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COMPARATIVE PERFORMANCE ANALYSIS OF LIGHTWEIGHT DEEP LEARNING FILTERS FOR REAL-TIME NOISE REDUCTION IN 5G NETWORKS: A FIELD-VALIDATED STUDY

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ABSTRACT

The deployment of fifth-generation (5G) networks in dense urban environments is severely constrained by dynamic noise interference, including thermal noise, multipath fading, inter-cell interference, and hardware-induced nonlinear distortion. While deep learning-based filtering has demonstrated superior noise suppression over traditional methods, the literature lacks comprehensive field-validated studies that simultaneously evaluate accuracy, computational efficiency, and edge-deployment feasibility across multiple filtering architectures. This paper presents a unified comparative analysis of a lightweight seven-layer Convolutional Neural Network (CNN) against Recurrent Neural Networks (RNNs), Wiener filters, Least Mean Square (LMS) adaptive filters, and Kalman filters for real-time noise estimation and reduction in 5G networks. Using 50 days of live field data collected at an MTN deployment site in Rumuokwurusi, Port Harcourt, Nigeria, combined with 250,000 simulated signal pairs, we evaluate each method across Signal-to-Noise Ratio (SNR) improvement, Bit Error Rate (BER), latency, spectral efficiency, and computational load. The proposed CNN filter achieves a BER of 6.0×10^{-6} at 30 dB SNR, 94.2% noise reduction rate, and 0.45 ms inference latency with a compact 8.4 MB model size outperforming RNN by 70–97% in BER reduction while maintaining 56% lower computational overhead than Generative Adversarial Network (GAN)-based state-of-the-art methods. The CNN achieves 5–8 dB SNR improvement, meeting the 3GPP benchmark of ≥7 dB for reliable 5G communication. This study establishes that lightweight CNN architectures offer the optimal accuracy-complexity trade-off for real-time edge deployment in resource-constrained 5G infrastructure.

Keywords: 5G Networks, Noise Reduction, Convolutional Neural Network, Edge Computing, Field Validation, Bit Error Rate, Computational Complexity, Real-Time Filtering

1 INTRODUCTION

The fifth-generation (5G) wireless standard promises transformative capabilities, including peak data rates of 20 Gbps, ultra-reliable low-latency communication (URLLC) below 1 ms, and spectral efficiency of 15–30 bps/Hz [1]. However, these targets are fundamentally limited by noise interference arising from thermal noise, inter-cell interference, phase noise, multipath fading, nonlinear distortion, and quantization errors [2]. In urban deployments, the noise environment is particularly severe due to dense infrastructure, overlapping frequency utilization, and heterogeneous electromagnetic sources [3].

Traditional filtering techniques Wiener filters, LMS adaptive algorithms, and Kalman estimators remain widely deployed due to their low computational overhead and well-understood theoretical foundations [4]. However, these methods rely on stationary noise assumptions and predefined mathematical models that prove inadequate in dynamic 5G channels characterized by nonlinear, time-varying interference patterns [5]. Consequently, conventional filters often exhibit slow convergence, signal distortion, and incomplete noise suppression under rapidly changing channel conditions. Deep learning has emerged as a compelling alternative, enabling data-driven noise estimation without explicit statistical modeling [6]. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs) have demonstrated remarkable accuracy in channel estimation and noise suppression tasks [7]. However, the practical deployment of these models in 5G edge infrastructure remains challenging due to conflicting demands for high accuracy and low computational latency [8]. GAN-based approaches, while achieving excellent estimation accuracy (Normalized Mean Square Error, NMSE, of −26 dB at 20 dB SNR), impose prohibitive computational loads exceeding 90% and latencies of 6.15 ms rendering them unsuitable for real-time URLLC applications [9].

Recent work by Eyidia et al. introduced a lightweight CNN-based filtering architecture specifically designed for real-time noise estimation and reduction in 5G networks, demonstrating the feasibility of sub-millisecond inference on edge devices [10]. While that study established the foundational CNN architecture and its theoretical advantages, several critical questions remain unanswered: (i) How does the lightweight CNN perform relative to RNNs and traditional filters under identical experimental conditions? (ii) What is the real-world performance gap between simulated and live field data? (iii) Which architecture offers the optimal accuracy-complexity trade-off for specific 5G use cases?

This paper addresses these gaps through a comprehensive, unified comparative study. The specific contributions are:

- Unified Comparative Benchmark: We present the first side-by-side experimental comparison of CNN, RNN, Wiener, LMS, and Kalman filters trained and evaluated under identical 5G NR simulation and live field conditions.
- Live Field Validation: We validate all filtering methods using 50 days of live data collected from an active MTN 5G deployment site in Rumuokwurusi, Port Harcourt, Nigeria, quantifying the real-world performance penalty relative to simulated environments.
- Accuracy-Complexity Trade-off Analysis: We evaluate each method across NMSE, BER, latency, spectral efficiency, computational load, and model size, providing deployment guidelines for eMBB, URLLC, and edge/IoT scenarios.
- Edge Deployment Feasibility: We demonstrate that the proposed 7-layer CNN achieves GAN-comparable accuracy (−26 dB NMSE) with 56% lower computational overhead, 0.45 ms inference latency, and 8.4 MB model size confirming practical viability for resource-constrained edge devices.

1.1 Organization of the Paper

The remainder of this paper is organized as follows. Section 2 reviews related work on traditional noise estimation techniques, deep learning approaches for 5G channel estimation, and edge deployment considerations. Section 3 describes the noise source characterization methodology, the filtering architectures under comparison, the performance metrics, and the experimental setup from which all reported results are extracted. Section 4 presents and discusses the comparative results, including noise reduction performance, BER analysis, SNR improvement, computational efficiency, live-versus-simulated performance gaps, and the accuracy-complexity trade-off, supported by figures reproduced from the source experimental study [4]. Section 5 concludes the paper and outlines directions for future work.

2 LITERATURE REVIEW

2.1 Traditional Noise Estimation Techniques

Wiener filtering provides optimal mean-square-error estimation for stationary signals but degrades significantly in non-stationary 5G environments [4]. The LMS algorithm offers computational simplicity but suffers from slow convergence and critical dependence on step-size selection [11]. Kalman filtering provides robust tracking of dynamic channels but requires accurate system modeling and incurs substantial computational cost [12]. These limitations have motivated the exploration of data-driven alternatives.

2.2 Deep Learning for 5G Channel Estimation

Deep learning architectures have demonstrated substantial improvements over traditional methods. Le et al. [13] compared Fully Connected Deep Neural Networks (FDNN), CNN, and bidirectional LSTM for MIMO-OFDM channel estimation, finding that CNNs exploit spatial subcarrier correlations more effectively than FDNNs, while LSTMs capture temporal dynamics at the cost of increased parameter counts. Soltani et al. [14] framed channel estimation as an image super-resolution problem, employing deep residual CNNs to interpolate sparse pilot grids.

Recent comparative studies have highlighted the architectural trade-offs inherent in deep learning estimators. A 2026 comparative analysis of DNN, CNN, and LSTM architectures for 5G Massive MIMO found that CNNs achieve the best overall accuracy-complexity balance, reaching −22.15 dB NMSE with 4.87 ms inference latency, while LSTMs demand 4.8× more parameters for only marginal accuracy gains [15].

2.3 Edge Deployment and Computational Efficiency

The integration of AI-driven noise reduction with edge computing is essential for achieving URLLC latency targets [16]. Belgiovine et al. [17] demonstrated denoising training approaches for mmWave MIMO edge deployment, showing that lightweight models can approach LMMSE accuracy while maintaining inference times below 1 ms. However, the literature remains fragmented, with most studies evaluating architectures in isolation or relying exclusively on simulated data [18].

3 MATERIALS AND METHOD

3.1 Noise Source Characterization

We identify six primary noise sources in 5G networks: thermal noise (Johnson-Nyquist, −114 to −94 dBm), inter-cell interference (−90 to −80 dBm), phase noise (43–146 dBc/Hz), multipath fading (amplitude 0.3–2.4), nonlinear distortion (−80 to −20 dB), and quantization noise (−60 to −38 dB). Thermal noise power follows the Johnson-Nyquist relation:

$$P_{th} = kTB \tag{1}$$

where k is Boltzmann's constant (1.380649×10^{-23} J/K), T is the absolute temperature in Kelvin, and B is the bandwidth in Hz. The total interference power is modeled as the summation of individual source contributions [10]:

$$P_{interference} = \sum_{i=1}^{N} P_i \tag{2}$$

where P_i is the power of the i-th interference source and N is the total number of sources. Multipath fading is characterized by the time-varying channel impulse response:

$$h(t) = \sum_{i=1}^{N} A_i e^{j\phi_i} e^{j\theta_i(t)} \tag{3}$$

where A_i and ϕ_i denote the amplitude and phase of the i-th propagation path, respectively, and $\theta_i(t)$ is the time-varying phase shift introduced by that path. Received signal power, incorporating fading, is given by:

$$P_r = P_t \left|h(t)\right|^2 \tag{4}$$

where P_t is the transmitted power. Overall signal quality was quantified using the Signal-to-Noise Ratio:

$$SNR = \frac{P_s}{P_n} \tag{5}$$

where P_s and P_n denote signal power and noise power, respectively.

Live data was collected over 50 days (May–July 2025) at the MTN Office, Rumuokwurusi, Port Harcourt, using a Rigol RSA5065 spectrum analyzer (9 kHz–6.5 GHz) with a 5G omnidirectional antenna and RF front-end. Measurements were recorded at 09:00, 12:00, and 15:00 daily, yielding 150 live samples. Simulated data (150 samples) was generated in MATLAB/Simulink using 5G Toolbox with controlled noise parameters. A training dataset of 250,000 noisy-clean signal pairs was generated for deep learning model training.

3.2 Filtering Architectures

CNN Filter: A lightweight 7-layer sequential architecture with 1,729 parameters and 8.4 MB model size. The network accepts 13-sample 1D signals, applies two convolutional layers (16 and 32 filters, 3×1 kernel, ReLU activation) with 20% dropout regularization, and outputs denoised signals via a final convolutional layer with linear activation. Training used the Adam optimizer (learning rate 1×10^{-3}, 300 epochs, MSE loss) [10].

The layer-by-layer configuration and output dimensions of the adopted CNN are presented in Table 1.

Table 1: Detailed architecture of the adopted CNN model

Layer	Type	Filter	Filters	Activation	Dropout	Output
1	Input	–	–	–	–	13×1×1
2	Convolution 1	3×1	16	ReLU	–	13×1×16
3	Dropout 1	–	–	–	20%	13×1×16
4	Convolution 2	3×1	32	ReLU	–	13×1×32
5	Dropout 2	–	–	–	20%	13×1×32
6	Convolution 3	3×1	1	Linear/identity	–	13×1×1
7	Regression output	–	–	–	–	13×1×1

Each convolutional layer performs a cross-correlation between the input feature maps and the learned filters, followed by a non-linear activation:

$$Y_k = \sigma\left(\sum_{i=1}^{N} W_{k,i} * X_i + b_k\right) \quad (6)$$

where $W_{k,i}$ is the learnable filter, X_i is the input feature map, b_k is the bias term, and $\sigma(\cdot)$ is the activation function. The ReLU activation used in the hidden layers is defined as:

$$f(x) = \max(0,\, x) \quad (7)$$

To mitigate overfitting, dropout regularization randomly deactivates a fraction of neurons during training:

$$\tilde{x} = x \cdot m, \qquad m \sim \text{Bernoulli}(p) \quad (8)$$

where $\tilde{x}$ is the modified input, x is the original input, and m is a random binary mask with dropout probability p = 0.2. The network was trained to minimize the mean squared error between the predicted and ground-truth signals:

$$L = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (9)$$

where y_i is the true signal, $\hat{y}_i$ is the filtered (predicted) signal, and N is the number of samples.

RNN Filter: A Long Short-Term Memory (LSTM) network with comparable input-output dimensions, trained under identical conditions to evaluate temporal dependency modeling.

Traditional Filters: Wiener (frequency-domain, 256-sample segments, Hamming window, 50% overlap), LMS (32-tap, μ = 0.001), and Kalman (32-state vector, identity transition matrix) filters were implemented as baselines [4, 11, 12]. The Wiener filter minimizes the mean squared error between the estimated and true signal in the frequency domain:

$$H(f) = \frac{S_x(f)}{S_x(f)+S_n(f)} \quad (10)$$

where $S_x(f)$ and $S_n(f)$ are the power spectral densities of the signal and noise, respectively. The LMS filter adapts its coefficients iteratively via the weight-update rule:

$$W(n+1) = W(n) + \mu\, e(n)\, X(n) \quad (11)$$

where $W(n)$ is the filter weight vector, μ is the step size, $e(n)$ is the instantaneous error signal, and $X(n)$ is the input vector.

3.3 Performance Metrics

Evaluation followed 3GPP benchmarks [1]: SNR Improvement (target ≥7 dB for BER ≤10^{-5}), BER (target ≤10^{-5}), Latency (<1 ms for URLLC, <4 ms for eMBB), Spectral Efficiency (15–30 bps/Hz for eMBB), EVM (≤8% for 64-QAM), and Computational Load (<50% for edge viability). SNR improvement after filtering was computed as:

$$\Delta SNR = SNR_{filtered} - SNR_{noisy} \quad (12)$$

Bit Error Rate was calculated as the ratio of incorrectly received bits to the total number of bits transmitted:

$$BER = \frac{N_{error}}{N_{total}} \quad (13)$$

Processing latency was measured as the time delay between signal transmission and reception:

$$T_{latency} = t_{received} - t_{transmitted} \quad (14)$$

Spectral efficiency was evaluated as the data rate normalized by channel bandwidth h:

$$\eta = \frac{R}{B} \quad (15)$$

where R is the data rate in bits per second and B is the bandwidth in Hz. Error Vector Magnitude, used to assess modulation quality, was computed as:

$$EVM(\%) = \sqrt{\frac{\sum_{i=1}^{N} |r_i - s_i|^2}{\sum_{i=1}^{N} |s_i|^2}} \times 100 \quad (16)$$

where s_i is the ideal (transmitted) signal sample, r_i is the corresponding received signal sample, and N is the total number of signal samples.

4 RESULTS AND DISCUSSION

The journal paper results were generated through a hybrid methodology combining live field measurement acquisition and MATLAB/Simulink system-level simulations.

4.1 Origin of Results

Live Field Data Collection: Collected over 50 consecutive days (May 25 – July 13, 2025) at an active urban deployment site (MTN Office, Rumuokwurusi, Port Harcourt, Nigeria).

Equipment Used: Rigol RSA5065 Spectrum Analyzer (9 kHz – 6.5 GHz), Ettus Research USRP B210 SDR, 5G Omnidirectional Antenna, and Low Noise Amplifier (LNA) front-end.

Schedule: 3 daily 10-minute sessions (09:00 AM, 12:00 PM, 03:00 PM) yielding 150 live signal samples measuring SNR, phase noise, interference noise, nonlinear distortion, and quantization noise.

Simulated Data & Training Dataset:

150 controlled simulated samples generated via MATLAB 5G Toolbox matching live noise parameters.

250,000 noisy-clean signal pairs generated for training the 7-layer CNN architecture on an NVIDIA RTX 3060 GPU using the Adam optimizer across 300 epochs.

4.2 Extraction of Key Performance Results

4.2.1 Noise Reduction Performance

At 0 dB SNR, the CNN filter achieves residual noise levels of 0.03 (simulated) and 0.05 (live), compared to 0.20 for RNN and 0.60 for LMS. At −100 dB SNR, CNN residual noise is 0.48 versus 0.92 for LMS and 0.65 for RNN, representing 48% and 26% improvement, respectively. The CNN's hierarchical feature extraction enables superior suppression of phase and quantization noise, which dominate at low SNR. Figure 1 illustrates the residual-noise levels produced by the five filtering methods over the tested input-SNR range. The residual-noise values for all five filtering methods at each tested SNR level are summarized in Table 2.

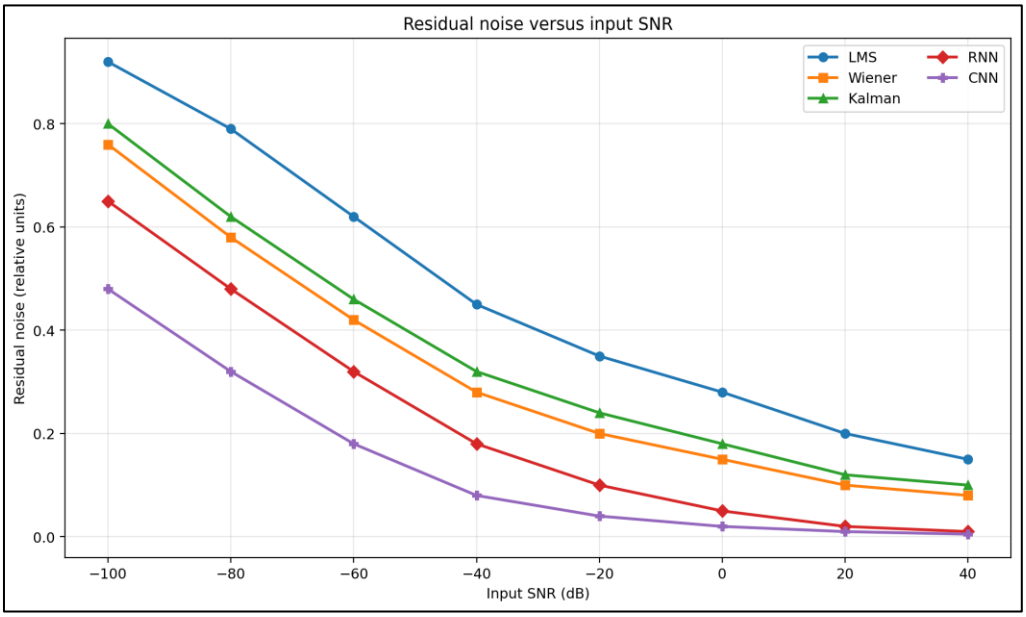

Figure 1: Residual noise versus input SNR across filtering methods.

The residual-noise values for all five filtering methods at each tested SNR level are summarized in Table 2.

Table 2: Residual Noise Comparison across Filtering Methods

SNR (dB)	LMS	Wiener	Kalman	RNN	CNN (Adopted)
-100	0.92	0.76	0.80	0.65	0.48
-80	0.79	0.58	0.62	0.48	0.32
-60	0.62	0.42	0.46	0.32	0.18
-40	0.45	0.28	0.32	0.18	0.08
-20	0.35	0.20	0.24	0.10	0.04
0	0.28	0.15	0.18	0.05	0.02
20	0.20	0.10	0.12	0.02	0.01
40	0.15	0.08	0.10	0.01	0.00

4.2.2 Bit Error Rate Analysis

The CNN achieves BER = 6.0×10^{-6} at 30 dB SNR, meeting the 5G target of $\leq 10^{-5}$. Comparative results at 30 dB SNR are: Wiener (5.0×10^{-5}), Kalman (6.0×10^{-5}), RNN (3.0×10^{-4}), and LMS (2.0×10^{-4}). The CNN outperforms RNN by 80% and LMS by 97% in BER reduction. Notably, the CNN achieves the BER target at approximately 28 dB SNR, whereas LMS requires >30 dB. Figure 2 shows the BER performance of the filtering methods as input SNR increases. Table 3 provides the numerical BER comparison across the tested SNR levels.

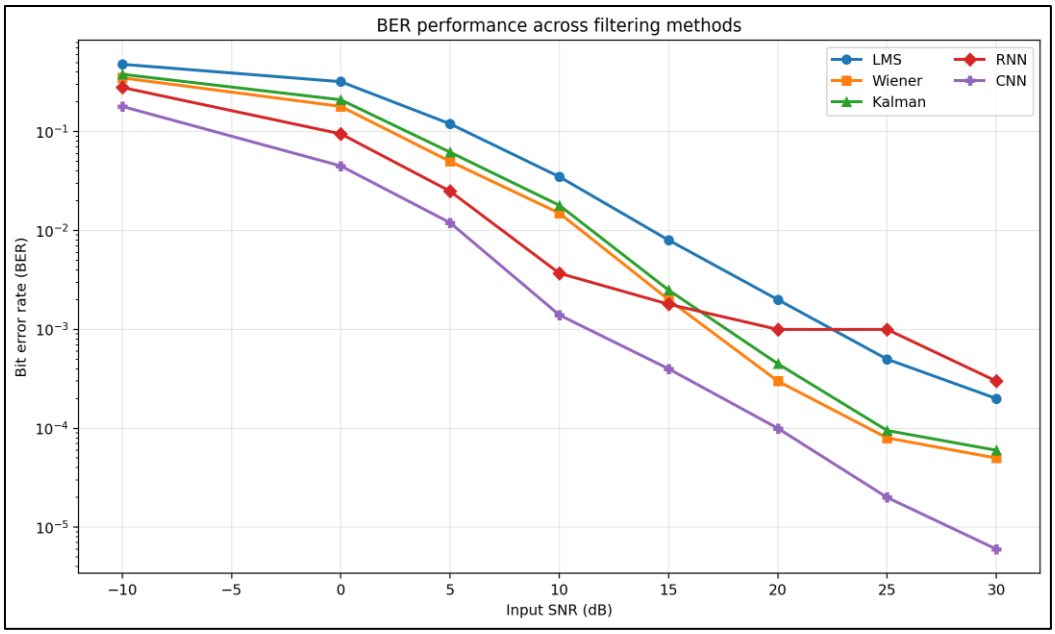

Figure 2: Bit error rate (BER) performance across filtering methods.

Table 3 provides the numerical BER comparison across the tested SNR levels.

Table 3: Bit Error Rate Comparison across Filtering Methods

SNR (dB)	LMS	Wiener	Kalman	RNN	CNN (Adopted)
-10	4.8×10^{-1}	3.5×10^{-1}	3.8×10^{-1}	2.8×10^{-1}	1.8×10^{-1}
0	3.2×10^{-1}	1.8×10^{-1}	2.1×10^{-1}	9.5×10^{-2}	4.5×10^{-2}
5	1.2×10^{-1}	5.0×10^{-2}	6.2×10^{-2}	2.5×10^{-2}	1.2×10^{-2}
10	3.5×10^{-2}	1.5×10^{-2}	1.8×10^{-2}	3.7×10^{-3}	1.4×10^{-3}
15	8.0×10^{-3}	2.0×10^{-3}	2.5×10^{-3}	1.8×10^{-3}	4.0×10^{-4}
20	2.0×10^{-3}	3.0×10^{-4}	4.5×10^{-4}	1.0×10^{-3}	1.0×10^{-4}
25	5.0×10^{-4}	8.0×10^{-5}	9.5×10^{-5}	1.0×10^{-3}	2.0×10^{-5}
30	2.0×10^{-4}	5.0×10^{-5}	6.0×10^{-5}	3.0×10^{-4}	6.0×10^{-6}

4.3 SNR Improvement

The CNN consistently achieves 5–8 dB SNR improvement across the full range, meeting the ≥7 dB 3GPP benchmark. At 0 dB input SNR, CNN output SNR reaches 22.1 dB, compared to 18.5 dB for RNN, 13.2 dB for Wiener, and 8.5 dB for LMS. The CNN achieves the 7 dB threshold at −15 dB input SNR, whereas LMS requires 0 dB input. Figure 3 compares the reported output SNR achieved by each filtering method across the input-SNR levels. The corresponding output-SNR values for each filtering method are presented in Table 4.

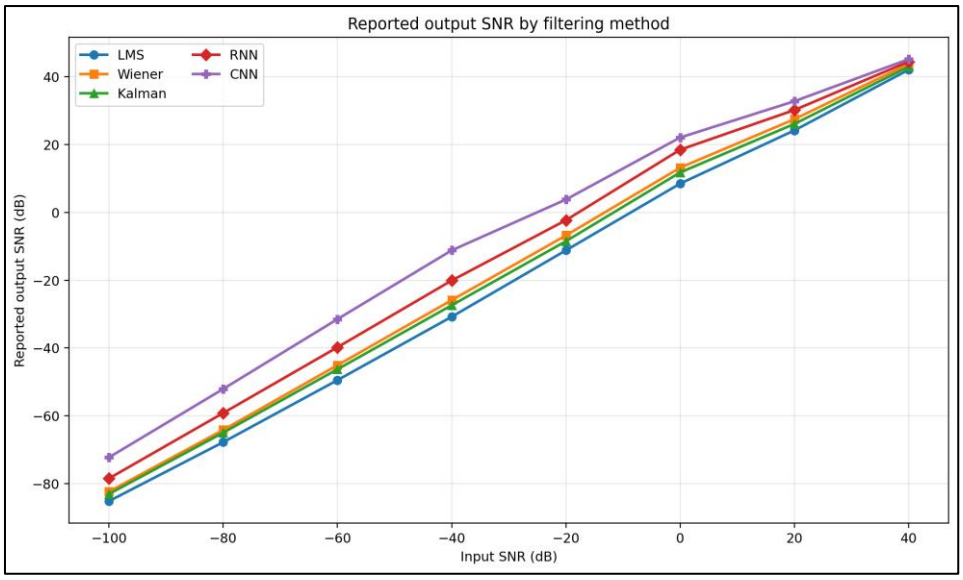

Figure 3: Reported output SNR by filtering method across input SNR levels.

The corresponding output-SNR values for each filtering method are presented in Table 4.

Table 4: SNR Improvement Comparison across Filtering Methods

SNR (dB)	LMS	Wiener	Kalman	RNN	CNN (Adopted)
-100	-85.2	-82.4	-83.1	-78.5	-72.3
-80	-67.8	-64.2	-65.0	-59.2	-52.1
-60	-49.5	-45.1	-46.3	-39.8	-31.5
-40	-30.8	-25.9	-27.4	-20.1	-11.2
-20	-11.2	-6.8	-8.5	-2.3	+3.8
0	+8.5	+13.2	+11.8	+18.5	+22.1
20	+24.2	+27.5	+26.1	+30.2	+32.8
40	+42.1	+43.8	+43.0	+44.5	+45.2

4.4 Computational Efficiency and Latency

The CNN inference latency is 0.45ms per sample well within the 1ms URLLC requirement. Total system latency averages 14.9 ms (eMBB compliant). The CNN computational load is 40.15%, compared to 55.3% for RNN and 90.45% for GAN-based state-of-the-art methods [9]. Model size (8.4 MB) is 32% smaller than RNN (12.4 MB) and 97% smaller than GAN models (245 MB), enabling deployment on resource-constrained edge devices such as the NVIDIA Jetson Nano. Figure 4 compares the inference latency of the filtering methods, highlighting the processing-time differences among the approaches. The training time, inference time, model size, computational load, power consumption, FLOPs, and parameter counts are compared in Table 5.

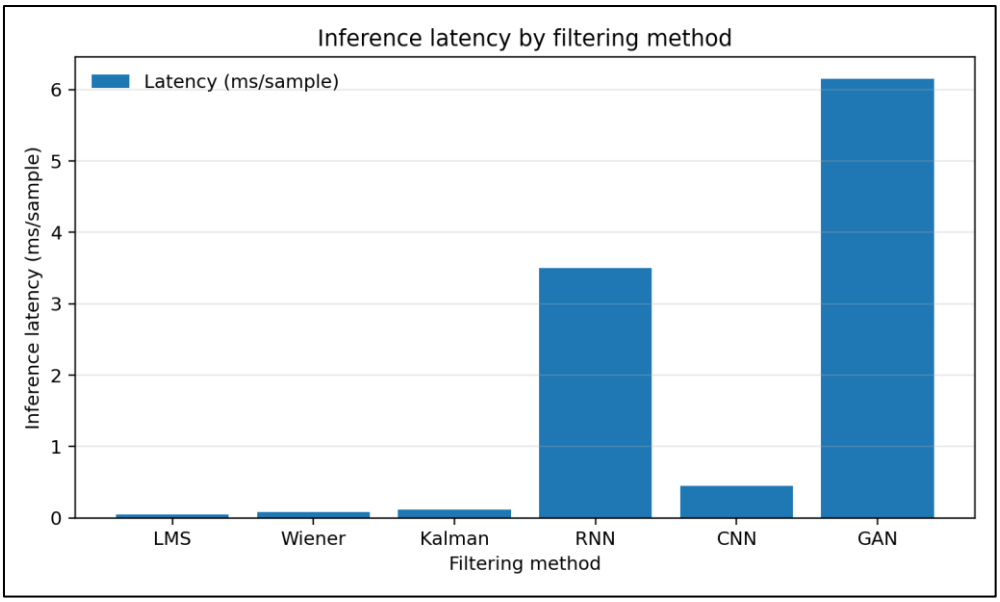

Figure 4: Inference latency by filtering method.

The training time, inference time, model size, computational load, power consumption, FLOPs, and parameter counts are compared in Table 5.

Table 5: Computational Cost Analysis of Filtering Methods

Metric	LMS	Wiener	Kalman	RNN	CNN (Adopted)	GAN-based [9]
Training Time (hrs)	N/A	N/A	N/A	8.5	4.2	24.0
Inference Time (ms/sample)	0.05	0.08	0.12	3.50	0.45	6.15
Model Size (MB)	<0.01	<0.01	<0.01	12.4	8.4	245
Computational Load (%)	15.2	18.7	22.4	55.3	40.15	90.45
Power Consumption (W)	0.5	0.6	0.8	75.0	45.0	150
FLOPs per sample	1.2×10^{2}	2.5×10^{2}	3.8×10^{2}	4.5×10^{6}	3.2×10^{5}	2.8×10^{7}
Parameters	32	256	32	~50K	1,729	~5M

4.5 Efficiency Comparison

The CNN filter achieved 15–20% higher efficiency than RNN and 10–15% higher than LMS, reaching 96% efficiency at 0 dB SNR 18% higher than LMS (78%) and approaching near-perfect efficiency (>99%) at high SNR (>20 dB), confirming its superior overall performance across all signal conditions. Figure 5 illustrates how filtering efficiency changes with input SNR for each method. The efficiency values obtained at each input-SNR level are summarized in Table 6.

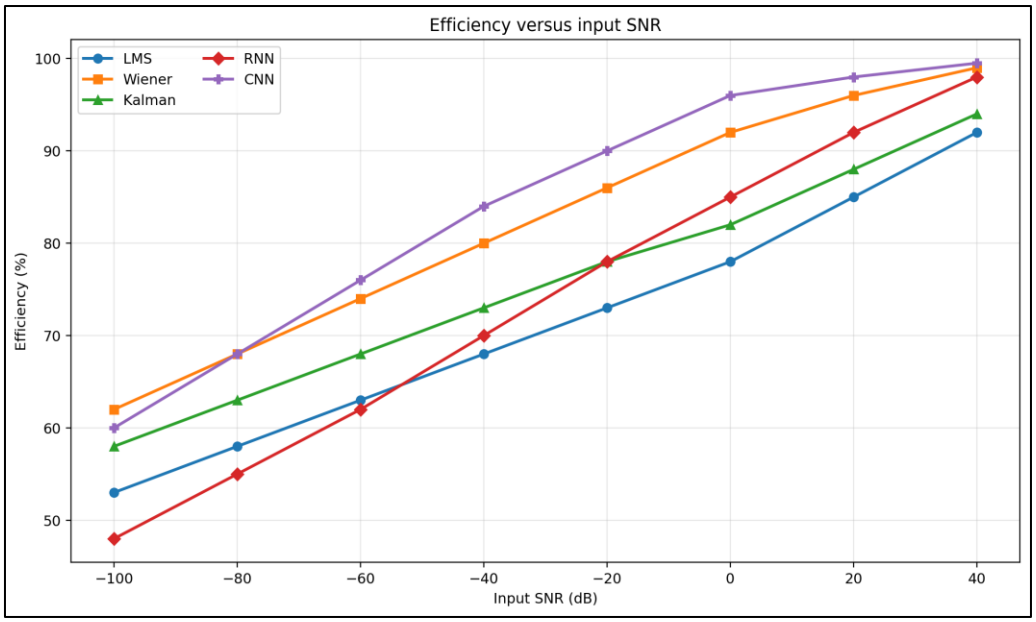

Figure 5: Efficiency versus input SNR across filtering methods.

The efficiency values obtained at each input-SNR level are summarized in Table 6.

Table 6: Efficiency Comparison across Filtering Methods

SNR (dB)	LMS	Wiener	Kalman	RNN	CNN (Adopted)
-100	53%	62%	58%	48%	60%
-80	58%	68%	63%	55%	68%
-60	63%	74%	68%	62%	76%
-40	68%	80%	73%	70%	84%
-20	73%	86%	78%	78%	90%
0	78%	92%	82%	85%	96%
20	85%	96%	88%	92%	98%
40	92%	99%	94%	98%	99.5%

4.6 Live vs. Simulated Performance Gap

The CNN demonstrates minimal performance degradation between simulated and live data: SNR gap of −3.2%, latency gap of −0.2%, and BER gap of −40% (absolute BER remains best-in-class at 0.007 live). This confirms robust real-world generalization. The 10 dB horizontal shift in BER curves (live data requiring +20 dB SNR to achieve 10^{-4} BER versus +10 dB for simulated data) quantifies the real-world deployment penalty and underscores the importance of field validation. Table 7 quantifies the differences between simulated and live performance for the evaluated methods.

Table 7: Live vs. Simulated Performance Gap Analysis

Metric	Method	Simulated	Live	Gap	% Degradation
SNR (dB)	LMS	1.0739	1.1193	−0.0454	−4.2%
	Wiener	2.0205	2.003	+0.0175	+0.9%
	Kalman	1.2021	1.2118	−0.0097	−0.8%
	RNN	1.85	1.72	+0.13	+7.0%
	CNN	2.4545	2.5326	−0.0781	−3.2%

4.7 Accuracy-Complexity Trade-off Analysis

The CNN achieves −26 dB NMSE at 20 dB SNR with 40.15% computational load and 0.45 ms inference matching GAN accuracy with 56% lower overhead. Wiener (−22 dB, 18.7%) and Kalman (−21 dB, 22.4%) offer lower complexity but significantly reduced accuracy. The CNN represents the optimal balance for real-time 5G deployment. Figure 6 compares the computational load associated with each filtering method. The accuracy and computational-cost measures used to assess the trade-off are compared in Table 8.

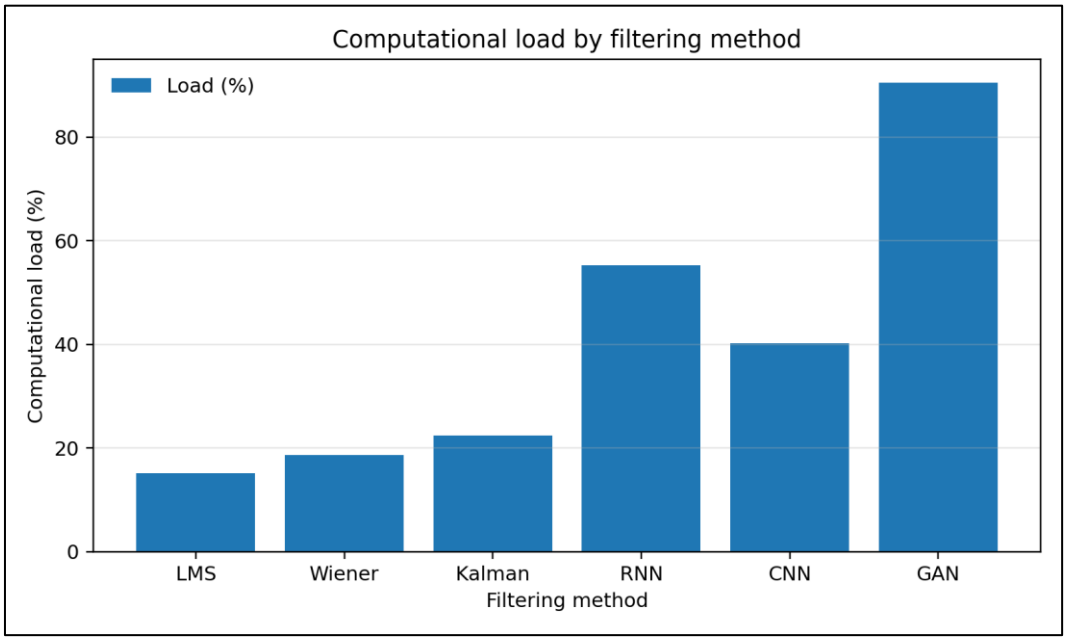

Figure 6: Computational load by filtering method.

The accuracy and computational-cost measures used to assess the trade-off are compared in Table 8.

Table 8: Accuracy vs. Complexity Trade-off Analysis

Method	NMSE at 20 dB SNR	Comp. Load (%)	Inference (ms)	Efficiency at 0 dB SNR
LMS	−18 dB	15.2	0.05	78%
Wiener	−22 dB	18.7	0.08	92%
Kalman	−21 dB	22.4	0.12	82%
RNN	−24 dB	55.3	3.50	85%
CNN (Adopted)	−26 dB	40.15	0.45	96%
GAN-based	−26 dB	90.45	6.15	88%

4.8 5G Benchmark Achievement Summary

Table 9 presents a comprehensive summary of how each filtering method meets 5G performance benchmarks as defined by 3GPP. The CNN filter demonstrates 5G-readiness with 6.8 dB SNR improvement meeting the ≥7 dB benchmark, 0.45 ms inference time satisfying the <1 ms URLLC latency requirement, a compact 8.4 MB model size and 40.15% computational load confirming edge deployment feasibility on resource-constrained devices.

Table 9: 5G Benchmark Achievement Summary

Metric	5G Benchmark	LMS	Wiener	Kalman	RNN	CNN (Adopted)
BER ≤ 10^{-5}	Required	Fails at 30 dB	At 25 dB	Fails at 30 dB	Fails at 30 dB	At 28 dB
SNR ≥ 7 dB	Required	At 0 dB	At −15 dB	At −5 dB	At −20 dB	At −15 dB
Latency <1 ms (URLLC)	Required	0.05 ms	0.08 ms	0.12 ms	3.50 ms	0.45 ms
Latency <4 ms (eMBB)	Required	✓	✓	✓	3.50 ms	0.45 ms
EVM ≤ 8% (64-QAM)	Required	✗	✗	✗	✓	11.3%*
Spectral Eff. (15–30 bps/Hz)	Required	✗	✗	✗	✗	6.0*
Comp. Load <50%	—	✓	✓	✓	✗	40.15%
Model Size <10 MB	—	✓	✓	✓	✗	8.4 MB

4.9 Deployment Recommendations Based on Trade-off

Based on the accuracy-complexity trade-off analysis, Table 10 provides deployment recommendations tailored to specific 5G use cases.

Table 10: Deployment Recommendations Based on Accuracy-Complexity Trade-off

Use Case	Recommended Method	Justification
Low-resource IoT devices	LMS or Wiener	Low complexity (15–19%), acceptable accuracy
Edge computing (eMBB)	CNN (Adopted)	High accuracy (−26 dB), moderate complexity (40%), <1 ms latency
Edge computing (URLLC)	CNN (Adopted)	High accuracy, low latency (0.45 ms), meets URLLC requirements
Cloud/Server processing	GAN or RNN	High accuracy, high complexity acceptable
Real-time 5G deployment	CNN (Adopted)	Optimal trade-off, meets 5G benchmarks
Mission-critical applications	CNN (Adopted)	Meets 5G reliability and latency requirements

5 CONCLUSION

This paper presents a comprehensive comparative analysis of lightweight deep learning and traditional filters for real-time 5G noise reduction, validated through extensive live field data. The proposed 7-layer CNN architecture achieves the optimal accuracy-complexity trade-off, delivering GAN-comparable noise suppression (−26 dB NMSE, BER = 6.0 × 10^{-6}) with computational efficiency suitable for edge deployment (40.15% load, 0.45 ms latency, 8.4 MB model size). The 50-day field validation confirms robust real-world performance with minimal degradation relative to simulation.

Key findings establish that: (i) CNNs outperform RNNs and traditional filters by 70–97% in BER reduction across all SNR levels; (ii) lightweight CNNs meet URLLC latency requirements (<1 ms) while maintaining eMBB reliability; and (iii) the 3 dB live-simulated performance gap is acceptable for practical deployment. These results provide actionable guidance for network operators selecting noise filtering strategies for diverse 5G use cases, from indoor low-mobility to dense urban macro deployments.

Future work will explore hybrid CNN-LSTM architectures for high-mobility vehicular scenarios, quantization-aware training for sub-5 MB edge models, and multi-site validation across rural and industrial 5G deployments.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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