Review of EEG signal classification approaches in finger movement recognition

Igor Boyko[†], Oleh Pastukh[†], Ivan Stefanyshyn[*,†] and Oleh Lyashuk[†]

Ternopil Ivan Puluj National Technical University, Rus'ka Street 56, 46025 Ternopil, Ukraine

Abstract

This article reviews and analyzes methods and software tools for electroencephalographic (EEG) signal classification in finger movement recognition tasks. A systematic review of recent studies and Automated Machine Learning (AutoML) solutions in brain-computer interfaces (BCI) was conducted. Attention is paid to EEG signal processing pipelines, algorithm evaluation, and software implementation. Typical pipeline stages are summarized, and key factors affecting an algorithm's effectiveness are identified. The review found an overreliance on accuracy as a metric and limited evaluation criteria, making fair comparison difficult. Popular AutoML platforms fail to reflect EEG/BCI specifics. The article justifies using graph-based pipeline representation and multi-criteria optimization with flexible metric weighting. It formulates requirements for new software able to provide reliable, reproducible, and efficient EEG-based finger movement recognition.

Keywords

Brain-computer interface, EEG signals, finger movement, classification, AutoML, multi-criteria optimization.

1. Introduction

Recognizing the motor activity of fingers of the upper limbs from EEG signals is one of the most challenging yet promising directions in the development of brain-computer interfaces. EEG allows non-invasive recording of brain activity related to movement intentions, but such signals are characterized by a high level of noise, non-stationarity, and significant differences between subjects. This makes it difficult to a build universal algorithm capable of accurately and consistently recognizing fine movements of the hands and fingers. Achieving acceptable accuracy requires a careful multi-stage processing pipeline: from filtering and artifact removal to forming informative features and classifying the signals. Each stage of this pipeline significantly influences the final result, so the system's effectiveness is determined not so much by individual algorithms as by the coordinated combination of all processing components.

At present, scientific studies present a wide range of approaches to EEG signal classification – from classical statistical methods to modern deep neural networks and ensemble algorithms. Numerous studies focus on motor imagery tasks and demonstrate gradual increases in classification accuracy thanks to improved algorithms and their combination. However, the open question remains: which specific combinations of preprocessing methods, feature extraction techniques, and classifiers are the most effective for recognizing movements of individual fingers. The lack of standard pipelines for building such systems makes it hard to compare different solutions and slows progress in the field. Thus, there is a need for a systematic review of current methods and software tools to summarize achievements, identify existing problems, and outline promising development paths.

[*] *AIT&AIS'2025: International Scientific Workshop on Applied Information Technologies and Artificial Intelligence Systems, December 18–19 2025, Chernivtsi, Ukraine*

[1*] Corresponding author.

[†] These authors contributed equally.

boyko.i.v.theory@gmail.com (I. Boyko); ol_pas@tntu.edu.ua (O. Pastukh); ivan_stefanyshyn0707@tntu.edu.ua (I. Stefanyshyn); oleglashuk@ukr.net (O. Lyashuk)

0000-0003-2787-1845 (I. Boyko); 0000-0003-4881-8568 (O. Pastukh); 0009-0008-6930-528X (I. Stefanyshyn); 0000-0002-0080-7053 (O. Lyashuk)

In this study, we present the results of a review and analysis of EEG-signal classification methods for finger movements, as well as the software tools for implementing such systems. Recent scientific works from the last few years describing the construction of classification pipelines for motor imagery are examined, and modern AutoML platforms that can be applied in BCI are analyzed. Based on this analysis, the main trends and challenges in the field are determined, and requirements are formulated for a new software system capable of overcoming the identified limitations. In the following sections, we describe in detail the typical structure of an EEG classification pipeline, provide a comparison of popular methods and algorithms, consider the specifics of performance evaluation and technical implementation, and discuss the shortcomings of existing AutoML solutions in the BCI context. This creates a complete picture of the state of the problem and provides a foundation for developing new approaches to automating the construction of effective EEG-based finger movement recognition systems.

2. Problem Statement

Despite significant progress in EEG-based BCI research, the development of reliable systems for recognizing finger motor activity remains limited by the lack of standardized and integrated approaches to constructing classification pipelines. Existing studies typically focus on improving isolated algorithms or preprocessing techniques, without considering the interaction and joint optimization of all pipeline stages. This fragmented approach leads to inconsistent evaluation results, reduced reproducibility, and limited applicability in real-time or large-scale environments.

Furthermore, modern AutoML systems are not fully adapted to the specific requirements of EEG/BCI data processing. They often lack explicit representation of domain-specific stages, support only single-objective optimization, and do not provide flexible control over metric weighting or resource constraints. As a result, researchers face difficulties in identifying optimal software component configurations that balance accuracy, robustness, and computational efficiency – a gap that this study aims to address.

3. Formulation of the Purpose of the Article

The purpose of this article is to analyze modern scientific research and existing software systems for classifying EEG signals in finger motor activity recognition tasks. The study aims to identify architectural and methodological limitations in current approaches and determine the key directions for improving the efficiency, robustness, and scalability of such systems. Special attention is paid to the analysis of AutoML solutions and classification pipelines used in BCI systems. The objective is to generalize typical structures of data processing pipelines, highlight shortcomings in current model evaluation practices, and formulate requirements for the development of an improved, flexible, and resource-efficient software framework for EEG signal classification.

4. 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 review focused on full-text journal articles and conference proceedings published between January 1, 2020, and May 13, 2025. The selection was strictly limited to English-language, open-access studies addressing EEG-based motor imagery classification using machine learning methods. The selection process involved a systematic multi-stage screening, starting with the removal of duplicates from the initial pool of 172 records. This was followed by a preliminary screening based on titles and abstracts, and subsequently, a full-text assessment against the eligibility criteria. During this process, records were excluded if they were abstracts, posters, book chapters, review articles, or theses, or if they failed to apply specific machine learning algorithms. Additionally, studies published by authors affiliated with scientific institutions of the Russian Federation were omitted. Ultimately, 69 publications were selected for the final analysis.

Typical EEG Processing Pipeline. An effective EEG-signal classification system is based on a sequence of coordinated data processing stages. Analysis of studies allowed us to highlight a typical pipeline used in the majority of studies (see Figure 1: Structure of a typical EEG signal classification pipeline) [1–69].

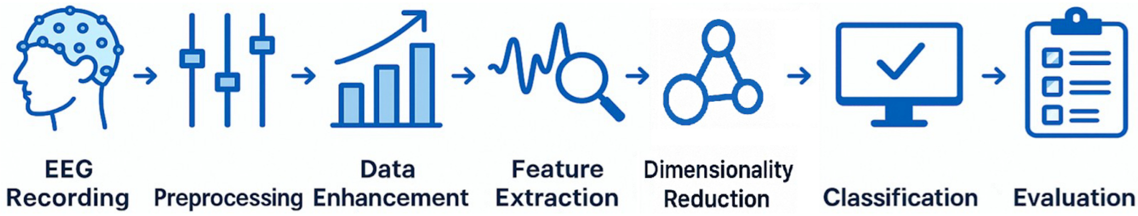

Figure 1: Structure of a typical EEG signal classification pipeline.

Building an effective EEG classification system is difficult because researchers often study each stage – preprocessing, feature extraction, and classification – separately. To understand what causes performance issues and how to improve the results, we will now look at each step of a typical EEG processing pipeline in more detail.

Here is an example of a numbered list:

1. Data collection. Recording multi-channel EEG signals using a standardized scheme with focus on motor cortex areas; for example, the "10–20" placement system [70].
2. Preprocessing. Filtering out noise, removing artifacts, and basic normalization of the signal to improve data quality.
3. Dataset formation. Splitting the continuous signal into short segments and balancing the classes by selecting an equal number of examples for each class; if needed, using artificial data augmentation to increase the algorithm's robustness to signal variability.
4. Feature extraction. Computing informative characteristics of the signal based on frequency, temporal-spatial, statistical, and other analysis methods. Often, dimensionality reduction is applied at this stage to reduce computational cost and lower the risk of algorithm overfitting.
5. Classification. Training the chosen machine learning algorithm on the extracted features to distinguish movement states. Both classical classifiers and modern ensemble methods and neural networks are used.
6. Results evaluation. Measuring the algorithm's quality by one or more metrics on test data or via cross-validation. This allows comparing alternative approaches and selecting the optimal algorithm configuration.

A strategically important aspect is the coordinated integration of all components within a single conveyor: how well the methods at all stages are chosen and assembled determines the balance between the system's accuracy, speed, and robustness. Most researchers design such pipelines empirically, guided by intuition or the popularity of approaches, which often leads to inconsistencies and lost efficiency. This underlines the need for more formalized approaches to designing classification pipelines that ensure reproducibility and optimal solutions.

To summarize the technological landscape analyzed in this study, the list below maps the most frequently used algorithms to their respective stages in the typical EEG signal classification pipeline:

1. Preprocessing: Common Spatial Patterns, Bandpass Filtering, Notch Filtering.
2. Data enhancement: Artifact Handling and Generation, Artifact Subspace Reconstruction.
3. Feature extraction: Independent Component Analysis, Statistical features.

4. Dimensionality reduction: Principal Component Analysis.
5. Classification: Support Vector Machine, Convolutional Neural Network.
6. Evaluation metrics: Accuracy, F1-score, AUC-ROC, Kappa.

Data and Experimental Scenarios. Data quality and structure significantly affect classification results, so the characteristics of datasets used in the reviewed works were analyzed. In the 69 studies included in the review, the vast majority of experiments were conducted with healthy volunteers 68 studies, whereas only 3 studies [10, 57, 64] focused on patients with neurological disorders. This shows that the problem of classifying finger movements has been studied mainly on healthy subjects and needs more attention for pathological conditions. Most tasks were binary two-class scenarios were used in 62 works [1–23, 25, 27–31, 33–43, 46, 48, 50–52, 54–55, 57, 58, 61–68]. Multi-class setups are much rarer: for example, experiments with 4 classes of movements are described in 21 studies [1, 3, 4, 7, 11, 17, 19, 22–24, 26, 28, 41, 47, 49, 51, 53, 56, 59, 61, 69], and classification of 3, 5, or more classes appear only in isolated cases [20, 32, 45]. This is because, as the number of classes increases, it becomes much more difficult to ensure reliable algorithm performance. Another limitation is the use of private datasets: in many works, the data are not publicly available, or the conditions of data collection are insufficiently described, which reduces the reproducibility of results. Thus, there is a deficit of unified open datasets in this field, especially for fine finger movements, as well as a lack of standards for documenting experiments.

Classification Algorithms and Their Effectiveness. There is a wide variety of algorithms applied for classifying motor activity from EEG, but we can single out the most common approaches and estimate their typical accuracy ranges. Researchers most often use classical machine learning algorithms. For example, the Support Vector Machine (SVM) method was used in 55 studies [1, 2, 4–6, 8, 9, 11–17, 19–21, 23–25, 28–32, 34, 37, 39–43, 45, 46, 50, 52–54, 56–61, 64–69], and Linear Discriminant Analysis (LDA) in 35 studies [2, 4–6, 8, 12, 13, 16, 17, 19, 20, 22, 25–28, 30, 32, 33, 35, 38, 40, 43, 46–48, 54, 59–63, 66–67]. The typical classification accuracy for SVM was around 70–80%, while for LDA it was 75–85%. Similar results were demonstrated by the k-Nearest Neighbors (k-NN) method [5, 6, 8, 9, 11, 12, 19, 23, 28, 31, 32, 36, 37, 40, 45, 48, 50, 58–60, 66, 67] and logistic regression [6, 7, 11, 19, 23, 28, 31, 40, 48, 59]. Decision trees provided somewhat lower but still stable accuracy on the order of 65–75% [5, 6, 8, 9, 11, 19, 21, 23, 28, 32, 40, 48, 59]. The highest average figures in the reviewed studies were achieved with ensemble methods, which had accuracies in the range of 85–95% [9, 10, 12, 14, 19, 23, 28, 30, 31, 59]. Neural networks were used less often for example, a multi-layer perceptron (MLP) appears in only 6 studies [6, 13, 19, 23, 28, 4d6], mainly in cases of large data volumes or more complex task setups. Some modern studies have introduced deep convolutional or recurrent neural networks, as well as transformer algorithms, to improve classification accuracy. In particular, specialized architectures such as TSGL-EEGNet have been proposed for recognizing movements in patients with spinal cord injuries [69]. However, neural network approaches require large training datasets and significant computational resources, so they are not always better than classical methods on small datasets. At the same time, methods for improving the effectiveness of classical algorithms are being actively researched – in particular, optimal selection of channels and features. For example, in the work by Kardam et al. [2], an evolutionary algorithm for channel selection and wavelet scattering was proposed to enhance motor imagery classification. Overall, the review showed that traditional approaches such as SVM, LDA, etc., still dominate due to their balanced accuracy and interpretability of results.

Evaluation Strategies and Metrics. For objective comparison of algorithms, validation methods, and the choice of quality metrics are very important. The analysis of publications shows that evaluation practices vary greatly. The most common approach is cross-validation: specifically, 5-fold cross-validation was used in 20 studies [5, 8, 12, 13, 16, 18, 20, 23–25, 32, 34, 43, 46, 47, 49, 52, 54, 59, 69], and 10-fold in 14 studies [10, 14, 26, 27, 40–42, 45, 51, 55, 58, 64, 66, 67]. However, 27 studies did not specify the validation method at all [1–4, 6-7, 9, 11, 17, 21, 22, 30, 33, 36–39, 44, 50, 53, 56, 57, 60–63, 65], which makes it difficult to interpret the results and compare between works.

Regarding metrics, the vast majority of authors evaluate algorithms by accuracy – this basic metric was used in 66 studies [1–18, 21-37, 39–69]. Much less often, additional values are reported: F1-score [2, 11, 13, 16, 17, 21, 28, 32, 37, 45, 46, 64] and Recall [2, 9, 11, 12, 16, 28, 30, 45, 48, 59, 64] in 12 and 11 cases each, Precision in 6 studies [2, 9, 11, 16, 28, 64], and Cohen's kappa in 6 studies [2, 4, 14, 22, 28, 45]. Specificity and the area under the ROC curve (AUC) appear only 5 times each [13, 28, 45, 46, 48]. Very rarely are criteria such as BCI information transfer rate, system response time, balanced accuracy, Fisher's criterion, or g-mean mentioned [2, 8, 13, 17, 27, 38, 55]. Thus, quality evaluation metrics are mostly limited to a single dimension, whereas aspects like algorithm robustness, speed, and other practical indicators are often ignored. The prevailing format is a direct comparison of average accuracies of several approaches on one dataset; multi-criteria or statistically grounded comparisons are almost never used. This confirms that evaluation practice is not yet mature: researchers tend to rely on simple metrics that do not always reflect an algorithm's suitability for real-world application. One direction for progress in this area is the call for mandatory reporting of result variability, the use of unified cross-validation schemes, and the inclusion of multiple types of metrics. Only under such conditions is it possible to make objective and fair comparisons of alternative methods.

Implementation and Practical Suitability. It is worth separately considering the issue of implementing classification solutions in practice, since the ultimate goal of research is to create working BCI systems. Here, a significant gap was found between laboratory prototypes and ready-to-use solutions. Firstly, very few works take into account computational resource constraints and energy consumption. Only 2 out of 69 analyzed papers include measures for optimizing energy consumption, for example, for wearable or implanted devices [53, 60]. Some authors note that even simple measures such as reducing the sampling rate, reducing the number of EEG channels, or selecting features can significantly reduce the load on hardware resources. However, the majority of studies focus exclusively on increasing accuracy, without analyzing the runtime of algorithms or energy efficiency, which are critical for autonomous systems. Secondly, only 29 works demonstrated moving beyond offline experiments – that is, implementing a system that works in real time or integrates into an application environment [6, 11, 14, 18, 22, 25, 27, 32–35, 37–40, 42–48, 50, 53, 56, 60, 63, 64, 67]. The other 40 studies were limited to offline analysis of recorded data or software emulations, not bringing the developments to the stage of real use [1–5, 7–10, 12, 13, 15–17, 19–21, 23, 24, 26, 28–31, 36, 41, 49, 51, 52, 54, 55, 57–59, 61, 62, 65, 66, 68, 69]. Thirdly, architectural scalability and distributed processing are practically not addressed: the overwhelming majority of solutions are implemented as local applications, without the ability to deploy them in the cloud or on a cluster. Only 4 works experimented with cloud services for EEG processing, and only in one case was the use of a national supercomputer mentioned [3, 53, 56, 60]. Where cloud technologies were applied, a positive experience is described: parallel signal processing on a cluster, centralized data storage, automated modeling pipelines, and web interfaces for remote configuration of preprocessing. This confirms the promise of such approaches, but at present they remain isolated experiments. In summary, the practical analysis revealed a number of unresolved issues: energy efficiency, scalability, and distributed computing are insufficiently covered in current research. This gap holds back the transfer of finger motor classification algorithms to portable devices and industrial applications.

Problem of Choosing the Optimal Pipeline. Summarizing the results of the methods review, we can conclude that the effectiveness of BCI systems is determined by a holistic approach to building the pipeline. Each step – from preprocessing to the classifier – must not only be well implemented, but also correctly composed with the others. In contrast, the current state of affairs is characterized by fragmentation: researchers often improve individual stages or propose a new feature extraction method or a new classification algorithm, without paying attention to how these stages align in the overall system. The absence of standardized methods for describing and evaluating pipelines leads to the impossibility of objectively comparing different configurations with each other. For example, two researchers might use similar algorithms, but with different sequences or settings of stages, and obtain different results – yet determining which variant is better is difficult due to the lack of a unified approach to reporting results. Moreover, the low reproducibility of experiments, due to unspecified randomness parameters, lack of published code, etc., makes it hard to verify claimed achievements. Insufficient attention is also given to computational efficiency: when choosing methods, considerations like processing delays or real-time requirements are rarely taken into account, so the proposed pipelines are not optimized for practical operation. The lack of automated tools for searching for the optimal pipeline forces manual tuning by trying out options, which requires a lot of time and does not guarantee finding the globally best solution. Therefore, an urgent scientific task is the development of approaches for the automatic synthesis of the optimal conveyor of software components for EEG classification. Such an approach should take into account method compatibility, the balance between accuracy and speed, and should ensure reproducibility and easy reconfiguration of the system for other conditions or data. The shortcomings of existing solutions identified in the review directly point to the directions for improvement, which will form the basis for the next stage of our research.

5. Modern Software Systems and AutoML Solutions for EEG/BCI

AutoML in BCI Tasks. The growing complexity of algorithms and the need for reproducibility of experiments in neurotechnology have led to the emergence of automated machine learning systems. AutoML platforms automatically select the optimal combination of algorithms and their hyperparameters, can perform feature selection, build ensemble algorithms, and evaluate their quality according to specified metrics. The advantage of AutoML is that it saves a lot of researcher time and reduces the role of human factor in building ensemble algorithms. In addition, such systems promote better reproducibility, since all pipeline configurations are documented automatically and the search process is carried out by formalized procedures. For the BCI field, where one often has to experimentally try many variants of preprocessing and classification, AutoML is especially attractive: it allows quick hypothesis testing and efficient use of computing resources thanks to smart search strategies.

While general-purpose software environments like Python and MATLAB have become dominant in BCI research due to their flexibility, extensive libraries, and strong community support, applying general-purpose AutoML platforms to biomedical signals requires taking domain specifics into account. In particular, typical AutoML systems have been developed mostly for tasks with ready-made tabular data or standard features, and they do not include built-in modules for processing raw biosignals. Therefore, when using them in neurointerfaces, researchers have to prepare the data themselves and then feed the already extracted features into the AutoML tool. Another problem is the limited ability to configure the optimization criteria. In practice, in BCI it is often important not only to maximize accuracy but also, for example, to minimize decision time or to account for build an ensemble algorithm stability across different sessions. Basic AutoML platforms allow setting only one target metric, without flexible balancing of multiple indicators. We should also mention validation and data variability: for EEG tasks, it is critical that algorithm evaluation considers inter-subject differences and potential signal drift between sessions. Thus, existing AutoML solutions need extended functionality for EEG/BCI. There is a need for tools to develop extendable pipelines with support for domain-specific biomedical signal preprocessing stages, flexible metric configuration mechanisms, and transparent validation methods that allow one to monitor an algorithm's generalizability to new subjects and sessions.

Analysis of Existing Platforms. As part of this review, three popular AutoML systems were selected for analysis: H2O AutoML, AutoGluon, and Google Cloud AutoML Tables. The selection criteria were their wide popularity, support for various algorithms, and claimed automatic optimization capabilities. The comparison showed that each of these platforms has limitations in terms of use for EEG signal classification tasks.

1 H2O AutoML handles building algorithm ensembles well, but it has no tools for processing raw EEG time series and does not support user-configurable metrics beyond the standard ones [71].
2 AutoGluon focuses on tabular data and computer vision tasks; applying it to EEG requires unconventional solutions to integrate signal filtering and spatial filtering stages [72].
3 Google AutoML Tables is a cloud service with limited user control over the process – this is acceptable for typical tasks, but in the BCI context, it lacks flexibility in choosing specific data transformations [73].

Overall, none of the analyzed AutoML systems provides an explicit representation of the stages of an EEG pipeline as controllable components. A user cannot, for example, change the artifact removal algorithm or add their own signal decomposition step – such stages are simply absent or fixed in advance. Parameter optimization is single-objective, with no ability to compromise between multiple metrics. The weight of metrics is hard-coded, and even if a platform displays additional metrics, they play a secondary role in algorithm selection. Experiment traceability – meaning detailed saving of all settings and obtained results – is incomplete: often only the final algorithm is recorded, without intermediate configurations, which complicates analysis and reproduction of the search process. Additionally, dependence on a particular execution environment creates difficulties in transferring solutions: for example, AutoGluon is currently oriented towards local execution, whereas Google AutoML is only a cloud service, and integrating them into a single workflow is not straightforward. In summary, even the most powerful existing AutoML tools currently take into account EEG/BCI specifics rather weakly, which does not allow for systematically finding a pipeline configuration that simultaneously satisfies accuracy, robustness, and resource-efficiency requirements.

Directions for Improvement and Proposed Solution. The identified shortcomings of existing solutions made it possible to formulate requirements for a new generation software system for automated EEG-signal classification. This system should combine the advantages of AutoML with consideration of BCI domain specifics. Based on the analysis, the following set of key features is proposed for an improved tool:

1. Interactive user interface. It is desirable to provide a convenient web-based interface in the form of a desktop application through which a researcher can configure the pipeline, launch experiments, and monitor their progress. Unlike tools with narrow or highly technical interfaces, a web-based GUI increases the system's accessibility to a wide range of users without requiring deep programming skills.
2. Computation resumption mechanism. The system should support automatic saving of the state of the current experiment and the ability to continue from the point of interruption after a failure or computer shutdown. This prevents the loss of data and time during long algorithm training runs, which is a common problem in resource-intensive BCI computations.
3. Versatility of execution environment. The tool should work flexibly both on local hardware and in cloud infrastructure. Such portability will allow using it for small experiments in the laboratory and for large-scale computations on clusters, depending on the project's needs.
4. Graph modeling of the pipeline. It is proposed to represent the sequence of EEG signal processing stages as a directed graph, where the nodes are separate components: filtering, feature extraction, classifier, etc., and the edges are data flows between them. The graph structure explicitly defines all dependencies and compatible connections between steps, which helps to avoid incorrect combinations of methods and ensures the reuse of components. This formalization also simplifies tracking and explaining the obtained pipelines, since each path in the graph corresponds to a specific solution configuration.
5. Multi-criteria optimization with flexible weights. Unlike typical AutoML, which optimizes one metric, the new system will consider several quality indicators simultaneously. The user

will be able to assign weight coefficients of importance for each metric – for example, 70% for accuracy, 30% for speed. The system will normalize the values of different metrics and compute a single aggregated efficiency criterion, for example, a weighted overall score, which will be used to compare algorithms. In this way, a convenient multi-criteria optimization mechanism is implemented that allows finding a balance between, say, accuracy and speed depending on the specifics of the task.

6. Complete traceability of experiments. All parameters, hyperparameters, intermediate results, and final algorithms should be automatically saved and available for analysis. This will ensure reproducibility: any obtained pipeline can be examined in detail or repeated on another dataset. Such an approach corresponds to best practices of open science and eliminates the problem of fragmentary reporting noted in the review.
7. Formal optimization methods for search. For intelligent exploration of pipeline configurations, it is planned to apply mathematical optimization methods, in particular linear or integer programming. The task of choosing the optimal pipeline can be expressed as an optimization problem on a graph with given constraints; for example, incompatibility of certain methods with each other, or limits on execution time. Using formal algorithms will guarantee finding a quasi-optimal solution in an acceptable time and will make the search process transparent and objective.

The above proposals form the basis for a new software complex that addresses the identified shortcomings and takes into account the specifics of finger movement classification. In particular, the graph-based representation of the component conveyor, combined with multi-criteria optimization, will allow the system to automatically prune ineffective or incompatible configurations, explore a wider space of solutions, and provide the user with explainable results – for example, in the form of a constructed graph of the optimal pipeline. Flexible control over metric weights will enable adapting the optimization criterion to a specific application: for some tasks, maximum accuracy is most important, while for others, a slightly lower accuracy is acceptable in exchange for a significant increase in system speed. The system's versatility and fault tolerance, supporting different environments and resuming computations, will increase the tool's practical value for researchers. Thus, the proposed solution will be a powerful means for automated construction of BCI systems, capable of considering a complex set of requirements and providing reliable recognition of finger movements from EEG signals even outside the laboratory.

6. Conclusions

This study provides a comprehensive analysis of existing methods and software tools for EEG-signal classification in finger movement recognition tasks, emphasizing the need for an integrated and systematic approach to pipeline design. The results demonstrate that the effectiveness of such systems depends on the coordinated selection and interaction of all processing stages, rather than the optimization of individual algorithms alone. A holistic conveyor of software components is essential to balance algorithm accuracy, processing speed, and robustness under real-world operating conditions.

The review also revealed significant inconsistencies in algorithm evaluation practices across studies. Most works rely on a single performance metric and rarely report result variability, which complicates objective comparison. Standardized cross-validation procedures, consistent reporting of robustness indicators, and the inclusion of computational efficiency measures alongside traditional quality metrics are proposed as necessary steps toward reproducible and fair assessment of EEG-based classification systems.

Based on the analyzed scientific studies, a typical EEG-signal classification pipeline was synthesized, describing the most frequently used and effective sequence of stages: data acquisition, preprocessing, dataset formation, feature extraction, dimensionality reduction, classification, and algorithm performance evaluation. This generalized structure provides a foundation for designing reproducible and comparable EEG-processing workflows in future research.

A comparative study of modern AutoML systems, such as H2O AutoML, AutoGluon, and Google Cloud AutoML Tables, showed that existing automation tools do not adequately meet the specific requirements of EEG/BCI research. Among the key limitations identified are the lack of explicit representation of domain-specific processing stages, single-objective optimization without metric trade-offs, fixed or inflexible metric weighting, incomplete experiment traceability, and dependence on particular execution environments. These findings, summarized here for the first time in the context of finger-movement classification, formed the basis for defining requirements for next-generation AutoML systems.

The proposed methodological framework and practical recommendations pave the way for developing a new AutoML platform that employs a graph-based pipeline architecture, supports flexible multi-criteria optimization, ensures full experiment traceability, and maintains independence from execution environments. Looking beyond algorithmic optimization, the future of BCI will also be shaped by parallel advancements in hardware and open science. The emergence of user-friendly, wireless EEG devices with dry sensors promises to lower the barrier for data collection in naturalistic environments. Simultaneously, supporting global data-sharing initiatives and creating large-scale standardized repositories will be essential for training robust, subject-independent models. These factors, combined with the proposed automated software framework, are key to moving finger movement recognition from research labs to daily usage. Implementing these solutions will mark a significant step toward practical, resource-efficient, and robust EEG-based BCI systems applicable to rehabilitation, neuroprosthetics, and other real-world domains.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT and Grammarly in order to: Grammar and spelling check, and as a smart Search Engine to find related works based on the context of conversation. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

References

[1] F. Xu, Y. Lou, Y. Deng, Z. Lun, P. Zhao, D. Yan, Z. Han, Z. Wu, C. Feng, L. Chen, J. Leng, Motor imagery EEG decoding based on TS-former for spinal cord injury patients, Brain Research Bulletin 224 (2025). doi:10.1016/j.brainresbull.2025.111298.

[2] V. S. Kardam, S. Taran, A. Pandey, BSPKTM-SIFE-WST: bispectrum based channel selection using set-based-integer-coded fuzzy granular evolutionary algorithm and wavelet scattering transform for motor imagery EEG classification, Signal, Image and Video Processing 19 (4) (2025). doi:10.1007/s11760-025-03851-z.

[3] X. Gao, K. Gui, X. Wu, B. Metcalfe, D. Zhang, Effects of different preprocessing pipelines on motor imagery-based brain-computer interfaces, IEEE Journal of Biomedical and Health Informatics 29 (5) (2025) 3343–3355. doi:10.1109/JBHI.2025.3532771.

[4] X.-C. Zhong, Q. Wang, D. Liu, Z. Chen, J.-X. Liao, J. Sun, Y. Zhang, F.-L. Fan, EEG-DG: a multi-source domain generalization framework for motor imagery EEG classification, IEEE Journal of Biomedical and Health Informatics 29 (4) (2025) 2484–2495. doi:10.1109/JBHI.2024.3431230.

[5] A. X. Gonzalez-Cely, C. F. Blanco-Diaz, C. D. Guerrero-Mendez, A. C. Villa-Parra, T. Bastos-Filho, Classification of opening/closing hand motor imagery induced by left and right robotic gloves through EEG signals, Transactions on Energy Systems and Engineering Applications 5 (2) (2024). doi:10.32397/tesea.vol5.n2.579.

[6] Z. T. Al-Qaysi, M. S. Suzani, N. Bin Abdul Rashid, R. D. Ismail, M. A. Ahmed, R. A. Aljanabi, V. Gil-Costa, Generalized time domain prediction model for motor imagery-based wheelchair

movement control, Mesopotamian Journal of Big Data (2024) 68–81. doi:10.58496/MJBD/2024/006.

[7] X. Jiang, L. Meng, X. Chen, Y. Xu, D. Wu, CSP-Net: common spatial pattern empowered neural networks for EEG-based motor imagery classification, Knowledge-Based Systems 305 (2024). doi:10.1016/j.knosys.2024.112668.

[8] S. Chen, N. Li, X. Kong, D. Huang, T. Zhang, Electroencephalography-based motor imagery classification using multi-scale feature fusion and adaptive Lasso, Big Data and Cognitive Computing 8 (12) (2024). doi:10.3390/bdcc8120169.

[9] S. G. Aslan, B. Yılmaz, Examining tongue movement intentions in EEG-based BCI with machine and deep learning: an approach for dysphagia rehabilitation, EuroBiotech Journal 8 (4) (2024) 176–183. doi:10.2478/ebtj-2024-0017.

[10] S. S. Baberwal, L. Magre, S. Gunawardhana, M. Parkinson, T. Ward, S. Coyle, Motor imagery with cues in virtual reality, audio and screen, Journal of Neural Engineering 21 (2024). doi:10.1088/1741-2552/ad775e.

[11] K. Belwafi, F. Ghaffari, Thought-controlled computer applications: a brain–computer interface system for severe disability support, Sensors 24 (20) (2024). doi:10.3390/s24206759.

[12] H. Xu, W. Haider, M. Z. Aziz, Y. Sun, X. Yu, Transforming motor imagery analysis: a novel EEG classification framework using AtSiftNet method, Sensors 24 (19) (2024). doi:10.3390/s24196466.

[13] M. H. Kabir, N. I. Akhtar, N. Tasnim, A. S. M. Miah, H.-S. Lee, S.-W. Jang, J. Shin, Exploring feature selection and classification techniques to improve the performance of an electroencephalography-based motor imagery brain–computer interface system, Sensors 24 (2024). doi:10.3390/s24154989.

[14] Y. Lu, W. Wang, B. Lian, C. He, Feature extraction and classification of motor imagery EEG signals in motor imagery for sustainable brain–computer interfaces, Sustainability 16 (2024). doi:10.3390/su16156627.

[15] S. Ruiz, S. Lee, J. L. Dalboni da Rocha, A. Ramos-Murguialday, E. Pasqualotto, E. Soares, E. García, E. Fetz, N. Birbaumer, R. Sitaram, Motor intentions decoded from fMRI signals, Brain Sciences 14 (2024). doi:10.3390/brainsci14070643.

[16] A. A. Shiam, K. M. Hassan, M. R. Islam, A. M. M. Almassri, H. Wagatsuma, M. K. I. Molla, Motor imagery classification using effective channel selection of multichannel EEG, Brain Sciences 14 (2024). doi:10.3390/brainsci14050462.

[17] X. Kong, C. Wu, S. Chen, T. Wu, J. Han, Efficient feature learning model of motor imagery EEG signals with L1-norm and weighted fusion, Biosensors 14 (2024). doi:10.3390/bios14050211.

[18] S. Kundu, A. S. Tomar, A. Chowdhury, G. Thakur, A. Tomar, Advancements in temporal fusion: a new horizon for EEG-based motor imagery classification, IEEE Transactions on Medical Robotics and Bionics 6 (2) (2024) 567–576. doi:10.1109/TMRB.2024.3387092.

[19] H. Ahmadi, L. Mesin, Enhancing motor imagery electroencephalography classification with a correlation-optimized weighted stacking ensemble model, Electronics 13 (2024). doi:10.3390/electronics13061033.

[20] I. Carrara, T. Papadopoulo, Pseudo-online framework for BCI evaluation: a MOABB perspective using various MI and SSVEP datasets, Journal of Neural Engineering 21 (2024). doi:10.1088/1741-2552/ad171a.

[21] R. Lin, C. Dong, P. Zhou, P. Ma, S. Ma, X. Chen, H. Liu, Motor imagery EEG task recognition using a nonlinear Granger causality feature extraction and an improved Salp swarm feature selection, Biomedical Signal Processing and Control 88 (2024). doi:10.1016/j.bspc.2023.105626.

[22] C. M. Thi, L. V. Thanh, K. N. Minh, Exploring motor imagery classification in brain–computer interfaces: case study of the Vietnamese BCI speller, Edelweiss Applied Science and Technology 8 (6) (2024) 8873–8891. doi:10.55214/25768484.v8i6.3884.

[23] M. Degirmenci, Y. K. Yuce, M. Perc, Y. Isler, EEG channel and feature investigation in binary and multiple motor imagery task predictions, Frontiers in Human Neuroscience 18 (2024). doi:10.3389/fnhum.2024.1525139.

[24] Y. Wang, L. Gong, Y. Zhao, Y. Yu, H. Liu, X. Yang, Dynamic graph attention network based on multi-scale frequency domain features for motion imagery decoding in hemiplegic patients, Frontiers in Neuroscience 18 (2024). doi:10.3389/fnins.2024.1493264.

[25] M. Sultana, S. Perdikis, Automatic feature selection for sensorimotor rhythms brain–computer interface fusing expert and data-driven knowledge, IEEE Transactions on Neural Systems and Rehabilitation Engineering 32 (2024) 3422–3431. doi:10.1109/TNSRE.2024.3456591.

[26] F. Rong, B. Yang, C. Guan, Decoding multi-class motor imagery from unilateral limbs using EEG signals, IEEE Transactions on Neural Systems and Rehabilitation Engineering 32 (2024) 3399–3409. doi:10.1109/TNSRE.2024.3454088.

[27] Y. Xu, L. Jie, W. Jian, W. Yi, H. Yin, Y. Peng, Improved motor imagery training for subject's self-modulation in EEG-based brain–computer interface, Frontiers in Human Neuroscience 18 (2024). doi:10.3389/fnhum.2024.1447662.

[28] H. Ahmadi, L. Mesin, Enhancing MI EEG signal classification with a novel weighted and stacked adaptive integrated ensemble model: a multi-dataset approach, IEEE Access 12 (2024) 103626–103646. doi:10.1109/ACCESS.2024.3434654.

[29] H. Yu, S. Baek, J. Lee, I. Sohn, B. Hwang, C. Park, Deep neural network-based empirical mode decomposition for motor imagery EEG classification, IEEE Transactions on Neural Systems and Rehabilitation Engineering 32 (2024) 3647–3656. doi:10.1109/TNSRE.2024.3432102.

[30] S. Yu, B. Mao, Y. Zhou, Y. Liu, C. Yi, F. Li, D. Yao, P. Xu, X. San Liang, T. Zhang, Large-scale cortical network analysis and classification of MI-BCI tasks based on Bayesian nonnegative matrix factorization, IEEE Transactions on Neural Systems and Rehabilitation Engineering 32 (2024) 2187–2197. doi:10.1109/TNSRE.2024.3409872.

[31] M. Lee, H.-Y. Park, W. Park, K.-T. Kim, Y.-H. Kim, J.-H. Jeong, Multi-task heterogeneous ensemble learning-based cross-subject EEG classification under stroke patients, IEEE Transactions on Neural Systems and Rehabilitation Engineering 32 (2024) 1767–1778. doi:10.1109/TNSRE.2024.3395133.

[32] N. Karakullukcu, F. Altindiş, B. Yilmaz, Object weight perception in motor imagery using Fourier-based synchrosqueezing transform and regularized common spatial patterns, IEEE Access 12 (2024) 52978–52989. doi:10.1109/ACCESS.2024.3386554.

[33] Y. Zhong, L. Yao, G. Pan, Y. Wang, Cross-subject motor imagery decoding by transfer learning of tactile ERD, IEEE Transactions on Neural Systems and Rehabilitation Engineering 32 (2024) 662–671. doi:10.1109/TNSRE.2024.3358491.

[34] H. Wang, Y. Qi, L. Yao, Y. Wang, D. Farina, G. Pan, A human–machine joint learning framework to boost endogenous BCI training, IEEE Transactions on Neural Networks and Learning Systems 35 (12) (2024) 17534–17548. doi:10.1109/TNNLS.2023.3305621.

[35] P. Dreyer, A. Roc, L. Pillette, S. Rimbert, F. Lotte, A large EEG database with users' profile information for motor imagery brain–computer interface research, Scientific Data 10 (2023). doi:10.1038/s41597-023-02445-z.

[36] S. Lyu, R. C. C. Cheung, Efficient multiple channels EEG signal classification based on hierarchical extreme learning machine, Sensors 23 (21) (2023). doi:10.3390/s23218976.

[37] M. Ahmadi, A. Farrokhi Nia, S. W. Michalka, A. L. Sumich, B. Wuensche, M. Billinghurst, Comparing performance of dry and gel EEG electrodes in VR using MI paradigms, in: Proceedings of the ACM Symposium on Virtual Reality Software and Technology, VRST '2023, ACM, New York, USA, 2023, pp. 1–2. doi:10.1145/3611659.3617436.

[38] D. Camargo-Vargas, M. Callejas-Cuervo, A. C. Alarcón-Aldana, Brain–computer interface prototype to support upper limb rehabilitation processes in the human body, International Journal of Information Technology (Singapore) 15 (7) (2023) 3655–3667. doi:10.1007/s41870-023-01400-w.

[39] T. Huang, Z. Luo, Y. Lyu, A2FWPO: anti-aliasing filter based on whale parameter optimization method for feature extraction and recognition of dance motor imagery EEG, Computer Science and Information Systems 20 (4) (2023) 1845–1868. doi:10.2298/CSIS221222033H.

[40] R. A. Khan, N. Rashid, M. Shahzaib, U. F. Malik, A. Arif, J. Iqbal, M. Saleem, U. S. Khan, M. Tiwana, A novel framework for classification of two-class motor imagery EEG signals using logistic regression classification algorithm, PLoS ONE 18 (2023). doi:10.1371/journal.pone.0276133.

[41] J. Zhang, K. Li, A multi-view CNN encoding for motor imagery EEG signals, Biomedical Signal Processing and Control 85 (2023). doi:10.1016/j.bspc.2023.105063.

[42] J. Tong, Z. Xing, X. Wei, C. Yue, E. Dong, S. Du, Z. Sun, J. Solé-Casals, C. F. Caiafa, Towards improving motor imagery brain–computer interface using multimodal speech imagery, Journal of Medical and Biological Engineering 43 (3) (2023) 216–226. doi:10.1007/s40846-023-00798-9.

[43] L. Batistić, D. Sušanj, D. Pinčić, S. Ljubic, Motor imagery classification based on EEG sensing with visual and vibrotactile guidance, Sensors 23 (11) (2023). doi:10.3390/s23115064.

[44] T. C. de Brito Guerra, T. Nóbrega, E. Morya, A. de M. Martins, V. A. de Sousa Jr., Electroencephalography signal analysis for human activities classification: a solution based on machine learning and motor imagery, Sensors 23 (9) (2023). doi:10.3390/s23094277.

[45] A. Maher, S. M. Qaisar, N. Salankar, F. Jiang, R. Tadeusiewicz, P. Pławiak, A. A. Abd El-Latif, M. Hammad, Hybrid EEG-fNIRS brain–computer interface based on non-linear features extraction and stacking ensemble learning, Biocybernetics and Biomedical Engineering 43 (2) (2023) 463–475. doi:10.1016/j.bbe.2023.05.001.

[46] M. H. Kabir, S. Mahmood, M. Al Shiam, M. A. S. Musa, J. Shin, M. K. I. Molla, Investigating feature selection techniques to enhance the performance of EEG-based motor imagery tasks classification, Mathematics 11 (8) (2023). doi:10.3390/math11081921.

[47] A. Dillen, F. Ghaffari, O. Romain, B. Vanderborght, U. Marusic, S. Grosprêtre, A. Nowé, R. Meeusen, K. De Pauw, Optimal sensor set for decoding motor imagery from EEG, Applied Sciences 13 (7) (2023). doi:10.3390/app13074438.

[48] H. A. Hashem, Y. Abdulazeem, L. M. Labib, M. A. Elhosseini, M. Shehata, An integrated machine learning-based brain–computer interface to classify diverse limb motor tasks: explainable model, Sensors 23 (6) (2023). doi:10.3390/s23063171.

[49] H. Hu, K. Yue, M. Guo, K. Lu, Y. Liu, Subject separation network for reducing calibration time of MI-based BCI, Brain Sciences 13 (2) (2023). doi:10.3390/brainsci13020221.

[50] R. Pawan, R. Dhiman, Electroencephalogram channel selection based on Pearson correlation coefficient for motor imagery–brain–computer interface, Measurement Sensors 25 (2023). doi:10.1016/j.measen.2022.100616.

[51] X. Xiong, Y. Wang, T. Song, J. Huang, G. Kang, Improved motor imagery classification using adaptive spatial filters based on particle swarm optimization algorithm, Frontiers in Neuroscience 17 (2023). doi:10.3389/fnins.2023.1303648.

[52] B. Shi, Z. Yue, S. Yin, J. Zhao, J. Wang, Multi-domain feature joint optimization based on multi-view learning for improving the EEG decoding, Frontiers in Human Neuroscience 17 (2023). doi:10.3389/fnhum.2023.1292428.

[53] K.-K. Shyu, S.-C. Huang, K.-J. Tung, L.-H. Lee, P.-L. Lee, Y.-H. Chen, Common spatial pattern and Riemannian manifold-based real-time multiclass motor imagery EEG classification, IEEE Access 11 (2023) 139457–139465. doi:10.1109/ACCESS.2023.3340685.

[54] W. Liang, J. Jin, R. Xu, X. Wang, A. Cichocki, Variance characteristic preserving common spatial pattern for motor imagery BCI, Frontiers in Human Neuroscience 17 (2023). doi:10.3389/fnhum.2023.1243750.

[55] P. Penava, R. Buettner, A novel small-data based approach for decoding yes/no-decisions of locked-in patients using generative adversarial networks, IEEE Access 11 (2023) 118849–118864. doi:10.1109/ACCESS.2023.3326720.

[56] X. Chen, J. An, H. Wu, S. Li, B. Liu, D. Wu, Front-end replication dynamic window (FRDW) for online motor imagery classification, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 3906–3914. doi:10.1109/TNSRE.2023.3321640.

[57] L. A. Fard, K. Jaseb, S. M. Mehdi Safi, Motor-imagery EEG signal classification using optimized support vector machine by differential evolution algorithm, New Armenian Medical Journal 17 (2) (2023) 78–86. doi:10.56936/18290825-2023.17.2-78.

[58] R. Ma, Y.-F. Chen, Y.-C. Jiang, M. Zhang, A new compound-limbs paradigm: integrating upper-limb swing improves lower-limb stepping intention decoding from EEG, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 3823–3834. doi:10.1109/TNSRE.2023.3315717.

[59] M. Degirmenci, Y. K. Yuce, M. Perc, Y. Isler, Statistically significant features improve binary and multiple motor imagery task predictions from EEGs, Frontiers in Human Neuroscience 17 (2023). doi:10.3389/fnhum.2023.1223307.

[60] M. Gemborn Nilsson, P. Tufvesson, F. Heskebeck, M. Johansson, An open-source human-in-the-loop BCI research framework: method and design, Frontiers in Human Neuroscience 17 (2023). doi:10.3389/fnhum.2023.1129362.

[61] K. Suemitsu, I. Nambu, Effects of data including visual presentation and rest time on classification of motor imagery of using brain–computer interface competition datasets, IEEE Access 11 (2023) 59542–59557. doi:10.1109/ACCESS.2023.3285236.

[62] H. Lou, Z. Ye, L. Yao, Y. Zhang, Less is more: brain functional connectivity empowered generalizable intention classification with task-relevant channel selection, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 1888–1899. doi:10.1109/TNSRE.2023.3252610.

[63] G. Huang, Z. Zhao, S. Zhang, Z. Hu, J. Fan, M. Fu, J. Chen, Y. Xiao, J. Wang, G. Dan, Discrepancy between inter- and intra-subject variability in EEG-based motor imagery brain-computer interface: evidence from multiple perspectives, Frontiers in Neuroscience 17 (2023). doi:10.3389/fnins.2023.1122661.

[64] T. D. Pham, Classification of motor-imagery tasks using a large EEG dataset by fusing classifiers learning on wavelet-scattering features, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 1097–1107. doi:10.1109/TNSRE.2023.3241241.

[65] F. Wei, X. Xu, T. Jia, D. Zhang, X. Wu, A multi-source transfer joint matching method for inter-subject motor imagery decoding, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 1258–1267. doi:10.1109/TNSRE.2023.3243257.

[66] R. Chen, G. Xu, Y. Jia, C. Zhou, Z. Wang, J. Pei, C. Han, Y. Wang, S. Zhang, Enhancement of time-frequency energy for the classification of motor imagery electroencephalogram based on an improved FitzHugh–Nagumo neuron system, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 282–293. doi:10.1109/TNSRE.2022.3219450.

[67] C.-R. Phang, C.-H. Chen, Y.-Y. Cheng, Y.-J. Chen, L.-W. Ko, Frontoparietal dysconnection in covert bipedal activity for enhancing the performance of the motor preparation-based brain–computer interface, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 139–149. doi:10.1109/TNSRE.2022.3217298.

[68] J. Jin, T. Qu, R. Xu, X. Wang, A. Cichocki, Motor imagery EEG classification based on Riemannian sparse optimization and Dempster–Shafer fusion of multi-time-frequency patterns, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2023) 58–67. doi:10.1109/TNSRE.2022.3217573.

[69] X. Deng, B. Zhang, N. Yu, K. Liu, K. Sun, Advanced TSGL-EEGNet for motor imagery EEG-based brain–computer interfaces, IEEE Access 9 (2021) 25118–25130. doi:10.1109/ACCESS.2021.3056088.

[70] K. Barnova, M. Mikolasova, R. V. Kahankova, R. Jaros, A. Kawala-Sterniuk, V. Snasel, S. Mirjalili, M. Pelc, R. Martinek, Implementation of artificial intelligence and machine learning-based methods in brain–computer interaction, Computers in Biology and Medicine 163 (2023). doi:10.1016/j.compbiomed.2023.107135.

[71] H2O.ai, H2O AutoML, Online documentation, 2025. URL: https://h2o.ai/platform/h2o-automl/.
[72] AutoGluon Team, AutoGluon: Open Source AutoML Toolkit, Online documentation, 2025. URL: https://auto.gluon.ai/stable/index.html.
[73] Google Cloud, Vertex AI Platform: innovate faster with enterprise-ready AI enhanced by Gemini models, Online documentation, 2025. URL: https://cloud.google.com/vertex-ai.