The Landscape of Machine Learning for EEG Hand Motor Imagery Decoding: A Scoping Review (2020-2025)

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Abstract. *EEG-based Brain-Computer Interfaces (BCIs) show promise for motor rehabilitation, with hand motor imagery (MI) being a key paradigm. This scoping review analyzed 128 studies, mapping machine learning and deep learning architectures, training strategies, and performance metrics. Results reveal predominance of deep learning, and methodological diversity, but most studies are offline and subject-dependent, limiting reproducibility and real-time application. The review aims to highlight gaps and standardized evaluation protocols to advance practical BCIs.*

1. Introduction

EEG-based Brain–Computer Interfaces (BCIs) have demonstrated strong potential in motor rehabilitation and assistive technologies [Lotte et al. 2018]. Their effectiveness depends on accurately translating neural activity into control commands, and recent years have witnessed a surge of methods ranging from traditional machine learning models to advanced deep learning architectures. Among the various paradigms, motor imagery (MI), the decoding of motor intentions from EEG signals, has been extensively explored. Hand movements, in particular, attract significant attention due to their functional complexity and critical role in daily activities [Liu et al. 2021].

Although existing reviews on hand movement provide valuable insight, they often have a limited scope. Some combine EEG with other modalities, such as fNIRS [Finnis et al. 2025]. Others focus exclusively on deep learning [Li et al. 2021] or on single classifier families like Transformers [Vafaei and Hosseini 2025]. This fragmentation highlights a clear gap: the absence of a recent, comprehensive mapping of classification methods specifically for EEG-based hand motor imagery.

2. Objectives

This study investigates which machine learning and deep learning models have been applied to EEG signal decoding in hand motor imagery research over the past five years. Its main goal is to map the predominant classification architectures and algorithms. Specifically, it aims to: (i) identify prevalent techniques for EEG data processing;(ii) summarize performance metrics used to evaluate classifiers; and (iii) outline research gaps to inform future studies.

3. Methodology

The methodological design is based on PRISMA-ScR recommendations, ensuring rigor and transparency [Tricco et al. 2018]. The search strategy intersected three core concepts: (1) electroencephalography, (2) data classification, and (3) hand motor imaging adapted to each database. The search string was:

> (‘eeg’ OR ‘electroencephalography’) AND (‘data classification’ OR ‘decoding’ OR ‘pattern recognition’ OR ‘predicting’ OR ‘machine learning’ OR ‘deep learning’) AND (‘motor imagery’ OR ‘motor intention’) AND (‘hand’ OR ‘finger’ OR ‘grasp’).

The article selection process for the final analysis is presented in the following flowchart.

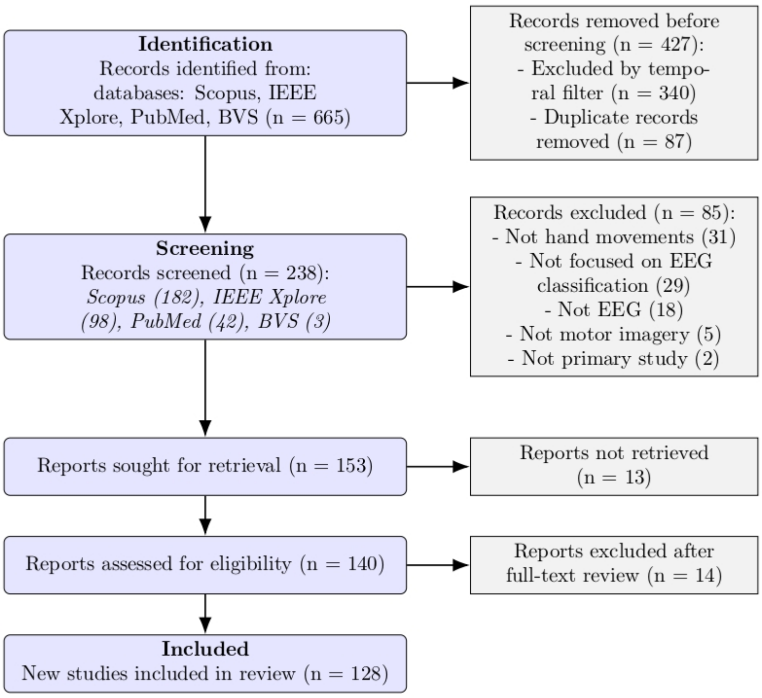

Figure 1. PRISMA flow diagram of article selection

4. Results

In terms of focus, 74 proposed new classifiers or architectures validated against recognized baselines, 41 works investigated a single model, and 13 conducted benchmarking across multiple architectures.

The analysis of classification models reveals a landscape dominated by two main paradigms. Traditional machine learning classifiers were the most frequent category (55 studies, 43.0%), with Support Vector Machines (SVM), Linear Discriminant Analysis (LDA) and Random Forest being the most common choices. Following closely, deep learning approaches were also prominent (39 studies, 30.5%), led by Convolutional Neural Networks (CNNs) and their variants, such as transformer and DeepConvNet. The methodological diversity was further enriched by more specialized techniques, including hybrid models with recurrent or attention mechanisms (13 studies, 10.2%), Riemannian-based methods (12 studies, 9.4%), and other EEG-specialized architectures (9 studies, 7.0%).

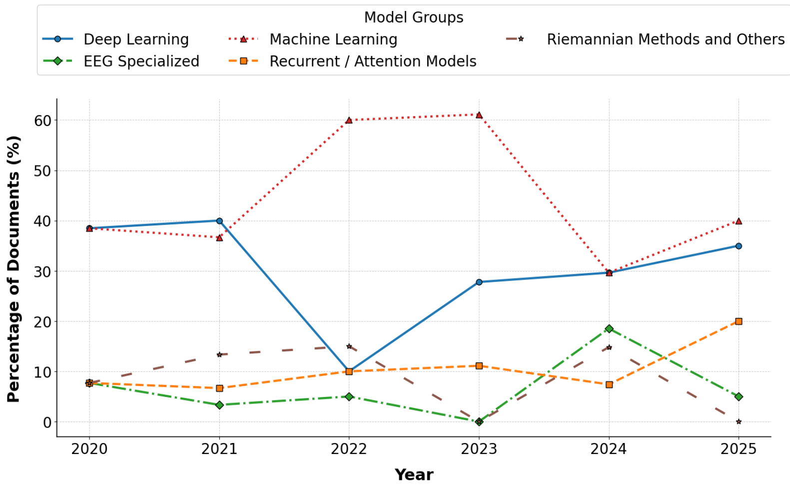

Figure 2. Temporal distribution of the percentage of documents across the five main classification categories.

Across the reviewed studies, the highest reported accuracy reached 99.8% using KNN [Firoz et al. 2024], with intermediate results around 86.5%. The best mean accuracy was 96.06%, achieved by a CNN+LSTM model [Das et al. 2025]. Regarding other performance measures, the maximum Cohen's Kappa value reported was 0.927 for the ESSDM-FTFG-CapsNet architecture [Bhalerao and Pachori 2024], while the highest F1-score reached 98.23% with the C-K S7 model [Li et al. 2023]. Most experiments were conducted offline (112 studies), whereas 16 were performed online.

The inputs included extracted features (68), raw signals (54), topological maps (3) and spectral images (3). Training strategies varied widely: K-Fold Cross-Validation was the most common (75 occurrences, mainly 5- and 10-fold), followed by hold-out/train-test splits (42), Leave-One-Subject-Out (18), Leave-One-Out (6), Monte Carlo/Grid Search (6), and cross-session or custom splits (17). Regarding subject dependence, 89 studies were subject dependent, 22 subject independent, and 17 unspecified.

5. Conclusion

This scoping review highlights substantial progress in EEG-based hand motor imagery classification, with many studies reporting high precision, Kappa, and F1 scores. Yet reproducibility and comparability remain limited due to heterogeneous designs and metrics, underscoring the need for standardized protocols. Research is still dominated by subject-dependent, offline approaches, while aspects such as information transfer rate, decoding time, and model complexity are often overlooked despite their relevance for practical BCI applications.

Addressing these gaps requires greater emphasis on online and cross-subject studies, clearer reporting standards, and systematic evaluation of performance–efficiency trade-offs to help translate EEG-based BCIs from controlled experiments into reliable tools for motor rehabilitation and assistive technologies.

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