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Machine Learning-Based Noise Reduction in Analog Communication Signals A Comparative Study of Deep Learning Architectures for Signal Denoising

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Abstract

Noise in analog communication channels significantly degrades signal quality, leading to increased bit error rates and reduced communication reliability. Traditional filtering approaches — including Wiener filters, Kalman filters, and wavelet-based methods — while effective under stationary conditions, fail to adapt to non-stationary, time-varying noise environments. This paper presents a comprehensive comparative study of three machine learning architectures — Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and a novel hybrid CNN-LSTM model — for noise reduction in analog communication signals across Additive White Gaussian Noise (AWGN), Rayleigh fading, and impulsive noise channels. We evaluate all models against classical baselines (Wiener filter, Empirical Mode Decomposition) using Signal-to-Noise Ratio improvement (ΔSNR), Mean Squared Error (MSE), and computational latency on a dataset of 50,000 synthetically generated and 10,000 real-world analog signal samples. Our proposed CNN-LSTM hybrid achieves a ΔSNR of 18.6 dB in AWGN channels, outperforming the next best baseline (Wiener filter) by 6.3 dB. In Rayleigh fading conditions, the model delivers an MSE of 3.2×10^{-4}, representing a 52% reduction over classical methods. Real-time inference is demonstrated at 4.2 ms per sample on embedded hardware, confirming deployment feasibility.

Keywords: Noise reduction, analog signals, deep learning, CNN, LSTM, Wiener filter, signal denoising, AWGN, Rayleigh fading.

1. Introduction

Analog communication systems remain foundational in a broad range of applications, including AM/FM radio broadcasting, telephony infrastructure, biomedical signal acquisition (ECG, EEG), industrial sensor networks, and satellite telemetry. Despite the proliferation of digital communication, analog transmission continues to be preferred in scenarios demanding wide frequency coverage, low-power passive reception, and continuous-time signal fidelity.

A persistent challenge in analog systems is the corruption of transmitted signals by various forms of noise — thermal noise originating from electronic components, atmospheric interference, channel fading, and impulsive disturbances from switching transients. The impact is measurable: in standard AWGN channels at 0 dB SNR, uncorrected analog audio signals exhibit a Perceptual Evaluation of Speech Quality (PESQ) score below 1.5, compared to an ideal score of 4.5. Industrial telemetry systems operating in high electromagnetic interference (EMI) environments report error rates exceeding 15% without effective noise mitigation.

Classical signal processing solutions such as the Wiener filter, Kalman filter, band-pass filtering, and wavelet shrinkage have been deployed for decades. These methods offer mathematical elegance and computational efficiency, but their core assumption of signal stationarity limits adaptability to real-world non-stationary channels. For instance, the Wiener filter requires knowledge of the signal's power spectral density (PSD), which is difficult to estimate in dynamic environments.

The advent of deep learning has introduced data-driven approaches capable of learning complex, non-linear input-output mappings directly from training data. Convolutional Neural Networks (CNNs) have demonstrated state-of-the-art results in image denoising [LeCun et al., 2015] and have been adapted for 1D signal processing tasks. Recurrent architectures, particularly Long Short-Term Memory (LSTM) networks, capture temporal dependencies in sequential data, making them well-suited for time-series signal denoising. Hybrid CNN-LSTM models that extract local features before modeling long-range temporal patterns have shown promise in speech enhancement tasks [Weninger et al., 2015].

This paper makes the following contributions:

1. A systematic comparison of CNN, LSTM, and CNN-LSTM architectures against classical baselines for analog signal denoising across three channel types.
2. A novel CNN-LSTM architecture with channel-attention mechanisms specifically designed for analog signal noise profiles.
3. An open-source dataset of 60,000 analog signal samples (synthetic + real-world) including multi-channel noise labels.
4. Embedded deployment benchmarks on Raspberry Pi 4 and NVIDIA Jetson Nano platforms.

2. Related Work

2.1 Classical Noise Reduction Methods

The Wiener filter, introduced by Norbert Wiener in 1949, remains a cornerstone of linear signal estimation theory. It minimizes the mean squared error between the estimated and true signal under the assumption of wide-sense stationarity. Empirical studies show peak SNR improvements of 8-10 dB in ideal Gaussian noise scenarios. The Kalman filter extends this to dynamic state-space models, offering sequential estimation well-suited to real-time systems but sensitive to model mismatch.

Wavelet-based denoising [Donoho & Johnstone, 1994] applies threshold-based coefficient shrinkage in the wavelet domain, effectively separating signal energy from noise for broadband signals. Empirical Mode Decomposition (EMD) [Huang et al., 1998] decomposes signals into Intrinsic Mode Functions (IMFs) adaptively, making no assumption about signal stationarity. Despite its flexibility, EMD suffers from mode mixing and lacks a principled denoising criterion.

2.2 Machine Learning Approaches

Deep learning for signal denoising emerged from speech enhancement literature. Xu et al. [2014] demonstrated that feedforward deep neural networks (DNNs) could outperform traditional spectral subtraction methods for speech denoising, establishing the viability of learned noise models. Zhao et al. [2018] applied convolutional encoder-decoder architectures (U-Net style) to electrocardiogram (ECG) denoising, achieving MSE reductions of 40% over wavelet methods.

For sequential signals, LSTM-based models have been explored by Choi et al. [2019] for audio source separation and by Reddy et al. [2021] for RF signal denoising in software-defined radio (SDR) contexts. The latter reported a 5.8 dB SNR improvement over classical adaptive filters at -5 dB input SNR. Hybrid models combining CNN feature extraction with LSTM temporal modeling were explored by Zhang et al. [2022] for EEG artifact removal, demonstrating that the combination yields superior generalization across subjects.

A notable gap in existing literature is the lack of systematic evaluation across multiple analog channel types (AWGN, Rayleigh, impulsive) using consistent evaluation metrics and real-world validation datasets. This work addresses that gap directly.

3. Methodology

3.1 Dataset Generation

Our dataset comprises 60,000 signal samples: 50,000 synthetically generated and 10,000 captured from real analog communication channels. Synthetic signals span AM-modulated carrier frequencies in the 100 kHz to 30 MHz range, FM signals at 88-108 MHz band, and baseband telemetry waveforms at 10-100 kHz. Noise was applied at SNR levels of -10, -5, 0, 5, 10, and 15 dB, across three noise models:

- AWGN (Additive White Gaussian Noise): Flat PSD across signal bandwidth, modeled as $N(0, \sigma^2)$.
- Rayleigh Fading: Multipath-induced amplitude and phase variations, simulated with a Doppler spread of 50 Hz.
- Impulsive Noise: Alpha-stable distribution (α=1.5) modeling switching transients and EMI bursts.

Real-world samples were acquired using a USRP B210 software-defined radio receiver in urban and semi-urban environments in Hyderabad, India, spanning AM broadcast and industrial telemetry bands. All signals were sampled at 10 MS/s and segmented into 1024-sample frames with 50% overlap.

3.2 Model Architectures

CNN Denoiser:

A 10-layer 1D convolutional architecture with residual connections (DnCNN-inspired) using 64 filters of size 3, batch normalization, and ReLU activations. The network learns a noise residual, and the clean signal estimate is obtained by subtracting the predicted noise from the input.

LSTM Denoiser:

A 3-layer bidirectional LSTM with 256 hidden units per direction, followed by a fully connected layer. Bidirectional processing captures both past and future context in each signal frame, improving temporal coherence of the denoised output.

CNN-LSTM Hybrid (Proposed):

The proposed architecture consists of a CNN front-end (5 convolutional layers with channel-attention via Squeeze-and-Excitation blocks) feeding a 2-layer bidirectional LSTM back-end. The channel attention mechanism learns to weight frequency sub-band features adaptively, improving performance under spectrally non-uniform noise. Total parameters: 2.3 million.

3.3 Training Protocol

All models were trained using Adam optimizer (lr = 1×10^{-4}, β_1=0.9, β_2=0.999) with a cosine annealing learning rate schedule over 100 epochs. Batch size: 64. Loss function: Mean Squared Error (MSE) between predicted and clean signal frames. Training was conducted on a cluster of 4× NVIDIA RTX 3090 GPUs, with data augmentation including random phase shifts and frequency warping. 80/10/10 train/validation/test splits were used, stratified by SNR level.

3.4 Evaluation Metrics

ΔSNR (dB): Improvement in output SNR over input SNR, measuring the absolute noise reduction gain. MSE: Mean squared error between denoised output and clean reference signal. PESQ: Perceptual Evaluation of Speech Quality score (1–4.5) for audio-band signals. Inference Latency (ms): Per-sample processing time on embedded hardware.

4. Experimental Results

4.1 SNR Improvement — AWGN Channel

Table 1 summarizes ΔSNR performance across all models at input SNR levels from -10 dB to +10 dB in AWGN channels. The CNN-LSTM hybrid consistently outperforms all baselines and single-architecture ML models across all SNR operating points.

Method	ΔSNR @ -10 dB	ΔSNR @ 0 dB	ΔSNR @ 5 dB	ΔSNR @ 10 dB
Wiener Filter	6.1 dB	8.4 dB	10.2 dB	12.3 dB
Wavelet Shrinkage	5.4 dB	7.8 dB	9.1 dB	11.0 dB
EMD-based	5.8 dB	8.1 dB	9.6 dB	11.7 dB
CNN (DnCNN)	9.3 dB	12.7 dB	14.1 dB	16.2 dB
BiLSTM	8.8 dB	11.9 dB	13.6 dB	15.8 dB
CNN-LSTM (Proposed)	11.4 dB	15.2 dB	17.0 dB	18.6 dB

Table 1: ΔSNR performance in AWGN channel (higher is better).

4.2 MSE Performance — Rayleigh Fading Channel

Rayleigh fading introduces multipath amplitude and phase distortions that classical linear filters struggle to compensate. Table 2 reports MSE values ($\times10^{-4}$) across models and input SNR conditions in Rayleigh fading channels. Lower MSE indicates better signal reconstruction fidelity.

Method	MSE @ -5 dB	MSE @ 0 dB	MSE @ 5 dB	MSE @ 10 dB
Wiener Filter	18.4	12.1	7.6	4.3
Kalman Filter	16.9	10.8	6.9	3.8
Wavelet Shrinkage	19.2	13.4	8.1	4.7
CNN (DnCNN)	9.7	6.3	4.1	2.2
BiLSTM	10.2	6.8	4.5	2.5
CNN-LSTM (Proposed)	7.1	4.8	3.2	1.7

Table 2: MSE ($\times 10^{-4}$) in Rayleigh fading channel (lower is better).

4.3 Performance in Impulsive Noise

Impulsive noise presents a particularly challenging scenario as its heavy-tailed distribution violates the Gaussian assumptions underlying most classical filters. Table 3 presents ΔSNR results in alpha-stable (α=1.5) impulsive noise, showing the relative robustness advantage of ML models trained with augmented impulsive noise samples.

Method	ΔSNR @ 0 dB	ΔSNR @ 5 dB	PESQ Score	Robustness Index
Wiener Filter	4.2 dB	5.8 dB	1.9	Low
Median Filter	5.6 dB	7.1 dB	2.1	Medium
Wavelet Shrinkage	5.0 dB	6.4 dB	2.0	Low-Medium
CNN (DnCNN)	9.6 dB	12.3 dB	3.1	High
BiLSTM	8.9 dB	11.4 dB	2.9	Medium-High
CNN-LSTM (Proposed)	11.8 dB	14.7 dB	3.6	Very High

Table 3: Impulsive noise performance (α=1.5 alpha-stable distribution).

4.4 Real-World Validation

Table 4 presents results on the 10,000 real-world signal samples acquired from the USRP B210 receiver. Real-world validation reveals a characteristic performance gap vs. synthetic testing, with all models showing some reduction in ΔSNR due to unmodeled noise sources such as narrowband interference and hardware non-linearities. The CNN-LSTM model degrades most gracefully, maintaining a 5.1 dB advantage over the Wiener filter baseline in real-world conditions.

Method	Real-World ΔSNR (dB)	PESQ Score	Inference Latency (ms)
Wiener Filter	7.2	2.3	0.08
Wavelet Shrinkage	6.8	2.1	0.21
EMD-based	7.0	2.2	1.40
CNN (DnCNN)	10.8	3.0	2.10
BiLSTM	10.1	2.8	3.40
CNN-LSTM (Proposed)	12.3	3.5	4.20

Table 4: Real-world validation results on USRP-acquired signals (Raspberry Pi 4 platform).

4.5 Ablation Study — CNN-LSTM Components

To quantify the contribution of each architectural component, we performed an ablation study removing the channel-attention mechanism and the bidirectional LSTM layer independently. Results at 0 dB input SNR in AWGN are shown in Table 5.

Model Variant	ΔSNR (dB)	MSE ($\times10^{-4}$)	Parameters (M)
CNN-LSTM (Full Model)	15.2	4.8	2.30
w/o Channel Attention	13.4	6.9	2.11
w/o Bidirectional LSTM	12.8	7.4	1.98
CNN Only (DnCNN)	12.7	7.5	1.20
LSTM Only	11.9	8.3	1.65

Table 5: Ablation study — CNN-LSTM component contributions at 0 dB SNR (AWGN).

The channel attention mechanism contributes +1.8 dB over the no-attention variant, confirming its role in selectively suppressing spectrally localized noise. The bidirectional LSTM adds +2.4 dB over the CNN-only baseline, validating the value of temporal context modeling in sequential signal denoising.

5. Discussion

The experimental results consistently establish the superiority of the proposed CNN-LSTM architecture over classical and single-paradigm ML approaches. Three key observations merit detailed discussion.

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First, the channel attention mechanism is most beneficial at low SNR operating points (-10 to 0 dB), where noise occupies a broad and variable portion of the signal spectrum. At high SNR (>10 dB), the attention gains diminish, suggesting that simple noise structures at high SNR are well-captured by the convolutional feature extraction alone. This insight suggests that adaptive attention gating based on estimated SNR could reduce computational overhead in high-SNR deployment scenarios.

Second, the transition from synthetic to real-world performance reveals that the greatest degradation occurs in CNN-only models (3.2 dB drop) compared to CNN-LSTM (2.9 dB drop), suggesting that temporal modeling provides more robust generalization. Real-world signals contain non-stationary, correlated noise components that pure convolutional models treat as spatially independent — a mismatch that LSTM temporal modeling partially compensates.

Third, the inference latency of 4.2 ms for the CNN-LSTM on Raspberry Pi 4 (ARM Cortex-A72 @ 1.8 GHz) confirms real-time feasibility for signals below 240 Hz effective bandwidth. For higher-bandwidth RF applications, deployment on NVIDIA Jetson Nano reduces latency to 0.9 ms, enabling real-time processing at 1 MS/s frame rates. This positions the model for SDR-based practical deployments.

A limitation of the current study is the restricted frequency range of real-world samples (100 kHz to 108 MHz), leaving higher UHF/microwave bands unvalidated. Future work will extend dataset coverage and explore knowledge distillation to reduce the CNN-LSTM model size by 60% while retaining >95% of denoising performance for ultra-low-power IoT deployments.

6. Conclusion

This paper presented a systematic evaluation of machine learning approaches for noise reduction in analog communication signals. The proposed CNN-LSTM hybrid architecture, incorporating channel-attention mechanisms, achieved the best performance across all tested noise channels — delivering ΔSNR of 18.6 dB in AWGN (6.3 dB over Wiener filter), MSE of 3.2×10^{-4} in Rayleigh fading (52% improvement), and PESQ of 3.6 in impulsive noise conditions. Real-world validation confirmed practical applicability with inference latency of 4.2 ms on embedded hardware.

The results demonstrate that data-driven denoising approaches can substantially outperform classical linear methods in non-stationary, real-world analog channel conditions, while remaining computationally tractable for embedded deployment. The ablation study quantified the independent contributions of channel-attention and bidirectional LSTM components, providing architectural guidance for future model design.

The dataset and pre-trained model weights are publicly available at github.com/iith-siglab/ml-analog-denoising to facilitate reproducibility and further research in this domain.

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