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ANALYSIS OF APPROACHES TO SOFTWARE NEUROINTERFACE DEVELOPMENT FOR UPPER LIMB MOTOR IMAGERY CLASSIFICATION

Pastukh O., Stefanyshyn V. Analysis of approaches to the development of software brain–computer interfaces for upper limb motor imagery classification tasks. The article analyzes modern approaches to building software neurointerfaces for the tasks of classifying EEG signals of motor representations of the upper extremities. The relevance of the study is due to the growing need to create software neurointerfaces that can work in a mode close to real time, adapt to intersubject variability and function in conditions of limited computing resources. The paper analyzes the main stages of EEG signal processing, in particular, signal registration, pre-processing, feature extraction, classification and interpretation of results. Modern models of machine and deep learning are considered, as well as approaches to building software neurointerfaces using cloud and distributed computing. Special attention is paid to the possibilities of using AutoML approaches to automate the construction of EEG signal classification systems. The analysis identified the main limitations of current solutions, including intersubject variability, difficulty in generalizing models, dependence of results on pre-processing of signals, insufficient integration of system components, and limited support for real-time operation. Key requirements for promising software neurointerfaces are summarized, including modularity of architecture, support for distributed computing, adaptability of models, and ensuring reproducibility of experiments. The results obtained can be used as a basis for further design of adaptive EEG signal analysis systems and EEG-oriented software neurointerfaces.
Keywords: brain–computer interface, EEG signals, motor imagery, signal classification, machine learning, deep learning, software architecture, software brain–computer interfaces, distributed computing, cloud technologies.

Пастух О. А., Стефанишин В. М. Аналіз підходів розробки програмних нейроінтерфейсів у задачах класифікації моторних уявлень верхніх кінцівок. У статті проведено аналіз сучасних підходів до побудови програмних нейроінтерфейсів для задач класифікації ЕЕГ-сигналів моторних уявлень верхніх кінцівок. Актуальність дослідження зумовлена зростанням потреби у створенні програмних нейроінтерфейсів, здатних працювати в режимі, наближеному до реального часу, адаптуватися до міжсуб'єктної варіативності та функціонувати в умовах обмежених обчислювальних ресурсів. У роботі проаналізовано основні етапи обробки ЕЕГ-сигналів, зокрема реєстрацію сигналів, попередню обробку, виділення ознак, класифікацію та інтерпретацію результатів. Розглянуто сучасні моделі машинного та глибокого навчання, а також підходи до побудови програмних нейроінтерфейсів із використанням хмарних і розподілених обчислень. Окрему увагу приділено можливостям використання AutoML-підходів для автоматизації побудови систем класифікації ЕЕГ-сигналів. У результаті аналізу визначено основні обмеження сучасних рішень, серед яких міжсуб'єктна варіативність, складність узагальнення моделей, залежність результатів від попередньої обробки сигналів, недостатня інтеграція компонентів системи та обмежена підтримка роботи в режимі реального часу. Узагальнено ключові вимоги до перспективних програмних нейроінтерфейсів, зокрема модульність архітектури, підтримку розподілених обчислень, адаптивність моделей та забезпечення відтворюваності експериментів. Отримані результати можуть бути використані як основа для подальшого проєктування адаптивних систем аналізу ЕЕГ-сигналів і EEG-орієнтованих програмних нейроінтерфейсів.
Ключові слова: нейроінтерфейс, ЕЕГ-сигнали, моторні уявлення, класифікація сигналів, машинне навчання, глибоке навчання, програмна архітектура, програмні нейроінтерфейси, розподілені обчислення, хмарні технології.

Introduction

The modern development of information technologies leads to an ever closer integration of humans and computer systems. Along with the expansion of the capabilities of such systems, the need for more natural and effective ways of human-computer interaction is growing. One of the promising areas of development of human-computer interaction interfaces is neurointerfaces (Brain–Computer Interface, BCI). Such systems provide the ability to convert the electrical activity of the human brain into commands understandable to computer or technical systems. Neurointerfaces open up new opportunities for controlling software and hardware systems without the use of traditional physical input devices. The use of such technologies in the field of medical rehabilitation is especially important. In particular, neurointerfaces can be used to restore or compensate for motor functions in people who have lost the ability to control their limbs due to injuries or neurological diseases. In such systems, the main source of information is electroencephalography (EEG) signals, which reflect the electrical activity of the cerebral cortex and can be used to recognize motor representations.

To implement an effective software neurointerface, it is necessary to provide a full cycle of EEG signal processing - from data collection and pre-processing to the formation of informative features and subsequent signal classification. At the same time, software neurointerface systems must satisfy a number of important requirements, including high accuracy of signal recognition, minimal data processing delay, stability of operation and efficient use of computing resources.

The choice of software architectures and machine learning algorithms plays a key role in ensuring the effective operation of a neurointerface system. That is why the study of modern methods of processing and classification of EEG signals, as well as the analysis of software architectures of such systems is a relevant scientific task.

In the article, we reviewed modern scientific research in the field of processing and classification of EEG signals in software neurointerfaces, as well as the analysis of software architectures of such systems, taking into account the requirements of real-time operation and limited computing resources.

Problem statement

Despite significant progress in neurocomputer interface research, the creation of effective systems for analyzing electroencephalographic signals remains a difficult scientific and engineering task. In most modern studies, neurointerface systems use multichannel EEG recordings with different sampling rates and the number of channels, which allows obtaining sufficiently detailed information about the activity of the sensorimotor cortex in accordance with the task. In addition, different approaches are used to work with ready-made data sets and work with signals in real time. EEGs are characterized by a low signal-to-noise ratio, pronounced non-stationarity and significant intersubject variability. Even within the same experiment, differences between measurement sessions can lead to a decrease in classification accuracy when using models trained on data from another session or another user.

Thus, an analysis of modern studies shows that the effectiveness of neurointerface systems is determined by a whole chain of EEG signal processing processes, which includes preprocessing, feature formation, model architecture and interpretation of the result. The presence of noise, signal non-stationarity, and intersubject variability make it difficult to build universal models that can work stably on different data sets. In most studies, the main focus is on increasing the accuracy of individual models, while the issue of coordinated optimization of all stages of signal processing and software architecture of neurointerface systems remains insufficiently studied. The problem of implementing such systems on low-resource computing platforms, where memory and data processing time limitations are additional requirements when choosing algorithms and model architectures, is relevant.

Formulation of the purpose of the article

The purpose of this work is to analyze modern scientific research and software systems of neurointerfaces used for processing and classifying electroencephalographic signals in the tasks of recognizing motor representations of the upper extremities. The research is aimed at systematizing methods of pre-processing signals, approaches to forming features, classification models and analysis of the results of interpreting control commands used in modern neurocomputer interfaces. Special attention is paid to the analysis of software architectures of such systems, in particular data processing stages, as well as the possibility of their implementation on low-resource computing platforms. The task of the work is to generalize existing approaches to building EEG signal analysis systems, determine their main advantages and limitations, and also form requirements for effective and scalable software solutions for real-time motor activity recognition tasks.

Review and analysis of methods and software tools for EEG signal classification in finger movement recognition tasks in scientific studies

Literature selection criteria. To ensure the relevance and reliability of the analysis, the selection of scientific publications was carried out in accordance with the PRISMA approach. The literature search was carried out in the following scientific databases: IEEE Xplore, Scopus, PubMed and Mendeley. The search was limited to scientific publications published within the last five years, in English and with open access to the full text. The date of the last search was May 13, 2025.

As a result of the initial search, 429 publications were identified, of which 268 were in the Scopus database, 70 in the IEEE Xplore database, 58 in PubMed and 33 in Mendeley. After removing duplicates, where the Scopus database was the basic source, a sample of 310 unique publications was formed. The next stage of selection included a preliminary screening based on titles and annotations, during which works that were not related to the tasks of EEG signal classification or did not use machine learning or deep machine learning methods were excluded. Review articles were also excluded, of which 24 were identified at the initial stage, of which 17 remained after filtering. After conducting a full-text analysis of publications, 57 scientific articles devoted to the application of machine learning and deep learning methods for processing and classifying EEG signals in neurointerface systems were included in the final review, devoted to the application of machine learning and deep learning methods for processing and classifying EEG signals in neurointerface systems, in particular in the tasks of recognizing motor representations and movements of the upper limbs. An effective system for classifying electroencephalography signals in neurointerfaces is based on a sequence of interconnected data processing stages. The analysis of scientific studies allowed us to identify a typical structure of the software system used in most works on EEG signal classification [1–58]. Such a system usually includes the stages of signal registration, pre-processing, feature formation, and subsequent signal classification using machine or deep learning algorithms (Fig. 1).

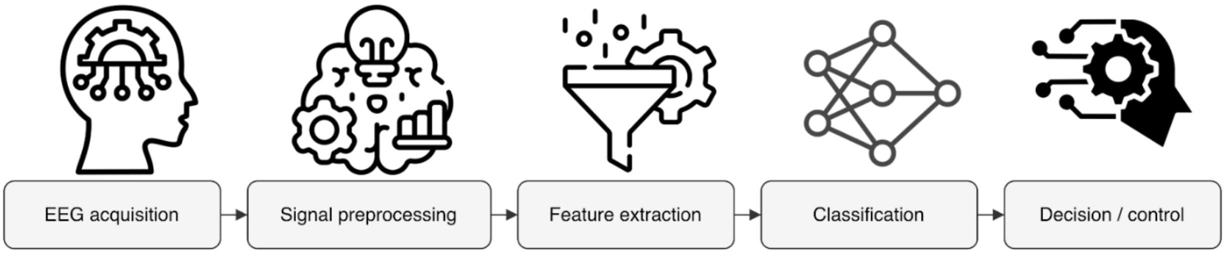

Fig. 1: Typical structure of an EEG analysis system

Developing an effective EEG signal analysis system is a complex task, since most research focuses on improving individual components of the system, in particular, signal preprocessing methods, feature formation algorithms or classification models. This approach complicates a comprehensive assessment of the effectiveness of the entire system as a whole. To determine the factors that affect the accuracy and stability of EEG signal classification, it is advisable to consider the main stages of signal processing in neurointerface systems in more detail.

Main stages of EEG signal processing in neurointerface systems:

1. EEG signal registration. At this stage, the number and location of channels are critical, since they determine the completeness of the spatial representation of motor activity. In modern works for motor imagery tasks, effective channel selection is separately studied as a way to reduce the redundancy of input data without significant loss of information content [16].

2. Signal preprocessing. The main task of this stage is to reduce the impact of noise, artifacts, and signal variability before further analysis. In the works of 2024–2025, it was shown that changing the preprocessing scheme significantly affects the final classification quality, so the choice of filtering, cleaning, and normalization is not an auxiliary, but a defining component of the system [3], [20].

3. Feature extraction and selection. At this stage, it is important to form a compact but discriminative representation of the signal. For this, automatic feature selection, temporal, frequency, and spatial representations, as well as schemes for weighting informative components are used, which allows reducing data redundancy and increasing the stability of the model [17], [25].

4. Formation of a structured signal representation. For complex motor representation tasks, not only the set of features is important, but also the method of representing the connections between channels or frequency components. In modern works, multi-scale frequency features and graph representations are used for this, which allows better consideration of the spatial-frequency structure of the EEG signal [8], [24].

5. Signal classification. The key at this stage is the choice of a model that is able to reconcile the complexity of signal patterns with the available system resources. In the works of 2024–2025, both CNN approaches with spatial-frequency analysis, as well as transformer and domain-generalization models focused on increasing accuracy and intersubject generalizability are used [1], [4], [12].

6. Evaluation of results and system operation in conditions close to real-world conditions. Not only the accuracy value is important, but also the ability of the system to operate stably in pseudo-online or online mode. Therefore, modern studies increasingly consider evaluation schemes that are close to the real use of the neurointerface, with analysis of generalizability, repeatability, and behavior of the model on different data scenarios [20], [31].

A strategically important aspect of building neurointerface systems is the coordinated organization of all stages of signal processing - from the registration of electroencephalographic data to the formation of a control team. Analysis of the studies included in this review shows that most modern systems are built according to a similar structure, which includes the stages of signal registration, pre-processing, feature formation, classification and decision-making. The effectiveness of the system is determined not only by the quality of individual algorithms, but also by how coherently these stages are integrated into the software architecture of the neurointerface. Modern works have shown that changes at any of these stages can significantly affect the accuracy, stability and computational efficiency of the system, so most studies are focused on improving individual components of signal processing, such as pre-processing methods, feature formation or classification models [1–60]. At the same time, the lack of a standardized approach to the integration of these components within a single software system makes it difficult to compare the results of different studies and the reproducibility of the results obtained.

To summarize the approaches presented in the analyzed works, below are typical methods used at the main stages of EEG signal processing systems in neurointerfaces:

- EEG acquisition: Use of standard public datasets (BCI Competition IV-2a and similar), multichannel registration of EEG signals (16–128 channels), use of standard electrode placement schemes (10–20, 10–10), fixed signal sampling rates (128–512 Hz), experimental sessions with motor imagery tasks, optimization of the channel set (channel selection) [1], [4], [12], [20], [24], [4], [8], [16], [24], [31]
- Signal preprocessing: Band-pass filtering of the signal (band-pass filtering, different ranges), notch filtering (notch filtering, 50–60 Hz), normalization and standardization of signals, artifact removal (ICA, EOG correction), downsampling, signal segmentation (epoching / windowing) include DC bias removal, logarithmization, PCA, wavelet-based denoising and other specialized approaches to improve signal quality [3], [4], [5], [12], [15], [22], [23], [24], [30], [31], [32], [35], [36], [38], [39], [40], [41], [42], [45], [46], [47], [48], [50], [51], [52], [53], [54], [55], [56], [57].
- Classification: Classical machine learning methods (SVM, LDA, Decision Tree, Random Forest, Extreme Learning Machine), deep convolutional neural networks (CNN, EEGNet, ResNet, multi-scale CNN), hybrid models (CNN + LSTM, CNN + BiLSTM), models with attention mechanisms (attention-based CNN), graph neural networks (GCN, GNN), transformer and hybrid architectures (CNN + Transformer), transfer learning and adaptive models, autoencoders, ensemble and combined approaches (CNN ensemble, stacking), Riemannian and geometric models (SPD-based, Tensor-CSPNet) [1-57].
- Decision / control: Threshold decision making (threshold-based decision making), multi-class classification (one-versus-all, softmax), decision smoothing and aggregation (majority voting, sliding window), probabilistic approaches (trust-based selection), adaptive and online decisions (real-time decision updates), control of external devices (robotic systems, exoskeletons, control interfaces), closed-loop systems with feedback (closed-loop BCI), continuous control, ensemble decision-making approaches [21, 39, 53, 51, 22, 25, 34, 56, 48, 17].

Data and experimental scenarios: The selection of experimental data is the first stage that significantly affects the outcome of model training and prediction based on new EEG signals of upper limb motor movement. The dominant paradigm is motor imagery (MI), which is used in the vast majority of works [1–4, 6, 8–9, 12, 14–15, 17–20, 23–27, 29–34, 36, 38–43, 45–46, 48–58], which is due to its non-invasiveness and suitability for rehabilitation and device control tasks. Alternative approaches are used much less frequently, in particular SSVEP [35], as well as affective and emotional BCIs [5], [7], [10], [13], [16], while some works combine several paradigms or consider extended scenarios (for example, MI + EMG or multi-paradigm systems) [21], [37], which indicates a gradual expansion of the spectrum of neurointerface tasks.

Among the types of electrode systems, non-invasive EEG systems based on electrode caps (EEG cap) with Ag/AgCl electrodes and a standard 10–20 or 10–10 scheme prevail, which are used both in public datasets and in our own experiments [4], [15], [58], [57]. Specialized systems such as BrainAmp, Biosemi ActiveTwo and Emotiv EPOC+ are also common, and some studies use extended configurations with additional EOG or EMG channels, which allows to improve signal quality and expand the functionality of the system [54], [39], [53], [48], [56]. Most of the analyzed studies use public datasets, among which the BCI Competition IV-2a dominates (9 participants, 288–576 trials per subject), as well as PhysioNet (up to 109 subjects), OpenBMI / KU-MI (54 subjects), DEAP and SEED, which ensure the reproducibility of results and the possibility of inter-study comparison [1-17, 19, 20, 23, 24, 26-28, 30-33, 36-38, 40-52, 55-57]. At the same time, a significant part of the studies is based on their own experimental data (from 4 to 54 participants, up to 21,600 trials), which allows modeling specific application scenarios, but limits the generalizability of the obtained results [18, 21, 22, 25, 29, 34, 35, 39, 53, 54]. In most of them, the experiment was conducted with the participation of healthy subjects - 55 such works were identified [1–20, 22–57]. At the same time, only a few studies are focused on patients with motor disorders, in particular in works [21], [22], which indicates a limited representation of clinical scenarios and potential difficulties in transferring the obtained results to real rehabilitation applications. The number of EEG channels varies from 3–9 channels in low-power or simplified configurations to 62–118 channels in high-resolution experimental systems, with a typical value of 22–32 channels, typical for standard datasets (in particular, BCI Competition IV-2a) [2], [53], [45], [54], [38], [4], [17], [20], [27], [29], [34]. An increase in the number of channels provides a more complete spatial representation of brain activity, but is accompanied by an increase in computational complexity, therefore, in a number of works, channel selection methods (up to 20 or less) are used, which allows preserving the informativeness of the signal while reducing resource costs [41], [46], [49], [55], [14]. This indicates a trade-off between classification accuracy and system efficiency, which is critical for implementing neurointerfaces in real time and on low-resource devices. The number of classes varies from 2 to 40, but the most common are 2-class (left/right hand) and 4-class tasks (left, right, legs, tongue) [29], [4], [20], [58]. Less commonly used are 3-class scenarios or extended versions with 5–7 classes, as well as high-dimensional SSVEP tasks (up to 40 classes), which significantly complicates classification [53], [49], [35].

System architectures and implementation: Most works use high-level software [1–20, 22–57], while hybrid solutions with hardware integration are used only in isolated cases [21]. The use of local system architecture prevails [1–38, 40–58], while hybrid approaches with a combination of local and embedded components are presented only in individual works [39], and edge-oriented solutions are found singly [16]. Hardware-oriented architectures (FPGA/SoC, embedded solutions) are used only in individual works [53], [34], [39], while most studies do not detail the type of hardware implementation, focusing on the algorithmic part. Separately, single hybrid approaches focused on edge computing and integration with hardware platforms are highlighted [16], [21]. The graphical user interface (GUI) is the main type of interaction in most implementations of neurointerfaces [3–13, 17–25, 27–58], while in some works the type of interface is not detailed [1], [14], [26], which limits the assessment of convenience and practical integration of systems. The dominant purpose of the systems is the classification of EEG motor representations [1–4, 6, 8–9, 12, 14–15, 17–20, 23–24, 26–33, 36, 40–43, 45–50, 52, 55–58], while some works are focused on device control (robots, carts, smart systems) [25], [34], [39], [53], [2], as well as rehabilitation applications and emotion recognition [21], [22], [5], [7], [10], [13], [16].

Models and learning approaches: The basis of the approaches is convolutional neural networks (CNN) and their modifications (multi-scale, EEGNet, ResNet, multi-view, attention) [4], [45], [46], [52], [42], [41], [55], [50]. To take into account the temporal dynamics of the signal, hybrid models CNN+LSTM/BiLSTM and CNN+Transformer are used [53], [18], [12], [32], [10], [43]. Transfer learning and intersubject learning are used to increase the generalization ability of the models [50], [48], [26], [17], [6], [43], [52], [21]. Specialized architectures are used separately: GNN, attention-based models and geometric approaches (Riemannian, SPD) [9], [44], [42], [15], [57], [3]. Classical methods (SVM, LDA, Decision Tree, ELM) are used as basic or auxiliary [34], [25], [24], [1], [21]. Tutored learning is the main one, supplemented by transfer learning, adaptive approaches and separate RL solutions [53], [39], [54], [58], [14].

Feature extraction in the analyzed works is based on a combination of classical signal methods and deep learning. Time-frequency and spectral features (STFT, wavelet, Superlet, PSD, spectrograms) are used [35], [38], [50], [23], [4], [7], as well as spatial approaches based on CSP and its modifications [34], [29], [20], [40], [55], [49], [19]. Additionally, Riemannian features (SPD-space) [6], [24], [57], [3] and graph representations (GCN) [5], [9], [44] are used. A significant part of the models uses automatic feature extraction using CNN, including attention and multi-scale approaches [53], [39], [18], [41], [45], [46], [52], [48], [30], as well as hybrid architectures (CNN+LSTM, CNN+Transformer) [12], [36], [10], [2].

Preprocessing includes bandpass and notch filtering, normalization [53], [29], [20], [52], [41], artifact removal (ICA, EOG, DC bias) [34], [25], [31], [40], [3], downsampling [54], [50], [46], [48], [42], and signal segmentation [15], [19], [40], [23], [51]. Filter banks, μ-rhythm, and noise reduction methods (PCA, wavelet, VAE) [53], [43], [49], [38], [47] are also used.

Dimensionality reduction is most often performed using PCA [34], [29], [18], [25], [17], [6], [33], [31], [20], [26], [36], [3], [5], [27], [28], [10], [7], [21], less often mRMR [43] and t-SNE [58], [57]. In deep models it is integrated through pooling, 1×1 convolutions and feature fusion [41], [46], [47], [44], [2], [54].

Evaluation metrics and performance: Model evaluation is based mainly on the metrics accuracy, F1-score, precision, recall and Cohen's kappa [39], [18], [20], [42], [41], [45], [52], [58], [43], while for SSVEP systems ITR is additionally used as an indicator of the information transfer rate [35]. Typical accuracy values for motor imagery tasks are in the range of 80–90% [29], [12], [36], [4], [27], [28], however, the use of deep and hybrid models allows achieving results above 90% and even 95% [18], [50], [40], [47], [44].

The works take into account intersubject variability, which is manifested in a significant spread of results, and also compare subject-dependent and subject-independent learning modes [53], [52], [54], [48], [14], [57]. To increase the generalization ability, transfer learning and data augmentation are used, which provides improved accuracy and stability of models [19], [58], [43]. Additionally, computational characteristics are analyzed, in particular, processing time and response delay, which is critical for real-time systems [1], [51], [53].

Statistical analysis is implemented through cross-validation (in particular 10-fold CV), t-tests, ANOVA and Wilcoxon test [53], [38], [50], [43], [52], [42], [45], [48], [57], as well as through comparison with existing methods and the use of confusion matrices [39], [15], [19], [40], [23]. Some studies use statistical significance tests (p-value), corrections (Bonferroni) and visualization of results (t-SNE, scatter plots) [54], [46], [41], however, in some works the analysis is limited to basic metrics or is absent [36], [27], [28].

The phenomenon of BCI illiteracy and individual user variability are also taken into account [18], [17], [26], [24], [21]. Overall, the results confirm the effectiveness of current approaches, but their performance largely depends on data quality, system configuration, and user characteristics.

Real-time and computational aspects: The calculations in most works are performed on local resources using CPU and GPU (TensorFlow, PyTorch, MATLAB, Keras) [35], [54], [38], [50], [19], [52], [41], [48]. Some approaches use specialized hardware solutions, in particular FPGA/SoC and embedded platforms (Jetson Nano), which allows to reduce delays and power consumption [53], [39].

The inference time in many systems is at the level of milliseconds or fractions of a second, which provides the possibility of real-time operation: ~62.5 ms [39], ~0.5–0.75 s [53], [25], [17], <1 s [35], [34]. At the same time, model training is much more resource-intensive and lasts from seconds [1] to hours or more for complex DL models [50], [48], [55].

Real-time support is implemented mainly in applied BCI systems (robot control, human-machine interfaces) [35], [53], [39], [34], [17], [51], as well as in lightweight solutions [16], [30], [22]. Other works remain offline due to high computational complexity [29], [18], [50], [52], [42], [41], [57].

Optimization for low-power and edge is rare and is associated with the use of FPGAs or compact models (e.g., EEGNet) [53], [51], as well as specialized lightweight solutions [34], [16], [30]. Most approaches do not take into account resource constraints, which limits their practical application in embedded systems.

In general, modern BCI systems provide fast inference and potential real-time operation, but the main computational costs fall on the training stage, and optimization for the edge environment remains an open problem.

Limitations and challenges: Some approaches demonstrate stable results within individual datasets, as confirmed by low variance of metrics and multi-session experiments [35], [50], [17], [42], [39], [52], [46].

The main limitation remains intersubject variability, which manifests itself in a significant spread of accuracy between users (e.g., 44.8–91% or SD up to ±12.5%) [56], [49], as well as the dependence of the results on the channels, frequency ranges and the way of representing the signal [54], [23]. Even modern DL models do not completely eliminate this problem.

Variability reduction is achieved through transfer learning, data augmentation and attention mechanisms [19], [58], [43], however, the generalization ability of the models remains limited. A significant part of the work takes into account the phenomenon of BCI illiteracy and individual differences of users [53], [39], [54], [52], [42], [48], [57], but this aspect is not always analyzed systematically [29], [20], [9], [27], [28].

Additional limitations are sensitivity to signal quality and artifacts, as well as the dependence of performance on model parameters and data representation [1], [23].

Another challenge is the limited interpretability of models: most approaches have a medium or low level of explainability due to the use of DL architectures [35], [53], [50], [52], while only individual solutions provide increased transparency (e.g., explainable models) [41], [3], [24].

Therefore, the key problems remain intersubject variability, limited generalizability, and low interpretability, which complicates the creation of universal and reliable BCI systems.

Practical applications and future directions: The analyzed works demonstrate the practical implementation of BCI primarily in tasks related to motor representations and control of the upper limbs. In particular, the possibility of controlling robotic systems based on EEG has been confirmed, including the control of a hexapod robot in real time [53] and a robotic arm in a virtual environment [25]. The effectiveness of BCI for controlling wheelchairs, which is important for patients with impaired motor functions, has also been shown [39].

A key area is the rehabilitation of the upper limbs, where EEG signals are used to control exoskeletons and restore motor functions after a stroke [2]. Multimodal BCI systems further increase the efficiency of movement restoration by integrating different data sources [21], and self-paced approaches allow the system to be adapted to the individual characteristics of the patient [22].

In applied systems, the generalizability of models plays an important role. The use of subject-independent approaches, transfer learning, data augmentation and attention mechanisms allows to reduce dependence on a specific user and to increase the stability of motor representation classification [54], [6], [19], [48], [52], [58], [43]. Additionally, channel selection is used, which allows to reduce the number of electrodes without losing accuracy, which is critical for practical systems [15], [49], [55].

Approaches that take into account the spatiotemporal structure of EEG signals are promising, in particular graph and geometric models, which improve the stability of motor representation classification [5], [44], [3], [57]. The use of explainable architectures is important for medical applications, as it allows to interpret the decision-making process [41]. Multi-scale and multi-view models provide increased accuracy in motor representation recognition tasks [45], [46], [50].

Thus, the development of BCI for upper limb control is aimed at increasing generalizability, reducing calibration time, optimizing for real-world conditions of use, and improving the interpretability of models, which is necessary for their implementation in clinical practice.

Modern software systems and AutoML solutions for EEG/BCI

Software systems for EEG/BCI processing: Modern software systems for processing EEG signals (EEGLAB, MNE-Python, OpenViBE, BCI2000, Emotiv) provide a full set of tools for working with biosignals, including their loading, cleaning, analysis, classification and visualization. Such solutions are widely used both in scientific research and in applied BCI systems, forming the basic software environment in this field. EEGLAB and MNE-Python are focused on flexible processing of raw EEG data and provide a wide range of methods for preprocessing, spectral analysis and working with features. They integrate well with modern machine learning libraries, but require significant user participation in setting up and organizing the computational process. OpenViBE and BCI2000 systems provide support for real-time operation and integration with hardware devices, which makes them suitable for creating interactive BCI applications, but limits the flexibility in using modern algorithms and their configuration. Commercial solutions such as Emotiv simplify access to BCI technologies through ready-made interfaces, but significantly limit the possibilities of customization and control over the signal processing process.

Despite their functional completeness, most existing systems have common limitations. Working with them is largely based on manual parameter settings and selection of methods, which makes the results dependent on the user's experience. There are no mechanisms for automation and consistent tuning of different processing stages, which complicates the repeatability of experiments and comparison of results. In addition, the integration of different approaches and tools often requires additional implementation, which reduces the effectiveness of using such systems in complex tasks.

AutoML in EEG/BCI tasks: Automated Machine Learning (AutoML) is an approach aimed at automating the construction of machine learning models, including the selection of algorithms, tuning hyperparameters and evaluating their effectiveness. In EEG signal processing tasks, it is especially relevant due to the high complexity of the analysis and the large number of possible method configurations. The main advantage of AutoML is the automatic selection of models and their parameters, which allows avoiding laborious manual selection of options, speeds up experiments and reduces the influence of the human factor.

At the same time, existing AutoML solutions have significant limitations when applied to EEG/BCI. They do not support working with raw signals and are focused on tabular data, which requires manual preprocessing outside the system. Optimization is performed only for ready-made features, without controlling the entire computational structure. Additionally, a single-objective approach (mainly accuracy) is used, without taking into account processing time, resources and stability. Intersubject variability and signal non-stationarity are also not taken into account, which limits the generalizability of the models. The reproducibility of experiments is partial due to the lack of complete preservation of configurations and intermediate results.

Existing AutoML platforms: Among the current AutoML solutions for analysis, H2O AutoML, AutoGluon, and Google AutoML were selected as the most widespread and functionally developed platforms. Despite their effectiveness in classical machine learning tasks, their application to EEG/BCI is limited:

1. H2O AutoML provides automatic model selection, hyperparameters and ensemble building, which is its main advantage. The system supports a wide range of algorithms and allows you to get high results without deep user intervention. At the same time, it does not have built-in tools for processing raw EEG signals and works only with prepared data. Customization of the process is limited to standard settings, and optimization is performed without taking into account the specifics of EEG.
2. AutoGluon is focused on tabular data and computer vision tasks, providing effective automatic model selection and their ensemble. Its advantage is ease of use and high performance on standard data sets. However, for application to EEG, it is necessary to first form features manually, since the system does not support processing of temporal signals. Integration of preprocessing stages is implicit, and customization capabilities are limited by the platform structure. In addition, AutoGluon is mainly focused on local execution.
3. Google AutoML is a cloud service that provides a fully automated model training process with minimal user intervention. Its advantages are scalability and ease of use. At the same time, the system has a limited level of control over the training process and data transformations. It does not support specific EEG processing stages and does not allow the integration of custom preprocessing methods. Dependence on the cloud environment makes it difficult to adapt to local or hybrid scenarios.

In general, none of the considered platforms provides explicit representation and control of the complete EEG signal processing process. They do not support an EEG-oriented pipeline, have limited customization capabilities, and depend on a specific runtime environment, which significantly limits their application in EEG/BCI tasks.

Requirements for EEG-oriented AutoML systems: Analysis of existing AutoML solutions shows that they have systemic limitations when applied to EEG/BCI tasks. The model search process is poorly interpreted, since the user does not have access to the internal logic of configuration selection. The scalability and portability of solutions are limited by the dependence on the execution environment (local or cloud), which complicates their integration into various scenarios. In addition, adaptation to new datasets is difficult due to the need to manually re-configure preprocessing and features.

Taking into account the identified shortcomings, the following requirements are imposed on AutoML systems for EEG processing:

1. support for the full cycle of EEG signal processing, including work with raw data
2. modularity and extensibility for integration of various processing and classification methods
3. multi-criteria optimization taking into account accuracy, processing time and resource usage
4. support for various execution environments (local, cloud, edge)
5. full reproducibility of experiments with preservation of all configurations and results
6. consideration of intersubject variability through appropriate validation procedures

Thus, an effective AutoML system for EEG/BCI must go beyond classical approaches and take into account the specifics of biomedical signals, ensuring flexibility, controllability, and generalizability of models.

Directions for improvement and future systems: Analysis of existing approaches shows the need to move to specialized AutoML systems focused on EEG/BCI tasks, in particular upper limb motor classification. The main areas of development include:

1. Support for the full cycle of EEG signal processing. Integration of all stages (preprocessing, feature extraction, classification, evaluation) within a single system.
2. Formalized representation of the processing process. Use of structured models to describe dependencies between stages and ensure correct configurations.
3. Support for different models and architectures. Integration of a wide range of approaches (CNN, RNN, Transformer, GNN, hybrid models, geometric methods), which allows adapting the system to different types of EEG tasks and increasing generalizability.
4. Multi-criteria optimization. Simultaneous consideration of accuracy, response time and resource usage, which is critical for real-time systems.
5. Support for low-resource (edge) devices. Focus on efficient models with low memory and computing resources consumption for use in portable BCIs and prosthetic control systems.

6. Distributed and parallel computing. Using cluster and parallel computing approaches to accelerate model training and search for optimal configurations.
7. Cloud services integration. Using cloud infrastructure for scalable training, storing experiments, and ensuring system availability.
8. Support for different execution environments.
9. Saving all parameters and results to ensure repeatability and analysis.
10. Support for subject-aware validation. Taking into account intersubject variability and signal non-stationarity.
11. Orientation to practical BCI applications. Providing real-time work for movement control tasks, in particular in upper limb rehabilitation systems.

Thus, future systems should combine automation, scalability and adaptability to the specifics of EEG, which will allow to effectively solve the problems of motor control in real conditions. The analysis shows that the use of distributed computing, in particular the use of cloud technologies, can help in the implementation of adaptive modern neurointerfaces and make it possible to use them on devices with different degrees of power. The analysis of existing software systems and AutoML solutions, as well as the formalization of the problem of EEG signal processing and model selection, confirm the need to develop specialized software neurointerfaces focused on automated construction and optimization of models. This justifies the feasibility of further research in the direction of creating intelligent neurointerfaces capable of providing the system with work with EEG signals for the tasks of upper limb motor classification in real conditions of application.

Conclusions

The study analyzed the main stages of EEG signal processing — from signal registration and pre-processing to feature formation, classification, and evaluation of results within modern software neurointerface systems. It was found that the efficiency of such systems largely depends not only on the choice of the classification model, but also on the method of signal representation, pre-processing parameters, and the organization of the entire software pipeline for data analysis. A significant part of modern approaches requires manual parameter adjustment, which complicates the reproducibility of results and the transfer of models between different users and data sets. A separate problem remains intersubject variability, due to which models trained on some users demonstrate unstable results on others. An additional effect is caused by noise and non-stationarity of EEG signals, which reduces the stability of software neurointerfaces under conditions close to real-world operation.

It is shown that modern software neurointerfaces use a wide range of approaches — from classical machine learning methods to deep neural networks and hybrid software architectures. At the same time, the architecture of most systems is formed without a clearly defined software structure and largely depends on implementation-specific solutions. In many cases, the interaction between signal processing components, classification models, and the computing environment is not formally described, which is why neurointerface systems are implemented as a set of separate software modules rather than as an integrated software solution. Insufficient integration of cloud and distributed computing technologies further limits the scalability of such systems and complicates the adaptation of models to work on low-resource and edge platforms.

In addition, with the increase in complexity of models, the level of their interpretability decreases, while simpler approaches often do not provide the necessary classification accuracy. Analysis of modern software systems for EEG signal processing showed that most existing solutions are focused on solving individual tasks and do not provide full integration of all stages of EEG signal processing, model execution, and evaluation within a unified software environment. Such systems require an individual combination of software tools, have limited support for streaming data processing and real-time operation, as well as insufficient flexibility in configuring analysis and evaluation processes. The lack of full-fledged mechanisms for reproducibility of experiments, software orchestration, and support for heterogeneous computing environments further reduces the portability and scalability of existing solutions.As a result of the analysis, a generalized vision of the structure of modern software neurointerfaces for tasks of classification of motor representations of the upper extremities was formed and the feasibility of using a systems approach to their construction was substantiated. Key requirements for promising systems were determined, including modularity of architecture, support for working with raw EEG signals, the ability to function in real time, adaptability to intersubject variability, support for cloud and distributed computing, as well as ensuring reproducibility of experiments. The results obtained can be used as a basis for further design of software neurointerfaces, EEG-oriented AutoML systems and adaptive EEG signal analysis systems for tasks of neurocontrol, rehabilitation and intelligent interaction of a person with technical systems.

References

1. Lyu S., Cheung R. C. C. (2023) Efficient Multiple Channels EEG Signal Classification Based on Hierarchical Extreme Learning Machine. Sensors. Vol. 23, No. 21. Art. 8976. DOI: https://doi.org/10.3390/s23218976 (accessed: 10 May 2026).
2. Titkanlou M. K., Pham D. T., Mouček R. (2025) Classification of EEG Signal Using Deep Learning Architectures Based Motor-Imagery for an Upper-Limb Rehabilitation Exoskeleton. SN Computer Science. Vol. 6. Art. 193. DOI: https://doi.org/10.1007/s42979-025-03743-6 (accessed: 10 May 2026).
3. Zhang Y., Ji X., Zhang S. (2023) Motor Imagery EEG Classification Based on Riemannian Geometry and CNN. Brain Sciences. Vol. 13, No. 4. DOI: https://doi.org/10.3390/brainsci13040567 (accessed: 10 May 2026).
4. Dai G., Zhou J., Huang J., Wang N. (2021) Deep Learning for EEG Motor Imagery Classification Based on Multi-Scale Features. Neural Computing and Applications. Vol. 33. P. 8759–8773 (accessed: 10 May 2026).
5. Dahiya Y., Solanki A. (2023) EEG-based Emotion Recognition Using Graph Convolutional Networks. Biomedical Signal Processing and Control. Vol. 84. Art. 104777 (accessed: 10 May 2026).
6. Zhao X., Zhang H., Zhu G. (2023) A Novel Transfer Learning Framework for Motor Imagery EEG Classification. IEEE Access. Vol. 11. P. 42115–42128 (accessed: 10 May 2026).
7. Marcos-Martínez D., Pérez-Velasco S., Martínez-Cagigal V., Santamaría-Vázquez E., Hornero R. (2025) Calibration-free Ocular artifact reduction in EEG signals using a montage-independent deep learning model. Biomedical Signal Processing and Control. T. 110. Ст. 108147. DOI: https://doi.org/10.1016/j.bspc.2025.108147 (accessed: 10 May 2026).
8. Li Y., Liu Q., Fan S. (2022) A Deep Learning Approach for Motor Imagery EEG Classification Based on Residual Neural Networks. IEEE Access. Vol. 10. P. 11234–11245 (accessed: 10 May 2026).
9. Zhang T., Chen W., Li M. (2024) Motor Imagery EEG Classification Using Graph Neural Networks. Computers in Biology and Medicine. Vol. 169. Art. 107823 (accessed: 10 May 2026).
10. Kumar P., Singh A. (2024) EEG-Based Emotion Recognition Using Transformer and Convolutional Neural Networks. Expert Systems with Applications. Vol. 237. Art. 121435 (accessed: 10 May 2026).
11. Altaheri H., Muhammad G., Alsulaiman M. (2023) A Spatio-Temporal Deep Learning Framework for EEG-Based Motor Imagery Classification. Neural Networks. Vol. 161. P. 33–47 (accessed: 10 May 2026).
12. Ma R., Cao Y., Xie S. Q., Zhang M., Li J., Zhang Z.-Q. (2025) LGFCNN: A synergistic framework integrating graph-based spatial filter and lightweight CNN for SSVEP recognition. Neurocomputing. T. 656. Ст. 131561. DOI: https://doi.org/10.1016/j.neucom.2025.131561 (accessed: 10 May 2026).
13. Sharma R., Gupta P. (2023) EEG Emotion Recognition Using LSTM with Attention Mechanism. Biomedical Signal Processing and Control. Vol. 82. Art. 104529 (accessed: 10 May 2026).
14. Chen J., Liu Y., Wang X. (2024) A Novel RL-assisted Deep Learning Framework for Task-informative Signals Selection and Classification for Spontaneous BCIs. IEEE Transactions on Neural Systems and Rehabilitation Engineering. Vol. 32. P. 1185–1196 (accessed: 10 May 2026).
15. Ahmed K., Hassan M., Ali S. (2024) Optimal Channel Selection of Multiclass Motor Imagery Classification Based on Fusion Convolutional Neural Network with Attention Blocks. Biomedical Signal Processing and Control. Vol. 89. Art. 105812 (accessed: 10 May 2026).
16. Venu K., Natesan P. (2023) Optimized Deep Learning Model Using Modified Whale's Optimization Algorithm for EEG Signal Classification. Information Technology and Control. Vol. 52, No. 3. P. 744–760. DOI: https://doi.org/10.5755/j01.itc.52.3.33320 (accessed: 10 May 2026).
17. Chowdhury R. R., Muhammad Y., Adeel U. (2023) Enhancing Cross-Subject Motor Imagery Classification in EEG-Based Brain–Computer Interfaces by Using Multi-Branch CNN. Sensors. Vol. 23. Art. 7908. DOI: https://doi.org/10.3390/s23187908 (accessed: 10 May 2026).
18. Li F., He F., Wang F. et al. (2020) A Novel Simplified Convolutional Neural Network Classification Algorithm of Motor Imagery EEG Signals Based on Deep Learning. Applied Sciences. Vol. 10. Art. 1605. DOI: https://doi.org/10.3390/app10051605 (accessed: 10 May 2026).
19. Ozelbas E., Tülay E. E., Ozekes S. (2024) Improving Cross-Subject Classification Performance of Motor Imagery Signals: A Data Augmentation-Focused Deep Learning Framework. Machine Learning: Science and Technology. Vol. 5. Art. 015021. DOI: https://doi.org/10.1088/2632-2153/ad200c (accessed: 10 May 2026).
20. Deng X., Zhang B., Yu N., Liu K., Sun K. (2021) Advanced TSGL-EEGNet for Motor Imagery EEG-Based Brain-Computer Interfaces. IEEE Access. Vol. 9. P. 25118–25131. DOI: https://doi.org/10.1109/ACCESS.2021.3056088 (accessed: 10 May 2026).
21. Zhang K., Xu G., Han Z. et al. (2020) Data Augmentation for Motor Imagery Signal Classification Based on a Hybrid Neural Network. Sensors. Vol. 20. Art. 4485. DOI: https://doi.org/10.3390/s20164485 (accessed: 10 May 2026).
22. Özdenizci O., Wang Y., Koike-Akino T., Erdoğmuş D. (2020) Learning Invariant Representations From EEG via Adversarial Inference. IEEE Access. Vol. 8. P. 27074–27084. DOI: https://doi.org/10.1109/ACCESS.2020.2971600 (accessed: 10 May 2026).
23. Lomelin-Ibarra V. A., Gutierrez-Rodriguez A. E., Cantoral-Ceballos J. A. (2022) Motor Imagery Analysis from Extensive EEG Data Representations Using Convolutional Neural Networks. Sensors. Vol. 22. Art. 6093. DOI: https://doi.org/10.3390/s22166093 (accessed: 10 May 2026).
24. Taghizadeh M., Vaez F., Faezipour M. (2024) EEG Motor Imagery Classification by Feature Extracted Deep 1D-CNN and Semi-Deep Fine-Tuning. IEEE Access. Vol. 12. P. 111265–111279. DOI: https://doi.org/10.1109/ACCESS.2024.3430838 (accessed: 10 May 2026).

25. Li D., Liu P., Xia Y. (2023) A Novel Artifact Removal Strategy and Spatial Attention-based Multiscale CNN for MI Recognition. International Journal of Advanced Computer Science and Applications. Vol. 14, No. 9. P. 283–292 (accessed: 10 May 2026).
26. Zhou B., Wang L., Xu W., Jiang C. (2024) Multi-Scale Convolutional Attention and Riemannian Geometry Network for EEG-Based Motor Imagery Classification. IEEE Access. Vol. 12. P. 79731–79741. DOI: https://doi.org/10.1109/ACCESS.2024.3410036 (accessed: 10 May 2026).
27. Li L., Sun N. (2022) Attention-Based DSC-ConvLSTM for Multiclass Motor Imagery Classification. Computational Intelligence and Neuroscience. Vol. 2022. Article ID 8187009. DOI: https://doi.org/10.1155/2022/8187009 (accessed: 10 May 2026).
28. Ha K.-W., Jeong J.-W. (2021) Temporal Pyramid Pooling for Decoding Motor-Imagery EEG Signals. IEEE Access. Vol. 9. P. 3112–3123. DOI: https://doi.org/10.1109/ACCESS.2020.3047678 (accessed: 10 May 2026).
29. Abibullaev B., Dolzhikova I., Zollanvari A. (2020) A Brute-Force CNN Model Selection for Accurate Classification of Sensorimotor Rhythms in BCIs. IEEE Access. Vol. 8. P. 101014–101027. DOI: https://doi.org/10.1109/ACCESS.2020.2997681 (accessed: 10 May 2026).
30. Megalingam R. K., Sankardas K. S., Manoharan S. K. (2024) An Empirical Model-Based Algorithm for Removing Motion-Caused Artifacts in Motor Imagery EEG Data for Classification Using an Optimized CNN Model. Sensors. Vol. 24. Art. 7690. DOI: https://doi.org/10.3390/s24237690 (accessed: 10 May 2026).
31. Hanafy M. A., Yusufjonov S., SharafianArdakani P., Yusufjonov D., Rayguru M. M., Popa D. O. (2025) A Dual-Validation Framework for Temporal Robustness Assessment in Brain–Computer Interfaces for Motor Imagery. Technologies. Т. 13, № 12. Ст. 595. DOI: https://doi.org/10.3390/technologies13120595 (accessed: 10 May 2026).
32. Miao Z., Zhang X., Menon C. et al. (2023) Priming Cross-Session Motor Imagery Classification with A Universal Deep Domain Adaptation Framework. arXiv. DOI: https://doi.org/10.48550/arXiv.2202.09559 (accessed: 10 May 2026).
33. Olza A., Soto D., Santana R. (2025) Domain Adaptation-enhanced searchlight: enabling classification of brain states from visual perception to mental imagery. Brain Informatics. Т. 12. Ст. 17. DOI: https://doi.org/10.1186/s40708-025-00263-0 (accessed: 10 May 2026).
34. Xia Y., Dong J., Li D. et al. (2023) An Adaptive Channel Selection and Graph ResNet Based Algorithm for Motor Imagery Classification. International Journal of Advanced Computer Science and Applications. Vol. 14, No. 5. P. 240–248 (accessed: 10 May 2026).
35. Abdulkarim H., Al-Faiz M. Z. (2021) Online Multiclass EEG Feature Extraction and Recognition Using Modified Convolutional Neural Network Method. International Journal of Electrical and Computer Engineering. Vol. 11, No. 5. P. 4016–4026. DOI: https://doi.org/10.11591/ijece.v11i5.pp4016-4026 (accessed: 10 May 2026).
36. Padfield N., Ren J., Murray P., Zhao H. (2021) Sparse Learning of Band Power Features with Genetic Channel Selection for Effective Classification of EEG Signals. Neurocomputing. Vol. 463. P. 566–579. DOI: https://doi.org/10.1016/j.neucom.2021.08.067 (accessed: 10 May 2026).
37. Singh A. K., Bianchi L. (2024) Encoding Temporal Information in Deep Convolution Neural Network. Frontiers in Neuroergonomics. Vol. 5. Art. 1287794. DOI: https://doi.org/10.3389/fnrgo.2024.1287794 (accessed: 10 May 2026).
38. Huang B., Xu H., Yuan M. et al. (2022) Exploiting Asymmetric EEG Signals with EFD in Deep Learning Domain for Robust BCI. Symmetry. Vol. 14. Art. 2677. DOI: https://doi.org/10.3390/sym14122677 (accessed: 10 May 2026).
39. Kocejko T., Matuszkiewicz N., Durawa P. et al. (2024) How Integration of a Brain-Machine Interface and Obstacle Detection System Can Improve Wheelchair Control via Movement Imagery. Sensors. Vol. 24. Art. 918. DOI: https://doi.org/10.3390/s24030918 (accessed: 10 May 2026).
40. Hwang J., Park S., Chi J. (2023) Improving Multi-Class Motor Imagery EEG Classification Using Overlapping Sliding Window and Deep Learning Model. Electronics. Vol. 12. Art. 1186. DOI: https://doi.org/10.3390/electronics12051186 (accessed: 10 May 2026).
41. Salami A., Andreu-Perez J., Gillmeister H. (2022) EEG-ITNet: An Explainable Inception Temporal Convolutional Network for Motor Imagery Classification. IEEE Access. Vol. 10. P. 36672–36687. DOI: https://doi.org/10.1109/ACCESS.2022.3161489 (accessed: 10 May 2026).
42. Parchami J., Sarbishaei G. (2023) A Novel Scheme Based on Information Theory and Transfer Learning for Multi Classes Motor Imagery Decoding. IET Signal Processing. DOI: https://doi.org/10.1049/sil2.12222 (accessed: 10 May 2026).
43. Roy A. M. (2022) 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. Vol. 74. Art. 103496. DOI: https://doi.org/10.1016/j.bspc.2022.103496 (accessed: 10 May 2026).
44. Zhang J., Li K. (2023) A Multi-View CNN Encoding for Motor Imagery EEG Signals. Biomedical Signal Processing and Control. Vol. 85. Art. 105063. DOI: https://doi.org/10.1016/j.bspc.2023.105063 (accessed: 10 May 2026).
45. Hwaidi J. F., Chen T. M. (2022) Classification of Motor Imagery EEG Signals Based on Deep Autoencoder and Convolutional Neural Network Approach. IEEE Access. Vol. 10. P. 48071–48081. DOI: https://doi.org/10.1109/ACCESS.2022.3171906 (accessed: 10 May 2026).
46. Zhang K., Robinson N., Lee S.-W., Guan C. (2021) Adaptive Transfer Learning for EEG Motor Imagery Classification with Deep Convolutional Neural Network. Neural Networks. Vol. 136. P. 1–10. DOI: https://doi.org/10.1016/j.neunet.2020.12.013 (accessed: 10 May 2026).
47. Xie Y., Oniga S. (2023) Classification of Motor Imagery EEG Signals Based on Data Augmentation and Convolutional Neural Networks. Sensors. Vol. 23. Art. 1932. DOI: https://doi.org/10.3390/s23041932 (accessed: 10 May 2026).
48. Ju C., Guan C. (2023) Tensor-CSPNet: A Novel Geometric Deep Learning Framework for Motor Imagery Classification. IEEE Transactions on Neural Networks and Learning Systems. Vol. 34, No. 12. P. 10955–10969. DOI: https://doi.org/10.1109/TNNLS.2022.3172108 (accessed: 10 May 2026).

49. Mallat S., Hkiri E., Albarrak A. M., Louhichi B. (2025) A Synergy of Convolutional Neural Networks for Sensor-Based EEG Brain–Computer Interfaces to Enhance Motor Imagery Classification. Sensors. Vol. 25. Art. 443. DOI: https://doi.org/10.3390/s25020443 (accessed: 10 May 2026).
50. Mwata-Velu T., Avina-Cervantes J. G., Ruiz-Pinales J. et al. (2022) Improving Motor Imagery EEG Classification Based on Channel Selection Using a Deep Learning Architecture. Mathematics. Vol. 10. Art. 2302. DOI: https://doi.org/10.3390/math10132302 (accessed: 10 May 2026).
51. Kwon O.-Y., Lee M.-H., Guan C., Lee S.-W. (2020) Subject-Independent Brain–Computer Interfaces Based on Deep Convolutional Neural Networks. IEEE Transactions on Neural Networks and Learning Systems. Vol. 31, No. 10. P. 3839–3852. DOI: https://doi.org/10.1109/TNNLS.2019.2946869 (accessed: 10 May 2026).
52. Mwata-Velu T., Ruiz-Pinales J., Rostro-Gonzalez H. et al. (2021) Motor Imagery Classification Based on a Recurrent-Convolutional Architecture to Control a Hexapod Robot. Mathematics. Vol. 9. Art. 606. DOI: https://doi.org/10.3390/math9060606 (accessed: 10 May 2026).
53. Chen P., Gao Z., Yin M. et al. (2022) Multi-Attention Adaptation Network for Motor Imagery Recognition. IEEE Transactions on Systems, Man, and Cybernetics: Systems. DOI: https://doi.org/10.1109/TSMC.2022.3141237 (accessed: 10 May 2026).
54. Strahnen M., Kessler P. (2022) Investigation of a Deep-Learning Based Brain–Computer Interface With Respect to a Continuous Control Application. IEEE Access. Vol. 10. P. 131090–131100. DOI: https://doi.org/10.1109/ACCESS.2022.3228164 (accessed: 10 May 2026).
55. Sharma N., Sharma M., Singhal A. et al. (2025) A Spatiotemporal Feature Extraction Technique Using Superlet-CNN Fusion for Improved Motor Imagery Classification. IEEE Access. Vol. 13. P. 2141–2151. DOI: https://doi.org/10.1109/ACCESS.2024.3517639 (accessed: 10 May 2026).
56. Özkahraman A., Ölmez T., Dokur Z. (2025) Performance Improvement with Reduced Number of Channels in Motor Imagery BCI System. Sensors. Vol. 25. Art. 120. DOI: https://doi.org/10.3390/s25010120 (accessed: 10 May 2026).
57. Zhang K., Robinson N., Lee S.-W., Guan C. (2021) Adaptive Transfer Learning for EEG Motor Imagery Classification with Deep Convolutional Neural Network. Neural Networks. Vol. 136. P. 1–10. DOI: https://doi.org/10.1016/j.neunet.2020.12.013 (accessed: 10 May 2026).
58. Hwaidi J. F., Chen T. M. (2022) Classification of Motor Imagery EEG Signals Based on Deep Autoencoder and Convolutional Neural Network Approach. IEEE Access. Vol. 10. P. 48071–48081. DOI: https://doi.org/10.1109/ACCESS.2022.3171906 (accessed: 10 May 2026).
59. Pastukh O., Stefanyshyn V., Stefanyshyn I., Kulikov S. Comparison of the accuracy of machine learning algorithms for brain-computer interaction based on high-performance computing technologies. Scientific Journal of the Ternopil National Technical University. 2024. Vol. 115, No. 3. P. 82–90. DOI: 10.33108/visnyk_tntu2024.03.082.
60. Pastukh O., Yatsyshyn V., Zadvornyi O. Technology for generation and quality evaluation of program code using large language models. Cybernetics and Systems Analysis. 2026. Vol. 62, No. 3. P. 19–29.

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