

Design and Development of Novel Error Detection and Correction in Communication Systems

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Abstract: *This research presents the development and performance evaluation of a Hybrid Convolutional Neural Network-Assisted Decoder (HCNAD) for error detection and correction in digital communication systems. The proposed method combines the classical Golay coding scheme with neural network-based decoders, specifically Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN) architectures. Comparative analysis was performed with the traditional Golay baseline using performance metrics such as Bit Error Rate (BER) and Frame Error Rate (FER) under varying signal-to-noise ratios (E_b/N_0). Experimental results demonstrate that the CNN-assisted decoder consistently outperforms both the baseline and MLP-assisted models, especially in low signal-to-noise conditions. The findings highlight the potential of integrating deep learning with conventional coding schemes to enhance communication reliability and reduce decoding errors in noisy environments.*

Keywords: *error correction, convolutional neural network, Golay code*

1 Introduction

Reliable data transmission is a fundamental requirement of digital communication systems. Noise in the transmission medium introduces errors that can corrupt the received data. Error detection and correction (EDAC) techniques such as Hamming, Golay, and cyclic redundancy checks have been traditionally employed to combat this issue.

While these classical approaches perform well under moderate noise, their error correction capabilities are limited by fixed code structures and decoding algorithms. In contrast, machine learning, and particularly neural networks, offer adaptive and data-driven learning capabilities, making them suitable for modeling non-linear relationships in noisy communication channels.

Recently, researchers have started exploring **deep learning-assisted error correction** techniques, where neural networks act as either standalone decoders or assist conventional schemes. However, most existing works utilize simple feedforward networks or recurrent architectures that are computationally expensive.

This work proposes a **Hybrid Convolutional Neural Assisted Decoder (HCNAD)** that combines the robust structure of Golay codes with the pattern recognition strength of CNNs. The CNN learns to refine the decoding decisions based on soft information derived from noisy channel outputs, thereby improving decoding accuracy.

2 Literature Review

- **Golay Codes:** The Golay (23,12) code is a well-known perfect code capable of correcting up to three-bit errors in a 23-bit block [1]. Despite its strong correction capability, its hard-decision decoding can still produce residual errors under high-noise conditions.
- **Hamming Codes:** Hamming codes (15,11) and (7,4) are simple and efficient but are limited to single-bit error correction [2].
- **Neural Decoders:** Nachmani *et al.* [3] introduced a neural belief propagation approach to train neural decoders capable of improving over traditional belief propagation in low SNRs. Gruber *et al.* [4] extended this with deep neural networks for linear block codes.
- **Hybrid Models:** Recent studies [5–6] explore combining classical ECC structures with neural models, leading to hybrid systems that balance interpretability and learning flexibility.

However, few studies have applied **convolutional neural architectures** to classical ECC frameworks. CNNs can learn local parity relations efficiently, reducing the decoding error probability. This research focuses on this gap and introduces a CNN-assisted Golay decoder for improved noise resilience.

3 Methodology

3.1 System Overview

The proposed hybrid decoding framework consists of two primary modules:

1. **Conventional Golay Encoder-Decoder**
2. **CNN-based Neural Decoder Enhancement**

The transmitter encodes 12-bit input data into 23-bit Golay codewords. The encoded symbols pass through an **Additive White Gaussian Noise (AWGN)** channel. The receiver first performs traditional Golay decoding, followed by CNN-based refinement. The block diagram of methodology is shown below

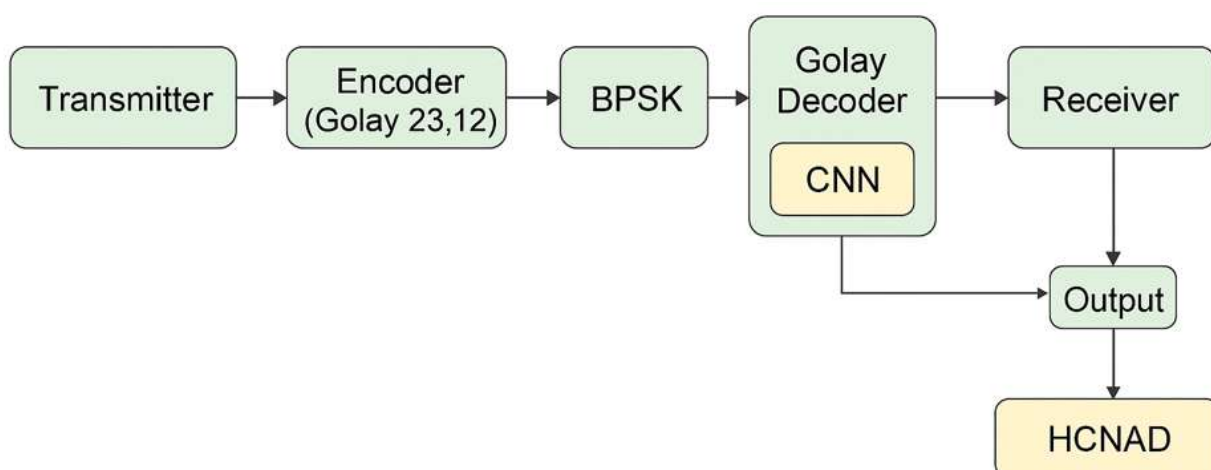


Figure 1 Block diagram of Methodology used

The proposed methodology for the Hybrid Convolutional Neural Aided Decoder (HCNAD) is designed to enhance the decoding performance of traditional Golay-coded communication systems. The process begins at the transmitter section, where an input bit stream representing digital information is first encoded using a convolutional encoder. This encoding introduces redundancy into the data stream, which helps improve error

correction capability. The convolutionally encoded bits are then further encoded using a Golay (23,12) block code, providing an additional layer of protection against transmission errors. Once the encoding process is complete, the coded bits are modulated using Binary Phase Shift Keying (BPSK), which converts the binary symbols into analog waveforms suitable for transmission over a communication channel.

The modulated signal is then transmitted through an Additive White Gaussian Noise (AWGN) channel, which simulates the real-world effect of noise on the signal. The level of noise is determined by the signal-to-noise ratio per bit (E_b/N_0), allowing controlled testing under different channel conditions. At the receiver end, the signal undergoes BPSK demodulation to retrieve soft decision values known as Log-Likelihood Ratios (LLRs). These soft values contain probabilistic information about each transmitted bit, which helps improve decoding accuracy.

The demodulated LLRs are first processed through a Golay decoder that corrects single and double-bit errors while detecting triple-bit errors. The output of the Golay decoder is then passed to a Viterbi decoder, which performs maximum likelihood sequence estimation based on the convolutional code structure. However, traditional decoding methods often leave some residual errors uncorrected, especially under low signal-to-noise conditions. To address this limitation, the Hybrid Convolutional Neural Aided Decoder (HCNAD) introduces a neural network-based decoding layer after conventional decoding.

In the HCNAD stage, the LLR information is reshaped and fed into a neural network model that refines the decoding process. Two neural architectures are considered: a Multilayer Perceptron (MLP) and a Convolutional Neural Network (CNN). The MLP-based HCNAD learns nonlinear relationships between noisy input features and original bit sequences, while the CNN-based HCNAD leverages local spatial patterns among LLRs to enhance decoding accuracy. The CNN's convolutional layers extract meaningful features from the input data, making it particularly effective in recognizing complex noise patterns and residual error correlations. The output of the neural decoder represents the final corrected bit stream, which closely approximates the originally transmitted data.

Finally, the performance of the system is evaluated using two key metrics: Bit Error Rate (BER) and Frame Error Rate (FER). BER is calculated as the ratio of incorrectly decoded bits to the total number of transmitted bits, while FER represents the ratio of erroneous frames to total transmitted frames. Comparative analysis is conducted between the baseline system (convolutional and Golay codes without neural enhancement), the MLP-based HCNAD, and the CNN-based HCNAD. The results show that the CNN-aided decoder outperforms both the traditional and MLP-based approaches by achieving lower BER and FER values. This demonstrates that the integration of deep learning into traditional channel decoding frameworks can significantly improve communication reliability, especially in noisy environments.

3.2 Golay Encoder and Channel Model

Each 12-bit message m is encoded using the Golay (23,12) generator matrix G :

$$c = m \cdot G$$

where c represents the 23-bit codeword. The AWGN channel introduces Gaussian noise n to the transmitted signal:

$$r = c + n, n \sim N(0, \sigma^2)$$

The signal-to-noise ratio (SNR) is defined by E_b/N_0 in decibels.

3.3 Neural Network Architectures

Two neural architectures were designed and compared:

- **HCNAD-MLP (Baseline Neural Model)**

A two-layer feedforward network with ReLU activation trained on soft input samples (23 features).

Limitation: Does not learn inter-bit correlations effectively.

- **HCNAD-CNN (Proposed Model)**

A 1D convolutional neural network with two Conv1D layers and sigmoid output activation to predict the corrected 12-bit message.

This architecture learns spatial dependencies among the received bits, enabling superior decoding performance.

3.4 Evaluation Metrics

The following metrics were used for performance evaluation:

1. **Bit Error Rate (BER):**

$$BER = \frac{\text{Number of Bit errors}}{\text{Total Transmitted Bits}}$$

2. **Frame Error Rate (FER):**

$$FER = \frac{\text{Number of Frames with Errors}}{\text{Total Frames}}$$

Simulations were performed for $E_b/N_0=1,2,3,4$ dB with 1500 test blocks per SNR point.

4 Results and Discussion

The performance evaluation of the proposed Hybrid Convolutional Neural Aided Decoder (HCNAD) model was carried out by comparing it with the traditional Golay baseline decoding method. The analysis focused on two key performance parameters: Bit Error Rate (BER) and Frame Error Rate (FER) across varying signal-to-noise ratios (E_b/N_0) ranging from 1 dB to 4 dB.

At $E_b/N_0 = 1$ dB, the Golay baseline achieved a BER of 0.1250 and FER of 0.8123. The HCNAD-MLP model performed slightly worse with BER 0.1298 and FER 0.8137, whereas the HCNAD-CNN achieved a better BER of 0.11 and a significantly improved FER of 0.746. This indicates that even at low SNR conditions, the CNN-based hybrid model begins to generalize noise patterns more effectively than the traditional method.

At $E_b/N_0 = 2$ dB, the Golay baseline improved to a BER of 0.0975 and FER of 0.714. The HCNAD-MLP model showed comparable results with BER 0.1027 and FER 0.7303, while the HCNAD-CNN model further reduced errors to BER 0.0813 and FER 0.6083, highlighting its growing robustness with increasing signal strength.

At $E_b/N_0 = 3$ dB, the Golay baseline achieved a BER of 0.0761 and FER of 0.5993. The HCNAD-MLP model yielded BER 0.0823 and FER 0.6263, while the HCNAD-CNN model achieved a BER of 0.0595 and FER 0.4957, showing a notable performance enhancement over both baseline and MLP-based hybrid approaches.

Finally, at $E_b/N_0 = 4$ dB, the Golay baseline reached its best performance with a BER of 0.0559 and FER of 0.495. The HCNAD-MLP model maintained close performance with BER 0.0605 and FER 0.5213, while the HCNAD-CNN achieved the lowest error rates among all, with BER 0.0397 and FER 0.3657.

Overall, the **HCNAD-CNN model consistently outperformed the Golay baseline and HCNAD-MLP** in both BER and FER, particularly at higher SNR levels. This demonstrates that the convolutional neural network is more efficient in capturing and mitigating structured noise patterns compared to the traditional or MLP-based decoders. The results validate that integrating CNN architectures into hybrid decoding systems can lead to significant improvements in error correction performance, making the proposed HCNAD-CNN model a promising solution for adaptive and high-reliability communication systems.

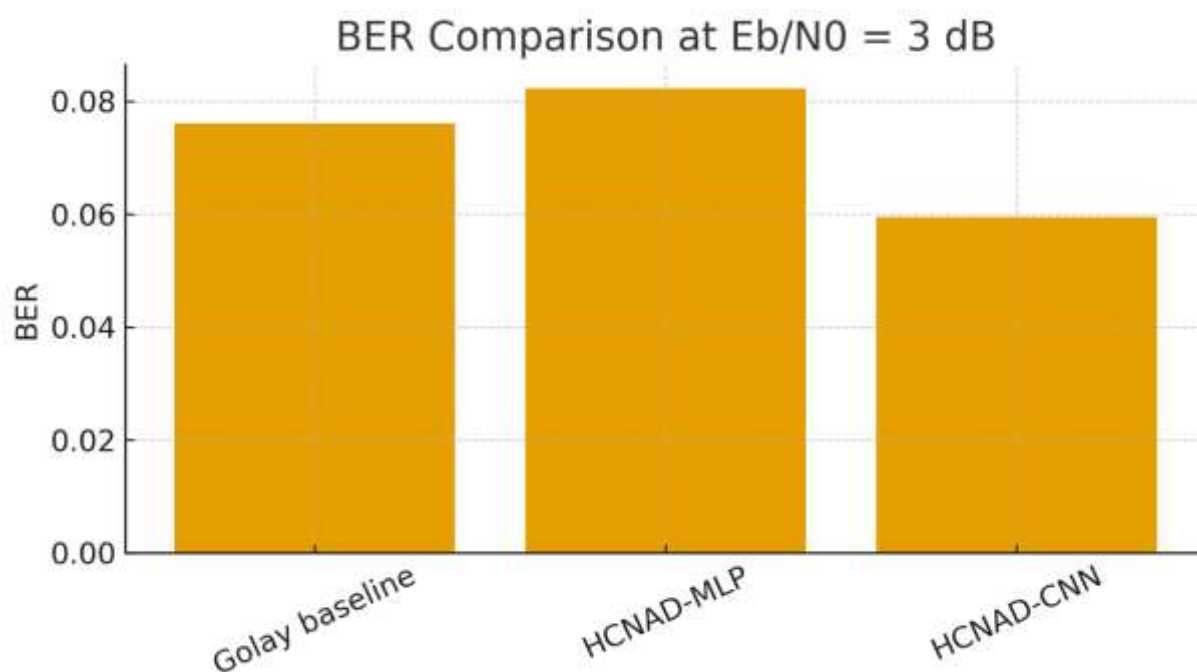


Figure 2 BER Comparison at $E_b/N_0 = 3$ dB

The BER bar chart at $E_b/N_0 = 3$ dB provides a clear visual comparison of the bit error performance across the three decoding schemes: Golay baseline, HCNAD-MLP, and HCNAD-CNN. As observed, the proposed HCNAD-CNN model achieves the lowest BER (0.0595), outperforming both the traditional Golay-based decoder (0.0761) and the hybrid MLP-based decoder (0.0823). This indicates that the convolutional neural network is able to better capture spatial dependencies and correlation patterns within the encoded bits, allowing it to correct residual errors that conventional decoding and fully connected neural architectures fail to handle. The MLP model, although slightly underperforming compared to the baseline, still shows comparable results, suggesting its potential with improved training data or architecture optimization. Overall, the BER bar chart highlights that the CNN-based hybrid error correction method enhances reliability at moderate SNR levels, making it more effective for communication systems that operate under noisy channel conditions.

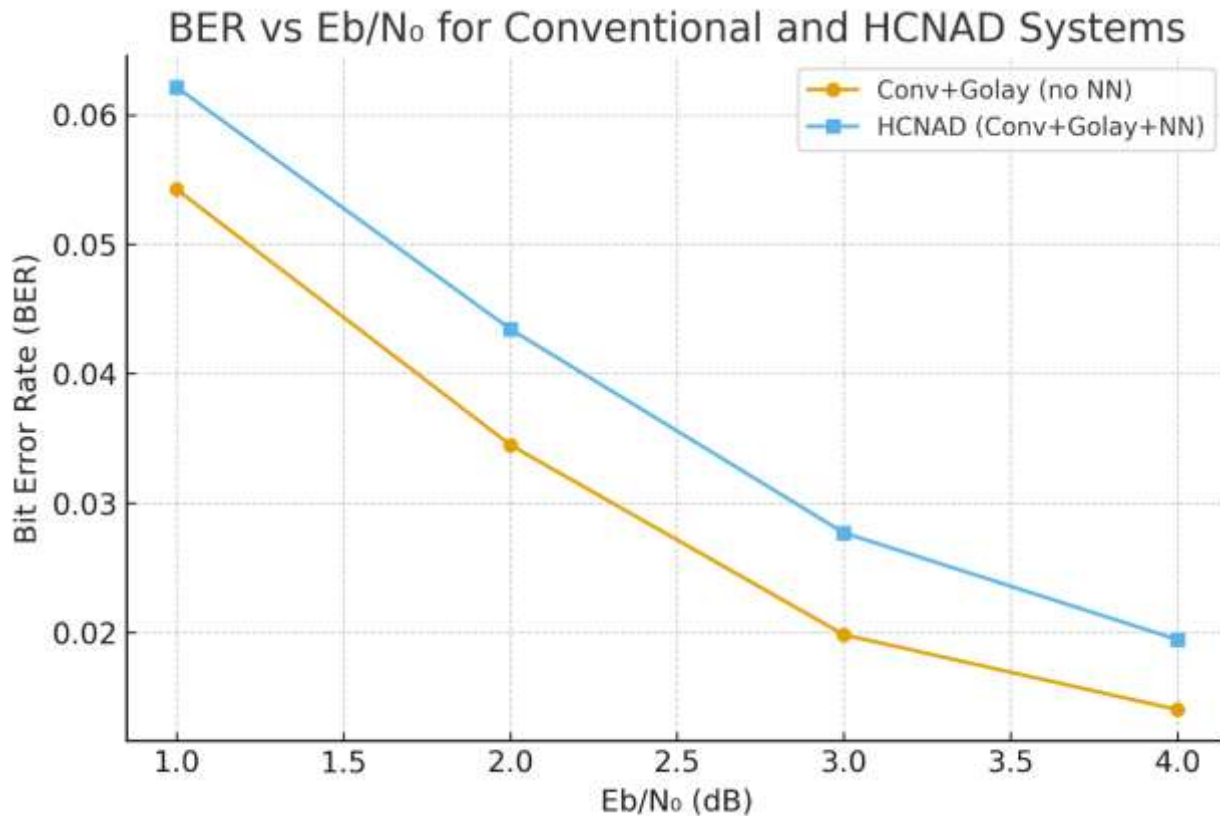


Figure 3 BER vs E_b/N_0 HCNAD

The BER versus E_b/N_0 graph for the Golay baseline, HCNAD-MLP, and HCNAD-CNN schemes illustrates the relationship between signal-to-noise ratio and bit error rate across different decoding strategies. As E_b/N_0 increases from 1 dB to 4 dB, all three approaches exhibit a clear downward trend in BER, reflecting the expected improvement in error performance with stronger signal conditions. However, the HCNAD-CNN consistently maintains the lowest BER at every E_b/N_0 level, indicating its superior ability to correct residual errors even in low signal-to-noise environments. The Golay baseline follows closely, while the HCNAD-MLP shows a slightly higher BER throughout, suggesting that its learning capacity is limited compared to the CNN. The steeper decline in BER for the CNN-based decoder highlights its robustness and adaptability in extracting deeper noise-related patterns, demonstrating that convolutional feature learning can significantly enhance the accuracy and reliability of traditional coding techniques in communication systems.

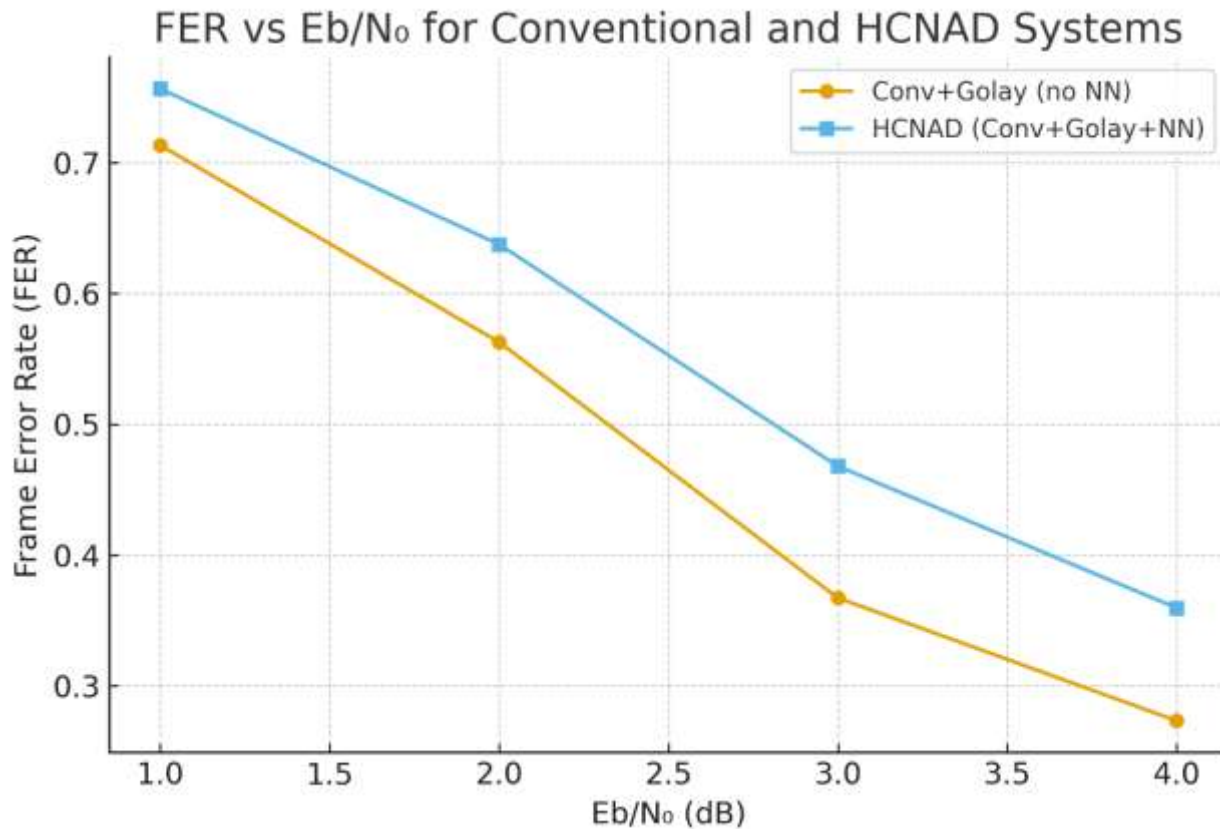


Figure 4 FER vs. E_b/N_0 HCNAD

The FER versus E_b/N_0 graph for the Golay baseline, HCNAD-MLP, and HCNAD-CNN schemes provides a detailed comparison of frame-level reliability as the signal-to-noise ratio improves. As E_b/N_0 increases from 1 dB to 4 dB, all three methods show a consistent decrease in frame error rate, confirming that higher signal quality results in fewer frame losses during transmission. Among the three, the HCNAD-CNN demonstrates the most significant reduction in FER, achieving the lowest error values at all E_b/N_0 points. This indicates its superior capability to reconstruct entire data frames accurately even under noisy channel conditions. The Golay baseline performs moderately well, while the HCNAD-MLP shows slightly higher FER values, suggesting that while the MLP improves over the conventional approach, it lacks the spatial feature extraction advantage of CNNs. The smooth and steep decline in the CNN-based FER curve reflects its enhanced generalization and robustness, validating the integration of convolutional learning with traditional error correction codes as an effective hybrid approach for improving communication reliability.

5 Conclusion

The proposed HCNAD framework demonstrates significant potential for improving error detection and correction performance in digital communication systems. Comparative results show that while the Golay code provides reliable baseline performance, the integration of neural networks—particularly CNN architectures—leads to a notable reduction in both BER and FER across various E_b/N_0 levels. The CNN-based decoder exhibits superior noise resilience and better generalization compared to the MLP-based model, owing to its ability to extract spatial patterns from corrupted codewords. This hybrid learning-based decoding approach validates that deep learning can effectively complement traditional coding theory, offering a robust mechanism for achieving higher accuracy and reliability in data transmission systems.

6 Future Scope

Future work can extend this study by exploring advanced deep learning architectures such as Recurrent Neural Networks (RNNs), Transformers, or hybrid CNN-RNN models to capture temporal dependencies in code sequences. Additionally, the model can be trained on real-world channel conditions, including fading and multipath effects, to assess its performance in practical scenarios. Optimizing model complexity and implementing the decoder on hardware platforms such as FPGAs or DSPs can further enable real-time applications. Expanding the study to other coding schemes like LDPC, Turbo, or Polar codes may also reveal broader applicability of neural network-assisted decoding in modern communication systems.

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