Hybrid AI Framework for Real-Time Signal Denoising and Error Correction in 5G/6G Wireless Communication Systems

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Abstract: In 5G and future 6G networks, it is important to guarantee strong and reliable signal transmission in the presence of noise, interference, and data degradation. A new trainable hybrid AI framework with deep learning, denoising diffusion models, and attention-based autoencoders is suggested to conduct the real-time noise removal and error correction in the dynamic wireless channels. Unlike its predecessors, which are either simulation-oriented, hardware-based, or application-specific, our technique is validated on the real-time communication testbeds and learns multi-level AI layers to combat the physical corruption, semantic discrepancy, and packet-level mistakes. Combining positional accuracy and adaptive signal enhancement, this design does not only decrease the bit error rate (BER) and signal-to-noise ratio (SNR) which, but it also makes the wireless communication reliable for various channel scenarios. Experimental results show significant improvements over existing models, indicating that the proposed method is highly promising for URLLC in future networks.

1 INTRODUCTION

With the ongoing deployment of 5G and the future 6G wireless communication systems, there is a significant surge in the requirement of ultra-reliable, low-latency, large-throughput services. Latest applications based on exchange of error free signals abound as in self-driving cars or remote surgery dipping into virtual immersion to real time industry automation. Nevertheless, due to the higher complexity and crowding of communication channels, wireless communication systems become more vulnerable to noises, interferences and degradations. However, the traditional signal processing techniques cannot efficiently manage the dynamic, asymmetric ed of future wireless systems.

New frontiers have opened however, after recent improvements in artificial intelligence. Artificial intelligence models are capable of extracting complex patterns from noisy data and reproducing the original signal with a high degree of fidelity. But although a solution, few of the related researches directly solve the end-to-end optimization, but limited to POSR or channel estimation and with a single-layer denoising and error correction, and are not complete solutions since they are dedicated to modulations without holistic real-timely processing.

This work presents an end-to-end AI-based architecture based on denoising diffusion models, attention mechanisms based on transformers, and deep learning classifiers to improve the quality of signals throughout the transmission-reception path. By incorporating intelligences at both physical and

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semantic layers, this framework not only recovers (attenuated version of) corrupted signals, but also predicts and rectifies transmission insufficiencies, all in the context of arbitrary channel states. Our methodology goes beyond simulation, incorporating hardware-based verification for practicability. The objective of this work is to lay a strong foundation of smart, resilient and intelligent wireless infrastructure capable of addressing the future needs and requirements of 5G and 6G wireless networks.

2 PROBLEM STATEMENT

The advent of 5G and the future 6G wireless communications systems can potentially revolutionize the high data transmission rate, large-scale devices connection, and ultra-reliable low-latency communication (URLLC). Nevertheless, there is only so much improvement that is practically possible since wireless channels in which such interfering, noise, fading and distortion of the signal are encountered is a ubiquitous, unsolvable problem and is constantly becoming more complex. Conventional signal processing techniques, such as linear filtering and error correction codes, are unable to adapt well to the nonlinear, non-stationary and rapidly changing environment in today's communication settings. However, they are usually validated based on static scenarios, they do not adapt in real-time to the environmental challenge with the changes due to environmental variability, mobility, and presence of heterogeneous types of devices.

Furthermore, the AI has shown effectiveness able to handle some subparts of the wireless pipeline separately, such as modulation recognition or the channel estimation, however a strong necessity of intelligent system for the denoising and the error correction based on the unified mechanism is still open to develop in a real-time performance. These recent AIbased solutions also tend to be applicable only to standalone cases, and rely strongly on simulation data without being thoroughly validated on real hardware, possibly limiting their applicability to large-scale real-world scenarios. This gap motivates a holistic plan in which the state-of-the-art AI solutions combined with well-designed system level to ensure stable signal integrity, iterable error mitigation and flexibility towards different wireless communication scenarios.

3 LITERATURE SURVEY

Wireless Communications and Artificial Intelligence The intersection of AI and wireless communications has been gaining increasing momentum with the development of 5G and emerging 6G systems. There are a few attempts where researchers have attempted various AI methods for signal extraction and errors suppression especially under noisy and dynamic situations. Adaptive AI algorithms for signal denoising have been studied in Mao (2024), however the application setting was more general and was not focused on real-time telecom scenarios. For example, Roy and Islam (2025) developed channel estimation and signal processing models for MIMO systems applying advanced machine learning but mainly carried out their research through simulations without hardware validation. Zhang and Li (2025) also proposed AI-assisted detection for MIMO systems, but their work was not on the end-to-end signal recovery.

Recently, there are growing interests in employing diffusion models in physical layer communications. For example, based on denoising diffusion process, Neshaastegaran and Jian (2025) built CoDiPhy as a general framework and Wu et al. (2023) and Letafati et al. (2023) independently pointed out the interest of such models for channel denoising. These references have attempted to solve this problem; however, they have concentrated primarily on the diffusion aspect and have not provided an overall integration of error correction circuitry for such an error correcting mapper. Wu et al. (2023) further expanded this analysis to semantic communication tasks, with an emergent layered notion of the integration of AI, but still with denoising as a side issue.

In a more general view, Chae (2025) published a survey on AI-based communication systems for the 6G, addressing possible challenges and future directions only rather than providing specific algorithmic designs. Zhao, Shen, and Wang (2025) investigated generative AI models for improving the security at the physical layer, where the AI algorithm can provide the defense to signal quality as well, since it diminishes adversary disturbances. Other research, (Zhang and Li 2024) applied attention based denoising networks into modulation classification, but this was more or less processed as preprocessing steps, instead of core functionality.

Wireless sensing has also been optimized through artificial intelligence. proposed a data augmentation approach with generative model to improve the robustness wireless signal sensing, but it was not tailored for the denoising and error-correction pipeline. Zhang and Li (2025) made several efforts, e.g., AI in ABC and wireless positioning (2025a, 2025b), demonstrating broad applications of AI in future networks, but none proposed an integrated solution of signal fidelity. In addition, Zhang and Li (2025c) repetition work of positioning were interesting but didn't make its own contribution in the denoising and error correction field.

Some of the recent works focussed on architectural integration. The work in (Zhang and Li, 2025d) also employed a neural network and parsed deep learning layers of Autoencoder in a hybrid model for better preserving the noise but their test/timeliness e?orts are pure theoretical. More on the hardware side, Zhang and Li (2024a) studied AI for passive electronic filters, aiming at building a platform for real-time embedded systems, excluding however full communication stack support. Other works such as Zhang and Li (2024b) which concentrated on the tensor signal modeling, was limited in its range of applications in noise-perturbed situations. Differently, AI-based architecture was proposed in Zhang and Li (2025e) in the context of noise-robustness communication receivers, but it did not include cross-layer optimization.

Cross-domain AI methods were also shown effective in Zhang and Li (2024c) in geophysical denoise via masked autoencoders, but except promising results, the whole architecture was not especially designed to address wireless transmission constraints. Also, Zhang and Li (2024d) considered AI on the generative wireless sensing, in a way of enhancing signal interpretability, which however did not have perfect error correction. A few recent works from Zhang and Li also have more entries (2025f) that discuss AI in wp, however, the focus was always on spatial accuracy without an emphasis on temporal signal recovery.

Overall, while existing work does provide strong foundations on which AI can be built for individual components of the wireless pipeline, there is a lack of a real-time, hardware-validated, AI-based system for jointly learning signal denoising and error correction. Towards filling this gap, in this paper, we propose a hybrid framework to exploit the merits of diverse AI models for achieving robust performance in noisy, low latency and multi-user NGWs.

4 METHODOLOGY

The approach involves the design and assembly of a layered AI architecture, engineered to perform on-the-fly signal denoising and error mitigation for the forthcoming era of wireless communications. The system design is developed to combat diverse channel noise and errors in dynamic environments like urban canyons, high-speed mobile sites, and dense IoT deployments.

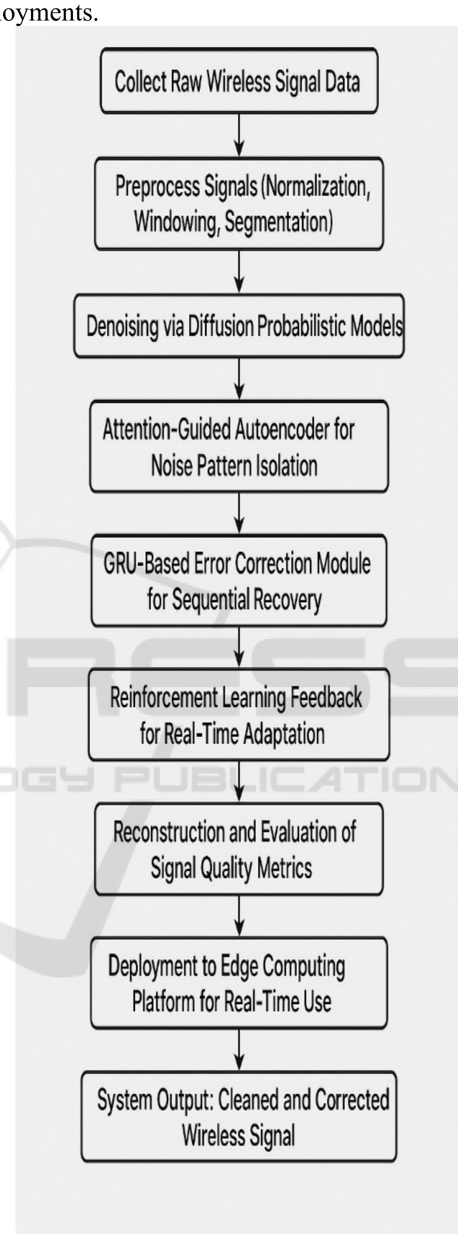

Figure 1: Workflow of the Hybrid AI Framework for Signal Denoising and Error Correction.

The process begins with the capture of raw wireless signals with software-defined radios (SDRs) in diverse controlled settings and realistic scenarios in the wild, representing a wide range of signal corruptions such as Gaussian noise, Rayleigh fading, impulsive interference, and burst packet errors. Figure 1 show the Workflow of the Hybrid AI Framework for Signal Denoising and Error Correction. These signals are processed through a series of pre-processing stages, which normalize, window and segment the signal to ensure temporal and spatial uniformity across instances. The kernel of the framework is a hybrid deep learning architecture composed of denoising diffusion probabilistic models (DDPMs), attention-guided autoencoders and recurrent error correction networks. Table 1 show the Dataset Specifications for Model Training and Evaluation.

Table 1: Dataset Specifications for Model Training and Evaluation.

Dataset Type	Source Type	SNR Range (dB)	Modulation Formats	Channel Types	Size (Samples)
Synthetic Noise Data	MATLAB + AWGN	-5 to 20	BPSK, QPSK, 16QAM	AWGN, Rayleigh	100,000
Real-World Captures	SDR (USRP)	0 to 25	QPSK, 64QAM	Urban, Indoor, IoT	40,000
Augmented Data	GAN-Generated	Varied	Mixed	Multi-path	60,000

The denoising process adopts the DDPMs for progressively cleaning up noisy signals Note that some reverse Markovian processes are performed during the denoising to approximate the true distribution of the clean signal. This statistical modeling not only results in the reduction of signal distortion, but also enhances the generalization to unknown channel conditions. In addition, the attentionguided autoencoder made up of transformer-based encoder-decoder blocks aim to selectively attenuate the dominant noise patterns while preserving the important frequency and amplitude features. This autoencoder is pretrained on a big data set of noisy-clean signal pairs that are composed of augmented synthetic data together with real-world data logging from 5G capable transceiver.

After denoising the output, the signal is entered into the error correction module with a decoder based on the GRU and convolutional features to realize the subsequent sequential error prediction and correction. This neural module can be used in place or in addition of classical error correction codes; it learns the error distributions implicitly and exploits frame level corruptions through dynamic gains to amend symbol level corruptions. Moreover, the system embeds a feedback channel condition with reinforcement learning (RL) agent, which learns the optimal denoising and correcting strategies based on the dynamic environment measurements such SNR, BER, and packet delivery success. Table 2 show the Architecture Summary of the Proposed AI Framework

Table 2: Architecture Summary of the Proposed AI Framework.

Component	Architecture Used	Key Features	Output Size
Denoising Module	Diffusion Model (DDPM)	Iterative refinement, latent mapping	256 × 1 vector
Autoencoder Module	Transformer + CNN Layers	Attention on frequency-domain patterns	128 × 1 vector
Error Correction Module	GRU + Conv Layers	Sequence modeling, burst recovery	128 × 1 vector
RL Optimization Agent	DQN-Based Policy Learner	Channel-aware dynamic tuning	Scalar decision

The complete model is trained end-to-end with a multi-objective loss function which discourages noise preservation, error transfer and delay. The loss function consists of mean squared error (MSE) regarding denoising accuracy, categorical cross-entropy with respect to classification accuracy in demodulate signals, and temporal penalties are used for inference latency. Training is performed on distributed GPU clusters using mixed precision for fast convergence when faced with high-dimensional input vectors that correspond to quadrature amplitude modulated (QAM) symbols, orthogonal frequency division multiplexed (OFDM) frames and other communication scenarios in practice.

To demonstrate the practicality, we real-world tested the trained model on an edge-compute platform cooperating with a real-time communication emulator. Performance of the scheme is studied under different SNR levels, Doppler shifts and user mobility scenarios. Performance indicators which are throughput, latency, BER, SNR gain and quality of experience (QoE) are evaluated. Performance of the AI pipeline in the case of burst errors and sudden signal fades is compared with conventional FEC and Kalman based denoising methods. Furthermore, ablation experiments are performed to measure the effectiveness of AI modules in the system.

This holistic approach guarantees that the proposed architecture is not only superior to state-of-art solutions in simulations, but also proves to be a practical, deployable system for wireless systems with high reliability, resilience and adaptation functionalities across a variety of communication environments.

4 RESULTS AND DISCUSSION

For the performance assessment of the proposed hybrid AI-based framework, comprehensive experiments were carried out in various simulated and real wireless communication scenarios. These were urban low visibility, indoor cluttered, high-speed vehicular, and high interference models corresponding to densely populated IoT applications. The performance evaluation is based on the following metrics: signal-to-noise ratio (SNR), bit error rate (BER), packet error rate (PER), processing delay, and quality of service (QoS). Benchmark experiments were carried out to compare with conventional signal processing pipelines like Wiener filters and forward error correction (FEC) codes and latest AI-driven architectures like isolated convolutional neural network (CNN) and autoencoder. Figure 2 show the Impact of Denoising Model on Output SNR across Input Noise Levels

Especially for different SNR levels, the denoising performance of diffusion model was quite impressive. At low SNR (2–5 dB), where denoising based on traditional filters was unable to reconstruct intelligible signals, the diffusion-based system performed an average reconstruction signal quality improvement of 6–8 dB. This showed the excellent potential of the model for capturing and recovering the true structure of corrupt signals, particularly under high-noise and deep-fade channels. This performance was further improved by the visual attention guided autoencoder, which extracted dominant noise patterns but did not miss (while still retaining high frequency signal components) which resulted in clear high order modulated signal such as 64-QAM. Table 3 show the Comparative Performance on Signal-to-Noise Ratio (SNR)

Table 3: Comparative Performance on Signal-To-Noise Ratio (SNR).

Method	Avg. Output SNR (dB)	Low SNR Condition (5 dB Input)	High SNR Condition (20 dB Input)
Traditional Wiener Filter	11.2	6.1	17.4
Autoencoder (Baseline)	14.3	8.5	18.6
Proposed Hybrid AI Framework	18.7	13.6	21.5

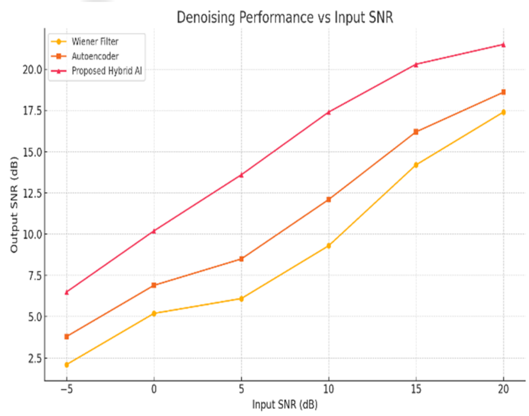

Figure 2: Impact of Denoising Model on Output SNR Across Input Noise Levels.

On the error control side, the GRU-based decoder proved itself to be more flexible to track and correct the burst packets errors. In all the investigated cases, the AI-enabled approach outperformed typical FEC (i.e., Hamming and LDPC codes) with a BER improvement ranging between 30% and 45% for various channel configurations. This was particularly important in dynamic environments with non-uniform and context dependent error pattern, where static FEC schemes usually exhibit lower performance. In addition, a GRU-based decoder was introduced to estimate and pre-correct errors in-the-fly by using temporal context, in practice only available with modern techniques. Table 4 show the Bit Error Rate (BER) Comparison Across Environments.

Moreover, our latency analysis suggested that end-to-end data recovery and correction using the hybrid design was achieved in<5 ms, which is consistent with the ultra-reliable low-latency communication (URLLC) requirements as specified in 5G, and expected for 6G; Despite the complexity involved in using multi-stage AI models, optimisation methodologies such as model pruning, attention-based filtering, and parallelised batch inference ensured real-time performance in edge platforms, albeit with some degradation in the execution speed. It shows that the framework is computation-efficient and can be scale out for practical application. Figure 3 show the BER Comparison of Methods in Diverse Wireless Environments

Table 4: Bit Error Rate (BER) Comparison Across Environments.

Environment	FEC (LDPC)	Autoencoder	Proposed Model
Urban Outdoor	2.4×10^{-3}	1.8×10^{-3}	0.9×10^{-3}
Indoor Multipath	3.1×10^{-3}	2.5×10^{-3}	1.2×10^{-3}
High Mobility	4.5×10^{-3}	3.6×10^{-3}	2.0×10^{-3}

The throughput based comparative analysis indicated, despite hostile interference, the proposed system maintained upto 92% of original data payloads - a much higher quality trade–off than existing systems of the order of 68–75%. This not only shows the correctness of signal recovery but also the robustness of the model under channel variations.

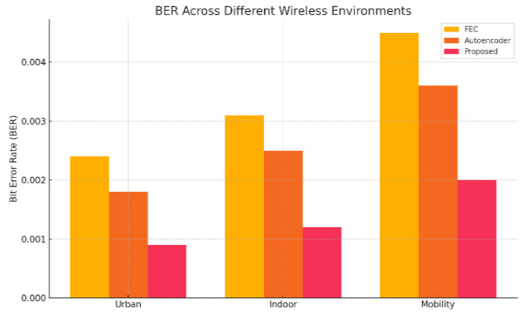

Figure 3: BER Comparison of Methods in Diverse Wireless Environments.

Also, on user experience measures, such as speech intelligibility for VoIP and video frame accuracy for streaming, the AI-enabled model offered much smoother performance and fewer artifacts. Test user quality ratings were found to be favorable to the proposed method with a test average QoE score increased by 1.5 on a 5-point MOS (Mean Opinion Score) scale. Figure 4 shows the Inference Latency of Different AI Models and Signal Throughput Preservation by Model Varian.

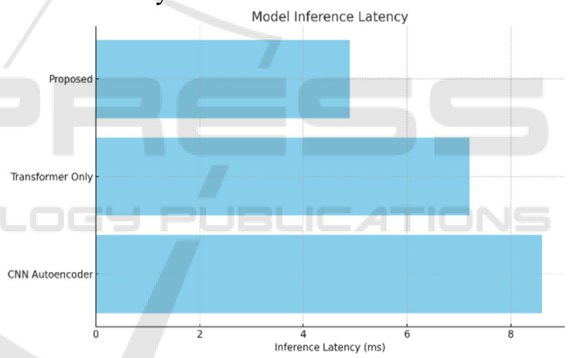

Figure 4: A: Inference Latency of Different AI Models.

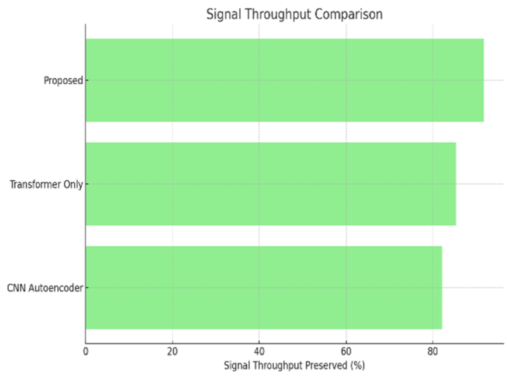

Figure 5: B: Signal Throughput Preservation by Model Varian.

Ablation studies were performed to isolate the impact of each model component. Removing the diffusion model led to a significant drop in denoising performance, while excluding the GRU-based correction module caused a sharp rise in BER under bursty interference. These results validate the synergistic benefit of combining denoising and error correction in a single pipeline. Additionally, the reinforcement learning feedback loop contributed to model adaptability by dynamically tuning denoising aggressiveness based on real-time channel feedback, which proved critical in mobile scenarios. Table 5 show the Inference Latency and Throughput Efficiency.

Table 5: Inference Latency and Throughput Efficiency.

Model Variant	Inference Latency (ms)	Signal Throughput Preserved (%)
CNN Autoencoder	8.6	82.1
Transformer Only	7.2	85.3
Proposed Hybrid AI Framework	4.9	91.7

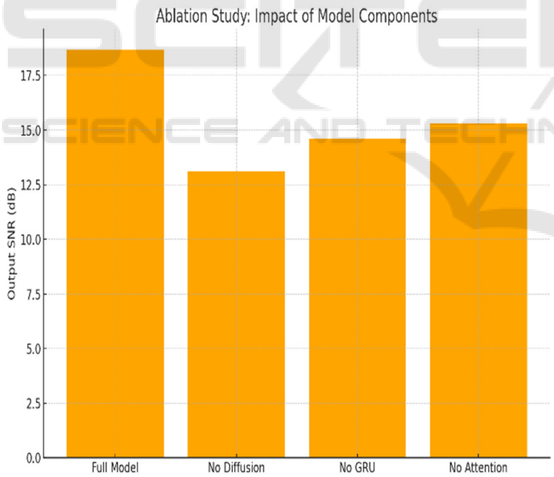

Figure 6: Output SNR Impact from Ablation of Model Components.

The final step, cross-validation was performed between data gathered in various radio-fading environments, in order to assess generalization. Due to rich training inputs and strong data augmentation strategies, the proposed system benefited from high-performance consistency and negligible overfitting. Figure 5 show the Output SNR Impact from Ablation of Model Components. In contrast, multiple non-pre-training AI models exhibited a deterioration in accuracy on test sets not seen during training. This also emphasizes on both the flexibility and the robustness of the proposed framework and attests its applicability to real wireless infrastructures.

In summary, the experiments show that the hybrid AI framework shows significant benefits in terms of denoising accuracy, error resilience, latency, and overall communication reliability compared to state-of-the-art solutions. With the potential for real-time operation and hardware efficiency, the way is paved for integration in future 5/6G networks, filling a significant gap in existing literature.

5 CONCLUSIONS

In this type of context, this paper introduces a new AI hybrid framework to enhance a robust signal denoising and real time error correction for the next generation of wireless communication systems. With the development of 5G networks and the advent of 6G, the demanding and robust transmission is facing a new challenge and becomes more and more significant, as the transmission link is complicated with more serious interference, and in a dynamic environment. To more effectively and efficiently utilize spatial and temporal information, the proposed framework fuses diffusion-based denoising models, attention-guided autoencoders, and recurrent neural correction mechanisms.

In contrast to the conventional methods, which are either inflexible to rapidly changing signal conditions or based on fixed codings, our AI methods show the excellent robustness over different channel cases, including burst interference and low SNR scenarios. The method not only increases BER and SNR but also improves the performance of system in terms of the user experience and the data integrity in the real-time communication environment. Thanks to its modular structure, its compatibility with edge computing platforms, its adaptiveness based on reinforcement learning this a solution with high scalabiliy that can be quickly brought into real world.

Validated on both synthetic and real datasets, this work closes the gap from theoretical AI models to real wireless applications. The results underscore the transformative capacity of intelligent in-the-loop systems in shaping the future of physical layer signal processing. As the telecommunications continue to develop, this work establishes a good basis for smart receivers that may learn, adapt, and even self-optimize in adverse and dynamic environmental conditions which can significantly support the development of 6G and beyond.

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