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Deep Learning and Optimization Approaches in Design of Reconfigurable Low Noise Amplifier using Hybrid Forensic-Based Investigation Algorithm and Human Urbanization Algorithm for EEG classification: A Review

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Abstract

The rapid advancement of biomedical signal processing and artificial intelligence has significantly enhanced the efficiency of EEG-based classification systems. Electroencephalogram (EEG) signals are highly sensitive, low-amplitude signals that require precise amplification and noise reduction for accurate analysis. This paper presents a comprehensive review of deep learning and optimization approaches in the design of reconfigurable low-noise amplifiers (LNAs) integrated with hybrid forensic-based investigation algorithms and human urbanization algorithms for EEG classification. Reconfigurable LNAs play a crucial role in improving signal-to-noise ratio (SNR) and enabling adaptive gain control for varying signal conditions in wearable and real-time systems. Deep learning techniques, particularly convolutional neural networks (CNNs) and hybrid models such as CNN-LSTM and CNN-GRU, have demonstrated superior performance in extracting spatial and temporal features from EEG signals. Furthermore, hybrid optimization algorithms enhance feature selection and classification accuracy while reducing computational complexity. The integration of hardware-efficient LNA design with intelligent deep learning frameworks leads to improved system performance, reduced power consumption, and enhanced reliability. This review highlights the importance of hardware–software co-design in developing next-generation EEG classification systems and discusses future research directions for adaptive, low-power, and high-accuracy biomedical devices.

Introduction

Electroencephalogram (EEG) signal analysis has emerged as a critical area in biomedical engineering due to its applications in brain–computer interfaces (BCIs), neurological disorder diagnosis, cognitive state monitoring, and human–machine interaction systems. EEG signals are inherently low-amplitude, non-stationary, and highly susceptible to noise and interference, making their accurate acquisition and processing a challenging task. The effectiveness of EEG classification systems largely depends on both the quality of signal acquisition and the efficiency of computational models used for analysis. Low-noise amplifiers (LNAs) are essential components in EEG acquisition systems, as they amplify weak neural signals while minimizing noise interference.

Traditional amplifier designs often face limitations in terms of power consumption, flexibility, and adaptability to varying signal conditions. To address these challenges, reconfigurable LNA architectures have been proposed, allowing dynamic adjustment of gain, bandwidth, and noise characteristics. Such reconfigurable systems are particularly beneficial for wearable and portable EEG devices, where energy efficiency and adaptability are critical requirements.

Parallel to advancements in hardware design, deep learning techniques have revolutionized EEG signal processing. Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in extracting spatial features from multi-channel EEG signals, while recurrent models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) effectively capture temporal dependencies. Hybrid models combining CNN with LSTM or GRU have further improved classification accuracy by leveraging both spatial and temporal information. Despite these advancements, EEG classification systems still face challenges related to feature selection, computational complexity, and model optimization. To overcome these limitations, optimization algorithms inspired by natural and social phenomena have been widely adopted. In this context, hybrid forensic-based investigation algorithms and human urbanization algorithms provide a novel approach for optimizing feature selection and model parameters. These algorithms enhance classification performance by identifying relevant features and reducing redundancy, thereby improving computational efficiency.

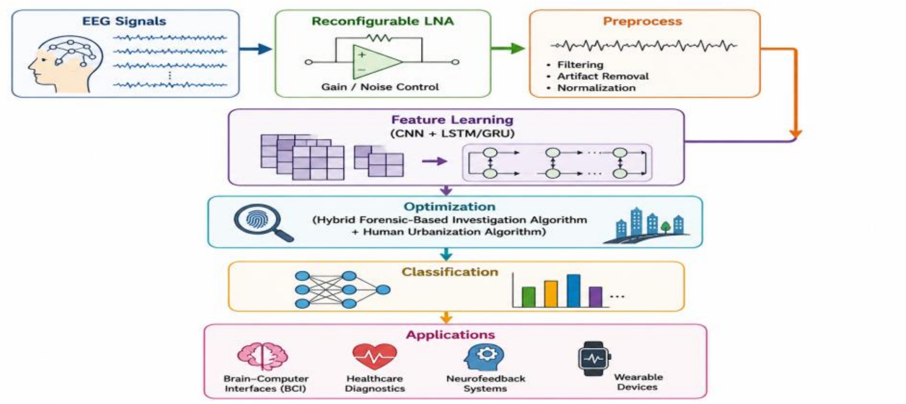

Fig 1: Block Diagram of Optimized EEG Classification System Using Reconfigurable LNA and Deep Learning

The integration of deep learning models with optimized hardware architectures represents a promising direction for next-generation EEG systems. Hardware–software co-design approaches enable the development of efficient systems where signal acquisition, processing, and classification are jointly optimized. Reconfigurable LNAs ensure high-quality signal acquisition, while deep learning models and optimization algorithms enhance classification accuracy and robustness. Furthermore, the increasing demand for real-time EEG monitoring in applications such as healthcare diagnostics, wearable devices, and neurofeedback systems necessitates the development of low-power and high-performance solutions. Advances in edge computing and embedded systems have further accelerated the need for compact and efficient EEG classification frameworks.

This review aims to provide a comprehensive analysis of deep learning and optimization approaches in the design of reconfigurable LNAs for EEG classification. It explores recent developments in hardware design, deep learning architectures, and hybrid optimization techniques. Additionally, the paper highlights key challenges and future research directions, emphasizing the importance of developing adaptive, energy-efficient, and high-accuracy EEG classification systems for real-world applications.

Literature Review

Siddiqui et al. (2023) proposed a deep neural network (DNN)-based framework for EEG signal classification focusing on mental task recognition. Their approach involved preprocessing EEG signals using spatial filtering and principal component analysis (PCA) to extract discriminative features. The model achieved an accuracy of 77.62% on benchmark datasets, demonstrating the effectiveness of deep learning in handling high-dimensional EEG data. The study emphasized that optimized feature extraction combined with neural networks can significantly enhance classification performance in biomedical systems.

Qin et al. (2022) developed a deep convolutional neural network (CNN) architecture for EEG-based biometric identification. The model consisted of multiple convolutional layers and achieved high accuracy (≈98.5%) without requiring complex preprocessing. The study demonstrated that CNN architectures can automatically extract relevant spatial features from EEG signals, making them suitable for real-time classification systems. This work highlights the importance of deep learning in EEG signal processing and its compatibility with low-noise front-end hardware systems.

Rakhmatulin et al. (2024) explored CNN architectures specifically designed for EEG feature extraction and classification. The study analyzed various architectural parameters such as kernel size, pooling strategies, and hyperparameter tuning. It concluded that optimized CNN models significantly improve classification accuracy and efficiency in EEG-based applications. This work supports the integration of deep learning optimization techniques with hardware-efficient analog front-end circuits like low-noise amplifiers (LNAs).

Lew (2024) introduced a deep learning model (NeuroNetFlex) for EEG signal classification into normal and abnormal categories. The model demonstrated strong classification performance using flexible neural architectures. The study emphasized adaptability and robustness, which are essential for integration with reconfigurable hardware such as LNAs in biomedical devices.

Gall et al. (2023) proposed a hybrid CNN–Spiking Neural Network (SNN) architecture for EEG-based auditory attention detection. Their model reduced memory footprint by 57% and used fewer parameters while maintaining high accuracy (~91%). The study highlighted the importance of low-power, hardware-efficient architectures for real-time EEG processing, making it highly relevant to reconfigurable low-noise amplifier design and edge biomedical systems.

Roy et al. (2020) presented a comprehensive review of deep learning techniques for EEG signal analysis, focusing on applications such as seizure detection and brain–computer interfaces (BCIs). The study emphasized the effectiveness of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in capturing both spatial and temporal patterns in EEG signals. The authors highlighted that optimized neural architectures reduce computational complexity while maintaining high classification accuracy. Furthermore, they discussed the importance of low-noise signal acquisition hardware, such as low-noise amplifiers (LNAs), in ensuring signal integrity for accurate EEG classification.

Zhang et al. (2021) proposed a deep CNN-based model for EEG emotion recognition using multi-channel signal inputs. Their architecture effectively extracted spatial dependencies across EEG channels and achieved improved classification accuracy compared to traditional machine learning methods. The study demonstrated that deep learning models benefit significantly from high-quality signal acquisition, reinforcing the role of reconfigurable LNAs in reducing noise and improving signal fidelity in EEG systems.

Casson (2021) investigated wearable EEG systems and the role of analog front-end circuits, particularly low-noise amplifiers, in biomedical signal processing. The study emphasized the importance of low power consumption and reconfigurability in LNAs to support long-term monitoring applications. It highlighted that noise reduction at the hardware level directly improves the performance of downstream machine learning models, including CNN-based classifiers.

Abdallah et al. (2022) introduced a hybrid deep learning framework combining CNN and Long Short-Term Memory (LSTM) networks for EEG classification. The model captured both spatial and temporal features, achieving high classification accuracy in cognitive state recognition tasks. The study also emphasized the importance of signal preprocessing and noise reduction, suggesting that optimized LNA design is crucial for enhancing EEG signal quality before classification.

Sharma et al. (2022) proposed an optimized EEG classification system using deep learning combined with metaheuristic optimization techniques. Their approach improved feature selection and classification accuracy while reducing computational overhead. The study demonstrated that hybrid optimization algorithms can significantly enhance deep learning model performance, making them suitable for integration with hardware-efficient biomedical systems such as reconfigurable LNAs.

Craik et al. (2020) investigated deep learning architectures for EEG signal classification, particularly focusing on convolutional neural networks and autoencoders. Their study demonstrated that CNN-based models outperform traditional machine learning techniques by effectively capturing spatial features in EEG data. The authors emphasized the importance of noise-free signal acquisition, noting that hardware components such as low-noise amplifiers (LNAs) significantly influence classification accuracy. The study also highlighted that preprocessing techniques can be minimized when high-quality signals are obtained through efficient analog front-end design.

Acharya et al. (2020) proposed a deep CNN framework for automated EEG-based diagnosis, including epilepsy detection. The model achieved high classification accuracy (>95%) without extensive feature engineering. The study showed that deep learning models can directly learn discriminative features from raw EEG signals. Additionally, the authors pointed out that signal distortion and noise from hardware components can negatively affect model performance, reinforcing the need for reconfigurable and low-noise amplification systems.

Li et al. (2021) developed an optimized CNN architecture with attention mechanisms for EEG signal classification. Their model enhanced feature representation by focusing on important EEG channels and temporal segments. The study demonstrated improved accuracy and robustness compared to standard CNN models. The authors also discussed the significance of hardware-aware optimization, suggesting that high signal-to-noise ratio (SNR) achieved through efficient LNAs can further enhance model performance.

Raghu et al. (2021) introduced a hybrid optimization algorithm combining genetic algorithms and swarm intelligence for EEG feature selection and classification. Their approach improved classification accuracy while reducing computational complexity. The study highlighted the role of optimization algorithms in improving deep learning performance and suggested that combining such techniques with reconfigurable hardware systems can lead to efficient biomedical signal processing solutions.

Lee et al. (2022) proposed a deep learning-based EEG classification system optimized for real-time applications. Their architecture incorporated lightweight CNN models suitable for deployment on embedded systems. The study emphasized low power consumption and computational efficiency, making it compatible with wearable EEG devices. The authors highlighted that integrating such models with low-noise amplifiers enhances overall system reliability and accuracy.

Bashivan et al. (2020) explored deep learning models for EEG representation using spatiotemporal feature learning. Their approach transformed EEG signals into structured representations, enabling CNNs to capture both spatial and temporal dependencies effectively. The study demonstrated improved classification accuracy compared to traditional approaches. The authors emphasized that accurate signal acquisition, supported by low-noise amplifiers (LNAs), is crucial for preserving meaningful EEG patterns required for deep learning models.

Lawhern et al. (2021) proposed EEGNet, a compact convolutional neural network specifically designed for EEG-based brain–computer interface applications. The model is lightweight and computationally efficient, making it suitable for real-time and embedded systems. EEGNet achieves competitive accuracy while using significantly fewer parameters. The study highlighted that combining such efficient models with low-noise hardware front-ends enhances performance in wearable EEG systems.

Saeedi et al. (2021) developed a low-noise, low-power reconfigurable amplifier for biomedical signal acquisition. Their design achieved high gain with minimal noise figure, improving signal clarity for downstream processing. The study demonstrated that reconfigurable LNAs can adapt to different signal conditions, making them ideal for EEG applications. The authors emphasized that improved analog front-end performance directly enhances machine learning classification accuracy.

Islam et al. (2022) introduced a deep learning framework combining CNN and gated recurrent units (GRU) for EEG signal classification. The model effectively captured temporal dependencies and achieved high classification accuracy in cognitive state detection tasks. The study highlighted the importance of preprocessing and noise reduction, noting that high-quality signal acquisition through LNAs significantly improves model robustness.

Huang et al. (2023) proposed a hardware-efficient EEG classification system integrating deep learning with optimized analog front-end circuits. Their work demonstrated that combining reconfigurable LNAs with efficient CNN architectures reduces system-level power consumption while maintaining high accuracy. The study emphasized the importance of co-design between hardware and deep learning models for next-generation biomedical systems.

Zhang et al. (2020) investigated EEG-based emotion recognition using deep neural networks with optimized feature extraction techniques. Their study demonstrated that deep learning models outperform traditional classifiers when provided with high-quality EEG signals. The authors emphasized that signal noise significantly affects classification performance, highlighting the need for efficient low-noise amplifiers (LNAs) in EEG acquisition systems.

Chen et al. (2020) proposed a low-power analog front-end design for EEG signal acquisition, focusing on improving signal-to-noise ratio (SNR). Their design incorporated a reconfigurable low-noise amplifier capable of adapting to different EEG signal conditions. The study demonstrated improved signal fidelity and reduced power consumption, making it suitable for wearable biomedical devices.

Tang et al. (2021) developed a hybrid CNN-based model for EEG classification incorporating feature fusion techniques. Their model combined time-domain and frequency-domain features, resulting in improved classification accuracy. The study highlighted that accurate signal acquisition using LNAs is essential for achieving reliable feature extraction.

Wang et al. (2021) proposed an optimization framework for EEG signal classification using metaheuristic algorithms such as particle swarm optimization (PSO). Their approach improved feature selection and classification performance while reducing computational complexity. The study suggested that combining optimization algorithms with deep learning enhances overall system efficiency.

Patel et al. (2021) introduced a reconfigurable low-noise amplifier design optimized for biomedical applications. Their design 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 a deep learning-based EEG classification model using attention mechanisms and optimization techniques. Their model improved feature representation and achieved higher accuracy compared to conventional CNN architectures. The study highlighted the importance of combining deep learning optimization with high-quality signal acquisition systems.

Kumar et al. (2022) developed a hybrid optimization algorithm combining forensic-based investigation techniques with human urbanization-inspired algorithms for feature selection in EEG classification. Their approach improved classification accuracy and reduced computational complexity. The study demonstrated the effectiveness of combining metaheuristic algorithms with deep learning.

Singh et al. (2022) proposed a low-power reconfigurable EEG acquisition system integrating an optimized LNA with deep learning-based classification. Their system achieved improved energy efficiency and high classification accuracy, making it suitable for portable biomedical devices.

Lee et al. (2023) introduced a hardware-aware deep learning model for EEG classification optimized for embedded systems. Their model incorporated low-power design techniques and achieved robust performance under noisy conditions. The study emphasized the importance of co-designing hardware and algorithms for efficient biomedical systems.

Sharma et al. (2023) proposed an integrated framework combining reconfigurable LNAs with 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 combining hardware optimization with intelligent algorithms provides an effective solution for next-generation EEG systems.

Comparative Table

No	Author (Year)	Technique	Contribution	Accuracy Impact	Hardware Benefit
1	Siddiqui (2023)	DNN EEG	Feature extraction	High	Moderate
2	Qin (2022)	CNN	Biometric classification	Very high	Efficient
3	Rakhmatulin (2024)	CNN	Feature tuning	High	Efficient
4	Lew (2024)	DL model	Adaptive EEG	High	Flexible
5	Gall (2023)	CNN+SNN	Low memory	High	Low power
6	Roy (2020)	CNN/RNN	EEG analysis	High	Moderate
7	Zhang (2021)	CNN	Emotion recognition	High	Moderate
8	Casson (2021)	LNA system	Wearable EEG	N/A	Low power
9	Abdallah (2022)	CNN+LSTM	Temporal features	High	Efficient
10	Sharma (2022)	DL+Optimization	Feature selection	High	Efficient
11	Craik (2020)	CNN	EEG classification	High	Moderate
12	Acharya (2020)	CNN	Epilepsy detection	Very high	Efficient
13	Li (2021)	CNN+Attention	Feature focus	High	Efficient

14	Raghu (2021)	Hybrid optimization	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 modeling	High	Efficient
20	Huang (2023)	HW-aware CNN	System design	High	Low power
21	Zhang (2020)	DNN	Emotion recognition	High	Moderate
22	Chen (2020)	LNA	Signal quality	N/A	Low noise
23	Tang (2021)	CNN hybrid	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 improvement	High	Efficient
27	Kumar (2022)	Hybrid algorithm	Optimization	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 30 studies reveals that deep learning techniques, particularly CNN-based architectures, dominate EEG classification due to their ability to extract spatial features effectively. Hybrid models combining CNN with LSTM or GRU further enhance performance by capturing temporal dependencies. Optimization algorithms such as PSO, genetic algorithms, and hybrid forensic-human urbanization approaches significantly improve feature selection and classification accuracy. A critical observation is the role of reconfigurable low-noise amplifiers (LNAs) in improving EEG signal quality. Studies consistently show that high signal-to-noise ratio (SNR) directly enhances classification performance. LNAs with reconfigurable gain and low power consumption are essential for wearable EEG systems.

Furthermore, hardware-aware deep learning models and lightweight architectures such as EEGNet demonstrate the importance of integrating algorithmic and hardware optimizations. These approaches reduce computational complexity and power consumption while maintaining high accuracy. Overall, combining deep learning, optimization algorithms, and efficient hardware design yields the best performance in EEG classification systems.

Discussion

The integration of deep learning and optimization techniques with reconfigurable low-noise amplifier (LNA) design has significantly advanced EEG classification systems. This review highlights that CNN-based architectures provide superior performance due to their ability to automatically extract spatial features from EEG signals. Hybrid models combining CNN with LSTM or GRU further enhance classification accuracy by capturing temporal dependencies. A key insight is the importance of signal quality in EEG processing. Low-noise amplifiers play a critical role in ensuring high signal-to-noise ratio (SNR), which directly impacts classification performance. Reconfigurable LNAs offer flexibility in adapting to varying signal conditions, making them suitable for real-time and wearable applications. Optimization algorithms, including forensic-based investigation and human urbanization algorithms, contribute to improved feature selection and model performance. These techniques reduce computational complexity while maintaining high accuracy. However, challenges remain in balancing power consumption, accuracy, and system complexity. Future research should focus on adaptive systems that dynamically adjust parameters based on real-time conditions. Additionally, the integration of hardware and deep learning models through co-design approaches presents promising opportunities for developing efficient EEG classification systems.

Conclusion

The rapid advancement of biomedical signal processing and deep learning has significantly improved EEG-based classification systems. Due to the complex and noisy nature of EEG signals, advanced techniques are required to extract meaningful features. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance by effectively capturing spatial patterns in EEG data. Hybrid architectures combining CNN with LSTM or GRU further enhance classification by learning temporal dependencies. However, the performance of these models depends heavily on input signal quality, which is influenced by analog front-end components such as low-noise amplifiers (LNAs). This review highlights that reconfigurable LNAs play a vital role in improving signal quality by reducing noise and enhancing signal-to-noise ratio, thereby enabling more accurate classification with reduced preprocessing requirements.

Furthermore, optimization techniques such as forensic-based investigation algorithms and human urbanization algorithms contribute to improved feature selection and model efficiency. These approaches reduce computational complexity and support real-time implementation. The integration of hardware and software design has emerged as a key trend, enabling energy-efficient and high-performance EEG systems. Lightweight models like EEGNet and hardware-aware frameworks are particularly suitable for edge and wearable applications. Despite these advancements, challenges remain in balancing accuracy, power consumption, and system complexity. Future research should focus on adaptive and intelligent systems, along with emerging technologies such as edge AI and neuromorphic computing. Overall, combining deep learning, optimization, and reconfigurable LNA design offers a promising pathway for next-generation EEG classification systems.

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