UDC 621
DOI: 10.15587/1729-4061.2022.266801

CLASSIFYING WIRELESS SIGNAL MODULATION SORTING USING CONVOLUTIONAL NEURAL NETWORK

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Deep learning has recently been used for this issue with superior results in automatic modulation classification. Previous studies state that it is challenging to categorize a variety of modulation formats using traditional approaches; however, modulation classification is a crucial component of non-cooperative communication in wireless communication. The deep learning network was applied to solve the issue and get decent outcomes. This work uses a deep learning convolutional neural network (DLCNN) to classify three analog and eight digital modulation techniques by generating channel-impaired and synthetic waveforms as training data. The obtained DLCNN is tested by over-the-air indicators and a Software Define Radio(SDR) platform. The trained DLCNN estimates the modulation kind of each frame by taking 1024 samples of channel-impaired signals. The method includes generating several frames of 4-arry pulse amplitude modulation (PAM4) that are impaired with sampling time drift, Additive white Gaussian noise (AWGN), center frequency, and Rician multipath fading. The DLCNN predicts real inputs when receiving a signal with complex samples of baseband. Before updating the network coefficients and on all iterations, the data store transforms data from files and records it. This network takes about 50 minutes to train using in-memory data and 110 minutes to train using disk data. The evaluation of the trained DLCNN is carried out by obtaining the classification accuracy for the test frames. The obtained outcome demonstrates that the developed network can achieve an accuracy of about 94.3 % in roughly 12 epochs for such types of waveforms, which elapsed about 26 minutes for training. This will increase the efficiency of spectrum usage and detect the modulation type of the wireless communication receivers

Keywords: wireless communications, digital modulation, deep learning convolutional neural network classifiers

Received date 02.09.2022
Accepted date 04.11.2022
Published date 30.12.2022

How to Cite: *Hamza, E., Aziez, S., Hummadi, F., Sabry, A. (2022). Classifying wireless signal modulation sorting using convolutional neural network. Eastern-European Journal of Enterprise Technologies, 6 (9 (120)), 70–79. doi: https://doi.org/10.15587/1729-4061.2022.266801*

1. Introduction

Automatic modulation categorization (AMC) is a tool for primary signal processing techniques of the wireless physical layers that are used to increase the efficiency of spectrum usage and intend to blindly detect the modulation kind for the received signal of the wireless communication receivers. Numerous contemporary AMC methods utilizing deep networks have been proposed to address the current limitations of conventional approaches, which are motivated by deep learning convolutional neural network (DLCNN) high-influence achievements in several informatics fields, including radio signal processing for communications. In order to recognize modulation patterns, DLCNN can efficiently learn the fundamental properties of radio signals. This enhances the modulation classification performance even when there are channel defects [1]. In order to determine the kind of wireless signal modulation and recover the signal by demodulation, automatic modulation classification is crucial in many fields [2].

It is challenging to categorize a variety of modulation formats using traditional approaches; however, modulation classification is a crucial component of non-cooperative communication in wireless communication. The deep learning network was applied to solve the issue and get decent outcomes. The input data length for the (DLCNN) is fixed [3–5]. The network is unable to use the input signal data to increase classification accuracy since the signal length varies during communication [6]. Wireless communications can use automatic modulation categorization in a wide variety of situations. Deep learning has recently been used for this issue with superior results. DLCNN-based modulation categorization typically uses fixed-size inputs. The actual radio signal burst's length can vary, though.

In resident communications such as cognitive radios and military signal reconnaissance, automatic modulation classification (AMC) is a crucial technique. The majority of previous studies concentrated on the AMC in additional white Gaussian noise channels; however, it is more feasible and difficult to implement the AMC in time-varying wireless channels [7].

Wireless networks in the 5G and outside will be more heterogeneous and dynamic, necessitating the use of multistrand waveforms. The identification of a specific modulation type that the transmitter employs at the specified time to correctly decode the data is one of the biggest obstacles in such a dynamic network, especially in non-cooperative instances [8].

Significant interest is shown in automatic modulation classification in the context of both present and future wireless communication systems. Deep learning has become a potent method for modulation classification because it enables concomitant learning of discriminative characteristics and the categorization of signals. However, optimizing DLCNN architectures for modulation classification is a labor-intensive, manual procedure that needs extensive domain expertise [9]. Therefore, wireless communications are essential to apply the automatic modulation classification in a wide variety of conditions, and using DLCNN has recently been used for this issue with superior results.

2. Literature review and problem statements

The study [1] provided a fundamental concept of a variety of architectures, such as DLCNN, long short-term recall, recurrent neural networks, and neural networks as an essential environment. This study then discussed the use of Deep Learning (DL) of adaptive modulation and coding (AMC) in wireless communications. Although the study investigated advanced designs and several sophisticated structures of DLCNN in various data kinds of constellation images, spectrum photos, and sequential radio signals to deal with a variety of channel impairments, it provides a survey and was limited to what has been done before. The paper [10] also reviews a variety of DLCNN models and algorithms for the classification and modulation recognition of wireless communication patterns. However, it didn't discuss the recognition between the analog and the digital modulation kinds such as Single sideband amplitude modulation (SSB-AM), Double sideband amplitude modulation (DSB-AM), Broadcast FM (B-FM), Continuous phase frequency shift keying (CPFSK), Gaussian frequency shift keying (GFSK), 4-array pulse amplitude modulation (PAM4), 64-array quadrature amplitude modulation (64-QAM), 16-array quadrature amplitude modulation (16-QAM), 8-array phase shift keying (8-PSK), Quadrature phase shift keying (QPSK), and the Binary phase shift keying (BPSK).

The paper [2] contributed to exploring the appropriate design of the DLCNN technique in the area of communication signals recognitions. Although the study adopted the de-noising auto-encoder to provide the ability to resist finite perturbations of the input and pre-process the received data, it fails to cover the analog and digital modulations. The research [6] proposed a revolutionary DLCNN technique that makes use of a multi-stream topology. The proposed shorter network structure makes it easier to compare and recognize some digital modulation signals and avoid over-fitting issues. However, only a limited number of communication signals have been recognized. The study [11] offered a multi-stream architecture to enrich the types of signal features obtained and increase the network width, but this study also didn't compare the analog and digital modulation types. A wide expansion for signal recognition has been done by the paper [12], where full use of the complete signal burst was used to get better classification accuracies. However, the results obtained showed only three types of recognized communication signals.

The article [7] investigated a time-varying AMC guide using the DLCNN technique to get high classification accuracies. Its experimental outcome showed that the presented AMC system achieved superior classification precision in both fast and slow fading, but it was with very complicated AMC architectures.

All this allows to assert that it is expedient to conduct a study on the use of a deep learning convolutional neural network (DLCNN) to classify analog and eight digital modulation signals with generated waveforms as training data. Then, the obtained DLCNN network is tested by a platform/hardware such as over-the-air signals and software-defined radio (SDR).

3. The aim and objectives of research

The aim of research is to classify wireless signal modulations by sorting them according to the type using deep learning convolutional neural network DLCNN. This will make it possible to categorize various modulation schemes as modulation classification is a crucial component of non-cooperative communication in wireless communication.

To achieve this aim, the following objectives are accomplished:

– to develop a DLCNN for classifying three analog and eight digital modulation techniques;

– to generate channel-impaired and synthetic waveforms as training data;

– to train and test the developed DLCNN.

4. Materials and methods

4. 1. Object and research hypothesis

This work develops a deep learning convolutional neural network (DLCNN) architecture to classify three analog and eight digital wireless modulation techniques by generating channel-impaired and synthetic waveforms as training data. The categorized modulation types include BPSK, QPSK, 8PSK, 16QAM, 64QAM, PAM4, GFSK, CPFSK, B-FM, DSB-AM, and SSB-AM. The obtained DLCNN is tested by over-the-air signals and software-defined radio (SDR) platform using MATLAB environment functions. The assumptions made in the work are described in section 4. 2, while the simplifications adopted are demonstrated in the following subsections.

4. 2. Using deep learning to predict modulation type

This work includes recognizing the analog and digital modulation kinds as listed in Table 1.

This stage includes performing the following steps:

1. Loading a pre-trained network.

2. Categorization of modulation types (["BPSK", "QPSK", "8PSK", "16QAM", "64QAM", "PAM4", "GFSK", "CPFSK", "B-FM", "DSB-AM", "SSB-AM"]).

3. Loading a trained network called "*trained-Modulation-Classification-Network*".

4. The trained DLCNN gets channel-impaired 1024 samples to predict the type of modulation for every frame.

5. Creating some frames of PAM4 to be impaired with Additive white Gaussian noise (AWGN), sampling time drift, center frequency, and Rician multipath fading.

6. Using the following MATLAB functions to create synthetic signals for testing the DLCNN.

7. Using the DLCNN to estimate the frames modulation types.

Table 1

List of the recognized analog and digital modulation types

No.	Discretion	Symbol
1	Single sideband amplitude modulation	(SSB-AM)
2	Double sideband amplitude modulation	(DSB-AM)
3	Broadcast FM	(B-FM)
4	Continuous phase frequency shift keying	(CPFSK)
5	Gaussian frequency shift keying	(GFSK)
6	4-array pulse amplitude modulation	(PAM4)
7	64-array quadrature amplitude modulation	(64-QAM)
8	16-array quadrature amplitude modulation	(16-QAM)
9	8-array phase shift keying	(8-PSK)
10	Quadrature phase shift keying	(QPSK)
11	Binary phase shift keying	(BPSK)

The algorithm for performing this step can be represented by the flowchart shown in Fig. 1.

Let's start by training the convolutional neural network (CNN) with labeled (known) data and generating synthetic data for training. Next, let's define, train, and test the network to classify the modulation. Finally, by using the platforms of software-defined radio (SDR), let's examine the CNN performance with over-the-air signals.

4. 3. Waveform generation for training

The proposed work generates about 10,000 frames for every modulation kind, of which 10 % is used for testing, 10 % is used for validation, and the rest 80 % is used for training. The validation and training frames are used throughout the training phase of the network. The ultimate accuracy of classification type is acquired via the testing frames. Every frame is with a sample rate of 200 kHz and is 1024 samples long. For digitally modulated types, a symbol is represented by eight samples. Instead of considering numerous consecutive frames, the network bases each judgment on a single frame. Let's assume that the middle frequencies for the digital and analog modulation kinds are 902 MHz and 100 MHz, correspondingly. Fig. 2 shows the flowchart of the algorithm assumptions.

The inaccuracy of transmitters' and receivers' internal clock sources results in clock offset. The sample rate of the digital-to-analog converter and the middle frequency, which are utilized to down-convert the signal to the baseband, deviate from the optimum values due to clock offset ($\Delta clock$). The clock offset factor C for the channel is given by $C=1+\Delta clock/10^6$. Each channel creates an arbitrary Δclock of homogeneous distribution domain from the range $[-\max\Delta clock; \max\Delta clock]$.

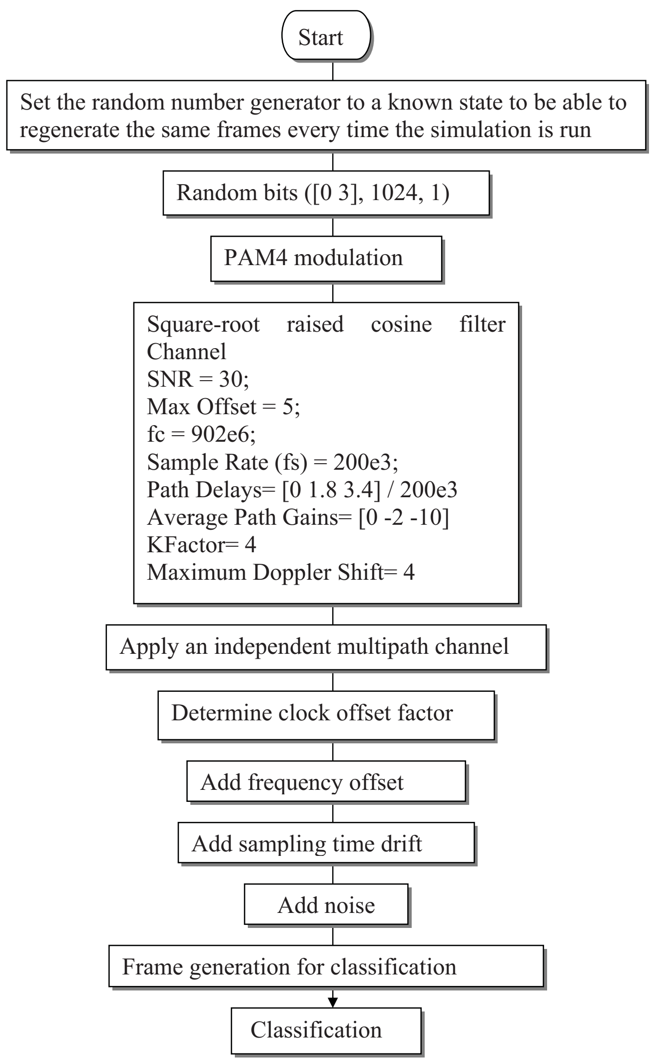


Fig. 1. Using deep learning to predict modulation type

For every modulation type, let's create a loop that produces channel-impaired frames and stores them in MAT files with the relevant labels. It is possible to avoid having to generate the data each time let's execute the function by storing the data in files. The data can be distributed more successfully as well. Therefore, the flowchart showing the waveform generation for training is shown in Fig. 3.

To get rid of transients and guarantee starting frames at an arbitrary location concerning the symbol limitations, let's take an arbitrary number of samples out of the beginning of each frame.

No. of Frames per Modulation Type = 10000;
Percent Training Samples = 80;
Percent Validation Samples = 10;
Percent Test Samples = 10;
Samples per symbol = 8;
Samples per frame = 1024;
Symbols per Frame = 1024 / 8;
Sample rate = 200e3;
Center frequencies = [902e6 100e6];

↓

Create Channel Impairments
Pass each frame through a channel with

- AWGN with an SNR of 30 dB.
- Rician multipath fading.

The delay profile is of [0 1.8 3.4] samples
The corresponding average path gains of [0 -2 -10] dB.
The K-factor is 4,
The maximum Doppler shift is 4 Hz, which corresponds to 902 MHz walking speed.

- Clock offset, resulting in sampling time drift and center frequency offset

Fig. 2. The flowchart of the algorithm assumptions

To be able to reproduce the same frames each time the simulation is run, set the random number generator to an identified state.

Check if data files exist

Analog modulation types use a center frequency of 100 MHz
Digital modulation types use a center frequency of 902 MHz

Generate random data and Modulate

Pass through independent channels

Remove transients from the beginning, trim to size, and normalize

Save data file

Plot the amplitude of the real and imaginary parts of the example frames against the sample number

Plot the spectrogram of the example frame

Create a Data store

Transform Complex Signals to real valued 4-D arrays.

Split into Training, Validation, and Test

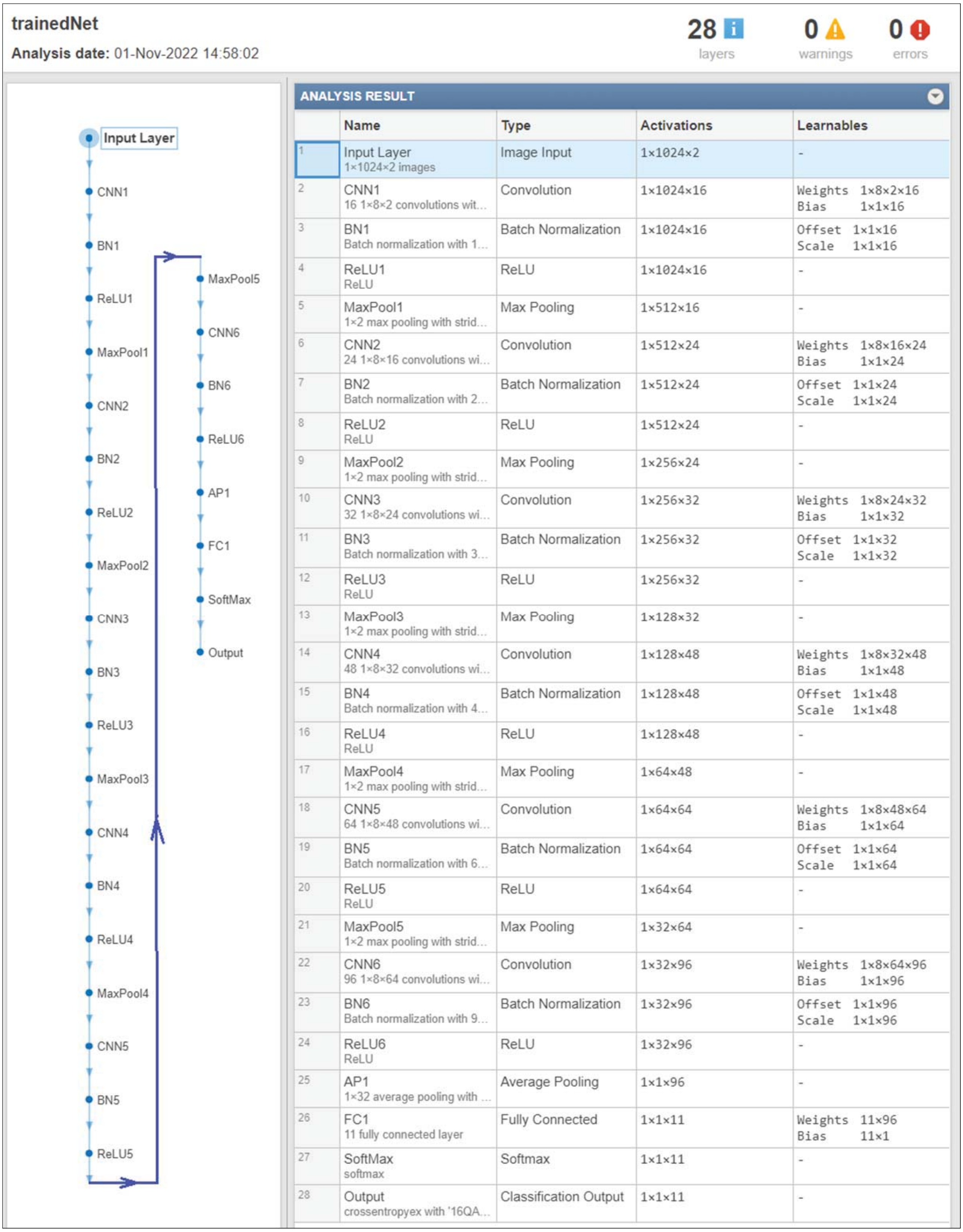
↓

Import Data into Memory

Fig. 3. Flowchart showing the training waveform creation

4. 4. Training the Deep Learning Network

This work employs a DLCNN with one fully connected layer and six convolution layers. Every convolution layer includes a max pooling layer, activation layer (rectified linear unit (ReLU)), and batch normalization layer except the final convolution level, where an average pooling level is used in place of the maximum layer. There is softmax activation in the output layer. The screenshot for the details of the developed network layers is shown in Fig. 4.



	Name	Type	Activations	Learnables
1	Input Layer 1×1024×2 images	Image Input	1×1024×2	-
2	CNN1 16 1×8×2 convolutions wit...	Convolution	1×1024×16	Weights 1×8×2×16 Bias 1×1×16
3	BN1 Batch normalization with 1...	Batch Normalization	1×1024×16	Offset 1×1×16 Scale 1×1×16
4	ReLU1 ReLU	ReLU	1×1024×16	-
5	MaxPool1 1×2 max pooling with strid...	Max Pooling	1×512×16	-
6	CNN2 24 1×8×16 convolutions wi...	Convolution	1×512×24	Weights 1×8×16×24 Bias 1×1×24
7	BN2 Batch normalization with 2...	Batch Normalization	1×512×24	Offset 1×1×24 Scale 1×1×24
8	ReLU2 ReLU	ReLU	1×512×24	-
9	MaxPool2 1×2 max pooling with strid...	Max Pooling	1×256×24	-
10	CNN3 32 1×8×24 convolutions wi...	Convolution	1×256×32	Weights 1×8×24×32 Bias 1×1×32
11	BN3 Batch normalization with 3...	Batch Normalization	1×256×32	Offset 1×1×32 Scale 1×1×32
12	ReLU3 ReLU	ReLU	1×256×32	-
13	MaxPool3 1×2 max pooling with strid...	Max Pooling	1×128×32	-
14	CNN4 48 1×8×32 convolutions wi...	Convolution	1×128×48	Weights 1×8×32×48 Bias 1×1×48
15	BN4 Batch normalization with 4...	Batch Normalization	1×128×48	Offset 1×1×48 Scale 1×1×48
16	ReLU4 ReLU	ReLU	1×128×48	-
17	MaxPool4 1×2 max pooling with strid...	Max Pooling	1×64×48	-
18	CNN5 64 1×8×48 convolutions wi...	Convolution	1×64×64	Weights 1×8×48×64 Bias 1×1×64
19	BN5 Batch normalization with 6...	Batch Normalization	1×64×64	Offset 1×1×64 Scale 1×1×64
20	ReLU5 ReLU	ReLU	1×64×64	-
21	MaxPool5 1×2 max pooling with strid...	Max Pooling	1×32×64	-
22	CNN6 96 1×8×64 convolutions wi...	Convolution	1×32×96	Weights 1×8×64×96 Bias 1×1×96
23	BN6 Batch normalization with 9...	Batch Normalization	1×32×96	Offset 1×1×96 Scale 1×1×96
24	ReLU6 ReLU	ReLU	1×32×96	-
25	AP1 1×32 average pooling with ...	Average Pooling	1×1×96	-
26	FC1 11 fully connected layer	Fully Connected	1×1×11	Weights 11×96 Bias 11×1
27	SoftMax softmax	Softmax	1×1×11	-
28	Output crossentropyex with '16QA...	Classification Output	1×1×11	-

Fig. 4. Screenshot for the details of the developed network layers

The training configuration is as follows:

1. Every nine epochs, the learning rate is decreased by a factor of 10.
2. Setting the initial learning rate to $2x10^{-2}$.
3. Setting the maximum number of epochs to 12.
4. Using an SGDM solver with a mini-batch size of 256.
5. Plotting the training progress.

5. Results of the proposed classifying wireless signal modulations

5. 1. Using deep learning network to predict modulation type

The probability of every frame containing the anticipated modulation kind is represented by the score shown in Fig. 5.

The network classifier predicts the analog decisions and successfully identifies the frames as PAM4 [7×1] categorical. A score vector of every frame can be represented by the classifier.

5. 2. Waveform generation for training

The sample numbers against the magnitude of the imaginary and real regions for the adopted frames are shown in Fig. 6, while the plotting of the spectrograms for the adopted frames is shown in Fig. 7.

All these Fig. 6, 7 represent the signal waveforms generated for training the network.

5. 3. Training the deep learning network

The training process has been performed over a Titan XpNVIDIA® GPU, which elapses about 54 minutes for training. The network converges to more than 95 % accuracy in roughly 12 epochs, as seen by the training progress graphic as shown in Fig. 8.

To obtain the classification accuracy for the test frames, a confusion matrix is prepared as shown in Fig. 9.

The obtained confusion matrix indicates that for this collection of waveforms, the network achieves an accuracy of roughly 94.5455 %.

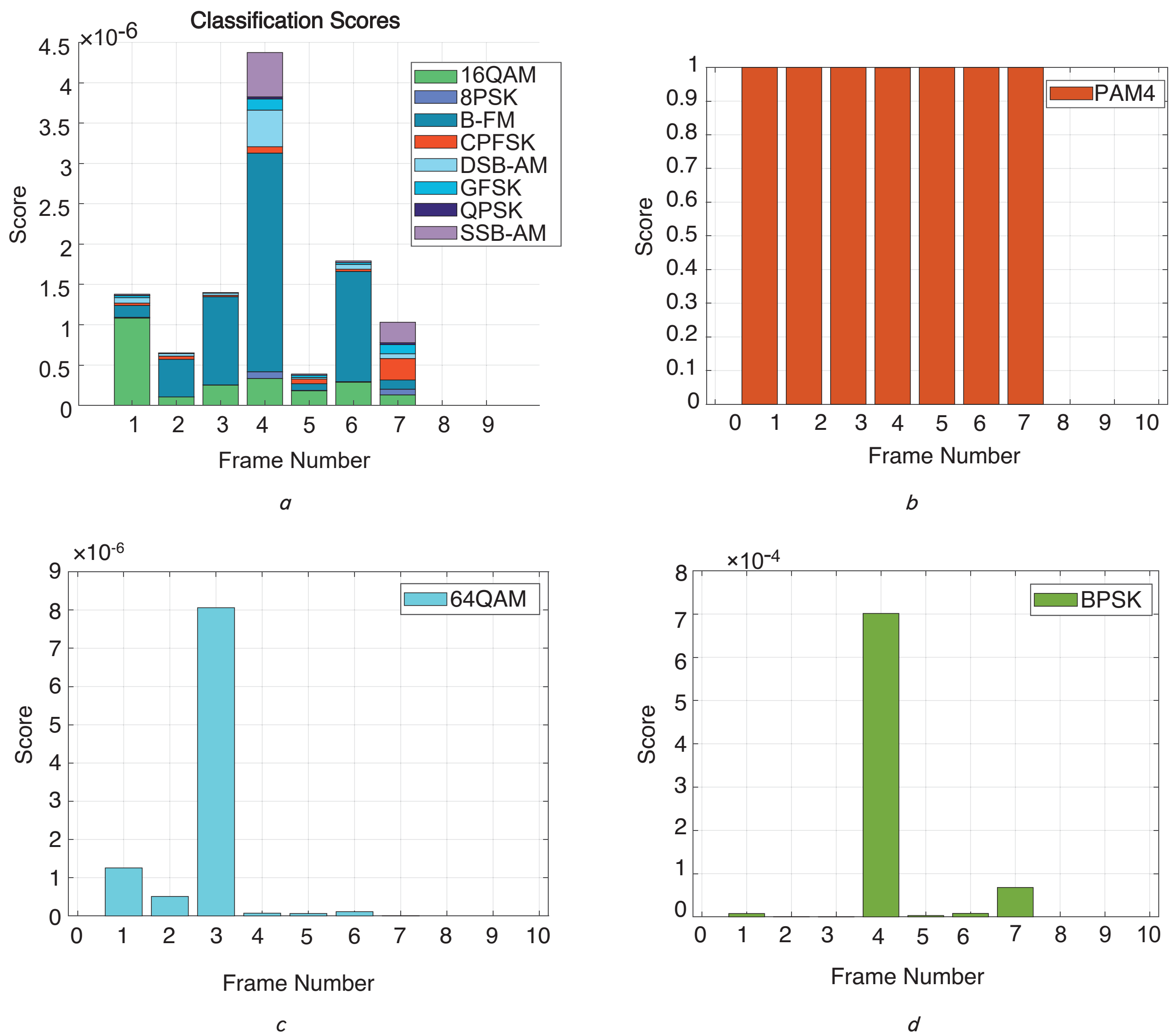


Fig. 5. The probability score of every frame contains the anticipated modulation kind: *a* – [QPSK, 8PSK, 16QAM, GFSK, CPFSK, B-FM, DSB-AM, SSB-AM]; *b* – PAM4; *c* – 64QAM, *d* – BPSK

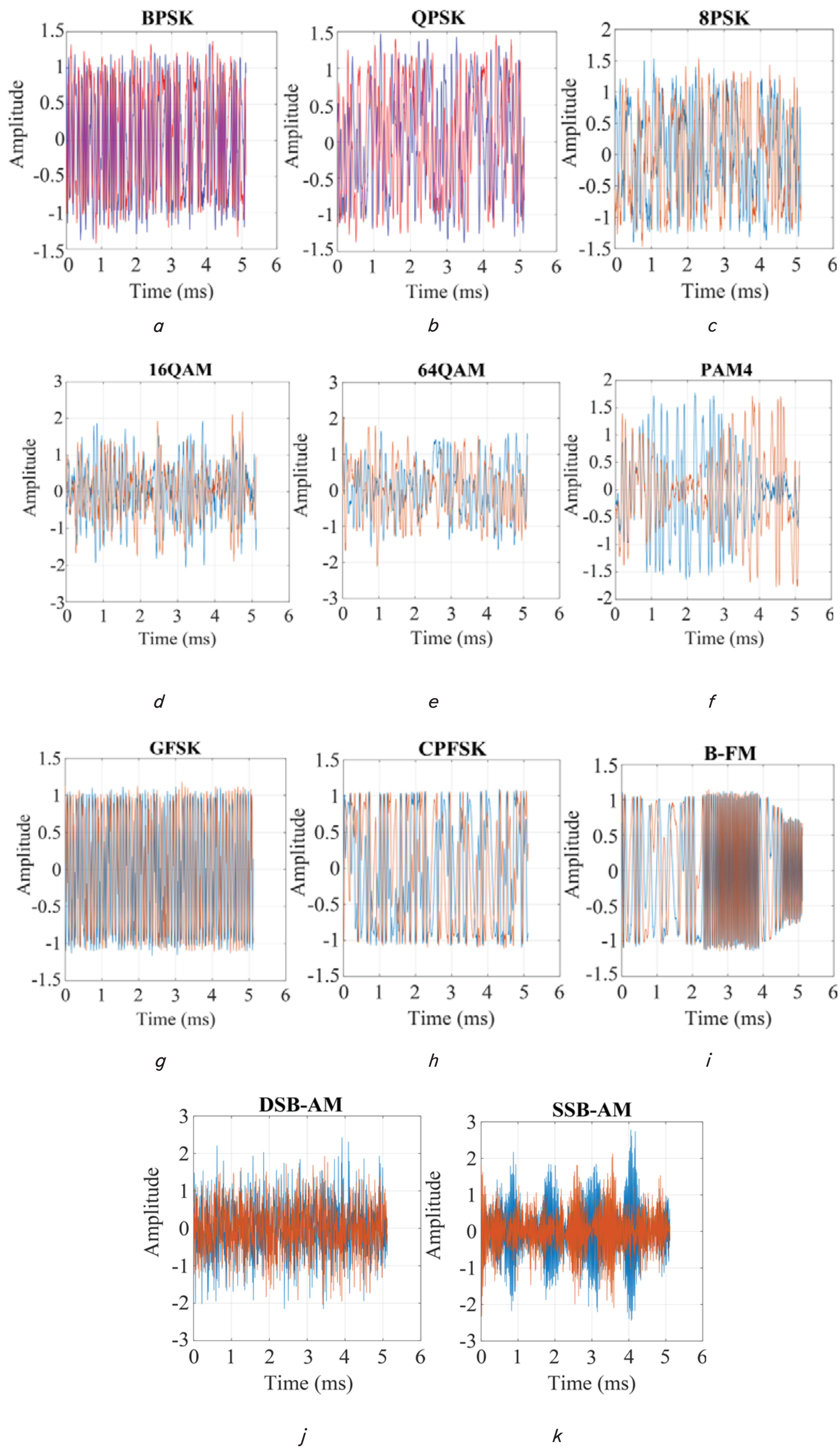


Fig. 6. The sample number vs the magnitude for the imaginary and real regions of the adopted frames: *a* – BPSK; *b* – QPSK; *c* – 8PSK; *d* –16QAM; *e* – 64QAM; *f* – PAM4; *g* – GFSK; *h* – CPFSK; *i* – B-FM; *j* – DSB-AM; *k* – SSB-AM

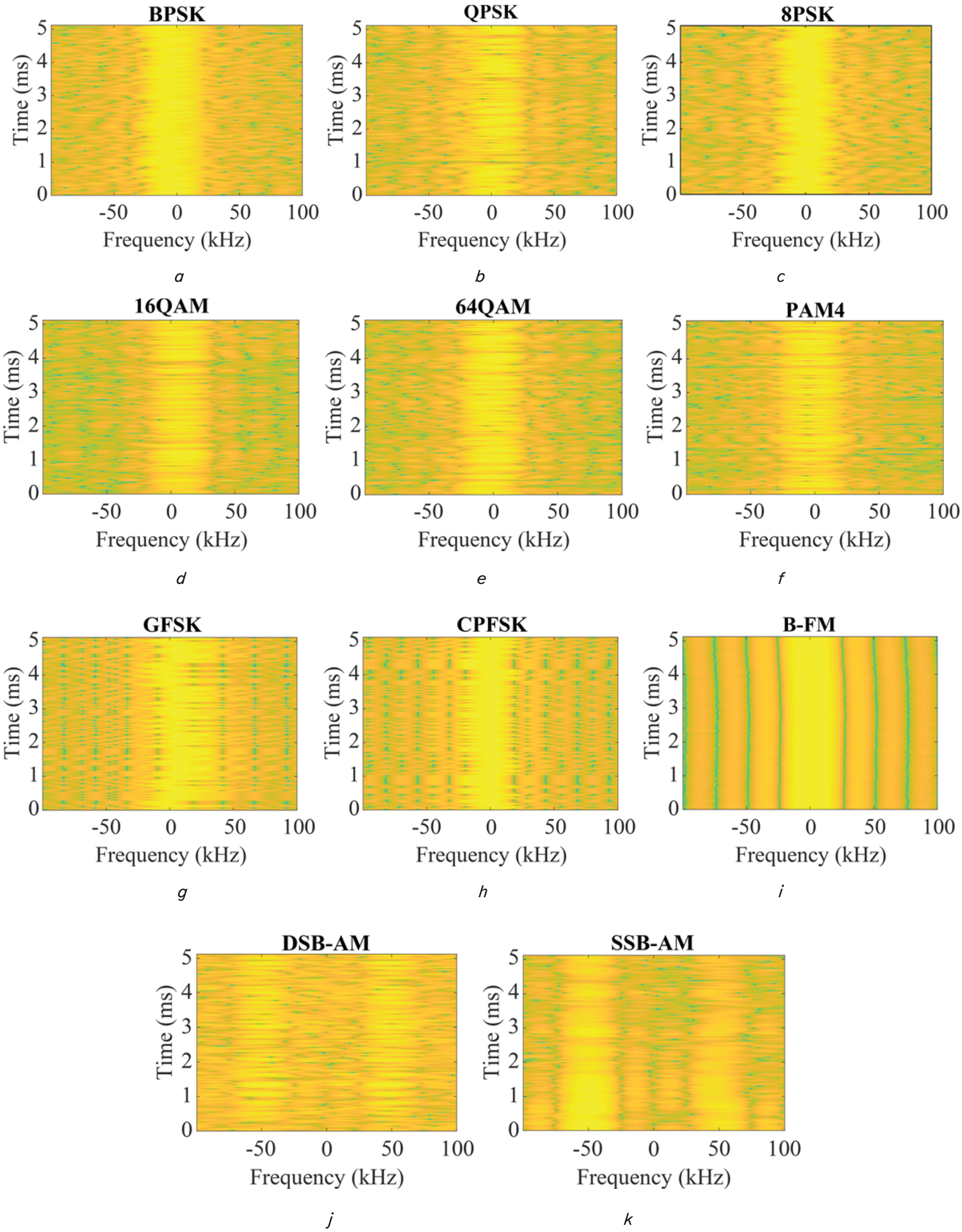


Fig. 7. Plotting the spectrogram of the adopted frames:
a – BPSK; *b* – QPSK; *c* – 8PSK;
d – 16QAM; *e* – 64QAM; *f* – PAM4;
g – GFSK; *h* – CPFSK; *i* – B-FM;
j –DSB-AM; *k* – SSB-AM

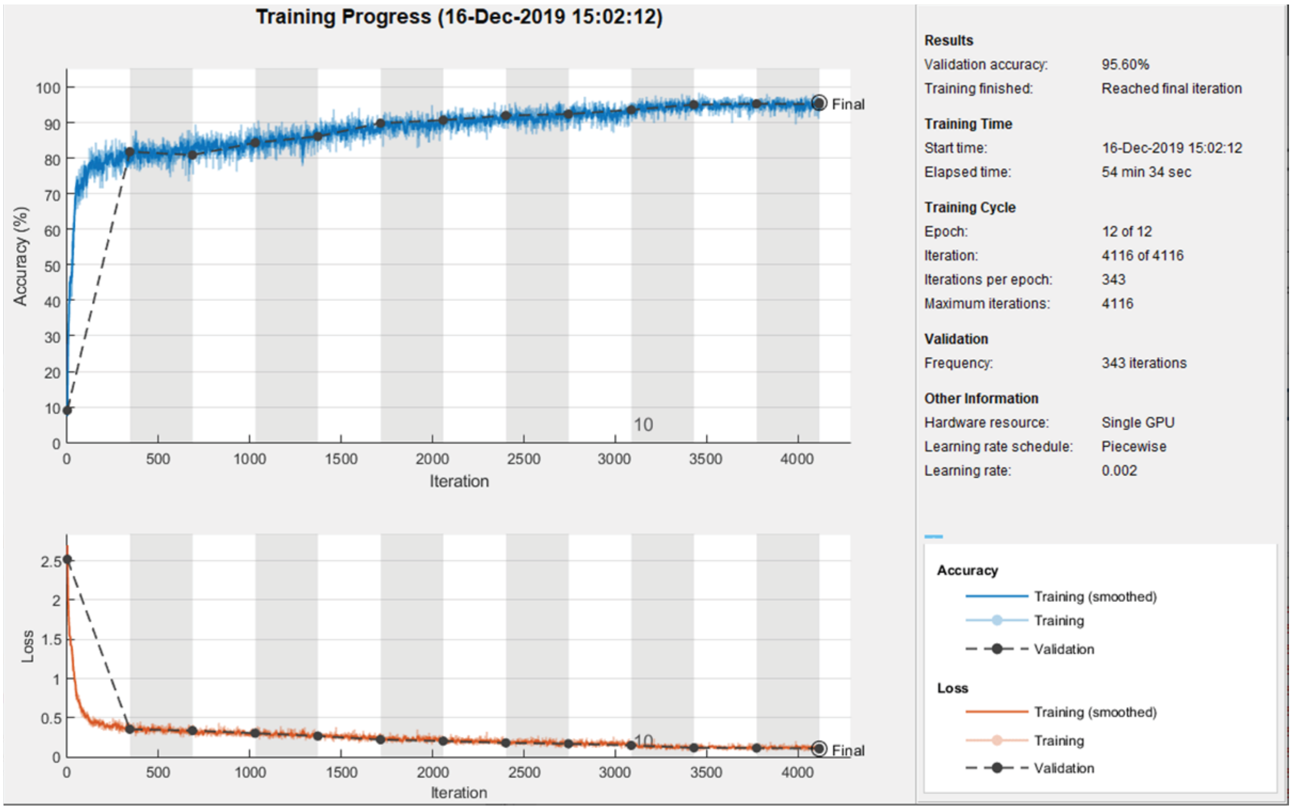


Fig. 8. Training progress graphic including the accuracy and loss of the network

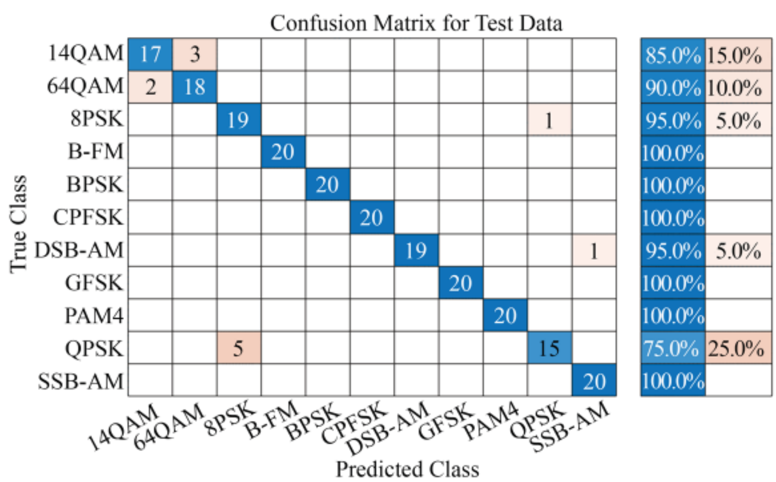


Fig. 9. The confusion matrix of the test frames

Table 2 shows a comparison between the presented approach and the existing studies in terms of the number of epochs, training elapsed time, and the maximum accuracy achieved.

Table 2

Comparison with previous related work

Reference	Number of epochs	Elapsed time (min)	Accuracy achieved
[13]	43–150	69	83.5 %
[14]	37	84	59.8 %
Proposed network	12	54	94.5455 %

6. Discussion of the results of the proposed classifying wireless signal modulations

The developed network classifier predicted the analog decisions and successfully identified the frames as PAM4 [7×1] categorical. The probability that every frame contains the anticipated modulation kinds is represented by the score as shown in Fig. 4. The sample numbers against the amplitude of the real and imaginary regions for the adopted frames are shown in Fig. 5, while the plotting of the spectrograms for the adopted frames is shown in Fig. 6.

The training process by measuring the accuracy and loss for the developed network has been shown in Fig. 7. The confusion matrix shown in Fig. 8 indicates that the network conflates 64/QAM and 16/QAM frames, as the matrix demonstrated.

Since each frame only contains 16/QAM and 128 symbols are a subset of 64/QAM, this issue is expected. Because the constellation of those modulation kinds appears related when rotated-phase caused by the frequency offset and fading channels, this network conflates 8/PSK and QPSK packets.

A comparison between the presented approach and the existing studies in terms of the number of epochs, training elapsed time, and the maximum accuracy achieved is shown in Table 2.

The use of the categorization of modulation types including ["BPSK", "QPSK", "8PSK", "16QAM", "64QAM", "PAM4", "GFSK", "CPFSK", "B-FM", "DSB-AM", "SSB-AM"] limits the applicability of the developed solutions. This will motivate us to test this proposed network on a wider range of modulation types.

The disadvantage of the proposed solution is the complexity of the number of hidden layers of the network of the classifier, which is increased with the number of classes. This can be eliminated by exploring more deep learning networks such as ResNet50, and ResNet80 networks over a more modern modulation categorization in the future.

7. Conclusions

1. A deep learning convolutional neural network (DLCNN) for classifying three analog and eight digital modulation types has been computed as a probability score of every frame containing the anticipated modulation type including QPSK, 8PSK, 16QAM, GFSK, CPFSK, B-FM, DSB-AM, SSB-AM, PAM4, 64QAM, and BPSK.

2. The presented work has successfully generated channel-impaired and synthetic waveforms as training data for the developed DLCNN. The process elapses about 54 minutes for training and the network converges to more than 95 % accuracy in roughly 12 epochs.

3. The trained DLCNN has been tested and achieved an accuracy of roughly 94.5455 %.

Conflict of interest

The authors affirm that they do not have any conflicts of interest with this research financial, authorship, personal, or otherwise that would have an impact on the findings of the study and how they are reported in this work.

Financing

The study was performed without financial support.

Data availability

Data will be made available on reasonable request.

Acknowledgments

All authors are acknowledging the University of Technology-Iraq for their assistance and support.

References

1. Huynh-The, T., Pham, Q.-V., Nguyen, T.-V., Nguyen, T. T., Ruby, R., Zeng, M., Kim, D.-S. (2021). Automatic Modulation Classification: A Deep Architecture Survey. IEEE Access, 9, 142950–142971. doi: https://doi.org/10.1109/access.2021.3120419
2. Xu, Y., Li, D., Wang, Z., Guo, Q., Xiang, W. (2018). A deep learning method based on convolutional neural network for automatic modulation classification of wireless signals. Wireless Networks, 25 (7), 3735–3746. doi: https://doi.org/10.1007/s11276-018-1667-6
3. Al-Shoukry, S., M. Jawad, B. J., Musa, Z., Sabry, A. H. (2022). Development of predictive modeling and deep learning classification of taxi trip tolls. Eastern-European Journal of Enterprise Technologies, 3 (3 (117)), 6–12. doi: https://doi.org/10.15587/1729-4061.2022.259242
4. Jwaid, W. M., Al-Husseini, Z. S. M., Sabry, A. H. (2021). Development of brain tumor segmentation of magnetic resonance imaging (MRI) using U-Net deep learning. Eastern-European Journal of Enterprise Technologies, 4 (9(112)), 23–31. doi: https://doi.org/10.15587/1729-4061.2021.238957
5. Shijer, S. S., Sabry, A. H. (2021). Analysis of performance parameters for wireless network using switching multiple access control method. Eastern-European Journal of Enterprise Technologies, 4 (9 (112)), 6–14. doi: https://doi.org/10.15587/1729-4061.2021.238457
6. Zhang, H., Wang, Y., Xu, L., Aaron Gulliver, T., Cao, C. (2020). Automatic Modulation Classification Using a Deep Multi-Stream Neural Network. IEEE Access, 8, 43888–43897. doi: https://doi.org/10.1109/access.2020.2971698
7. Zhou, Y., Lin, T., Zhu, Y. (2020). Automatic Modulation Classification in Time-Varying Channels Based on Deep Learning. IEEE Access, 8, 197508–197522. doi: https://doi.org/10.1109/access.2020.3034942
8. Clement, J. C., Indira, N., Vijayakumar, P., Nandakumar, R. (2020). Deep learning based modulation classification for 5G and beyond wireless systems. Peer-to-Peer Networking and Applications, 14 (1), 319–332. doi: https://doi.org/10.1007/s12083-020-01003-3
9. Perenda, E., Rajendran, S., Bovet, G., Pollin, S., Zheleva, M. (2022). Evolutionary Optimization of Residual Neural Network Architectures for Modulation Classification. IEEE Transactions on Cognitive Communications and Networking, 8 (2), 542–556. doi: https://doi.org/10.1109/tccn.2021.3137519
10. Zhou, R., Liu, F., Gravelle, C. W. (2020). Deep Learning for Modulation Recognition: A Survey With a Demonstration. IEEE Access, 8, 67366–67376. doi: https://doi.org/10.1109/access.2020.2986330
11. Ujan, S., Navidi, N., Landry, R. J. (2020). Hierarchical Classification Method for Radio Frequency Interference Recognition and Characterization in Satcom. Applied Sciences, 10 (13), 4608. doi: https://doi.org/10.3390/app10134608
12. Zheng, S., Qi, P., Chen, S., Yang, X. (2019). Fusion Methods for CNN-Based Automatic Modulation Classification. IEEE Access, 7, 66496–66504. doi: https://doi.org/10.1109/access.2019.2918136
13. Ji, K., Chang, S., Huang, S., Chen, H., Jia, S., Lu, H. (2021). Modulation Classification of Active Attack Signals for Internet of Things Using GP-CNN Network. 2021 IEEE International Conference on Communications Workshops (ICC Workshops). doi: https://doi.org/10.1109/iccworkshops50388.2021.9473800
14. Al-Nuaimi, D. H., Akbar, M. F., Salman, L. B., Abidin, I. S. Z., Isa, N. A. M. (2021). AMC2N: Automatic Modulation Classification Using Feature Clustering-Based Two-Lane Capsule Networks. Electronics, 10 (1), 76. doi: https://doi.org/10.3390/electronics10010076