AUT Journal of Electrical Engineering

AUT J. Elec. Eng., 54(1) (2022) 67-78
DOI: 10.22060/eej.2021.19826.5409

# Deep Learning for Recognition of Digital Modulations: A Detailed Study

M. M. Jadidi, A. Mohammadi*

Department of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran

**ABSTRACT:** The automatic modulation recognition of the received signal is very attractive in both military and civilian applications. In the recent years, deep learning techniques have received much attention due to their excellent performance in signal, audio, image and video processing. This paper examines the feasibility of using deep learning algorithms on automatic recognition of the received radio signals' modulation schemes. Modulation recognition has been performed on eight digital modulation types with a Signal-to-Noise Ratio (SNR) from -20dB to 20dB. Primarily, a Vanilla Neural Network is used to classify the type of modulation. Afterwards, convolutional Neural Network (CNN) and Recurrent Neural Network are applied for modulation recognition. These neural networks are widely used in image and signal processing applications. This is followed by designing the other architectures, including Densely Connected Neural Network (DenseNet), inception network, Recurrent Neural Network (RNN), Long-Short Term Memory network (LSTM), and Convolutional Long-Short Term Memory Deep Neural Network (CLDNN) for modulation recognition problem, and their results are presented. During this investigation, a basic model is initially considered for each architecture, and the network performance is studied afterwards by adjusting its parameters. The simulation results show that the proposed modified CLDNN model can provide an accuracy of 98% in high SNRs.

**Review History:**

Received: Apr. 06, 2021
Revised: Sep. 22, 2021
Accepted: Sep. 26, 2021
Available Online: Jun. 01, 2022

**Keywords:**

Modulation Recognition
Modulation Classification
Deep Learning
Convolutional Neural Networks
Recurrent Neural Networks

## 1- Introduction

Wireless communication plays an essential role in modern telecommunications, and modulation is an inseparable part of this process. There are generally many unknown radio signals in the environment and due to various reasons, the specifications of these signals are required. The purpose of automatic modulation recognition is to identify the type of received signal modulation with the slightest prior knowledge of signal parameters [1, 2].

Automatic modulation recognition has many applications and has become significant with the expansion of modulation, especially digital modulation. Modulation recognition plays a significant role in many intelligence systems. With the increasing demand for telecommunications, monitoring and controlling the transmission of electromagnetic signals in the radio spectrum became important [3]. The Applications of automatic modulation recognition are both military and civilian applications. The technique is applied in frequency spectrum monitoring, detection of unauthorized transmitters, user identification, interference identification [4, 5], network traffic management [2], electronic surveillance, electronic warfare, and threat analysis [6]. Another application used both in military and in civilian is making intelligent receivers. According to the received signal and channel conditions, intelligent receivers select the most appropriate modulation scheme to send the message, and the receiver can instantly recognize modulation [7]. Automatic modulation recognition has first emerged in the military field, where it was necessary to detect the modulation of enemy signals to generate jamming signals or recover the information contained in them [2].

In recent years, machine learning has improved significantly for various reasons. The algorithms have improved in many ways, and computational power has increased. Additionally, high-level programming models that can run simultaneously on multiple processors are available. Deep learning algorithms have shown excellent capabilities in image, video, and signal processing, especially in supervised learning. Therefore, deep learning can be considered a candidate for multiclass classification problems (e.g. modulation recognition). There are several advantages to using deep learning methods in communications systems. Primarily, due to many communication devices and high amount of data, the data required for deep learning are available in communication systems. Secondly, deep learning can extract features independently, and there is no longer a need to extract features manually. Thirdly, since deep learning is advancing rapidly, it can be used in other wireless communications fields [8].

Modulation recognition methods can be divided into

*Corresponding author's email: abm125@aut.ac.ir

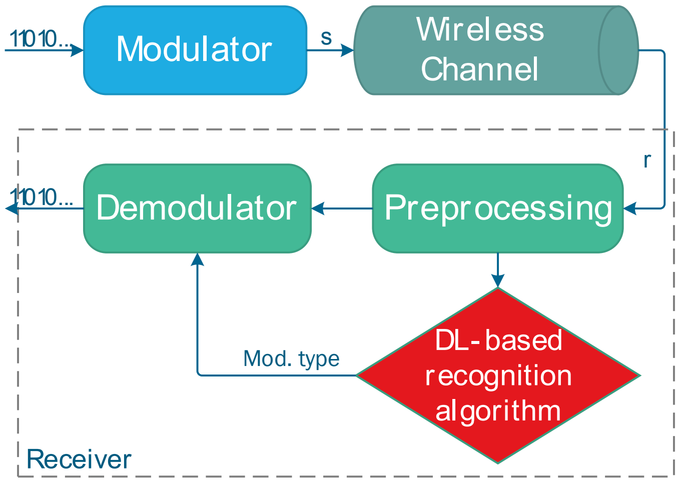


**Fig. 1. System model**

three general categories, Maximum Likelihood (ML) [9, 10], feature-based [11], and blind [12]. The ML-based method achieves the optimal solution but has a high computational cost. The feature-based method consists of two parts, feature extraction and classifier. In the third method, there is no need for prior knowledge. Early articles on modulation recognition were published in the 1990s by Azzouz and Nandi [1, 2, 4, 11, 13]. In these papers, different features are derived from the intercepted signal's instantaneous amplitude, phase, and frequency. Afterwards, the decision tree or artificial network has been used as a classifier. In [14, 15], two traditional machine learning algorithms, which are the Support Vector Machine (SVM) and the K Nearest Neighbor (KNN), are also used as a classifier. Additionally, deep learning-based modulation recognition has been investigated. In [16-18], the Convolutional Neural Network has been used. A classifier using convolutional autoencoders is proposed in [12]. It has been shown with little preprocessing in [19, 20] that LSTM model can achieve good accuracy. Various deep neural networks such as Residual Neural Network (ResNet) and DenseNet were studied in [21-23].

This paper examines the possibility of using deep learning algorithms for automatic modulation recognition of radio signals. Primarily, a traditional model used in the previous papers is considered for each different architecture, then modified models are introduced by changing its various parameters. Afterwards, these modified models are trained with dataset, and their performance is improved to obtain better results.

The rest of this paper is organized as follows. Section 2 defines the problem, section 3 describes the types of neural networks architectures and introduces the modified models. In Section 4, the dataset and the hardware are discussed. Moreover, the training details and the numerical results are presented. Finally, the paper has been concluded in Section 5.

## 2- Problem Definition

The modulation recognition problem can generally be considered as a multi-class classification problem. The system model is shown in Fig. 1. The received signal is in the form of:

$$r(t) = s(t) * h(t) + n(t), \tag{1}$$

where $s(t)$ is the transmitted signal, $h(t)$ is the channel impulse response, $n(t)$ is additive noise and $*$ denotes convolution. The main goal in any modulation recognition method is to find the value of $i$ in relation $\Pr\{s(t) \in M_i \,|\, r(t)\}$, so that this probability is maximized. In this phrase, $M_i$ represents different modulation classes. Due to the simplification of mathematical operations, $r(t)$ is usually shown as in-phase and quadrature components [2]. The modulation recognition models presented in this paper receive $r(t)$ signal as input, and later determine the probability of belonging to each modulation classes. All models trained in the following sections are based on DL-based recognition block that is illustrated in Fig. 1.

## 3- Models Description

Deep learning is a branch of machine learning that can solve classification problems. In recent years, deep learning has been used in many different fields. It refers to a set of machine learning algorithms that are usually based on artificial neural networks. Deep neural networks are divided into three general parts: feed-forward, feed-back and bi-directional. The most popular deep networks are the vanilla neural network (also called multilayer perceptron and is usually used for

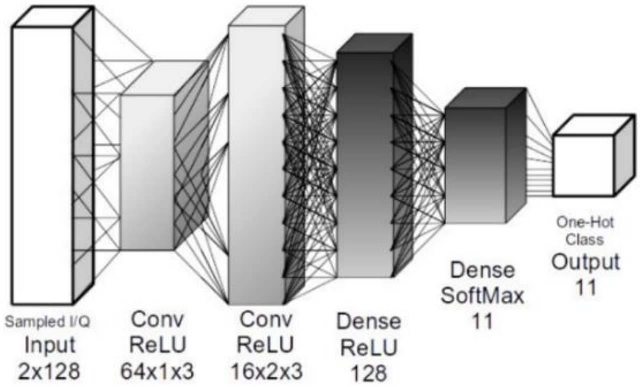


**Fig. 2. The proposed convolutional network in [17].**

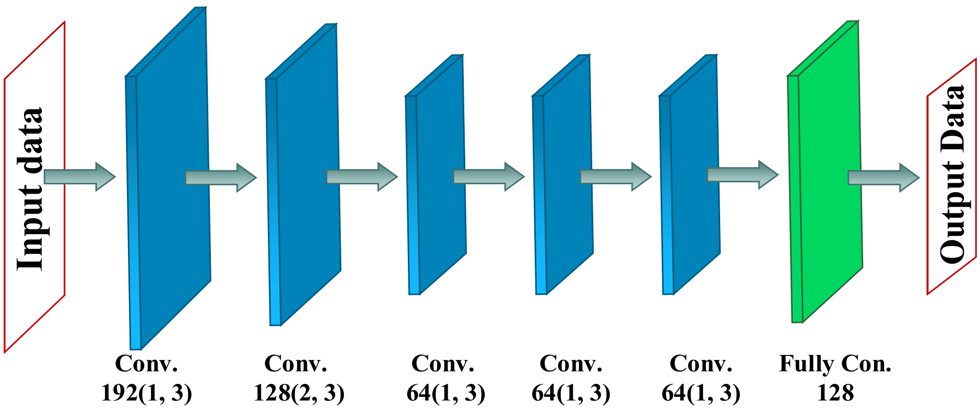


**Fig. 3. Five-layer convolutional network. The first number under each layer indicates the number of filters, and the second and third numbers indicate the filter's size.**

classification and regression), the convolutional network (usually used for machine vision), and the Recurrent Neural Network (usually used for time series analysis). This article focuses on these three networks [24, 25].

### 3- 1- Vanilla Neural Network

Primarily, we consider a vanilla neural network with 256 input and 8 output neurons that connect all the neurons in successive layers (fully connected). We changed the network's various parameters, such as the number of hidden layers, the number of neurons in each hidden layer, and the dropout value. It is demonstrated that if more neurons are in the hidden layers, the network is more accurate. On the other hand, as the number of layers increases and stops at seven hidden layers, the accuracy also increases. However, more increase in hidden layers result in degradation in accuracy of the network. It should be noted that with increasing the number of layers and neurons, the training time also increases. The proposed neural network has four hidden layers, each with 264 neurons, and a dropout value of 0.1.

### 3- 2- Convolutional Neural Network

First, the Convolutional Neural Network proposed in paper [17] was considered. This network's architecture is shown in Fig. 2, containing 64 and 16 filters in layers 1 and 2 and 128 neurons in layer 3. Afterwards, its various parameters such as the number and the size of filters in each layer, the number of layers, and the dropout value for higher accuracy were changed. It was observed that the network accuracy, which has a higher number of filters near the input and a smaller number of filters at the output, is higher than in other cases. Furthermore, the large filter size near the input and the small filter size near the output give better accuracy. Similar to the vanilla neural network, as the number of layers increases until it reaches five hidden layers, the accuracy also increases. However, more increase in hidden layers results in degradation in accuracy of the network. Additionally, as the number of layers increases, the convergence time increases as well. The proposed Convolutional Neural Network has five convolutional layers, which are shown in Fig. 3. In this figure, the first number indicates the number of filters under

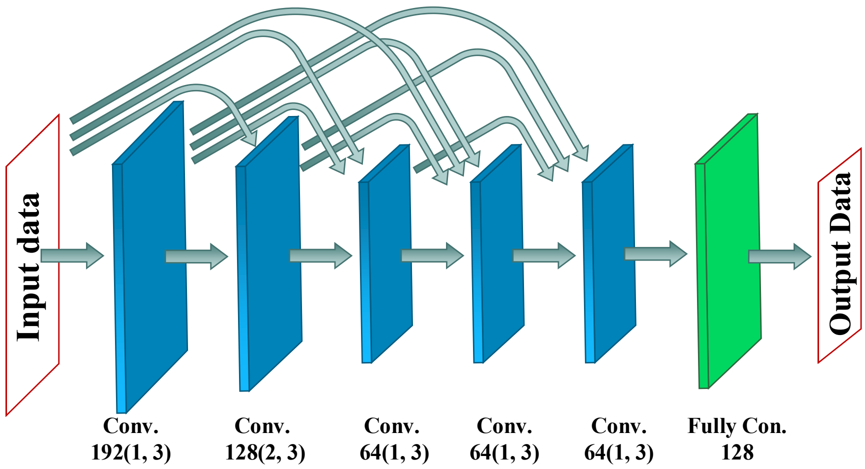


**Fig. 4. Five-layer densely network.**

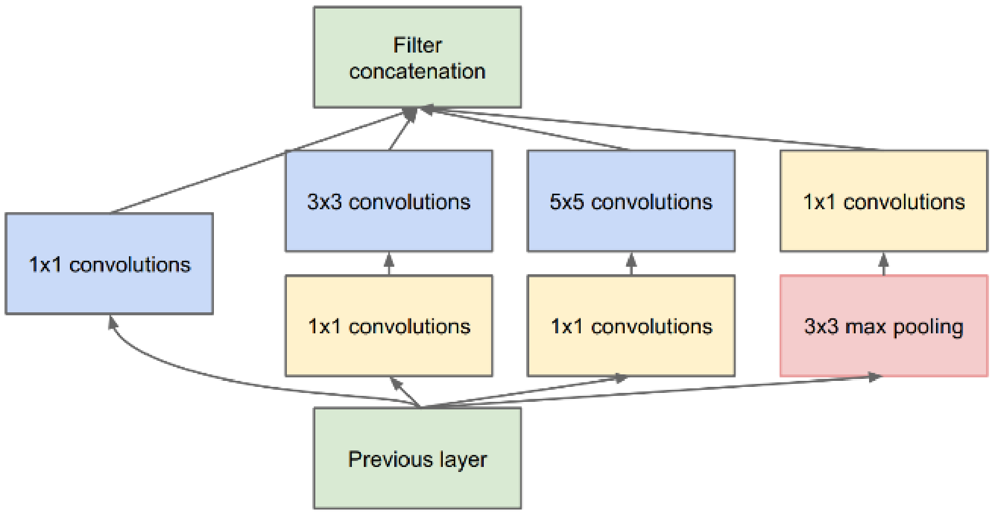


**Fig. 5. Inception module [27].**

each layer, and the second and third numbers demonstrate the size of the filter.

In addition to the Convolution Neural Network, two other architectures have been proposed based on the convolution layers. The first architecture is the Densely Connected Network (DenseNet). This architecture was presented in 2017 [26]. In this architecture, shortcut connections are used to make layers more accessible, hence each layer has access to all its previous layers. In the Convolution Neural Network, the layers close to the input extract low-level features (such as image edges), and the final layers extract high-level features (such as an object in the image). Recently, low-level features may be more important in classification operations and improve network accuracy. In DenseNet architecture, due to the initial layers' connection to the end layers, the network can also use low-level features directly. Therefore, one of the essential advantages of this architecture is improving the flow of information and gradient throughout the network (each layer has direct access to both network input and gradient of error function), which can make network training easier. The proposed network of DenseNet architecture is the same as Fig. 3, which all shortcuts are added and shown in Fig. 4.

The second architecture is the inception network and was introduced in 2015 [27]. In general, the inception network is a combination of inception modules and concatenation layers. Each inception module has four parallel paths, the output of which is the concatenation of all four paths outputs. This module is shown in Fig. 5. The advantages of using this module include the ability to increase network depth and the availability of various scale features. The proposed module is shown in Fig. 6 after adjusting its parameters. The proposed inception network is made by these modules.

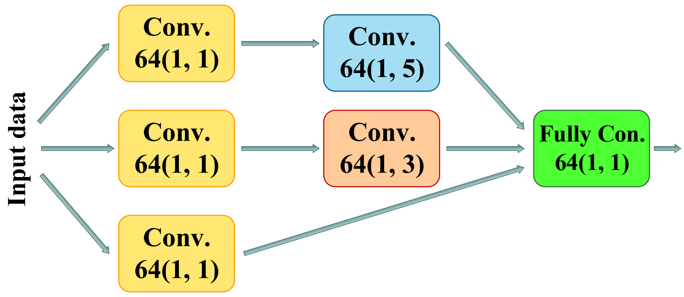


Fig. 6. The proposed module which is inspired by the inception module.

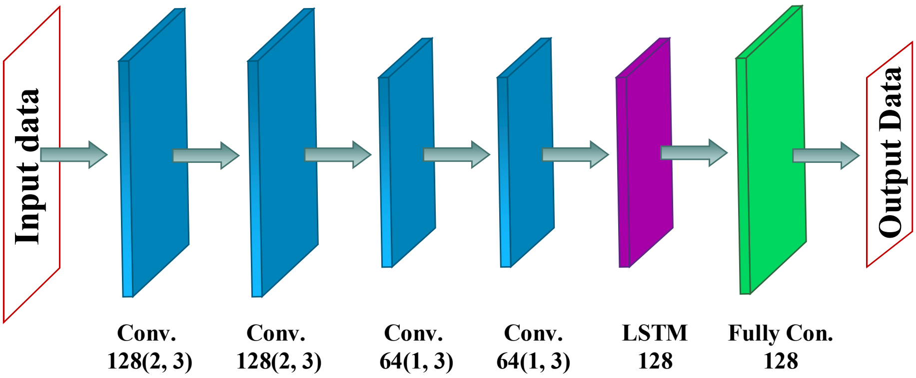


Fig. 7. The proposed CLDNN network.

## 3- 3- Recurrent Neural Network

Many of the available data is time series. The most popular data of this type are audio, speech, video, text and financial data. Recurrent Neural Networks are a type of neural network designed to process this type of series data and allow previous outputs to be used as current inputs. In a simple neural network, the inputs are considered independent, and no information about the previous state remains in the network. In Recurrent Neural Networks, this problem is solved by adding a loop that allows information to remain within the network. This type of neural network has been used in sound recognition, language modeling, and image captioning.

Most of these success has been achieved with Long-Short Term Memory (LSTM), which is a type of recurrent network. The advantages of this network include processing the input with any length, not increasing the size of the model by increasing the size of the input, considering the past information in the current calculation, and the same weights over time. However, recurrent networks do not have long-term dependence in practice due to the vanishing and exploding gradients. To solve this problem, certain types of gates are used in some types of recurrent neural networks. LSTM is a type of recurrent network that uses these gates to solve vanishing and exploding gradient problems.

In the next step, Convolutional Long Short-term Memory Deep Neural Network (CLDNN) architecture was used. This architecture was introduced in 2015 [28]. The network consists of a sequential combination of a convolutional network, an LSTM network, and a fully connected network. This architecture extracts both local and temporal features; thus it is expected that the results obtained through this architecture be better than networks that use only one feature. After adjusting the parameters, the proposed model for this architecture is a network with four convolutional layers, one LSTM layer, and one fully connected layer, which is shown in Fig. 7. In the last step, instead of connecting the convolutional layers and the LSTM layers being connected one after the other, they are parallelized and their outputs are concatenated.

**Table 1. Summary of dataset parameters**

| Modulation | **BPSK, QPSK, 8PSK, 16QAM, 64QAM, 4PAM, GFSK, CPFSK** |
|---|---|
| Sample per symbol | **8** |
| Length of sample | **128** |
| SNR | **-20dB to +20dB** |
| Number of training data | **12800** |
| Number of testing data | **3200** |

## 4- Simulation and Discussion

This section describes the dataset that have been used for simulation. Afterwards, the simulation settings and training presumptions are declared. Finally, numerical results and discussion are given.

### 4- 1- Dataset

This paper uses the dataset presented in [29], which has been used in several articles such as [8, 17, 19, 30-35]. This dataset includes modulated signals generated by GNU Radio. In this dataset, the sample length is 128, and each sample contains eight symbols. These data have several effects, such as central frequency deviation, sample rate deviation, fading, and Additive White Gaussian Noise (AWGN).

Each time signal generated using rectangular windows is slice to a length of 128. Additionally, the energy of each sample is normalized to one. Each sample is stored in two dimensions corresponding to I/Q components as a matrix of 2 × 128. Furthermore, the SNR is varied between -20dB to +20dB with step 2. This paper considers eight types of digital modulation, including BPSK, QPSK, 8PSK, 16QAM, 64QAM, 4PAM, GFSK, and CPFSK. In this dataset, there are 1000 samples for each modulation in each SNR. The total amount of data is 160,000 two-row matrix, which 80% of it is training set, and the rest is test set. The dataset is stored as a python pickle file with complex 32-bit floating-point samples. The summary of the parameters of the dataset is shown in Table 1.

### 4- 2- Hardware and Training Presumption

All simulations were performed in the Google Colab environment, using the Tesla K60 GPU. Codes, including preprocessing and neural network models are written in Python 3 using the Keras 2.2.4 library. All codes in Colab Notebook format are available at github.com/MohsenJadidi. Adam optimizer categorical cross-entropy error function, softmax activation function in the last layer, and Rectified Linear Unit (ReLU) function for other layers have been used for training the models. The networks input data are matrices with dimensions of 2 × 128, and since eight types of modulation classes are assumed, the output layer has eight neurons.

### 4- 3- Numerical Results

The highest accuracy obtained for the vanilla neural network in the high SNRs is 70%. The network was trained in 15 minutes. In general, when the signal power is less than the noise power, the neural network cannot recognize the type of modulation. Whenever signal power increases, the accuracy of the network increases as well. One instance of a network confusion matrix is shown in Fig. 8. In the confusion matrix, each matrix row represents the true class while each column represents a predicted class. For instance, consider the 4PAM modulation. This modulation has been correctly identified in 83% of the cases, but in 17% of the cases it has been recognized as a BPSK modulation. Note that the test time is fast and does not depend very much on the used model. In general, the training time is the main issue in neural networks, and the test time is trivial. In training phase, all training data is given to the network several times (in our work, 12,800 data are given to the network 100 times), and calculations are needed to update the weights. In comparison to the test phase, only one data is given to the network, and the network output is determined.

The convolutional neural network proposed in [17], shown in Fig. 2, was trained and 82% accuracy was obtained. Various network parameters are evaluated to find the best Convolutional Neural Network. Fig. 9 shows the accuracy of convolutional networks with a different number of convolutional layers versus SNR. In low SNRs, all models have low accuracy and cannot recognize the modulation type. By adding a convolutional layer, the accuracy is increased to reach a maximum in five layers, and later the accuracy is reduced by adding a convolutional layer due to vanishing gradients. Additionally, with the increase of layers, the training time and convergence of network accuracy will be longer. The proposed convolutional network model in Fig. 3 has a 92% accuracy, which is an improved 10%. The network was trained in 110 minutes. The accuracy of this network is 20% better than the vanilla neural network. One instance of

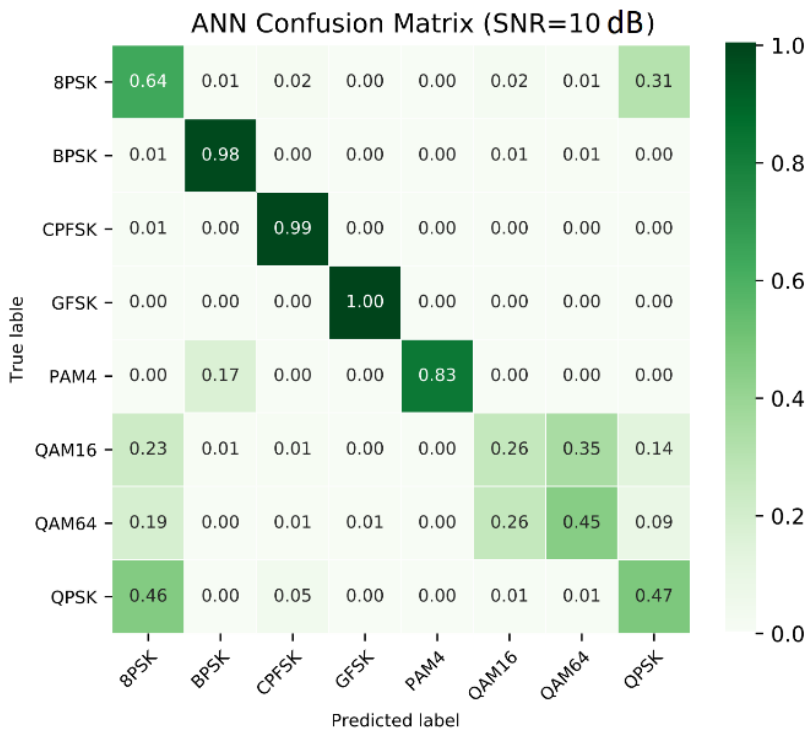


**Fig. 8. Confusion matrix of proposed neural network at SNR= +10dB.**

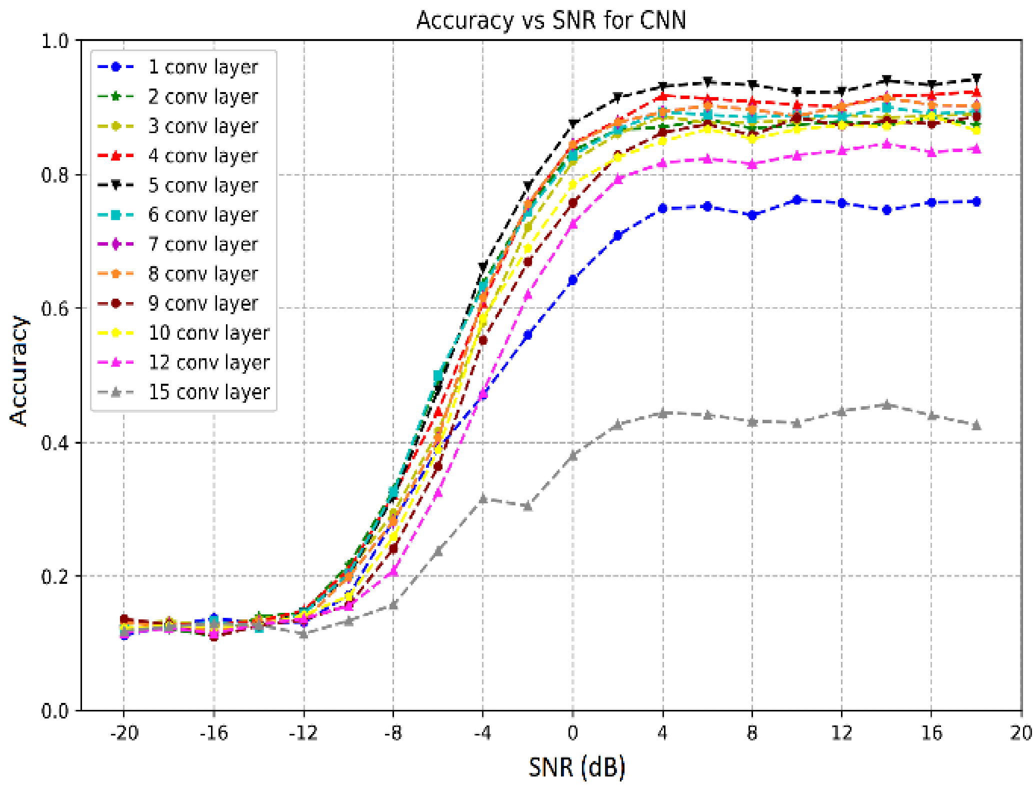


**Fig. 9. Accuracy versus SNR for the convolutional network with changing the number of layers.**

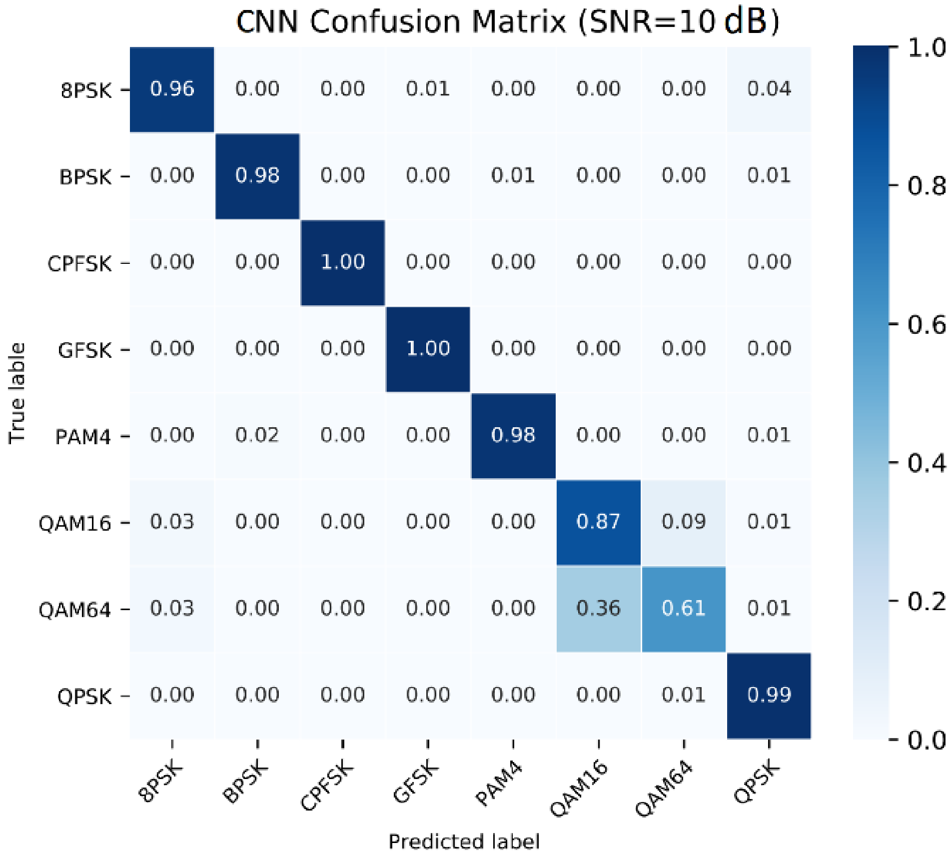


**Fig. 10. Confusion matrix of proposed convolutional network in Fig. 3 at SNR = +10dB.**

the confusion matrix of this model is shown in Fig. 10. The most significant classification error occurs in distinguishing between QPSK and 8PSK, and between 16QAM and 64QAM. This inaccuracy is due to the similarity of these modulations constellations and the closeness of the symbols to another, making the network unable to learn the difference between them properly.

The proposed densely neural network model was trained and the accuracy reached 92.4%. The network was trained in 150 minutes. Due to shortcuts, computing has increased and Densely networks have more training time than their corresponding convolutional networks. One instance of a network confusion matrix is shown in Fig. 11. The simulations showed that the densely networks are more accurate in the same number of layers than the convolutional networks, and have less convergence time.

The inception network model, which has several modules in the form of Fig. 6, was trained and 79% accuracy was achieved. The network was trained in 45 minutes. The inception network is more accurate than the vanilla neural network, but less accurate than the convolutional network.

Simple recurrent neural networks and networks composed only of LSTM layers did not achieve acceptable accuracy. For a simple recurrent neural network, 62% accuracy was achieved, and for an LSTM neural network, it was 69%. As mentioned, simple recurrent networks are not long-term dependent; therefore, their low accuracy was expected. LSTM networks are more accurate than recurrent neural networks, but both have low accuracy in general. LSTM networks extract the time features input. Therefore, it can be concluded that acceptable accuracy cannot be achieved by using time features alone. It should be noted that both networks have much less training time than the previous networks.

With the training of CLDNN parallel type model, the accuracy reached 92%. This network was trained in 60 minutes. Additionally, the proposed CLDNN network, which is shown in Fig. 7, has 98% accuracy. The training time for this network was 105 minutes. This architecture extracts the temporal features of the data (something that did not exist in previous architectures), hence an increase in accuracy was expected compared to previous architectures. It should be noted that this model extracts the temporal features of the features that were extracted by the convolutional neural network. In fact, the input of the LSTM layer in the CLDNN model is the spatial features of input that were obtained by the convolutional neural network. Two instances of this model's confusion matrix are shown in Fig. 12. Fig. 13 shows the accuracy of the best models examined as a function of SNR. As can be illustrated, the CLDNN model is the most accurate of the studied models. The accuracy is drawn according to

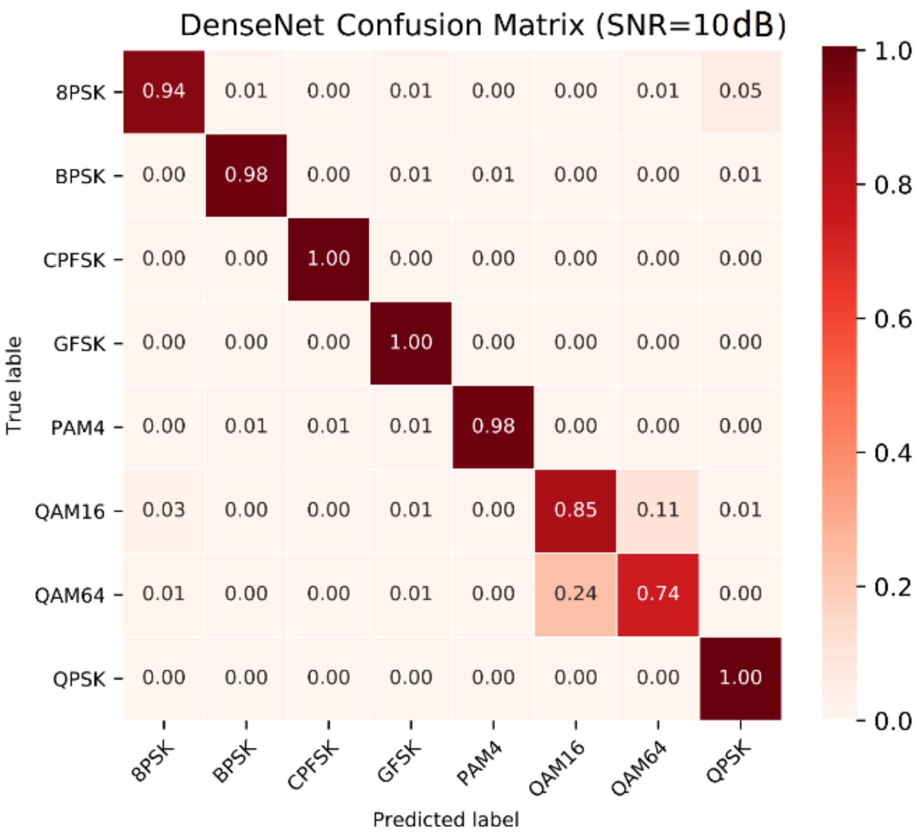


**Fig. 11. Confusion matrix of proposed denesly network in Fig. 4 at SNR = +10dB.**

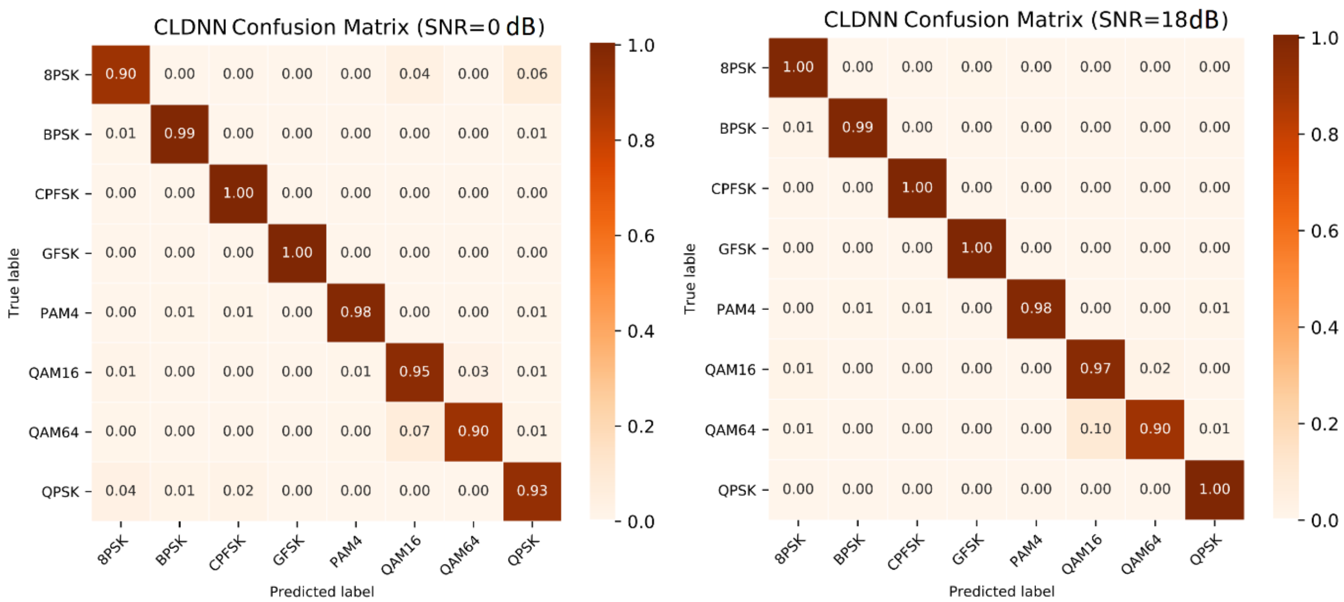


**Fig. 12. Confusion matrix of proposed CLDNN in Fig. 7 at SNR=+18dB and 0dB.**

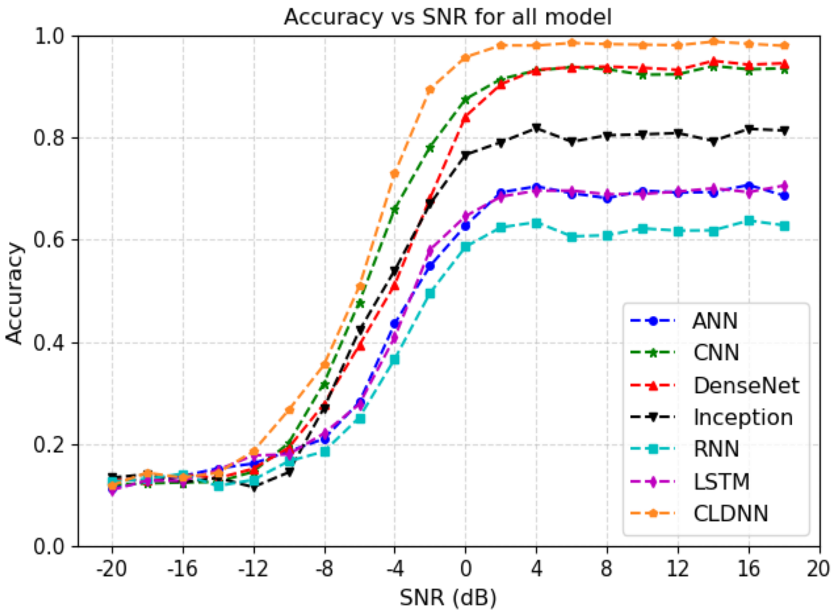


**Fig. 13. Accuracy versus SNR for all architectures that studied.**

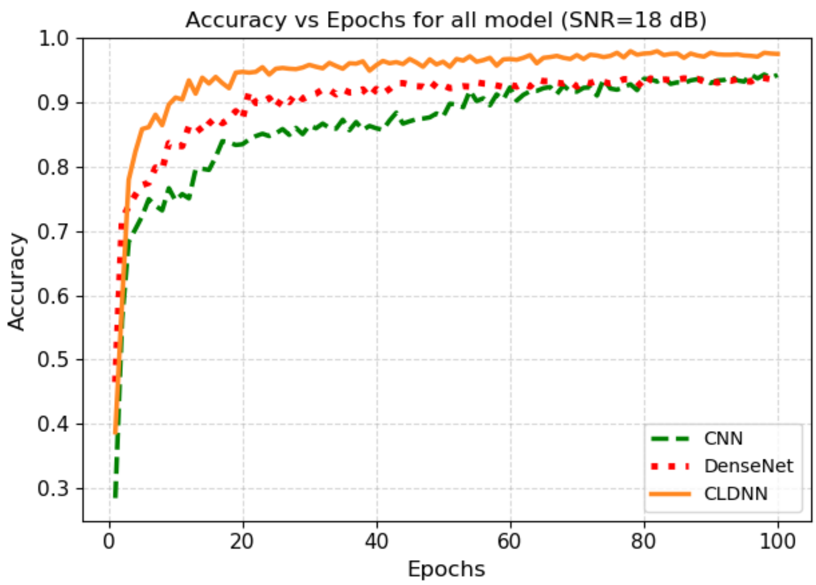


**Fig. 14. Accuracy versus epoch for architectures that have high accuracy**

the period in Fig. 14 for the three models with an accuracy of over 90%. CLDNN model has a higher convergence rate.

## 5- Conclusion

We studied seven deep learning neural network architectures for automatic modulation recognition in this paper. Eight types of digital modulation were considered as a dataset in the form of in-phase and quadrature components. More than 150 models were trained and tested. The trained models have high accuracy and gain some advantages compared to the traditional methods due to less complexity of their preprocessing. The simulation results show that the accuracy of the vanilla neural network did not exceed over 70%. The best accuracy among convolutional networks was about 90%. As the depth of the convolutional network increased, the accuracy decreased, and convergence time increased; hence, DenseNet was used. Moreover, it is observed that the inception network achieves an accuracy of about 80%. On the other hand, the recurrent network and the LSTM network did not have acceptable accuracy. Eventually, the CLDNN network has been investigated. It is shown that this network provides 98% accuracy, which was the best accuracy among the models.

## References

[1] A. K. Nandi and E. E. Azzouz, "Automatic analogue modulation recognition," Signal processing, vol. 46, no. 2, pp. 211-222, 1995.

[2] Z. Zhu and A. K. Nandi, Automatic modulation classification: principles, algorithms and applications. John Wiley & Sons, 2015.

[3] N. Ghani and R. Lamontagne, "Neural networks applied to the classification of spectral features for automatic modulation recognition," in Proceedings of MILCOM'93-IEEE Military Communications Conference, 1993, vol. 1, pp. 111-115: IEEE.

[4] M. D. Wong and A. K. Nandi, "Automatic digital modulation recognition using spectral and statistical features with multi-layer perceptrons," in Proceedings of the sixth international symposium on signal processing and its applications (Cat. No. 01EX467), 2001, vol. 2, pp. 390-393: IEEE.

[5] G. Arulampalam, V. Ramakonar, A. Bouzerdoum, and D. Habibi, "Classification of digital modulation schemes using neural networks," in ISSPA'99. Proceedings of the Fifth International Symposium on Signal Processing and its Applications (IEEE Cat. No. 99EX359), 1999, vol. 2, pp. 649-652: IEEE.

[6] I. A. H. El Rube and N. E.-d. El-Madany, "Cognitive digital modulation classifier using artificial neural networks for NGNs," in 2010 Seventh International Conference on Wireless and Optical Communications Networks-(WOCN), 2010, pp. 1-5: IEEE.

[7] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, "Survey of automatic modulation classification techniques: classical approaches and new trends," IET communications, vol. 1, no. 2, pp. 137-156, 2007.

[8] S. Peng et al., "Modulation classification based on signal constellation diagrams and deep learning," IEEE transactions on neural networks and learning systems, vol. 30, no. 3, pp. 718-727, 2018.

[9] A. E. El-Mahdy and N. M. Namazi, "Classification of multiple M-ary frequency-shift keying signals over a Rayleigh fading channel," IEEE Transactions on Communications, vol. 50, no. 6, pp. 967-974, 2002.

[10] F. Hameed, O. A. Dobre, and D. C. Popescu, "On the likelihood-based approach to modulation classification," IEEE Transactions on Wireless Communications, vol. 8, no. 12, pp. 5884-5892, 2009.

[11] A. K. Nandi and E. E. Azzouz, "Algorithms for automatic modulation recognition of communication signals," IEEE Transactions on communications, vol. 46, no. 4, pp. 431-436, 1998.

[12] Z.-L. Tang, S.-M. Li, and L.-J. Yu, "Implementation of deep learning-based automatic modulation classifier on FPGA SDR platform," Electronics, vol. 7, no. 7, p. 122, 2018.

[13] E. E. Azzouz and A. K. Nandi, "Modulation recognition using artificial neural networks," in Automatic Modulation Recognition of Communication Signals: Springer, 1996, pp. 132-176.

[14] Z. Wu, X. Wang, Z. Gao, and G. Ren, "Automatic digital modulation recognition based on support vector machines," in 2005 International Conference on Neural Networks and Brain, 2005, vol. 2, pp. 1025-1028: IEEE.

[15] M. W. Aslam, Z. Zhu, and A. K. Nandi, "Automatic modulation classification using combination of genetic programming and KNN," IEEE Transactions on wireless communications, vol. 11, no. 8, pp. 2742-2750, 2012.

[16] X. Lin, R. Liu, W. Hu, Y. Li, X. Zhou, and X. He, "A deep convolutional network demodulator for mixed signals with different modulation types," in 2017 IEEE 15th Intl Conf on Dependable, Autonomic and Secure Computing, 15th Intl Conf on Pervasive Intelligence and Computing, 3rd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), 2017, pp. 893-896: IEEE.

[17] T. J. O'Shea, J. Corgan, and T. C. Clancy, "Convolutional radio modulation recognition networks," in International conference on engineering applications of neural networks, 2016, pp. 213-226: Springer.

[18] A. P. Hermawan, R. R. Ginanjar, D.-S. Kim, and J.-M. Lee, "Cnn-based automatic modulation classification for beyond 5g communications," IEEE Communications Letters, vol. 24, no. 5, pp. 1038-1041, 2020.

[19] 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, 2018.

[20] M. Alameh, Y. Abbass, A. Ibrahim, G. Moser, and M. Valle, "Touch Modality Classification Using Recurrent Neural Networks," IEEE Sensors Journal, 2021.

[21] X. Liu, D. Yang, and A. El Gamal, "Deep neural network architectures for modulation classification," in 2017 51st Asilomar Conference on Signals, Systems, and Computers, 2017, pp. 915-919: IEEE.

[22] R. Zhou, F. Liu, and C. W. Gravelle, "Deep learning for modulation recognition: a survey with a demonstration," IEEE Access, vol. 8, pp. 67366-67376, 2020.

[23] R. M. Al-Makhlasawy, A. A. Hefnawy, M. M. Abd Elnaby, and F. E. Abd El-Samie, "Modulation classification in the presence of adjacent channel interference using convolutional neural networks," International Journal of Communication Systems, vol. 33, no. 13, p. e4295, 2020.

[24] A. Shrestha and A. Mahmood, "Review of deep learning algorithms and architectures," IEEE Access, vol. 7, pp. 53040-53065, 2019.

[25] I. Goodfellow, Y. Bengio, and A. Courville, Deep learning. MIT press, 2016.

[26] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional

networks," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 4700-4708.

[27] C. Szegedy et al., "Going deeper with convolutions," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 1-9.

[28] T. N. Sainath, O. Vinyals, A. Senior, and H. Sak, "Convolutional, long short-term memory, fully connected deep neural networks," in 2015 IEEE international conference on acoustics, speech and signal processing (ICASSP), 2015, pp. 4580-4584: IEEE.

[29] T. J. O'shea and N. West, "Radio machine learning dataset generation with gnu radio," in Proceedings of the GNU Radio Conference, 2016, vol. 1, no. 1.

[30] N. E. West and T. O'Shea, "Deep architectures for modulation recognition," in 2017 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN), 2017, pp. 1-6: IEEE.

[31] 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, 2018.

[32] M. Sadeghi and E. G. Larsson, "Adversarial attacks on deep-learning based radio signal classification," IEEE Wireless Communications Letters, vol. 8, no. 1, pp. 213-216, 2018.

[33] Y. Zeng, M. Zhang, F. Han, Y. Gong, and J. Zhang, "Spectrum analysis and convolutional neural network for automatic modulation recognition," IEEE Wireless Communications Letters, vol. 8, no. 3, pp. 929-932, 2019.

[34] S. Hu, Y. Pei, P. P. Liang, and Y.-C. Liang, "Deep neural network for robust modulation classification under uncertain noise conditions," IEEE Transactions on Vehicular Technology, vol. 69, no. 1, pp. 564-577, 2019.

[35] W. Lee, M. Kim, and D.-H. Cho, "Deep power control: Transmit power control scheme based on convolutional neural network," IEEE Communications Letters, vol. 22, no. 6, pp. 1276-1279, 2018.

**HOW TO CITE THIS ARTICLE**

*M. M. Jadidi, A. Mohammadi, Deep Learning for Recognition of Digital Modulations: A Detailed Study, AUT J. Elec. Eng., 54(1) (2022) 67-78.*

**DOI:** 10.22060/eej.2021.19826.5409