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Automatic modulation classification based deep learning with mixed feature

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ABSTRACT

The automatic modulation classification (AMC) plays an important and necessary role in the truncated wireless signal, which is used in modern communications. The proposed convolution neural network (CNN) for AMC is based on a method of feature expansion by integrating I/Q (time form) with r/Ɵ (polar form) in order to take advantage of two things: first, feature expansion helps to increase features; the second is that converting to polar form helps to increase classification accuracy for higher order modulation due to diversity in polar form. CNN consists of six blocks. Each block contains symmetric and asymmetric filters, as well as max and average pooling filters. This paper uses DeepSig: RadioML which is a dataset of 24 modulation classes. The proposed network has outperformed many recent papers in terms of classification accuracy for 24 modulation types, with a classification accuracy of up to 96.06 at an SNR=20 dB.

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1. INTRODUCTION

The signal modulation patterns are becoming more intricate and diverse, and the radio environment is becoming increasingly harsher, thanks to the extraordinary advancement of wireless communication [1]. automatic modulation classification (AMC) has a wide range of applications as cognitive radio (CR), spectrum is rapidly depleting due to the development and growing demand for wireless services. [2], [3]. Here comes the radio cognitive technology to meet this challenge, which increases spectrum efficiency by sharing the licensed band between licensees and unlicensed users [4], [5]. CR networks depend on AMC in that they recognize the received signal without knowing the type of modulation used.

There are two types of AMC approaches likelihood-based (LB) and feature-based (FB) methods [6]–[8]. The likelihood functions of all possible modulation schemes of the received signal are calculated using LB methods, and the scheme with the highest likelihood value is chosen [9]. Although the LB technique can deliver optimal performance, it necessitates a precise understanding of the received signals and is computationally costly.

The FB technique, on the other hand, bases its conclusion on the extracted properties of received signals, such as higher-order statistics (HOS) and power spectral density. Compared to the LB strategy, the FB approach is easier to apply and achieves near-optimal results. Many researchers are now using machine learning (ML) approaches as classifiers with extracted features, such as support vector machines, k-nearest neighbor (KNN), and genetic programming [10].

Since ML techniques continue to make important advancements in numerous disciplines. Without the requirement for hand-engineered features, deep learning (DL) can learn high-level features automatically.

It has attracted a lot of interest due to its outstanding performance in challenges requiring complicated and deep architectural recognition [11]–[14]. In [15]–[17], for example, a one-dimensional convolutional neural network is used to generate promising results using only raw real and imaginary (I/Q) samples.

In addition, Peng *et al.* [18] translates incoming symbols to scatter points on the complex plane as the input for a two-dimensional convolution neural network (CNN) that performs better. In one of the best papers that achieved good results in the field of AMC it is suggested to use CNN-based AMC (CNN-AMC) to automatically extract features from the lengthy symbol-rate observation sequence [19]. This network has achieved an accuracy rating of up to 63.44% when SNR=20 dB. Although this network was among the first networks to classify 24 types of modulation, the accuracy of the classification was not up to the required level. So, after that, a lot of research was conducted to try to improve performance and increase the accuracy of classification such as in [16]. The researcher used a network: visual geometry group (VGG) (developed from a network (Google Net)), and residual neural (RN) to classification modulation

In network, VGG, the features of this network are (I/Q) 2×1024 and DL CNN classify, containing the convolution layer, and it becomes less every time until it reaches the SoftMax layer 1×24. In the second network RN, the features are also (I/Q) 2×1024 and DL called deep residual networks. VGG achieved an accuracy of 64.68% when SNR=20 dB, while RN achieved 75.07% when SNR=20 dB. In [20] used distinct asymmetric convolution kernels plus a number of specialized convolutional blocks to achieve an accuracy of 93.59%.

After that, the development of CNN networks continues to increase the classification efficiency to reach 94.97% when SNR=20 dB by using a bottleneck and asymmetric convolution structure [21]. In 2021, [22] the best performance at the level of classification accuracy was achieved, reaching 95.9% when SNR=20 dB, by input size is extended as 4×N size by copying I/Q components. The following are the paper’s contributions: i) the network can extract deep features from the enlarged frame using a unique technique that extends the frame size from 2×1024 to 4×1024 by integrating I/Q (time domain) features components with (r and Ɵ) (polar form) features components; ii) create a CNN network containing many layers up to 128.

2. METHOD

2.1. Dataset

Radio ML 2018.01A dataset this dataset is a large dataset of Oshea’s [16] modulation classifications. Across a broad range of signal-to-noise ratio (SNR) values, measurements of 24 different kinds of modulation schemes are included. More than 2.5 million signals with simulated channel effects are included in it. There are 26 SNRs for each type of modulation (OOK, 4ASK, 8ASK, BPSK, QPSK, 8PSK, 16PSK, 32PSK, 64APSK, 128APSK, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, AM-SSB-WC, AMSSB-SC, AM-DSB-WC, AM-DSB-SC, FM, GMSK, OQPSK4096 frames per modulation, 1024 complex time-series samples per frame. The effects of the channel are (carrier frequency offset (CFO), symbol rate offset (SRO), multipath fading, and thermal noise).

2.2. Input features

As shown in Figure 1, in the classification network, 16QAM can be considered as part of 64QAM in the I/Q level, and this causes confusion among them in the classification, which affects the reduction in the efficiency of the classification accuracy because the images are treated by the network as a matrix, and in this case, the two matrixes will be the same. In the polar plane, 16QAM does not appear as part of 64QAM as in the real and imaginary pattern. Figure 1 also shows that it is possible to take advantage of diversity in the transformation of real and imaginary form (I/Q) to polar form (r/Ɵ), which helps increase the accuracy of classification, especially in high-order modulation. Another way to help get increase the accuracy of classification is to extend the input features because it contributes to more features and many of the samples in the frame include high-impact elements that are evident representations of each modulation style. This is proposed in this paper is the merging of I/Q with r/Ɵ to benefit from the above. The input matrix will have the largest number of rows of 4. The first row represents (I), the second is (Q), the third is (r), and the fourth is (Ɵ), and the columns=1024 columns with the length of the signal, so the matrix is (4×1024).

2.3. Proposed CNN model

The suggested model distinguishes 24 forms of modulation, as shown in Figure 2. The network is made up of three blocks: A, B, and C, with the last block (C) containing four convolutional layers to increase the number of characteristics recovered. Because the input after merging the features is relatively huge (4×1024), the first block is critical in minimizing the size of the input.

This is accomplished by employing maximum pooling layers (M Pool), which keep the basic characteristics, whereas max pool divides the features in half every time (2×1) is used (M Pool), When compared to filters (2×2) or (3×3) kernels, block B contains asymmetric filters (3×1) whose purpose is to extract vertical qualities over the spatial dimension in a superior manner while reducing trainable parameters by roughly half. The (5×1) filters have been evaluated and shown to have no substantial impact on performance accuracy while also slowing down the training process. Before entering block C, the size of the feature must be reduced from 4×256 to 2×256, which will be done by the maximum-pooling layer (A Pool) (2×1) with stride (2×1). Maximum pooling is significant in lowering computational complexity and affecting classification accuracy because the average aggregation approach drops from 4×256 to 2×256 with the ability to retain key information from the input.

The CNN networks proposed in this paper consist of a convolution layer and a batch normalization layer, in addition to an activation layer rectified linear unit (ReLU). The average pooling (A Pool) has the benefit of reducing the size of the received features from C-Block 4 to 24 in order to move it completely to the SoftMax layer. The last layer is responsible for calculating the probability.

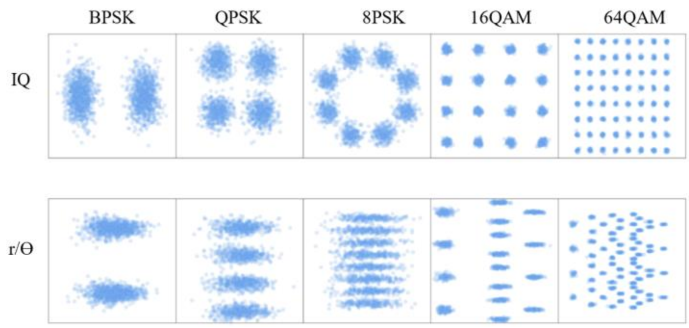


Figure 1. Compare between I/Q and polar form

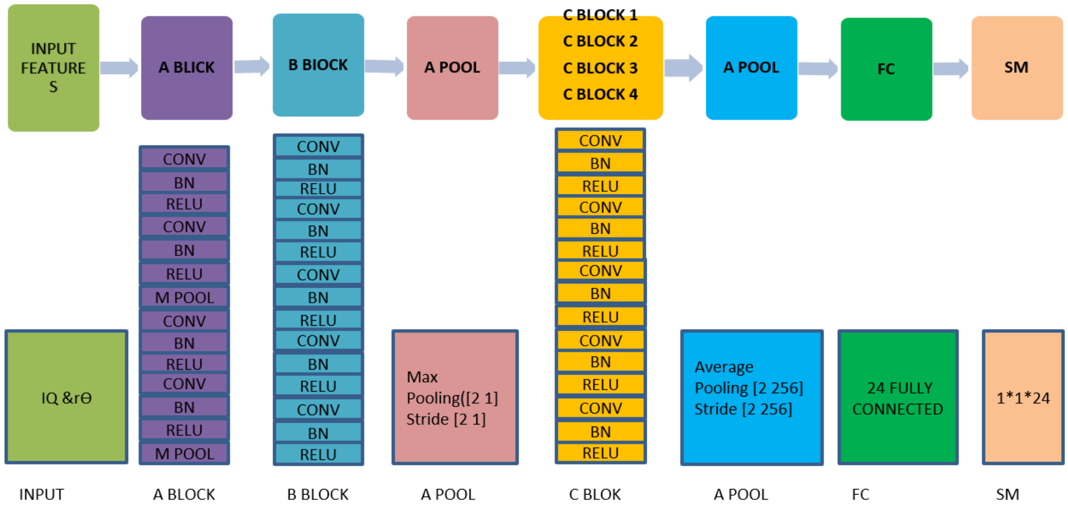


Figure 2. Structure of the proposed CNN

3. RESULTS AND DISCUSSION

With 24, modulation, the simulation results were obtained. The data is visualized to show how effective it is. A new approach to making the frame bigger, the network CNN is deep and has specifications that allow it to take full advantage of the features by integrating I/Q with r/Θ Table 1 summarizes the results of the simulation. 80% of the data set is used in the training phase, while the remaining 20% is used in the test, simulated by MATLAB 2020b.

The results of the proposed network will be compared with the results of recent papers that used the same types of modulation and the same dataset. All networks compared to the proposed network are deep learning networks. As shown in Figure 3, the least accurate networks in the classification are CNN-AMC

[19] and VGG [16], and it appears that their performance is convergent. Although they use the same basic chassis, VGG is equipped with a broad bypass, so VGG is superior to CNN-AMC. In most SNR, the performance of the best networks is the most recent models (MCNet) [20], LCNN Net [21], and Kim Net [22], sparsely connected CNN with Kim [23] being the most recent network, superior to the aforementioned models.

Table 1. Configuration for the simulation

Type	Value
Max Epochs	60
Mini Batch Size	100
Initial Learning Rate	3e-4
Learning Rate Drop Period	20
Learning Rate Drop Factor	0.1
Optimizer	Adam

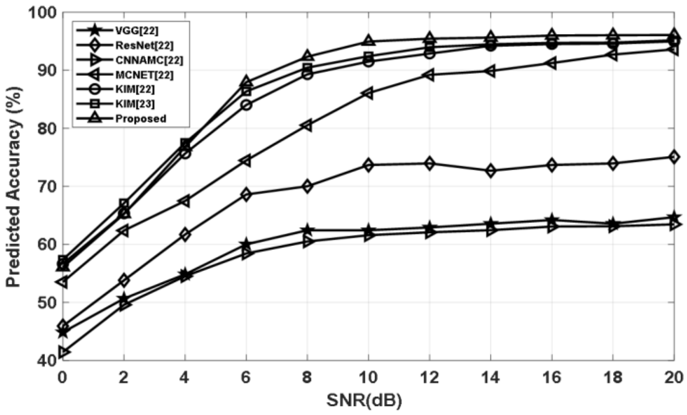


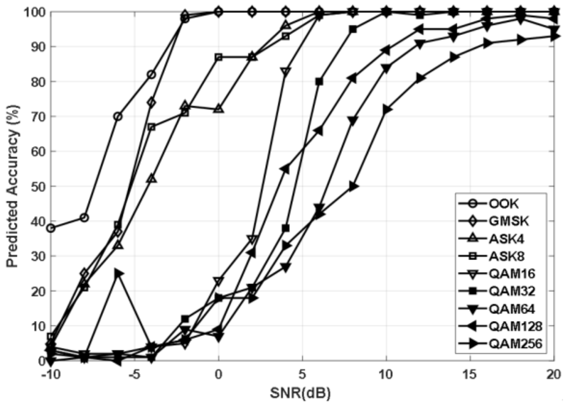
Figure 3. The evaluation of accuracy using several models

The proposed network will be compared to Kim *et al.* [22], whose classification accuracy is 87.4 at SNR=6 dB and 94.06 at SNR=10 dB, while the proposed model's accuracy is 87.93 at SNR=6 dB and 94.93 at SNR=10 dB. Table 2 shows a comparison of the proposed network with the latest research that achieved the best results in terms of classification accuracy with the use of the same dataset. Theoretical reasons for the superiority of the proposed network are: i) extending the input from 2×1024 to 4×1024 leads to more features extracted which improves network efficiency; ii) we expanded the input by merging real and imaginary form (I/Q) with polar form (r\ϴ), which helps increase the accuracy of classification, especially in high-order modulation, because in the polar plane, 16QAM does not appear as part of 64QAM as shown Figure 1, which improves network efficiency; iii) the proposed network CNN contains asymmetric filters (3×1) whose purpose is to extract vertical qualities over the spatial dimension in a superior manner; iv) through experience, we have shown asymmetric filters (3×1) better use of other types of asymmetric filters such as (5×1); and v) the proposed network CNN contains many layers up to 128. Which helps to take advantage of most of the features in the network. Thus, the classification accuracy increased. In the future, we are thinking of getting the same results by forming a network that is smaller in size than the current network. also introduced different augmented and optimization techniques as working techniques in papers [24], [25].

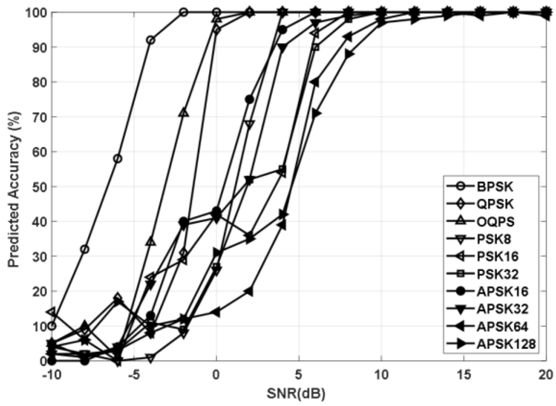
Then the proposed network will continue to outperform all networks when it has an SNR 6≥6 dB. It can also be seen that the proposed network has achieved an improvement of 0.6% at SNR=6 dB, and 0.92% at 10 dB SNR over Kim Net [22]. According to the above results, the proposed network can also be considered superior to other recent research, such as SCG Net [23] at SNR=10 dB accuracy=89, while the proposed CNN At SNR=10 dB, accuracy is=94.06. The classification accuracy results for each model are shown in three groups, as shown in Figure 4. In Figure 4(a), We note that OOK is the best type of modulation in terms of accuracy, as it reaches SNR=0 to 100% approximately, while the worst is QAM256) because there are not any features that are exactly the same. In Figure 4(b), we find The APSK128 needs to be SNR>8 dB in order for the accuracy to reach more than 90%, as it is the worst type in terms of accuracy. Since APSK128 is difficult to predict, the lower the SNR, the more difficult the channel conditions. While the rest of the types can achieve an accuracy of more than 90% even when the SNR is less than 8 dB, and the best type is BPSK, which reaches an accuracy of 100% when SNR is equal to 0 dB, which means that BPSK is less affected by the conditions of the channel. It is possible to consider FM, which is clear in Figure 4(c), as the best type in terms of accuracy, as it reaches 100% where SNR=-5 dB. At low SNRs, both AM-SSB-SC and AM-DSB-SC show comparable performance trends. It can be noted that although the transfer of features from I/Q to r/Θ (polar form) decreases processes partially nested in modulations such as 16QAM and 64QAM, the models with the highest order are still the least accurate in the classification. It also seems that 256QAM is confused with 32QAM and 64QAM, and AM-SSB-WC is confused with AM-SSB-SC. Consequently, this modulation has minimum accuracy, while QPSK and FM signals were not confused with any modulation, so accuracy is high for these modulations. Also, the fluctuation phenomena can arise if the high-level features are not removed. It also seems that it affects the network deposit and causes a decrease in accuracy. Most modulations are excellently identified at SNR=10.

Table 2. Compares between proposed CNN and related work

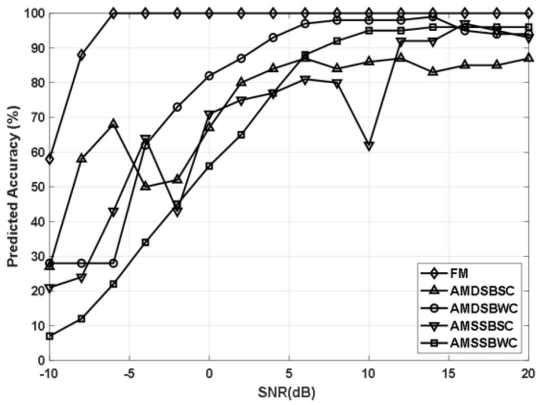
SNR (dB)	VGG [16]	CNN-AMC [19]	MCNet [20]	LCNN [21]	KIM [22]	Proposed CNN
0	44.84	41.43	53.51	56.64	57.51	56.07
2	50.65	49.58	62.38	65.32	67.67	65.23
4	54.84	54.51	67.48	75.65	77.93	76.79
6	60.00	58.42	74.45	84.01	87.4	87.93
8	62.42	60.49	80.52	89.29	92.04	92.32
10	62.42	61.57	86.06	91.84	94.15	94.93
12	62.9	62.07	89.02	92.86	95.07	95.43
14	63.55	62.44	89.86	94.21	95.28	95.62
16	64.19	63.06	91.23	94.50	95.62	95.97
18	63.55	63.11	92.69	94.59	95.5	96.02
20	64.68	63.44	93.59	94.97	95.9	96.06



(a)



(b)



(c)

Figure 4. Classification accuracy results for each model are shown in three groups, (a) classification accuracy of (M-PSK and M-APSK), (b) classification accuracy of (M-PSK and M-APSK), and (c) classification accuracy of (FM, AM-SSB, and AM-DSB)

4. CONCLUSION

In this paper, the proposed network is a way to extend the features by integrating I/Q with r/Θ (polar form) in order to benefit from two things. The first is that the extension of the features helps to increase the features, and the other thing is a conversion to the polar formula that contributes to increasing the accuracy of the classification for the higher-order modulation due to the diversity in the polar form. Then we enter these features into a matrix 4×1024 for the proposed CNN network, which consists of six blocks containing asymmetric filters to take advantage to extract vertical qualities over the spatial dimension in a superior manner while reducing trainable parameters by roughly half by using average pooling or maximum pooling dataset: RadioML 2018.01A, which contains 24 modulation types, is used for the simulation evaluation. According to simulation findings, the suggested model's classification accuracy outperforms previous models in the SNR range of +6 dB to +20 dB, with an accuracy of 94.93% at 10 dB SNR and 96.06% at 20 dB SNR. From the results, it can be concluded that the efficiency of converting data to polar and reconfiguring the structure of the network achieved satisfactory results compared to other methods. It noticed the speed of learning in high SNR signals compared with low SNR signals because the signal is clear and makes the neural network learn quickly.

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REFERENCES

[1] Z. Zhang, C. Wang, C. Gan, S. Sun, and M. Wang, "Automatic modulation classification using convolutional neural network with features fusion of SPWVD and BJD," *IEEE Transactions on Signal and Information Processing over Networks*, vol. 5, no. 3, pp. 469–478, Sep. 2019, doi: 10.1109/TSIPN.2019.2900201.

[2] I. Kakalou, K. E. Psannis, P. Krawiec, and R. Badea, "Cognitive radio network and network service chaining toward 5G: challenges and requirements," *IEEE Communications Magazine*, vol. 55, no. 11, pp. 145–151, Nov. 2017, doi: 10.1109/MCOM.2017.1700086.

[3] S.-H. Kim, J.-W. Kim, and D.-S. Kim, "Energy consumption analysis of beamforming and cooperative schemes for aircraft wireless sensor networks," *Applied Sciences*, vol. 10, no. 12, Jun. 2020, doi: 10.3390/app10124374.

[4] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201–220, Feb. 2005, doi: 10.1109/JSAC.2004.839380.

[5] K. W. Choi, "Adaptive sensing technique to maximize spectrum utilization in cognitive radio," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 2, pp. 992–998, Feb. 2010, doi: 10.1109/TVT.2009.2036631.

[6] X. Li, F. Dong, S. Zhang, and W. Guo, "A survey on deep learning techniques in wireless signal recognition," *Wireless Communications and Mobile Computing*, pp. 1–12, Feb. 2019, doi: 10.1155/2019/5629572.

[7] H. M. Hamee and J. Wadi, "Automatic modulation recognition for MFSK using modified covariance method," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 5, no. 3, pp. 429–435, 2015, doi: 10.11591/ijece.v5i3.pp429-435.

[8] S. S. Hreshee, "Automatic recognition of the digital modulation types using the artificial neural networks," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 6, pp. 5871–5882, Dec. 2020, doi: 10.11591/ijece.v10i6.pp5871-5882.

[9] Y. A. Eldemerdash, O. A. Dobre, and M. Oner, "Signal identification for multiple-antenna wireless systems: achievements and challenges," *IEEE Communications Surveys and Tutorials*, vol. 18, no. 3, pp. 1524–1551, 2016, doi: 10.1109/COMST.2016.2519148.

[10] M. W. Aslam, Z. Zhu, and A. K. Nandi, "Automatic modulation classification using combination of genetic programming and KNN," *IEEE Transactions on Wireless Communications*, pp. 1–9, 2012, doi: 10.1109/TWC.2012.060412.110460.

[11] M. Kulin, T. Kazaz, I. Moerman, and E. De Poorter, "End-to-end learning from spectrum data: a deep learning approach for wireless signal identification in spectrum monitoring applications," *IEEE Access*, vol. 6, pp. 18484–18501, 2018, doi: 10.1109/ACCESS.2018.2818794.

[12] S. Rajendran, W. Meert, D. Giustiniano, V. Lenders, and S. Pollin, "Deep learning models for wireless signal classification with distributed low-cost spectrum sensors," *IEEE Transactions on Cognitive Communications and Networking*, vol. 4, no. 3, pp. 433–445, Sep. 2018, doi: 10.1109/TCCN.2018.2835460.

[13] M. K. Hussein, T. M. Salman, A. H. Miry, and M. A. Subhi, "Driver drowsiness detection techniques: a survey," in *2021 1st Babylon International Conference on Information Technology and Science (BICITS)*, Apr. 2021, pp. 45–51, doi: 10.1109/BICITS51482.2021.9509912.

[14] N. Phruksahiran, "Amateur radio sensing technique using a combination of energy detection and waveform classification," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 1, pp. 399–410, Feb. 2022, doi: 10.11591/ijece.v12i1.pp399-410.

[15] N. E. West and T. O'Shea, "Deep architectures for modulation recognition," in *2017 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN)*, Mar. 2017, pp. 1–6, doi: 10.1109/DySPAN.2017.7920754.

[16] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 168–179, Feb. 2018, doi: 10.1109/JSTSP.2018.2797022.

[17] Y. Wang, M. Liu, J. Yang, and G. Gui, "Data-Driven deep learning for automatic modulation recognition in cognitive radios," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 4074–4077, Apr. 2019, doi: 10.1109/TVT.2019.2900460.

[18] S. Peng, H. Jiang, H. Wang, H. Alwageed, and Y.-D. Yao, "Modulation classification using convolutional neural network based deep learning model," in *2017 26th Wireless and Optical Communication Conference (WOCC)*, Apr. 2017, pp. 1–5, doi: 10.1109/WOCC.2017.7929000.

[19] F. Meng, P. Chen, L. Wu, and X. Wang, "Automatic modulation classification: a deep learning enabled approach," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 10760–10772, Nov. 2018, doi: 10.1109/TVT.2018.2868698.
[20] T. Huynh-The, C.-H. Hua, Q.-V. Pham, and D.-S. Kim, "MCNet: an efficient CNN architecture for robust automatic modulation classification," *IEEE Communications Letters*, vol. 24, no. 4, pp. 811–815, Apr. 2020, doi: 10.1109/LCOMM.2020.2968030.
[21] S.-H. Kim, J.-W. Kim, V.-S. Doan, and D.-S. Kim, "Lightweight deep learning model for automatic modulation classification in cognitive radio networks," *IEEE Access*, vol. 8, pp. 197532–197541, 2020, doi: 10.1109/ACCESS.2020.3033989.
[22] S.-H. Kim, J.-W. Kim, W.-P. Nwadiugwu, and D.-S. Kim, "Deep learning-based robust automatic modulation classification for cognitive radio networks," *IEEE Access*, vol. 9, pp. 92386–92393, 2021, doi: 10.1109/ACCESS.2021.3091421.
[23] G. B. Tunze, T. Huynh-The, J.-M. Lee, and D.-S. Kim, "Sparsely connected CNN for efficient automatic modulation recognition," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 15557–15568, Dec. 2020, doi: 10.1109/TVT.2020.3042638.
[24] A. R. Luaibi, T. M. Salman, and A. H. Miry, "Detection of citrus leaf diseases using a deep learning technique," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 2, pp. 1719–1727, Apr. 2021, doi: 10.11591/ijece.v11i2.pp1719-1727.
[25] M. K. Hussein, T. M. Salman, and A. H. Miry, "A deep learning approach for noisy image classification in automated driver drowsiness detection," *Journal of Engineering and Sustainable Development*, vol. 25, pp. 73–80, Sep. 2021, doi: 10.31272/jeasd.conf.2.1.10.

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