approach outperforms four regularly used group learning methods and contemporary methods in terms of recognition accuracy. They also employed a database of EEG recording signals gathered by three electrodes developed by Peking University of Chinese Medi-cine and tested on healthy or stroke-affected participants while exposed to five distinct colored planes. These individuals are known to be otherwise healthy or to have suffered from strokes. For 70% of the population, logs were utilized to train each algorithm, and performance was evaluated for the remaining 30%. The process is then repeated a hundred times when the training and testing sets are switched. The statistical data obtained utilizing each strategy for comparison were then considered. Their findings revealed that the SVM algorithm is the most accurate in terms of results accuracy, and it can predict stroke illness with a reliability of up to 70%.
In their study *Thejaswini S et al.* [35], they applied three standard machine learning models to a database they were able to acquire by means of a unique method. They showed virtual reality films of eight distinct emotions in order to collect EEG data. Then, 34 characteristics in the time and frequency domain were retrieved. They used discrete wavelet four-level transforms to decompose the frequency bands. The data were divided into four, three, and two emotional states using the feature vectors produced by the SVM, KNN, and ANN algorithm-based classifiers. Because of this, the overall accuracy for all four categories using the KNN, SVM, and ANN classifiers was 66.75%, 73.50%, and 85.50%, respectively. In comparison to the other models, the ANN classifiers performed better in terms of accuracy.

Table 2
A Summary of The Prior Research Works Using Machine Learning Algorithms (Publication Year, Feature Extraction, Selection Method and Classification Method)

Ref.	Publication Year	Feature Extraction / Selection Method	Classification Method
[26]	2020	Wavelet ICA	Fuzzy kernel-SVM
[27]	2020	FAWT	Subspace KNN, LDA, SVM, Decision Trees, standard KNN
[45]	2020	Continuous WT	Autoencoder, SVM, logistic regression, MLP
[46]	2020	Fisher score, PCA, SFS	SVM, LDA, KNN, Random Forest
[47]	2020	CSP	MLP
[48]	2020	-	Linear regression
[29]	2021	DWT	Fuzzy Rough Nearest Neighbor (FRNN)
[30]	2021	Multivariate Fourier-Bessel series expansion based empirical wavelet transform	Autoencoder based random forest
[31]	2022	PCA	SVM, Random Forest
[32]	2022	L1-norm regularization	SVM, NB, KNN
[35]	2023	Notch filter, DWT	KNN, SVM, ANN
[33]	2023	FIR filter, Shannon's entropy	Random Forest, LR, KNN, SVM, Decision Tree, CatBoost
[38]	2023	ICA	Random Forest, SVM
[37]	2023	Butterworth, bandpass filter	Random forest
[36]	2023	Band-pass filter	ANN, SVM, KNN, RF
[49]	2023	CAR filters, CSP algorithm	LDA, SVM
[50]	2023	PREP, ICA, Butterworth filter	SVM with radial basis function kernel (rbf-SVM)
[24]	2024	Power Spectral Density (PSD)	DT, RF, LDA, KNN, SVM
[25]	2024	DWT, PCA	NB, SVM, DT, RF, KNN, NN
[28]	2024	PLI, Band-pass filter, ICA	XGBoost, CatBoost, LightGBM, Ensemble models
[40]	2024	DWT	NB, SVM, DT, LDA, KNN, NN, Ensemble models

Using four ML-based algorithms for multiclass human emotion recognition from EEG waves, the performance of several frequency bands was compared by Baloju Revanth et al. [36]. Then, they separated the five frequency bands delta, theta, alpha, beta, and gamma into which the raw

EEG data were initially divided. The statistical, time, and frequency domain features were then extracted. They supplied these variables to four ML-based classifiers to classify emotions using the SEED dataset into three categories: positive, negative, and neutral. Their research showed that ML-based classifiers are more effective than conventional classifiers. As a result, the random forest classifier reported a delta domain mean classification accuracy of 95.71%. The theta range likewise has the second-highest average accuracy by KNN, 80.32%. Other frequency bands have followed a similar pattern.

In the research of *A.M.Mahmud Chowdhury et al.* [37], on the basis of captured EEG data, they created a software system to automatically identify people. They made use of a general dataset created especially for testing biometric EEG methods. Over the course of three successive sessions, they gathered data on 21 people and 12 different stimuli. The recorded EEG test pattern was compared to the corresponding template kept in the database during validation. Their tests revealed that a machine learning model based on random forests could obtain an authentication accuracy of about 83.2%. This shows that the EEG may be trusted for identification and authentication in a variety of settings.

Because it can increase knowledge retention compared to conventional learning methods, virtual reality (VR) is frequently employed in a variety of educational scenarios. However, due to stress, mental distraction, undesired noises/sounds, irrelevant stimuli, etc., distraction is an inescapable issue in an educational VR setting. EEG data and eye gaze were combined in an investigation by *Sarker M. Asish et al.* [38] to identify student diversions in a virtual reality learning environment. To identify distracted pupils, they created a VR classroom and training three machine learning algorithms (Random Forest, CNN-LSTM and SVM). The preliminary study's findings demonstrate that CNN-LSTM and Random Forest offer more accuracy (98%) than SVM.

In 2024 [24], an important stage was worked on in a study, which is classification using two different types of original databases, open source and available to everyone, with different classifications (binary and multi). It relied on the latest and best machine learning algorithms used in this field. It also made sure to improve the performance of each algorithm by changing and modifying the input data for each of them several times until reaching the best. Then the effectiveness of the developed classifiers was evaluated by measuring the accuracy rate and then choosing the best and displaying it in the confusion matrix. Decision tree, random forest, LDA, KNN, and SVM are the five classifiers used in the work to classify the data. The random forest classifier in that study achieved the best results on both databases with 100% accuracy on the first and more than 86% on the second. This makes it recommended as a suitable, effective, and ready-to-use classifier for researchers interested in working on the same databases used in that study. As an idea for subsequent work, the study suggested the possibility of relying on the idea of amplifying the data itself to test the efficiency of deep learning techniques on it, and then modifying the inputs of the algorithms to improve them as well.

A machine learning framework for identifying between normal and epileptic EEG recordings is presented in a paper by *Ali M. Ali et al.* [25]. Their methodology comprised feature extraction utilizing statistical techniques and the discrete wavelet transform (DWT), feature selection to find the most discriminating features, and multiple algorithm classification. In particular, they represent time-frequency by transforming discrete waves through the analysis of nonstationary data. Robust feature selection is aided by cosine similarity and principal component analysis. Signals are classified by supervised classifiers such as support vector machines, k-nearest neighbors, neural networks, naive Bayes, decision trees, and forests. Their findings showed that neural networks may be used to classify data with 100% accuracy, suggesting the possibility of extremely dependable automated categorization. Show which machine learning pipeline is best by comparing several methods. This work has led to the development of an EEG categorization framework for epilepsy, which shows how artificial intelligence may greatly advance neurological illness screening, diagnosis, treatment, and management.

Early stress detection in students prevents suicidal thoughts and illnesses, and appropriate therapy is also offered to enhance learning. EEG characteristics including relative sub potential powers and EEG amplitude ratios were taken into consideration to enhance the classification model's performance measures. *V. G. Rajendran et al.* used machine learning techniques in their study [40] to create two levels of classification, such as stress and non-stress states. Using an 8-channel Enobio wireless device, they experimentally performed an EEG signal recorded from 25 people un-der two conditions: relaxation (non-stress) and during a mental task (stress). The EEG features were extracted through the application of the discrete wave transform technique, relative sub band power (alpha, theta, and beta energies), and relative band ratios (arousal index, heart rate, performance improvement index, cognitive performance attention resources index (CPARI), and organ arousal) calculated from the sub band energies of two states. Symmetry and the central nervous system. Using a non-parametric technique like the Wilcoxon signed rank test, they selected EEG features by statistically significant analysis ($p < 0.05$) for both data cases. They also conducted brain functional connectivity analysis of sub band energies. Ultimately, 89.74% classification accuracy was attained by the cubic SVM classifier model that was made public.

Jiaqi Fang et al.'s study [28] aims to build a diagnostic framework for triadic classifications while examining the mechanisms underlying depressive illness, generalized anxiety disorder, and healthy controls (HC). Electroencephalogram (EEG) signals from 42 patients with depressive disorders, 45 patients with generalized anxiety disorders, and 38 healthy controls were specifically collected as part of the experiment. They measured brain functional connectivity using the phase lag index (PLI) and examined variations in functional connectivity among the three groups. Additionally, they investigated how classification performance was affected by time window feature computations using ensemble models, XGBoost, CatBoost, and LightGBM. They put forth a feature optimization approach based on Autogluon Tabular to enhance the classification performance. According to their findings, the three groups performed best in the classification task within a 12-second time window, with the ensemble model obtaining the greatest accuracy of 97.33%. Significant brain remodeling was also found by the research, with the frontal lobes and beta rhythm showing the most notable alterations. Their research provided credence to the idea that DD and GAD are associated with aberrant brain functional connectivity, which may help understand the neurological mechanisms underlying these disorders.

In his paper [47] *Haibo Yil* created an EEG training suite employing EEG equipment for using the suggested methods for systolic matrix multiplication, systolic matrix multiplication, and systolic matrix multiplication, he modeled the connection between two variable samples X and markers Y based on the fit of a linear equation $Y = \theta X$ to the training set. Then, using Docker technology, he created a development environment. He then used the packaged training set to build active EEG modeling in the development environment.

Table 3

A Summary of The Prior Research Works Using Machine Learning Algorithms (Performance Measure, Accuracy Level, BCI Task)

Ref.	Performance Measure	Accuracy Level	BCI Task
[26]	Specificity, Accuracy, Sensitivity	Fuzzykernel-SVM (86.1%)	EEG signal categorization
[27]	Accuracy, Specificity, Kappa value, F1-score, Sensitivity	SubspaceKNN (99.33%) LDA (81.1%) SVM (95.72%) DT (91.79%) Standard KNN (92.8%)	MI classification
[45]	Accuracy, recall, Precision, f-score	AE (92.09%) SVM (88.48%) LR (89.25%) MLP (95.58%)	EEG signal categorization
[46]	Accuracy, f1-score	Anger (98.02%) Joy (100%) Surprise (96%) Disgust (95%) Fear (90.75%) Sadness (90.08)	Emotion classification
[47]	Mean square error, accuracy	(97.82%)	EEG signal categorization
[48]	Accuracy	(95%)	EEG signal categorization
[29]	Accuracy	Bonn : (99.25%) CHB-MIT : (96.08%)	Diseases classification
[30]	Accuracy, F1-score	Arousal (85.4%) Valence (86.2%) Dominance (84.5%) SEED (94.4%)	Emotion classification
[31]	Accuracy	SVM (71.8%) RF (81.4%)	Emotion classification
[32]	Accuracy, F1-score, Precision, Recall, ROC, AUC	DEAP: Arousal (65.7%) Valence (64.22%) SEED: (84.44%)	Emotion classification
[35]	Accuracy, Confusion matrix	ANN (85.50%) SVM (73.50%) KNN (66.75%)	Emotion classification
[33]	Accuracy	Best: SVM (70%)	Diseases classification
[38]	Accuracy, Precision, Recall, F1-scores	RF (98%)	Dispersion classification

[37]	Accuracy, Precision, Recall, F1 score	RF (83.2%)	Biometrics classification
[36]	Accuracy	ANN (33.2%) SVM (64.64%) RF (71.02 %) KNN (70.66 %)	Emotion classification
[49]	Accuracy	SS-BCI: LDA (76.85%) SVM (94.20%) SI-BCI: LDA (80.30%) SVM (83.23%)	MI classification
[50]	Accuracy, specificity, sensitivity, F1-score	(85%)	EEG signal categorization
[24]	Accuracy, Confusion matrix	DATA (1): DT (100%) SVM (75.5%) RF (100%) KNN (95%) LDA (78%) DATA (2): DT (78.07%) SVM (65.09%) RF (86.47%) KNN (73.37%) LDA (65.71%)	EEG signal categorization
[25]	Accuracy	Neural Networks (100%)	Diseases classification
[28]	Accuracy, F1-Macro, Gmean-Macro, Kappa	Ensemble model (97.33%) XGBoost (96.40%) CatBoost (95.53%) LightGBM (96.73%)	Diseases classification
[40]	Accuracy, Sensitivity, Specificity, Precision	Ensemble model (95.83%)	Diseases classification

To evaluate the concept, he put together an EEG test suite employing EEG equipment. The model's accuracy was 95% after testing. He also talked about how it may be used for EEG modeling in BCIs. Then, using the suggested techniques for systolic matrix multiplication, systolic matrix inversion, and systolic matrix multiplication, he increased the machine learning efficiency. His suggested methodology is based on the conventional equation approach. The suggested algorithm should be enhanced to include different machine learning techniques.

Low accuracy, delayed convergence, and fit in local minima are some drawbacks of conventional methods for training NNs, such as gradient ratios and recursive algorithms. In order to solve these issues. The combination of particle swarm optimization and gravity search method (PSOGSA), which was suggested for their classification issue by Sajjad *Afrakhteh et al.* [48] was used to train MLP-NN in their research. They contrasted this approach with other heuristic algorithms like particle swarm optimization (PSO), gravity search algorithm (GSA), and newer iterations of PSO in order to demonstrate the benefits of utilizing PSOGSA to train NNs. In their study, convergence velocity and classification accuracy measures are covered. Their findings demonstrated that, when compared to the alternatives, the algorithm they provided performed better or at least acceptable levels in the majority of the EEG dataset participants.

In [45] the authors propose a new multimodal machine learning (ML)-based approach to integrate geometric features of EEG for automatic classification of brain states. Where EEGs were obtained from neurological patients with mild cognitive impairment (MCI) or Alzheimer's disease (AD) the aim was to distinguish healthy control (HC) patients from patients. Specifically, in order to effectively deal with the instability, 19-channel EEG signals were rendered in the time-frequency domain (TF) by continuous wavelet transform (CWT) and a set of appropriate features (referred to as CWT features) were extracted from the bands. Subtypes δ, θ, $\alpha1$, $\alpha2$, and β EEG. Furthermore, to exploit the nonlinear phase coupling information of the EEG signals, higher order statistics (HOS) were extracted from a bispectrum (BiS) representation. BiS generated a second set of features (referred to as BiS features) that were also evaluated in the five EEG subscales. CWT and BiS features were entered into a number of ML classifiers to perform both 2-way (AD vs HC, AD vs MCI, MCI vs HC) and 3-way (AD vs MCI vs HC) classifications. As an experimental standard, they analyzed a balanced EEG dataset that included 63 AD, 63 MCI, and 63 HC. Their comparative results showed that when using a sequence of CWT and BiS features (which they referred to as multimodal features (CWT + BiS)) as input, the classifier is multimodal. Layered (MLP) outperforms all other models, namely, unit autoencoder (AE), logistic regression (LR) and support vector machine (SVM). As a result, they concluded that the proposed multimodal ML scheme can be considered as a viable alternative to the latest computationally intensive deep learning approaches.

In 2023, *Eliana M et al.* [49] Their objective was to produce a ready-to-use system that required little setup time. As a result, their objective was to create a subject-independent BCI (SI-BCI) that could be used by any new user without the limits of individual calibration. They used the findings of other research to create comparisons and corroborate our findings. They employed a mixture of delta (0.5-4 Hz), alpha (8-13 Hz), and beta + gamma (13-40 Hz) bands to analyze the EEG input earlier in the process for feature extraction. They then collected features from a 27-channel EEG using a combined spatial pattern (CSP) and used linear discriminant analysis (LDA) and vector machine classifiers (SVM) to conduct binary classification (MI for right and left hand). These analyses were carried out for both the SS-BCI and SI-BCI models. They also evaluated their SI-BCI and SS-BCI systems using leave-in-from-single-subject ordering (LOSO) and 10-fold validation, respectively. In comparison to two other investigations, theirs was the only one that demonstrated a superior accuracy of the LDA classifier in the SI-BCI than the SS-BCI. In both situations (SI-BCI and SS-BCI), however, the accuracy of LDA was lower than that of SVM. Their SS-BCI accuracy was 76.85% using LDA and 94.20% using SVM, while their SI-BCI accuracy was 80.30% using LDA and 83.23% using SVM. As a result, they determined that SI-BCI may be a viable and useful choice. Use it in situations when individuals are unable to present themselves for lengthy training sessions or for a rapid assessment of 'BCI illiteracy'. In comparison, their technique proved more efficient, yielding the best SI-BCI score when compared to the categorization performance of the other three research, even when the limitation of utilizing different datasets in evaluating the four studies was taken into consideration.

Michael Lacey and others [50] recently assessed the capacity of numerous EEG measurements to distinguish between levels of upper limb disability in a proven machine learning architecture. Within 72 hours after the stroke, EEG data from 28 acute stroke survivors were obtained, coupled with the Fugl-Meyer Upper Limb Assessment Scale (FMAUE) motor subscore. They collected 221 characteristics from the EEG signals' spectral and conductivity domains and chose the best predictive features using two feature-ranking algorithms (ReliefF and Minimum Related Frequency). The support vector machine classifier was given sets of the top performing features, which were then tuned in terms of hyperparameters. The best-performing model attained an accuracy of more than 85% in categorizing individuals into high and low FMAUE using cross-validation. The brain symmetry score and its derivatives were key indications of a patient's motor condition. They anticipate that this discovery may open the way for automated, EEG-based recording of motor dysfunction following a stroke.

In their article, *Oana Bălan et al.* [46] suggested a comparison of various deep learning and machine learning methods, with or without feature selection, to binary classify the six basic emotions anger, disgust, fear, happiness, sorrow, and surprise into two related categories (emotion and no). The DEAP data (a dataset for emotion analysis utilizing EEG, physiological cues, and video inputs) contains subjective judgments of arousal, valence, and dominance as well as physiological records of emotion. According to their findings, the highest accuracy ratings for each emotion were as follows: Anger: 98.02%, Joy: 100%, Disgust: 95%, Fear: 90.75%, Surprise: 96%, and Sadness: 90.08%. Without feature selection, classification accuracy for four emotions (anger, fear, disgust, and sorrow) was greater. They found that their method of considering emotion.

4. Emerging trends and future challenges

As a emerging trend in deep learning for feature learning, recent developments, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), enable the automatic extraction of features from EEG data. It offers features for choosing an extraction procedure and a classifier for the dataset, eliminating the hassle of choosing a segmentation process [51]. This reduces the reliance on manual feature engineering and improves performance in applications such as emotion recognition, motion imaging, and cognitive state detection. We can also talk about transfer learning and domain adaptation, where transfer learning techniques are increasingly being adopted to address the problem of interpersonal variability in EEG signals. By reusing knowledge from pre-trained models, researchers can achieve better generalization and efficiency, especially with small datasets. In the context of explainable AI, there is an increasing focus on interpretability in brain-computer interface applications. Techniques such as SHAP (SHapley Additive Explanations) and LIME (Locally Uninterpretable Model Explanations) are being used to interpret machine learning models, which is particularly important for critical applications such as medical diagnosis.

As for future challenges, data quality and artifacts are one of the most important, as EEG signals are susceptible to noise and artifacts (e.g., muscle movements, eye blinks). Developing robust preprocessing techniques and artifact removal algorithms is crucial to improving the reliability of BCIs. Also, inter-subject variability as the highly individual nature of EEG signals remains a major hurdle. Despite advances in domain adaptation, achieving universal models that work consistently across different users remains a challenge. In addition to scalability and accessibility, current EEG-based BCI systems often require expensive hardware and specialized expertise, limiting their widespread adoption. Affordable, easy-to-use, and scalable solutions are essential for mainstream applications. With the reliance on AI and its tools, the issue of privacy remains an ever-present issue. With the increasing use of brain-computer interfaces to monitor and control human behavior, issues related to privacy, data security, and the ethical use of EEG data have become of paramount importance. Establishing robust frameworks for ethical compliance is essential. Continuous use of EEG-based brain-computer interfaces can also lead to user fatigue, both physically (due to wearing the devices) and mentally (due to cognitive load). Improving usability and comfort is critical for long-term adoption.

5. Conclusion

A The most popular machine learning techniques for handling classification and regression issues in EEG-based BCI systems are reviewed in this work. The content of 21 recent scientific articles (from 2020 to 2024) was discussed and the results of machine learning algorithms were highlighted in each research. Additionally, a few of the most well-known and common machine learning approaches are described. It is necessary to highlight the concerns associated with the employment of the rank algorithm. Although it is obvious that classification algorithms have helped to characterize task-related brain states, using these methods by non-experts may lead to a number of difficulties. The major cause of problems is overfitting of the algorithms as well as bias and variation in the estimated error of the algorithms. The classifier will only be able to categorize training data or comparable data if it is overfitted. By keeping categorization techniques simple, over-fitting may be avoided. In summary, this study aims to inform future research by offering guidance on experimental protocols, choosing appropriate instrumentation, and employing AI methodologies. It equips readers with information enabling them to identify optimal machine learning algorithms suited to their particular problem-solving contexts, thereby fostering the advancement and utilization of EEG-based BCI systems.

Declaration on Generative AI

While preparing this work, the authors used quillbot in some paragraphs for paraphrasing and rewording. After using this tool, the authors reviewed and edited the content as needed and bear full responsibility for the content of the publication.

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