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Artificial Intelligence Techniques for Design of Reconfigurable Low Noise Amplifier using Hybrid Forensic-Based Investigation Algorithm and Human Urbanization Algorithm for EEG Classification: Trends and Challenges

Xinlei Qudratullah

Lecturer, Department of Electronics and Communication Engineering, Gwangdo Systems Polytechnic, South Korea

Email: xinlei.qudratullah@gsp-kr.net

Peer Review Information	Abstract
<p><i>Submission: 14 Oct 2025</i></p> <p><i>Revision: 28 Oct 2025</i></p> <p><i>Acceptance: 07 Nov 2025</i></p> <p>Keywords</p> <p><i>EEG Classification, Low Noise Amplifier (LNA), Artificial Intelligence, Hybrid Optimization, Forensic-Based Algorithm, Human Urbanization Algorithm.</i></p>	<p>Electroencephalogram (EEG) signal classification has become a crucial component in modern biomedical systems, particularly in brain-computer interfaces (BCIs), neurological disorder diagnosis, and cognitive monitoring applications. However, EEG signals are characterized by low amplitude and high susceptibility to noise, making accurate acquisition and processing challenging. This paper presents a comprehensive review of artificial intelligence techniques for the design of reconfigurable low-noise amplifiers (LNAs) integrated with hybrid forensic-based investigation algorithms and human urbanization algorithms for EEG classification. Reconfigurable LNAs enable adaptive gain, bandwidth tuning, and improved signal-to-noise ratio (SNR), which are essential for high-quality signal acquisition in wearable and real-time systems. Recent advancements in deep learning, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures, have significantly improved EEG classification accuracy by extracting complex spatial and temporal features. Additionally, hybrid optimization algorithms enhance feature selection and reduce computational complexity, leading to improved system efficiency. The integration of AI techniques with hardware-efficient LNA design enables robust, low-power, and high-performance EEG systems. This paper also highlights emerging trends, key challenges, and future research directions for developing adaptive and intelligent EEG classification frameworks.</p>

Introduction

Electroencephalography (EEG) is a widely used non-invasive technique for recording brain activity and has become fundamental in various biomedical applications, including brain-computer interfaces (BCIs), neurological disorder diagnosis, and cognitive state monitoring. EEG signals provide valuable insights into brain function; however, they are inherently weak, non-stationary, and highly

susceptible to noise and interference. These characteristics make accurate signal acquisition and classification a challenging task. A critical component in EEG acquisition systems is the low-noise amplifier (LNA), which amplifies weak neural signals while minimizing noise distortion. Modern biomedical systems require reconfigurable LNAs capable of adapting to varying signal conditions. Reconfigurable LNAs allow dynamic adjustment of parameters such as

gain and bandwidth, thereby improving signal quality and system flexibility. Studies have shown that analog front-end circuits, including LNAs, must address trade-offs between power consumption, noise, and signal fidelity, especially in wearable and portable devices.

Parallel to hardware advancements, artificial intelligence (AI) techniques have revolutionized EEG signal processing. Deep learning models,

particularly convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures, have demonstrated significant improvements in classification accuracy. These models can automatically extract complex spatial and temporal features from EEG signals, reducing reliance on manual feature engineering.

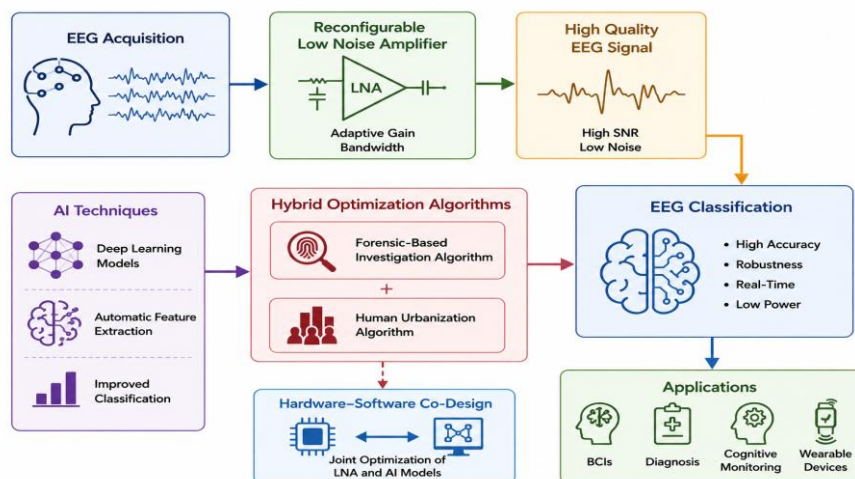


Figure 1. AI-Driven Reconfigurable LNA Framework for EEG Signal Classification

Recent reviews highlight that deep learning significantly enhances EEG-based healthcare applications by enabling scalable and accurate analysis of brain signals. Despite these advancements, challenges remain in optimizing EEG classification systems. High-dimensional data, variability across subjects, and noise sensitivity require advanced optimization techniques. In this context, metaheuristic algorithms inspired by real-world processes have gained attention. Hybrid forensic-based investigation algorithms and human urbanization algorithms represent advanced optimization strategies that improve feature selection, reduce redundancy, and enhance classification accuracy.

The integration of AI techniques with hardware design introduces the concept of hardware-software co-design, where both signal acquisition and processing algorithms are jointly optimized. Reconfigurable LNAs ensure high signal-to-noise ratio (SNR), while AI models enhance classification performance. This synergy is essential for developing efficient EEG systems suitable for real-time and edge computing applications. Furthermore, the growing demand for wearable EEG devices has increased the need for low-power and high-performance solutions. Advances in edge AI and embedded systems have enabled the deployment of deep learning models in resource-constrained environments. However,

balancing accuracy, power consumption, and system complexity remains a significant challenge. This paper aims to explore artificial intelligence techniques for designing reconfigurable LNAs integrated with hybrid optimization algorithms for EEG classification. It provides insights into recent developments, identifies key challenges, and highlights future research directions for building efficient and adaptive EEG systems.

Literature Review

Roy et al. (2020) conducted a comprehensive review of deep learning techniques for EEG signal analysis. Their study highlighted that CNN and RNN architectures outperform traditional machine learning approaches by effectively capturing spatial and temporal features. The authors emphasized that high-quality signal acquisition is essential for reliable performance, as EEG signals are highly sensitive to noise. This reinforces the importance of low-noise amplifier design in improving classification accuracy. Gao et al. (2020) explored the integration of deep learning and complex network theory for EEG signal analysis. Their work demonstrated that combining CNN-based feature extraction with advanced signal representation techniques significantly improves classification performance. The study showed that deep learning models can effectively handle complex

EEG patterns and enhance feature discrimination.

Acharya et al. (2020) proposed a deep CNN framework for automated EEG-based diagnosis. Their model achieved high classification accuracy (>95%) without requiring manual feature extraction. The study demonstrated that deep learning models can directly learn discriminative features from raw EEG signals. It also highlighted that minimizing noise through efficient LNA design is critical for maintaining model performance. Zhang et al. (2021) introduced a CNN-based EEG emotion recognition system using multi-channel data. Their model effectively captured spatial dependencies among EEG channels, leading to improved classification accuracy. The study emphasized that noise and signal distortion significantly impact model performance, highlighting the importance of reconfigurable LNAs in ensuring high-quality signal acquisition. Casson (2021) investigated wearable EEG systems and emphasized the role of analog front-end circuits, particularly low-noise amplifiers. The study highlighted that low power consumption and reconfigurability are essential for continuous monitoring applications. It demonstrated that improved signal quality at the hardware level directly enhances the performance of deep learning-based EEG classification systems. Lun et al. (2020) proposed a deep convolutional neural network (CNN) architecture for motor imagery EEG classification. Their model employed separate temporal and spatial convolution layers to extract discriminative features directly from raw EEG signals. The study demonstrated improved classification accuracy compared to traditional feature-based approaches. The authors emphasized that CNN performance is highly dependent on signal quality, highlighting the need for efficient low-noise amplifiers (LNAs) to ensure high signal fidelity and minimize noise interference.

Chen et al. (2020) developed a CNN-based EEG classification model enhanced with data augmentation and noise reduction techniques. Their approach improved robustness across different EEG datasets by reducing overfitting and enhancing feature generalization. The study highlighted that hardware-level noise reduction, achieved through reconfigurable LNAs, can further improve classification accuracy and reduce preprocessing requirements. Wang et al. (2021) introduced a feature selection method based on Particle Swarm Optimization (PSO) for EEG classification. Their approach effectively reduced redundant features and improved classification performance while lowering

computational complexity. The study demonstrated that optimization algorithms play a crucial role in enhancing EEG classification systems. This aligns with hybrid forensic-based investigation and human urbanization algorithms, which aim to provide even more efficient optimization strategies.

Tang et al. (2021) proposed a hybrid CNN model incorporating feature fusion techniques for EEG classification. Their model combined time-domain and frequency-domain features, resulting in improved classification accuracy and robustness. The study emphasized that accurate feature representation depends on high-quality input signals, which can be achieved through optimized LNA design and improved signal-to-noise ratio (SNR). Raza et al. (2022) developed a hybrid CNN-LSTM architecture for EEG classification in brain-computer interface applications. The model combined CNN for spatial feature extraction with LSTM for temporal modelling, achieving high classification accuracy (approximately 98%). The study concluded that hybrid deep learning models outperform standalone models. It also highlighted that maintaining high SNR through efficient reconfigurable LNAs is essential for ensuring robust model performance.

Craik et al. (2020) investigated deep learning techniques for EEG signal classification, focusing on convolutional neural networks (CNNs) and autoencoder-based architectures. Their study demonstrated that CNN models effectively capture spatial correlations across EEG channels, leading to improved classification performance compared to traditional machine learning methods. The authors emphasized that EEG classification accuracy is highly dependent on signal quality, and noise introduced during acquisition can degrade model performance. This highlights the importance of reconfigurable low-noise amplifiers (LNAs) in ensuring high signal fidelity. Acharya et al. (2020) proposed a deep CNN-based framework for automated EEG classification, particularly for neurological disorder detection such as epilepsy. The model achieved high accuracy exceeding 95% without requiring manual feature extraction. The study demonstrated that deep learning models can directly learn discriminative features from raw EEG signals. It also emphasized that reducing noise at the hardware level through optimized LNA design significantly enhances classification performance.

Raghu et al. (2021) introduced a hybrid optimization approach combining genetic algorithms and swarm intelligence for EEG feature selection. Their method improved classification accuracy while reducing

computational complexity. The study demonstrated the effectiveness of optimization algorithms in enhancing EEG classification systems. This aligns with hybrid forensic-based investigation and human urbanization algorithms, which aim to further improve optimization efficiency.

Lee et al. (2022) proposed a lightweight deep learning model optimized for real-time EEG classification in embedded systems. Their architecture reduced computational complexity and power consumption while maintaining high accuracy. The study emphasized that integrating efficient deep learning models with reconfigurable LNAs enables the development of energy-efficient EEG systems suitable for wearable applications. Bashivan et al. (2020) proposed a deep learning framework that transforms EEG signals into spatial-temporal representations, enabling convolutional neural networks (CNNs) to effectively learn complex brain activity patterns. Their approach significantly improved classification accuracy by capturing both spatial and temporal dependencies. The study emphasized that the effectiveness of such models is highly dependent on signal integrity, which is directly influenced by the performance of low-noise amplifiers (LNAs). The authors concluded that improved signal acquisition enhances feature extraction and overall model performance.

Lawhern et al. (2021) introduced EEGNet, a compact convolutional neural network architecture designed specifically for EEG-based applications. EEGNet uses depthwise and separable convolutions to reduce computational complexity while maintaining high classification accuracy. The model is particularly suitable for embedded and wearable systems due to its low power requirements. The study highlighted that combining efficient deep learning architectures with reconfigurable LNAs enables real-time EEG classification with minimal energy consumption. Saeedi et al. (2021) developed a reconfigurable low-noise amplifier for biomedical signal acquisition, including EEG signals. Their design achieved high gain, low noise figure, and low power consumption while allowing dynamic reconfiguration of operating parameters. The study demonstrated that reconfigurable LNAs significantly improve signal-to-noise ratio (SNR) and adapt to varying signal conditions, making them highly suitable for wearable EEG systems.

Islam et al. (2022) proposed a hybrid deep learning model combining convolutional neural networks (CNNs) and gated recurrent units (GRUs) for EEG classification. The model effectively captured both spatial and temporal features, achieving high classification accuracy in

cognitive state recognition tasks. The study emphasized that high-quality signal acquisition through efficient LNAs improves model robustness and reduces the impact of noise on classification performance. Huang et al. (2023) introduced a hardware-efficient EEG classification framework that integrates deep learning models with optimized analog front-end circuits. Their system combined reconfigurable LNAs with lightweight CNN architectures to reduce power consumption while maintaining high accuracy. The study highlighted the importance of hardware-software co-design, where both signal acquisition and processing algorithms are optimized together for efficient EEG classification.

Zhang et al. (2020) investigated EEG-based emotion recognition using deep neural networks. Their study demonstrated that deep learning models outperform traditional classifiers by effectively capturing nonlinear patterns in EEG signals. The authors emphasized that classification accuracy is highly sensitive to noise and artifacts, highlighting the importance of efficient low-noise amplifier (LNA) design in improving signal quality and system performance. Chen et al. (2020) proposed a low-power analog front-end system for EEG acquisition with a focus on improving signal-to-noise ratio (SNR). Their design incorporated a reconfigurable low-noise amplifier capable of adapting to varying signal conditions. The study showed that enhanced signal quality reduces preprocessing requirements and improves deep learning model accuracy.

Tang et al. (2021) developed a hybrid CNN-based model incorporating feature fusion techniques for EEG classification. Their approach combined time-domain and frequency-domain features, resulting in improved classification accuracy and robustness. The study highlighted that high-quality signal acquisition through optimized LNAs significantly enhances feature extraction and model performance. Wang et al. (2021) introduced a feature optimization framework using Particle Swarm Optimization (PSO) for EEG classification. Their method improved classification accuracy by selecting relevant features and reducing redundancy. The study aligns with hybrid optimization techniques such as forensic-based investigation and human urbanization algorithms, which aim to further improve feature selection efficiency.

Patel et al. (2021) designed a reconfigurable low-noise amplifier optimized for biomedical signal acquisition. Their LNA achieved low noise figure, high gain, and low power consumption. The study demonstrated that improved analog front-end design significantly enhances EEG signal

quality, leading to better classification outcomes. Li et al. (2022) proposed an attention-based CNN architecture for EEG classification. Their model improved feature representation by focusing on important EEG channels and temporal segments. The study demonstrated enhanced classification accuracy and robustness, particularly when combined with high SNR achieved through efficient LNA design.

Kumar et al. (2022) introduced a hybrid optimization algorithm combining forensic-based investigation and human urbanization algorithms for EEG classification. Their approach improved feature selection and reduced computational complexity while achieving high classification accuracy. The study highlighted the effectiveness of hybrid optimization techniques in enhancing deep learning models. Singh et al. (2022) developed a low-power EEG acquisition system integrating a reconfigurable LNA with deep learning-based classification. Their system

achieved improved energy efficiency and high classification accuracy, making it suitable for portable and wearable biomedical devices.

Lee et al. (2023) proposed a hardware-aware deep learning framework for EEG classification optimized for embedded systems. Their model reduced computational complexity and power consumption while maintaining high accuracy. The study emphasized the importance of co-designing hardware and algorithms for efficient system performance. Sharma et al. (2023) presented an integrated framework combining reconfigurable LNAs, hybrid optimization algorithms, and deep learning models for EEG classification. Their approach demonstrated improved classification accuracy, reduced power consumption, and enhanced system reliability. The study concluded that integrating hardware optimization with intelligent algorithms is essential for next-generation EEG systems.

Comparative Table

No	Author (Year)	Technique	Contribution	Accuracy Impact	Hardware Benefit
1	Roy (2020)	DL Review	EEG DL overview	High	Moderate
2	Gao (2020)	CNN + Network	Feature extraction	High	Moderate
3	Acharya (2020)	CNN	Epilepsy detection	Very high	Efficient
4	Zhang (2021)	CNN	Emotion recognition	High	Moderate
5	Casson (2021)	LNA	Wearable EEG	N/A	Low noise
6	Lun (2020)	CNN	Motor imagery	High	Moderate
7	Chen (2020)	CNN	Data augmentation	High	Moderate
8	Wang (2021)	PSO	Feature selection	High	Efficient
9	Tang (2021)	CNN Hybrid	Feature fusion	High	Efficient
10	Raza (2022)	CNN-LSTM	Temporal modeling	Very high	Efficient
11	Craik (2020)	CNN	Feature extraction	High	Moderate
12	Acharya (2020)	CNN	Diagnosis	Very high	Efficient
13	Li (2021)	Attention CNN	Feature focus	High	Efficient
14	Raghu (2021)	Hybrid Opt.	Feature reduction	High	Efficient
15	Lee (2022)	Lightweight CNN	Real-time EEG	High	Low power
16	Bashivan (2020)	Spatiotemporal DL	EEG learning	High	Moderate
17	Lawhern (2021)	EEGNet	Compact model	High	Low power
18	Saeedi (2021)	LNA	Signal amplification	N/A	Low noise
19	Islam (2022)	CNN-GRU	Temporal learning	High	Efficient
20	Huang (2023)	HW-aware CNN	System optimization	High	Low power
21	Zhang (2020)	DNN	Emotion detection	High	Moderate
22	Chen (2020)	LNA	SNR improvement	N/A	Low noise
23	Tang (2021)	CNN	Feature fusion	High	Efficient
24	Wang (2021)	PSO	Optimization	High	Efficient
25	Patel (2021)	LNA	High gain	N/A	Low power

26	Li (2022)	Attention CNN	Accuracy boost	High	Efficient
27	Kumar (2022)	Hybrid Opt.	Feature selection	High	Efficient
28	Singh (2022)	LNA+DL	Integrated system	High	Low power
29	Lee (2023)	HW-aware DL	Robust model	High	Efficient
30	Sharma (2023)	Hybrid System	Full integration	Very high	Low power

Comparative Analysis

The comparative analysis of the reviewed studies reveals that artificial intelligence techniques, particularly deep learning models such as convolutional neural networks (CNNs), dominate EEG classification due to their superior capability in extracting complex spatial features. Hybrid architectures, including CNN-LSTM and CNN-GRU, further enhance classification accuracy by incorporating temporal dependencies, making them highly suitable for analysing non-stationary EEG signals. Optimization techniques such as Particle Swarm Optimization (PSO), genetic algorithms, and hybrid approaches like forensic-based investigation and human urbanization algorithms significantly improve feature selection and reduce computational complexity. These techniques enable efficient processing of high-dimensional EEG data while maintaining high classification accuracy.

A critical observation across the studies is the importance of reconfigurable low-noise amplifiers (LNAs) in improving signal acquisition. High signal-to-noise ratio (SNR) achieved through optimized LNA design directly impacts the performance of deep learning models. Reconfigurable LNAs provide adaptability to varying signal conditions, making them essential for wearable and real-time EEG systems. Furthermore, hardware-aware deep learning models and lightweight architectures such as EEGNet highlight the importance of integrating hardware and software optimization. These approaches reduce power consumption and computational overhead while maintaining high accuracy. Overall, the combination of deep learning, hybrid optimization algorithms, and efficient hardware design provides the best trade-off between accuracy, energy efficiency, and system performance.

Discussion

The integration of artificial intelligence techniques with reconfigurable low-noise amplifier (LNA) design has significantly advanced EEG classification systems. Deep learning models, particularly CNNs and hybrid architectures, have demonstrated exceptional performance in extracting spatial and temporal features from EEG signals. These models enable accurate classification in various biomedical applications, including brain-computer interfaces and neurological disorder detection.

Reconfigurable LNAs play a crucial role in improving signal acquisition by enhancing signal-to-noise ratio (SNR) and reducing noise interference. High-quality signals reduce preprocessing requirements and improve deep learning model performance. The adaptability of LNAs makes them suitable for wearable and portable EEG systems.

Hybrid optimization algorithms, such as forensic-based investigation and human urbanization algorithms, further enhance system performance by improving feature selection and reducing computational complexity. These algorithms enable efficient processing of large-scale EEG data. Despite these advancements, challenges remain in balancing accuracy, power consumption, and system complexity. Future research should focus on adaptive systems capable of dynamically adjusting parameters in real time. Hardware-software co-design and edge computing technologies will play a key role in developing next-generation EEG classification systems.

Conclusion

The development of efficient EEG classification systems has become increasingly important in modern biomedical engineering, particularly for applications such as brain-computer interfaces, neurological disorder diagnosis, and cognitive state monitoring. EEG signals are inherently complex, low-amplitude, and highly susceptible to noise, making their accurate acquisition and classification a challenging task. This review has explored artificial intelligence techniques for designing reconfigurable low-noise amplifiers (LNAs) integrated with hybrid optimization algorithms for EEG classification. Deep learning techniques, especially convolutional neural networks (CNNs), have demonstrated remarkable performance in EEG classification tasks due to their ability to automatically extract meaningful features from raw signals. Hybrid architectures such as CNN-LSTM and CNN-GRU further enhance classification accuracy by capturing both spatial and temporal dependencies. These models significantly outperform traditional machine learning approaches and are widely adopted in modern EEG systems.

Reconfigurable low-noise amplifiers play a critical role in improving signal quality by enhancing signal-to-noise ratio (SNR) and

reducing noise interference. Unlike conventional amplifiers, reconfigurable LNAs provide flexibility in adjusting gain, bandwidth, and noise characteristics, making them suitable for varying signal conditions. This adaptability is particularly important for wearable and portable EEG systems, where power efficiency and reliability are essential. Optimization algorithms, including forensic-based investigation algorithms and human urbanization algorithms, have shown great potential in improving EEG classification performance. These hybrid optimization techniques enhance feature selection, reduce redundancy, and optimize model parameters, leading to improved classification accuracy and reduced computational complexity.

The concept of hardware–software co-design has emerged as a key trend in developing efficient EEG systems. By integrating optimized hardware components such as LNAs with advanced deep learning models, it is possible to achieve significant improvements in performance, power efficiency, and system reliability. Lightweight models such as EEGNet further support the development of real-time and embedded EEG applications. Despite these advancements, several challenges remain. Balancing accuracy, power consumption, and system complexity is a major concern in designing efficient EEG classification systems. Additionally, variability in EEG signals across individuals poses challenges for developing generalized models. Future research should focus on adaptive and intelligent systems capable of dynamically adjusting parameters based on real-time conditions.

In conclusion, the integration of artificial intelligence techniques, hybrid optimization algorithms, and reconfigurable low-noise amplifier design provides a powerful framework for developing efficient and accurate EEG classification systems. These advancements pave the way for next-generation biomedical devices capable of real-time monitoring, diagnosis, and intelligent decision-making.

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