COLOMBO SCIENTIFIC PUBLISHING

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM
E-ISSN: 2536-7919
P-ISSN: 2536-7900

https://doi.org/10.55640/ijcsis/Volume11Issue08-05 PAGE NO: 46-58

Intelligent Channel Selection Using Advanced Computational Intelligence Methods

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ARTICLE INFO

Article history:
Submission: June, 2026
Accepted: July 31, 2026
Published: August 12, 2026
VOLUME: Vol.11 Issue 08 2026

Keywords:
Brain-Computer Interface, EEG, Channel Selection, Computational Intelligence, Deep Learning, Feature Selection, P300 Speller, Machine Learning, Signal Processing, Artificial Intelligence.

ABSTRACT

Brain–computer interface (BCI) technology has emerged as a transformative communication paradigm by enabling direct interaction between the human brain and external computing systems. Electroencephalography (EEG)-based BCIs, particularly P300 speller systems, have demonstrated considerable potential for assistive communication, neurorehabilitation, and intelligent human–computer interaction. However, the high dimensionality of EEG recordings, redundancy among channels, and susceptibility to noise significantly reduce classification accuracy while increasing computational complexity. Consequently, intelligent channel selection has become a critical research area for improving the efficiency, reliability, and scalability of EEG-based BCI systems. This review synthesizes recent developments in computational intelligence approaches for channel selection, including filter, wrapper, embedded, hybrid, and deep learning-based techniques. The article critically examines theoretical foundations, algorithmic characteristics, performance trade-offs, and practical implications of these approaches within modern BCI environments. Furthermore, an integrated intelligent computational framework is proposed to explain how advanced computational intelligence can optimize channel selection while balancing classification accuracy, computational cost, and real-time processing requirements. Comparative analysis of existing studies demonstrates that hybrid computational intelligence strategies consistently outperform conventional statistical approaches by effectively capturing nonlinear EEG relationships and adaptive channel importance. The review also identifies current research challenges involving subject variability, model interpretability, computational scalability, and deployment in real-world clinical environments. Overall, Intelligent Channel Selection Using Advanced Computational Intelligence Methods provides a comprehensive research perspective that supports future development of adaptive, explainable, and computationally efficient EEG signal processing systems.

INTRODUCTION

1.1 Background

Transportation Brain–computer interfaces (BCIs) establish a direct communication pathway between neural activity and external devices without relying on conventional muscular movements. Electroencephalography (EEG) remains the most widely adopted acquisition technique because it is non-invasive, portable, relatively inexpensive, and capable of providing high temporal resolution. Since the pioneering work on BCI communication systems, EEG-based interfaces have become increasingly important for assistive technologies, neurorehabilitation, cognitive monitoring, and intelligent healthcare applications (Wolpaw et al., 2002).

Among various EEG paradigms, the P300 event-related potential has attracted substantial attention because of its reliability and effectiveness in communication systems. The P300 speller introduced a practical method enabling patients with severe motor disabilities to communicate through selective attention toward flashing characters (Farwell & Donchin, 1988). Subsequent developments have enhanced system robustness, classification accuracy, and user adaptability, making P300-based BCIs one of the most successful practical implementations in neuroscience and biomedical engineering (Krusienski et al., 2008).

Despite continuous progress, EEG signals remain highly complex due to their nonlinear behavior, low signal-to-noise ratio, inter-subject variability, and high-dimensional recording characteristics. Modern EEG systems may collect signals from dozens or even hundreds of electrodes simultaneously. Although increasing channel numbers potentially capture richer neural information, they also introduce redundant features, higher computational costs, increased training time, and greater susceptibility to artifacts. Consequently, intelligent channel selection has emerged as a fundamental preprocessing task that directly influences classifier performance and system efficiency (Alotaiby et al., 2015).

The growing availability of computational intelligence techniques—including machine learning, optimization algorithms, hybrid learning models, and deep neural architectures—has fundamentally transformed channel selection methodologies. Rather than relying solely on expert knowledge or statistical heuristics, intelligent computational models automatically identify informative EEG channels while adapting to subject-specific neural characteristics. This evolution forms the central motivation behind **Intelligent Channel Selection Using Advanced Computational Intelligence Methods**, which emphasizes computational adaptability, predictive optimization, and efficient signal representation.

1.2 Problem Statement

EEG datasets inherently contain substantial redundancy because neighboring electrodes frequently record correlated neural activity. Incorporating all available channels into classification models often leads to unnecessary computational burden without proportional improvements in predictive accuracy. Moreover, redundant channels may amplify noise, increase model overfitting, and reduce generalization across different users and recording sessions.

Traditional manual channel selection depends heavily upon neurophysiological expertise and anatomical knowledge. Although expert-driven selection remains valuable, it lacks scalability, reproducibility, and adaptability across heterogeneous EEG datasets (Alotaiby et al., 2015). Statistical feature selection methods partially address these limitations but often fail to model complex nonlinear dependencies among EEG channels.

Recent computational intelligence methods have demonstrated promising capabilities for adaptive channel optimization. Nevertheless, existing approaches exhibit considerable diversity regarding algorithmic complexity, optimization objectives, computational efficiency, and classification performance. Consequently, there remains a need for a systematic synthesis that evaluates intelligent computational approaches under a unified analytical framework.

1.3 Research Relevance

The significance of intelligent channel selection extends beyond computational optimization. Efficient electrode reduction directly improves user comfort by minimizing electrode placement time and simplifying wearable EEG devices. Reduced channel configurations also decrease hardware costs, accelerate signal processing pipelines, lower power consumption, and facilitate real-time deployment in portable BCI platforms.

Advanced computational intelligence enables adaptive learning from complex EEG patterns that cannot be effectively modeled using conventional linear algorithms. Deep learning architectures, optimization-based feature selection, ensemble learning, and knowledge distillation methods have collectively expanded the capability of intelligent EEG analysis. These innovations contribute toward more reliable communication systems for individuals with neurological disorders while simultaneously supporting broader applications in cognitive assessment and human–computer interaction.

Therefore, **Intelligent Channel Selection Using Advanced Computational Intelligence Methods** represents a timely research direction that integrates computational intelligence with practical BCI implementation.

1.4 Research Objectives

This review aims to achieve several interconnected objectives.

First, it critically examines the theoretical foundations of EEG channel selection within brain–computer interface systems.

Second, it analyzes existing computational intelligence approaches used for intelligent channel optimization.

Third, it compares algorithmic strengths, limitations, and practical performance across diverse channel selection methodologies.

Fourth, it proposes an integrated computational intelligence framework capable of improving channel selection efficiency while maintaining classification accuracy.

Finally, the study identifies future research opportunities involving adaptive learning, explainable artificial intelligence, and personalized EEG optimization.

1.5 Scope and Significance

The scope of this article focuses exclusively on computational intelligence techniques for EEG channel selection within P300-based brain–computer interfaces and related EEG classification systems. Rather than reviewing all EEG preprocessing methods, emphasis is placed on intelligent optimization strategies responsible for selecting informative electrode subsets.

From a scientific perspective, the review contributes by integrating findings across multiple computational paradigms into a coherent analytical framework. From an engineering perspective, the study provides practical guidance regarding algorithm selection under varying computational constraints. Clinically, intelligent channel selection has important implications for improving accessibility of assistive communication technologies for patients with severe motor impairments.

LITERATURE REVIEW

2.1 Evolution of EEG-Based Brain–Computer Interfaces

The conceptual foundation of modern BCIs was established through the demonstration that EEG signals could be translated into meaningful control commands for external systems. Wolpaw et al. (2002) provided one of the earliest comprehensive discussions of brain–computer communication, emphasizing the integration of neurophysiology, signal processing, and adaptive learning for effective BCI operation. Their work established channel selection as an essential component influencing signal quality, computational complexity, and communication reliability.

The introduction of the P300 speller represented another landmark advancement. Farwell and Donchin (1988) demonstrated that event-related potentials generated through selective attention could enable users to communicate without muscular activity. Their findings established the P300 paradigm as one of the most influential EEG applications, motivating decades of research into signal enhancement, feature extraction, and channel optimization.

Later developments significantly improved system performance through algorithmic refinement. Schalk et al. (2004) introduced the BCI2000 platform, providing a standardized software architecture that facilitated reproducible experimentation across different laboratories. This flexible platform accelerated investigation into intelligent signal processing techniques and comparative evaluation of channel selection strategies.

2.2 Importance of Channel Selection in EEG Signal Processing

Channel selection addresses one of the central challenges of EEG analysis: identifying informative electrodes while eliminating redundant or noisy channels. Excessive channel numbers increase dimensionality, computational cost, and overfitting risk without necessarily improving classification accuracy.

Alotaiby et al. (2015) presented one of the most comprehensive reviews of EEG channel selection methodologies. Their analysis categorized existing approaches into manual selection, filter methods, wrapper methods, embedded techniques, and hybrid optimization strategies. The review concluded that no universal algorithm consistently outperforms others because optimal channel subsets depend on recording conditions, classifier architecture, and application objectives.

Manual channel selection remains computationally inexpensive but relies heavily on expert neurophysiological knowledge. Conversely, automated computational approaches improve reproducibility and scalability while adapting to subject-specific neural activity.

2.3 Computational Intelligence Approaches

Computational intelligence has substantially expanded the capability of EEG channel optimization by incorporating adaptive learning and nonlinear decision-making.

Filter-based approaches independently evaluate channel relevance using statistical criteria. Their computational efficiency makes them suitable for large-scale EEG datasets, although they frequently ignore interactions among selected channels (Baig et al., 2020).

Wrapper methods integrate feature selection directly with classifier performance, enabling identification of channel subsets optimized for predictive accuracy. However, iterative search procedures substantially increase computational requirements, particularly for high-dimensional EEG datasets (Alotaiby et al., 2015).

Embedded techniques incorporate feature selection within model training, reducing overfitting while improving computational efficiency. These methods balance predictive accuracy and optimization complexity more effectively than purely filter-based strategies.

Hybrid computational intelligence models combine multiple optimization paradigms to exploit complementary strengths. Such approaches increasingly dominate recent literature because they improve robustness under varying EEG characteristics.

2.4 Machine Learning and Intelligent Classification

The increasing complexity of EEG data has accelerated the adoption of machine learning for intelligent channel selection. Unlike conventional statistical methods, machine learning algorithms learn discriminative channel patterns directly from data, enabling adaptive optimization under varying recording conditions. This capability is particularly valuable because EEG signals exhibit substantial inter-subject and intra-subject variability, making fixed channel configurations less effective.

El Dabbagh and Fakhr (2011) demonstrated that ensemble support vector machine (SVM) classifiers improve P300 speller recognition compared with single-classifier approaches. Their work showed that classifier diversity enhances robustness against noisy EEG measurements and indirectly supports intelligent channel selection by emphasizing channels contributing most significantly to ensemble decision making. This study illustrates how classification performance and channel optimization are closely interconnected rather than independent preprocessing stages.

Krusienski et al. (2008) further highlighted that classifier performance depends heavily on the quality and distribution of selected EEG channels. Their investigation into enhanced P300 speller performance demonstrated that optimizing electrode placement significantly improves recognition accuracy while reducing computational overhead. Rather than simply increasing electrode numbers, intelligently selecting informative channels provides greater practical benefit.

These findings collectively suggest that computational intelligence should not only identify relevant channels but should simultaneously optimize feature representation and classifier learning.

2.5 Deep Learning and Knowledge Distillation

Recent advances in computational intelligence have shifted research toward deep neural architectures capable of learning hierarchical EEG representations. Deep learning eliminates much of the manual feature engineering traditionally required in EEG signal processing by automatically extracting discriminative characteristics from raw or minimally processed signals.

An important contribution is presented by Kshirsagar and Londhe (2022), who proposed DS-P3SNet, an efficient convolutional neural network incorporating channel-wise convolution and knowledge distillation for Devanagari script-based P300 spelling. Their framework significantly reduced computational complexity while maintaining competitive classification accuracy. Knowledge distillation transferred information from a larger teacher model to a compact student network, producing efficient deployment without substantial performance degradation.

The importance of this contribution extends beyond deep learning itself. Channel-wise convolution implicitly learns spatial importance across EEG electrodes, enabling simultaneous feature learning and channel optimization. Consequently, deep computational intelligence integrates channel selection directly into representation learning rather than treating it as an isolated preprocessing stage.

Such developments strongly support the research direction proposed in **Intelligent Channel Selection Using Advanced Computational Intelligence Methods**, where adaptive learning replaces manually designed feature engineering.

2.6 Feature Extraction and Channel Optimization

Feature extraction remains closely associated with channel selection because discriminative information depends upon both spatial electrode locations and temporal EEG characteristics.

Zahra et al. (2013) compared multiple feature extraction approaches for P300 detection and demonstrated that classification performance varies considerably according to extracted signal representations. Their comparative evaluation emphasized that channel selection alone cannot guarantee improved accuracy unless accompanied by appropriate feature extraction strategies.

Similarly, Baig et al. (2020) reviewed filtering techniques for motor imagery EEG applications and concluded that effective channel selection requires balancing computational efficiency with preservation of discriminative neural information. Excessive dimensionality reduction may eliminate informative channels, whereas insufficient reduction introduces redundant features that degrade classifier generalization.

Therefore, intelligent computational intelligence frameworks should jointly optimize feature extraction and channel selection rather than considering them independent tasks.

2.7 Clinical Applications and Adaptive BCI Systems

One of the principal motivations for intelligent EEG processing is improving assistive communication for individuals suffering from severe neurological disorders.

Nijboer et al. (2008) investigated P300-based BCI systems for patients with amyotrophic lateral sclerosis (ALS), demonstrating that intelligent EEG analysis can restore communication capabilities even when voluntary muscular control is absent. Their findings emphasize that computational efficiency directly influences practical usability because clinical environments require reliable real-time processing under varying physiological conditions.

Similarly, BCI2000 introduced by Schalk et al. (2004) provides an adaptable experimental platform supporting multiple signal acquisition protocols, classification algorithms, and channel configurations. Such flexibility facilitates continuous improvement of computational intelligence models while promoting reproducible evaluation across laboratories.

Collectively, these studies demonstrate that intelligent channel selection extends beyond algorithmic optimization; it directly contributes to improving quality of life through accessible assistive technologies.

2.8 Research Gap

Despite significant advances, several important research gaps remain evident.

Most existing channel selection approaches optimize either classification accuracy or computational efficiency rather than simultaneously balancing both objectives. High-performing wrapper methods frequently exhibit excessive computational cost, whereas efficient filter methods often overlook nonlinear channel interactions (Alotaiby et al., 2015).

Deep learning architectures demonstrate impressive predictive capabilities but generally require extensive training data and computational resources. Their internal decision processes also remain relatively opaque, limiting interpretability in clinical applications (Kshirsagar & Londhe, 2022).

Furthermore, subject-specific variability continues to challenge generalization. Channel subsets identified for one individual frequently perform poorly when applied to different users, indicating the need for adaptive computational intelligence capable of personalized optimization (Baig et al., 2020).

Current literature also lacks comprehensive frameworks integrating preprocessing, feature extraction, intelligent channel selection, classifier optimization, and continuous adaptive learning within a unified computational architecture.

Accordingly, **Intelligent Channel Selection Using Advanced Computational Intelligence Methods** addresses these gaps by proposing an integrated computational intelligence framework emphasizing adaptive optimization, computational efficiency, explainability, and practical deployment.

METHODOLOGY

3.1 Research Design

This article adopts a systematic research review methodology combined with conceptual framework development. The methodology synthesizes evidence exclusively from the provided literature to construct an integrated computational intelligence model for EEG channel selection. Rather than introducing a novel experimental dataset, the study evaluates theoretical principles, algorithmic developments, and practical implementation strategies reported across previous investigations.

The methodology consists of five interconnected phases:

1. EEG signal acquisition
2. Signal preprocessing
3. Intelligent channel selection
4. Machine learning classification

5. Adaptive performance optimization

This sequential architecture ensures that computational intelligence contributes throughout the complete EEG processing pipeline instead of functioning solely as a preprocessing component.

3.2 Conceptual Intelligent Computational Framework

The proposed framework integrates traditional EEG processing with modern computational intelligence techniques to maximize classification performance while minimizing computational complexity.

Phase 1: EEG Data Acquisition

Raw EEG signals are collected using multiple scalp electrodes positioned according to standardized recording protocols. Multi-channel acquisition captures spatial neural activity associated with P300 responses and cognitive processes.

However, raw EEG signals contain substantial redundancy because neighboring electrodes often measure correlated brain activity. Consequently, intelligent optimization begins immediately after acquisition.

Phase 2: Signal Preprocessing

Preprocessing removes unwanted artifacts before computational analysis.

Major preprocessing operations include:

- Noise suppression
- Baseline correction
- Signal normalization
- Artifact removal
- Temporal segmentation

These operations improve signal quality while preserving neurologically meaningful information required for subsequent computational learning.

Phase 3: Intelligent Channel Selection

This phase represents the core contribution of **Intelligent Channel Selection Using Advanced Computational Intelligence Methods**.

Rather than selecting electrodes manually, computational intelligence evaluates channel importance through adaptive optimization.

Potential intelligent approaches include:

- Filter-based relevance estimation
- Wrapper optimization
- Embedded feature learning
- Deep neural channel weighting
- Hybrid optimization algorithms

Each candidate channel receives an importance score based on predictive contribution rather than anatomical assumptions alone.

Adaptive learning continuously updates channel rankings as additional EEG observations become available.

Phase 4: Feature Learning and Classification

Following channel optimization, informative EEG signals undergo feature extraction and intelligent classification.

Representative computational intelligence algorithms include:

- Support Vector Machines
- Artificial Neural Networks
- Convolutional Neural Networks
- Ensemble Learning Models
- Knowledge Distillation Networks

Deep learning architectures simultaneously optimize feature representation and classification, reducing dependence upon manually engineered EEG descriptors.

Phase 5: Adaptive Feedback Optimization

The final phase continuously evaluates classification accuracy, computational cost, processing latency, and robustness.

Performance feedback is used to refine:

- Channel subsets
- Feature representations
- Classifier parameters
- Learning strategies

This adaptive optimization loop enables personalized channel selection across different users and recording sessions.

3.3 Theoretical Foundation

The proposed methodology is supported by three complementary theoretical principles.

First, computational intelligence assumes that nonlinear relationships among EEG channels contain valuable discriminative information beyond simple statistical correlations.

Second, adaptive learning theory suggests that optimal channel configurations vary across individuals, requiring continuous model updating instead of static electrode selection.

Third, intelligent optimization theory emphasizes multi-objective learning, simultaneously maximizing classification accuracy while minimizing computational complexity.

The integration of these principles enables computational intelligence to outperform conventional manually designed channel selection procedures in increasingly complex BCI environments.

3.4 Computational Intelligence-Based Channel Selection Model

The proposed framework employs an intelligent computational pipeline that combines adaptive learning with feature optimization. Unlike conventional methods that rely on fixed electrode configurations, the model dynamically evaluates the contribution of each EEG channel to classification performance. The computational workflow consists of four sequential stages:

1. **Channel Evaluation:** Individual EEG channels are assessed using relevance measures derived from machine learning models.

2. **Feature Optimization:** High-quality temporal and spatial features are extracted from the selected channels while eliminating redundant information.

3. **Classifier Training:** Optimized features are supplied to computational intelligence classifiers such as ensemble learning models, support vector machines, or convolutional neural networks.

4. **Performance Feedback:** Classification outcomes are continuously monitored to update channel rankings, ensuring adaptive optimization across different recording sessions.

This adaptive architecture minimizes computational cost while preserving discriminative neural information, making it suitable for real-time BCI applications.

3.5 Performance Evaluation Criteria

To assess the effectiveness of intelligent channel selection methods, four major performance indicators are considered.

Evaluation Metric	**Purpose**	**Importance**
Classification Accuracy	Measures prediction correctness	Indicates overall system performance
Computational Time	Measures processing efficiency	Critical for real-time BCI systems
Channel Reduction Rate	Measures dimensionality reduction	Indicates efficiency of channel selection
Model Robustness	Evaluates performance under noisy conditions	Determines practical reliability

These metrics collectively provide a balanced evaluation because channel selection should improve prediction accuracy without introducing excessive computational complexity.

3.6 Comparative Analysis of Intelligent Channel Selection Methods

Method	**Strengths**	**Limitations**	**Typical Applications**
Filter-Based Selection	Fast, computationally efficient	Ignores channel interactions	Large EEG datasets

Method	Strengths	Limitations	Typical Applications
Wrapper-Based Selection	High predictive accuracy	Computationally expensive	Offline optimization
Embedded Learning	Joint feature and channel optimization	Model-dependent	Machine learning classifiers
Deep Learning	Automatic feature extraction	Requires large datasets	Advanced EEG classification
Hybrid Computational Intelligence	Balances accuracy and efficiency	Complex implementation	Real-time adaptive BCIs

The comparison demonstrates that hybrid computational intelligence methods provide the most balanced trade-off between computational efficiency and predictive performance, supporting the central argument of **Intelligent Channel Selection Using Advanced Computational Intelligence Methods**.

RESULTS

The synthesized literature demonstrates that intelligent computational approaches consistently outperform conventional manual and statistical channel selection techniques across multiple evaluation criteria.

Traditional manual channel selection provides low computational overhead but suffers from poor reproducibility because electrode selection depends heavily on expert knowledge (Alotaiby et al., 2015). Statistical filter methods improve processing speed but frequently overlook nonlinear relationships among EEG channels, reducing classification effectiveness in complex datasets (Baig et al., 2020).

Wrapper-based approaches produce highly accurate channel subsets by directly optimizing classifier performance. However, their iterative search strategies substantially increase computational requirements, limiting real-time implementation. Embedded methods partially overcome this limitation by integrating channel selection into classifier training, thereby improving computational efficiency without significant performance degradation.

Recent deep learning architectures demonstrate the greatest potential for intelligent channel optimization. The DS-P3SNet model illustrates how channel-wise convolution and knowledge distillation enable simultaneous feature learning and channel selection while maintaining efficient computational performance (Kshirsagar & Londhe, 2022). This represents a significant advancement over traditional preprocessing techniques because feature extraction and channel optimization are learned automatically rather than manually engineered.

Clinical studies further indicate that optimized channel subsets improve communication performance in P300 speller systems without requiring large electrode arrays (Krusienski et al., 2008; Nijboer et al., 2008). Reduced channel configurations simplify EEG acquisition, improve user comfort, and facilitate deployment in portable assistive technologies.

Overall, the reviewed evidence supports several major findings:

- Intelligent computational intelligence significantly improves channel selection efficiency compared with manual methods.

- Hybrid and deep learning approaches provide superior classification performance by modeling nonlinear EEG relationships.
- Adaptive channel optimization reduces computational complexity while maintaining high predictive accuracy.
- Personalized channel selection remains essential because optimal electrode configurations vary among individuals.
- Future BCI systems will increasingly integrate adaptive computational intelligence with explainable learning strategies to support reliable clinical deployment.

These findings collectively validate the importance of **Intelligent Channel Selection Using Advanced Computational Intelligence Methods** as an emerging research direction for intelligent EEG signal processing.

DISCUSSION

The reviewed literature demonstrates a clear transition from expert-driven electrode selection toward adaptive computational intelligence capable of learning informative EEG representations directly from data. This transition reflects broader developments in artificial intelligence, where automated learning increasingly replaces manually designed decision rules.

One of the most important observations concerns the relationship between channel quantity and classification quality. Increasing electrode numbers does not necessarily improve predictive performance because redundant channels introduce additional computational burden and may amplify noise. Consequently, intelligent optimization should prioritize informative channel subsets rather than maximizing sensor coverage.

Theoretical analysis further indicates that computational intelligence offers advantages beyond prediction accuracy. Adaptive learning algorithms continuously update channel importance according to evolving EEG characteristics, enabling personalized optimization for different users. Such adaptability is particularly valuable in clinical BCI environments where neurological variability substantially influences signal characteristics.

Deep learning introduces another significant advancement by integrating feature extraction, channel weighting, and classification within a unified optimization process. Nevertheless, these models often require extensive computational resources and large training datasets, limiting deployment in resource-constrained clinical settings. Hybrid computational intelligence approaches therefore represent a practical compromise by combining efficient statistical preprocessing with advanced nonlinear learning.

Despite encouraging progress, several limitations remain. Many existing studies evaluate algorithms using relatively small datasets, reducing confidence in large-scale generalization. Furthermore, computational complexity remains an important barrier for real-time portable BCIs. Another challenge involves explainability. Deep neural networks frequently operate as black-box models, making clinical interpretation difficult. Future research should therefore integrate explainable artificial intelligence with adaptive channel optimization to improve transparency and user trust.

Overall, the evidence suggests that intelligent computational intelligence provides the most promising direction for future EEG channel selection. Continued development of adaptive, explainable, and computationally efficient models will facilitate broader adoption of BCI technologies across healthcare, rehabilitation, and human–computer interaction applications.

CONCLUSION

Intelligent EEG channel selection has become a fundamental component of modern brain–computer interface systems because it directly influences classification accuracy, computational efficiency, and practical usability. This review systematically examined computational intelligence techniques for channel optimization using only the selected literature. The analysis demonstrated that filter, wrapper, embedded, hybrid, and deep learning approaches each provide unique advantages while exhibiting different computational trade-offs.

The proposed conceptual framework integrates EEG acquisition, preprocessing, intelligent channel selection, adaptive feature learning, machine learning classification, and continuous performance optimization into a unified computational architecture. Comparative analysis indicates that hybrid computational intelligence and deep learning approaches consistently provide superior balance between prediction accuracy and computational efficiency compared with conventional manual methods.

The study contributes by synthesizing current knowledge into an integrated research perspective while highlighting future directions involving personalized optimization, explainable artificial intelligence, lightweight deep learning, and adaptive real-time BCI systems. As computational intelligence continues to evolve, intelligent channel selection will remain a central research area supporting more accurate, efficient, and clinically deployable EEG-based communication technologies.

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