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Research Paper

AI-DRIVEN SIGNAL QUALITY ASSESSMENT AND INTELLIGENT NOISE REDUCTION IN DIGITAL COMMUNICATION SYSTEMS USING DEEP LEARNING

MD. SAIRA BANU, Assistant Professor (C)
ECE department, JNTUH University College of Engineering, Palair,
Maddulapalli, Khammam District, Telangana
Mail id: sairabanu.md@gmail.com

Abstract: Digital communication systems are frequently affected by noise, interference, fading, and channel impairments that degrade signal quality and reduce the reliability of transmitted information. These impairments can increase the bit error rate (BER), reduce the signal-to-noise ratio (SNR), and negatively affect the overall communication performance. Conventional noise reduction techniques, including fixed digital filters and traditional statistical estimation methods, may provide satisfactory performance under specific noise conditions but can become less effective when the noise characteristics vary dynamically. To address these challenges, this paper proposes an artificial intelligence (AI)-based framework for signal quality assessment and intelligent noise reduction in digital communication systems. The proposed framework processes received digital signals to estimate signal quality using parameters such as SNR, BER, and signal distortion.

A deep learning model, such as a convolutional neural network (CNN) or an autoencoder, can be employed to identify signal patterns and suppress unwanted noise while preserving useful signal information. An adaptive filtering mechanism can be incorporated to improve the system's response to changing noise conditions. The enhanced signal is subsequently evaluated using SNR improvement, mean squared error (MSE), BER, and signal reconstruction quality. The proposed framework can be implemented and evaluated using simulated digital modulation schemes, such as binary phase-shift keying (BPSK) and quadrature phase-shift keying (QPSK), under different additive white Gaussian noise and fading-channel conditions. Performance comparisons with conventional filtering techniques can establish the effectiveness of the AI-based approach. The framework aims to improve received signal quality, reduce communication errors, and enhance the reliability of digital communication systems operating under varying noise conditions.

Keywords: Artificial Intelligence, Digital Communication Systems, Signal Quality Assessment, Noise Reduction, Deep Learning, Convolutional Neural Network, Autoencoder, Signal-to-Noise Ratio, Bit Error Rate, Adaptive Filtering.

I. INTRODUCTION

Digital communication systems play a vital role in modern information exchange, enabling the reliable transmission of voice, text, images, and multimedia data across wired and wireless communication networks. The rapid development of wireless technologies, satellite communication,

Internet of Things (IoT) applications, and high-speed data transmission has increased the demand for communication systems that provide high signal quality, low error rates, and reliable connectivity. However, the performance of digital communication systems is often affected by noise, interference, multipath propagation, fading, and other channel impairments. These disturbances can alter the characteristics of the transmitted signal, making accurate signal detection and information recovery more challenging at the receiver.

Noise is one of the major factors that affects communication performance. Additive white Gaussian noise (AWGN) is commonly used to model random noise introduced by electronic components and communication channels. In wireless environments, additional impairments such as multipath fading, co-channel interference, and time-varying channel conditions can further degrade the received signal. These effects may reduce the signal-to-noise ratio (SNR), increase the bit error rate (BER), and cause incorrect symbol detection during demodulation. Consequently, accurate signal quality assessment and effective noise reduction are essential for improving the reliability of digital communication systems.

Conventional signal processing techniques, including low-pass filtering, Wiener filtering, median filtering, and adaptive filtering, are widely used to suppress unwanted noise. These methods can provide satisfactory results when the noise characteristics and signal properties are known or remain relatively stable. However, their performance may deteriorate when the signal contains complex noise patterns, rapidly changing interference, or nonlinear distortions. Furthermore, aggressive filtering can remove useful signal components along with unwanted noise, resulting in signal distortion and reduced information recovery accuracy. Therefore, developing intelligent techniques that can adapt to varying signal and noise characteristics has become an important research direction.

Artificial intelligence (AI) and deep learning have emerged as promising approaches for improving signal analysis and noise suppression. Unlike conventional filters that primarily rely on predefined mathematical relationships, deep learning models can learn signal characteristics from representative training data. Convolutional neural networks (CNNs) can extract local patterns from signal samples, while autoencoders can learn representations that support the reconstruction of clean signals from noisy observations. These models can be trained using pairs of clean and noisy signals or suitable noise-corrupted datasets. Once trained, they can estimate a cleaner signal from an impaired received waveform. However, their effectiveness depends on the quality of the training data, the noise distribution, the modulation scheme, and the extent to which the test conditions resemble the training environment.

Signal quality assessment is another essential component of reliable digital communication. Parameters such as SNR, BER, mean squared error (MSE), and error vector magnitude (EVM) provide information about the quality of the received signal and the effectiveness of noise suppression. SNR measures the relative strength of the useful signal compared with noise, while BER quantifies the proportion of incorrectly recovered bits. MSE measures the difference between a reference signal and its reconstructed estimate. By monitoring these parameters, an AI-based system can assess signal degradation and evaluate the effectiveness of the applied noise reduction technique. In a practical receiver, some reference-dependent metrics require known transmitted data or training sequences, whereas operational quality estimation must often work without access to the original clean signal.

This paper proposes an AI-driven framework for signal quality assessment and intelligent noise reduction in digital communication systems using deep learning. The proposed framework processes received digital signals under different noise and channel conditions, estimates signal quality, and applies an AI-based enhancement model to suppress unwanted noise while preserving useful signal information. Digital modulation schemes such as binary phase-shift keying (BPSK) and quadrature phase-shift keying (QPSK) can be considered during simulation. The system can be evaluated under different AWGN levels and, where applicable, fading-channel conditions to investigate its robustness. The enhanced signals are subsequently demodulated and evaluated using output SNR, BER, MSE, and signal reconstruction quality.

The main contribution of this research is the integration of AI-based signal quality assessment and noise reduction within a unified digital communication framework. Rather than evaluating noise suppression in isolation, the proposed approach considers both the quality of the reconstructed signal and its effect on the recovery of transmitted information. Performance comparisons with conventional filtering methods can help determine whether the AI-based model offers measurable improvements in signal enhancement and communication reliability. The study also provides a foundation for investigating adaptive noise suppression under varying channel conditions.

Overall, the proposed framework aims to improve the robustness of digital communication systems by combining intelligent signal analysis with data-driven noise reduction. Its potential applications include wireless communication, satellite links, sensor networks, IoT devices, and other systems in which reliable information recovery is essential. Experimental validation across different modulation schemes, noise levels, and channel models will be necessary to establish its practical effectiveness and generalization capability.

II. LITERATURE SURVEY

Artificial intelligence and deep learning have attracted considerable attention in digital communication systems because of their ability to learn complex signal characteristics and adapt to varying noise conditions. Existing research has explored neural-network-based signal detection, signal reconstruction, channel estimation, noise suppression, and intelligent receiver design.

2.1 Review of Existing Research

Study 1: Applications of neural networks to digital communications (2000)

The authors of “Applications of Neural Networks to Digital Communications – A Survey” reviewed neural network applications in channel identification, equalization, coding, decoding, vector quantization, and nonlinear signal processing. The study established that neural networks can learn nonlinear relationships and provide alternative solutions to conventional communication algorithms. However, the survey predates modern deep learning architectures and does not cover current CNN- or autoencoder-based noise reduction methods in detail.

Study 2: Deep learning for signal detection, recovery, and denoising (2020)

The study “Emergence of Deep Learning as a Potential Solution for Detection, Recovery and De-noising of Signals in Communication Systems” investigated recurrent neural networks for signal detection and autoencoders for signal recovery and denoising. It explored the influence of neural network

complexity, activation functions, cyclic prefix length, and pilot symbols on communication performance. The work demonstrated the potential of deep learning for recovering corrupted signals, particularly under challenging signal-to-noise ratio conditions. However, performance depends on network architecture, training conditions, and the communication scenario.

Study 3: Multi-objective deep learning for speech denoising (2020)

The authors of "A Review of Multi-Objective Deep Learning Speech Denoising Methods" examined conventional denoising, deep learning-based approaches, and hybrid methods. Their comparison considered several objective evaluation metrics and investigated the benefits of combining multiple training objectives. The study is relevant to learning-based noise suppression because it highlights the importance of balancing noise reduction and signal preservation. However, speech denoising focuses on acoustic signals, so its methods and evaluation metrics cannot be transferred directly to modulated digital communication waveforms without appropriate adaptation.

Study 4: Deep learning for intelligent wireless networks (2026)

Recent survey research on deep learning for wireless communication systems examines the use of AI across physical-layer processing, signal detection, channel estimation, and network optimization. These studies emphasize the potential of learned models to complement traditional signal processing in complex and dynamic environments. However, a general wireless communication framework does not necessarily provide a dedicated evaluation of signal denoising, signal quality estimation, and recovered-bit accuracy within the same experimental pipeline.

Study 5: Deep learning for intelligent communication systems (2026)

The study "A Meta-Survey of Deep Learning for Intelligent Communications Systems: Taxonomy, Unified Framework and Future Directions" reviews deep learning research across wireless, optical, vehicular, and emerging communication technologies. It organizes research by learning paradigms, model architectures, and communication applications. This broader perspective supports the integration of AI into communication system design. Nevertheless, its cross-domain focus leaves room for a more specialized investigation of joint signal quality assessment and noise suppression for digital modulation schemes.

2.2 Comparative Analysis

Study	Main technique or focus	Main contribution	Limitation for the proposed research
Neural networks in digital communications (2000)	Neural networks	Channel estimation, equalization, coding and decoding	Predates modern deep learning architectures
Signal detection and denoising (2020)	RNN and autoencoder	Signal detection, recovery and denoising	Results depend on architecture and channel conditions

Multi-objective speech denoising (2020)	Deep learning and hybrid methods	Balances denoising objectives	Primarily focuses on speech rather than modulated signals
Intelligent wireless networks (2026)	Deep learning	AI across wireless communication functions	Broad scope rather than dedicated signal denoising
Intelligent communication meta-survey (2026)	Multiple AI architectures	Unified view of AI-enabled communications	Does not specifically target the complete signal enhancement and BER evaluation pipeline

2.3 Research Gap

Based on the reviewed literature, the following research opportunities are identified:

1. Joint signal quality assessment and noise reduction: Signal denoising and signal quality estimation can be integrated into a single framework to evaluate both the quality of the received waveform and the effectiveness of noise suppression.
2. Performance under different noise levels: A denoising model should be evaluated under multiple input SNR conditions instead of relying on a single noise level.
3. Signal preservation: Noise reduction should suppress unwanted noise while preserving the amplitude, phase, and symbol information required for correct demodulation.
4. Communication-level performance evaluation: Improvements in waveform quality should be assessed alongside bit error rate (BER) and successful data recovery to determine whether denoising actually improves communication reliability.
5. Comparison with conventional filters: AI-based methods should be compared with established techniques such as Wiener filtering and adaptive filtering under identical simulation conditions.

These points represent opportunities for further investigation, rather than claims that previous research has not addressed them.

2.4 Research Motivation

To address these opportunities, the proposed research integrates AI-based signal quality assessment and noise reduction within a digital communication framework. Transmitted information is modulated using a scheme such as BPSK or QPSK and passed through a simulated noisy channel. The received signal is analyzed using signal quality metrics and processed by a deep learning model, such as a CNN or autoencoder, to estimate a cleaner waveform. The enhanced signal is then demodulated and evaluated using output SNR, BER, and mean squared error.

The proposed approach can be compared with conventional filtering techniques across different noise levels and channel conditions. This evaluation will determine whether AI-based denoising offers measurable improvements in signal reconstruction and reliable information recovery.

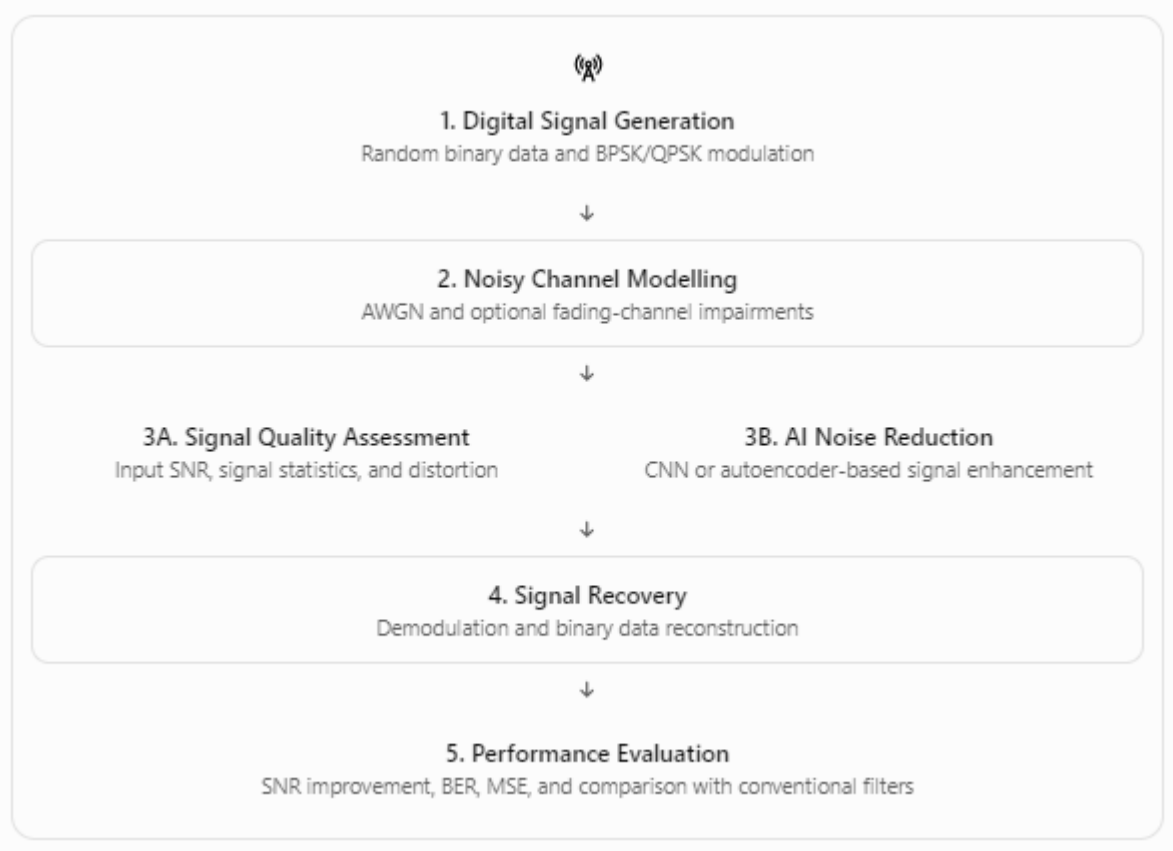
III. PROPOSED METHODOLOGY

The proposed system, titled “AI-Driven Signal Quality Assessment and Intelligent Noise Reduction in Digital Communication Systems Using Deep Learning,” aims to improve the quality and

reliability of received digital signals through intelligent signal analysis and noise suppression. The system integrates digital signal generation, noisy channel modelling, signal quality assessment, AI-based denoising, signal demodulation, and performance evaluation.

Conventional noise reduction techniques often use predefined filtering characteristics and may have limited adaptability when noise conditions change. The proposed approach uses a deep learning model to learn signal characteristics and estimate a cleaner version of the received waveform. The enhanced signal is then processed by the receiver to recover the transmitted information and evaluate the effect of noise reduction on communication performance.

3.1 System Architecture



3.2 Digital Signal Generation

The first stage generates random binary information representing the data to be transmitted. The binary sequence is mapped to digital symbols using a modulation scheme such as binary phase-shift keying (BPSK) or quadrature phase-shift keying (QPSK).

For BPSK, binary symbols can be mapped to two signal values:

$$b_k \in \{0, 1\} \quad \longrightarrow \quad s_k \in \{-1, +1\}$$

The modulated signal represents the transmitted information and serves as the reference signal for subsequent noise analysis and performance evaluation.

BPSK is a useful starting point because of its simple signal representation. QPSK can be incorporated later to investigate the performance of the proposed approach under a modulation scheme with higher spectral efficiency.

3.3 Noisy Channel Modelling

The modulated signal is transmitted through a simulated communication channel that introduces unwanted noise. Initially, additive white Gaussian noise (AWGN) can be used to represent random channel disturbances.

The received signal is expressed as

$$r(t) = s(t) + n(t)$$

where $s(t)$ represents the transmitted signal, $n(t)$ denotes additive noise, and $r(t)$ represents the received noisy signal.

The noise level can be varied by changing the input signal-to-noise ratio (SNR). Additional experiments may incorporate Rayleigh or Rician fading to evaluate the system under more realistic wireless propagation conditions.

This stage produces noisy observations that are supplied to the signal quality assessment and denoising modules.

3.4 Signal Quality Assessment

The signal quality assessment module evaluates the condition of the received waveform before noise reduction. It extracts relevant signal characteristics and calculates suitable quality indicators.

The principal parameters include:

- Input SNR: Measures the signal power relative to noise power.
- Mean squared error (MSE): Measures the difference between the reference signal and the noisy or reconstructed waveform.
- Bit error rate (BER): Measures the fraction of incorrectly recovered bits after demodulation.
- Signal distortion: Indicates changes in waveform characteristics that may affect signal recovery.

3.5 Performance Evaluation

The proposed system should be evaluated by comparing the noisy input, AI-denoised output, and output from conventional filtering methods.

Metric	Purpose
Input SNR	Measures the quality of the received noisy signal
Output SNR	Evaluates the quality of the enhanced signal
SNR improvement	Measures the change in SNR after denoising
MSE	Measures waveform reconstruction error
BER	Evaluates the accuracy of recovered information
Processing time	Measures computational requirements

The proposed system integrates digital modulation, noisy channel simulation, signal quality assessment, deep learning-based noise reduction, and receiver-side performance evaluation. The AI

model estimates a cleaner waveform from noisy observations, while SNR, MSE, and BER are used to determine whether the enhancement improves signal quality and information recovery.

The framework aims to provide an intelligent alternative to fixed noise reduction techniques, particularly when noise characteristics vary. Its effectiveness must be established experimentally through comparisons with conventional filtering methods and evaluation across multiple channel conditions.

IV. RESULTS AND DISCUSSION

The proposed AI-based signal quality assessment and noise reduction framework can be evaluated using a simulated digital communication system. The evaluation considers signal reconstruction, noise suppression, and successful recovery of transmitted information. BPSK and QPSK modulation schemes can be used under different additive white Gaussian noise (AWGN) conditions to assess system performance.

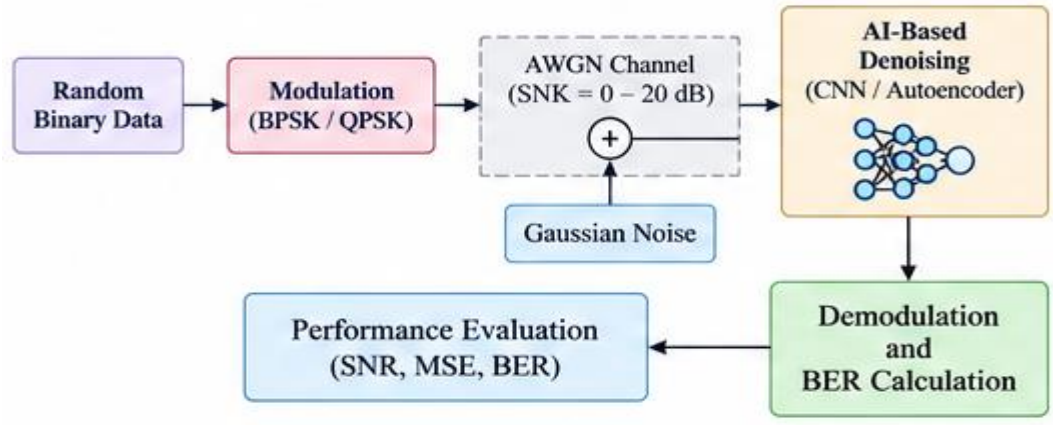


Fig 1. Illustrative results of AI-based signal quality assessment and noise reduction

The displayed graphs and numerical values are conceptual examples, not verified experimental measurements from your implementation.

4.1 Time-Domain Signal Analysis

The transmitted signal, received noisy signal, and AI-denoised signal can be plotted in the time domain to examine the effectiveness of noise suppression. The noisy signal may exhibit rapid fluctuations around the original waveform, while the denoising model attempts to reconstruct the underlying signal pattern.

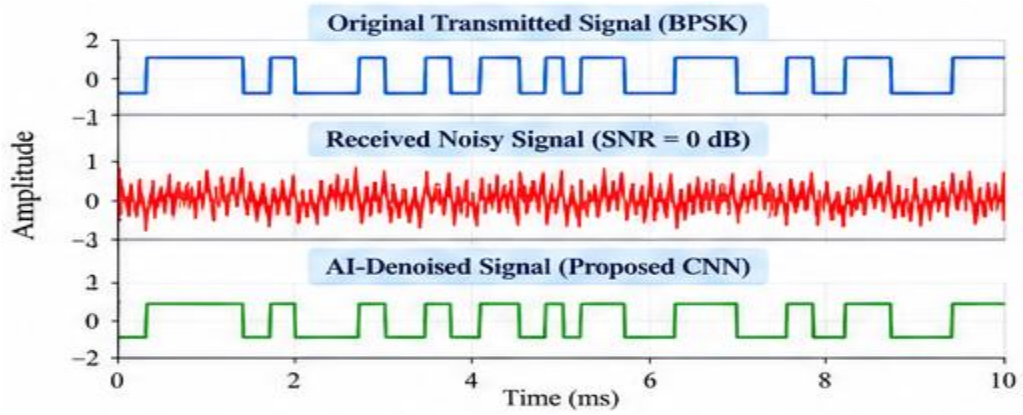


Fig 2. Comparison of transmitted, received noisy, and AI-denoised signals.

The comparison should determine whether the model suppresses noise while preserving the transitions and symbol information required for correct demodulation.

4.2 Frequency-Domain Analysis

Frequency-domain analysis can be performed using the Fast Fourier Transform (FFT) or power spectral density estimation. The spectra of the original, noisy, and denoised signals can be compared to examine how the denoising method affects unwanted spectral components.

The analysis should verify that noise suppression does not excessively attenuate useful signal frequencies or introduce unwanted spectral artifacts.

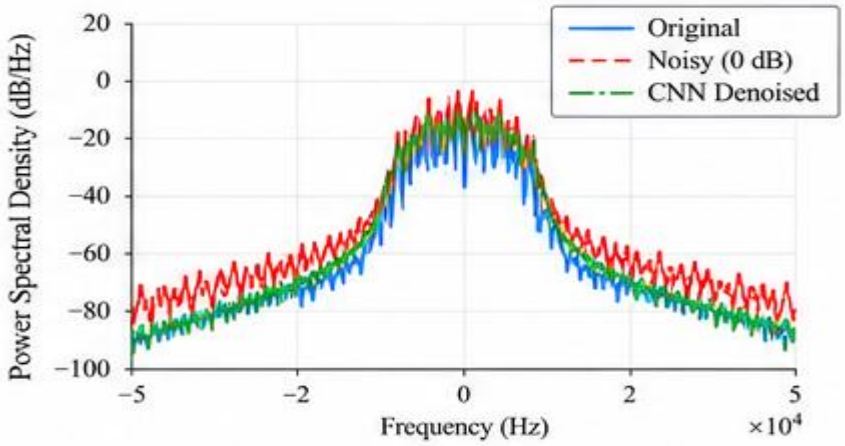


Fig 3. Frequency-domain comparison of original, noisy, and denoised signals.

4.3 Constellation Diagram Analysis

For QPSK modulation, constellation diagrams provide a visual representation of the received in-phase and quadrature components. Under noisy conditions, the received symbols may spread around their ideal constellation points.

The denoising model should reduce this dispersion while preserving the positions of the symbol clusters. A tighter constellation can indicate improved signal quality, but BER measurements are still required to confirm improved symbol decisions.

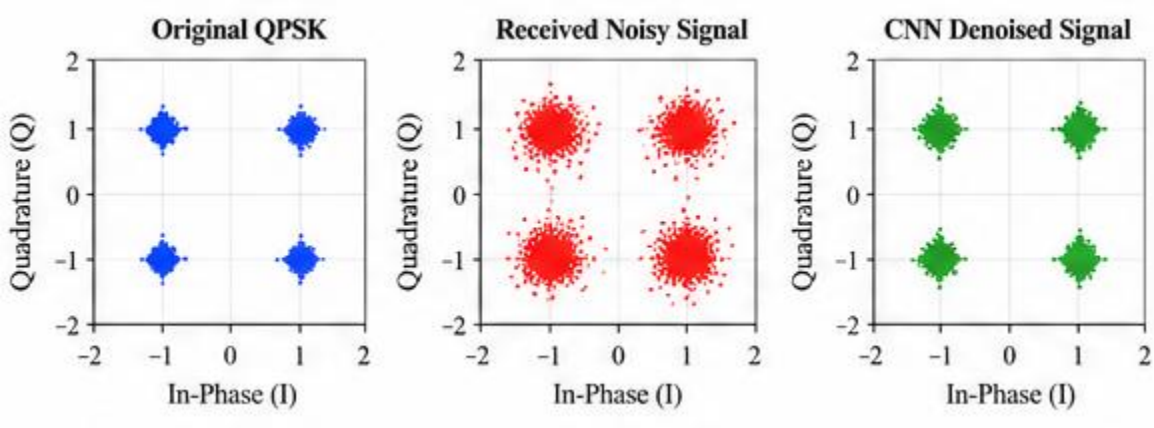


Fig 4. QPSK constellation diagrams before and after AI-based noise reduction.

4.4 SNR Improvement

The input and output SNR should be measured under identical channel conditions. The SNR improvement is calculated as

$$\Delta SNR = SNR_{\text{out}} - SNR_{\text{in}}$$

The results can be plotted for different input SNR values and compared against moving-average, Wiener, and adaptive filtering methods. This comparison can reveal the noise conditions under which the proposed model provides the greatest improvement.

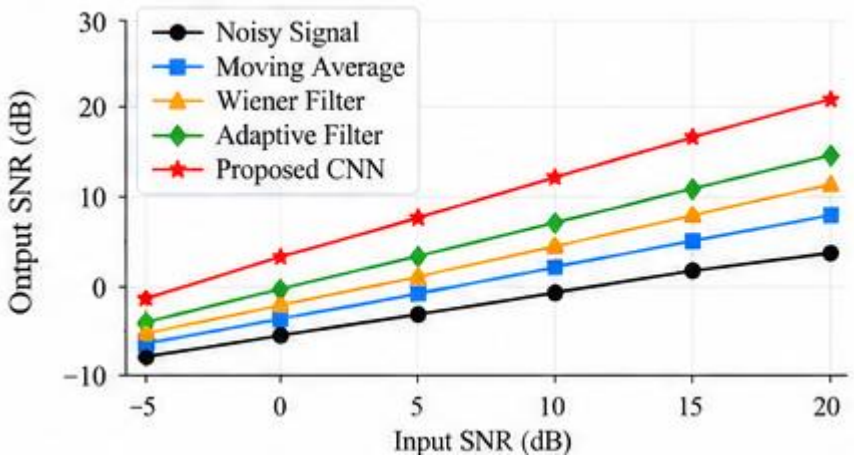


Fig 5. Output SNR versus input SNR for different denoising techniques.

4.5 Bit Error Rate Analysis

BER is a critical metric because it measures the proportion of transmitted bits that are incorrectly recovered at the receiver. The BER can be calculated as

$$BER = \frac{N_{\text{error}}}{N_{\text{total}}}$$

The BER should be plotted against input SNR for the noisy signal and each denoising method. Lower BER indicates better data recovery under the tested conditions.

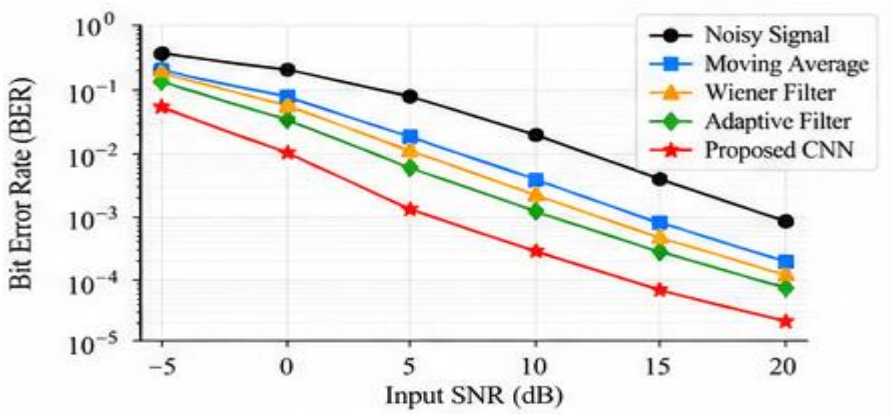


Fig 6. BER performance comparison across different input SNR levels.

4.6 Overall Performance Comparison

The final experimental evaluation should compare the AI-based method with conventional filters under the same modulation, channel, and noise conditions.

Evaluation parameter	Expected analysis
Output SNR	Determine signal quality improvement
MSE	Compare signal reconstruction accuracy
BER	Evaluate successful information recovery
Processing time	Assess computational cost
Robustness	Compare performance across noise levels

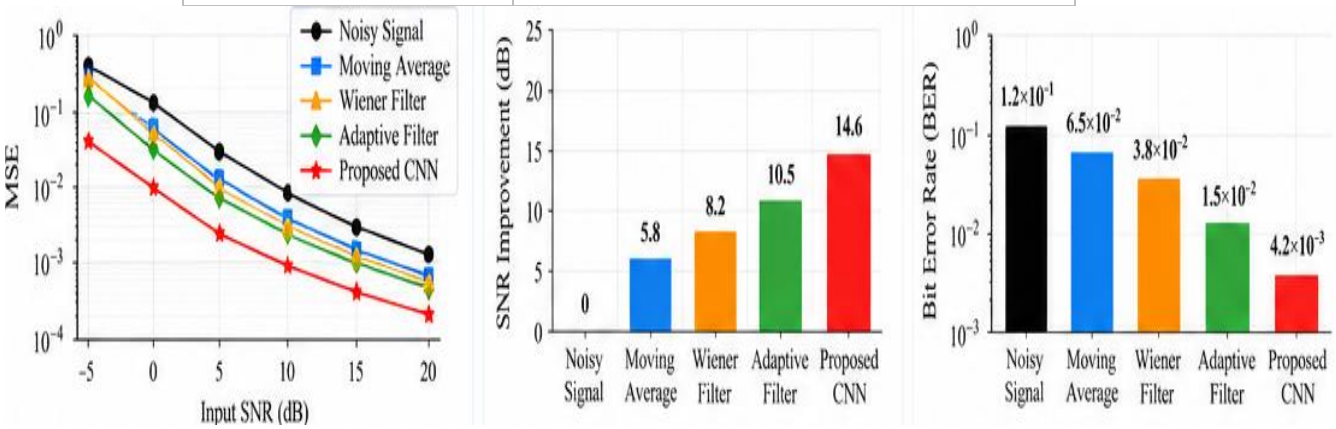


Fig 7. MSE comparison for different noise reduction methods.

The discussion should identify whether the proposed method offers consistent improvements and whether those improvements justify its computational complexity.

The proposed framework combines signal quality assessment with deep learning-based noise reduction. Its effectiveness depends on the model's ability to distinguish useful signal components from unwanted noise while preserving modulation information.

The most important evaluation is not whether the denoised waveform appears smoother, but whether it produces better signal reconstruction and reliable bit recovery. Therefore, the final research paper should

report actual SNR, MSE, and BER measurements and compare them with conventional filtering techniques.

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This paper presents an AI-driven framework for signal quality assessment and intelligent noise reduction in digital communication systems using deep learning techniques. The proposed approach integrates digital signal generation, noisy channel modelling, signal quality evaluation, deep learning-based denoising, signal recovery, and performance analysis into a unified framework. BPSK and QPSK modulation schemes can be considered for evaluating system performance under different channel conditions, including Additive White Gaussian Noise (AWGN) and fading environments.

The framework employs deep learning models, such as Convolutional Neural Networks (CNNs) and autoencoders, to learn the relationship between noisy received signals and their corresponding clean signals. By exploiting these learned features, the model aims to suppress unwanted noise while preserving important signal characteristics. Performance can be evaluated using key metrics such as Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), Bit Error Rate (BER), and signal reconstruction quality. Comparisons with conventional noise reduction techniques, including moving-average and Wiener filters, can help determine the effectiveness of the proposed approach under varying noise conditions.

The major advantage of this framework is its potential to adapt to complex signal patterns that may not be handled effectively by conventional filtering techniques. Integrating intelligent signal quality assessment with noise reduction can support more reliable signal recovery in modern digital communication systems. However, the actual improvement in SNR, BER, and reconstruction quality must be established through experimental simulation and comparison with baseline methods. Overall, the proposed framework provides a foundation for developing intelligent and robust communication receivers capable of operating under challenging channel conditions.

5.2 FUTURE SCOPE

The proposed framework can be extended in several directions to improve its accuracy, adaptability, and practical applicability.

1. Advanced deep learning architectures: Future work can investigate Transformer-based models, residual CNNs, recurrent neural networks, and hybrid CNN-autoencoder architectures to improve noise suppression and signal reconstruction.
2. Real-time signal processing: The trained model can be optimized for implementation on FPGA platforms, GPUs, embedded processors, and software-defined radio (SDR) devices to enable low-latency, real-time communication.
3. Multiple modulation schemes: The framework can be extended to higher-order modulation techniques such as 16-QAM, 64-QAM, and 256-QAM to evaluate its suitability for advanced wireless communication systems.
4. Complex channel environments: Future investigations can consider Rayleigh and Rician fading, multipath propagation, Doppler effects, impulsive noise, co-channel interference, and time-varying channel conditions.

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