

A Reliable Cervical Image Reconstruction Framework for Mobile Health Data Transmission in Low-Resource Environment: A Case Study of AVIVA App

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Abstract: Reliable transmission of cervical image data is essential to mobile health (mHealth) applications like the AVIVA App that enables the transmission of cervical screening images between remote or resource-constrained clinics and cloud-based diagnostics systems. However, wireless channels are usually impaired by Additive White Gaussian Noise (AWGN) and Rician fading that can impair the image quality and diagnostic accuracy. This work presents the comparative performance study of Hard Decision, Soft Decision, and Neural Network decoding methods over AWGN and Rician fading conditions to identify the most effective and robust reconstruction method of mobile health data transmission in low-resource settings. The performance metrics used in the evaluation included the Bit error rate (BER), signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR), Structural similarity index measure (SSIM), latency, and computational complexity. Findings showed that the Soft Decision Decoder provided the best trade-off between accuracy, perception quality, and computational cost under the AWGN conditions with the best SNR (30.60 dB), PSNR (34.73 dB), and SSIM (0.87). Conversely, the Soft Decision method and the Neural Network decoders worked better than the Hard Decision method, having a better image fidelity and being less sensitive to multipath distortion in the case of the Rician fading. Overall, the Soft Decision Decoder proved to be more reliable and resource-efficient, thus making it the most appropriate for implementation in low-resource mobile health systems. Although the Neural Network Decoder is computationally expensive, there is much potential for its implementation in the future upon optimization and training with large-scale cervical image datasets. These results highlight the importance of balancing between accuracy, robustness, and efficiency as the key to maintaining mHealth communication systems in a low-connectivity and low-computing resource environment.

Keywords: Wireless Health Communication, Additive White Gaussian Noise (AWGN), Rician Fading, Soft Decision Decoding, Neural Network Decoder

Nomenclature

Abbreviation	Description
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
CNN	Convolutional Neural Network
LOS	Line-of-Sight
LLR	Log-Likelihood Ratio
MAP	Maximum A Posterior
mHealth	Mobile Health
MIMO	Multiple-Input Multiple-Output
MSE	Mean Squared Error
OFDM	Orthogonal Frequency Division Multiplexing
PDF	Probability Density Function
PSNR	Peak Signal-to-Noise Ratio
PSNRS	Peak Signal-to-Noise Ratio Structural
SNR	Signal-to-Noise Ratio
SSIM	Structural Similarity Index Measure
WBAN	Wireless Body Area Network

1. Introduction

The explosive growth of mobile applications has transformed the manner in which people can receive healthcare services and has provided an opportunity to introduce mHealth applications that can enable remote monitoring, real-time communication, and better patient outcomes in resource-constrained settings

[18]. These tools are increasingly being used in rural and underserved regions to fill the gaps in the healthcare service delivery, increase patient outcomes, and monitor health remotely. This is evidenced in Nigeria, where mobile-based applications such as the AVIVA app have proved pivotal in increasing both cervical cancer screening and follow-up of treatment in Women Living with HIV [13].

A critical factor to mHealth intervention success is reliability in data transmission, particularly when medical images, cardiovascular vital signs, or other structured patient records are transmitted. The wireless or mobile networks used to transfer data are prone to channel noise, interference, packet loss, and fading that may cause health data corruption or incompleteness [4]. These technical constraints have a direct impact on the reliability, accuracy, and timeliness of the transmission of clinical data. In serious applications, like screening for cervical cancer, loss of integrity of data, including corrupted image files or missing records, may result in misdiagnosis, lost follow-up care, or delayed treatment.

To solve these problems, conventional error correcting and decoding algorithms like hard and soft decision decoding have been used. Although the hard decision decoding is simple and fast, it might not work effectively in a noisy environment. Soft decision decoding is more accurate but computationally more expensive [9]. Recent developments in deep learning have presented neural decoding methods that directly learn the patterns of decoding on noisy input data, and could be more efficient in unpredictable channel conditions. Matsumine and Ochiai (2024) [10] present a state-of-the-art survey devoted to the Deep Learning enabled channel coding and decoding, and highlighting both advances and unresolved challenges regarding the 6G communication systems. Doha and Abdelhadi (2025) [5] also analyzed the way in which Deep Learning-based receivers that incorporate features such as decoding, modulation classification, and interference cancellation are transforming wireless communication design in challenging conditions.

This study aims to evaluate the efficiency of the hard decision, soft decision, and neural decoding methods with regard to mHealth information transmission. Considering the AVIVA App, noisy conditions will be simulated, and the effectiveness of each decoding technique to recover the original cervical image data will be determined. The results of this study will therefore give an idea of the best decoding strategy that can be implemented to improve the mHealth systems that will be used in the resource-limited settings.

2. Review of Related Works

Reliable wireless health data delivery has become more and more popular with respect to its use in remote patient monitoring and mHealth, and wearable health systems. Various researches have explored the causes of errors, decoding mechanisms, and how neural networks can be used to enhance signal detection and decoding efficiency.

Shannon (1948) [17] was the first to lay down the theoretical background of information transmission because he introduced the concept of channel capacity and a measurement of the largest rate at which information could be transmitted through a noisy channel. His work is the pillar of current theory in communication, which had an impact later on error detection and correction strategies.

In their study, Nachmani *et al.* (2016) [12] suggested a decoder that is a neural network that learns to decode linear block codes through deep learning. Their model, which introduces learnable weights into the belief propagation algorithm, had a high degree of improvement in decoding accuracy, indicating that it is possible to incorporate machine learning into classical decoding algorithms.

Equally, Gruber *et al.* (2017) [8] investigated the neural-based channel decoding, where neural decoders can reach the MAP performance with short codewords. As presented in their results, they found the promise of data-driven techniques in enhancing the capacity and resilience of decoding in the context of dynamic wireless environments that are prevalent in mHealth data transmission.

In their study, O'Shea and Hoydis (2017) [14] proposed an autoencoder-based model of the design of the end-to-end communication system that showed that neural networks can optimize the transmitter, channel, and receiver jointly. They are more efficient than the traditional systems in non-linear as well as time-varying channels, thus highlighting the possibilities of end-to-end learning in medical communication networks, which require reliability and flexibility.

Ye *et al.* (2018) [20] used deep learning to estimate channels and detect signals in the OFDM systems. Their approach has avoided explicit channel modeling and highly enhanced detection accuracy, which provides lessons to wireless health systems in an unpredictable hospital or rural setting.

Samuel *et al.* (2019) [16] designed DetNet, which is a deep learning detector of MIMO systems based on models. Their network design made the algorithms in iterative form run in neural layers, which was interpretable and had better performance in detection. This model is especially applicable to medical IoT systems where numerous physiological signals are transmitted with high volumes with the help of several antennas or channels.

Zhang *et al.* (2019) [21] surveyed the deep learning application in mobile and wireless networking. They described how neural networks can be used in resource allocation, signal detection, decoding, and

security, finding issues like high computation requirements and lack of data as key factors to be considered in deploying mHealth in low-resource environments.

Al-Janabi *et al.* (2017) [1] conducted a review of security and reliability concerns in WBANs to underline that encryption and authentication overhead may cause latency and compromise data integrity. Their analysis supported the importance of super-light and efficient decoding processes that ensure reliability as well as real-time performance of health communication systems.

Lastly, Wang *et al.* (2017) [19] also argued about the opportunities and challenges of deep learning of the wireless physical layer. They also reviewed the use of neural networks to synchronize and estimate channels, and also to decode, and found that deep learning provides unmatched flexibility and efficiency in the case of their optimization to wireless communication systems.

All these studies demonstrate a clear indication of the metamorphosis of the traditional-based decoding models into intelligent and data-driven strategies. Besides supporting error correction and adaptability, neural network-based decoding is also in line with the advancement of secure, reliable, and real-time transmission of health information in mobile and IoT-based healthcare settings.

Although there have been tremendous improvements in wireless health communication systems and decoding, a major gap exists in adopting powerful error correction and decoding systems in mHealth in both resource-limited and field-based healthcare settings, such as the AVIVA app that was developed to help screen cervical cancer and manage new cervical cancer cases in Nigeria.

The majority of current research on the decoding strategies and the neuro-network-based decoding is carried out in reference to generic wireless communication systems or theoretical simulations [12][3] without being translated into real-world healthcare applications. Moreover, the direct impact of channel impairments associated with multipath fading, additive noise, interference, and loss of data packets on the accuracy and timeliness of the transmission of sensitive health data in mobile diagnostic systems, such as the AVIVA app, is not adequately investigated.

3. Methodology

This study employs the experimental research design to develop, implement, and test an error decoding system to support wireless health data transmission, based on the AVIVA mobile application. The experimental design is selected because of its capability to allow manipulation of variables and systematic observation of their effects, which is closely needed to establish the effectiveness of various decoding methods in enhancing data reliability in diverse conditions of wireless channels. The research procedure will follow three key steps, which include system modelling, implementation, and performance evaluation. The workflow diagram of the wireless health data transmission decoding strategies in the AVIVA app is presented in Fig. 1.

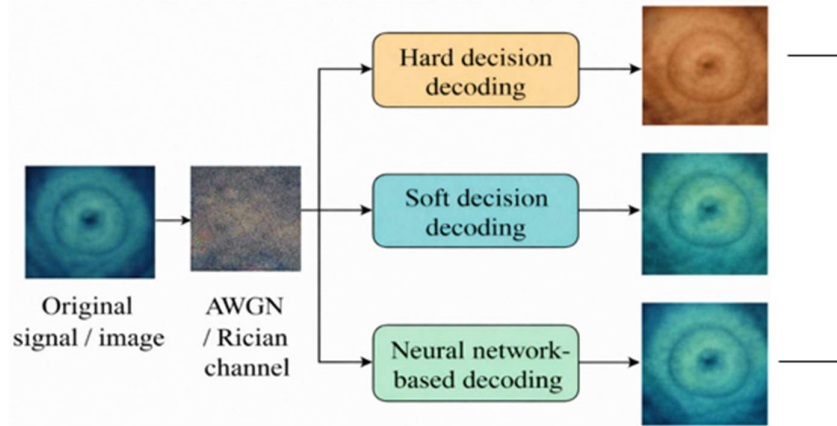


Fig. 1. Workflow Diagram of the Wireless Health Data Transmission Decoding Strategies in the AVIVA app.

The system modelling stage will involve the development of a simulation environment that will replicate the communication environment that mHealth applications normally experience. The environment will include real-world channel impairments that include AWGN and Rician fading. These impairments will be applied to emulate the real issues encountered during the transmission of diagnostic images via the AVIVA app, especially in rural and unreliable network conditions.

The implementation stage will consist of integrating hard decision decoding, soft decision decoding, and neural network methods of error decoding into the simulation model. Specifically, the machine

learning techniques will be employed to train and optimize the neural decoding model to become more robust in identifying and correcting the errors created by the noisy transmission channels. The adjusted AVIVA data flow will be adopted to test the ability of each decoding method to address the corrupted or incomplete information when communicating wirelessly.

In the evaluation phase, the model will be evaluated using the dataset generated by the AVIVA health records to check its performance on various channel conditions. Such metrics will allow comparing the decoding strategies of traditional and machine learning-based decoding, and as a result, the most effective of them in improving the reliability of transmission in the mHealth systems will be determined.

Overall, the experimental research design offers a quantitative basis for justifying the effects of advanced error decoding strategies on the reliability of wireless health communication. The study will provide empirical evidence of how the development of improved decoding methods can highly improve data integrity, clinical judgment, and patient compliance, particularly in the resource-constrained healthcare setting, by integrating a simulated transmission experiment with real-world AVIVA app data.

3.1 Channel Simulation

Wireless communication systems have several impairments that distort signals transmitted over the medium. The AWGN and the Rician fading channels are two basic models that are employed to model these impairments.

3.1.1 AWGN

One of the most famous and easy-to-use digital communication models is the AWGN channel. It represents the effect of random noise, which is introduced to the signal sent through the channel [2].

Mathematically, the signal received $s(t)$ can be expressed as:

$$s(t) = r(t) + m(t) \quad (1)$$

where $r(t)$ is the signal transmitted, and $m(t)$ is the Gaussian noise with zero mean and variance σ^2 . The noise amplitude follows a Gaussian PDF:

$$p(n) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{n^2}{2\sigma^2}\right) \quad (2)$$

AWGN is a model that represents the thermal noise and interference that are experienced when transmitting mHealth data. It is crucial when assessing the performance of error decoding schemes.

3.1.2 Rician Fading Channel

The Rician fading model is a representation of wireless channels in which the signal received comprises a strong LOS component and several scattered multipath components [6][11]. It offers a more realistic description of mHealth data transmission in semi-urban or built environments. The signal received $r(t)$ can be represented as follows:

$$r(t) = h(t)s(t) + n(t) \quad (3)$$

where $h(t)$ is the complex fading coefficient and $n(t)$ is additive Gaussian noise. The amplitude of the received signal is distributed according to the Rician PDF as follows:

$$p(r) = \frac{r}{\sigma^2} \exp\left(-\frac{r^2 + A^2}{2\sigma^2}\right) I_0\left(-\frac{Ar}{\sigma^2}\right), r \geq 0 \quad (4)$$

In this case, A is the amplitude of the LOS component, σ^2 is the variance of scattered components, and $I_0(\cdot)$ is the zero-order modified Bessel function of the first kind. The Rician K-factor, $K = A^2/2\sigma^2$, characterizes the ratio between LOS and multipath power, influencing fading severity. When $K = 0$, the channel reduces to Rayleigh fading; when $K \rightarrow \infty$ it approaches AWGN [6].

Rician fading is applied especially to mHealth applications like the AVIVA app, where clinical images and screening data may be sent in areas that include both direct LOS paths (e.g., open spaces) and substantial multipath scattering of buildings, vegetation, and surrounding structures.

3.2 Error Decoding Approaches in Wireless Health Data Transmission

This study applies and compares the hard, soft, and neural network-based decoding methods of wireless health information data in AWGN and Rician fading networks to improve the data integrity, image quality, and transmission reliability of the AVIVA mobile app.

3.2.1 Hard Decision Decoding

Hard decision decoding is a typical error correction technique used in digital communication, where the signal at the receiver is represented in discrete binary values (0 or 1) and then is decoded. A decision threshold is compared to the received bits, and the closest valid codeword of a linear block code (e.g., Hamming or Bose-Chaudhuri-Hocquenghem codes) is chosen as the transmitted data [15]. Let the transmitted codeword be:

$$\mathbf{C} = [C_1, C_2, \dots, C_n] \in \{0,1\}^n \quad (5)$$

and the received signal after channel impairments (AWGN or Rician fading) be:

$$\mathbf{r} = [r_1, r_2, \dots, r_n] \quad (6)$$

Step 1: Hard Quantization

Each received symbol r_i is mapped to 0 or 1 using a threshold (typically 0.5 for normalized signals):

$$\hat{C}_i = \begin{cases} 0 & r_i < 0.5 \\ 1 & r_i \geq 0.5 \end{cases} \quad (7)$$

Step 2: Syndrome Decoding

Let $\mathbf{H}$ be the parity-check matrix of the linear block code. The syndrome $\mathbf{S}$ is computed:

$$\mathbf{S} = \hat{\mathbf{C}} \cdot \mathbf{H}^T \quad (8)$$

- If $\mathbf{S} = 0$, no errors are detected.
- If $\mathbf{S} \neq 0$, the syndrome points to $\mathbf{a}$ correctable error pattern $\mathbf{e}$.
- Corrected codeword:

$$\mathbf{C}_{\text{decoded}} = \hat{\mathbf{C}} \oplus \mathbf{e} \quad (9)$$

where $\oplus$ denotes modulo-2 addition.

Hard decision decoding is computationally simple, but it ignores the magnitude information of the received signal, making it less effective in noisy channels.

3.2.2 Soft Decision Decoding

Soft decision decoding is an advanced error correction approach that leverages probabilistic information rather than strict binary thresholds, providing superior performance in noisy and fading wireless channels [15]. Unlike hard decision decoding, which assigns each received bit as either '0' or '1' based solely on a fixed threshold, soft decision decoding evaluates the confidence level or likelihood of each bit before making a decision. This added layer of information enables more accurate reconstruction of transmitted health data, especially in environments affected by AWGN and Rician fading, as commonly experienced in rural and mHealth applications.

When a symbol is received, the decoder does not immediately force it into binary form. Instead, it calculates metrics such as the LLR or Euclidean distance to estimate how likely the bit represents a '0' or '1'. These soft metrics are then used by decoding algorithms, such as Viterbi, MAP, or belief propagation, to minimize the probability of error (Proakis & Salehi, 2008).

$$LLR(b_i) = \ln \left(\frac{p(b_i=1|r_i)}{p(b_i=0|r_i)} \right) \quad (10)$$

Where $LLR(b_i)$ represents the confidence level that the bit is '1' or '0', b_i is the transmitted bit, r_i is the received symbol affected by channel noise, $p(b_i=1|r_i)$ and $p(b_i=0|r_i)$ are conditional probabilities based on channel statistics, and $\ln(\cdot)$ is the natural logarithm for numerical stability.

In the AVIVA cervical cancer screening workflow, images transmitted over unstable mobile networks may suffer from noise and fading. Soft decision decoding ensures that even partially corrupted pixel data is intelligently reconstructed, thereby maintaining diagnostic reliability and supporting remote medical evaluation.

3.2.3 Neural Network-Based Decoding

Neural Network-Based Decoding introduces a data-driven approach to error correction, in contrast to traditional rule-based decoders such as hard and soft decision decoding. Deep learning models, particularly CNNs and Autoencoders, learn to reconstruct transmitted signals by modelling the statistical characteristics of the wireless channel, including AWGN and Rician fading, through supervised training on large datasets (Gruber et al., 2017). These models are capable of correcting both linear and non-linear distortions that conventional decoders fail to capture. Given a noisy received signal $\mathbf{y}$, the objective of a neural network decoder is to approximate the optimal decoding function $f_\theta(\cdot)$, parameterized by network weights θ , to estimate the transmitted codeword $\hat{\mathbf{b}}$:

$$\hat{\mathbf{b}} = f_\theta(\mathbf{y}) \quad (11)$$

During training, the network minimizes a loss function, commonly MSE or Cross-Entropy Loss, between the predicted output and the true transmitted bit sequence:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N \|b_i - f_\theta(y_i)\|^2 \quad (12)$$

or, for binary classification:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N [b_i \log(\hat{b}_i) + (1 - b_i) \log(1 - \hat{b}_i)] \quad (13)$$

The trained decoder f_θ learns to approximate the MAP decision rule:

$$f_\theta(\mathbf{y}) \approx \arg \max_b P(b|\mathbf{y}) \quad (14)$$

This enables the neural network to perform near-optimal decoding without explicit channel modelling, making it robust to varying SNR levels, fading conditions, and burst errors.

3.3 Performance Evaluation Metrics

To assess the effectiveness of the proposed decoding techniques in wireless mHealth communication, particularly within the AVIVA application context, several performance metrics are employed. These metrics include BER, SNR, Latency, and Computational Complexity, which are widely used in wireless communication research [7].

3.3.1 BER

BER quantifies the reliability of the transmission system by measuring the proportion of erroneously received bits.

$$\frac{N_{error}}{N_{total}} \quad (15)$$

where N_{error} denotes the number of incorrectly received bits and N_{total} represents the total number of transmitted bits. A lower BER indicates higher decoding accuracy.

3.3.2 SNR

SNR evaluates the signal quality relative to background noise, expressed in linear and logarithmic scales:

$$\frac{P_{signal}}{P_{noise}} \quad (16)$$

It is often expressed in decibels (dB):

$$SNR_{dB} = 10 \log_{10} \left(\frac{P_{signal}}{P_{noise}} \right) \quad (17)$$

Higher SNR generally results in fewer decoding errors and improved reconstruction of medical images in mHealth applications.

3.3.3 Latency

Latency refers to the time delay experienced between data transmission and reception.

$$Latency = t_{receive} - t_{transmit} \quad (18)$$

3.3.4 Computational Complexity

Describes the resources required (time or memory) for encoding/decoding algorithms. Usually expressed using Big-O notation.

$$Complexity = O(f(n)) \quad (19)$$

3.3.5 SSIM

The SSIM metric evaluates the perceptual quality of an image by comparing structural information, luminance, and contrast between two images. It mimics the human visual system's sensitivity to these properties.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (20)$$

3.3.6 PSNR

The PSNR measures the ratio between the maximum possible signal power and the power of corrupting noise that affects the fidelity of the image. It quantifies how much noise has distorted the image relative to the original.

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \quad (21)$$

4. Results and Discussion

4.1 Visual Analysis of Channel Effects on Cervical Images

Fig. 2 depicts the Original, the AWGN, and the Rician Fading cervical images, illustrating the impact of different channel impairments on image quality during wireless transmission.

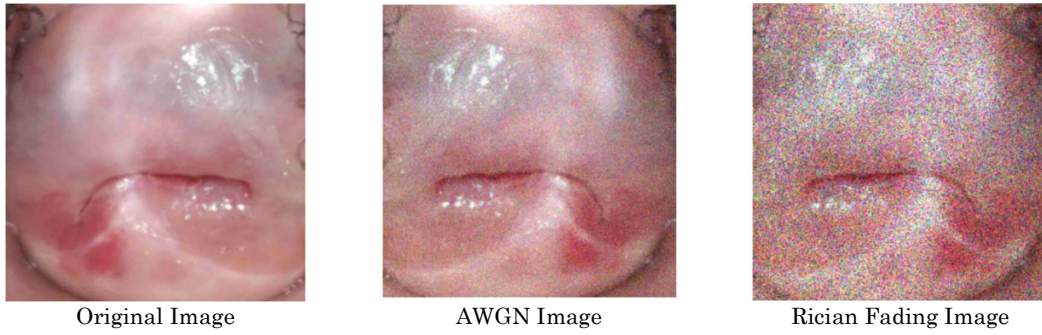


Fig. 2. Visual Representation of Channel Effects on Image Quality in Wireless Health Data Transmission

The Original, AWGN, and Rician Fading images simulate real-world wireless transmission conditions commonly encountered in mHealth systems. The AWGN image represents random electronic noise, while the Rician fading image captures distortions caused by multipath propagation in practical wireless environment. Comparing these images with the original image provided a qualitative basis for assessing decoding performance using metrics such as SNR, PSNR, and SSIM. This visual assessment highlights how different decoding strategies preserve image quality, ensuring reliable and accurate medical data transmission essential for diagnosis and treatment in mHealth applications.

4.2 Performance Under AWGN Channel

Fig. 3 illustrates the effects of AWGN and Rician fading on cervical image transmission, along with the recovered images using Hard Decision, Soft Decision, and Neural Network-based decoding methods. Under AWGN, the Soft Decision decoder produced the highest visual and structural quality, preserving edges and textures with minimal distortion. The Hard Decision output appeared grainy due to binary thresholding, while the Neural Decoder achieved good structural recovery but exhibited slight blurriness due to limited training data. For Rician fading, all decoders experienced reduced clarity, but the Soft Decision method again provided the best balance between denoising and detail preservation. The Neural approach showed greater resilience than Hard Decision, indicating potential adaptability to multipath fading with further optimization.

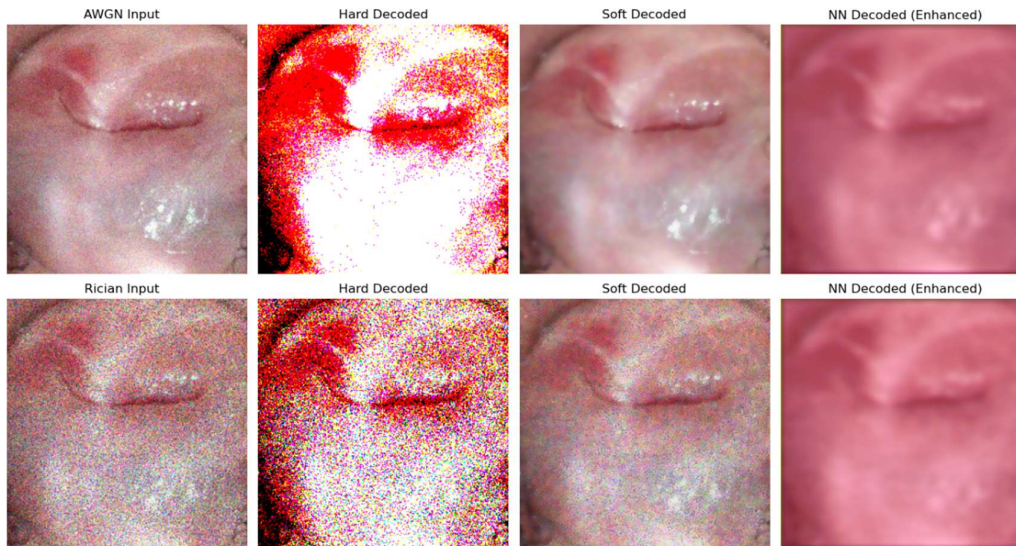


Fig. 3. Reconstructed Cervical Images under AWGN and Rician Fading Using Hard, Soft, and Neural Decoding Methods.

Table 1 summarizes the performance metrics under AWGN noise. The results indicate a clear hierarchy in decoding performance. The Hard Decision method, which uses strict thresholding to determine bit states, achieved a BER of 0.4786, SNR of 4.54 dB, and SSIM of 0.314. These values reflect poor reconstruction accuracy and substantial signal degradation. Although the latency (0.001 s) and computational complexity (196,608 operations) are minimal, the trade-off in signal quality renders this approach unsuitable for systems requiring high-fidelity data transmission, such as medical image or sensor

data exchange in mHealth systems. Soft Decision decoding demonstrated the highest overall performance across AWGN metrics, achieving a BER of 0.2819, SNR of 30.60 dB, PSNR of 34.73 dB, and SSIM of 0.875. These results represent a significant improvement in both noise tolerance and perceptual similarity. The moderate increase in latency (0.005 s) and complexity (393,216 operations) is an acceptable trade-off for real-time applications where accuracy is prioritized over minimal processing time. The Neural Network decoder produced intermediate performance with a BER of 0.4573, SNR of 14.51 dB, and SSIM of 0.775. Although its SNR and BER values did not surpass those of Soft Decision decoding, the SSIM improvement suggests better structural preservation of transmitted signals, attributable to the NN's non-linear learning capacity. However, its latency (40.09 s) and computational cost (743,939 operations) underline the substantial overhead of neural decoding, which currently limits real-time deployment without hardware acceleration.

Table 1. Performance metrics under AWGN noise

Method	BER (AWGN)	SNR (AWGN)	PSNR (AWGN)	SSIM (AWGN)	Latency (s)	Complexity
Hard Decision	0.47857	4.544533	8.673525	0.314191	0.001	196608
Soft Decision	0.28197	30.597047	34.726041	0.874632	0.005	393216
Neural Network	0.457335	14.50681	18.635802	0.774816	40.08523	743939

4.3 Performance Under Rician Fading Channel

Table 2 presents the results for Rician fading. As expected, all methods experienced performance degradation due to the combined effects of multipath interference and amplitude variation. Nevertheless, the magnitude of degradation varied significantly across methods. The Hard Decision decoder exhibited the weakest performance, with a BER of 0.4802, SNR of 3.34 dB, PSNR of 7.46 dB, and an almost negligible SSIM of 0.018. These results confirm the method's inadequacy in non-linear and dynamic channel conditions, reinforcing that simple threshold-based decoding is unsuitable for mobile environments where signal fading is prevalent. The Soft Decision decoder retained relatively strong performance, recording a BER of 0.4220, SNR of 15.87 dB, PSNR of 20.00 dB, and SSIM of 0.209. Despite the observed drop from its AWGN values, it remained substantially more robust than Hard Decision decoding. Its moderate latency and complexity confirm its viability for real-world wireless health applications, where decoding precision directly impacts diagnostic accuracy or data reliability. Interestingly, the Neural Network decoder maintained comparable SNR (15.30 dB) and PSNR (19.43 dB) to the Soft Decision decoder but achieved a much higher SSIM (0.778). This stability under fading indicates that the NN successfully learned and compensated for the channel's non-linear characteristics, preserving perceptual and structural signal features even with multipath interference. The consistent latency and computational requirements again highlight its processing burden, suggesting the need for model compression or edge-based inference acceleration for practical deployment.

Table 2. Performance metrics under Rician Fading

Method	BER (Rician)	SNR (Rician)	PSNR (Rician)	SSIM (Rician)	Latency (s)	Complexity
Hard Decision	0.480157	3.335772	7.464764	0.018326	0.001	196,608
Soft Decision	0.421974	15.869397	19.998389	0.208941	0.005	393,216
Neural Network	0.442397	15.304353	19.433346	0.777591	40.08523	743,939

4.4 Comparative Analysis of Decoding Methods

A cross-channel comparison reveals that AWGN channels produce consistently higher SNR, PSNR, and SSIM values than Rician fading channels, confirming that multipath fading introduces significant quality degradation. Across all decoding methods, BER increases under Rician fading due to amplitude fluctuations and phase distortions. Structural degradation, as measured by SSIM, is particularly pronounced for Hard and Soft Decision decoding, whereas the neural network-based decoder demonstrates comparatively stronger robustness, preserving structural information more effectively under fading conditions.

5. Conclusion

This study comprehensively evaluated the performance of three decoding strategies—Hard Decision, Soft Decision, and Neural Network-based decoding—under AWGN and Rician fading channels for wireless cervical image transmission. The results demonstrated that Soft Decision Decoding consistently achieved the best trade-off between BER, SNR, PSNR, SSIM, and computational efficiency. Its superior ability to preserve image fidelity and structural details while maintaining low computational complexity and latency

makes it particularly suitable for real-time diagnostic applications in low-resource settings. In contrast, the Neural Network-based decoder achieved competitive PSNR and SSIM values, highlighting its potential for adaptive noise suppression and intelligent signal recovery. However, its high computational cost and latency limit immediate deployment on low-power mobile devices. Nonetheless, as lightweight neural architectures and on-device AI accelerators evolve, neural decoding could become a transformative approach for robust, self-optimizing wireless medical imaging systems. Within the context of the AVIVA App, which enables mobile transmission of cervical images from screening sites to cloud-based diagnostic centers, the findings underscore that Soft Decision Decoding currently offers the most practical and reliable solution for ensuring diagnostic image integrity during transmission over noisy wireless channels. In future work, optimizing neural decoding models and integrating hybrid decoding frameworks could further enhance transmission reliability and quality, advancing the deployment of AI-driven telemedicine platforms in resource-constrained healthcare environments.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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