Machine Learning Supported Design of Alternative Detection for Wireless Communication Systems

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Abstract- The problem of detecting signals in a Rayleigh fading channel is a constant challenge for conventional communication receivers. Traditional maximum likelihood (ML) detectors rely on precise mathematical models of the channel, which are affected by actual fading. This paper presents a new signal detector using a CNN which classifies the symbols directly from the image of the constellation diagram at the receiver. Both binary phase shift keying (BPSK) and quadrature phase shift keying (QPSK) modulations are tested over a Rayleigh fading channel and additive white Gaussian noise (AWGN) over an SNR range of 0 to 30 dB. The CNN classifier is given the following two inputs as follows: the received signal constellation diagram (RSCD) and the channel-equalized signal constellation diagram (CED). In this work, three image resolutions were considered: 30×30, 50×50 and 100×100 pixels. Input normalization impact on the bit error rate (BER) is also explored. For both BPSK and QPSK modulations, results indicate that CNN Scenarios II (50×50) and III (100×100) provide BER performance similar to that of the ML detector. Normalization decreases the dispersion of pixels in the constellation diagram and always enhances the classification rate. The results validate the feasibility of image-based CNN classification over a fading wireless channel for replacing the traditional ML detection.

Keywords—Blockchain, Bitcoin, Financial Analytics, e-crime, cryptocurrency

I. INTRODUCTION

Design and analysis of an end-to-end communication system, signal transmission, signal propagation, receiver noise, etc., is based on the development of mathematical models that describe most of its other components. The basis of an end-to-end wireless communication system is to send and receive a message signal in a way that is resistant to channel distortions, reliably recovered at the receive. In line with these goals. The transceiver is divided into subtasks: source coding, channel coding, modulation, demodulation, and equalization. The use of deep learning (DL) assisted systems in an end-to-end communication system was first proposed by Dorner et al. [1]. Recently, its use has become widespread in literature by utilizing different deep learning networks for different purposes. DL network techniques are convolutional neural networks (CNN), long short-term memory (LSTM), deep reinforcement learning (DRL), and auto-encoders (AE). Ye et al. proposed that all models of an end-to-end communication system were designed with

GANs [2]. Albawi et al. used CNN for modulation classification in communication systems. In this study, signals were detected at the receiver using a 3-layer CNN network that processed pictures [3]. The CNN network's error performance in signal estimating is comparable to that of traditional machine learning in signal detection. The classical detectors rely on mathematical models of channels. These models have been shown to decay in real fading. Most of the existing DL-based methods are tested on few types of modulation. This study attempts to overcome the above limitations.

In this study, DL-CNN is proposed, which is a new method for estimating the signal performed at the receiver. Unlike signal detection methods such as maximum likelihood (ML) detection used in conventional communication system receivers, an attempt is made to detect the signal from the constellation diagram of the signal arriving at the receiver. In such a system comprising BPSK and QPSK modulation on a Rayleigh fading channel, the input signal was estimated and demodulated using a receiver CNN classifier. The CNN was taught symbol by symbol, assuming that the receiver was aware of the channel. This paper's major contributions are: CNN based Detector using Constellation Diagram images. Evaluations in Rayleigh fading channel with AWGN noise. Performance comparison with ML detection for BPSK and QPSK.

The remainder of the paper is organized as follows. Section 2 reviews related work. Section 3 describes the system model and DL parameters. Section 4 presents the simulation results. Section 5 concludes the paper. In Section 4, simulation results are shown and discussed. In section 5, the results obtained are evaluated, the advantages that will contribute to the literature are explained, and future studies are included.

II. Related Work

Lu et al. investigated the accuracy of modulation classification under different fading channel models (Rayleigh, Rician, etc.) [5]. CNN has been used to estimate channels in orthogonal frequency division multiplexing (OFDM) systems. Channel estimation and signal estimation for OFDM were performed using LSTM networks [4]. Although the use of DL networks instead of mathematical models for signal estimation is not limited to OFDM, it has become an alternative in many other wireless communication systems.

Jiang (2020) suggests a new CNN-based AE communication system that can operate intelligently with arbitrary block length, support different output rates, and operate on Rayleigh fading channels with additive white Gaussian noise (AWGN). DL networks are also an alternative for large-scale multi-input/multi-output communication systems. DL has also been used for signal estimation in non-orthogonal multiple access (NOMA) techniques for fifth-generation (5G) communications systems [6] [7]. In NOMA systems, apart from signal estimation, DL networks have been used for power allocation, resource allocation, and increasing system throughput. Also visible light modulation, millimeter wave communications, index modulation, etc. The use of DL has become widespread in many current fields.

In a separate study, Ye et al. proposed a CNN-based system Ye et al. proposed a new CNN-based system that can work with an artificial intelligence system and support different output rates [8]. DL networks have also been adopted as an alternative to large-scale communications systems.

From the above studies, it can be seen that DL has the potential in wireless communication. Yet, the majority of them are based on OFDM or NOMA systems. There is limited research on constellation diagram images to detect Rayleigh fading channel under BPSK and QPSK modulation. This is a paper that is intended to address this gap

III. PROPOSED METHODOLOGY

In this study, a downlink communication system between a user (UE) and a base station (BS) is considered. Signal sent from BS:

Equation (1) $$y = \sqrt{PhX + N}$$

where h ~ CN(0, σ^2) and n ~ CN(0, N_0)

Equation (2) $$l_{eq} = \frac{L}{H}$$

Here, x is the modulated version of the UE's message signal (m). P is the total transmission power of the base station. The BS and UE are the Rayleigh fading coefficient with σ2 variance between, and n is the AWGN with N0/2 spectral density at the receiver. In order to reduce the channel effect on the signal coming to the receiver, channel equalization is applied.

When data is sent via a single symbol, L and l_{eq} are shown together, and an example model of the constellation diagram at the receiver is given in Figure 1. The circular drawing represents y, the square drawing represents l_{eq}.

In the signal diagram, L and l_{eq} were normalized with their own amplitudes and converted into an image format of a certain width and length. Thus; It is aimed to determine which bits are sent to the receiver from the signal coming to the receiver and the equalized signal. For this reason, the 8-bit grayscale image of the incoming signal and the signal constellation of the channel equalized signal are given as input to the CNN network.

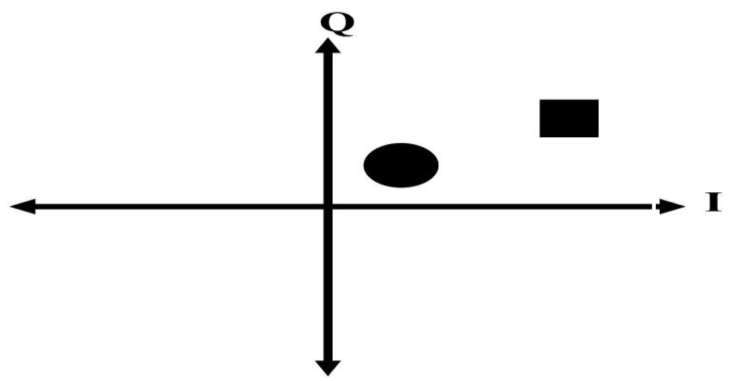


Figure 1. Signal Constellation of L and l_{eq}

For BPSK and QPSK modulation types, examples of CNN input data obtained according to the signal reaching the receiver when the signal to noise ratio (Signal-to-Noise Ratio) is 10dB as shown in Figure 2. Depending on the modulation type, CNN trains data over 2 classes (0,1) for BPSK modulation and 4 classes (0,1,2,3) for QPSK modulation. These class values are {0},{1} respectively in BPSK; In QPSK, {00}, {01}, {10} and {11} are representations of message signals. Class values (S) indicate that they represent the decimal equivalent of the message signals (m) sent from the transmitter in the end-to-end communication system. CNN makes signal prediction through 4 classes because there are 2 bits of data in the QPSK message signal, and there are 4 different symbol options, and for BPSK, it makes signal prediction through 2 classes because there is 1 bit of data in the message signal, and there are 2 separate symbol options. Since BPSK and QPSK training options for both two and four classes are not possible in the CNN network, two networks are required for two separate classifications. For this reason, two similar CNN networks were designed for BPSK and QPSK.

Proposed CNN Model

In order to estimate the sent signal, it is necessary to extract the features of the beacon constellation image. One of the DL networks that perform this process is CNN networks. CNN networks are based on the LeNet architecture developed by Yann LeCun in 1988. The CNN used in our study has a 3-layer structure, as shown in Figure 3. Each CNN layer consists of a convolution filter, batch normalization (BN), activation function and maximum pooling layers [9].

Convolution filters perform feature extraction, kernel operations, and convolution operations of areas created by selecting 3x3 regions in the beacon constellation diagram [10]. The convolution process here is the response of the images in these micro areas to their own stimulus.

Between the convolution layer and the activation function, BN is employed. BN is a deep neural network training method that unifies inputs into a single layer for every mini-batch. Additionally, it stabilizes the learning process and dramatically lowers the number of training epochs needed for deep network training. In this layer, the data acquired from the convolution is first subtracted from the group average (μ) for each training example. The resultant value is then divided by the group variance (Q^2). The outcome is scaled in accordance with the learnt γ and shifted by the learnt β parameter. Equations (3) and (4) illustrate the mathematical equations for BN processes.

Equation (3)

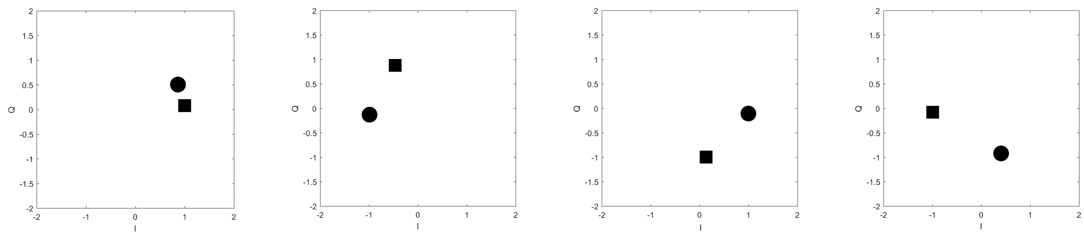
$$z = \frac{\mathrm{y-U}}{\sqrt{Q^2}}$$

Equation (4)

$$BN = \gamma\, z + \beta \qquad (4)$$

m={0} (S=0) m={0} (S=0)

a)



m={00} (S=0) m={01} (S=1) m={10} (S=2) m={11} (S=3)

Figure 2 shows that, in accordance with modulation type A, there are two classes (0, 1) for BPSK CNN input data and four classes (0, 1, 2, 3).

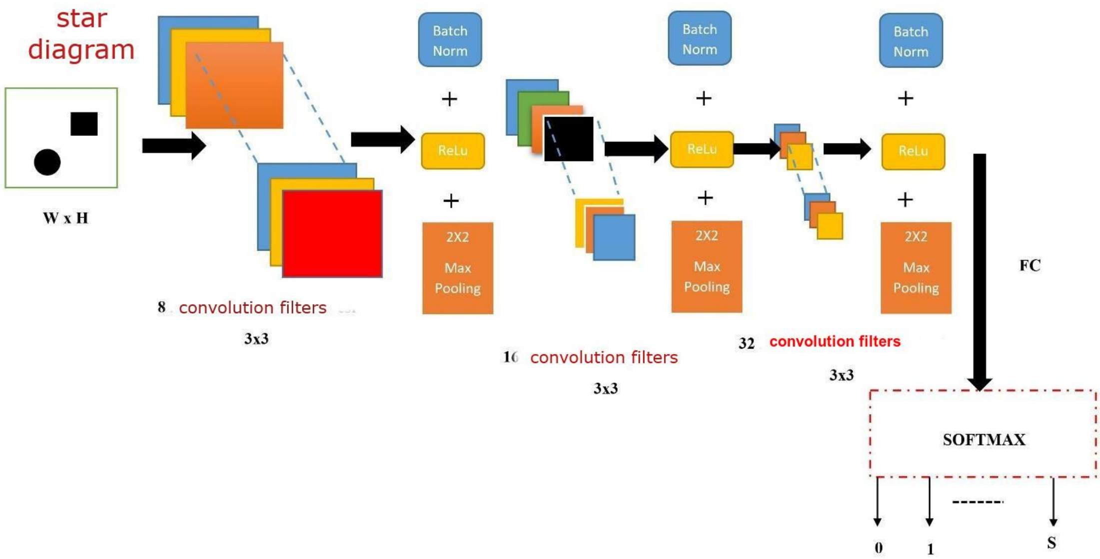


Figure 3. CNN System Model

In (3), L shows the convolution outputs.

After BN operations, the ReLu function was used as the activation function. ReLu function is as in Equation (5):

$$f(BN) = \begin{cases} 0 & ,BN < 0 \\ L'' & ,BN \geq 0 \end{cases} \quad (5)$$

As seen in Equation (5), BN is the output of BN operations.

Maximum pooling is an instance-based discretization process. The purpose of max pooling is to reduce the number of samples by sparing samples from an input (image, matrix, hidden layer output, etc.). In this way, assumptions can be made about the characteristics of subregions. In this investigation, the greatest value in the 2x2 rectangle areas obtained from the ReLu function's result is recorded into the new result matrix by the 2x2 maximum pooling function.

The first CNN layer has eight convolution filters, the second layer has sixteen, and the third layer has thirty-two. The reason for using a large number of convolution filters is that the square and circle pixels in the signal diagram image are located in a small area compared to the image, and therefore, it is difficult to extract features.

After the CNN layers, there is a fully connected layer (FC). The FC layer multiplies the result obtained after the feature acquisition process by a certain weight matrix and adds a final threshold (bias).

The last layer is the SoftMax layer, also known as the normalized exponential function. SoftMax normalizes the output of a network to a probability distribution over its output classes. For example, K is the mini-group size in a training sample, zi. The output of the SoftMax function is calculated as follows to show the outputs in the group [11]:

$$Q(\mathrm{zi}) = \frac{\mathrm{e}^{\mathrm{zi}}}{\sum_{j=1}^{k} \mathrm{e}^{\mathrm{zj}}}$$

According to the softmax function results, the class that gives the best probability result is the result found by the CNN network. As shown in Figure 3, these classes are the decimal equivalent of the message signs in the input.

Supervised learning is the method of instruction employed in this study. Supervised learning is a machine learning technique that identifies a function that translates an input to an output based on sample input-output pairs. Every example in supervised learning is a pair that consists of a desired output value and an input object (vector, matrix, etc.). This indicates that the input and output set sample is used to train the CNN network.

The trained network can classify the message signal as follows.

$$_{eq}m^{est} = classifier([y; l_{eq}]) \quad ,i = 1,2 \quad (7)$$

$$\frac{n(X_J - X_J^{EST})2}{2!} + \cdots$$

Here, the classifier is the function that classifies the incoming signal and the equalized signal of the incoming signal. Mest is the S classification found by CNN.

x being the modulated signal at the input; The loss function between the estimated modulated signal xest is expressed. The network is trained using categorical cross-entropy loss (HMSE):

$$E = \frac{\sum_{N}^{J=1} \left(X_J - X_J{}^{EST}\right)^2}{\mathrm{N}}$$

I. Simulation Results

According to BPSK and QPSK modulation, two different CNN networks are trained to classify the symbol sent at the receiver. The signal received at the receiver is the input parameter of the data set, and the constellation diagram image of the channel equalized signal of the received signal; The symbol at the input of the transmitter is taken as the output parameter. The dataset consists of 10^6 samples generated through Monte Carlo simulation. 80% of the data set was used for training, and 20% was used for testing (validation) the trained network. The Adam optimizer was used with a learning rate of 0.001. The mini-batch size indicates the number of data samples that the network will train at a time. Epochs are the number of iterations after which we have trained the entire data sample for the first time. The entire data sample can be trained in 1000 iterations. The training period was chosen as 20 epochs. Optimization is the updating algorithm of training parameters after each iteration. During the training phase, the training resulted in 99% accuracy. The validation accuracy reached 99% for BPSK and 97% for QPSK at SNR = 10 dB Simulations were conducted over an SNR range of 0 to 20 dB. An ML detector is implemented as a baseline. BER curves for both CNN and ML are compared under identical channel conditions.

This study has several limitations. The CNN models are trained and tested on simulated data only. Performance under hardware impairments or real channel measurements is not evaluated. The approach is limited to BPSK and QPSK modulations. Retraining is necessary for extension to higher order modulations. The larger the constellation, the more expensive the computations for larger data sets will be.

Table 1. Simulation Parameters

Program Used	MATLAB
Number of users	2 (1 BS 1 UE)
Communication Channel	Rayleigh + AWGN
Modulation	BPSK, QPSK
DL	CNN
Learning type	Supervised
Data Set Input Parameters	Signal diagram image of the signal received at the receiver and the Rayleigh channel
Dataset Output Parameters	Symbol at the Entrance
Dataset Training-Test Ratio	80% training, 20% testing.
Signal diagram image dimensions of the signal received at the receiver and the Rayleigh channel	30x30,50x50,100x100
Number of Epochs in Training	20

Number of Training Examples	106
Number of Iterations	20000
Mini group size	one thousand
Training Optimization Algorithm	SGDM
Training Accuracy	99%

Two distinct CNN networks are trained to categorize the symbol transmitted at the receiver based on BPSK and QPSK modulation. The symbol at the transmitter's input was taken as the output parameter; the signal received at the receiver was used as the data set's input parameters, and the constellation diagram image represented the channel-balanced form of the received signal. The dataset consists of 10^6 samples generated through Monte Carlo simulation. 80% of the data set was used for training, and 20% was used for testing (validation) the trained network. During training, a mini-batch size of 64 samples was used.. Epoch refers to the number of iterations in which an entire data sample is trained. Each epoch consists of [X] iterations based on the dataset size and batch size. Training was conducted for 20 epochs. Optimization is the updating algorithm of training parameters after each iteration. Simulations were also made with Rmsprop, Adadelta and Adam optimization algorithms, and similar error performances were obtained. For this reason, SGDM was preferred specifically for this study. In future studies, the effects of different optimization types on DL-supported wireless communication problems will be examined. Training during the training phase resulted in 99% accuracy. SGDM was used with a learning rate of 0.01 and momentum of 0.9

The training parameters given in Table 1 were chosen to minimize the possibility of end-to-end errors. Three different scenarios were determined according to the restriction of the signal diagram image used as CNN input to different sizes. CNN was trained according to these three different scenarios and used for symbol prediction. Scenario I selects the constellation diagram image dimensions as 30 pixels wide and 30 pixels high (30x30), Scenario II selects 50x50 dimensions, and Scenario III selects 100x100.

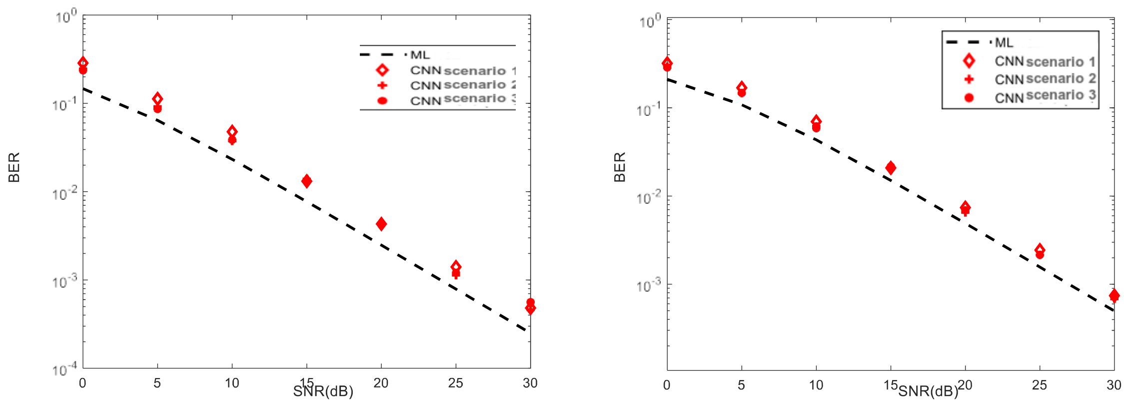
CNN networks identified the system's input symbols based on the three distinct situations that were previously discussed, using the un-normalized constellation diagram representations of the incoming signal and the balanced signal. Figure 4 compares the bit error rate (BER) from CNN scenarios with the BER results from traditional machine learning detectors.

Figure 4. a shows the BER results for BPSK, and Figure 4.b shows the BER results for QPSK. As shown in Figure 4, in the case of the un-normalized constellation diagram image, the error performances of CNN Scenarios II and III approach the standard ML detector. The error performance graph of CNN Scenario I is slightly lower than the others.

As another method, the input symbols of the system were detected with CNN networks from the normalized constellation diagram images of the incoming signal and the balanced signal, according to the three different scenarios explained above. In Figure 5, the BER performances obtained with CNN scenarios and the BER performances of classical ML detection are compared. In Figure 5. a, BPSK and QPSK results are shown in Figure 5.b. As shown in Figure 5, CNN

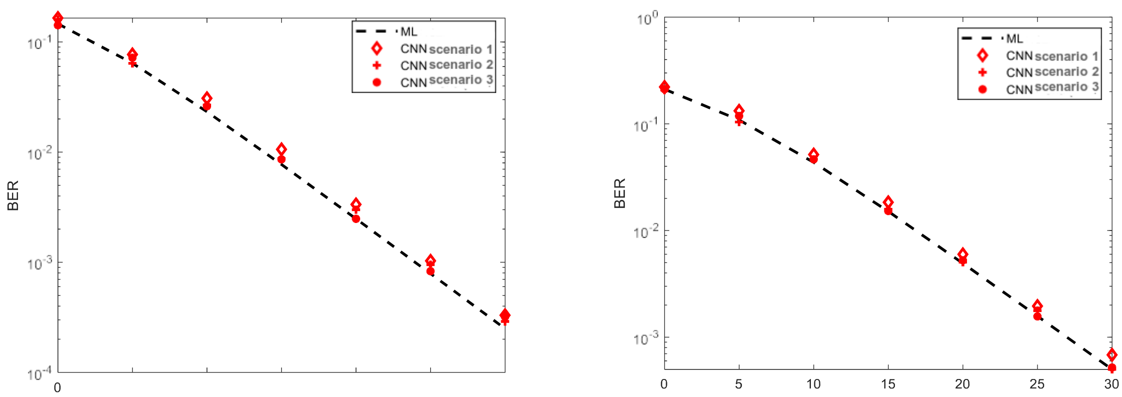
Scenarios II and III achieve BER performance comparable to the standard ML detector. The error performance graph of CNN Scenario I is slightly behind the others.

When Figures 4 and 5 are considered together, the necessity of normalization in the constellation diagram at the CNN input is clearly seen. Without normalization, BER performance was negatively affected because the scatter in the sign-star diagram image would be greater. By avoiding scattering, normalization brings the received signal and channel-equalized signal data in the picture data closer together, improving classification and prediction. Better picture resolution may be achieved by using bigger sections in the star diagram image. Additionally, as the resolution of the star diagram image increases, the ability of CNN classification also increases.



BPSK CNN Results Without Normalization QPSK CNN Results Without Normalization

Figure 4. CNN classifier BER performance
Without normalization, the pixel distribution in the constellation diagram is spread over a wider area. This reduces the CNN's ability to distinguish between symbol classes. The effect is more pronounced in Scenario I due to the low image resolution (30×30 pixels)



CNN Results with BPSK Normalization CNN Results with QPSK Normalization

Figure 5. CNN CNN classifier BER performance with normalization

II. Result and Discussion

In recent years, using DL instead of mathematical models for signal estimation in wireless communication systems has been considered as an alternative solution. In this study, the effect on error performance when a CNN is used in the receiver in the Rayleigh fading channel with BPSK or QPSK modulation was investigated. Since maximum likelihood (ML) detector, it was seen that DL could be an alternative to ML detector. It is emphasized in the study that the constellation diagram of the incoming signal and the channel equalized signal can be converted into an image format, and the input symbols can be estimated at the receiver with the help of a CNN.

In all the three scenarios, Scenario III (100×100) performs the best compared to Scenario I (30×30). The higher the image resolution the more fine spatial features of the constellation diagram are preserved. This directly enhances the class separability of the CNN. Normalization will also minimize inter-class overlap by restricting the signal distribution to a standard image region.

In the past, several studies have adopted DL-based approaches for signal detection and modulation classification for wireless channels. Albawi et al. [3] utilized a 3-layer CNN that processes images of signals for modulated signal classification that resulted in high classification accuracy in AWGN conditions. However, their scheme is not tested in Rayleigh fading channels. Lu et al., [5] analyzed the modulation classification accuracy for various fading models (such as Rayleigh and Rician channels) and showed that lower BER is achieved at higher SNR values. Their approach uses a statistical feature extraction approach instead of image classification. In Jiang [ref], an autoencoder was proposed for Rayleigh fading channels with AWGN with flexible support of block-lengths using CNN. However, for the typical BPSK and QPSK modulations, that system demands full “end-to-end” retraining without symbol-level detection evaluation. The LSTM-based method in [4] is designed for the channel estimation of OFDM system and is not easily adapted for single-carrier symbol detection.

The proposed method has two distinguishing features when compared to previous works. It does not involve any manual feature extraction, but directly takes the images of the normalized constellation diagram as CNN input. Second, compares the performance of BPSK / QPSK modulation transmitted on the Rayleigh fading channel with AWGN. In the BPSK modulation, the proposed CNN (Scenario III, 100×100) has almost the same BER performance as that of the ML detector, achieving lower BER at higher SNR values. In the case of QPSK, a comparably lower BER is obtained under Scenario III at the same SNR. These results are in line with and competitive to those of the BER performance of a similar DL-based classifiers [3][5] under similar channel conditions.

The constellation diagram on bit error performance are discussed. In future studies, the signal estimation error performances of CNN and other DL networks and systems, such as NOMA and index modulation, which are considered for 5G systems, will be examined

REFERENCES

[1] S. Dorner, S. Cammerer, J. Hoydis, and S. ten Brink, "Deep learning-based communication over the air," *IEEE Journal on Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 132–143, 2018, doi: **10.1109/JSTSP.2017.2784180**.
[2] H. Ye, L. Liang, G. Y. Li, and B.-H. Juang, "End-to-end wireless communication systems with conditional GANs as unknown channels," *IEEE Transactions on Wireless Communications*, vol. 19, no. 5, pp. 3133–3143, 2020, doi: **10.1109/TWC.2020.2970336**.
[3] M. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in *Proc. Int. Conf. Engineering and Technology (ICET)*, 2017, pp. 1–6, doi: **10.1109/ICEngTechnol.2017.8308186**.
[4] N. Farsad and A. Goldsmith, "Detection of data sequences in communication systems using neural networks," *IEEE Transactions on Signal Processing*, vol. 66, no. 21, pp. 5663–5678, 2018, doi: **10.1109/TSP.2018.2868322**.
[5] B. Luo, , Peng, Q., Cosman, P. C., & Milstein, L. B.,2019. A. Deep modulation recognition robustness of AWGN and Rician Fading Asilomar Conference on Signals, Systems, and Computers in Conference Record .2019.
[6] S. Peng, H. Jiang, H. Wang, H. Alwageed, and Y. D. Yao, "Modulation classification using convolutional neural network-based deep learning model," 2017.
[7] H. Hojatian, J. Nadal, J.-F. Frigon, and F. Leduc-Primeau, "Unveiling deep learning for massive MIMO hybrid beamforming," 2020.
[8] H. Ye, G. Y. Li, and B.-H. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Communications Letters*, vol. 7, no. 1, pp. 114–117, 2018, doi: **10.1109/LWC.2017.2757490**.
[9] Y. LeCun *et al.*, "Handwritten digit recognition with a back-propagation network," in *Advances in Neural Information Processing Systems*, 1989.
[10] Y. Xu, C. Yang, M. Hua, and W. Zhou, "NOMA vehicular communications: A deep deterministic policy gradient (DDPG)-based resource allocation scheme," *IEEE Access*, vol. 8, pp. 18797–18807, 2020, doi: **10.1109/ACCESS.2020.2968345**.
[11] L. Chen, M. Zhou, W. Su, M. Wu, J. She, and K. Hirota, "Softmax regression-based deep sparse autoencoder network for facial emotion recognition in human–robot interaction," *Information Sciences*, vol. 428, pp. 49–61, 2018, doi: **10.1016/j.ins.2017.10.044**.