



INTEGRATED REVIEW OF EEG SIGNAL CLASSIFICATION MODELS FOR SSVEP, ATTENTION AND MOTOR IMAGERY USING MACHINE AND DEEP LEARNING ALGORITHMS

Pradeep Kr. Sharma¹, Pankaj Dadheech²

¹Department of Computer Science & Engineering, Swami Keshvanand
Institute of Technology, Management & Gramothan, Jaipur, Rajasthan,
India-302017.

Email: ¹sharma4203@gmail.com, ²pankaj@skit.ac.in

Corresponding author's Email: **Pradeep Kr. Sharma**

<https://doi.org/10.26782/jmcms.2026.04.00009>

(Received: January 27, 2026; Revised: March 31, 2026; Accepted : April 12, 2026)

Abstract

New developments in the Brain-Computer Interface (BCI) technology have increased the rate at which research has been done on precise and quick electroencephalography (EEG)-based signal classification models. This review analyses new trends, procedures, problems, and gaps in research on EEG signal classification in three large cognitive paradigms: Steady-State Visual Evoked Potential (SSVEP), detection of the attention focus, and motor imagery (MI). These paradigms form the focus of real-time BCI applications, e.g., assistive technologies, neurorehabilitation, adaptive learning, and augmented interaction systems. The analysis presented in the paper on the development of the traditional machine learning (ML) and the modern deep learning (DL) models of the EEG interpretation systematically reviews the progression of the original ideas in the EEG interpretation field. Power spectral density analysis, Common Spatial Patterns (CSP), wavelet transform, and empirical mode decomposition (EMD) techniques of feature extraction, and Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) techniques are critically examined. Some of the performance evaluation metrics that are widely employed in the literature are also addressed. Special attention is paid to the real-life issues that accompany real-world EEG data, such as low signal-to-noise ratio, artifact contamination, inter-subject variability, limited diversity of datasets, and bad model interpretability. It is believed that such public benchmark datasets as BCI Competition datasets, PhysioNet, and other multi-subject repositories can be used to support comparative analysis. Additional requirements of unified evaluation frameworks, real-time system-aware assessment, hybrid models, multimodal fusion strategies, transfer learning, and explainable AI have been identified in the review in an attempt to enhance the accuracy, robustness, and trustworthiness of EEG-based cognitive systems. On the

Pradeep Kr. Sharma et al.

whole, the given study can be used as a consolidated basis for the creation of future-generation EEG-based BCI frameworks.

Keywords— EEG signal classification, Steady-State Visual Evoked Potential, attention focus detection, motor imagery, Brain-Computer Interface, machine learning, deep learning

I. Introduction

The Brain-Computer Interface (BCI) systems based on electroencephalography (EEG) have received broad interest in recent years since they would allow direct communication between the human brain and other devices. The ability is very useful in assistive technologies, immersive gaming, neurorehabilitation, monitoring mental workload, and human augmentation. EEG is one of the most successful methods of acquisition of neural signals among the existing ones due to its non-invasive nature, relative low-cost, portability, and high temporal resolution. The present review is dedicated to the classification of EEG signals within three significant cognitive paradigms that include the Steady-State Visual Evoked Potential (SSVEP), attention focus detection, and motor imagery (MI). These paradigms are particularly applicable to the BCI research since they necessitate strong decoding of complex neural activity into valid and real-time system responses.

SSVEP is a frequency response of the brain to a visual stimulus of constant frequency defined by a user's attentiveness to the stimulus. These reactions are habitually identified in the occipital region and are broadly applicable in BCI systems due to their relatively high signal-to-noise ratio as well as few training requirements. Attention detection, in its turn, attempts to estimate cognitive involvement, occupational load, or mental concentration based on non-seasoned and not constant EEG activity. This is a very topical task that is applied in adaptive user interface, neuroergonomics, and highly intelligent learning systems. Another motor imagery is the mental simulation of movement that is not carried out and is the most significant in the control of neuroprosthetic and rehabilitation. Nevertheless, motor imagery EEG is still challenging to classify due to the low amplitude of its signals, inter-subject associations, and time dynamics.

EEG attention focus detection has become a powerful tool to measure users' cognitive load, engagement, and task performance. Accurate detection of a user's attention state can prove instrumental to the adaptive user interface, adaptive learning environment, and neuroergonomics. Attention-related EEG patterns are, however, subtle and nonstationary, and can thus not be detected using the traditional statistical methods. With the complex and dynamic nature of attention-related brain activity, recent studies of attention have thus turned to ML and DL approaches to model it. The aim is to select a set of features out of the raw EEG data that can be classified as different cognitive states as accurately as possible. The other extensively researched domain is motor imagery (MI), where one simulates the movement of the internal representation of the body or movement without actually performing the movement. The importance of this paradigm is especially noted in rehabilitative and prosthetic control. In MI-based BCIs, the brain activity corresponding to imagined movements (such as moving the left or

Pradeep Kr. Sharma et al.

right hand) is sought to be decoded from the sensorimotor cortex. The signals of EEGs are low signal amplitude and high inter-subject variability, which make it difficult to classify MI. Certain signal processing techniques, as applied, e.g., Common Spatial Patterns (CSP), have shown some success, but integrating DL models such as CNN & RNN have led to great improvements in classification accuracy as well as adaptability. To that end, machine and deep learning techniques have converged in the EEG signal classification in all three of the cognitive domains. After extensive dimensionality reduction, traditional feature-based classification has been done using Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Decision Tree (DT), and Random Forests (RF). However, although efficient, these models are flawed because of their dependence on handcrafted features and their inability to generalize to other datasets. On the other side, the DL models, especially the CNNs and LSTMs, have demonstrated great potential for learning the features from the raw EEG signals. Because LSTMs are good at modelling temporal dependencies, and CNNs do a good job of modelling spatial and frequency patterns, CNNs and LSTMs are appropriate for time series data such as EEG. With such a shift, hybrid architectures of CNNs and LSTMs, or DL models and signal processing algorithms, have been reaching further in the capability of classification.

The standard metrics to evaluate these models are accuracy, precision, recall, and F1 score, among others, and their efficiency. Besides, the set of preprocessing, feature extraction, and classifier tuning that the user chooses also has an important impact on the model performance. Common techniques to clean and prepare EEG signals are band pass filtering, Independent Component Analysis (ICA), wavelet transform, power spectral density estimation, empirical mode decomposition, etc. In addition, some of the limitations of limited training data and inter-subject variability have also been addressed by the recent emergence of transfer learning, domain adaptation, and data augmentation, which makes the models more robust and generalizable. Standardized datasets are a large contribution to modern EEG classification research, and it is used as a contribution to benchmarking and comparative studies. For example, reproducible research has been driven by datasets from BCI Competitions, PhysioNet, and multi-subject publicly available repositories.

To be practically implemented, EEG-based BCI systems should meet tight real-time specifications as opposed to reporting offline classification accuracy. The overall response lag in a closed-loop BCI should not be too high so that user control, system responsiveness, and neurophysiological relevance are not compromised. The system latency can be calculated as the total of the delay in the entire system, as:

$$\tau_{total} = \tau_{acq} + \tau_{pre} + \tau_{seg} + \tau_{feat} + \tau_{inf} + \tau_{post} + \tau_{comm}$$

where τ_{acq} denotes signal acquisition delay, τ_{pre} preprocessing delay, τ_{seg} segmentation/windowing delay, τ_{feat} feature extraction time, τ_{inf} model inference time, τ_{post} post-processing or decision smoothing time, and τ_{comm} communication or actuator transmission delay. To achieve a responsive BCI, the end-to-end delay is preferably less than 300 ms in general interactive applications, whereas a latency of less than 100 -150 ms is desirable in conditions of high-speed control, neurofeedback, and assistive systems. The throughput of the decision pipeline can be defined as

Pradeep Kr. Sharma et al.

$$\Gamma = \frac{1}{\tau_{total}}$$

and this is the number of reliable decisions that one can produce with a given amount of time.

Besides latency, computational complexity can be a factor of four since embedding, wearable, and edge computing heavily rely on it. Conventional machine learning algorithms, including SVM, k-NN, and Random Forest, tend to have lower inference cost than deep neural architectures, as opposed to needing handcrafted features, which in turn adds to the preprocessing cost. For a feature vector of dimension d and n training samples, a linear SVM typically requires $O(d)$ inference after training, while k-NN classification may require $O(nd)$ distance computations during testing. Random Forest inference scales approximately with the number of trees and tree depth, often represented as $O(T \cdot h)$, where T is the number of trees and h is the average depth. By comparison, CNN-based networks are proportional to the count of convolutional filters, convolutional kernel size, channel depth, and length of time series of the input, whereas recurrent models, like LSTM, incorporate temporal dependency and consequently an increased inference cost since the state at a specific time-step is dependent on the state at other time-steps. In turn, light CNNs like EEGNet are more appropriate as a real-time BCI instead of being able to use deeper hybrid CNN-LSTM models in a situation with limited hardware.

In the system perspective, it is the combination of three interdependent criteria, that is, (i) classification effectiveness, (ii) inference latency, and (iii) computational/energy cost, that can be used to determine real-time feasibility. One where offline errors are slightly less can prove more practical when models that previously met timing constraints are found to be more practical, or if they consume too much power. This is especially relevant to wearable BCI, VR-built-in, and home automation platforms, whereby the processor, memory, and battery space are constrained. Therefore, future studies of the EEG classification should present not only the information about the accuracy, precision, recall, and F1-score, but also about the average inference time/per window, memory footprint, the cost of the floating-point operations, and the platform characteristics, such as the CPU /GPU type, RAM, sampling rate, and window length.

A realistic real-time evaluation procedure must minimize the following metrics, which should be reported: average decision latency by trial, worst-case latency, decisions per second, megabytes of model size, and average power consumption, provided the model is to be used in the mobile or wearable environment. This type of reporting would establish a direct association between the performance of the algorithms and usability in the operations. Here, the idea of shallow CNNs, compressed networks, quantized networks, and edge-friendly signal processing networks seems particularly threatening for future BCI systems.

The datasets presented here are usually recordings from several cognitive tasks, and the research is presented within the single framework of SSVEP, MI, and attention classification. Along with these offline evaluations, real-time BCI implementation is currently a priority, which necessitates the priority of low latency and energy efficiency as performance indicators.

Pradeep Kr. Sharma et al.

However, many research gaps remain. However, most deep learning models have an interpretability problem, so it is hard to know what features the model uses for the brain. However, in clinical and wide applications, such a lack of transparency is a problem. Additionally, the EEG signals used in generalization are quite variable, as a result of electrode placement, user fatigue, environmental noise, and physiological conditions. In order to address these concerns, explainable AI models, robust signal normalisation techniques, and user-adaptive systems need to be developed that can recalibrate in real time in response to feedback. The need to consolidate the immeasurably vast and diverse literature on EEG-based classification for SSVEP, attention focus, and motor imagery emerges as the motivation behind this review, which uses machine and deep learning algorithms. This review analyses existing methodologies, performance metrics, and application scenarios to provide existing knowledge to the researchers to get a complete awareness of trends, strengths, and limitations. It also addresses some promising future directions, including multimodal fusion, hybrid neural architectures, reinforcement learning-based BCI training, and neuromorphic computing in order to build more responsive and intelligent EEG-based systems. Finally, EEG signal classification is a very promising and evolving research area for healthcare, assistive technology, and human-computer interaction. With the integration of advanced ML and DL techniques, researchers are moving closer to realizing highly accurate, robust, and personalized BCI systems. This review serves as both a knowledge repository and a roadmap for future exploration in EEG-based cognitive state decoding, emphasizing the importance of interdisciplinary collaboration between neuroscience, computer science, and engineering domains.

II. Literature Review

Brain Computer Interface (BCI) systems are a revolutionary means for the translation of human neural activity into an external device, based on the reading of brain signals. Recently, these systems have become of interest because it has been proposed that they are applicable to neurorehabilitation, assistive technologies, and research in cognitive monitoring. Consequently, the fundamental building block of BCI development depends on the precise acquisition and accurate discrimination of brain signals for developing efficient communication channels between the user and machine [XXXV, XI]. Two domains of application for BCIs are possible: feed-forward, in which brain activity is explored, and external device control occurs, and closed-loop, in which brain activity is artificially influenced in a way that promotes plasticity [XIII, IX].

The brain signal acquisition techniques can be classified into different types of neuroimaging techniques that are either invasive or non-invasive. This is typically the most common invasive method used, namely, electrocorticography (ECoG), which records activity from the cortical surface. ECoG is extremely high spatial resolution, but is constrained by its surgical risks and slowly degrading signal quality over time [VI, XX, XXI]. In contrast, many of these techniques are of the non-invasive type, including electroencephalography (EEG), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and near infrared spectroscopy (NIRS), because of their safety of using them. Amongst these, EEG has become the most popular for its high temporal resolution, portability, clinical translation, and

Pradeep Kr. Sharma et al.

affordability. EEG is made of electrodes that record voltage fluctuations caused by ionic current flows in the neurons of the brain. For training such as neurofeedback and communication systems for individuals with physical impairments, these signals are used extensively [III].

The difficulty with EEG-based BCI is in the accurate detection and understanding of the brain activity patterns related to the user's intention. An effective BCI framework requires obtaining useful signals from users via robust task-specific protocols and paradigms and extracting their cognitive states [XIV, XXVIII, XIX]. The steady state visually evoked potential (SSVEP) paradigm is widely used and one of the paradigms with a high signal-to-noise ratio, no training needed, and excellent information transfer rate (ITR) [VIII, XXIX]. When a person looks at a visual stimulus flickering at a particular frequency, SSVEPs are elicited, and the brain produces brain oscillations at that same frequency. The frequency domain response can be easily detected, which makes it a robust one for classification. It has been found that harmonics caused by SSVEP stimulation can be uninformative for high ITR BCIs and, therefore, additional distinct frequencies are needed for the corresponding stimulus [XXII]. Additionally, flickering stimuli impose visual discomfort and limits that do not allow this paradigm to be applied in real-world scenarios.

An alternative paradigm to elicit transient responses based on distinct waveform components (P1, N2, and P2) is motion onset visual evoked potentials (mVEP). However, they are usually masked by background EEG activity and therefore temporally encoded, such that complex algorithms are needed for detection and classification [IV, XXV, XXXIV]. Steady state motion visual evoked potentials (SSMVEP) is a novel hybrid paradigm that combines features of both SSVEP and mVEP in order to reduce mental load and reduce visual fatigue [XXVI] [XXXII]. Motor imagery-based (MI BCI) has become popular due to its intuitive control scheme operating in parallel. MI is to imagine (mentally) a movement without actually doing while engage similarity areas of the brain which are involved during the physical action. The strategy is promising for neuroprosthetic control and rehabilitation. However, there are several challenges regarding MI classification: low signal amplitudes and high inter-subject variability [X].

For the SSVEP, MI, and attention classification tasks, the machine learning (ML) and deep learning (DL) based EEG signal classification has been recently improved significantly. Contrary to typical ML algorithms where the features of the data are provided at the hands of the human, DL models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can automatically learn hierarchical feature representations from raw data. The problem with EEG signal classification is that EEG signals are inherently nonlinear and nonstationary, and hence DL is well-suited to model such patterns. For instance, CNNs have been applied to extract spatial and spectral features from EEG time-frequency representations, which enhanced the classification accuracy [I, II]. That is to say, both parameter sharing and sparse interactions are key advantages of CNNs, which make it easier to localize features and reduce the model's complexity and computational burden.

Therefore, CNNs and autoencoders with long short-term memory networks (LSTM), and attention [XII, XXXIII] have been shown to perform well on different EEG-based

Pradeep Kr. Sharma et al.

tasks. In their work, Mattioli et al. [XVIII] used a 10-layer 1D CNN for classifying five different brain states in motor imagery tasks using transfer learning. High accuracy was obtained by this approach at the expense of high regional selectivity, and without any need for subject-specific training data. In [XIV], Roy and Arunabha developed an MI EEG data classification system using a CNN, combining the wavelet and the STFT features for BCI Competition IV-2b. But the reduction of performance across different subjects with their model suggested their feature extraction was effective.

In [XVI], Luo et al. presented a hybrid BCI consisting of SSVEP and MI signals by means of a two-stream CNN architecture (TSCNN). By band pass filtering and channel selection in preprocessing, they made their design improve temporal resolution and accuracy. In the same way, Du et al. [VII] suggested IENet, a CNN model with multi-scale convolution layers to actively extract high-dimensional EEG features with a relatively small number of parameters. The performance of this model was strong for classification, at the expense of low granularity of the parameters.

The hardware integrations are also being explored and are innovative. The purpose of using this type of setup in such a BCIs study is to develop a wireless soft scalp EEG interface developed by Mahmood et al. [XVII] embedded in a virtual reality setup for MI-based BCIs. It allowed for real-time signal acquisition and visual feedback, which then had the effect of increasing user engagement and classification consistency. But translating motoric signals from the brain to the scalp is technically difficult. To reduce inter-subject variability of the MI classification problem, Luo et al. [XV] adopted an overlapping frequency sub-band with a spatial filtering filter bank CNN (OFBCNN). The model was effective, but it was unable to detect subtle motor imagery features.

Later, Roots et al. [XXIII] introduced a fusion CNN imitation of EEGNet with depth-wise convolution layers and feature fusion to enhance cross-subject MI classification. It had reduced efficacy compared to their approach in baseline tests, but they performed well against their approach during epileptic activity. Zhang et al. [XXXI] used a deep CNN framework with three hidden layers and fully connected layers for binary classification of motor intentions for robust decoding. Although the method was accurate for the signal, the spatial resolution was low. Building on this, Zhang et al. [XXX] presented EEG-Inception, a robust neural network featuring inception and residual modules for multiscale feature extraction. While it offered high performance, the model required substantial training data.

In a more practical application, Yang et al. [XXVII] proposed a bipolar-channel hybrid BCI for home automation using both SSVEP and eye-blink signals. Their lightweight EEG acquisition system used STFT and CNN-based classification, allowing users to control devices through gaze and blink patterns. Although useful, this method faced precision issues in subjects with poor mental health or attention disorders. The review of these works reveals a clear trajectory: from handcrafted feature-based classifiers to end-to-end deep learning systems that combine modularity, robustness, and real-time capability.

In conclusion, the integration of machine learning and deep learning algorithms into EEG-based BCIs has revolutionized how brain signals are interpreted for practical applications. While CNNs, LSTMs, and hybrid models offer substantial improvements

Pradeep Kr. Sharma et al.

in performance, there remain challenges in generalizability, explainability, and computational resource management. The future of BCI research lies in refining these models for real-world deployment by incorporating domain adaptation, transfer learning, and explainable AI frameworks. Additionally, the development of robust benchmark datasets and standardized evaluation protocols is essential to facilitate reproducibility and cross-study comparisons. This literature review establishes a comprehensive foundation for understanding the current landscape and emerging trends in EEG-based BCI classification, paving the way for next-generation neurotechnological systems.

III. Analysis and Findings

Recently, due to the increasing need for BCI systems that are real-time, intuitive, and accurate, the exploration of EEG-based Brain Computer Interface (BCI) systems through machine learning and deep learning techniques has rapidly grown over the past decade. This review of the literature shows the coverage of the different dimensions from the signal acquisition modalities, paradigm classification, modelling approaches, to dataset usage, evaluation techniques, and challenges. This section not only expands on the fact that the findings of the reviewed papers were not clear, but also presents a detailed analytical discussion based on five structured tables and six interpretative Figures to further elucidate the findings.

Thus, Table 1 provides a summary of the range of EEG signal acquisition modalities used in BCI systems. EEG is the most dominant among modalities, and this is because of its good temporal resolution, portability, and affordability, as well as its use in clinical and research settings. Indeed, while such invasive techniques as Electrocorticography (ECoG) allow provide high spatial resolution and signal fidelity, they entail great surgical risks and moral questions. However, fMRI, MEG, and NIRS are too slow in execution or need huge and expensive equipment, preventing them from being applied to real-time mobile or wearable BCI. As illustrated in Figure 2, Figure 2, the temporal resolution of almost all modalities, including EEG and MEG, is on the millisecond level, whereas the hemodynamic response in fMRI and NIRS causes them to lag.

Table 2 presents the most commonly used EEG-based paradigms in terms of application-specific paradigms: SSVEP, mVEP, SSMVEP, MI, and attention focus detection, making their strengths and weaknesses known. Compare the information transfer rates resulting from the frequency domain feature of SSVEP systems with those of other systems based on EEG. In support of this, Figure 4 also validates ITR comparisons amongst paradigms, where the novel SSVEP is found to perform significantly better than alternative paradigms, including MI and SSMVEP. The strong signal regularity of SSVEP and its requirement for minimal training are the reasons for its high ITR potential. Nonetheless, they have limitations such as producing visual fatigue and sensitivity to flicker. However, it is much closer to self-paced operation with natural control but possesses limited signal amplitude and high inter-subject variabilities. Challenges yet remain in decoding subtle cognitive states, and current attention detection still remains an emerging domain, particularly in adaptive interfaces and smart learning environments. It must be noted, though, that these comparative patterns do not suggest the strict 1:1 superiority in all these studies since the reported

Pradeep Kr. Sharma et al.

results carry an impact of disparities in data set composition, the class balance, preprocessing pipelines, channel configurations, and validation protocols.

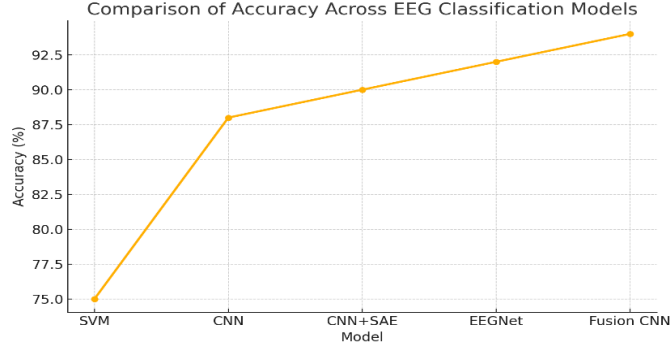


Fig. 1. Comparison of Accuracy across EEG Classification Models

One of the biggest obstacles in the epistemic examination of EEG classification studies is that values given for performance may not be directly comparable across datasets, paradigms, and validation strategies. D is an abbreviation denoting the properties of the dataset, M is an abbreviation denoting the structure of the model, and P is an abbreviation denoting the evaluation protocol. Then the results of a performance of the classifier observed can be of the form D:

$$E = f(D, M, P)$$

where D are class distribution, EEG number of channels, record time, noise-to-short signal ratio, subject variability, and type of paradigm, M is feature extraction strategy, the complexity of the classifier, and trainable parameters, and P are train-test split, cross trade strategy, dependency of the subject, and preprocessing parameters. Hence, the raw accuracy measurements, as opposed to heterogeneous research, cannot be understood as the direct evidence of model superiority unless these three dimensions are thought of together.

A normalized comparative framework is necessary in order to decrease this irregularity. To start with, assessment needs to involve balanced accuracy and macro-F1 besides the traditional accuracy since numerous EEG datasets are either class-imbalanced or vary with the target number of classes. Reporting of Cohen's kappa should also be done to explain the chance agreement, particularly where the multi-class is used. The normalized score of performance may be taken to mean

$$S_{norm} = w_1 \cdot BA + w_2 \cdot F1_{macro} + w_3 \cdot \kappa$$

where BA is balanced accuracy, $F1_{macro}$ is the macro-averaged F1-score, κ is Cohen's kappa coefficient, and $w_1 + w_2 + w_3 = 1$. In the event of no application-specific priority being defined, equal weights can be applied. This formulation lays the heterogeneous results in an analytic space.

Second, the difficulty of the datasets needs to be taken into consideration. In fact, the difficulty of a dataset, represented by $\Delta(D)$, should be a factor that is contingent upon the number of channels, subject variability, level of noise, the number of

classes, and the imbalance ratio. Then, a modified comparison score can be given as follows:

$$S_{adj} = \frac{S_{norm}}{\Delta(D)}$$

so that the performance on the simpler datasets is not over-interpreted as compared to the results of the more challenging cross-subject or noisy datasets. Although specific numbers of $\Delta(D)$ can play out differently, the inclusion of this term is important to recognize that model performance as reported by researchers is inseparable from dataset complexity.

Third, the validation protocols will have to be standardized. Random splits involving subjects tend to inflate performance over leave-one-subject out (LOSO), session-independent, or cross-dataset assessment. So as much as possible, models can be compared on one of the following standard procedures: (i) within-subject validation, (ii) LOSO cross-subject validation, and (iii) cross-dataset transfer validation. In such a framework, superiority of CNN-based or hybrid models claims is only analytically significant when made within the same data set family and comparison protocol.

Based on this, the findings highlighted in this review must be taken as trend-level evidence but not one-to-one ranking. An example of deep learning models that exhibit a higher representation learning power includes EEGNet, EEG-Inception, OFBCNN, and Fusion CNN; however, the advantages need to be put into perspective depending on the data format, preprocessing steps, and the methodology used to validate the results. This standard framework offers a more stringent point of comparison in models, datasets, and performance measures among EEG-based BCI experiments.

Table 1: EEG Signal Acquisition Modalities and Their Characteristics

Modality	Type	Invasiveness	Temporal Resolution	Spatial Resolution	Application Domain	Limitations
EEG	Non-invasive	Low	High	Low	MI, SSVEP, Attention Detection, Rehab	Noise-sensitive, low SNR
ECoG	Invasive	High	High	High	Advanced prosthetics, Neurology labs	Surgical risk, long-term stability issues
fMRI	Non-invasive	Low	Low	High	Cognitive workload, Deep brain mapping	Expensive, poor temporal resolution
MEG	Non-invasive	Low	High	High	Real-time brain mapping	Bulky and costly setup
NIRS	Non-invasive	Low	Low	Moderate	Attention studies, Infant BCI research	Limited depth penetration

Table 2: BCI Paradigms and Cognitive Tasks

BCI Paradigm	Brain Activity Triggered	Feature Domain	Primary Components	Advantages	Limitations
SSVEP	Visual flicker (frequency-locked)	Frequency domain	Harmonics, fundamental freq.	High ITR, low training effort	Visual fatigue, frequency overlap
mVEP	Motion-onset stimuli	Temporal domain	P1, N2, P2	Less visual strain	Needs complex recognition models
SSMVEP	Combined motion + flicker	Frequency domain	Combined harmonics	Minimal mental load	Less distinct with hazy motion stimuli
Motor Imagery	Mental rehearsal of movement	Spatial + Temporal	μ , β rhythms	Intuitive, self-paced control	Low amplitude, subject-dependent features
Attention Focus	Task-specific concentration	Mixed (TF/spatial)	Theta/Alpha fluctuations	Useful in adaptive UIs and education	Non-stationary patterns, difficult detection

Table 3: Machine and Deep Learning Models for EEG Classification

Model Type	Model Name/ Approach	Feature Extraction	Classifier Type	Application	Strengths	Weaknesses
Machine Learning	SVM, k-NN, RF	CSP, WT, STFT	Supervised	MI, SSVEP	Low computation, well-understood	Needs manual features, low generalizability
Deep Learning	CNN	End-to-End	Deep Convolution	MI, SSVEP, Attention	Auto feature learning, high accuracy	Needs more data, opaque interpretation
Deep Learning	CNN + SAE	WT + Autoencoding	Hybrid CNN-AE	MI	Feature compression + abstraction	High memory usage
Deep Learning	EEGNet, OFBCNN, EEG-Inception	Multiscale, Multi-CSP	CNN + Attention	Cross-subject MI	Cross-domain generalization	Complex tuning, overfitting risk
Hybrid	TSCNN, Fusion CNN	SSVEP + MI signals	Parallel CNN blocks	Hybrid BCIs	Multi-paradigm integration	Increased latency

Pradeep Kr. Sharma et al.

Table 4: Dataset Usage and Evaluation Metrics Across Studies

Dataset	Used By (Study)	Cognitive Task	Channels Used	Preprocessing Applied	Metrics Used
BCI Competition IV-2b	Roy and Arunabha [XXIV]	MI	3-5	STFT, Filtering	Accuracy, F1-score
OpenBMI Dataset	Luo et al. [XVI]	MI	Full EEG	CSP, Bandpass Filter	Accuracy
EEG Motor Imagery Dataset	Roots et al. [XXIII], Mattioli [XVIII]	MI	Variable	ICA, Band-pass	Precision, Recall, F1
PhysioNet Online Dataset	Zhang et al. [XXX]	Motor decoding	64	Low-pass, segmentation	Binary Accuracy
MNIST Hybrid Dataset	Yang et al. [XXVII]	SSVEP + Blink	2	STFT, Normalization	Accuracy, User comfort

Table 5: Key Challenges and Proposed Solutions in EEG-Based BCI Research

Research Challenge	Description	Proposed Solution/Technique	Limitation of Solution
Low Signal-to-Noise Ratio (SNR)	EEG signals are weak and often corrupted by artifacts	Band-pass filtering, ICA, Denoising Autoencoders	May also remove useful components
Inter-Subject Variability	EEG patterns differ significantly across users	Transfer learning, domain adaptation	Subject-specific calibration is still needed
Temporal and Spatial Complexity	MI and attention EEG features are nonlinear and sparse	CNN, LSTM, Hybrid CNN-LSTM models	Computational complexity increases
Small Datasets and Data Scarcity	Many models fail to generalize due to limited training data	Data augmentation, GANs, and synthetic EEG generation	Synthetic data may not preserve real dynamics
Explainability and Trust in Models	Deep learning models are often black boxes	XAI (Explainable AI), saliency mapping, layer-wise relevance	Not yet fully adopted in medical applications

Table 3, it shows how the computational methodologies dive deeper into the machine and deep learning models used for EEG classification. For instance, though not new, the use of traditional machine learning models, such as SVMs, k-NN, or Random Forests, remains for the EEG systems, collectively with feature extraction methods like the CSP, WT, and STFT. Nevertheless, they hinge on handcrafted features hindering their adaptiveness in a dynamic, real-world setting. Convolutional Neural Networks (CNNs), Long Short Term Memory (LSTM) networks are among others, which have redefined the entire EEG classification landscape with deep learning models. As a matter of fact, they automatically learn relevant features by means of hierarchical representations and can represent nonlinear and non-stationary EEG patterns in a smart way. This trend is shown clearly in Figure 1, in which there is a clear accuracy

Pradeep Kr. Sharma et al.

advantage of the deep learning models, like EEGNet and Fusion CNN, over traditional methods like SVM. It is due to their ability to capture both the spatial and the temporal EEG dynamics without cumbersome manual feature engineering.

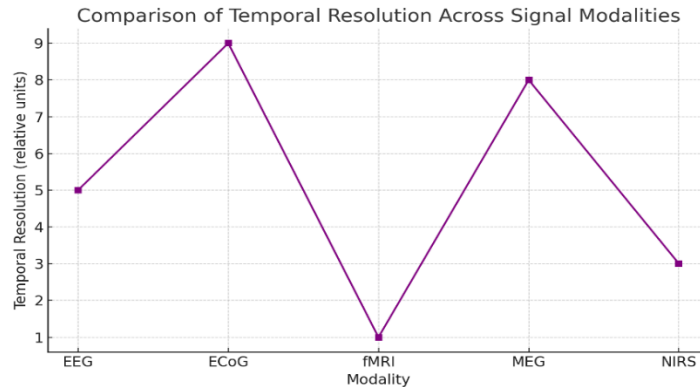


Fig. 2: Comparison of Temporal Resolution Across Signal Modalities

The performance is further enhanced through the integration of a feature extraction technique into the deep models. For example, using CNNs with STFT or wavelet-based images has been applied for translating EEG time series into rich spatially interpretable feature maps. Additionally, Figure 5 demonstrates how soon we have become increasingly dependent on other feature extraction methods, as they are being used more than other methods. However, CSP is the most commonly used because of its simple and efficient spatial features extraction, and is particularly helpful for MI tasks. STFT and wavelet transforms stay mostly the same, which are useful for time-frequency decomposition in general and EEG in particular, as the signal will ideally not be stationary. I am not surprised that ICA and Empirical Mode Decomposition (EMD) are lagging, since they are much less used, perhaps because of their computational complexity or not being robust to subjects. Table 4 details commonly used EEG datasets and the evaluation metrics used to evaluate the model performance and dataset variety. It serves as a benchmark using standard datasets such as BCI Competition IV-2a/2b, OpenBMI, EEG Motor Imagery Dataset, and PhysioNet. The number of EEG channels, the type of task, and the demographics of the participants vary from one dataset to another. Datasets such as OpenBMI yield rich motor imagery data, and they have been used in novel multi-paradigm applications with datasets that derive from the MNIST family. Different aspects of the classification performance are captured by evaluation metrics like accuracy, precision, recall, F1 score, and mean squared error (MSE). Figure 3 shows the comparison of model accuracy on the different datasets and constantly shows the superiority of the simple EEGNet models over other CNN architectures in cross-subject settings. Importantly, accuracy tends to decrease in datasets of high noise and inter-subject variability, indicating a need for transfer learning and domain adaptation.

The main contribution of this review is in the identification and mapping of key challenges in EEG-based BCI systems, as listed in Table 5. MI and attention paradigms remain strongly hampered by performance on low signal-to-noise ratio (SNR). However, the performance of classification is greatly deteriorated by signal

Pradeep Kr. Sharma et al.

contamination from eye blinks, muscle artifacts, or environmental interference. However, to combat noise, ICA and autoencoders are used to reduce noise, but the result is to suppress signal components that are useful. Another important challenge is subject variability between subjects, which results in making the model non-generalizable and requires calibration for each subject. Meta-learning, few-shot learning, and domain adaptation have been proven to have promise, but have not been implemented yet in practice. Moreover, available labeled EEG datasets are small, thus preventing the use of large-scale deep learning frameworks. Despite mixed results, solutions like synthetic data generation, generative adversarial networks (GANs), and transfer learning have been proposed to address this issue.

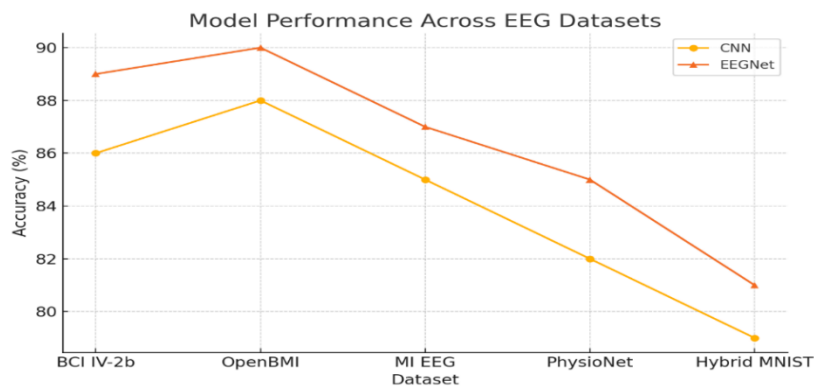


Fig. 3. Comparison of Model Performance Across Datasets

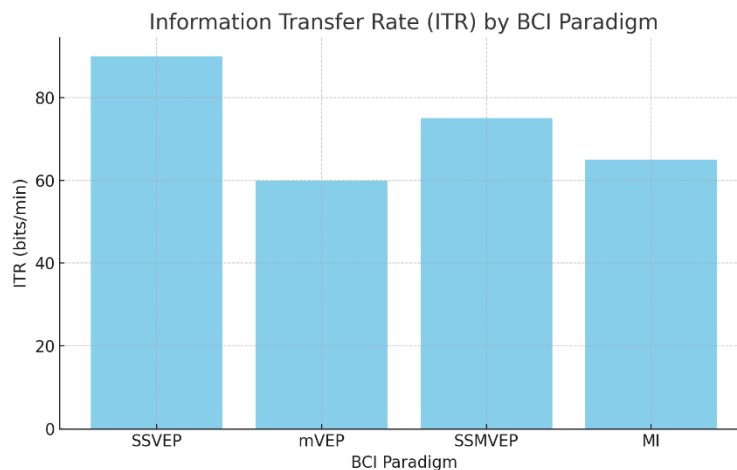


Fig. 4. Comparison of ITR with respect to BCI

Figure 6 shows frequencies of challenges mentioned in the literature that include low SNR, inter-subject variability as the most cited, followed by data scarcity and model interpretability. Interestingly, recently, explainability is becoming second nature and is being considered as deep learning models become more present in sensitive applications for clinical diagnostics or neurofeedback. To solve the 'black box' of neural networks, tools such as Layer-wise Relevance Propagation (LRP), saliency maps, and

Pradeep Kr. Sharma et al.

attention mechanisms are being investigated. Nevertheless, interpretability frameworks for EEG-based systems are early to adopt.

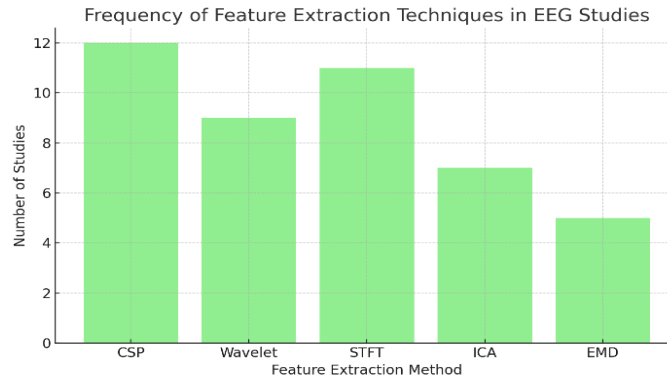


Fig. 5: Frequency of Feature Extraction Techniques in EEG

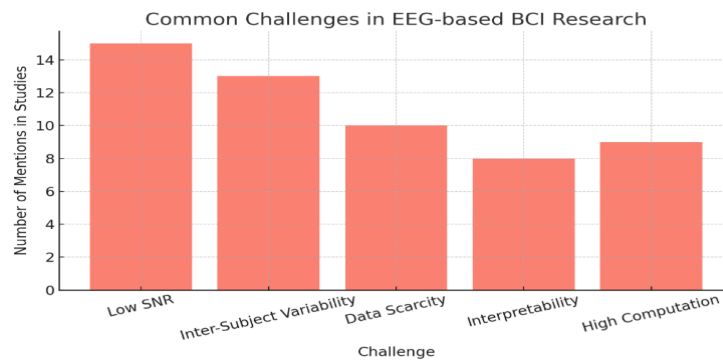


Fig. 6. Comparison of Common Challenges in EEG-Based BCI Research

Corroborating these findings, the literature reviewed also includes a few state-of-the-art implementations. To improve the MI classification with limited training data, Mattioli et al. [XVIII] have proposed a 1D CNN using transfer learning abilities to adapt to different MI using retraining of the layers. Similar to STFT-based CNNs, Roy and Arunabha [XXIV] have shown, but also reported lower cross-subject accuracy. Luo et al. [XVI] also further integrated SSVEP and MI paradigms into a hybrid model with a two-stream CNN, which leads to better accuracy while decreasing response latency. Similar to this, Du et al. [VII] proposed IENet, an efficient CNN-based network with inception modules, along with Mahmood et al. [XVII] introducing a wireless EEG interface with real-time virtual feedback to increase the user engagement.

Luo et al.'s [XV] further innovations, including OFBCNN for multi-subject MI classification based on overlapping filter banks and spatial pattern extraction, are also further innovations. This important aspect of scalable BCI systems, fusion strategies in CNNs for cross-subject generalization, was highlighted by Roots et al. [XXIII]. Zhang et al. [XXXIII, XXXVI] have provided two separate models: deep CNNs and EEG Inception, which try to improve classification robustness by using deeper and wider architectures, respectively. Yang et al. [XXVII] also showed that a low-cost hybrid BCI

Pradeep Kr. Sharma et al.

based on two electrodes can be able to capture both SSVEP and blink signals for home automation, thus making BCIs even more possible for use in everyday applications.

Future directions should focus on processing explicitly in real time, generalization across users and sessions, explainable model decisions, and integration into a broader environment, which involves multimodal sensors like eye tracking, electromyography (EMG) for added context understanding. The potential of EEG-based BCIs is enormous, but solving both technical and human-centered design problems brings its challenges.

IV. Research Gap In EEG-Based BCI Systems

Despite the significant achievement in developing EEG-based Brain Computer Interface (BCI), one of the persistent and major research gaps to deploy BCI in a ubiquitous and practical manner is the absence of robust generalization across subjects in EEG classification models. However, most modern BCI systems provide impressive performance under subject-specific calibration, though they do poorly under unseen users. One of the biggest bottlenecks on the path toward BCI technologies that can be scaled from the controlled laboratory to real-world clinical and commercial applications has been a lack of cross-subject generalizability.

The problem with this generalization is inherently due to the nature of the EEG signal. EEG is also extremely nonstationary with significant variability from session to session, from task to task, and even more critically from subject to subject. Anatomical differences, electrode placement, mental state, fatigue, scalp impedance, as well as psychological or environmental conditions, introduce unpredictable patterns into EEG data. The results of these variations encourage a type of variability, referred to as inter-subject variability, in which EEG features learned from one subject do not generalize well to a different subject. However, this nullifies the power of ML and DL models, which overlearn the training data and fail to perform properly on unseen subjects.

Recently tested on many different models (including Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and hybrid approaches), that kind of performance is similar to the case in subject specificity, but has much less cross-subject accuracy. Similarly, Mattioli et al. (2022) and Luo et al. (2023) report that even with the use of modern DL and data augmentation techniques, models need fine-tuning of the individual user data for accuracy. Severe limitation in the usability of BCIs is brought by this need for long calibration or retraining, particularly for situations in which the system must operate dynamically, e.g., in neurorehabilitation, assistive communication, or consumer-grade applications such as gaming and smart home control.

The real-time BCI performance under the generalization constraints is not well explored. Almost all studies report 'offline' classification accuracy that demonstrates no fidelity to latency, computational efficiency nor error recovery from real-world usage. In some cases, an offline running system behaves well (well for its design, from its designers' perspective), whereas the same system cannot cope well (again, from the perspective of its designers) with the constraints of its online environment. This implies that generalization has to be evaluated in a real-time closed-loop context.

Additionally, another dimension of the generalization problem is that current deep learning models are not interpretable. On the occasion of misclassification, it is often

Pradeep Kr. Sharma et al.

unclear whether the failure is caused by inter-subject variability, data noise, or some other unaccounted features. It jeopardizes trust in the model and prevents it from being used in sensitive environments like neurotherapy and mental health assessment. Solving the generalization gap thus requires explainability to be embedded into model architectures in order for clinicians or users to understand how decisions are made.

A multi-prong strategy must be developed to bridge this gap. One thing to note here is that there is an urgent and immediate need for a consortium-level initiative to produce a comprehensive EEG dataset with annotations of multiple paradigms (MI, SSVEP, Attention), demographics, and real-world noise conditions. The second is to allow the research community to develop standard evaluation protocols, including leave-one-subject-out validation, cross-dataset, and real-time trials. Third is that the resulting models need to incorporate contextual information (e.g., eye tracking, muscle activity) that will allow disambiguation of EEG patterns across users. As the fourth, adaptive BCI systems need to be explored, which can learn from user feedback in real time and adapt their parameters rather than completely retraining. In a last bit, regulatory and ethical frameworks will have to be made to accommodate the changes induced by the nonexistent revalidation requirement in these models. In summary, the most prominent research gap in EEG-based BCI systems is the **challenge of cross-subject generalization**. This issue stands as a barrier to the scalability, usability, and clinical deployment of BCI systems across domains. Addressing it requires foundational innovations in model architecture, training strategies, dataset development, evaluation standards, and human-centered design. Only by systematically tackling this challenge can the promise of BCI technology be fully realized for inclusive, real-world applications.

Table 6: Research Gap in Cross-Subject Generalization of EEG-Based BCI Systems

Aspect	Current Limitation	Effect on BCI Systems	Proposed Research Direction
Inter-subject Variability	EEG signals vary significantly across individuals due to biological and cognitive differences	Reduced model performance on unseen users	Develop subject-invariant feature learning and normalization techniques
Model Dependence on Calibration	Most models require retraining or calibration for each new user	Increased time, reduced usability	Apply meta-learning, few-shot learning, and adaptive online fine-tuning
Small and Homogeneous Datasets	Available EEG datasets lack demographic and task diversity	Poor generalization and overfitting	Establish large, diverse, multi-paradigm public EEG datasets
Static Model Architectures	Models trained offline lack adaptability to real-time signal changes	Failures in real-world, online environments	Build dynamic models that update continuously with user feedback (online learning)
Lack of Cross-Dataset Validation	Evaluation is often confined to a single dataset	Inflated performance metrics, poor robustness	Standardize leave-one-subject-out and cross-dataset evaluation protocols

Pradeep Kr. Sharma et al.

Interpretability of Deep Models	Deep learning models operate as "black boxes"	Limited trust and clinical adoption	Integrate explainable AI (XAI) methods into EEG classifiers for transparent decision-making
Signal Quality and Noise Sensitivity	Low SNR due to artifacts and environmental noise	Misclassifications and unstable responses	Enhance preprocessing with ICA, DAE, adaptive filtering; consider multimodal data integration
Limited Use of Hybrid Contextual Inputs	Focus only on EEG without context (e.g., EMG, eye-tracking)	Insufficient signal disambiguation	Combine EEG with contextual sensors for multimodal cognitive state classification

Formal Multimodal Fusion Framework for Hybrid EEG-Based BCI Systems

A combination of EEG with other modalities, e.g., electromyography (EMG), eye tracking, electrooculography (EOG), inertial sensing, or contextual behavioral stimuli, may be a trend to enhance robustness and cross-subject generalization. Nevertheless, the multimodal combination needs a computational fuse framework since the modalities vary in sampling rate, noise settings, resolution of time, and feature representation. Let $X_{EEG}(t)$, $X_{EMG}(t)$, and $X_{ET}(t)$ denote synchronized EEG, EMG, and eye-tracking streams. A general multimodal classifier may be represented as

$$\hat{y} = F(X_{EEG}, X_{EMG}, X_{ET})$$

where $F(\cdot)$ is a fusion operator that can be implemented at different levels of the processing pipeline.

In **early fusion**, signals or features are aligned in time and concatenated before classification:

$$Z_{early} = [\phi_{EEG}(X_{EEG}) \parallel \phi_{EMG}(X_{EMG}) \parallel \phi_{ET}(X_{ET})]$$

where $\phi_{(\cdot)}$ denotes modality-specific feature extraction and \parallel denotes concatenation. The model is able to directly learn cross-modal interactions with early fusion, but it is especially demanding that modalities have to be strictly synchronized, normalized, and compatible in their dimensionality. Late fusion makes use of separate processing of each modality and combines the decision ultimately at the classifier level:

$$\hat{y} = G(f_{EEG}(X_{EEG}), f_{EMG}(X_{EMG}), f_{ET}(X_{ET}))$$

where $f_{(\cdot)}$ are unimodal predictors and $G(\cdot)$ is a decision-level fusion rule such as weighted voting, Bayesian aggregation, or confidence-based selection. Late fusion is less sensitive to missing or noise in modalities; however, it can be unaware of useful low-level interdependences. In hybrid fusion, the intermediate latent representations in either of the branches are optimized jointly:

$$H = \Psi(h_{EEG}, h_{EMG}, h_{ET}), \hat{y} = C(H)$$

where $h_{(\cdot)}$ are latent feature embeddings, Ψ is a learnable fusion block such as attention or gating, and C is the final classifier. In hybrid fusion, there is a consistency between representational power and flexibility.

All multimodal systems must have temporal alignment. When one sample at frequency f_1 is sampled, and the other at f_2 , then either resampling, interpolation, or window-based synchronization is needed so that overlapping decision regions are associated with the same

Pradeep Kr. Sharma et al.

cognitive event. In practical terms, multimodal windows should be aligned using a common time index t_k , and the synchronization error ϵ_{sync} should remain bounded:

$$\epsilon_{sync} = |t_k^{EEG} - t_k^{EMG}| \leq \delta$$

where δ is the maximum tolerable temporal mismatch. The absence of such alignment can only bring noise to the fusion and not enhance the robustness. In addition, the normalization of every modality should be done with modality-specific scaling, artifact, and confidence weight due to its vastly different dynamic ranges and noise components of EEG, EMG, and eye-tracking cues.

Thus, future studies working on hybrid BCI systems should not be their generic recommendations anymore, but rather a careful transition to concretely defined fusion architectures, syncing pipelines, confidence-conscious decision-generating functions, and understanding of robustness when modalities are missing or corrupted. An effective multimodal fusion model can make a significant contribution to the real-life BCI reliability, and such a model should work well with fatigue, motion artifact, and heterogeneous users.

V. Conclusions

Recently, Brain-Computer Interface (BCI) research has made great improvements in EEG-based research, in both machine learning and deep learning applications to decode SSVEP, attention, and motor imagery tasks. Reviewed literature demonstrates that traditional classifiers, including SVM, k-NN, Decision Tree, and Random Forest, are still useful with a comprehensive feature engineering, but deep learning methods, in the form of CNN, LSTM, EEGNet, EEG-Inception, OFBCNN, and CNN-based hybrids among others, exhibit more effective end-to-end representation learning using only raw or unprocessed EEG data. The advances have enhanced more accurate classification, manual feature reduction, and increased the use of BCI systems in assistive communication, neurorehabilitation, home automation, and cognitive monitoring.

Nevertheless, the review, too, exposes that high offline performance in itself cannot be enough to demonstrate the practical contract of BCI feasibility. The practical systems should meet clear limits regarding latency, throughput, computational complexity, memory usage, and energy production. Similarly, cross-study comparisons need to be handled with great care due to the fact that performance is a joint factor, with dataset properties, model structure, and assessment protocol. This is why in the current critical review, the classification of EEGs is considered more serious in terms of an analytic perspective, where the classification performance is considered as a factor of the dataset characteristics, structure of the model, and validation conditions, instead of just a single indicator.

Cross-subject generalization is the most outstanding unresolved issue. Majority of the EEG classifiers continue to be largely subject-dependent on their calibration and have poor performance on unknown users. Such a limitation directly impacts the usability, scalability, and clinical translation. Moreover, it has been suggested to use multimodal fusion as a solution; however, proper hybrid BCI design requires modalities to be formally defined and to have rules of synchronization and modalities normalization.

Pradeep Kr. Sharma et al.

Interpretability is another significant issue, as deep models are not usually easily explainable and thus become more challenging to rely on in a safety or clinical situation.

Altogether, the results of this review suggest that further EEG-based BCI studies have four priorities, namely: standardized and normalized comparative assessment, real-time system-aware model assessment, robust cross-subject learning, and explainable multimodal systems. The solution to these problems will be critical to reduce EEG-based BCI systems evolving from laboratory fancies to reliable neurotechnological instruments in practice.

To conclude, the future of EEG-based BCI research does not lie in the increased classification accuracy, but also in the possible tightness, readability, scalability, and deployability in the real-world environment.

VI. Recommendations

The following recommendations are proposed to improve the practical and scientific rigor of EEG-based BCI research:

1. **Prioritize cross-subject generalization:** Future research ought to center on subject-oriented representations learning, transfer learning, domain adaptation, meta-learning, and few-shot calibration in order to ensure models can count on utilizing unseen individuals with minimum re-training.
2. **Report real-time system constraints explicitly:** As well as accuracy-based metrics, future work should also report, where available, end-to-end latency, model size, inference time per window, memory footprint, model size, and energy consumption on realistic hardware platforms.
3. **Adopt standardized comparative evaluation:** The standardized comparative evaluation can be reported with the usage of balanced accuracy, macro-F1, and Cohen's kappa, particularly with uneven or multiclass data. Cross-studies should be restricted to those results available in similar conditions of datasets and validation.
4. **Develop formal multimodal fusion pipelines:** In case EEG is used with EMG, eye tracking, EGO, or other modalities, it must be trended to the signal, feature, or decision plane with precision in terms of synchronization, normalization, as well as confidence-handling mechanisms.
5. **Expand large-scale public datasets:** The community is to create multi-subject, multi-paradigm scale, and realistic noise EEG repositories with demographic diversity and standardized metadata that can be used to effectively benchmark.
6. **Promote explainable and trustworthy BCI models:** Clarifying AI models like saliency maps, attention visualization, relevance propagation, and feature attribution ought to be combined with EEG classes to enhance transparency, clinical trust, and ethical usage.
7. **Evaluate online and closed-loop performance:** Emphasis should be more on adaptive learning in real-time, integration of user feedback, and online testing instead of using the results of offline classification only.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

Pradeep Kr. Sharma et al.

References

- I. Amin, Syed Umar, Hamdi Altaheri, Ghulam Muhammad, Wadood Abdul, and Mansour Alsulaiman. "Attention-inception and long-short-term memory-based electroencephalography classification for motor imagery tasks in rehabilitation." *IEEE Transactions on Industrial Informatics* 18, no. 8 (2021): 5412-5421.
- II. Bagh, Niraj, and M. Ramasubba Reddy. "Hilbert transform-based event-related patterns for motor imagery brain computer interface." *Biomedical Signal Processing and Control* 62 (2020): 102020.
- III. Casarotto, Silvia, Matteo Fecchio, Mario Rosanova, Giuseppe Varone, Sasha D'Ambrosio, Simone Sarasso, Andrea Pigorini et al. "The rt-TEP tool: real-time visualization of TMS-Evoked Potentials to maximize cortical activation and minimize artifacts." *Journal of Neuroscience Methods* 370 (2022): 109486.
- IV. Cho, Jeong-Hyun, Ji-Hoon Jeong, and Seong-Whan Lee. "Neurograsp: Real-time eeg classification of high-level motor imagery tasks using a dual-stage deep learning framework." *IEEE Transactions on Cybernetics* 52, no. 12 (2021): 13279-13292.
- V. Cui, Jian, Liqiang Yuan, Zhaoxiang Wang, Ruilin Li, and Tianzi Jiang. "Towards best practice of interpreting deep learning models for EEG-based brain computer interfaces." *Frontiers in Computational Neuroscience* 17 (2023).
- VI. Deng, Xin, Boxian Zhang, Nian Yu, Ke Liu, and Kaiwei Sun. "Advanced TSGL-EEGNet for motor imagery EEG-based brain-computer interfaces." *IEEE access* 9 (2021): 25118-25130.
- VII. Du, Yipeng, and Jian Liu. "IENet: a robust convolutional neural network for EEG based brain- computer interfaces." *Journal of Neural Engineering* 19, no. 3 (2022): 036031.
- VIII. Duan, Lili, Jie Li, Hongfei Ji, Zilong Pang, Xuanci Zheng, Rongrong Lu, Maozhen Li, and Jie Zhuang. "Zero-shot learning for EEG classification in motor imagery-based BCI system." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28, no. 11 (2020): 2411-2419.
- IX. Gu, Xiaotong, Zehong Cao, Alireza Jolfaei, Peng Xu, Dongrui Wu, Tzyy-Ping Jung, and Chin- Teng Lin. "EEG-based brain-computer interfaces (BCIs): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications." *IEEE/ACM transactions on computational biology and bioinformatics* 18, no. 5 (2021): 1645-1666.
- X. Han, Yuexing, Bing Wang, Jie Luo, Long Li, and Xiaolong Li. "A classification method for EEG motor imagery signals based on parallel convolutional neural network." *Biomedical Signal Processing and Control* 71 (2022): 103190.
- XI. Hossain, Khondoker Murad, Md Ariful Islam, Shahera Hossain, Anton Nijholt, and Md Atiqur Rahman Ahad. "Status of deep learning for EEG-based brain-computer interface applications." *Frontiers in computational neuroscience* 16 (2023): 1006763.

- XII. Izzuddin, Tarmizi Ahmad, Norlaili Mat Safri, and Mohd Afzan Othman. "Mental imagery classification using one-dimensional convolutional neural network for target selection in single- channel BCI-controlled mobile robot." *Neural Computing and Applications* 33 (2021): 6233- 6246.
- XIII. Ko, Wonjun, Eunjin Jeon, Seungwoo Jeong, Jaeun Phyo, and Heung-II Suk. "A survey on deep learning-based short/zero-calibration approaches for EEG-based brain–computer interfaces." *Frontiers in Human Neuroscience* 15 (2021): 643386.
- XIV. Li, Minglun, Dianning He, Chen Li, and Shouliang Qi. "Brain–computer interface speller based on steady-state visual evoked potential: A review focusing on the stimulus paradigm and performance." *Brain sciences* 11, no. 4 (2021): 450.
- XV. Luo, Jing, Jundong Li, Qi Mao, Zhenghao Shi, Haiqin Liu, Xiaoyong Ren, and Xinhong Hei. "Overlapping filter bank convolutional neural network for multisubject multicategory motor imagery brain-computer interface." *BioData Mining* 16, no. 1 (2023): 19.
- XVI. Luo, Wenwei, Wanguang Yin, Quanying Liu, and Youzhi Qu. "A Hybrid Brain-Computer Interface Using Motor Imagery and SSVEP Based on Convolutional Neural Network." *Brain- Apparatus Communication: A Journal of Bacomics* just-accepted (2023): 1-15.
- XVII. Mahmood, Musa, Shinjae Kwon, Hojoong Kim, Yun-Soung Kim, Panote Siriaraya, Jeongmoon Choi, Boris Otkhmezuri et al. "Wireless Soft Scalp Electronics and Virtual Reality System for Motor Imagery-Based Brain–Machine Interfaces." *Advanced Science* 8, no. 19 (2021):2101129.
- XVIII. Mattioli, F., C. Porcaro, and G. Baldassarre. "A 1D CNN for high accuracy classification and transfer learning in motor imagery EEG-based brain-computer interface." *Journal of Neural Engineering* 18, no. 6 (2022): 066053.
- XIX. Meers, Rosie, Helen E. Nuttall, and Stefan Vogt. "Motor imagery alone drives corticospinal excitability during concurrent action observation and motor imagery." *Cortex* 126 (2020): 322- 333.
- XX. Meng, Lubin, Xue Jiang, and Dongrui Wu. "Adversarial robustness benchmark for EEG-based brain–computer interfaces." *Future Generation Computer Systems* 143 (2023): 231-247.
- XXI. Meng, Lubin, Xue Jiang, Jian Huang, Zhigang Zeng, Shan Yu, Tzyy-Ping Jung, Chin-Teng Lin, Ricardo Chavarriaga, and Dongrui Wu. "EEG-based brain-computer interfaces are vulnerable to backdoor attacks." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* (2023).
- XXII. Rashid, Mamunur, Bifta Sama Bari, Md Jahid Hasan, Mohd Azraai Mohd Razman, Rabi Muazu Musa, Ahmad Fakhri Ab Nasir, and Anwar PP Abdul Majeed. "The classification of motor imagery response: an accuracy enhancement through the ensemble of random subspace k- NN." *PeerJ Computer Science* 7 (2021): e374.
- XXIII. Roots, Karel, Yar Muhammad, and Naveed Muhammad. "Fusion convolutional neural network for cross-subject EEG motor imagery classification." *Computers* 9, no. 3 (2020): 72.

- XXIV. Roy, Arunabha M. "An efficient multi-scale CNN model with intrinsic feature integration for motor imagery EEG subject classification in brain-machine interfaces." *Biomedical Signal Processing and Control* 74 (2022): 103496.
- XXV. Sridhar, Saraswati, and Vidya Manian. "Eeg and deep learning based brain cognitive function classification." *Computers* 9, no. 4 (2020): 104.
- XXVI. Tiwari, Smita, Shivani Goel, and Arpit Bhardwaj. "MIDNN-a classification approach for the EEG based motor imagery tasks using deep neural network." *Applied Intelligence* (2022): 1-20.
- XXVII. Yang, Dalin, Trung-Hau Nguyen, and Wan-Young Chung. "A bipolar-channel hybrid brain- computer interface system for home automation control utilizing steady-state visually evoked potential and eye-blink signals." *Sensors* 20, no. 19 (2020): 5474.
- XXVIII. Yilmaz, Bahar Hatipoglu, Cagatay Murat Yilmaz, and Cemal Kose. "Diversity in a signal-to- image transformation approach for EEG-based motor imagery task classification." *Medical & Biological Engineering & Computing* 58 (2020): 443-459.
- XXIX. Yoxon, Emma, and Timothy N. Welsh. "Motor system activation during motor imagery is positively related to the magnitude of cortical plastic changes following motor imagery training." *Behavioural brain research* 390 (2020): 112685.
- XXX. Zhang, Ce, Young-Keun Kim, and Azim Eskandarian. "EEG-inception: an accurate and robust end-to-end neural network for EEG-based motor imagery classification." *Journal of Neural Engineering* 18, no. 4 (2021): 046014.
- XXXI. Zhang, Jing, Dong Liu, Weihai Chen, Zhongcai Pei, and Jianhua Wang. "Deep convolutional neural network for eeg-based motor decoding." *Micromachines* 13, no. 9 (2022): 1485.
- XXXII. Zhang, Kai, Guanghua Xu, Zezhen Han, Kaiquan Ma, Xiaowei Zheng, Longting Chen, Nan Duan, and Sicong Zhang. "Data augmentation for motor imagery signal classification based on a hybrid neural network." *Sensors* 20, no. 16 (2020): 4485.
- XXXIII. Zhang, Ruilong, Qun Zong, Liqian Dou, Xinyi Zhao, Yifan Tang, and Zhiyu Li. "Hybrid deep neural network using transfer learning for EEG motor imagery decoding." *Biomedical Signal Processing and Control* 63 (2021): 102144.
- XXXIV. Zhao, Xuefei, Dong Liu, Li Ma, Quan Liu, Kun Chen, Shane Xie, and Qingsong Ai. "Deep CNN model based on serial-parallel structure optimization for four-class motor imagery EEG classification." *Biomedical Signal Processing and Control* 72 (2022): 103338.
- XXXV. Zhu, Hao, Dylan Forenzo, and Bin He. "On the deep learning models for EEG-based brain- computer interface using motor imagery." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 30 (2022): 2283-2291.