Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 5584481, 9 pages
https://doi.org/10.1155/2022/5584481

Research Article

Combined Classifier-Demodulator Scheme Based on LSTM Architecture

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Received 22 February 2021; Revised 13 May 2022; Accepted 27 May 2022; Published 15 June 2022

Academic Editor: Dario Bruneo

When it comes to studies on smart receiver designs, using machine learning and deep learning techniques for the development of automatic modulation classifiers as well as demodulators which require little to no information about the transmitted signal or the channel state is an area of interest. Through this study, we have proposed a combined classifier-demodulator system that is entirely deep learning-based and one that is focused on higher-order quadrature amplitude modulation (QAM) schemes such as 64QAM and 256QAM that can be used in next-generation mobile technologies. The system was developed by training a bidirectional long-short-term memory (BiLSTM) and long-short-term memory (LSTM) network for the classifier and demodulator, respectively, using randomly generated data, demodulated using binary phase shift keying (BPSK), quadrature phase shift keying (QPSK), 16QAM, 64QAM, and 256QAM transmitted through a simulated additive white Gaussian noise (AWGN) channel of varying signal to noise ratio (SNR) levels. The classifier was then tested for its prediction accuracy while the demodulator models were tested against traditional mathematical models while calculating the effective capacity. The results showcased that the classifier worked extremely well for the QAM schemes across all SNR levels and less so with the PSK models. Considering the demodulator models' performance, all schemes except the 256QAM demodulator were able to reach a zero or near zero bit error rate (BER) level within minimum acceptable SNR ranges.

1. Introduction

Communications technologies of the future will work in extremely noisy and dynamic radio spectrum environments where, in a given situation, the exact status of the environment is unknown or hard to discern. In the of designing smart receivers, two areas that get widespread attention are automatic modulation classification and demodulation. Deep learning provides promising performance when in the above areas due to its ability to work with data that would otherwise require complex feature engineering and because they can be trained using large synthetically generated datasets which can be easily produced in the communications sphere [1].

1.1. Demodulation. Traditional demodulators are designed for theoretical additive white Gaussian noise (AWGN) channels. Both channel state information and channel noise distribution are required at the same time [2]. Since the channel model is not known at the receiver, designing an optimum demodulator for each channel model is challenging. Fang and Wu [3] state that the traditional method of demodulation uses an equalizer to equalize multipath effects and intersymbol interference before signal detection which increases the overall computational complexity and causes wastage of frequency resources. Furthermore, any demodulation type is highly challenged by the noise condition and fading effects caused in the path from the transmitter to the receiver.

Previous research conducted by Wang et al. [4] investigated deep learning-enabled signal demodulation methods including deep belief network (DBN), support vector machine (SVM), Adaptive Boosting (AdaBoost), and a combination of DBN-SVM. Apart from that, they introduced the first open dataset of real modulated signals instead of synthetic data. The information which is binary phase shift keying (BPSK) or M–quadrature amplitude modulation (M-QAM) modulated could be demodulated at the receiver by these models.

Fang and Wu [3] applied the existing deep learning methods of DBN and stacked autoencoder (SAE) for signal demodulation. Apart from that, they also introduced a novel deep learning method named twice training network (TTN) with a lower computational complexity compared to SAE and DBN methods. The models were proposed for binary phase shift keying (BPSK). Further showed that all the other methods except the maximum likelihood method can be used without channel equalization in a multipath channel.

Mohammad et al. [5] compare the performance of the deep convolutional neural network (DCNN) with other machine learning classifiers such as support vector machine, linear discriminant analysis (LDA), multilayer perception (MLP), and quadrature discriminant analysis (QDA). Demodulation was performed for a Rayleigh-faded wireless data signal.

Wu [6] combines the ability of convolutional neural network (CNN) to extract features and recurrent neural network's (RNN) ability to time series modeling. They simulated frequency shift keying (FSK), phase shift keying (PSK), quadrature amplitude modulation (QAM) demodulation over an additive white Gaussian noise (AWGN) and Raleigh fading channel.

Experimental results of Ma et al. [7] prove that AdaBoost short for Adaptive Boosting is the best model out of CNN, DBN, and AdaBoost models for visible light communication(VLC).

However, no research has been done on producing demodulators using an LSTM network. Hence, this is the first research that produced a demodulator using an LSTM network.

1.2. Modulation Classification. The current method for dealing with unknown modulation schemes at the receiver end is to use multiple demodulators in parallel which leads to a wastage of both power and hardware resources [8]. According to Jolly et al. [9], automatic modulation classification in the early days was done by creating hand-crafted features from raw temporal signals like statistical moment classifiers and square law classifiers. These were mostly based on likelihood and features and were limited to specific modulation schemes and signal to noise ratio levels.

The main motivation behind the development of modulation classifiers is to facilitate the accurate demodulation of signals without prior knowledge of their state at transmission [10]. Studies conducted by O'Shea and Hoydis [11] and Kulgod et al. [8] introduced modulation classifiers based on convolutional neural networks (CNNs). Furthermore, Kulgod et al. followed two approaches training over both positive and negative signal-to-noise ratios (SNRs) and training over positive SNRs only. Hence, they experimentally proved that the model trained for positive SNRs has higher peak accuracy. However, the other model performs better at low SNRs.

Tekbıyık et al. proposed an interesting approach where a multitier deep learning network for modulation classification with the first tier recognizes the general modulation family (Analog, FSK, QAM, etc.) and then passes on the data to the second tier to identify the specific scheme (BPSK, QPSK, 64QAM, etc.) [12].

Besides them, multiple other types of research have been done based on the topic [9, 13–15] and all of them reached an accuracy of around 80% alone with considerable complexity. However, neither of them tried an LSTM network for the purpose.

1.3. Motivation and Contributions. Adaptive modulation and coding allow for the selection of a modulation scheme that provides the highest throughput and spectral efficiency for a given channel state which includes selecting a higher order scheme when higher bits per symbol rate are required as well as reverting to a lower order scheme when a high level of noise is present [16]. Our research will focus on developing a system that can receive and demodulate signals transmitted using adaptive modulation with no channel state information or indication from the transmitting device.

Hence, the main contributions of our study are:

(1) Evaluation of an LSTM-based network architecture as an effective modulation classifier and demodulator. This will include higher-order 64QAM and 256QAM schemes

(2) Propose a combined classifier-demodulator model using the said LSTM networks

Throughout the remainder of this paper, we discuss the basic model of the classifier-demodulator system as well as the methodology we followed during synthetic data generation and the development and performance evaluation of the said system in Section 2, the results of the performance evaluation are reported in Section 3, and the conclusions reached based on said results are presented in Section 4.

2. System Model and Methodology

2.1. System Overview. An overview of the proposed classifier-demodulator system is as follows (Figure 1).

A summary of the operation of the above system is as follows. There are two trained deep learning-based components, i.e., the modulation classifier and the demodulator models for each considered modulation scheme, i.e., BPSK, quadrature phase shift keying (QPSK), 16QAM, 64QAM, and 256QAM in a demodulator library. The input data is modulated and transmitted via a simulated AWGN channel with a given SNR level. The classifier takes in the received signal as a sequence input and outputs its prediction. Based on the prediction, the correct demodulator is selected from the library and is used to demodulate the received signal. An example of the vector transposition that takes place between the classifier and the demodulator is as follows:

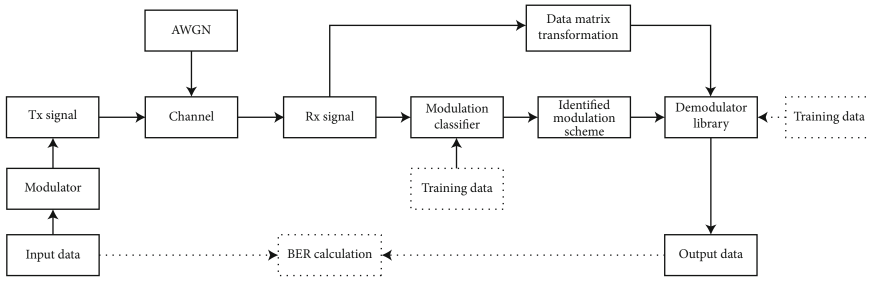

Figure 1: Classifier-demodulator system diagram.

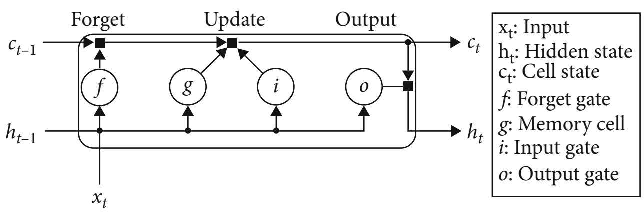

Figure 2: LSTM block diagram.

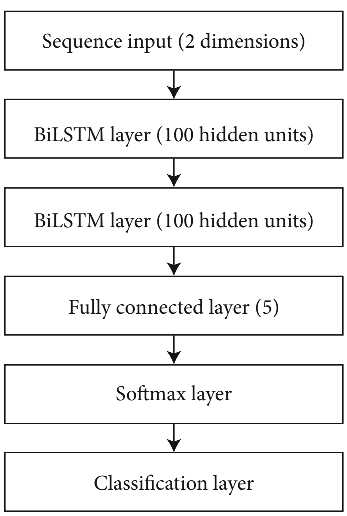

Figure 3: Modulation classifier layers.

e.g.,

$$\begin{array}{cccc} 43.9025 & 116.5765 & -47.0877 & \cdots, \\ 48.9890 & 31.9539 & -44.6110 & \cdots, \end{array} \tag{1}$$

$$\longrightarrow \begin{array}{cc} 43.9025 & 48.9890, \\ 116.5765 & 31.9539, \\ -47.0877 & -44.6110, \\ \vdots & \vdots \end{array} \tag{2}$$

The demodulator then outputs the demodulated data which, if done correctly, will be equivalent to the input data. In the performance evaluation stage, the input and output data bits will be used to perform a bit error rate (BER) calculation.

The above system was entirely developed and tested on MathWorks® MATLAB R2020b.

2.2. Data Representation. The modulated signals were represented numerically as a series of complex numbers for each symbol. The real part represented the in-phase (I) component of the signal expressed by:

$$A(t)\bullet\sin\,(2\pi f t)\bullet\cos\,[\varphi(t)]. \tag{3}$$

The imaginary part represented the quadrature component of the signal expressed by:

$$A(t)\bullet\sin\left(2\pi f t + \frac{\pi}{2}\right)\bullet\sin\,[\varphi(t)], \tag{4}$$

where f is the carrier frequency, $A(t)$ is the message signal, and $\varphi(t)$ is the carrier signal.

If we were to consider a 16QAM modulation as an example, the matrix transformation of the input data undergone during modulation is as follows:

e.g.,

$$\begin{array}{cccc} 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \end{array} \longrightarrow \begin{array}{c} -3.0000 + 1.0000\boldsymbol{i}, \\ -1.0000 - 3.0000\boldsymbol{i}, \\ -1.0000 + 3.0000\boldsymbol{i}, \\ \vdots \end{array} \tag{5}$$

2.3. Deep Learning Models: Long-Short-Term Memory (LSTM) Networks. LSTM networks (Figure 2) improve on recurrent neural networks (RNN) and were chosen for our purpose due to them being a popular and well-performing choice when it comes to sequential or time-series data [17]. Furthermore, bidirectional LSTM (BiLSTM) layers were utilized specifically in the classifier model for their ability to "learn from the complete time series at each time step" [18].

2.4. Optimization. For the optimization of hyperparameters, we performed an exhaustive search with the learning rate as well as tested two separate optimization algorithms: adaptive moment estimation (Adam) and stochastic gradient descent with momentum (SGDM), and the results are depicted in Figure 1.

2.5. Combined Model. The final network design for the classifier model consisted of dual BiLSTM layers of 100 units

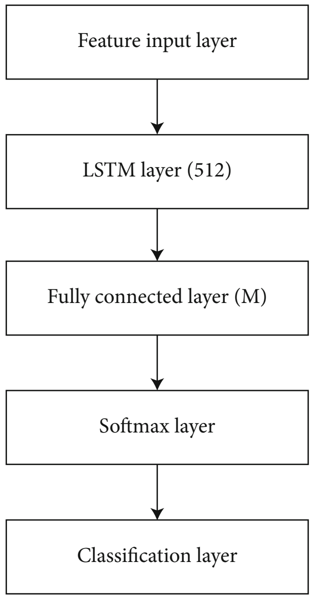

Figure 4: Demodulator layers.

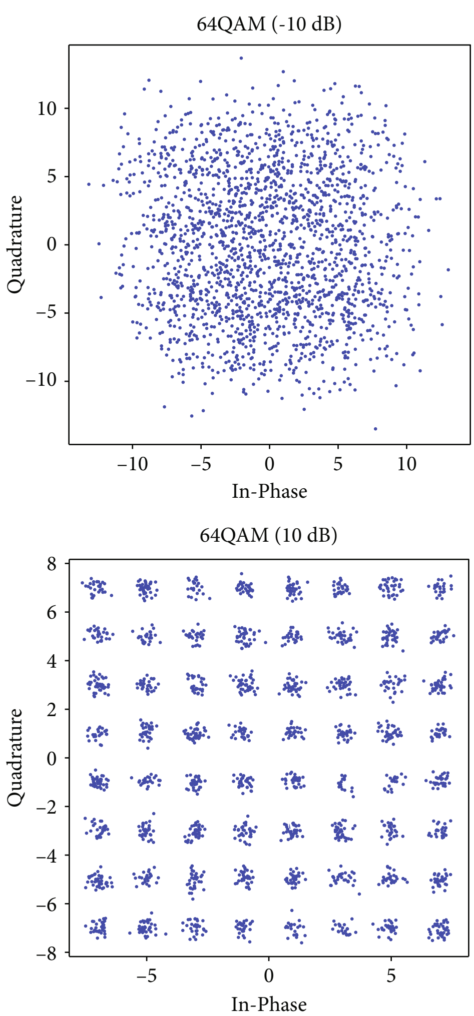

Figure 5: 64QAM signal received at various SNR levels through an AWGN channel.

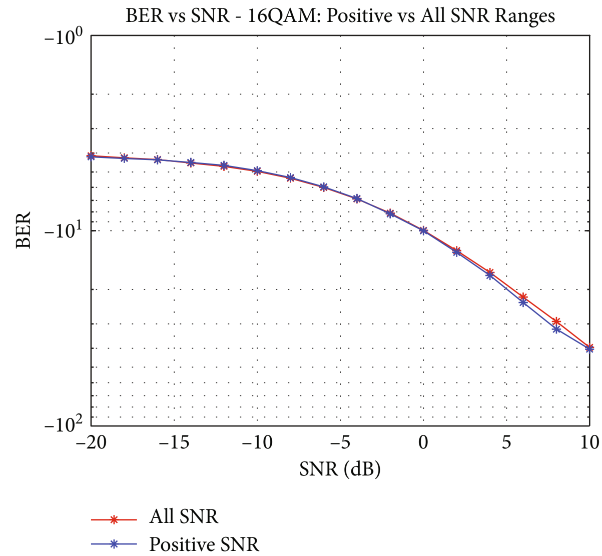

Figure 6: BER vs. SNR-16QAM: positive vs. all SNR ranges.

each, 5 neurons fully connected layer, a softmax function layer, and a classification layer as depicted in Figure 3.

The demodulator model (Figure 4) consists of two LSTM layers with the number of hidden units tweaked for performance (usu. 256 or 512), batch normalization, and rectified linear unit (ReLU) activation layer followed by a dropout layer with a 0.5 dropout probability to reduce overfitting, a fully connected layer with several neurons corresponding to the specific modulation scheme's M-ary number, and a softmax function layer.

2.6. Training. The classifier model was trained for a total of 100 epochs with a minibatch size of 8. The demodulator module was trained for a minibatch size of 8 and was manually monitored and stopped when training accuracy saturated.

2.7. Performance Evaluation

2.7.1. Classifier Evaluation. The ability of the classifier model to distinguish between the different modulation schemes was evaluated through the generated confusion matrices for both a dynamic range between -10 dB and 20 dB SNR as well as specific SNR values within that range.

2.7.2. Demodulator Evaluation. The demodulator model was evaluated by obtaining the BER vs. SNR plots for an SNR range between -20 dB and 20 dB and comparing its performance against the *pskdemod* and *qamdemod* MATLAB functions. The effective capacity was also calculated by recording the time elapsed for the demodulation of a given number of bits.

2.7.3. Combined System Evaluation. The performance of the combined classifier-demodulator model as an adaptive demodulator was analyzed statistically.

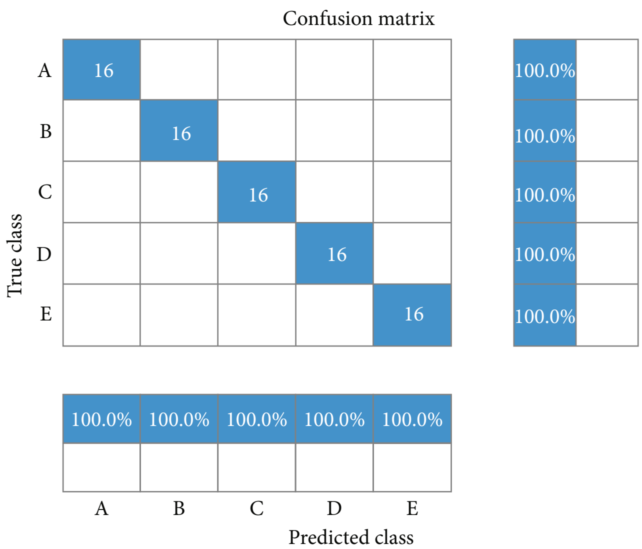

FIGURE 7: Classifier confusion matrix for SNR = −10 ~ 20 dB.

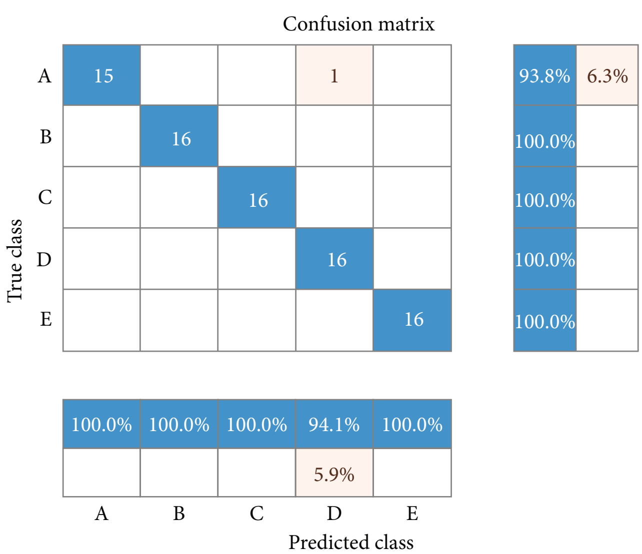

FIGURE 8: Classifier confusion matrix for SNR = −10 dB.

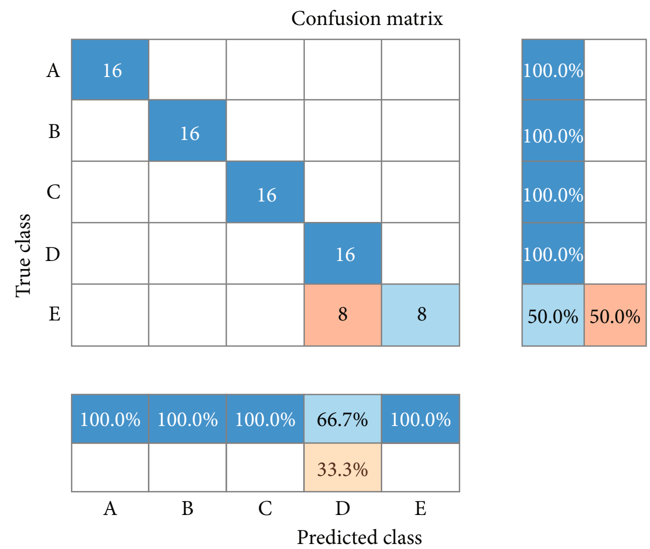

FIGURE 9: Classifier confusion matrix for SNR = 0 dB.

3. Results and Discussion

3.1. Channel Simulation. The generated I/Q signals were further distorted through the introduction of AWGN noise. An example of how AWGN at various SNRs affect the signal is represented by the constellation diagrams in Figure 5.

3.2. Training Results. The QAM models were also trained using datasets consisting of both negative and positive SNR samples as well as only positive SNR samples and compared. We observed that for the lower order 16QAM and 64QAM schemes, the positive SNR trained models performed better while in the higher-order 256QAM scheme, the model trained over the broader SNR range performed better as presented in Figure 6.

3.3. Modulation Classifier Performance. The classifier when trained for an SNR range from -10 dB to 20 dB showcased exceptional performance (Figure 7). In the test, it was able to correctly identify all data sequences, 16 sequences per modulation scheme. Note that, here, A =16QAM, B = 64QAM, C =256QAM, D = BPSK, and E = QPSK.

Next, we tested the same network for different SNR levels. A sample of results produced when tested is presented in Figures 8–10.

When observing the above matrices, we can see that the QAM modulation schemes show a good level of performance across all SNR levels. The same cannot be said, however, of the BPSK and QPSK schemes.

3.4. Statistical Evaluation Results of the Combined Model. Here, only the QAM models were considered to give a fairer representation of the system's practical promise due to the classifier's poor performance with PSK schemes. The mean BERs, sample standard deviations, and margins of error for SNR levels from 10 to 40 dB are reported (Table 1).

3.5. Hyperparameter Tuning Results. The results showcased that both optimizers with Adam and SGDM optimizers perform similarly for negative SNR levels. However, for positive SNR levels, Adam optimizer performed better. The performance by the Adam optimizer at 0.001 and 0.01 was similar. Hence, we chose the Adam optimizer with a learning rate of 0.01. The overall hyperparameter tuning results are presented in Figure 11.

3.6. Demodulator Model Performance. The BER vs. SNR plots obtained for the BPSK, QPSK, 16QAM, 64QAM, and 256QAM demodulator models are presented in Figures 12–16, respectively.

Considering the above, we can see that all demodulators except for 256QAM reach a 0 BER level at functional SNR levels [16].

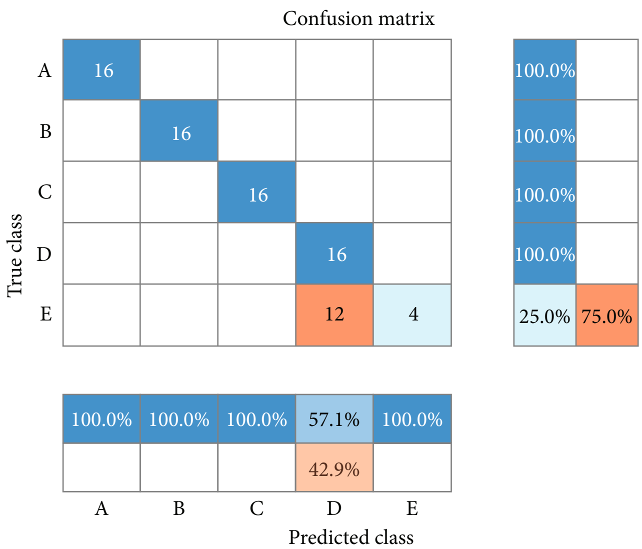

Figure 10: Classifier confusion matrix for SNR = 14 dB.

Table 1: Confidence levels.

SNR (dB)	x (BER)	s (BER)	$1.960s_{\bar{x}}$ (BER) 95% conf. level
10	0.0529	0.1475	±0.0289 (±54.61%)
15	0.0530	0.1499	±0.0294 (±55.46%)
25	0.0383	0.1290	±0.0253 (±65.93%)
40	0.0423	0.1338	±0.0262 (±61.86%)

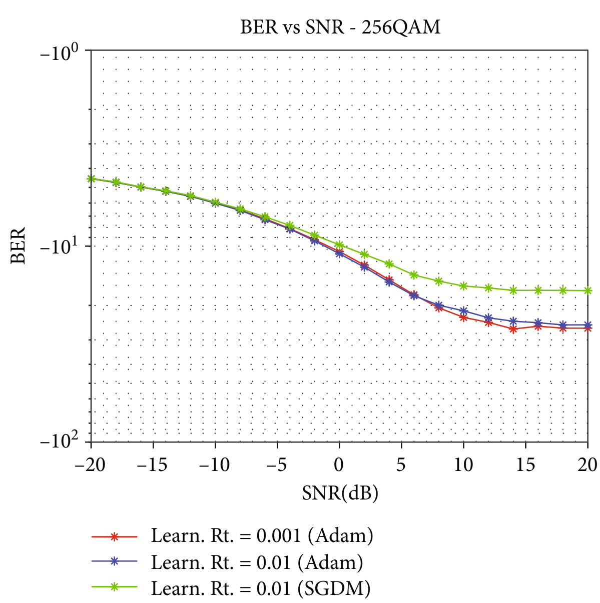

Figure 11: Hyperparameter optimization (e.g., 256 QAM model).

The effective capacities of the demodulator models in bits s^{-1} are given below in Table 2. The effective capacities were calculated by timing the total amount of time taken to demodulate the allocated number of bits. According to the effective capacities, for higher modulation schemes like

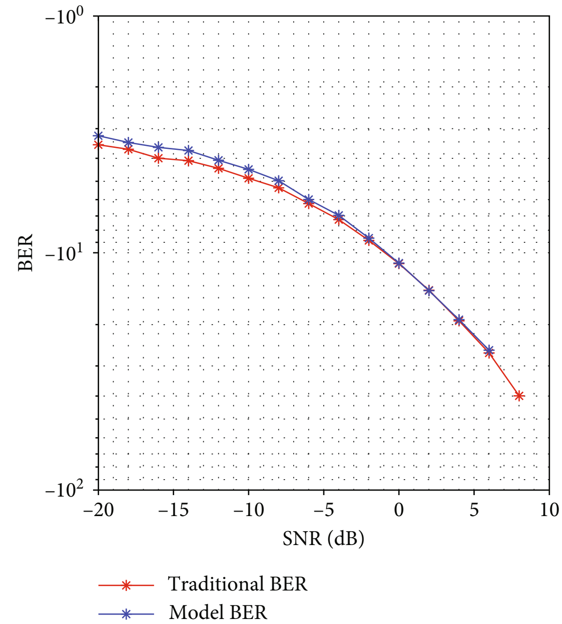

Figure 12: BPSK demodulator—BER vs. SNR. 0 BER level was reached at SNR = 8 dB.

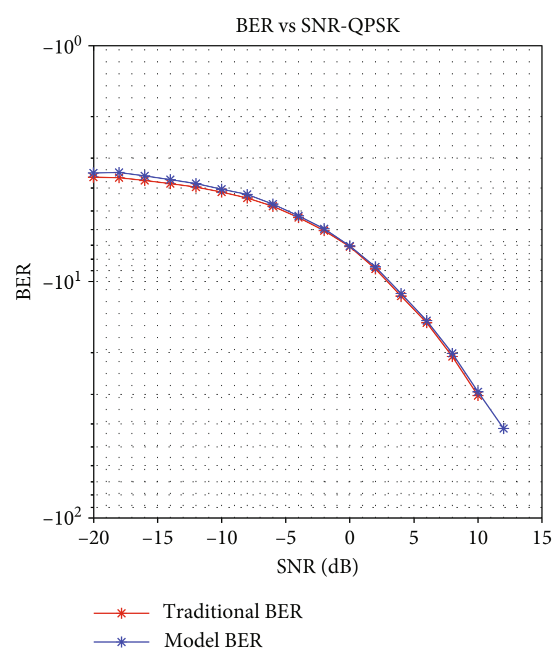

Figure 13: QPSK demodulator—BER vs. SNR. 0 BER level was reached at SNR = 14 dB.

256 QAM, the data throughput is at its highest. This value however is very much hardware constrained.

Hardware note: the above tests were carried out on a 2.4 Ghz single-core CPU.

When the demodulation accuracy is compared with the data throughput, a deviation from the general behavior is observed. The results showcased that even with higher modulation schemes like 64QAM which results in higher

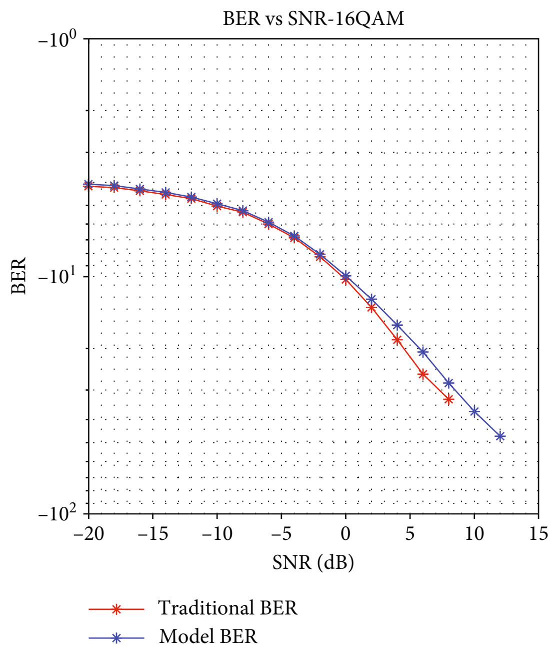

Figure 14: 16QAM demodulator—BER vs. SNR. 0 BER level was reached at SNR = 12 dB.

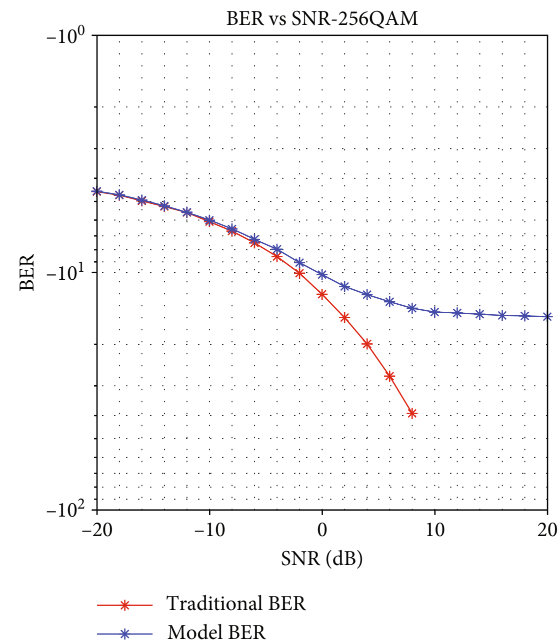

Figure 16: 256QAM demodulator—BER vs. SNR. 0 BER level was not reached within SNR = −20 ~ 20 dB.

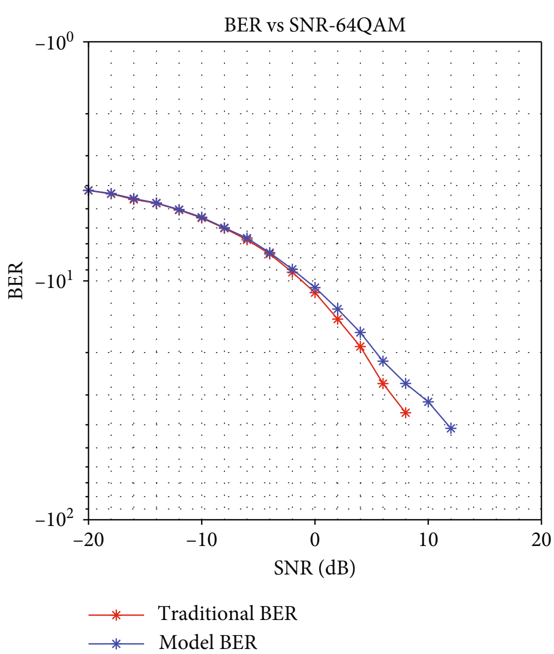

Figure 15: 64QAM demodulator—BER vs. SNR. 0 BER level was reached at SNR = 14 dB.

Table 2: Effective capacities of demodulator models.

Demodulator model	Effective capacity (bits s^{-1})
BPSK	1240
QPSK	3985
16QAM	3844
64QAM	3616
256QAM	4650

throughput and a better accuracy level compared to other lower modulation schemes.

3.7. Statistical Analysis of the Combined System. The performance of the combined system is an adaptive demodulation system in simulated AWGN channels at SNR = 10 dB, 15 dB, 25 dB, and 45 dB [5] The PSK schemes were omitted due to their poor performance with the modulation classifier. The results are given in Table 1.

According to the statistical analysis, it is observable that at higher SNRs, the BER decreases increasing the confidence level.

There are two main reasons for the errors we see in the statistical analysis:

(1) Errors are caused by the erroneous classification of QAM schemes as PSK

(2) The nonzero BER of the 256QAM demodulator model

Despite these errors, our testing shows that at acceptable SNR levels, the system can demodulate, adapting across the different QAM schemes, oftentimes with zero-bit errors with no coding whatsoever.

All demodulator models, at this stage of development, do not show a significant advantage over traditional mathematical models. However, we also observe that, except for

256QAM, all other models show zero or close to zero BER performance within minimum acceptable SNR levels for radio telecommunication usage(around > 15 dB) [16].

4. Conclusion

Through this study, we proposed a combined classifier-demodulator system based on LSTM network deep-learning models and tested the performance of its components across five different modulation schemes.

The modulation classifier showed exceptional performance when it comes to identifying the different QAM schemes across all SNR levels but less so with the PSK schemes. Furthermore, the proposed model showed higher accuracy at higher throughputs. Proving the fact that using deep learning-based methods for adaptive demodulation will provide a solution to the tradeoff between modulation accuracy and data throughput.

The tradeoff between the demodulation accuracy and the effective capacity is a universal truth when it comes to traditional methods of demodulation where deep learning is not involved. However, the results showcased that the proposed deep learning-based model showed a deviation from this behavior, which is a good sign. This proves that we can go with a deep learning-based models like this when it comes to demodulation of higher modulation schemes.

This, combined with the other pragmatic advantages of using a software-based deep learning model, such as the ability to function without prior knowledge of the transmission signal state and channel state, the flexibility to be easily modified and retrained, etc., seems to suggest that such models would have viable use cases in the future with some improvement, and this is the only model which does both modulation classification and demodulation using a deep learning algorithm allowing adaptive modulation.

5. Future Works and Limitations

When it comes to improvements, major areas include improving performance for 256QAM and possibly higher-order modulation schemes as well as improvements to the effective capacity of the models. While a low effective capacity may suggest that this model, at this stage, is not ready for general telecommunications, it may be used for signals intelligence-related applications. A comparison of the complexity of the existing deep learning based models cannot be done since the system is modeled only for an AWGN channel. Furthermore, it is worth exploring how channel coding can be integrated into the system to improve demodulation accuracy and reduce bit errors.

Future studies may include replicating the system using software-defined radio (SDR) modules as well as testing may be done for additional types of noise (e.g., exponential noise distributions) and propagation effects (e.g., Rayleigh fading), thus, allowing a genuine comparison between the existing deep learning-based models with the proposed model regarding the complexity.

Data Availability

All data generated or analyzed during this study are summarized in this published article. The original datasets are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no competing interests.

Supplementary Materials

Figure 1: LSTM Layer. Figure 2: sample training progress plot for modulation classifier. Figure 3: input data generation. Figure 4: statistical analysis of combined system performance. Figure 5: PSK and QAM modulated signals. Figure 6: BER vs. SNR-64QAM: positive vs. all SNR ranges. Figure 7: BER vs. SNR-256QAM: positive vs. all SNR ranges. Figure 8: 16QAM demodulator performance for various LSTM hidden unit nos. and layer nos. Figure 9: classifier confusion matrix for SNR = −8 dB. Figure 10: classifier confusion matrix for SNR = −2 dB. Figure 11: classifier confusion matrix for SNR = 2 dB. *(Supplementary Materials)*

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