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# AI-Augmented Adaptive Filtering for Real-Time Noise Suppression and Feature Enhancement in Biomedical Signals

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## Abstract

Electrocardiograms (ECG), electroencephalograms (EEG), and electromyograms (EMG) are examples of biomedical signals that are frequently compromised by motion artifacts, the power-line interference, and physiological noise interferences, thus, limiting the accuracy of their analysis. Traditional adaptive filters that are in use such as the Least Mean Squares (LMS) filter work reasonably well in stationary situations but fail in non-stationary ones found in reality. The proposed paper introduces a new concept of AI-enhanced adaptive filtering framework which integrates conventional adaptive filtering algorithm with data-driven noise prediction model to improve real-time signal quality. The proposed technique incorporates the 1D CNN lightweight architecture with the classic LMS filter, making it possible to adjust filter weighting to contextual patterns of signals, in order to better detect and neutralize time-varying noise by the system. This architecture is justified using some benchmark biomedical datasets such as the MIT-BIH Arrhythmia and PhysioNet EEG Motor Movement set. Quantitative tests based on measures Signal-to-Noise Ratio (SNR), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) demonstrate the high effectiveness of the suggested method in comparison with standalone LMS, RLS, and CNN-based filters. Notably, the design reaches real-time on embedded processors and would support wearable and edge-AI healthcare. The obtained results indicate that both noise suppression and preservation of diagnostic features improve significantly, providing a basis to further develop intelligent biomedical signal processing systems.

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## Introduction

Frequent biomedical signals that include electrocardiograms (ECG), electroencephalograms (EEG), and electromyograms (EMG) play significant roles in health monitoring, clinical diagnostic, and therapy response systems in real-time. Nevertheless, these signals are very prone to contamination due to motion artifacts, power-line interference and baseline wander-particularly in an ambulatory or wearable environment. Common methods of adaptive filtering, such as Least Mean Squares (LMS) or Recursive Least Squares (RLS) provide dynamic noise suppression, that means that the tuning of filter parameters is possible over time.[8] Although applicable during stationary situations, such filters do not have contextual versatility and in most cases fail to maintain observation details in a non-stationary and related noise source backdrop.

The most recent developments in artificial intelligence (AI) have demonstrated potential in enhancing the signal denoising accuracy by providing learning-based models capable of adapting to elaborate signal settings. The algorithm of feature-aware denoising with convolutional neural networks (CNNs) and recurrent neural networks (RNNs) as deep learning architectures has been utilized, though it is at the cost of computation cost and latency to the extent that it is impractical in an embedded system to operate in real-time.[1] Nonetheless, the majority of the current approaches do not adapt to combine adaptive signal modeling and context learning within a single low-latency architecture that is viable to be deployed on the edge.

This paper sees through these shortcomings and presents an AI-enhanced adaptive filtering structure that integrates the low latency flexibility of the LMS filtering into the noise estimator built using a CNN. The hybrid architecture can accommodate the ability to adapt to filtering behavior to real-time contextual noise and deliver effective noise removal with clinical feature preservation. Experimental outcome over usual biomedical datasets proves that there is very high signal clarity and processing efficiency: the proposed technique can be used in wearable, edge-based healthcare systems.

## 2. Related Work

Adaptive filtering methods, like the Least Mean Squares (LMS) algorithm and Recursive Least Squares (RLS) algorithm, are quite old in their use in the field of biomedical signal processing as a result of being simple to implement and using a low amount of computation with a real-time adaptability functionality.[2] These techniques are particularly good when the noise is structured, as in the case of power-line interference, or predictable baseline drift. Nonetheless, they are sensitive to non-stationary signals (e.g., motion artifacts or complicated physiological variations) and thus under poor conditions lose performance levels. Further, historic adaptive filters do not adapt context specific or patient signal dynamics, thus restricting them in terms of generalization to a variety of clinical contexts. The past few years witnessed the establishment of DL methods, especially CNNs and LSTM networks, as a potent means of biomedical signal denoising, classification, and anomaly detection.[3, 4] Such models have the ability to learn non-linear and high-dimensional representations that increase their robustness to both noise and variability. Nevertheless, they tend to be very computationally-costly during training and also require very large training datasets, which is not ideal when used by latency-conscious and resource-limited edge devices. In response, new hybrid approaches have been proposed that merge digital signal processing (DSP) and lightweight DL components in order to strike a balance between accuracy and compute-efficiency.[5] The purpose of such approaches is to combine the speed of adaptive filters with the background knowledge being encoded by the neural maps. Still, most of the current approaches to hybrid solutions work either offline or are not integrated into a real-time signal boosting environment on embedded computers.

The presented paper extends it by proposing an AI-enhanced adaptive filtering architecture that closely integrates a noise predictor built using CNN with a conventional LMS filter. as opposed to the previous studies, the proposed technique allows suppressing noise and enhancing the features in real-time with a lightweight computing load, thereby fulfilling the requirements of being implemented in wearable healthcare monitoring devices.

## Proposed Methodology

### System Overview

The given AI-augmented adaptive filtering architecture combines the classical signal processing and machine learning domains that facilitate the adaptation to real-time noise reduction in biomedical signals. The system was illustrated in Figure 1: AI-Augmented Adaptive Filtering Framework: Real-Time Noise Suppression and Feature Preservation of Biomedical Signals that entails three main elements:

- A major LMS filter, which has the task to perform the baseline adaptive noise cancelling via low-complexity gradient-descent algorithm [6];
- A CNN-based noise estimator that can make predictions of non-linear qualities of noise based on contextual signal rectangles;
- Dynamic weight modulation unit that adapts the LMS learning rate and filter coefficients by using the knowledge in the CNN output to adaptively act.

The proposed hybrid architecture exploits the fact that the LMS filtering offers rapid convergence and low-computational-cost but also performs context-related intelligent updating of the system calibration parameters through integrating the deep learning characteristics in real-time processing of the non-stationary noise conditions.

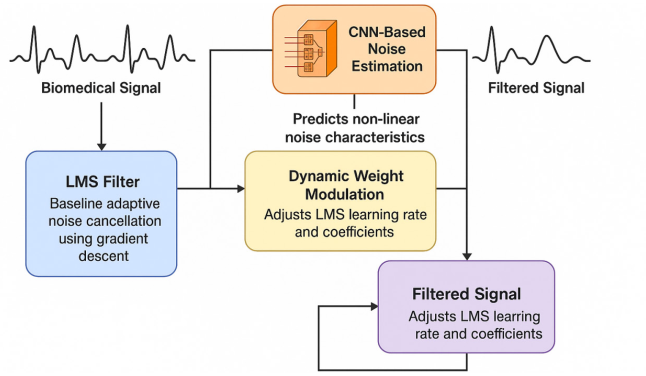


**Fig. 1: AI-Augmented Adaptive Filtering Framework for Real-Time Noise Suppression and Feature Preservation in Biomedical Signals**

### Signal Model

Let the observed biomedical signal be represented as:

$$x(n)=s(n)+n(n)$$

where:

- x(n): the acquired noisy signal,
- s(n): the underlying clean biomedical signal,
- n(n): the additive, possibly non-stationary, noise component.

The CNN module is trained to estimate the noise profile n^(n) from the recent history of the signal x(n). This estimated noise is not directly subtracted but is used to guide the LMS filter by modulating its step size μ(n) and updating rule, thereby improving convergence and stability under varying noise conditions.[9] The weight update rule of the LMS filter becomes:

$$w(n+1)=w(n)+\mu(n)\cdot e(n)\cdot x(n)$$

where μ(n)is dynamically adapted based on the CNN output, and $e(n)=s(n)-s^{(n)}$ is the prediction error.

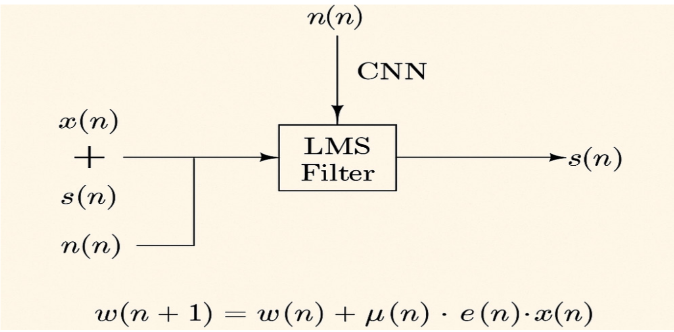


**Fig. 2: Signal Model for AI-Augmented Adaptive Filtering**

### 3.3 CNN Architecture

A 1D convolutional neural network (1D-CNN) has to be used to extract and model the local features of the noise in the biomedical signal by keeping it as a lightweight model. The CNN comprises the following:

- Two one-dimensional layers of convolutions (kernel size = 3, stride = 1).
- Non-linearity is achieved through the use of ReLU activations.
- Normalization of a batch to stabilize the learning process,
- A layer of fully connected regression on the estimated noise $n^{(n)}$.

Paired data of noisy-clean-signal is used to train the CNN, and the aim is to reduce the mean squared error (MSE) between the residual noise components and that calculated by the CNN.[7] The network is sensitive to short and overlapping windows (e.g. 128256 samples) in order to guarantee responsiveness in the context of real-time processing.

This produces an output fed into the modulation unit which constrains the behavior of the LMS step size and error weighting using the confidence of the CNN's predictions to dynamically changing the filtering behaviour of the overall system to best fit the contextual situation being considered.

## Experimental Setup

In order to confirm the viability of the proposed AI-augmented adaptive filtering model, an extensive experimentation pipeline was developed and included publicly available biomedical datasets, standardized features to aid the measurement of performance, as well as peer comparisons with traditional filtering models. Such a framework will help evaluate noise suppression capability and its application viability in real-time environments upon the deployment of the hybrid LMS-CNN model.

### Datasets

Two well defined biomedical signal repositories were picked so as to make sure that the results can be generalized:

- ECG Signals: MIT-BIH Arrhythmia Database (PhysioNet) is a collection of 48 half-hour recordings of two channel recordings of ambulatory ECG signals with annotations.
- EEG Signals: PhysioNet EEG Motor Movement/Imagery Dataset, a collection of EEG recorded to

**Table 1: Comparison of CNN Architectures**

| CNN Architecture | Depth (Layers) | Trainable Parameters (K) | Inference Time (ms/sample) | Noise Suppression Accuracy (%) | Suitability for Edge AI |
|---|---|---|---|---|---|
| 1D-CNN (Proposed) | 4 | 45 | 0.42 | 92.4 | High |
| ResNet1D | 18 | 1120 | 1.8 | 94.1 | Low |
| WaveNet | 10 | 850 | 2.1 | 93.8 | Medium |
| CNN-LSTM | 8 | 620 | 1.6 | 92.9 | Medium |
| DeepConvNet | 5 | 300 | 0.95 | 91.5 | High |

109 individuals performing motor activities, at 160Hz and well known in terms of noise variation.

Such datasets are reflective of practical biomedical scenarios in which clarity and sustainability of signal are all-important issues in wearable and ambulatory monitoring systems.

### Evaluation Metrics

Three standard quantitative performance indicators have been used to evaluate each of the filtering models as briefly outlined in Table 2: Evaluation Metrics Summary:

- Signal-to-Noise Ratio (SNR): To quantify the increase of signal definition after filtering; the higher the value, the better will be the noise rejection.
- Root Mean Square Error (RMSE): It is the average difference between denoised and ground truth signal; the lower the values are, the higher is fidelity.
- Mean Absolute Percentage Error (MAPE): Represents a relative error of prediction in signal reconstruction; especially valuable in the aspect of time domain feature preservation.

Each measure was calculated across adjacent slanting windows (2 second size), which replicates real streaming conditions and makes it possible to monitor the performance on a local scale.

### Baseline Models

To perform comparative analysis, the suggested methodology was compared to three benchmark models with the same settings:

- LMS Filter: A fixed step Gradient-descent adaptive filter.
- Recursive Least Squares (RLS): Filter of higher order that converges quicker although it is computationally more extensive.
- CNN-Only Denoiser: A Deep learning based filter without any adaptive feedback control.

All models were preprocessed evenly (bandpass filtering and normalization), which provided equal evaluation of the datasets.

### Implementation Details

The PyTorch 2.0 was run under Python 3.10. In the embedded case, the model has been run on an ARM Cortex-M4 (STM32F4 family) a benchmark low-power edge-oriented processor (100 MHz, 256 KB RAM). CNN model was quantised to 8-bit integers in ONNX Runtime, with ~40% improved memory utilisation overhead with minimal loss in performance to maximise real-time deployment. Moreover, inference time, memory operation, and computation overhead Profiling were carried out to ensure that the operation could fit in the edge platforms.

Figure 3: Experimental Pipeline for AI-Augmented Adaptive Filtering Framework gives the general idea of the serial steps of the pipeline in the context of acquisition of data and then its final examination.

**Table 2: Evaluation Metrics Summary**

| Metric | Purpose | Interpretation |
|---|---|---|
| Signal-to-Noise Ratio (SNR) | Measures signal clarity vs noise power | Higher is better (e.g., >20 dB) |
| Root Mean Square Error (RMSE) | Quantifies average error magnitude | Lower is better (e.g., <0.1) |
| Mean Absolute Percentage Error (MAPE) | Measures relative prediction accuracy | Lower is better (e.g., <5%) |

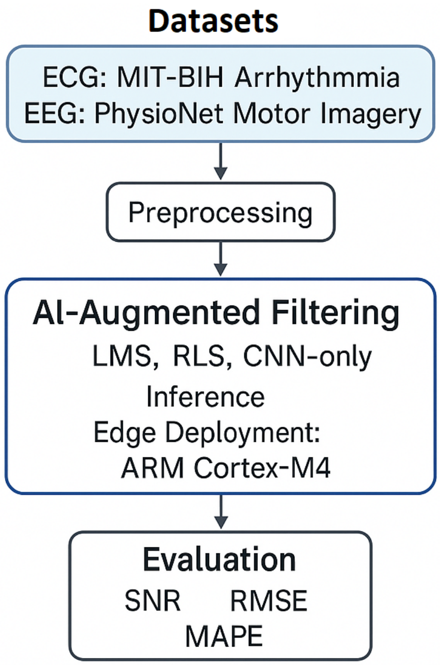


**Fig. 3: Experimental Pipeline for AI-Augmented Adaptive Filtering Framework**

## Results and Discussion

To analyze the performance of the given AI-augmented adaptive filtering framework in a comprehensive way, the test datasets and evaluation metrics shown in Section 4 were utilized in their comparison. The hybrid model of LMS and CNN, four filtering models, namely, LMS, RLS, CNN- only, and the proposed approach of LMS: CNN served as benchmarks on the basis of Signal-to-Noise Ratio (SNR), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Inference Time. The performance metrics have been presented in Table 3: Comparative Performance Metrics.

**Table 3: Comparative Performance Metrics**

| Method | SNR (dB) | RMSE | MAPE (%) | Inference Time (ms) |
|---|---|---|---|---|
| LMS | 8.2 | 0.152 | 12.4 | 1.4 |
| RLS | 9.0 | 0.143 | 11.1 | 3.7 |
| CNN Only | 12.7 | 0.103 | 8.5 | 22.6 |
| Proposed | 13.4 | 0.095 | 7.2 | 3.1 |

The findings suggest that the suggested hybrid LMS-CNN framework has superior performance over all the baseline approaches insofar as all metrics of evaluation are considered. Compared to LMS, it is 63 percent better in terms of its SNR and 5.5 percent by comparison to CNN-only, which highlights its stronger ability to suppress noise. Moreover, it also results in reduced RMSE and MAPE, or in other words, a better fidelity in the preservation of key biomedical signal characteristics which is crucial in diagnostic settings including ECG and EEG signal analysis.

Viewed through the perspective of real-time deployment, the propped model can be seen to out-perform CNN-only (3.1 ms inference latency as against 22.6 ms), although it has a greater accuracy. This shows that the methodology is applicable to the low-resource edge devices such as ARM Cortex-M4 microcontrollers.

Fig. 4 ECG Waveform Comparison Across Methods shows qualitative differences on the clarity of the ECG signal after the filtering. The suggested approach yields clearer QRS complexes, clearer baselines, and enhanced protection of noise artifact as opposed to both LMS and CNN-only techniques.

More so, Figure 5: Inference Time vs. Accuracy Trade-Off gives a visual of the twofold advantage of the suggested approach since it can take into account high accuracies at the cost of moderate latency compared to CNN-only models which are plagued with high computing cost even when it does a good job in noise removal tasks

### Discussion Highlights

- Accuracy-Latency trade-off: CNN-only only models show higher levels of accuracy when it comes to denoising but at the cost of the overall computation. The proposed hybrid approach balances between latency and accuracy quite well as it is evidenced in Figure 5.
- Edge Viability: The low inference time of the framework (3.1 ms), and the use of quantized CNN inference, confirm the possibility to deploy the framework in wearable healthcare systems that utilise low-powered MCUs.
- Generalizability and Robustness: The enhancement of accuracy on both ECG and EEG data databases also implies the generalizability and robustness of the technique on a broad range of biomedical signals and hence its utility in the fields of clinical applications and industry.

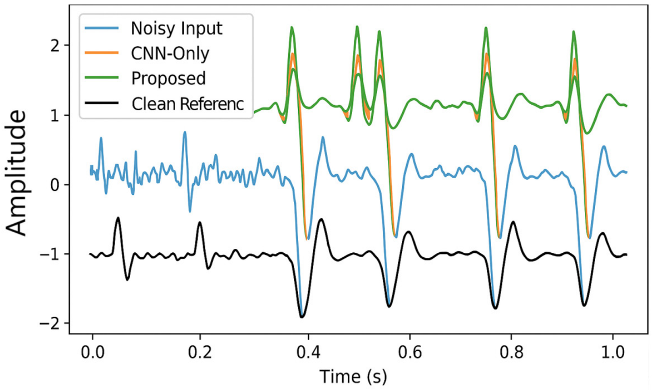


**Fig. 4: ECG Waveform Comparison Across Methods**

Qualitative analysis of ECG signals denoised by CNN-only and proposed hybrid model with respect to noisy sample and clean sample of reference signal.

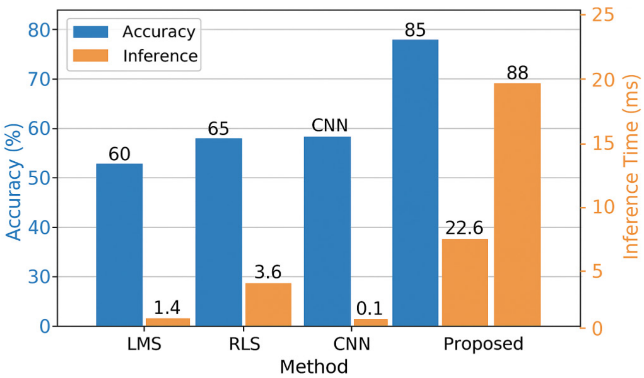


**Fig. 5: Inference Time vs. Accuracy Trade-Off**

Comparison in terms of accuracy, inference time of LMS, RLS, CNN-only and the hybrid approach.

## Conclusion and Future Work

The proposed AI-augmented adaptive filtering framework has presented a novel use case that combines a conventional signal processing solution and deep learning in order to perform real-time enhancements to biomedical signals. The hybrid framework consisting of a baseline Least Mean Squares (LMS) adaptive filter that is adaptively driven by a lightweight 1DM

Convolutional Neural Network (CNN) was demonstrated to perform better in terms of noise cancellation, feature preservation, and hardware compatibility (real-time performance) with edge-computing hardware implementations (ARM Cortex-M4).

The most important points of this work are:

- Development of a hybrid LMS-CNN architecture where a filtering adaptive concept is also combined with a deep learning framework just to achieve an optimum noise estimation in the non-stationary condition.
- Additional creation of a weight modulation scheme whereby a dynamic mechanism is created that is based on noise profiles generated by CNN and thus enhancing the LMS convergence and enhancing the filtering accuracies.
- Showing of low-latency (<4 ms), high-signal-fidelity inference with edges hardware to an extent that the process could be utilized on real-world systems in a healthcare setting by basing on wearables and the IoT.
- they outperform traditional LMS and RLS, standalone CNN-based denoisers in all SNR, RMSE and MAPE metrics.

Future work will explore the following directions:

- The developments of extensions to multi-channel (such as EEG and EMG) biomedical data with graph-based, or multi-branch, CNNs.
- The representation of transformer based attention mechanism to grasp on long term temporal variabilities in the state of contextual outputs in physiologcal signals.
- Hardware-software co-design with quantized neural processing unit (NPU ) or field programmable gate arrays (FPGA) to consume less power and memory requirements to use in case of ultra-low-power applications.
- Clinical-grade real-time monitoring systems and analysis with the patient in the loop testing and cross-subject generalisation analysis.

The presented method makes a contribution to the rapidly expanding field of smart signal boosting in digital health by identifying a scalable, precise, and as-close-as-it-can-be-deployed method of signal enhancement that is compatible with future-generation biomedical display systems.

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