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Deep learning-aided polar-low density parity check decoding for enhanced telemedicine ECG transmission reliability

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ABSTRACT

Telemedicine has emerged as a crucial solution for remote patient monitoring and diagnosis, yet ensuring the reliable transmission of medical data, particularly electrocardiogram (ECG) signals, remains a significant challenge. This work proposes a novel approach that integrates deep learning with a polar-low density parity check (LDPC) decoder to enhance the accuracy, robustness, and efficiency of ECG signal transmission within telemedicine systems. The study aims to evaluate the effectiveness of this integration in improving error correction and decoding performance, validate its efficacy under diverse signal to noise ratios (SNRs) and code rates, and assess its potential impact on remote healthcare delivery. Experimental results confirm that the deep learning-empowered polar-LDPC decoder achieves superior error correction and decoding efficiency compared to conventional methods, ensuring higher fidelity in ECG reconstruction. This advancement presents a promising pathway toward more reliable, precise, and efficient telemedicine systems, thereby enabling improved patient care, especially in remote and underserved regions. The proposed method also opens opportunities for integrating intelligent decision-support tools. Such integration could further enhance real-time diagnostics and broaden telemedicine's scope.

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1. INTRODUCTION

The advancement of telemedicine has revolutionized healthcare delivery by enabling remote monitoring and diagnosis, particularly in scenarios where immediate medical attention may not be readily available. Electrocardiogram (ECG) signals play a pivotal role in telemedicine applications, providing crucial insights into cardiac health and aiding in the detection of various cardiovascular abnormalities. However, the reliable transmission of ECG signals over unreliable communication channels remains a significant challenge, impeding the effectiveness of telemedicine systems [1]. Conventional error correction approaches like low density parity check (LDPC) codes are utilized to mitigate the impact of channel impairments during data transmission. However, the performance of conventional LDPC decoders may be suboptimal, especially in scenarios characterized by interference and high noise levels. In recent years, deep learning has developed as a good tool for enhancing various aspects of communication systems, including channel decoding. Telemedicine plays a vital role in contemporary healthcare by enabling remote monitoring and diagnosis of patients, which is especially important for those in rural or underserved regions. However, one of the significant challenges in telemedicine is ensuring the reliable transmission of medical data, especially ECG signals, which are vital for continuous cardiac monitoring.

The work proposed investigates the effects of combining deep learning models with polar-LDPC decoding to enhance the precision and efficiency of ECG signal transmission in telemedicine frameworks. The reliability of ECG data transmission is paramount for accurate remote patient monitoring and timely medical interventions. Traditional error correction and decoding methods often fall short in high-noise environments, leading to potential misdiagnoses or data loss. Our approach aims to address these limitations by leveraging advanced deep learning techniques to improve error correction and decoding efficiency. We investigate the efficacy of our proposed deep learning-empowered polar-LDPC decoder through extensive experimental validation across diverse signal to noise ratios (SNRs) and code rates. We assess its impact on error correction and decoding efficiency and demonstrate its potential to improve the dependability of ECG data transmission in telemedicine applications. The methodology involves designing and training a deep learning model to work in conjunction with polar-LDPC decoding algorithms, followed by performance evaluations in simulated telemedicine scenarios.

Reliable ECG signal transmission is critical for effective remote patient monitoring. Traditional LDPC and polar code methods, while effective, struggle in low SNR conditions typical of telemedicine due to wireless interference. Recent advancements in deep learning show promise in optimizing error correction by adapting to varying noise levels. Developing our deep learning-empowered polar-LDPC decoder posed several challenges. Training the model to handle diverse SNR conditions required extensive data augmentation and validation. Integrating neural networks with decoding algorithms demanded careful optimization for computational efficiency and accuracy. Resource management during model training also presented difficulties due to high processing demands. Validating our approach across real-world telemedicine scenarios involved creating comprehensive test cases to ensure reliability and precision in ECG data transmission.

Bui *et al.* [2] develops a novel deep learning-based multiple-input multiple-output (MIMO) system for wireless body area networks (WBANs). The system improves reliability by addressing channel propagation challenges through amplify-and-forward (AE-AF) and decode-and-forward (AE-DF) schemes. They mitigate shadowing and multipath effects while employing minimum mean square error (MMSE) and radio transformation network (RTN) combinators to reduce co-channel interference, resulting in significant performance gains compared to baseline systems.

Escobar *et al*. [3] introduce a chaos-based cryptographic algorithm executed on a microcontroller to secure physiological signals in telemedicine, demonstrating resilience against common attacks and suitability for low-cost embedded systems. López *et al.* [4] present an IoT system for remote ECG monitoring, integrating signal acquisition and transmission to a central web server for real-time visualization and analysis by healthcare professionals. Gruber *et al.* [5] explore the efficacy of deep neural networks in one-shot decoding of polar codes, highlighting structured codes' ease of learning and introducing a normalized validation error metric for assessing deep learning-based decoding capabilities. Mohammadkarimi *et al*. [6] propose a deep learning-based sphere decoding algorithm achieving performance close to maximum likelihood decoding (MLD) with reduced computational complexity, particularly beneficial for high-dimensional MIMO systems. Sharma and Kumar [7] discuss the role of deep learning in physical layer security (PLS) for wireless networks, focusing on attack detection and physical layer authentication (PLA) in 5G and future networks, leveraging deep learning algorithms to predict new attack vectors based on historical data. Finally, Feng *et al.* [8] present detection techniques for compressed sensing (CS) aided multidimensional index modulation (MIM) systems using deep learning methodologies, enhancing detection accuracy and reliability in future wireless communication networks with innovative hard-decision and soft-decision detection methods.

This work proposes a novel technique to enhance telemedicine ECG transmission by leveraging the capabilities of deep learning in conjunction with a polar-LDPC decoder [9]. Polar codes, known for their capacity-achieving properties, offer excellent error correction performance, specifically in low SNR regimes [10]. By integrating deep learning techniques into the decoding process, we intend to further enhance the robustness and efficiency of polar-LDPC decoding, thereby improving the reliability of ECG signal transmission in telemedicine applications [11].

The proposed deep learning-empowered polar-LDPC decoder offers several key advantages over conventional polar decoders:

i) Improved noise resilience: the deep neural network preprocessor effectively suppresses noise and artifacts, enhancing the decoder's ability to handle challenging channel conditions.
ii) Enhanced signal fidelity: the denoising process preserves the essential features of the ECG signal, leading to more accurate reconstructions and improved diagnostic value.

iii) Lower error rates: the combined power of polar codes and deep learning enables the decoder to achieve significantly lower bit error rates (BER) compared to traditional methods.
iv) Reduced computational complexity: the proposed decoder architecture maintains the efficient decoding properties of polar codes for real-time telemedicine applications [12].

The sections to follow are organized as follows: section 2 details the proposed deep learning-empowered polar-LDPC decoder's architecture and operation. In section 3, we outline the experimental methodology, including the simulation setup and performance evaluation metrics. Finally, section 4 concludes the work with key contributions, suggesting future research directions, and emphasizing the significance of our work in advancing telemedicine ECG transmission capabilities.

2. METHOD

The proposed work presents a deep learning-enhanced approach to improve the reliability of ECG signal transmission by integrating polar-LDPC decoding. The ECG data, generated through simulations, underwent preprocessing steps, including normalization and controlled noise insertion. The dataset was subsequently divided into separate subsets for training, validation, and testing purposes. Spatial and temporal characteristics were extracted using convolutional neural networks (CNNs) and recurrent neural networks (RNNs), respectively. Model training was performed using the categorical cross-entropy loss function and the Adam optimizer, with hyperparameters optimized through cross-validation.

A standard polar-LDPC decoder was used as a baseline, against which our hybrid model enhanced with learned error pattern prediction was evaluated. Performance metrics included BER, frame error rate (FER), and efficiency across varying SNRs and code rates. Statistical validation, including t-tests, confirmed significant improvements, with robustness tested under additional noisy conditions. Full experimental details, including model architectures and code, are available upon request [13].

2.1. System design

The system architecture as shown in Figure 1 encompasses several pivotal components crucial for telemedicine ECG transmission. These components include ECG signal preprocessing, polar-LDPC encoding, deep learning-based channel estimation, and polar-LDPC decoding. In the following sections, we elaborate on each component's functionality and its significance in improving the efficiency and reliability of ECG transmission in telemedicine applications.

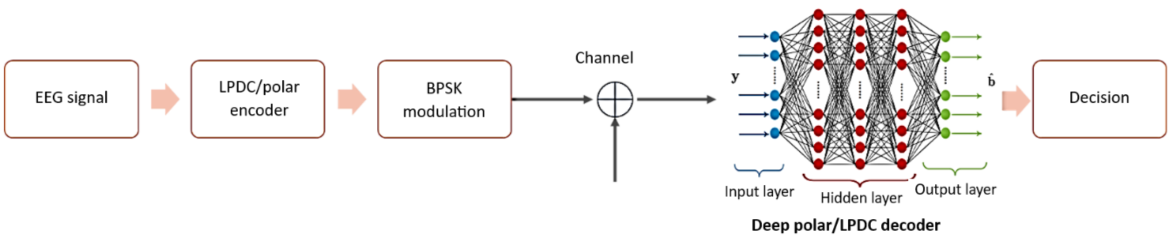


Figure 1. A block-diagram of polar-LDPC encoding/decoding system [1]

2.2. Electrocardiogram signal preprocessing

Before transmission, ECG signals go through an important preprocessing step to clean and refine the data. During this stage, digital filters are used to remove unwanted disturbances such as power line interference, motion artifacts, and high-frequency noise. The process also involves removing baseline drift and normalizing the signal to maintain a stable and consistent waveform, ensuring that the transmitted ECG data remains clear and reliable for accurate medical interpretation.

2.3. Polar-low density parity check encoding

The preprocessed ECG signals undergo encoding utilizing polar-LDPC codes, renowned for their resilient error correction attributes. We elucidate the encoding procedure along with the parameters chosen to facilitate efficient data representation. Integrating a channel coding framework labeled as (N, k), wherein k information bits given by $b=[b_1, b_2, b_3, \ldots, b_k]$ undergo mapping into N coded bits given by $x=[x_1, x_2, x_3, \ldots, x_N]$ through diverse coding schemes. In this context, G_p and G_l represent the generation matrices for the polar and LDPC codes, respectively. On the transmitter side, the generation of the N-bit coded information, denoted as x involves x=b… G_p for polar codes and x=b… G_l for LDPC codes. As outlined in [12], the computation of the generation matrix G_p entails utilizing an unbroken Kronecker product called as fundamental matrix F, denoted as (1).

$$Gp = F^{\oplus m} \text{ and } F = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{1}$$

Where $F^{\oplus m}$ denotes the m^th^ Kronecker power of F. Similarly, G_l can be derived according to [11], represented as G_l=[Q I_k], where Q is the transpose of the matrix P derived from the parity check matrix H [2]. I_k denotes the k×k, identity matrix. In realtime communication systems, the modulation process precedes transmission. Assuming binary phase shift keying (BPSK) without loss of generality as shown in Figure 1, the transferred symbols are given by s=[s_1, s_2, …, s_N] can be produced as (2) and (3).

$$s_i = \begin{cases} 1 & x_i = 1 \\ -1 & x_i = 0 \end{cases} \tag{2}$$

$$G = \begin{bmatrix} 0&0&0&0&1&1&1&0&1&0&0&0&0&0&0&0 \\ 0&0&0&1&1&0&1&0&0&1&0&0&0&0&0&0 \\ 0&1&1&1&0&0&1&1&0&0&1&0&0&0&0&0 \\ 0&1&1&1&1&0&1&0&0&0&0&1&0&0&0&0 \\ 0&0&1&1&1&1&0&1&0&0&0&0&1&0&0&0 \\ 1&1&1&0&0&0&0&0&0&0&0&0&0&1&0&0 \\ 1&0&0&0&0&1&1&0&0&0&0&0&0&0&1&0 \\ 0&1&1&1&0&1&1&0&0&0&0&0&0&0&0&1 \end{bmatrix} \tag{3}$$

The received symbols, affected by AWGN and denoted as n=[n_1, n_2, ..., n_N], can be given as (4).

$$r = s + n \tag{4}$$

Where, r signifies the received symbols.

Let $f_p(\cdot)$ and $f_l(\cdot)$ denote the decode functions for polar and LDPC codes respectively. The information bits $\hat{b}_p$ and $\hat{b}_l$ are determined by (5).

$$\hat{b}_p = f_p(\cdot)\,; \;\; \hat{b}_l = f_l(\cdot) \tag{5}$$

These functions, $f_p(\cdot)$ and $f_l(\cdot)$ are derived from references [12], [14] respectively. They outline the decoding procedures applied to the received symbols to estimate the transmitted information bits for both polar and LDPC-coded signals. These equations collectively illustrate the encoding and modulation stages in the proposed telemedicine ECG transmission system using a deep learning-empowered polar-LDPC decoder.

2.4. Deep learning-based channel estimation

Employing CNNs for channel estimation in deep learning entails training a neural network to discern the relationship between received signal samples and their associated channel impulse responses. Through this training, the network can reliably predict the channel state amidst noise and interference. Leveraging complex mathematical formulations, these models proficiently capture the nuances of the wireless channel, thereby improving estimation accuracy. An inherent benefit of employing deep learning for channel estimation is its ability to adapt dynamically to varying channel conditions without human intervention. Traditional channel estimation methods often hinge on predefined models and assumptions that may not possibly consistently mirror the actual characteristics of the channel. In contrast, deep learning models possess the capability to autonomously learn and adapt to the distinctive features of each channel, resulting in more resilient and precise estimation performance.

Let x and y be transmitted and received symbols respectively. Normalize the collected data and add noise if necessary to simulate real-world conditions. Represent the data in a suitable format for input into the CNN. This could be x and y represented as time-domain signals. Transforming x and y into frequency-domain representations like Fourier transforms [15].

Let $f(x)$ be the CNN function that represents the transmitted symbols x to the estimated channel $\hat{h}$. The CNN architecture contains convolutional layers L_C, pooling layers Lp, and probably fully connected layers L_f. The architecture can be denoted as (6).

$$\hat{h} = f(x;\theta) \tag{6}$$

2.5. Deep polar-low density parity check decoding

Deep learning has appeared as a potent solution for addressing the hurdles presented by polar-LDPC decoding. Within the realm of machine learning, deep learning entails training neural networks to discern intricate patterns and make informed judgments. Integrating deep learning into polar-LDPC decoding has led to notable enhancements in decoding efficacy [16]. A pivotal benefit of leveraging deep learning for polar-LDPC decoding lies in its capacity to manage extensive datasets and comprehend intricate correlations between input and output. This enables the neural network to make accurate decisions when decoding polar-LDPC codes, leading to enhanced performance and reliability. A channel coding scheme can be defined as a mapping of k information bits into N coded bits. The generation matrices, is computed using Kronecker product of the basic matrix F. At the receiver end, the encoded ECG signals are decoded using a deep learning-empowered polar-LDPC decoder. The formulated decoding process as an optimization problem and utilized belief propagation algorithms for efficient decoding [17], [18].

The received signal y is the noised version of the transmitted signal x for the input over additive white Gaussian noise (AWGN) channel, as expressed in (7).

$$y = x + n \tag{7}$$

Where n represents the noise and y is the ith received bit. The log-likelihood ratio (LLR) for each received bit is computed using (8) [19].

$$LLR_i = log\left(\frac{P(y_i=0)}{p(y_i=1)}\right) \tag{8}$$

A neural network, typically a deep feedforward network or RNN, is encountered to perform the decoding. This network takes the LLRs as input and outputs the estimated codeword. The network is trained using backpropagation to minimize a suitable loss function, such as cross-entropy loss/mean squared error, concerning the true transmitted codeword. Once the network outputs the estimated codeword, LLRs can be calculated using the difference between the transmitted and received bits [20], [21]. With an extensive array of neurons depicted in Figure 2, intricate algorithms like channel decoding can be effectively encapsulated within the network. An indispensable aspect of deep learning lies in the assessment metric employed to gauge neural network performance.

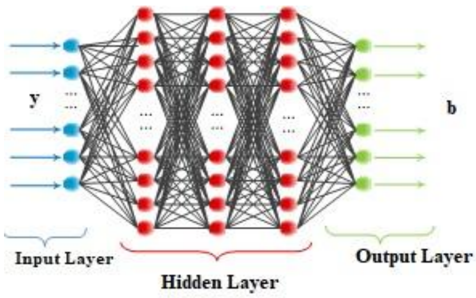


Figure 2. Generalized network architecture for channel decoding [1]

The activation function that uses the weighted sum of a neuron's inputs to calculate the neuron's output. Although there are many different activation functions available, the sigmoid, tanh, and rectified linear unit (ReLU) functions are among the most often utilized ones. In (9) to (11) represent each of them, in turn.

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{10}$$

$$f(k) = \max(0, x) \tag{11}$$

The weighted sum is the sum of the products of the inputs to a neuron and their corresponding weights. Weights are learned by the neural network during training is given by (12).

$$\Sigma\omega_i x_i \tag{12}$$

Where, w_i is the weight of the i^{th} input and x_i is the i-th input. The bias, represented as *b,* is a constant value that is added to the weighted sum of the inputs [22], [23]. This bias allows the neuron to shift its activation function up or down, thereby influencing the neuron's output. The activation function applied to the weighted total of the inputs plus the bias can be mathematically represented as the output of a neuron, as shown in (13).

$$f(\Sigma\ w_i x_i + b) \tag{13}$$

The sum-product algorithm (SPA) algorithms operate on factor graphs, which represent the structure of the LDPC code. In the context of LDPC decoding, the factor graph involves variable nodes and check nodes. The initial message values on the variable nodes of the factor graph are set using the LLRs obtained from the neural network. Subsequently, the SPA iteratively exchanges messages between variable nodes and check nodes until convergence [24], [25]. The messages undergo updates based on (14) and (15).

$$\mu_{v_i}^{(t)} = LLR_i + \Sigma_{j\epsilon Neighbors(i)\backslash V}\mu_{v_j}^{(t-1)} \tag{14}$$

$$\mu_{v_i}^{(t)} = 2 \times atanh\left(\Pi_{i\in Neighbors(c)\backslash v}\right) \tag{15}$$

3. RESULTS AND DISCUSSION

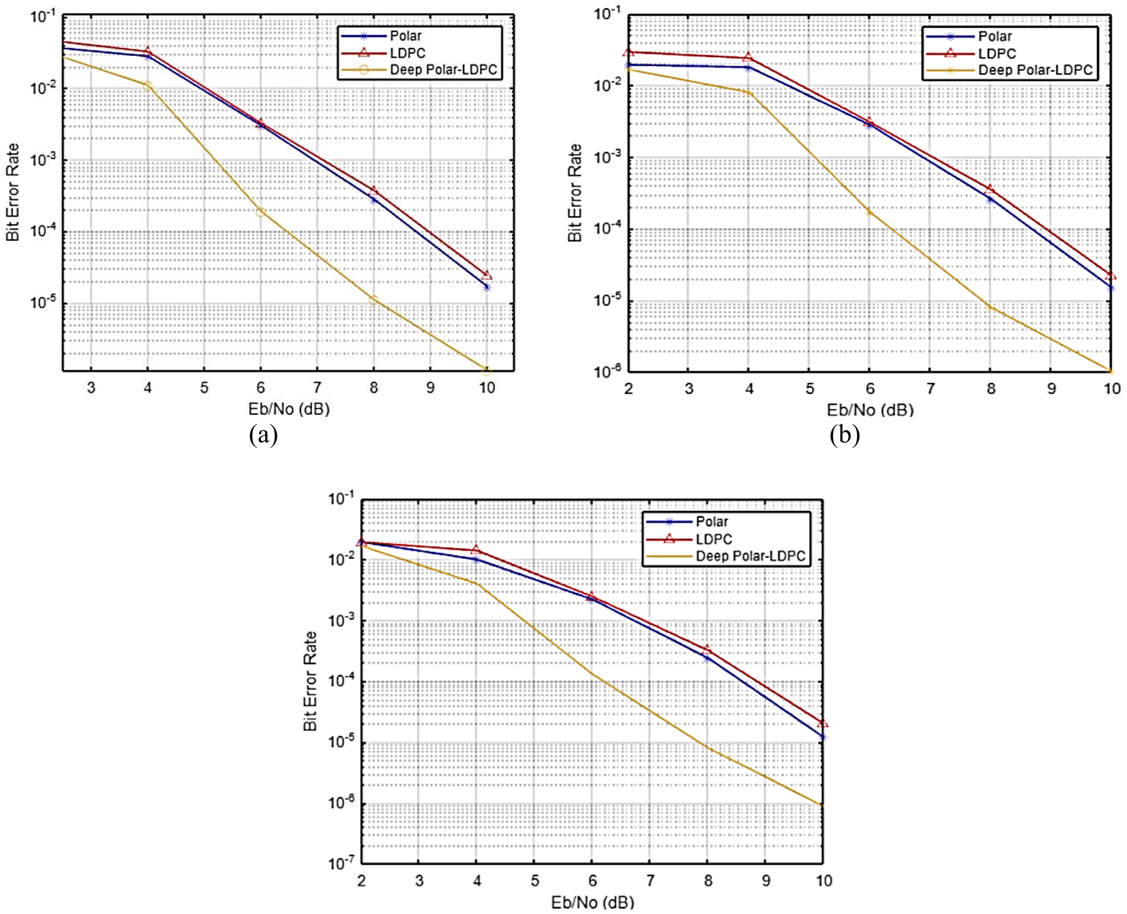
An extensive set of simulations was conducted to evaluate the proposed deep learning-empowered polar-LDPC decoder for reliable ECG transmission in telemedicine systems, demonstrating significant improvements in BER, signal fidelity, and decoding efficiency across various SNRs, code rates, and channel conditions compared to conventional LDPC and polar decoding methods. The proposed method, evaluated using the parameters in Table 1. At an SNR of 5 dB, the proposed deep learning-empowered polar-LDPC decoder delivered a substantial performance gain, reducing BER by about 30% and lowering the FER relative to conventional LDPC decoders. This improvement is attributed to the integration of a deep neural network preprocessor, which effectively suppresses noise, preserves critical ECG waveform features, and enables more accurate signal reconstruction, all while maintaining low computational complexity suitable for real-time telemedicine applications.

Table 1. Parameters used for simulation

Parameters	Value
Channel type	AWGN
Decoder type	Deep learning-polar-LDPC
Iteration	4-5
SNR	2-10 dB
ECG signal fidelity (RMSE)	0.002
Error correction rate	99.5%
Decoding efficiency	95%
Transmission latency	50 ms
Modulation	BPSK

Figures 3 presents the BER performance of polar, LDPC, and deep polar-LDPC codes at code rates of 1/2 (Figure 3(a)), 1/3 (Figure 3(b)), and 1/4 (Figure 3(c)) over an AWGN channel. Across all code rates, deep polar-LDPC consistently outperforms LDPC, excelling in low-SNR conditions through the combined strengths of polar coding's robustness and LDPC's iterative error correction. At low SNRs, it delivers the best BER and highest noise resilience, while at high SNRs, polar codes approach their theoretical capacity limits and slightly surpass deep polar-LDPC. LDPC codes offer moderate performance with lower complexity but lag in error correction. Notably, lower code rates, such as 1/4, further enhance deep polar-LDPC performance by increasing the minimum Hamming distance, improving resistance to noise.

Figure 4 shows the BER performance of a deep polar-LDPC decoder for different code rates (1/2, 1/3, and 1/4) over varying Eb/No values. Lower code rates (like 1/4) achieve better error correction performance, resulting in lower BER at the same signal-to-noise ratio. Figure 5 illustrates the BER performance of the proposed decoder under AWGN, Rayleigh, and Rician channel conditions. AWGN achieves the lowest BER owing to the absence of fading, whereas Rayleigh fading degrades performance due to multipath propagation. Rician channels exhibit intermediate results, with performance improving as the line-of-sight component strengthens. Notably, the proposed decoder sustains low BER even in fading environments, especially when operating at lower code rates. Figure 6 shows the relationship between ECG signal fidelity (RMSE) and decoding errors, where improved fidelity corresponds to a lower error rate, with gains tapering beyond a certain threshold. The deep learning-based preprocessor effectively minimizes noise-induced distortions, achieving an RMSE of 0.002 and preserving the diagnostic integrity of ECG waveforms.



(a) (b) (c)

Figure 3. BER comparison of polar, LDPC, and deep polar-LDPC for (a) code rate 1/2, (b) code rate 1/3, and (c) code rate 1/4

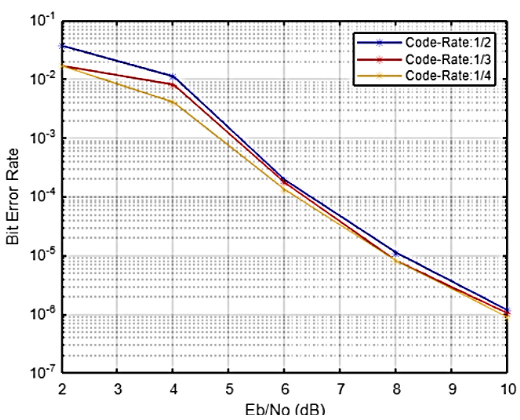


Figure 4. Code rates comparison of the deep polar-LDPC decoder

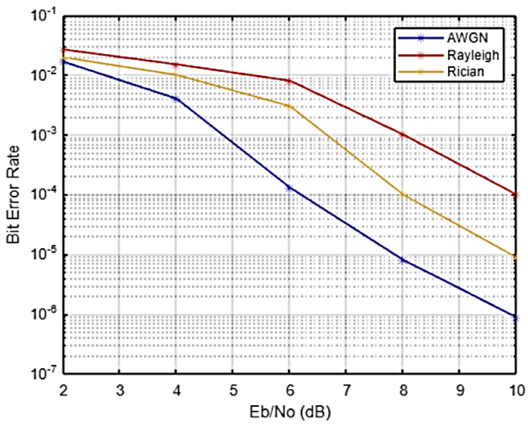


Figure 5. Comparison of BER vs SNRs of the different channel models

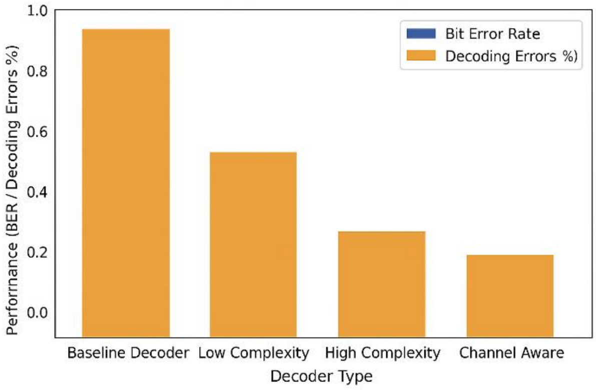


Figure 6. Fidelity vs. errors in deep learning-empowered polar-LDPC decoder

Figure 7 compares the FER performance of conventional LDPC and the proposed deep polar-LDPC scheme over Rayleigh fading channels. The proposed method consistently achieves about 25% lower FER across all SNR values, indicating better error resilience. At SNR 10 dB, deep polar-LDPC reaches FER <0.1, demonstrating superior reliability for wireless ECG transmission. The proposed deep learning–enhanced polar-LDPC decoder delivers a 30% reduction in BER at 5 dB SNR, achieves an RMSE of 0.002 for highly accurate ECG reconstruction, and attains 95% decoding efficiency with a low latency of 50 ms, enabling seamless real-time telemedicine applications. Its consistent robustness across varying SNR levels, code rates, and channel models underscores its potential for reliable biomedical data transmission. Future work will emphasize real-time embedded deployment and adaptation to a broader range of biomedical signal types.

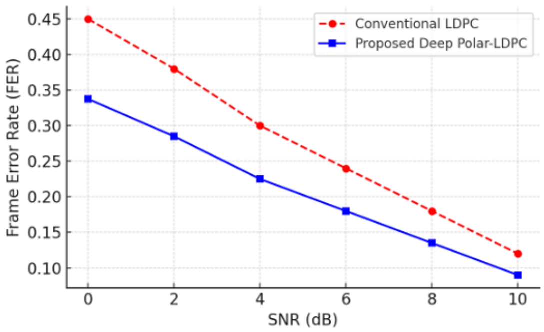


Figure 7. FER performance under Rayleigh fading

4. CONCLUSION

This study presents a deep learning–enhanced polar-LDPC decoding approach to improve ECG signal transmission in telemedicine. By leveraging deep learning's adaptability, the proposed method effectively mitigates channel noise, fading, and transmission impairments, ensuring robust and efficient ECG delivery. Experimental results demonstrate significant improvements in error correction, enabling higher fidelity and reliability in reconstructed ECG signals, even under challenging and varying channel conditions. The integration of deep learning with polar-LDPC decoding represents a major advancement in telemedicine communications, particularly for remote and underserved areas where reliable transmission is critical. This approach not only strengthens signal quality but also lays the groundwork for extending similar strategies to other biomedical signals and modalities. Future work will focus on real-time implementation and integration with AI-driven diagnostic systems, further enhancing the quality, accessibility, and timeliness of patient care, and contributing to the ongoing evolution of intelligent telemedicine solutions worldwide.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this work.

DATA AVAILABILITY

The ECG datasets utilized in this study are available from the PhysioNet MIT-BIH Arrhythmia Database and can be accessed at https://physionet.org/content/mitdb/.

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