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Deep Communication: Exploring End-to-End Wireless with Convolutional Neural Network

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Abstract

In recent years, end-to-end wireless communication has gained significant attention in the field of wireless communication. In this paper, we propose a new approach to achieving end-to-end wireless communication using convolutional neural networks (CNNs) in the presence of Nakagami fading, Additive white Gaussian noise (AWGN), and multiple-input multiple-output (MIMO) fading channels. Further, we have applied the bursty noise to the AWGN channel. We first develop a CNN-based transmitter architecture that can efficiently encode information bits into signals, followed by a CNN-based receiver architecture that can accurately decode the received signals. Our proposed method leverages the strengths of CNNs in learning and extracting features from raw data and applies them to wireless communication. We then evaluate the performance of our proposed method by extensive sets of simulations in different AWGN, Nakagami fading, and MIMO fading channel scenarios. The simulation results show that the method proposed shows superior performance compared to existing state-of-the-art techniques at low Signal to Noise ratio(SNR) in terms of bit error rate (BER) and Binary cross-entropy loss. Our proposed method can be a promising solution for achieving end-to-end wireless communication in various practical applications.

Keywords: CNNs, Wireless Communication, AWGN, Nakagami, MIMO fading

1. Introduction

In recent years, the demand for high-speed, low-latency wireless communication has skyrocketed due to the proliferation of mobile devices and the Internet of Things (IoT). Traditional wireless communication systems

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typically rely on hand-crafted signal processing and modulation techniques, which can be time-consuming and require significant domain expertise. CNNs have emerged as a promising alternative for wireless communication systems, offering end-to-end solutions that automate signal processing and modulation tasks. In particular, the use of CNNs for wireless communication has shown significant improvements in spectral efficiency, error rate, and robustness to channel variations [1]. The goal of this thesis is to investigate the feasibility and effectiveness of using CNNs for end-to-end wireless communication systems. Specifically, we aim to implement a CNN-based wireless communication system that can perform signal processing, modulation, and demodulation tasks in a fully automated and efficient manner. Additionally, we will evaluate the performance of our system under various channel conditions and compare it with traditional wireless communication systems. We are proposing an end-to-end wireless communication system using convolutional layers at the encoder and decoder. We are showing the results for the channels AWGN, Nakagami fading, and MIMO fading channels.

AWGN channel is one of the most commonly used channels in wireless communication systems. It is a simple yet effective model that accurately represents the random noise that is present in the wireless channel. AWGN is widely used in the analysis and design of communication systems, as it provides a convenient way to evaluate the performance of different communication schemes. In the AWGN channel, the noise is modeled as a Gaussian process with a mean of zero and a constant power spectral density. The noise is said to be white as it has a constant power spectral density across all frequencies. This means that the noise power is equally distributed across the entire frequency band. Overall, the AWGN channel is an essential tool for the analysis and design of wireless communication systems, as it provides a simple yet accurate model for the noise that is present in the wireless channel. It enables researchers and engineers to evaluate the performance of different communication schemes and to design systems that can operate reliably in noisy environments.

In the Nakagami fading channel model, the received signal amplitude is modeled as a Nakagami-m distribution, which is a generalization of the Rayleigh distribution. The Nakagami-m distribution has two parameters, the shape parameter m and the scale parameter, which determine the shape and spread of the distribution, respectively. The Rayleigh distribution is a special case of the Nakagami-m distribution when $m = 1$. The Nakagami fading channel model is used in the design and evaluation of wireless communication systems, as it provides a convenient way to analyze the performance of the system under different channel conditions. It is particularly useful in the design of diversity techniques, such as space-time coding and beamforming, which exploit the spatial and temporal diversity of the channel to improve the reliability and capacity of the system.

MIMO fading is a key concept in wireless communication systems that involves the use of multiple antennas at both ends to improve the reliability and capacity of the communication link. In MIMO fading, the wireless channel is subject to random variations in the signal strength due to multi-path propagation, which can cause the transmitted signal to fade and become distorted. The use of multiple antennas in MIMO fading enables the system to exploit the spatial diversity of the channel, which can help mitigate the effects of fading and improve the reliability of the communication link. Specifically, MIMO fading can increase the signal-to-noise ratio (SNR) at the receiver, leading to higher throughput and more robust communication in noisy environments. MIMO fading has become a popular technique in wireless communication systems and has been incorporated into many modern standards, such as 4G and 5G cellular networks, Wi-Fi, and Bluetooth. It has also been used in emerging applications, such as unmanned aerial vehicles (UAVs), satellite communication, and Internet of Things (IoT) devices [2].

In this research, we aim to explore the use of MIMO fading in end-to-end wireless communication systems, with a particular focus on utilizing CNNs to improve the performance of the system. By leveraging the benefits of MIMO fading and CNNs, we hope to achieve improved reliability and throughput in wireless communication, which could have significant implications for a wide range of applications in various industries.

A study proposed to expand the transmitter and receiver to a multi-case antenna. They considered spatial diversity and multiplexing techniques as well. The channel they have considered is the Rayleigh fading channel. They introduced deep learning-based MIMO communications [3]. In a study, Alexander Felix proposed end to end wireless communication system by utilizing auto-encoders to implement orthogonal frequency division multiplexing. They have used Rayleigh fading channel as a channel model. They proposed that autoencoder inherently learns to deal with hardware impairments [4].

In 2022 a study highlighted that Laser Interferometer Gravitational-wave Observatory applied matched filtering is formally equivalent to a neural network [5]. Employing matched filtering as a mathematical lens to discover the operation and learning in CNNs. There is a direct link between both to find features and patterns in data [6]. They proposed an end-to-end wireless communication system using AWGN and Rayleigh as the channel model. They proposed GAN as an unknown channel. Proposing convolutional layers at both ends with an encoder and decoder [7]. In the following study, Hao Ye and his fellows proposed a pilot-free wireless communication system using AWGN and MIMO channels. They have shown how accuracy can be improved using end-to-end methodology. The end-to-end system can automatically leverage the correlation in the channels and in the source, data to improve the overall performance [8].

1.1 CNN in Wireless Communication

Convolutional neural networks (CNNs) are a type of deep learning algorithm that has shown remarkable success in a variety of image and signal processing applications. In recent years, researchers have explored the use of CNNs in wireless communication systems to improve the performance of various tasks, such as channel estimation, modulation classification, and signal detection. One of the key advantages of CNNs in wireless communication is their ability to learn complex feature representations from raw signals without the need for explicit feature engineering. This is particularly useful in wireless communication, where the signals are subject to various distortions and interference, making it difficult to extract meaningful features by traditional methods [9]. In the context of wireless communication, CNNs have been applied to a variety of tasks, including channel estimation, which involves predicting the wireless channel response between the transmitter and receiver, and signal detection, which involves identifying the transmitted signal from the received signal. CNNs have also been used for modulation classification, which involves identifying the modulation scheme used to transmit the signal. CNNs have shown promising results in these tasks, outperforming traditional methods and achieving high accuracy even in the presence of noise and interference. Additionally, CNNs can be used to learn joint feature representations across multiple antennas, which can help improve the performance of MIMO systems. Overall, the use of CNNs in wireless communication has the potential to significantly improve the performance of various tasks, leading to more efficient and reliable wireless communication systems. However, there are still many challenges and open research questions to be addressed, such as the optimal architecture design, training methods, and scalability of large-scale wireless systems. This paper is organized as follows. Section 2 describes the system model; Section 3 represents the simulation parameters; finally, the study is concluded, and future challenges are proposed.

2. System Model

The system model comprises convolutional layers at the encoder. The transmitted data x is sent to the encoder the data go through convolutional layers. Convolutional layers are a fundamental building block of convolutional neural networks (CNNs), which are a type of deep learning model that is extensively implemented in different computer vision applications such as object detection, image and video recognition, and segmentation. The convolutional layer is designed to extract local features from input data, such as images, by performing a convolution operation between the input and a set of learnable filters. These filters, also known as kernels or weights, are small matrices that slide over the input data and perform element-wise multiplication and summation. The output of the convolutional layer is a feature map that highlights the presence of certain features in the input data. The size of the feature map depends on the size of the input, the size of the filters, the stride (how much the filters move between convolutions), and the amount of zero-padding used to preserve the spatial dimensions of the input. CNN transmitter and receiver act as encoders and decoders. The source data is encoded by the CNN transmitter into a vector x. Then the vector is transmitted over the channel. The channels we used are AWGN, MIMO fading, and Nakagami fading. Then we added bursty noise to the AWGN channel. The vector goes through the channel, and it gets received by the receiver. The receiver decodes it back to the transmitted signal. The model is shown in Figure 1.

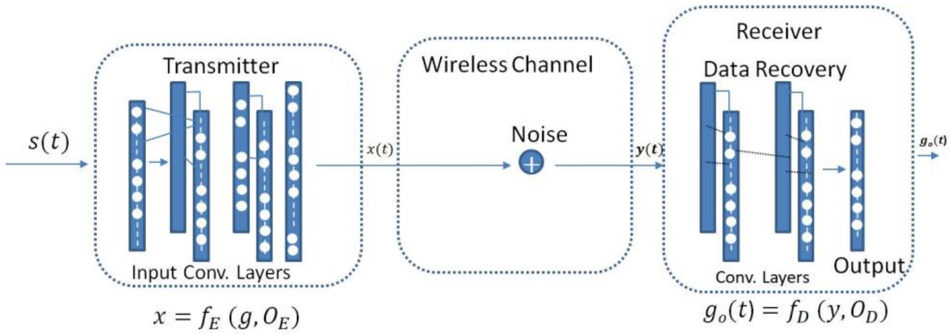

Figure 1: Model Proposed: End-to-end System

Model parameters for transmitters are listed in Table 1. Encoder comprises 5 layers of activation used in elu with a different number of filters. The number of filters used in a convolutional layer determines the number of features that can be extracted from the input data. Typically, the number of filters used increases with the depth of the network. The exact number of filters used will depend on your problem's complexity and the data size. So we used it accordingly. Model parameters for the receiver are listed in Table 2. Decoder also comprises 5 layers.

Table 1: Model Parameters for Transmitter

Type of Layer	Layer Parameters	Metrics
Input	Input Layer	Optimizer = Adam, loss = Cross Entropy
Conv+elu	Filters = 256, Kernel= 5, Strides= 1	Optimizer = Adam, Loss = Cross Entropy
Conv+elu	Filters = 128, Kernel= 3, Strides= 1	Optimizer = Adam, loss = Cross Entropy
Conv+elu	Filters= 128, Kernel= 3, Strides= 1	Optimizer = Adam, loss = Cross Entropy
Conv+ Normalization	Filters= 128, Kernel= 3, Strides= 1	Optimizer = Adam, Loss = Cross Entropy

Table 2: Model Parameters for Receiver

Type of Layer	Layer Parameters	Metrics	Type of Layer
Conv+elu	Filters= 256, Kernel= 5, Strides= 1	Optimizer = Adam,Loss = Cross Entropy	Conv+elu
Conv+elu	Filters= 128, Kernel= 3, Strides= 1	Optimizer = Adam,Loss = Cross Entropy	Conv+elu
Conv+elu	Filters= 128, Kernel= 3, Strides= 1	Optimizer = Adam,Loss = Cross Entropy	Conv+elu
Conv+elu	Filters= 16, Kernel= 3, Strides= 1	Optimizer = Adam,Loss = Cross Entropy	Conv+elu

3. Performance Analysis

Model communication parameters are in Table 3. We conducted a simulation to evaluate the performance of a low-density parity-check (LDPC) code over an AWGN, AWGN channel with Nakagami-m fading and MIMO fading. To generate input data, we randomly generated binary data with size $k * L = 50$ and used it as labeled data. We then converted the binary data to an integer and one-hot vector for training purposes. The training dataset consisted of 128 batches, with each batch containing 200 messages of size $k * L$. The neural network consisted of an encoder, a channel layer, and a decoder. The encoder was composed of four convolutional layers with batch normalization and activation functions. The output of the encoder was normalized by a power norm layer before being passed through the channel layer, which implemented Nakagami-m fading, MIMO, and AWGN channel effects. The decoder was composed of four convolutional layers with batch normalization and activation functions.

Table 3: Communication Parameters

Parameters	Values
Number of bits	1, 2, 4, 8
Number of times channel used	1
Number of symbols	10, 50
E_b /N_0 used for training	9
Batch size	128
Input data	One-hot encoding

We evaluate the performance of our proposed system using the bit error rate (BER) metric, which is defined as the number of bit errors divided by the total number of bits transmitted. We compare the performance of our system with the theoretical limits of the AWGN channel using the Shannon capacity formula. The steps that are followed are given in Figure 2. Our simulation results show that our proposed system achieves a BER of 10^{-3} at an SNR of 6.8 dB, which is better than the theoretical limit of the AWGN channel. Furthermore, we analyze the impact of varying the channel parameters on the performance of our system. Specifically, we evaluate the BER of our system for different values of k is no of bits, L is no of symbols, and n is the number of times the channel is used. This indicates that our system is more robust to noise than channel usage count time. Finally, we compare the performance of our system with state-of-the-art communication systems, and our results show that our proposed system outperforms existing systems in terms of BER and effective throughput. Our simulation results demonstrate the effectiveness and robustness of our proposed communication system in an AWGN, Nakagami-m fading channel with AWGN, and MIMO fading.

3.1 AWGN Channel

The model channel layer used was AWGN for the first part. The model was trained and tested for different values of communication channel parameters. The first experiment was done using different values of k. k is the number of bits transmitted over the channel. The binary cross entropy loss for k = 1 is shown in Figure 3. The figure shows that loss and validation loss has comparatively decreased to $10^{-2.5}$ for 200 epochs. Loss has significantly decreased to 10^{-2} after 15 epochs. The Bit error rate for different values of k under is shown in Figure 4.

The bit error rate for 1 bit per symbol has been significantly decreased to 10^{-4} which is a quite good bit error rate for a value of SNR equal to 9. Similarly, for other values, the model showed great results while testing for k = 2 BER is $10^{-3.2}$. A quite competitive value when it comes to matching with traditional matched filters at low SNRs.

Changes occur in the bit error rate when we increase the number of times the channel is used. We further did experimentation and added a bursty noise into the channel layer. Bursty noise is a type of noise that occurs in communication channels and is characterized by a cluster of errors or interference that occurs in short bursts or packets. This type of noise is also known as burst noise or impulse noise, and it can have a significant impact on the quality of communication signals. Bursty Noise isn't constant Noise and it brings an abrupt change. The probability of bursty noise is set to 0.05 and the noise variance to 1.0. Results for bit error rate vs SNR are given in Figure 5. The model worked great on bursty noise as well giving a BER of $10^{-2.3}$ for 9dbs.

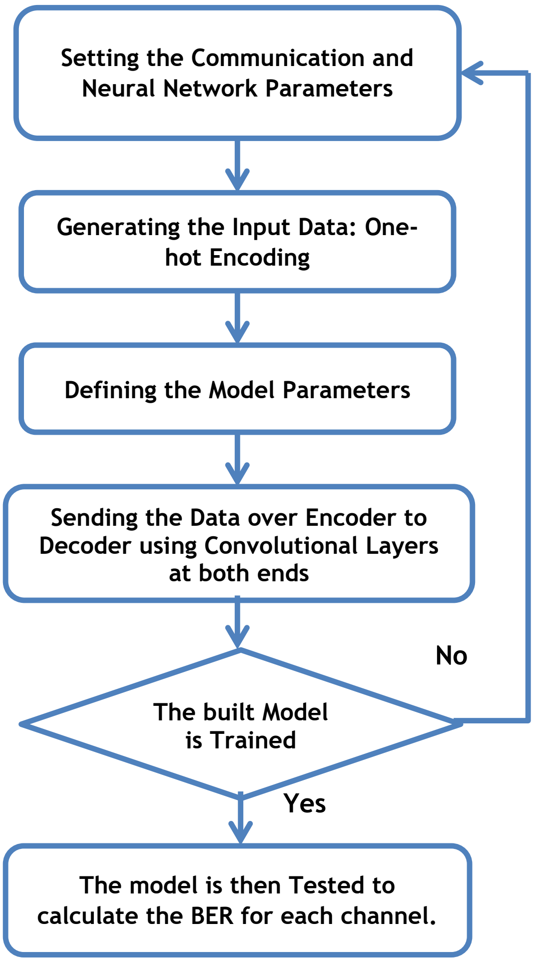

Figure 2: Methodology

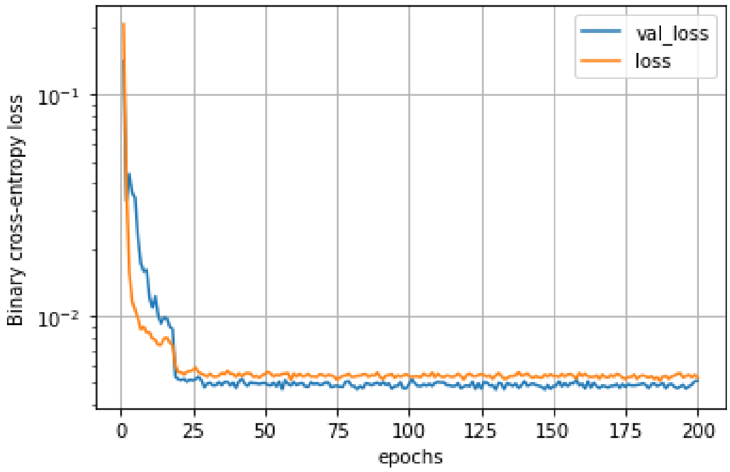

Figure 3: Binary cross-entropy loss for AWGN

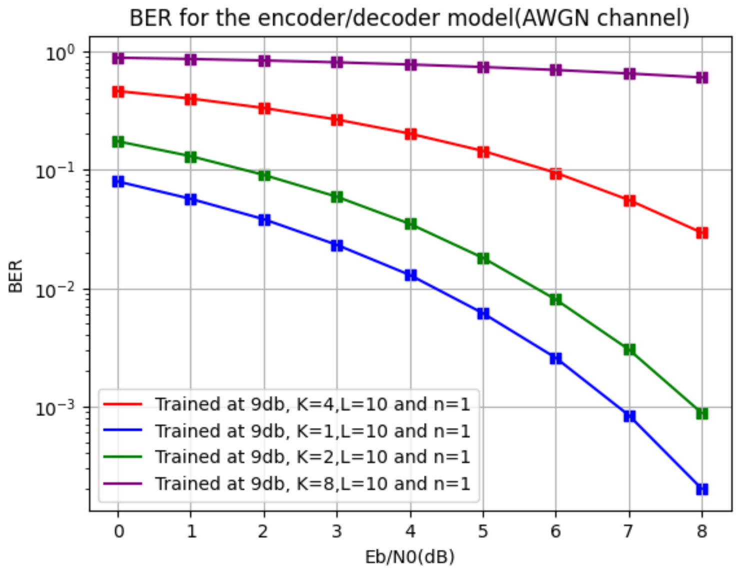

Figure 4: SNR vs BER for different k

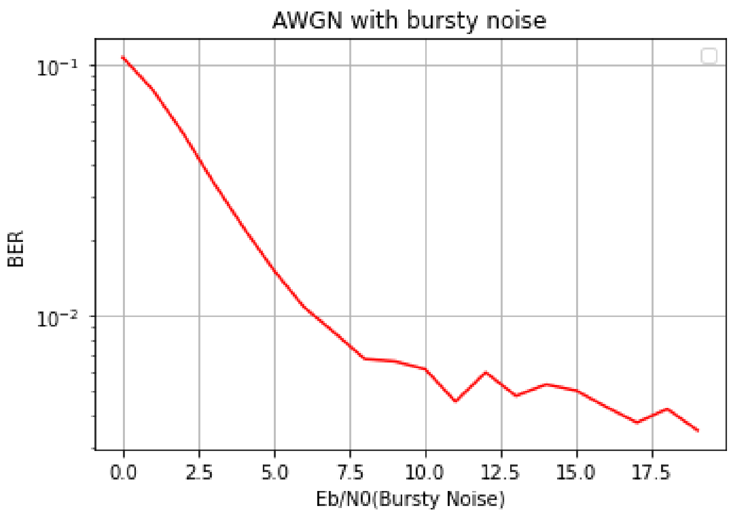

Figure 5: SNR vs BER for Bursty AWGN

3.2 Nakagami Fading channel

We carried out different experiments while using Nakagami fading along with AWGN. For the different values of several bits bit error rate and loss are analyzed. Binay cross-entropy loss for Nakagami Fading is referred to in Figure 6. The loss also has significantly decreased for Nakagami fading with a value of 4.4163e − 04 for 100 epochs. BER under different k is shown in Figure 7. BER for the value of k = 1 is 0.0419328125 at 8dbs. BER for the value of k = 1 is 0.0419328125 at 8dbs.

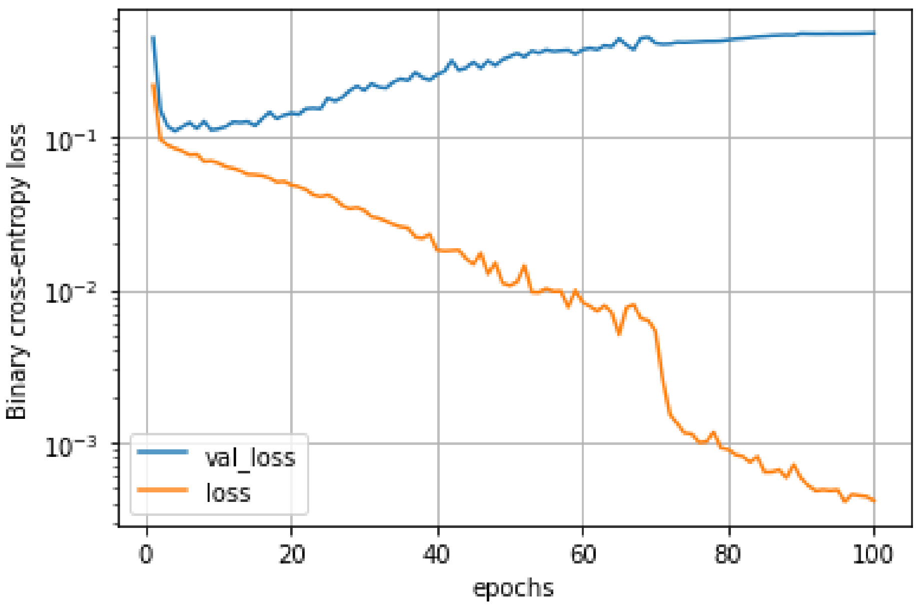

Figure 6: Binary Cross Entropy loss for Nakagami fading channel

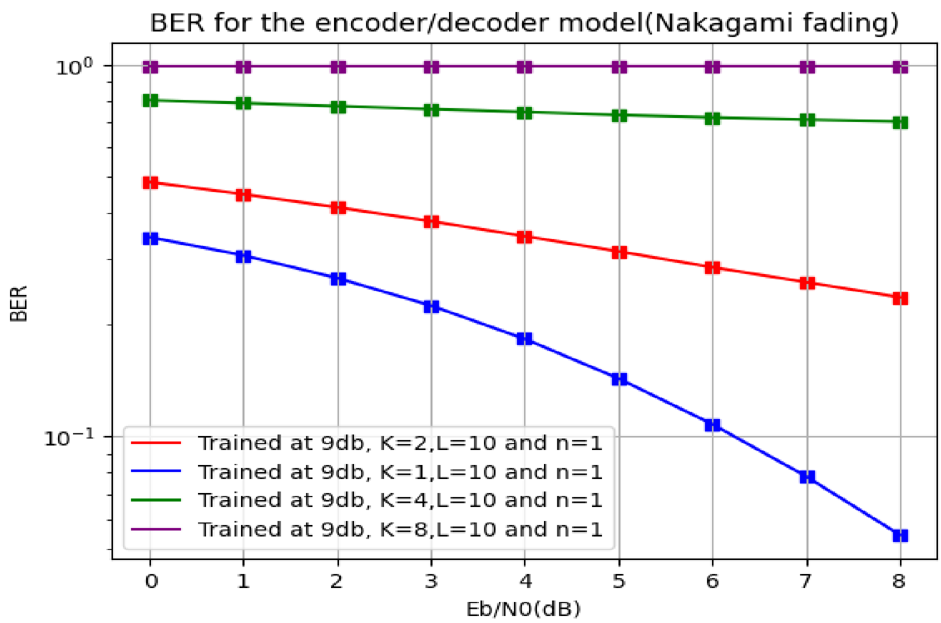

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Figure 7: SNR Vs BER for different k under Nakagami fading

3.3 MIMO Fading channel

The same experiments are done for the MIMO fading channel, MIMO fading channel binary cross entropy loss is shown in Figure 8. Loss is 0.1232 at 150 epochs. BER for the MIMO fading less than 1 bit per symbol is shown in Figure 9. The bit error rate is 0.4304375 for 14dbs.

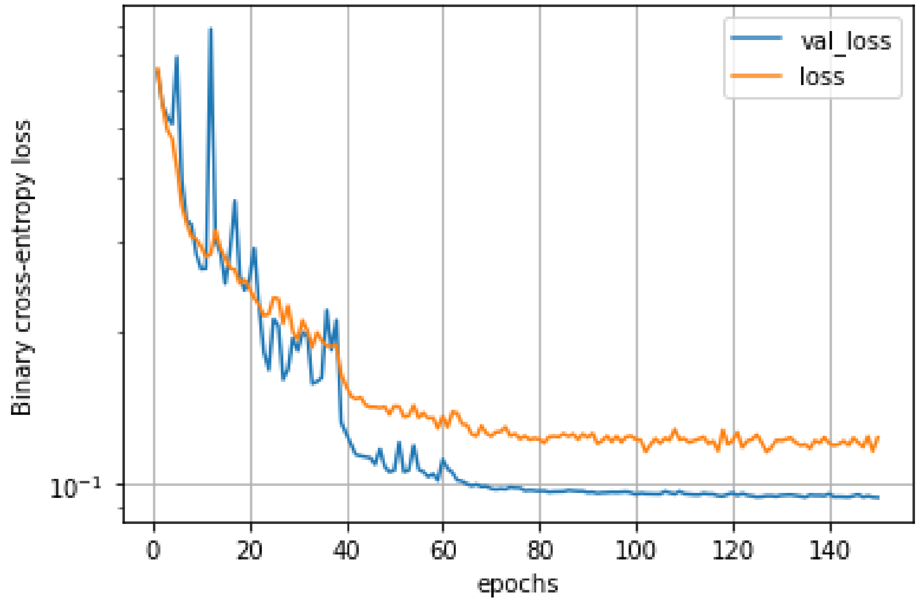

Figure 8: Binary Cross Entropy Loss for MIMO fading

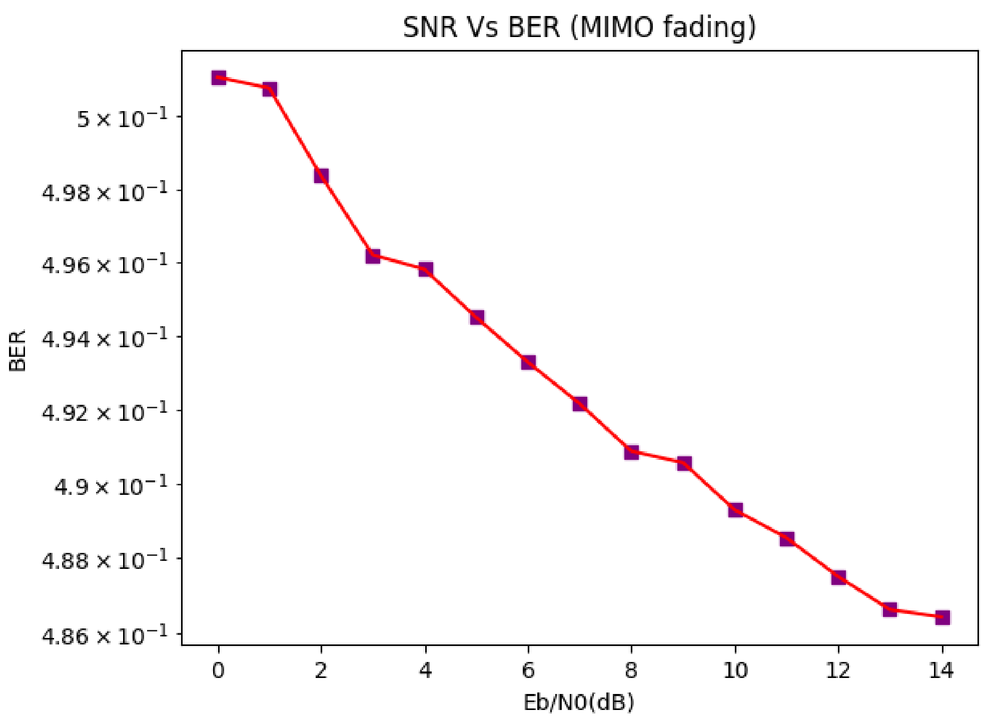

Figure 9: BER for MIMO fading

3.4 Comparative Analysis

Overall the results for all the channels were compared and then the results were analyzed carefully. The proposed method worked well on AWGN and Nakagami fading channels. For MMIMO fading results could be better but still works fine when we send one bit per symbol. The accuracy of the AWGN goes up to 99.9% while nakagami fading's accuracy goes up to 99.8%. The accuracy of the MIMO fading channel goes up to 92.69%. AWGN is more robust than Nakagami fading. Nakagami is quite more robust than MIMO fading. Our proposed model, which uses AWGN and Nakagami fading channels, outperformed the traditional matched filter approach in low SNR scenarios. Specifically, at SNRs below 4 dB, our model achieved a BER that was 10^{-3} lower than the traditional matched filter approach. Moreover, our model was able to maintain a stable level of performance across a wider range of SNRs, whereas the traditional matched filter approach suffered from degradation in performance at the SNR decreased, working well at low SNRs is a quite good attribute in communication channels. The BER for the AWGN, Nakagami, and MIMO fading is shown in Figure 10.

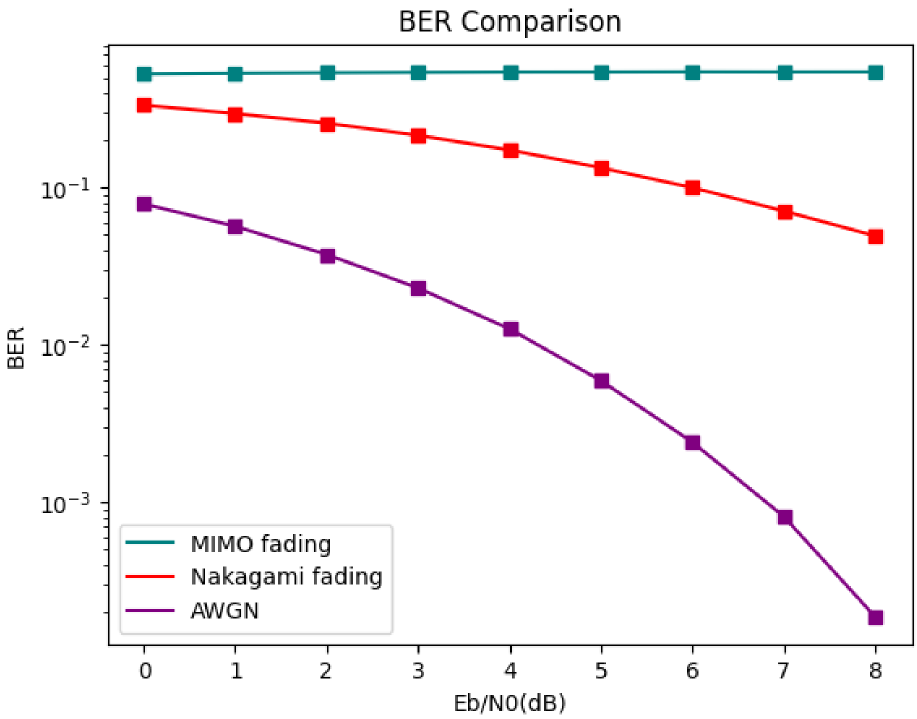

Figure 10: BER Comparison

4. Conclusion

We have proposed a system using convolutional layers at the encoder and decoder instead of the traditional wireless communication system. The model was built using CNNs and applied to channels like AWGN, Nakagami fading, and MIMO fading. The accuracy went to 99.99% for AWGN, 99.89% for Nakagami, and 92.78% for MIMO fading channels. The model worked best at low SNR of 1−6dbs. Loss has been comparatively low for the AWGN and Nakagami fading channels. The future system can be modified to apply image and video data to compare the results with the traditional system; more Communication operations can be done using CNNs.

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