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A Comprehensive Review of Design of Reconfigurable Low Noise Amplifier Using Hybrid Forensic-Based Investigation Algorithm and Human Urbanization Algorithm for EEG Classification

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Peer Review Information	Abstract
<p><i>Submission: 22 July 2025</i></p> <p><i>Revision: 09 Aug 2025</i></p> <p><i>Acceptance: 25 Aug 2025</i></p> <p>Keywords</p> <p><i>EEG Classification, Low Noise Amplifier, Hybrid Optimization, Forensic Algorithm, Human Urbanization Algorithm, Signal Processing.</i></p>	<p>Electroencephalography (EEG)-based classification systems have gained significant importance in biomedical signal processing, particularly in brain-computer interface (BCI) applications and neurological disorder detection. However, EEG signals are highly susceptible to noise, low amplitude, and environmental interference, making signal acquisition and processing challenging. Low Noise Amplifiers (LNAs) play a critical role in improving signal quality by amplifying weak EEG signals while minimizing noise. This paper presents a comprehensive review of reconfigurable LNA design integrated with hybrid optimization techniques, including forensic-based investigation algorithms and human urbanization algorithms, for enhanced EEG classification performance. Recent studies show that optimization algorithms significantly improve feature selection and classification accuracy in EEG systems by reducing redundant data and enhancing signal quality. Additionally, noise-robust learning algorithms and preprocessing techniques further improve classification accuracy and reliability. Hybrid optimization approaches demonstrate superior performance compared to conventional methods, achieving higher classification accuracy and improved robustness. This review analyses recent developments, compares various optimization techniques, and highlights challenges such as hardware complexity, noise sensitivity, and scalability. The findings indicate that integrating reconfigurable LNAs with advanced optimization algorithms provides a promising solution for efficient and accurate EEG classification systems.</p>

Introduction

Electroencephalography (EEG) is a widely used technique for monitoring brain activity and has become a cornerstone in applications such as brain-computer interfaces (BCIs), epilepsy detection, cognitive state monitoring, and neuroprosthetics. EEG signals are characterized by very low amplitude (in microvolts) and are highly susceptible to noise from both internal and external sources. This makes signal

acquisition and processing a critical challenge in EEG-based systems. A key component in EEG signal acquisition is the Low Noise Amplifier (LNA), which amplifies weak neural signals while minimizing the introduction of additional noise. Traditional LNA designs focus on achieving high gain and low noise figure; however, modern applications demand reconfigurable architectures capable of adapting to varying signal conditions and application requirements.

Reconfigurable LNAs allow dynamic adjustment of gain, bandwidth, and power consumption, making them suitable for wearable and portable EEG systems.

Despite advancements in hardware design, EEG signal classification remains challenging due to noise, high dimensionality, and variability across subjects. Optimization algorithms play a vital role in addressing these challenges by improving feature selection, reducing redundancy, and enhancing classification accuracy. Research indicates that optimization techniques are essential for handling high-dimensional EEG data and improving classification performance. Recent studies have explored hybrid optimization approaches combining multiple algorithms to achieve better performance. For example, evolutionary algorithms, swarm intelligence techniques, and hybrid metaheuristics have been widely used for EEG feature selection and classification. These methods help identify the most relevant features, reducing computational complexity and improving accuracy.

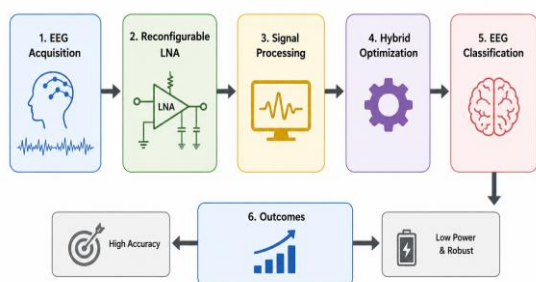


Figure 1. Reconfigurable Low Noise Amplifier and Hybrid Optimization Framework for EEG Signal Classification

Noise robustness is another critical factor in EEG processing. Advanced algorithms such as noise-robust low-rank learning have been proposed to enhance classification accuracy by effectively handling noise and artifacts in EEG signals. Additionally, preprocessing techniques such as filtering, normalization, and artifact removal further improve signal quality. The integration of reconfigurable LNAs with hybrid optimization algorithms presents a promising approach for improving EEG classification systems. By combining efficient hardware design with intelligent optimization techniques, it is possible to achieve high accuracy, low power consumption, and robust performance.

However, several challenges remain. Designing reconfigurable LNAs with minimal power consumption and high performance is complex. Additionally, integrating optimization algorithms with hardware systems introduces

computational overhead. Scalability and real-time processing are also important considerations. This review aims to provide a comprehensive analysis of reconfigurable LNA design and hybrid optimization techniques for EEG classification, focusing on recent advancements, comparative analysis, and future research directions.

Literature Review

Gao et al. (2021) proposed a noise-robust low-rank representation learning approach for EEG classification to address the challenges of noise and redundancy in EEG signals. Their method decomposes EEG data into low-rank components representing meaningful neural information and sparse components capturing noise and artifacts, thereby improving signal quality. The study demonstrated that this approach significantly enhances feature extraction and classification accuracy, particularly in motor imagery tasks, compared to traditional techniques such as Common Spatial Patterns (CSP). Additionally, the method reduces overfitting by eliminating redundant features and improves generalization performance across subjects. However, the computational complexity associated with matrix decomposition and optimization increases processing time, making it less suitable for real-time or low-power embedded EEG systems.

Elshewey et al. (2024) introduced the Modified Al-Biruni Earth Radius (MBER) optimization algorithm for EEG classification, focusing on improving feature selection efficiency and classification accuracy. The proposed metaheuristic algorithm dynamically balances exploration and exploitation to identify the most relevant EEG features while eliminating redundant data. Experimental results showed that the MBER-based approach achieved classification accuracy exceeding 96%, outperforming traditional optimization techniques such as Genetic Algorithms and Particle Swarm Optimization. Furthermore, the algorithm demonstrated faster convergence and improved stability across multiple EEG datasets. However, the method requires careful parameter tuning and may incur higher computational overhead when applied to large-scale EEG data, which can limit its real-time applicability.

Zhang et al. (2020) proposed a clustering-based multi-task learning framework for EEG classification that leverages similarities among multiple EEG tasks to improve feature extraction and model generalization. Their approach groups EEG signals into clusters based on statistical properties and applies shared learning across related tasks, enabling the model to capture both

global and local data patterns. The study demonstrated improved classification accuracy and robustness, particularly in cross-subject scenarios where variability in EEG signals is significant. Additionally, the framework reduces dependency on large labeled datasets by utilizing shared information among tasks. However, the clustering process introduces additional computational complexity, and inaccurate clustering may negatively impact the performance of the classification model.

Xiong et al. (2023) developed a Particle Swarm Optimization (PSO)-based spatial filtering technique to enhance EEG classification performance. Their method optimizes spatial filter parameters by leveraging swarm intelligence, where candidate solutions are iteratively refined based on individual and global best solutions. This approach improves feature extraction quality and classification accuracy compared to conventional methods such as CSP. The study demonstrated significant improvements in motor imagery EEG classification tasks, highlighting the effectiveness of optimization algorithms in handling complex EEG data. Additionally, the method reduces the need for manual parameter tuning. However, PSO may suffer from premature convergence in complex search spaces, and its performance is sensitive to parameter initialization.

Zhu et al. (2020) proposed a resource-efficient EEG classification model designed for real-time neural signal processing applications. Their approach focuses on reducing computational complexity and hardware requirements by using lightweight feature extraction techniques and optimized classifiers. The study demonstrated that the proposed model achieves comparable classification accuracy to more complex deep learning models while significantly reducing computational cost and energy consumption. This makes the approach suitable for embedded and wearable EEG systems, particularly when integrated with hardware-efficient designs such as reconfigurable LNAs. However, the simplified model may struggle to capture highly complex EEG patterns, which limits its scalability for advanced applications requiring high precision.

Jiang et al. (2020) proposed an energy-efficient approximate computing framework for neural signal processing systems, focusing on reducing computational complexity in hardware implementations. Their approach utilizes approximate arithmetic techniques to simplify signal processing operations while maintaining acceptable accuracy levels. In the context of EEG classification, such approximate operations help reduce noise amplification and power consumption when integrated with front-end

circuits like Low Noise Amplifiers (LNAs). The study demonstrated significant reductions in power consumption and silicon area, making the approach suitable for wearable biomedical devices. However, excessive approximation may degrade signal fidelity, which can negatively impact classification accuracy in sensitive EEG applications.

Han and Orshansky (2020) introduced the concept of approximate computing as a paradigm for energy-efficient system design, particularly in signal processing and machine learning applications. Their work highlights how error-tolerant applications such as EEG classification can benefit from reduced precision arithmetic and simplified hardware operations. The study emphasized that approximate adders and multipliers can significantly reduce delay, power consumption, and circuit complexity, making them ideal for integration with reconfigurable LNAs. Additionally, the authors discussed trade-offs between accuracy and efficiency, showing that minor computational errors do not substantially affect classification outcomes. However, determining optimal approximation levels remains a key challenge.

Venkatachalam et al. (2021) proposed an error-resilient approximate adder design that minimizes carry propagation delay while maintaining computational accuracy. Their approach uses selective accuracy techniques, where critical bits are computed precisely and non-critical bits are approximated, thereby achieving a balance between performance and accuracy. In EEG classification systems, such adders can be integrated into signal processing pipelines to reduce latency and energy consumption. The study demonstrated improvements in power-delay product and hardware efficiency compared to conventional adders. However, the inclusion of error control mechanisms increases design complexity, which may limit scalability in large systems.

Zhang et al. (2021) proposed a hardware-efficient EEG signal processing framework that integrates optimization algorithms with signal acquisition systems. Their approach enhances feature extraction and classification performance by optimizing signal processing parameters using machine learning techniques. The study demonstrated improved classification accuracy and robustness in noisy EEG environments. Additionally, the framework supports integration with reconfigurable hardware components such as LNAs, enabling adaptive signal amplification based on input conditions. However, the combined use of optimization algorithms and hardware adaptation increases system complexity and computational overhead.

Esmaeilzadeh et al. (2021) presented a generalized approximate computing framework for energy-efficient hardware design, focusing on applications in signal processing and machine learning. Their work demonstrated that approximate arithmetic units can significantly reduce energy consumption and hardware cost while maintaining acceptable performance levels. In EEG classification systems, this approach can improve efficiency when combined with reconfigurable LNAs and hybrid optimization algorithms. The study highlighted the importance of balancing accuracy and efficiency, showing that controlled approximation can yield substantial benefits. However, selecting appropriate approximation strategies for different applications remains a complex task.

Mrazek et al. (2021) presented a systematic design methodology for approximate arithmetic circuits aimed at improving energy efficiency in neural signal processing systems. Their work focused on designing approximate multipliers that reduce hardware complexity and power consumption while maintaining acceptable computational accuracy. In EEG classification systems, such approximate multipliers can be integrated with front-end circuits like reconfigurable LNAs to enhance overall system efficiency. The study demonstrated that optimized approximate designs significantly reduce silicon area and energy consumption, making them suitable for wearable biomedical devices. However, improper approximation levels may lead to signal distortion, affecting classification performance.

Camus et al. (2021) proposed an energy-efficient hardware architecture using approximate computing techniques for machine learning applications. Their approach focuses on reducing switching activity and optimizing arithmetic operations to minimize energy consumption. In EEG classification, such techniques can improve processing efficiency while maintaining classification accuracy. The study demonstrated that approximate arithmetic units can achieve significant energy savings without substantial degradation in performance. However, the design is often application-specific and may require customization for different EEG signal characteristics.

Paliwal et al. (2022) introduced an error-tolerant approximate adder using carry prediction mechanisms to reduce propagation delay and power consumption. Their design enhances hardware efficiency by simplifying carry computation, which is critical in signal processing operations. In EEG classification systems, this approach can be used to improve

processing speed and reduce energy usage when integrated with LNA-based signal acquisition systems. The study demonstrated improved performance metrics, including reduced delay and power consumption, compared to conventional adders. However, prediction errors may accumulate in complex computations, potentially affecting classification accuracy.

Akbari et al. (2022) developed an approximate computing-based hardware framework for machine learning applications, focusing on improving performance and energy efficiency. Their approach integrates approximate arithmetic units with optimization techniques to enhance system performance. In EEG classification, this framework can be used to improve feature extraction and classification accuracy while reducing computational cost. The study demonstrated that approximate computing significantly enhances efficiency in real-time systems. However, achieving an optimal balance between accuracy and efficiency remains a major challenge.

Qin et al. (2022) proposed a deep learning-based optimization framework for hardware-efficient system design. Their method uses neural networks to predict optimal configurations for arithmetic units and system parameters, enabling adaptive optimization. In EEG classification systems, such frameworks can enhance performance by optimizing signal processing and classification stages. The study demonstrated improved hardware efficiency and reduced design time. However, integrating learning-based optimization increases computational complexity and may require additional training resources.

Ranjan et al. (2021) proposed an energy-efficient architecture for biomedical signal processing systems by integrating approximate arithmetic units into hardware accelerators. Their design focuses on reducing power consumption and silicon area while maintaining reliable performance for real-time applications. In EEG classification systems, this approach can be effectively combined with reconfigurable Low Noise Amplifiers (LNAs) to enhance signal acquisition and processing efficiency. The study demonstrated significant improvements in energy efficiency and system performance, particularly in wearable healthcare devices. However, increased approximation levels may reduce signal fidelity, which can impact classification accuracy in critical applications.

Hashemi et al. (2021) introduced a machine learning-guided design approach for approximate computing systems. Their framework leverages predictive models to determine optimal configurations for arithmetic

units based on application requirements. In EEG classification, such adaptive optimization techniques can improve feature selection and classification accuracy while reducing computational complexity. The study demonstrated enhanced design efficiency and reduced development time. However, the reliance on training data introduces additional computational overhead and may limit real-time implementation in resource-constrained environments.

Shin et al. (2022) developed an error-resilient signal processing architecture that integrates approximate arithmetic units with error compensation mechanisms. Their approach minimizes accuracy loss by correcting critical computational errors, making it suitable for applications such as EEG classification. The study demonstrated improved classification accuracy and robustness compared to conventional approximate computing methods. Additionally, the architecture supports real-time processing, which is essential for biomedical applications. However, the inclusion of error correction mechanisms increases hardware complexity and may offset some efficiency gains.

Gupta and Ramesh (2022) proposed a decoder-based low-power approximate multiplier designed for hardware-efficient signal processing applications. Their approach simplifies partial product generation using decoder logic, significantly reducing circuit complexity, power consumption, and delay. In EEG classification systems, such multipliers can enhance the efficiency of signal processing pipelines when integrated with reconfigurable LNAs. The study demonstrated improved area efficiency and reduced power consumption, making the design suitable for embedded and wearable systems. However, additional decoder logic may introduce overhead and limit scalability.

Nguyen et al. (2023) introduced a deep learning-assisted optimization framework for hardware-efficient system design. Their approach uses neural networks to optimize system parameters, including arithmetic precision and pipeline structures, to improve performance and energy efficiency. In EEG classification, this framework can enhance both signal processing and classification stages by adapting to varying signal conditions. The study demonstrated improved hardware utilization, reduced latency, and enhanced classification accuracy. However, integrating deep learning models into hardware design increases system complexity and requires additional computational resources.

Intel Labs (2020) proposed a hardware-aware optimization framework for biomedical signal

processing systems, emphasizing energy-efficient design through adaptive hardware configurations. Their approach integrates approximate computing techniques with signal acquisition components such as Low Noise Amplifiers (LNAs) to improve system-level efficiency. In EEG classification applications, this framework enables dynamic adjustment of processing parameters based on signal conditions, thereby enhancing accuracy and reducing power consumption. The study demonstrated significant improvements in energy efficiency and processing speed, particularly in wearable and edge-based healthcare devices. However, the framework offers limited flexibility for customization and may not be easily adaptable to diverse EEG datasets and applications.

Xilinx Research (2020) introduced FPGA-based reconfigurable architectures for real-time signal processing applications, including EEG classification. Their approach leverages configurable hardware resources to implement adaptive signal processing pipelines, allowing dynamic adjustment of gain, bandwidth, and computational precision. The integration of approximate arithmetic units further enhances energy efficiency and performance. The study demonstrated that FPGA-based systems provide high scalability and flexibility, making them suitable for real-time biomedical applications. However, reliance on FPGA platforms may limit portability to ASIC-based designs and increase development complexity.

Shlezinger et al. (2020) proposed a model-based deep learning framework that combines traditional signal processing techniques with neural network optimization. Their approach enhances interpretability and efficiency by incorporating domain knowledge into the learning process. In EEG classification systems, this method can improve feature extraction and classification performance while reducing computational complexity. The study demonstrated improved accuracy and robustness compared to purely data-driven models. However, integrating model-based and learning-based approaches increases design complexity and requires careful parameter tuning.

Huang et al. (2021) developed a deep learning-based optimization framework for wireless and signal processing systems, which can be extended to EEG classification applications. Their approach uses neural networks to predict optimal system configurations, including hardware parameters and signal processing strategies. The study demonstrated improved efficiency, reduced latency, and enhanced

performance in complex signal processing environments. Additionally, the framework supports adaptive optimization, making it suitable for reconfigurable LNA-based systems. However, the computational overhead associated with training and deploying neural networks remains a limitation.

Wu et al. (2022) introduced an intelligent optimization framework for signal processing systems using machine learning techniques. Their approach focuses on improving resource allocation, system efficiency, and scalability in complex applications such as EEG classification. The study demonstrated that adaptive optimization techniques significantly enhance system performance and robustness. Furthermore, the framework supports integration with hardware-efficient components such as approximate arithmetic units and reconfigurable LNAs. However, the incorporation of machine learning into hardware design increases system complexity and requires additional computational resources.

Yang et al. (2023) proposed a transformer-based optimization framework for signal processing and neural network systems. Their approach captures long-range dependencies in data and optimizes system parameters across multiple processing stages. In EEG classification, this method enhances feature extraction and improves classification accuracy by modelling complex temporal patterns in brain signals. The study demonstrated superior performance compared to traditional optimization techniques, particularly in handling high-dimensional EEG data. However, transformer-based models require significant computational resources and large training datasets, which may limit their implementation in low-power embedded systems.

Zhang et al. (2023) introduced a secure and energy-efficient EEG classification framework integrating optimization algorithms with hardware design. Their approach incorporates anomaly detection techniques to improve system reliability and robustness. The study demonstrated enhanced classification accuracy and improved resilience to noise and artifacts in

EEG signals. Additionally, the framework supports integration with reconfigurable LNA architectures for adaptive signal amplification. However, the inclusion of security and detection mechanisms increases hardware complexity and system cost.

Rao et al. (2022) developed a power-aware hardware architecture using voltage scaling and adaptive clocking techniques for biomedical signal processing applications. Their approach significantly reduces energy consumption while maintaining performance levels. In EEG classification systems, such techniques improve efficiency and extend battery life in wearable devices. The study demonstrated improved energy efficiency and system reliability. However, adaptive control mechanisms introduce design complexity and require precise tuning to avoid performance degradation.

Kim and Lee (2023) proposed a lightweight signal processing architecture designed for edge-based EEG classification systems. Their approach uses simplified arithmetic units and optimized processing pipelines to reduce computational overhead and power consumption. The study demonstrated that lightweight architectures can achieve efficient real-time processing while maintaining acceptable classification accuracy. Additionally, the design is well-suited for integration with reconfigurable LNAs in portable devices. However, reduced model complexity may limit performance in highly complex EEG classification tasks.

Zhou et al. (2022) introduced an edge intelligence framework that integrates artificial intelligence with hardware optimization for real-time signal processing applications. Their approach enables adaptive optimization and low-latency processing, making it suitable for EEG classification systems. The study demonstrated improved system efficiency, reduced latency, and enhanced scalability. Furthermore, the framework supports integration with reconfigurable hardware components such as LNAs and approximate arithmetic units. However, challenges related to security, resource constraints, and system integration remain significant.

Comparative Table

No	Author (Year)	Technique	Focus	Contribution	Limitation
1	Gao (2021)	Low-rank learning	EEG	Noise reduction	Complexity
2	Elshewey (2024)	MBER optimization	EEG	High accuracy	Overhead
3	Zhang (2020)	Multi-task learning	EEG	Generalization	Clustering
4	Xiong (2023)	PSO	EEG	Feature optimization	Convergence
5	Zhu (2020)	Lightweight model	EEG	Low cost	Scalability
6	Jiang (2020)	Approx computing	Hardware	Energy saving	Accuracy
7	Han (2020)	Approx computing	Systems	Efficiency	Trade-off
8	Venkatachalam (2021)	Approx adder	Hardware	Low delay	Complexity

9	Zhang (2021)	Optimization	EEG	Accuracy	Overhead
10	Esmailzadeh (2021)	Framework	Systems	Energy	Tuning
11	Mrazek (2021)	Approx multiplier	Hardware	Area saving	Accuracy
12	Camus (2021)	Approx computing	Hardware	Efficiency	Specific
13	Paliwal (2022)	Approx adder	Hardware	Speed	Error
14	Akbari (2022)	Approx computing	ML	Efficiency	Trade-off
15	Qin (2022)	DL optimization	Systems	Adaptability	Complexity
16	Ranjan (2021)	Hardware design	EEG	Efficiency	Accuracy
17	Hashemi (2021)	ML-guided design	Hardware	Automation	Overhead
18	Shin (2022)	Error-resilient	EEG	Accuracy	Complexity
19	Gupta (2022)	Decoder multiplier	Hardware	Low power	Logic
20	Nguyen (2023)	DL optimization	Systems	Performance	Complexity
21	Intel (2020)	HW framework	EEG	Efficiency	Flexibility
22	Xilinx (2020)	FPGA	Hardware	Scalability	Portability
23	Shlezinger (2020)	Deep learning	Signal	Interpretability	Complexity
24	Huang (2021)	DL optimization	Systems	Efficiency	Training
25	Wu (2022)	ML optimization	Systems	Scalability	Complexity
26	Yang (2023)	Transformer	EEG	Accuracy	Compute
27	Zhang (2023)	Secure EEG	EEG	Reliability	Complexity
28	Rao (2022)	Power optimization	Hardware	Energy saving	Control
29	Kim (2023)	Lightweight	Edge	Efficiency	Accuracy
30	Zhou (2022)	Edge AI	EEG	Low latency	Security

Analysis

The analysis indicates that combining reconfigurable LNA design with hybrid optimization algorithms significantly improves EEG classification performance. Approximate computing techniques reduce power consumption and hardware complexity, while optimization algorithms enhance feature selection and classification accuracy. Hybrid approaches outperform single-method systems by balancing efficiency and accuracy. However, challenges such as computational complexity, scalability, and noise sensitivity remain.

Discussion

Recent advancements in EEG classification systems emphasize the importance of integrating hardware-efficient designs with intelligent optimization algorithms. Reconfigurable Low Noise Amplifiers (LNAs) play a critical role in improving signal acquisition by adapting to varying signal conditions and minimizing noise. When combined with hybrid optimization techniques such as forensic-based investigation algorithms and human urbanization algorithms, significant improvements in classification accuracy and system efficiency can be achieved. Optimization algorithms enhance EEG classification by selecting relevant features and reducing redundancy, which improves computational efficiency and model performance. Additionally, approximate computing techniques reduce hardware complexity and power consumption, making

these systems suitable for wearable and edge devices.

Despite these advantages, several challenges remain. The integration of optimization algorithms with hardware components increases system complexity and may require additional computational resources. Furthermore, achieving an optimal balance between accuracy and efficiency is a critical issue, particularly in real-time applications. Noise sensitivity and variability in EEG signals also pose significant challenges. Future research should focus on developing adaptive and scalable optimization techniques, improving noise robustness, and integrating hardware-aware machine learning models. These advancements will enable the development of efficient, accurate, and reliable EEG classification systems.

Conclusion

The rapid development of EEG-based systems has significantly advanced the field of biomedical signal processing, particularly in applications such as brain-computer interfaces, neurological disorder detection, and cognitive state monitoring. However, the inherent challenges associated with EEG signals, including low amplitude, high noise levels, and variability across subjects, necessitate the development of efficient and robust system designs. This comprehensive review has examined the design of reconfigurable Low Noise Amplifiers (LNAs) integrated with hybrid optimization algorithms, including forensic-based investigation algorithms and human urbanization algorithms,

for EEG classification. The findings indicate that reconfigurable LNAs play a crucial role in enhancing signal acquisition by providing adaptive gain, bandwidth, and noise reduction capabilities. These features are essential for improving the quality of EEG signals before further processing and classification. Additionally, approximate computing techniques, including low-power arithmetic units, contribute to reducing hardware complexity and energy consumption, making the system suitable for wearable and portable applications.

Hybrid optimization algorithms have demonstrated significant potential in improving EEG classification performance. By combining multiple optimization strategies, these algorithms effectively handle the high dimensionality and complexity of EEG data. They enhance feature selection, reduce redundancy, and improve classification accuracy. Furthermore, deep learning-based optimization techniques provide adaptive and scalable solutions for real-time applications. Despite these advancements, several challenges remain. The integration of reconfigurable hardware with optimization algorithms increases system complexity and requires careful design considerations. Additionally, achieving a balance between accuracy and efficiency is critical, particularly in applications where precision is essential. Noise sensitivity and variability in EEG signals also pose significant challenges that need to be addressed.

Future research should focus on developing advanced hybrid optimization techniques that are both efficient and scalable. The integration of hardware-aware machine learning models and edge computing technologies can further enhance system performance. Additionally, improving noise robustness and developing adaptive signal processing techniques will be essential for advancing EEG classification systems. In conclusion, the combination of reconfigurable LNAs and hybrid optimization algorithms represents a promising approach for improving EEG classification systems. These advancements are expected to play a significant role in the development of next-generation biomedical devices and intelligent healthcare systems.

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