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To cite this article: Jiahao Cheng, Peng Chen, Yufeng Deng, Yi Luo, Fengyan Chen, Jiwang Ma, Fei Wang, Fen Xu, Sheng Guo, X. San Liang & Tao Zhang (2025) EEG feature extraction methods in motor imagery-based brain-computer interfaces: a systematic review and network meta-analysis, Brain-Apparatus Communication: A Journal of Bacomics, 4:1, 2523303, DOI: [10.1080/27706710.2025.2523303](https://doi.org/10.1080/27706710.2025.2523303)

To link to this article: <https://doi.org/10.1080/27706710.2025.2523303>



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Published online: 27 Jun 2025.



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EEG feature extraction methods in motor imagery-based brain-computer interfaces: a systematic review and network meta-analysis

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ABSTRACT

Background: Brain-computer interfaces (BCIs) enable direct interaction between human cognition and external devices by interpreting brain activity via electroencephalogram (EEG) signals. However, the performance of motor imagery (MI)-based BCIs is often limited by the efficiency and accuracy of EEG feature extraction methods. Challenges such as class separability, noise resilience, and computational complexity. **Aim:** This study systematically evaluates various feature extraction methods used in MI-based BCIs, with a specific focus on their performance in binary and multi-class classification tasks. **Methods:** A literature database from resources like Web of Science, PubMed, and Google Scholar, conducting statistical and network meta-analyses. **Results:** Results highlight a strong preference for hybrid methods for their robustness and versatility. The Common Spatial Pattern (CSP) method remains the most common single method, often integrated into hybrids. The network meta-analysis shows that while wavelet transforms perform well in specific contexts, they struggle with task complexity and variability. Hybrid methods, in contrast, demonstrate superior stability, achieving a surface under the cumulative ranking curve (SUCRA) value of 0.811, making them ideal for high-precision tasks. **Conclusion:** This study highlights the critical role of effective feature extraction, advocating for the benefits of hybrid methods while underscoring the need to further refine traditional approaches.

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1. Introduction

Brain-computer interfaces (BCIs) are transformative technologies that enable direct interaction between human cognition and external devices by interpreting electrical brain activity, typically through EEG signals. By bypassing the need for conventional physical inputs such as keyboards or touchscreens, BCIs allow users to control external systems with their thoughts [1–3]. BCIs have empowered paralyzed individuals to control devices like robotic limbs and computer cursors, showcasing their potential to restore functionality and improve the quality of life for individuals with motor disabilities [4–6]. This ability to restore some control for people who have lost motor functions underscores the revolutionary potential of BCIs [7]. In contrast to non-invasive approaches, invasive methods have also shown promising results. As noted by previous studies: Brain-computer interfaces (BCIs) using signals acquired with intracortical implants have achieved successful high-dimensional robotic device control useful for completing daily tasks. However, the substantial amount of medical and surgical expertise required to correctly implant and operate these systems greatly limits their use beyond a few clinical cases. [8] One of the most widely researched paradigms in BCI applications is MI. In MI-based BCIs, users mentally simulate movements, such as imagining moving a hand or foot, to control external devices [9,10]. Unlike motor execution, which involves physical movement, MI relies solely on the user's imagination of movement, generating recognizable EEG patterns [8,11–14]. This non-invasive method offers a practical and flexible solution for controlling external devices, such as exoskeletons, wheelchairs [15], or robotic arms [8,16–18], making it a widely researched area in both clinical and non-clinical settings. By tapping into the brain's motor system without requiring physical execution of movement, MI-BCIs provide a non-invasive and direct interface between the brain and devices. Accurately translating these signals into reliable commands for external devices remains a major challenge in MI-BCI research [19–21].

Motor imagery BCIs depend on their ability to classify mental states accurately, which involves distinguishing EEG patterns that correspond to specific imagined movements. Binary classification tasks, such as differentiating between left- and right-hand movements, are the most common in MI-based BCI research, as these tasks produce easily recognizable EEG

patterns [9,22,23]. Their simplicity allows machine learning algorithms to identify and interpret user intentions with high accuracy. This has made binary tasks a focal point in MI-BCI research, but there is growing interest in more complex classification tasks involving multiple movements, such as left-hand, right-hand, and foot movements. These multi-class tasks are essential for making MI-BCI systems more functional and applicable in dynamic environments [24–26]. In MI-based BCIs, feature extraction plays a critical role in determining classification accuracy. Feature extraction involves isolating relevant and meaningful data from raw EEG signals, enhancing the classifier's ability to differentiate between mental imagery tasks [27–29]. Effective feature extraction techniques help mitigate EEG signal noise and variability, improving system performance and reducing errors. Traditional feature extraction methods, such as Common Spatial Pattern and Autoregressive models, have been widely used due to their simplicity and effectiveness [30–35]. In particular, CSP is highly effective in binary classification tasks, where it optimizes spatial filters to discriminate between two classes of EEG signals [36–39]. However, CSP and similar traditional methods may struggle in multi-class tasks, where they are less capable of distinguishing between subtle EEG variations associated with different motor imagery tasks [40–42]. This limitation has driven the development of hybrid feature extraction techniques, which combine multiple methods to leverage their respective strengths. Hybrid methods, such as combining CSP with deep learning algorithms, aim to improve the robustness and adaptability of MI-BCI systems [28,43–45]. These approaches capitalize on the strengths of different methods, enhancing generalization and model accuracy. For example, CNNs have emerged as powerful tools for MI classification, particularly in multi-class tasks [46–48]. CNNs can automatically learn complex spatial and temporal patterns in EEG data, offering improved classification accuracy compared to traditional methods [49]. The ability of CNNs to learn feature representations autonomously makes them well-suited to handling the complex, multi-dimensional nature of EEG data in MI-BCIs [50,51]. As MI tasks become more complex, the need for more advanced feature extraction techniques becomes even more critical. By improving the ability of classifiers to recognize and interpret EEG signals, these techniques can significantly enhance the performance of MI-BCI systems, especially in multi-class scenarios [24,52]. Hybrid methods and deep learning approaches offer promising avenues for achieving this, helping MI-BCIs to perform reliably across a range of applications.

In conclusion, the continued evolution of MI-BCIs depends heavily on improving both the accuracy and robustness of classification systems [53]. While simpler motor imagery tasks, such as left- and right-hand

movements [54], remain dominant due to their ease of classification, more complex tasks are becoming a focal point as researchers aim to expand the functionality of BCIs [55–57]. Traditional methods like CSP, although still effective for simpler tasks, must evolve to meet the demands of more complex multi-class classification scenarios [25,58–60]. Hybrid and deep learning-based methods provide a way forward, offering greater flexibility and accuracy in processing EEG signals [36,53]. By refining feature extraction techniques, researchers can significantly improve the performance and adaptability of MI-BCIs, paving the way for more reliable and user-friendly systems in the future [61]. This study aims to contribute to the ongoing development of MI-based BCI systems by systematically analyzing the performance of various feature extraction methods across different experimental conditions. Through rigorous evaluation and comparison, it seeks to provide empirical evidence that will guide future research in selecting appropriate techniques for both simple and complex motor imagery classification tasks. By refining the feature extraction process, researchers can improve the overall functionality of MI-BCIs, paving the way for more reliable, accurate, and adaptable BCI systems in the future. As the field of MI-BCIs continues to grow, so too will the need for innovative solutions to the challenges posed by EEG signal processing. These advancements will ultimately lead to more sophisticated BCI systems capable of handling increasingly complex tasks, thereby broadening the scope of their application in both clinical and everyday settings.

2. Relate works

Traditional feature extraction methods are central to MI-BCI systems and are generally classified into time domain, frequency domain, spatial domain, and time-frequency domain. Time-domain techniques, such as autocorrelation analysis and variance, capture the temporal characteristics of signals. Frequency-domain methods, including PSD and Fourier transform, highlight spectral features by analyzing the signal's frequency characteristics. Spatial-domain approaches, like CSP, focus on enhancing the distinctions between different motor imagery tasks [62–64]. Time-frequency domain methods, such as wavelet transform, capture signal features across both time and frequency dimensions. Additionally, methods like complex network analysis and entropy-based features offer new perspectives for analyzing EEG signals [65–67]. Table 1 presents various feature extraction methods, encompassing mathematical formulas and symbolic explanations, ranging from basic linear analyses to nonlinear and deep learning approaches. For example, CNNs, a deep learning technique, can automatically extract features from raw EEG data, significantly

Table 1. Classification and examples of various feature extraction methods.

References	Feature category	Sample feature extraction algorithm	Algorithm formula and symbol explanation
[68]	Time domain feature extraction method	Autoregressive analysis	$R(\tau) = \frac{1}{N} \sum_{t=0}^{N-1} x(t)x(t+\tau)$; Variance = $\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$ $R(\tau)$: autocorrelation function; $x(t)$: signal value; N : Number of samples; τ : Delay; μ : Mean of the signal; x_i ; $i - th$ sample $S(f) = \lim_{T \rightarrow \infty} \frac{1}{T} X(f) ^2$; $X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft} dt$ $S(f)$: Spectrum; T : Observation time; $X(f)$: Fourier transform of the signal; j : Imaginary unit; f : Frequency $Y = W^T X$; $W = \operatorname{argmax}_{\sigma_1^2 + \sigma_2^2} \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}$ Y : Extracted features; W : Transformation matrix; X : Input signal; μ_1, μ_2 : Means of the two classes; σ_1^2, σ_2^2 : Variances of the two classes; $X(a, b) = \frac{1}{\sqrt{ a }} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt$; $C_{ij} = \sum_{j=1}^N X(a, b_i) ^2$; $X(a, b)$: Wavelet transform coefficients; a : Scale factor; b : Time shift; ψ : Mother wavelet function; C_{ij} : Energy of the wavelet decomposition coefficients; N : Number of wavelet decomposition levels; $C_B = \frac{1}{N-1} \sum_{i \neq B} d_{Bi}$; $C_B = \sum_{i \neq B} \frac{1}{d_{Bi}}$; C_B : Centrality of node B ; d_{Bi} : Shortest path length from B to node i ; N : Total number of nodes; Reflects the importance of node B in the network; $H(X) = - \sum_{i=1}^n p(x_i) \log p(x_i)$; $H(X)$: Entropy; $p(x_i)$: Probability of event x_i ; n : Number of events; $D \approx \frac{\log(N_e)}{\log(1/r)}$, Lyapunov Exponent = $\lim_{t \rightarrow \infty} \frac{1}{t} \log \left(\frac{\ x(t)\ }{\ x(0)\ } \right)$; D : Dimension; N_e : Number of points within scale ϵ ; $x(t)$: State of the system at time t ; $\ x(t)\ $: Norm of the state vector at time t ; $\ x(0)\ $: Norm of the initial state vector;
[69]	Frequency-domain feature extraction	Power spectral density (PSD)	
[70]	Spatial-domain feature extraction	Common spatial patterns (CSP)	
[71]	Time-frequency domain feature extraction	Wavelet transform	
[72]	Complex network feature extraction	Network centrality	
[73]	Entropy feature extraction	Shannon entropy	
[74]	Nonlinear feature extraction	Correlation dimension	

(continued)

Table 1. Continued.

References	Feature category	Sample feature extraction algorithm	Algorithm formula and symbol explanation
[75]	Deep learning feature extraction	Convolutional neural network (CNN) features	$Y = f(W * X + b)$, $Z = f(W_2 * f(W_1 * X + b_1) + b_2)$; Y : Output; W :Convolutional kernel; X : Input image; b : Bias term; f : Activation function; Z : Output of the second layer; W_1, W_2 : Convolutional kernels for the first and second layers; b_1, b_2 : Bias terms for the first and second layers; $F_{mixed} = f(F_1, F_2, ..., F_n)$; F_{mixed} : Hybrid feature; F_i : Individual feature;
[76]	Hybrid feature extraction method	Integrated features	

improving both the efficiency and accuracy of feature extraction. Hybrid feature extraction techniques that combine multiple strategies leverage the strengths of different methods to enhance classifier performance. As technology continues to advance, the application of diverse feature extraction methods is expanding, providing a solid foundation for further optimization of MI-BCI systems.

3. Materials and methods

3.1. Literature search strategy and database management

In this review, we adopted a comprehensive literature screening strategy to ensure the inclusion of high-quality studies related to BCI and MI. The strategy was meticulously designed to prioritize scientific rigor and relevance, rather than merely focusing on the volume of literature. Our literature search covered key academic databases, including Web of Science, Google Scholar, and PubMed, which provided a broad spectrum of resources and data support essential for our study. To manage the large volume of identified literature, we utilized EndNote, a reference management software, to facilitate efficient organization and citation. This approach streamlined the literature screening process, improved traceability, and standardized the research workflow, thus enhancing the overall reliability of the study. Through this software, all identified references were collated, systematically reviewed, and categorized based on pre-established inclusion criteria.

3.2. Search formulation and article filtering process

The literature search formula was carefully constructed to capture studies relevant to motor imagery, brain-computer interfaces, feature extraction, and signal processing. Keywords such as “motor imagery” (MI), “brain-computer interface,” “brain-machine interface,” and a range of feature extraction methods (e.g. “common spatial pattern” (CSP), “power spectral density” (PSD), “wavelet transform,” and “independent component analysis” (ICA)) were employed to ensure comprehensive coverage. This multifaceted search strategy provided a solid foundation for the identification of relevant research. [Figure 1](#) shows the article filtering process. Following the initial search, a total of 1217 articles were retrieved. These articles were imported into EndNote for unified management, where a duplication check reduced the total to 945 unique entries. The preliminary screening process was governed by stringent criteria: only articles published in the last ten years, involving EEG data, and focused on motor imagery classification were included. This initial filtering was critical in

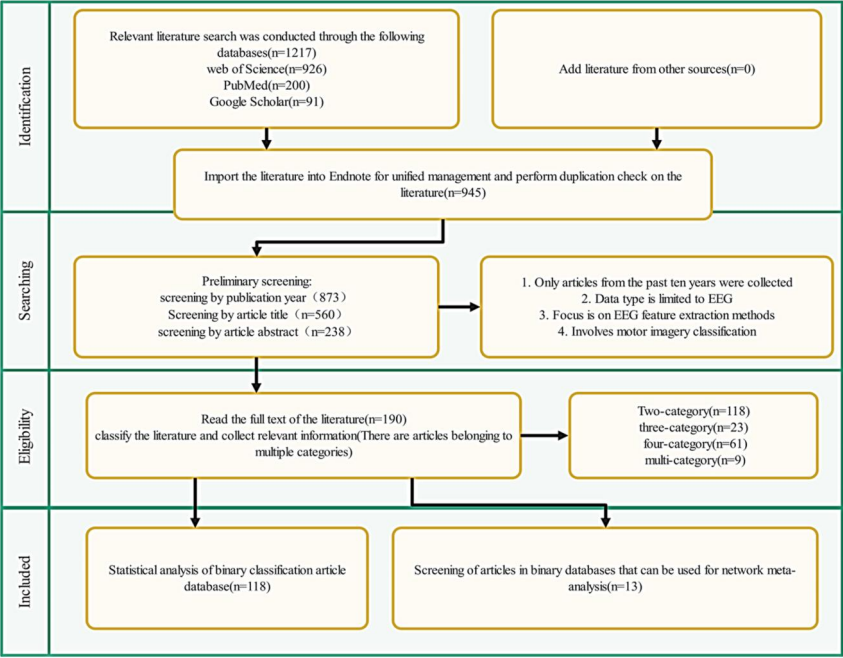


Figure 1. Article database establishment and analysis flow chart.

ensuring that only high-quality, up-to-date research was considered for further review.

3.3. Data extraction and study classification

The final screening led to a full-text review of 190 articles. These articles were further categorized based on their classification methods: two-category ($n = 118$), three-category ($n = 23$), four-category ($n = 61$), and multi-category ($n = 9$). Throughout this meticulous screening process, the literature analyzed in this study was ensured to be both relevant and of high quality, meeting all predefined inclusion standards. Key information extracted from the selected articles includes author names, publication years, study titles, dataset names, number of subjects, motor imagery movements, feature extraction methods, method types, corresponding classifiers, average accuracies, and other relevant performance indicators. This systematic data extraction provided a robust foundation for subsequent. Articles that did not meet the criteria were excluded during the full-text review, reinforcing the reliability and integrity of the selected studies. It is important to note that the majority of the articles included in this review are based on offline analysis or pre-collected datasets. These studies primarily focus on evaluating feature extraction and

classification methods using static datasets, rather than data generated or processed in real-time. This limitation is inherent to the current state of research, as real-time studies in motor imagery-based BCIs often require additional experimental setups and computational resources.

The final analysis of this review focused on the binary classification article database, consisting of 118 studies. A detailed breakdown was performed, examining key aspects such as publication year, motor imagery movements, and feature extraction methods. This analysis provided the foundation for evaluating the effectiveness of various feature extraction techniques in BCI motor imagery classification. Additionally, 13 articles from this dataset met the criteria for network meta-analysis, allowing for further investigation into the comparative efficacy of different methods. A partial database of the analyzed binary classification articles is presented below in [Table 2](#), which summarizes critical information such as the first author, publication year, dataset name, number of subjects, MI actions, feature extraction methods, corresponding method types, classifiers, and average accuracy for a clearer overview of the studies included in this review.

3.4. Data preparation and standardization

During the construction of the database, 118 binary classification studies from the total of 190 articles were further screened and preprocessed to ensure they met the requirements for network meta-analysis. Only studies that compared two or more feature extraction methods were selected. The primary objective of this screening step was to ensure that the chosen articles could provide effective data support for subsequent meta-analysis, allowing for an accurate comparison of the performance of different feature extraction methods. Additionally, the feature extraction methods cited in each eligible article were renumbered to facilitate subsequent data analysis and statistical evaluation. This approach enhanced data integration and provided clear identification for comparing different methods. To ensure uniformity and comparability, the names of the feature extraction methods were standardized. As shown in [Figure 2](#), all methods derived from CSP variants are collectively referred to as “optimized CSP,” while wavelet transform variants are classified as “optimized wavelet transform.” Other transform methods are classified as “other transforms,” and methods based on AR variants are called “optimized AR.” Methods that combined the aforementioned features were collectively referred to as “hybrid feature extraction methods,” whereas those based on convolutional network variants were designated as “convolutional networks.”

Table 2. Overview of binary classification literature (abbreviated).

First author (year)	Data set name	Number of subjects	MI actions	Feature extraction method	Corresponding method type	Classifier	Average accuracy
Wei, Qingguo et al. (2015) [77]	BCI C III IVa	5	RHMI-RFMI	CSP	SF-FE	LDA	90.49%
	BCI C III IVa	5	LHMI-RFMI	CSP	SF-FE	LDA	87.10%
	BCI C III a	5	RHMI-RFMI	Optimized WT	FD-FE	LS-SVM	98%
Muhammad Tariq Sadiq et al. (2019) [78]	BCI C III b	1	LHMI-RFMI	Optimized WT	FD-FE	LS-SVM	100%
	BCI C IV 2b	9	LHMI-RSMI	CNN	DL-FE	CWT-CNN	81.30%
	BCI C IV 2b	9	LHMI-RSMI	Optimized WT	TFF-FE	CWT-CNN	77.22%
Yang, Jun et al. (2020) [79]	BCI C IV 2b	9	LHMI-RSMI	CSP	SF-FE	LDA	71.29%
	...	...	...	...	...	...	...
Lin, Ruijing et al.(2022) [80]	IMUT dataset	6	LHMI-RSMI	Hybrid FEM	S + T + FF-FE	SVM	76.50%
	BCI C III	1	LHMI-RSMI	Hybrid FEM	S + T + FF-FE	SVM	70.90%
	BCI C 2b	5	LHMI-RSMI	Hybrid FEM	S + T + FF-FE	SVM	72.50%
Bin Shi et al. (2023) [81]	BCI C IV 1	7	LHMI-RHMI	CSP	SF-FE	SVM	82.86%
	BCI C IV t1	7	LHMI-RFMI	Optimized CSP	SF-FE	SVM	88.29%
	BCI C III t	5	RHMI-RFMI	CSP	SF-FE	SVM	83.57%
Juan, J. V. et al. (2023) [82]	BCI C III IVa	5	RHMI-RFMI	Optimized CSP	SF-FE	SVM	87.21%
	BCI C III c	1	LHMI-RFMI	Optimized WT	FD-FE	LS-SVM	97%
	Self-collection	13	RCMI-MCMI	CSP	SD-FE	CSP-LDA	64.20%
Self-collection	Self-collection	13	RCMI-MCMI	CNN	DL-FE	IF-Net	65.40%

Note: The original names of the abbreviations in the table above are as follows (partially): BCI C III IVa (Brain-Computer Interface Competition Category III and IVa), RHMI-RFMI (Recurrent Hybrid Motor Imagery – Recursive Feature Selection and Multiple Imputation), CSP (Common Spatial Patterns), SF-FE (Spatial Filtering – Feature Extraction), and LDA (Linear Discriminant Analysis).

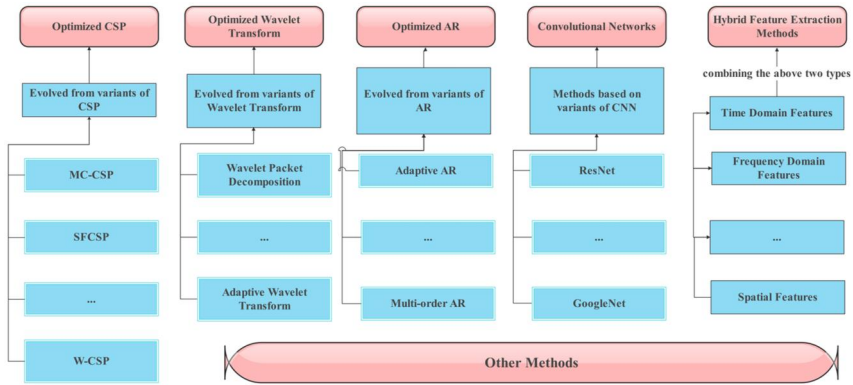


Figure 2. Method name standardization.

By analyzing the number of subjects in each article, the weighted standard deviation of the average accuracy and other key statistical indicators corresponding to each feature extraction method can be estimated. This process involves calculating the weighted average accuracy, standard error, and its 95% confidence interval to effectively reflect the performance of each method and its associated uncertainty. The resulting data Table 3 will summarize the average accuracy, weighted standard deviation, and corresponding confidence intervals for each feature extraction method. This table provides a reliable data foundation for subsequent meta-analysis and significantly enhances the statistical significance and reproducibility of the research findings [83].

3.5. Bayesian network meta-analysis

Network Meta-Analysis (NMA) is a statistical method that combines direct and indirect comparisons to evaluate the relative effects of multiple interventions simultaneously. At the core of this approach is a network of interventions, where each node represents an intervention and each edge represents the comparative relationships across studies. This allows researchers to directly compare interventions and derive effects for those not directly compared, making NMA valuable in various clinical scenarios. The first step in conducting an NMA is to determine the network structure, where nodes reflect interventions and edges represent study comparisons. Effect sizes, such as standardized mean difference (SMD) or hazard ratio (HR), are typically used to quantify the differences between interventions. Researchers must also consider heterogeneity among studies, often addressed using a random effects model, which accounts for unique effect sizes per study, better reflecting real-world variability. The analysis should include an assessment of bias risk using tools like the Cochrane risk of bias tool.

Table 3. Meta-analysis literature preprocessing information.

Article numbers	Methods	Sample size	Mean	Std. dev
BB	Optimized CSP	9	0.325	0.12665
BB	CSP	9	0.393	0.10303
DD	Other methods	5	0.375	0.14790
DD	Optimized CSP	5	0.394	0.13766
...	...	...	...	...
CB	Other transformations	5	0.3114	0.17494
CB	CSP	5	0.3501	0.15964
CD	CSP	7	0.3286	0.14243
CD	Optimized CSP	7	0.3829	0.12153

Note: BB, ..., CD = Article numbers in network meta-analysis.

Bayesian network meta-analysis further enhances NMA by incorporating prior knowledge into the analysis, forming posterior distributions of parameters by combining prior information with observed data. A multi-level Bayesian model is typically used, and effect sizes are treated as random variables. The Markov Chain Monte Carlo (MCMC) method is commonly employed for posterior parameter sampling, allowing researchers to estimate intervention effects and their uncertainty, often visualized using tools like forest or network plots. Sensitivity analyses can be performed to assess the robustness of the results to various factors.

In this study, a Bayesian network meta-analysis was conducted to evaluate the effects of different interventions on specific health outcomes. The analysis was implemented in R, with necessary packages loaded and the working directory set for data processing. The data, imported from a CSV file, included comparisons of interventions and related statistical information. A visual intervention network was constructed to observe relationships and provide a framework for analysis. A consistency model was selected with key parameters established, such as the number of chains and the likelihood function. Multiple iterations were performed to ensure convergence, and results were summarized, including quantitative information on intervention effects, which was visualized using forest plots. Ranking probabilities were calculated, and the Gelman-Rubin diagnostic tool was used to assess model convergence. Additionally, a funnel plot and the Egger test were used to evaluate publication bias. Finally, an ANOHE analysis was performed to assess the overall effect of the network, with results reported in tabular format to provide a comprehensive view of the continuous and binary outcomes, supporting both clinical practice and policy development.

4. Results

4.1. Description of included studies

The search across three databases yielded 1,217 relevant documents: 926 from Web of Science, 200 from PubMed, and 91 from Google Scholar. After a

thorough review, 945 valid documents were retained, with 190 selected for further analysis. Notably, articles focused on binary classification represented 55.9%, underscoring their importance in motor imagery brain-computer interfaces (MI-BCI), while multi-class tasks comprised the remainder. Additionally, 85% of the documents utilized EEG data, highlighting its dominance in the field. This study emphasizes binary classification within MI-BCI, which is particularly suited for real-time applications such as medical devices due to its simplicity. A network meta-analysis was conducted to assess the performance of various feature extraction methods in binary classification, aiming to provide valuable insights for future research and technological advancements.

Figure 3 shows the trend from 1998 to 2024 reveals a steady rise in publications, particularly after 2010, fueled by advancements in EEG technology and its expanding practical applications. Key drivers include improvements in EEG equipment, reduced costs, and growing interest in leveraging machine learning and AI for optimizing EEG signal processing. The period between 2015 and 2020 saw notable growth, spurred by technological breakthroughs, increased research funding, and the demand for MI-BCI, especially in healthcare. Although the 2020 pandemic caused a brief dip in publications, rates rebounded in 2021. Binary classification research remains a central focus in 2023 and 2024, with ongoing developments in medical devices and rehabilitation continuing to drive interest and ensure further progress in MI-BCI technology.

4.2. Overview and analysis of motor imagery binary classification

This section provides a preliminary analysis of the binary classification text database to evaluate the current research status of two-category

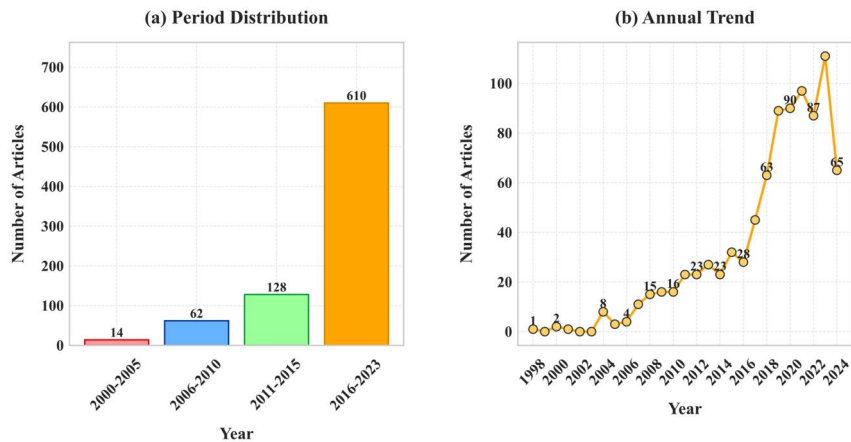


Figure 3. Trend chart of the number of articles in recent years.

motor imagery in brain-computer interfaces (BCIs). The first focus is the statistical analysis of motor imagery actions, highlighting their distribution. Figure 4 reveals that most motor imagery actions are infrequent, with only a few, such as left-hand and right-hand imagery, exceeding 150 occurrences. In contrast, other actions occur fewer than 25 times, indicating that left and right-hand imagery dominate experimental designs, while other actions are less commonly used. The category labeled “Other” encompasses a variety of infrequent motor imagery actions. For example, combinations like right-hand fist clenching versus right-foot movement imagery and left-hand little finger versus tongue movement imagery each occur three times, as do left-hand versus right-hand grasping imagery. Additionally, actions such as shoulder horizontal abduction versus adduction and cursor movement imagery (up versus down) are represented only twice. Several actions, including elbow flexion versus extension, foot movement versus left-hand movement, and sensory imagery (SI), appear just once, highlighting their limited use in experimental designs compared to more prevalent tasks like hand movement imagery.

Next, we analyze the types and distribution of feature extraction methods. It is important to note that the articles considered here include only those that propose new feature extraction methods for binary classification or compare other methods with those proposed. The results reveal a diverse range of methods: hybrid feature extraction methods are mentioned 87 times, while CSP methods are used 55 times. However, the actual application of CSP methods far exceeds 55 instances. Hybrid feature extraction methods are frequently employed to extract spatial features, while many CSP-based methods have been enhanced and are classified as improved CSP approaches in this study. This highlights the

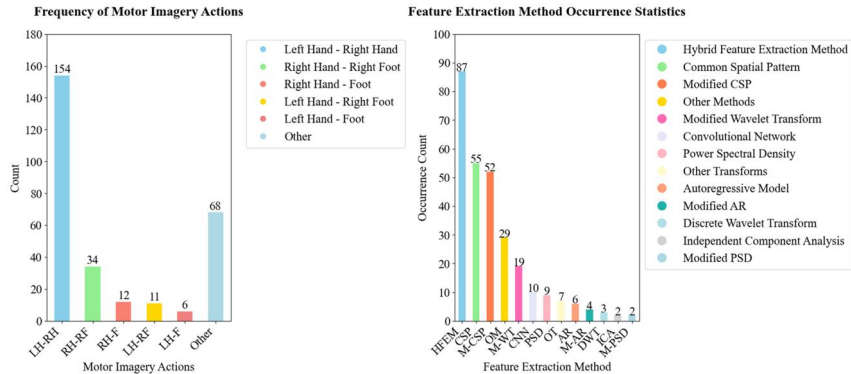


Figure 4. Statistics of research actions and methods for motor imagery classification. The left figure shows the current status of research on motor imagery actions. The right figure shows the current status of research on feature extraction methods.

high prevalence of CSP methods among traditional feature extraction techniques. In contrast, AR models are used less frequently. The popularity of hybrid feature extraction methods can be attributed to their ability to integrate multiple technologies, providing greater robustness and generalization across tasks. On the other hand, CSP, as a traditional spatial filtering method, is widely adopted for addressing EEG signal classification challenges, prompting researchers to combine it with other techniques to enhance accuracy and stability.

Figure 5 shows the usage trends of feature extraction methods from 2014 to 2024. It is worth noting that the hybrid feature extraction method surges to 34 applications in 2024. The modified CSP method exhibited a gradual increase from 2019, with significant activity in 2023 and 2024. Conversely, the usage frequencies of other methods, such as PSD and AR models, remained stable but lower than mainstream methods. An increasing adoption of hybrid feature extraction methods reflects a growing trend among researchers to integrate multiple signal processing techniques for the analysis of complex EEG signals. Concurrently, the increasing adoption of modified CSP reflects ongoing efforts to optimize traditional approaches and enhance classification performance. This trend demonstrates a demand for hybrid methods, likely linked to the need for higher accuracy in classification tasks and the expansion of their application areas.

The analysis highlights trends in action types and feature extraction methods utilized in motor imagery research from multiple perspectives. Left- and right-hand motor imagery movements, along with hybrid

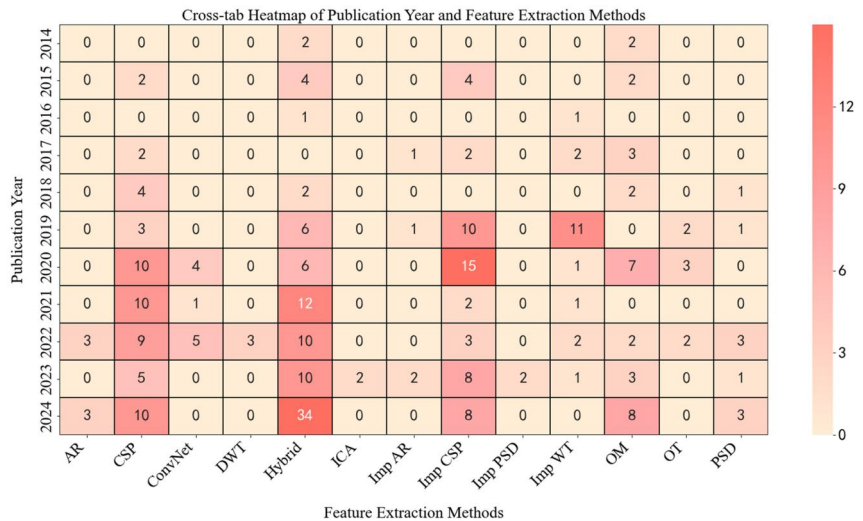


Figure 5. Heat map of correlation between year and feature extraction method.

feature extraction methods, are the most prevalent in studies, likely due to their significant contributions to improving EEG signal classification accuracy. Additionally, the rapid growth in the use of modified CSP methods in recent years indicates a recognition of their optimization potential.

The diversity of motor imagery movements, particularly the commonly used left- and right-hand movements, directly influences the selection of feature extraction methods. Simple motor tasks are well-suited for classic approaches like CSP, while more complex tasks promote the advancement of hybrid methods. Over time, the evolution of feature extraction methods and the complexity of experimental designs have mutually influenced one another. The continuous refinement of feature extraction techniques has allowed researchers to address increasingly complex motor imagery tasks, and the demands of these tasks have driven the development of new methodologies.

4.3. Network meta-analysis

This section utilizes a network meta-analysis to thoroughly assess the comparative efficacy of various feature extraction methods in MI-BCI. The analysis permits direct comparisons between methods and, through indirect comparisons, allows us to gauge the relative strengths and weaknesses of methods that have not been directly contrasted. The network diagram, which serves as an introduction to the network meta-analysis, visualizes the interrelationships among different feature extraction methods, providing a basis for evaluating their classification performance. Each node in the network diagram represents a specific feature extraction method. The connecting lines between nodes indicate direct comparisons made between different methods; the thickness of these lines corresponds to the frequency of such comparisons, with thicker lines representing more frequent direct comparisons. [Figure 6](#) highlights that methods such as CSP (A), Improved CSP (B), and PSD (H) are frequently compared methods, as indicated by the number of lines connecting them to other nodes. The network's density suggests extensive comparisons among methods, enabling the inclusion of methods with fewer direct comparisons through indirect analysis. The methods depicted in the network diagram have been widely studied, confirming the suitability of this dataset for network meta-analysis.

4.3.1. Statistical evaluation of MI-BCI feature extraction methods

This network meta-analysis conducted a thorough statistical evaluation of multivariable feature extraction methods employed in MI-BCI. Utilizing

iterations between 20,001 and 25,000 and four chains with a sample size of 5,000 per chain, this robust design ensures high statistical power and convergence, facilitating reliable comparisons among various methods. Means and standard deviations were calculated for each variable to assess the effectiveness of the methods. The specific comparison of standard deviations, mean values and more information are shown in Table 4. The analysis revealed nuanced differences in performance. For instance, the comparison between the CSP approach and modified CSP indicated a slight positive effect, suggesting minimal differences between these two approaches. However, a significant negative effect was observed when comparing the CSP approach with modified AR, highlighting the considerable variability in effectiveness depending on specific applications. Notably, comparisons involving the CSP approach with CNN and Hybrid feature extraction method demonstrated more pronounced positive effects, suggesting these methods excel in high-precision tasks. This variability underscores the necessity for careful selection of feature extraction methods tailored to specific BCI applications.

In this network meta-analysis, we comprehensively assessed the performance of CSP-A relative to other feature extraction methods. The quantile analysis in Table 5 and Figure 7 shows that CSP-A performs slightly worse than Improved CSP-B, with a median difference of 0.03 and small variance, suggesting that the improvements in the CSP model lead to enhanced performance. However, when compared to AR-C, CSP-A demonstrates similar performance with a median difference of -0.01 , highlighting their comparable effectiveness. The large variance observed in the comparison with Improved AR-D (median difference of -0.20209 ,

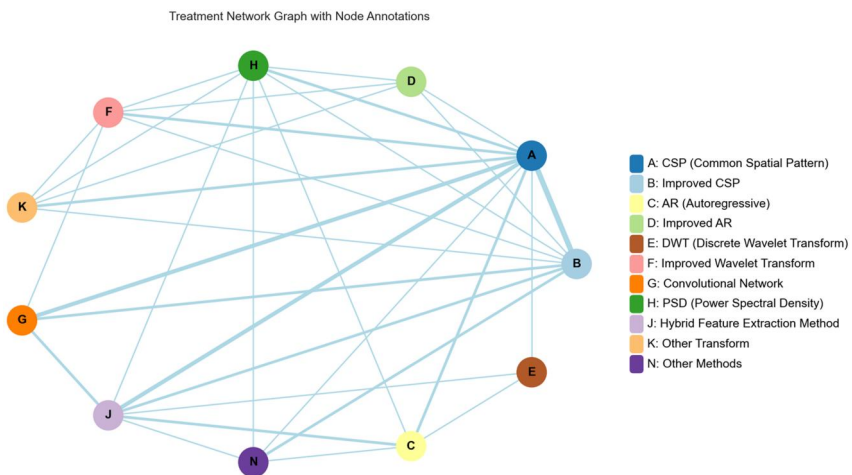


Figure 6. Network diagram of feature extraction methods.

Table 4. Empirical mean and standard deviation for each variable.

Variable	Mean	SD	Naïve SE	Time-series
<i>d.A.B</i>	0.030	0.040	0.000	0.001
<i>d.A.C</i>	−0.011	0.071	0.000	0.001
<i>d.A.D</i>	−0.200	0.535	0.004	0.050
<i>d.A.E</i>	−0.033	0.113	0.001	0.002
<i>d.A.F</i>	0.055	0.082	0.001	0.002
<i>d.A.G</i>	0.089	0.040	0.000	0.001
<i>d.A.H</i>	0.031	0.085	0.001	0.002
<i>d.A.J</i>	0.094	0.044	0.000	0.001
<i>d.A.K</i>	−0.019	0.114	0.001	0.003
<i>d.A.N</i>	0.024	0.066	0.000	0.001
<i>Sd.d</i>	0.068	0.021	0.000	0.001

Note: *d.A.B* ... *d.A.N* represent the differences in effect size between the first method (CSP) and other feature extraction methods. Specifically, *d.A.B* refers to the comparison between traditional CSP and improved CSP, *d.A.C* refers to the comparison between traditional CSP and another method, and so on, with *d.A.N* representing the comparison between traditional CSP and the last method in the list. The values indicate the effect size differences in pairwise comparisons. Naïve SE and Time-series SE refer to the standard errors that measure the uncertainty of the mean, with smaller values indicating less uncertainty in the estimates. The feature extraction methods represented by the letters in the figures are as follows: A stands for CSP, B for Improved CSP, C for AR-C, D for Improved AR, E for DWT, F for Improved Wavelet Transform, G for Convolutional Network, H for PSD, I for ICA, J for Hybrid Feature Extraction Method, K for Other Transform, M for Improved PSD, and N for Other Methods.

Table 5. Quantiles for each variable.

Variable	2.5%	25%	50%	75%	97.5%
<i>d.A.B</i>	−0.050	0.004	0.030	0.055	0.109
<i>d.A.C</i>	−0.149	−0.058	−0.012	0.035	0.130
<i>d.A.D</i>	−1.190	−0.564	−0.202	0.140	0.890
<i>d.A.E</i>	−0.254	−0.108	−0.034	0.043	0.191
<i>d.A.F</i>	−0.105	0.001	0.056	0.109	0.218
<i>d.A.G</i>	0.009	0.065	0.090	0.115	0.168
<i>d.A.H</i>	−0.135	−0.026	0.031	0.087	0.200
<i>d.A.J</i>	0.010	0.065	0.093	0.122	0.186
<i>d.A.K</i>	−0.237	−0.095	−0.019	0.058	0.208
<i>d.A.N</i>	−0.105	−0.019	0.024	0.068	0.154
<i>Sd.d</i>	0.037	0.054	0.065	0.080	0.118
Model fit			<i>Dbar</i>	<i>pD</i>	<i>DIC</i>
			31.260	29.22	60.487

Note: Different percentiles (2.5, 25, 50, 75, and 97.5%) are used to observe the distribution of variable values in different intervals and to evaluate the uncertainty range of the variables and the distribution characteristics of the results.

variance difference is 0.535) suggests that the performance of AR-D is unstable, and thus, a clear superiority relationship cannot be established. This indicates the need for further examination of Improved AR-D's performance, especially its sensitivity to data characteristics, which may account for the large variability.

While CSP-A performs reasonably well in comparison to methods like DWT-E, with a median difference of −0.03, it shows a noticeable gap when compared to more advanced methods such as the Hybrid Feature Extraction Method-J and Convolutional Networks (CNN), where the

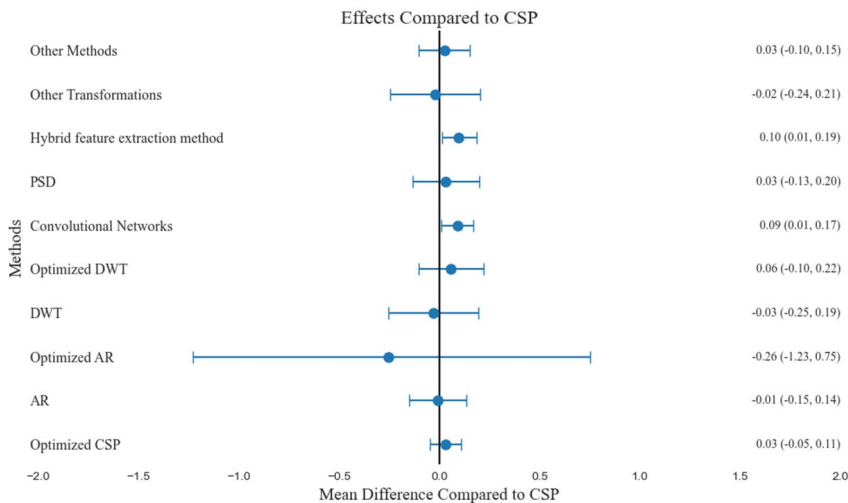


Figure 7. Forest plot for comparison between meta-analysis and CSP.

median differences are 0.1 and 0.09, respectively. These results suggest that Hybrid-J and CNN outperform CSP-A significantly in terms of performance, although the computational complexity of these methods is much higher, making them less practical in resource-constrained environments. The trade-offs between performance and computational cost are crucial when selecting an appropriate feature extraction method for specific applications. These findings underscore the need for a nuanced approach in evaluating feature extraction methods, where factors like stability, computational efficiency, and performance gains must be carefully balanced.

Additionally, the DIC value for model fit assessment is 60.487, signifying a good model fit. An overall heterogeneity measure of 0% suggests no significant variability among the included samples, providing a reliable quantitative foundation for evaluating feature extraction methods in MI-BCIs. These findings underscore the need for further research and optimization, emphasizing the importance of a nuanced understanding of each method's performance across diverse experimental conditions.

4.3.2. Sorting probability analysis

Analysis of the individual ranking probability plots in Figure 8 reveals significant performance differences among the examined methods. Modified AR emerges as the top performer, achieving a first-place ranking probability of 0.24815. However, this method also demonstrates polarized performance, with a substantial probability of 0.56780 for ranking 11th. Such

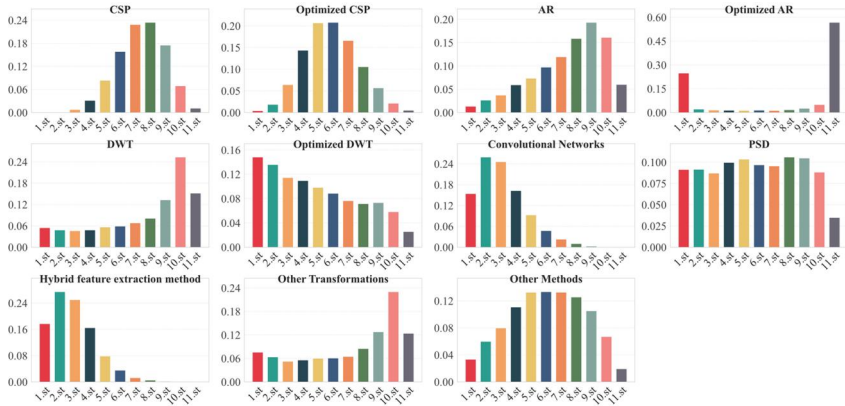


Figure 8. Ranking probability plot of 11 feature extraction methods. The short lines on the bar chart indicate small values.

variability indicates that while Modified AR excels in certain contexts, it may struggle under different conditions. This underscores the necessity for optimization across diverse datasets and tasks to ensure stable outcomes in practical applications [84].

In contrast, CSP and modified CSP demonstrate more consistent and balanced performance. Both methods generally rank between 4th and 8th, making them suitable choices for applications that prioritize reliability over peak performance. CSP has a probability of 0.15845 for achieving 6th place and 0.22855 for 7th place, indicating its robustness. Method B shows a slight advantage, with probabilities favoring ranks between 2nd and 5th, particularly achieving a 0.14360 probability for 4th place. The broader distributions of these two methods make them favorable for scenarios with moderate demand [85]. Additionally, some methods stand out in higher rankings, specifically CNN and Hybrid feature extraction method. GNN has a notable probability of 0.25940 for securing 2nd place and 0.24595 for 3rd place. Its success can be attributed to its deep learning architecture, which facilitates effective feature extraction from complex EEG signals. Similarly, Hybrid feature extraction method displays high probabilities for 2nd and 3rd places at 0.27440 and 0.25015, respectively. Given the cumulative probabilities, GNN and Hybrid feature extraction method are distinguished by their superior overall performance and stability, indicating significant potential for development. On the lower end of the spectrum, other transformations and other methods consistently perform poorly, often appearing in the 7th to 11th rankings. Their higher probabilities for lower positions suggest limited effectiveness and applicability, reinforcing the importance of careful selection when choosing feature extraction techniques for practical use.

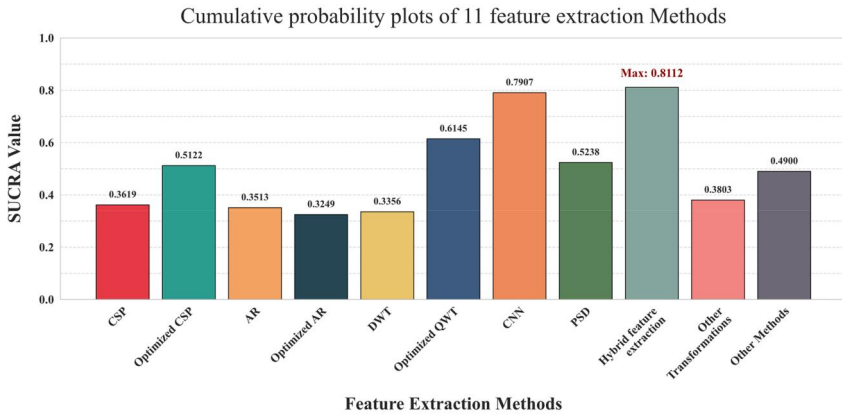


Figure 9. Cumulative probability plots of 11 feature extraction methods. SUCRA (Surface Under the Cumulative Ranking Curve) values represent the probability that a particular method is the best among all methods compared in the analysis. A SUCRA value of 1 indicates that the method has a 100% chance of being the best, while a value closer to 0 indicates a lower probability. SUCRA values provide a comprehensive ranking of the methods, taking into account both direct and indirect comparisons within the network meta-analysis. Higher SUCRA values indicate better performance and a higher likelihood of superiority in the context of the classification tasks evaluated.

4.3.3. Cumulative probability analysis

The comparative performance of these methods in the binary classification task is further illustrated by the cumulative probability data analyzed by SUCRA values shown in Figure 9. Hybrid feature extraction method leads with a SUCRA value of 0.811, indicating that it has excellent classification ability and is well suited for applications requiring high accuracy. modified wavelet transform also shows good results with a SUCRA value of 0.614, indicating good classification ability and stability under various conditions [86]. Conversely, improved CSP and PSD achieve SUCRA values of 0.512 and 0.523, respectively, indicating their reliability and effectiveness in moderate precision tasks. Traditional methods, such as CSP and AR, exhibit weaker performance, with SUCRA values of 0.362 and 0.351, respectively, suggesting that they may not be suitable for high-stakes applications. Furthermore, improved AR and Other Transformations present SUCRA values below 0.4, indicating significant uncertainty regarding their classification effectiveness.

5. Discussion and conclusion

This review focuses on MI-BCI technology and aims to systematically evaluate the role of various feature extraction methods in motor imagery

classification to enhance classification accuracy. The article summarizes trends in the number of publications related to motor imagery classification over the past two decades, revealing the research intensity and developmental dynamics in this field. By combining motor imagery actions with the selected feature extraction methods, the study employs statistical analysis to observe current research trends, providing deep insights into the forefront of the field [87–89]. Furthermore, the review conducts an in-depth statistical analysis and network meta-analysis on popular binary classification tasks, uncovering deeper insights within the data. This analysis helps identify performance differences among various feature extraction methods and reveals their effectiveness and limitations in practical applications [90]. Through this systematic evaluation, we aim to provide valuable references for future research and contribute to the development and innovation of motor imagery classification technology, ultimately promoting its practical implementation in applications such as medical devices and rehabilitation training [13]. It is important to note that the majority of the studies evaluated in this review are based on offline analyses, utilizing pre-collected datasets. These studies primarily focus on feature extraction and classification methods applied to static datasets, rather than real-time data streams. As such, while the performance of methods like the Hybrid Feature Extraction Method and CNN is exceptional in these offline contexts, the effectiveness of these methods in real-time systems may vary depending on factors such as computational resources and task complexity. This limitation should be taken into account when interpreting the applicability of these results to real-time BCI systems.

This meta-analysis highlights the varying effectiveness of different feature extraction methods in MI-BCI, particularly in both binary and multi-class classification tasks [91]. A key observation is the performance variability associated with certain methods, notably Improved Wavelet Transform. While this method demonstrates exceptional capabilities in suitable contexts, it may underperform in specific scenarios compared to other techniques. This variability underscores the necessity for context-specific optimization, as its effectiveness can significantly depend on the nature of the task and the complexity of the EEG signals involved. In contrast, methods like the Hybrid Feature Extraction Method and Convolutional Neural Network consistently exhibit substantial advantages, showcasing strong performance in classification accuracy and stability, especially in high-precision scenarios. The Hybrid Feature Extraction Method achieves the highest SUCRA value of 0.811, underscoring its outstanding overall performance. However, despite its advantages, the Hybrid Feature Extraction Method can be complex to implement and computationally demanding, as it often requires careful integration of multiple features, which may increase the overall processing time and

hinder real-time application. Similarly, while CNNs exhibit remarkable accuracy, their effectiveness can be limited by the need for large labeled datasets and the significant computational resources required for model training [1]. These methods can also be less suitable for environments with limited resources, such as in portable BCI systems. Consequently, these advanced feature extraction methods should be prioritized in future research aimed at high-performance classification tasks, but researchers should also explore ways to address these challenges, such as improving computational efficiency and developing methods that require fewer data to achieve comparable performance [16,92].

As task complexity increases, there is a clear trend toward the adoption of hybrid methods [74,93–95]. Researchers increasingly recognize the need for sophisticated signal processing solutions to tackle the challenges posed by intricate classification tasks. The integration of multiple feature extraction techniques facilitates a more comprehensive capture of the multi-dimensional information inherent in EEG signals, thereby enhancing classification accuracy and model adaptability. While classic methods like CSP remain dominant for simpler motor imagery tasks due to their suitability for straightforward identification, hybrid methods and deep learning-based approaches are becoming focal points of research as task complexity rises—particularly with more intricate movements such as shoulder or finger motions. This trend indicates that as experimental designs evolve, researchers increasingly rely on robust feature extraction methods to effectively manage intricate EEG signals and improve classification accuracy and stability. Given that most studies included in this review are based on offline data, the findings should be interpreted with caution when considering real-time applications. Future research should aim to validate these methods in real-time systems and explore optimizations for reducing computational demands and increasing adaptability to real-world conditions.

In summary, the performance of feature extraction methods in MI-BCI is largely determined by task complexity and method adaptability. Notably, Improved Wavelet Transform, the Hybrid Feature Extraction Method, and CNN exhibit outstanding classification performance, especially in high-precision tasks, and should be prioritized in future research and applications. Meanwhile, classic methods such as CSP, AR, and Improved AR remain valuable in certain contexts but require further optimization to effectively tackle more complex tasks [66,96]. The relatively lower SUCRA values associated with these traditional methods suggest that while they may still be applicable for simpler motor imagery tasks, their effectiveness diminishes with more intricate movements. The emergence of hybrid methods reflects the current demand for efficient signal

processing techniques and underscores the evolving direction of research in the field [97]. By integrating various feature extraction techniques, hybrid methods are better positioned to capture the multi-dimensional information inherent in EEG signals, thus enhancing classification accuracy and model adaptability. These findings provide a solid theoretical foundation for selecting and optimizing feature extraction methods in future BCI studies, especially in scenarios involving complex classification challenges. Researchers are encouraged to explore the potential of advanced methods while continuing to refine classic techniques to ensure comprehensive coverage of the diverse requirements in motor imagery tasks.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the Project of Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai) [#SML2023SP203] and National Natural Science Foundation of China [#62006197]; the Project of Science and Technology Department of Sichuan Province [#2018JY0526].

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