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VISIÓN ELECTRÓNICA

A RESEARCH VISION

Design and implementation of a digital modulation classification system using intelligent algorithms

Diseño e implementación de un Sistema de clasificación de modulaciones digitales usando algoritmos inteligentes

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ABSTRACT

Neural networks present a variety of applications, among them is the classification of modulations for application un cognitive radio. This area has been studied over the years because the work of both technologies facilitates the administration and optimization of the radio spectrum. In this research, a dataset composed of 6 different types of digital modulations obtained by software for training a proposed neural network in search of the classification of signals for application in cognitive radio networks. The model is evaluated by being trained and tested with the dataset created in this study, analyzing metrics such as percentage error and precision.

RESUMEN

Las redes neuronales presentan una gran variedad de aplicaciones, entre ellas se encuentra la clasificación de modulaciones para aplicación en radio cognitivo. Esta área ha sido estudiada a lo largo de los años porque el trabajo conjunto de ambas tecnologías facilita la administración y optimización del espectro radioeléctrico. En esta investigación se propone un dataset compuesto de seis tipos de modulaciones digitales diferentes obtenidas mediante software para el entrenamiento de redes neuronales en búsqueda de la clasificación para la aplicación en radio cognitivo, evaluando un modelo de red neuronal entrenado y probado con el dataset creado en esta investigación, mediante métricas de porcentaje de error y precisión.

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1. Introduction

The radio spectrum is a non-renewable natural resource that plays a vital role in telecommunications and cannot be wasted, for that reason, over the years research has been conducted in search of optimizing spectrum waste [1]. In 1999 it is proposed for the first time that wireless communication can manage the use of the spectrum according to the needs of users using new optimization methods in the use of the spectrum [2][3], this opens the way to the term cognitive radio that uses statistical algorithms responsible for the classification of signals in search of a correct management of the spectrum. In 1999 some of the first researches in classification are evidenced of digital modulations using neural networks [4][5] presents a new method for automatic classifiers, which, at the time, used mathematical and statistical algorithms to achieve good prediction.

Automatic modulation classifiers are mainly categorized by probability-based and feature-based classifiers [6], probability-based classifiers compare the received signal with a predetermined value using an algorithm, while feature-based classifiers extract the qualities of the received signal and compare them with values similar to already known signals to make the classification [7]. Neural networks as signal classifiers are similar to feature-based classifiers with the difference that, depending on the type of neural network, it will determine the type of features that are extracted along with how the signal is processed for classification.

The combination of neural networks and the possibility of linking it with cognitive radio represents a great importance since, being the receiver capable of recognizing the type of signal, it is not necessary for the transmitter to include additional information of the type of modulation it is transmitting [8]. Following in this reasoning, in 2016 appears the proposal of a deep neural network or better known in English as Deep Neural Network (DNN) for the classification of different types of modulation both digital and analog in search of testing the effectiveness of this for application in cognitive radio working with the dataset "Deepsig Dataset:RadioML 2016.10A" [9] being the most robust at the time with 11 different types of modulations generated by simulation, opening doors to the research of neural networks focused on cognitive radio application as they do in [10]. If although it is true that the dataset proposed in [8] contemplated a great variety of signals, it lacks adverse effects that a signal faces in a real environment and for this reason in 2018 and the dataset "Deepsig Dataset:RadioML 2018.01A" [11] was created, composed of 24 types of digital and analog modulations that were transmitted in a controlled environment, testing convolutional neural network models with a considerable amount of real signals; used in different investigations [12-14]. These investigations propose adjustments in the neural network models looking for effectiveness and better extracting the characteristics of the signals or transforming the training data.

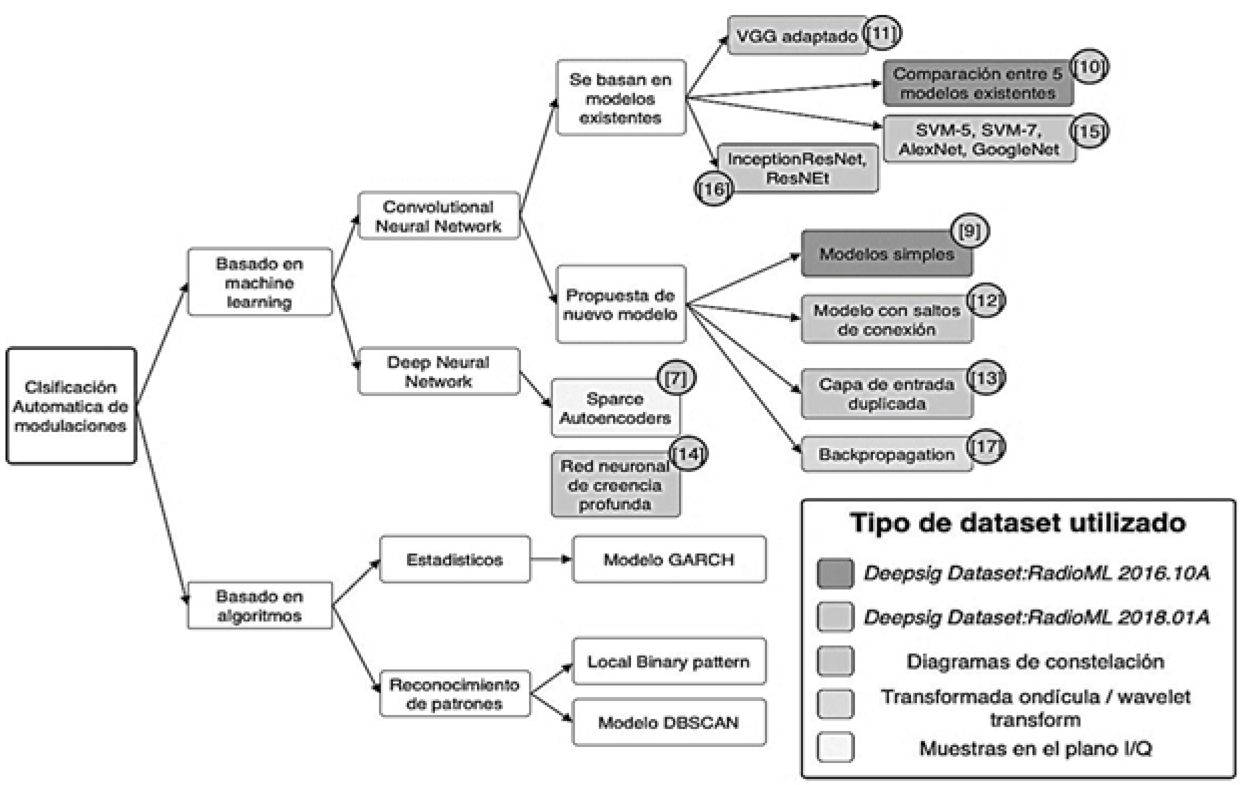
It should be noted that the training of the convolutional neural networks mentioned above was not performed with images, but with samples in the I/Q plane, and this is possible since this plane comprises 2 dimensions as well as a black and white image, in addition, training with images can result in models with millions of parameters and hundreds of thousands of neurons, which leads to changes in the images. In [15] they perform the classification of digital modulations using the constellation diagram by taking the image and transforming it for comparison, first a black and white diagram is worked, then it goes through a processing that enhances the points of the diagram and finally the same image is enhanced but in color, being the option with the best accuracy of the three. In [16] a GoogleNet model is presented being trained with constellation diagrams of PSK modulation at low SNR obtaining excellent results. In other cases, the wavelet transform is used as a parameter in the classification of signals being the case of [17] where using Matlab they generate the transform of 6 types of modulation different signals to then be subjected to training in a convolutional neural network. To better appreciate the distribution of the signal classifiers, a diagram shown in Figure 1, where two methods used in this application are presented together with the proposals of the previously cited articles and the type of dataset they have used.

It is important to note that over the years techniques have been implemented to classify different types of signals to work together with cognitive radio, the reason for this search is that cognitive radio alone identifies whether the spectrum is being used without obtaining any additional information from the channel [18-20], thanks to the joint work of a classification method cognitive radio would be able to identify the type of signal or even the user who is making use of the spectrum [21]. That is why this research presents the neural network model InceptionResNetV2 that classifies different types of digital modulation that would help the cognitive radio, likewise a dataset of images of constellation diagrams of 6 different types of digital modulations that are BPSK, QPSK, 8PSK, 16QAM, 32QAM and 64QAM obtained by simulation in GNURadio and Matlab was built building a dataset of 1377 training images and 462 test images. This document presents a documentary contextualization in its introduction; section 2 shows the proposed methodology for network design and dataset acquisition. Section 3 presents the results obtained and their analysis and finally the conclusions in section 4.

2. Methodology

The research proposes a development methodology and is shown in Figure 2. 3 work phases are defined for the implementation of the digital modulation classifier system. In phase 1 a documentary compilation and the

Figure 1. Diagram of the state of the art



Source: Own.

state of the art was performed and summarized in Figure 1. Phase 2 was defined to obtain the signals using the GNURadio software and to obtain the corresponding constellation diagram of each signal using the Matlab software this allowing to create the dataset for the training and testing stages. Finally, phase 3 evaluates the network using the percentage error and accuracy metrics in conjunction with the confusion matrix to determine its performance.

Figure 2. Methodology diagram

Source: Own.

2.1. Design and implementation phase

2.1.1. Signal generation

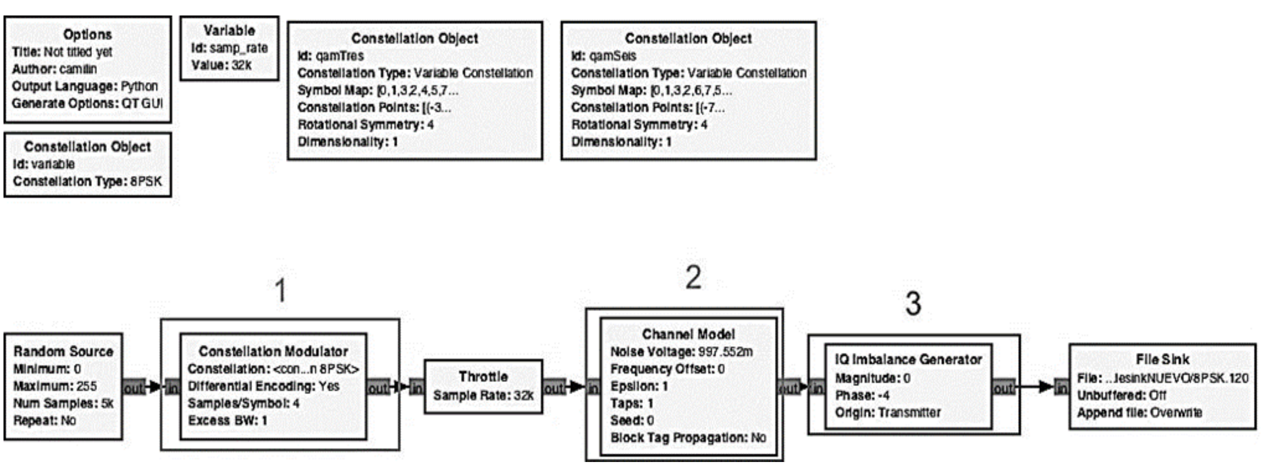
GNURadio, a free software that provides a set of tools for the implementation of block radios, is used to generate the signals. In addition, it can be used with external RF hardware at low cost to create software defined radio or without hardware in a fully simulated environment [22]. Once the signal samples generated by GNURadio are obtained, it is ensured that the constructed signals were all different taking into account 3 aspects: The random generation of 5000 sample points, signal offset varying from -4º to +4º with steps of 1º and the signal to noise ratio change from 0 dB to +30 dB with steps of 1 dB. The block diagram constructed for the elaboration of the samples complying with the parameters already mentioned is shown in Figure 3, where the 6 types of modulation BPSK, QPSK, 8PSK, 16QAM, 32QAM and 64QAM are generated.

2.1.2. Obtaining the constellation diagram

Matlab is a platform for numerical calculations used in the design and analysis of technological systems [23], which in this research allowed the processing of the signal samples to then obtain the constellation diagrams as an image.

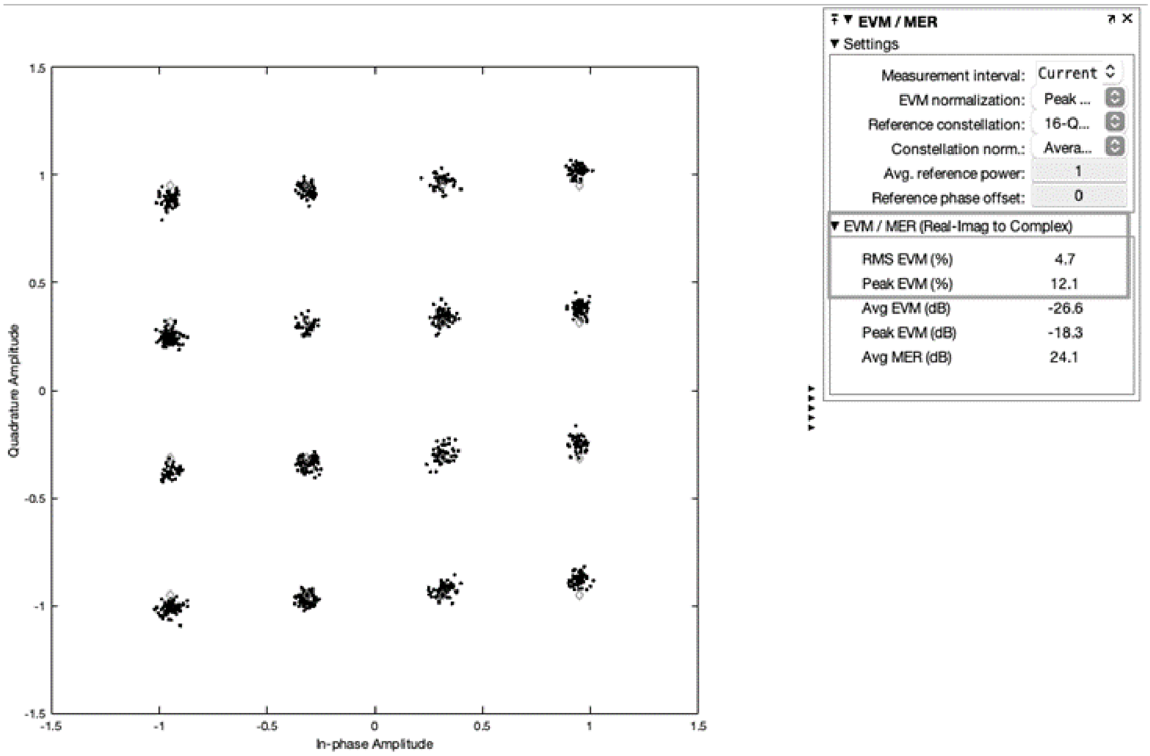
The signal samples in the I/Q plane are processed by code to be separated in each plane and subsequently generate the constellation diagram with the help of the constellation viewer, a tool that allows us to observe parameters of the error vector magnitude (EVM). Figure 4 shows the constellation diagram represented by black dots and their respective EVM measurements can be seen in the box on the right. The constellation shown corresponds to a 16QAM signal with a signal to noise ratio of +14dB and an offset of +4º, these

Figure 3. Block diagram in GNURadio



Source: Own.

Figure 4. Constellation viewer in Matlab



Source: Own.

parameters cannot be visualized in the Matlab interface.

This process is repeated for all the samples of all the signals and 1839 images are obtained in PNG format without a specific order waiting to be categorized in the elaboration of the dataset.

2.1.3. Elaboration of the dataset

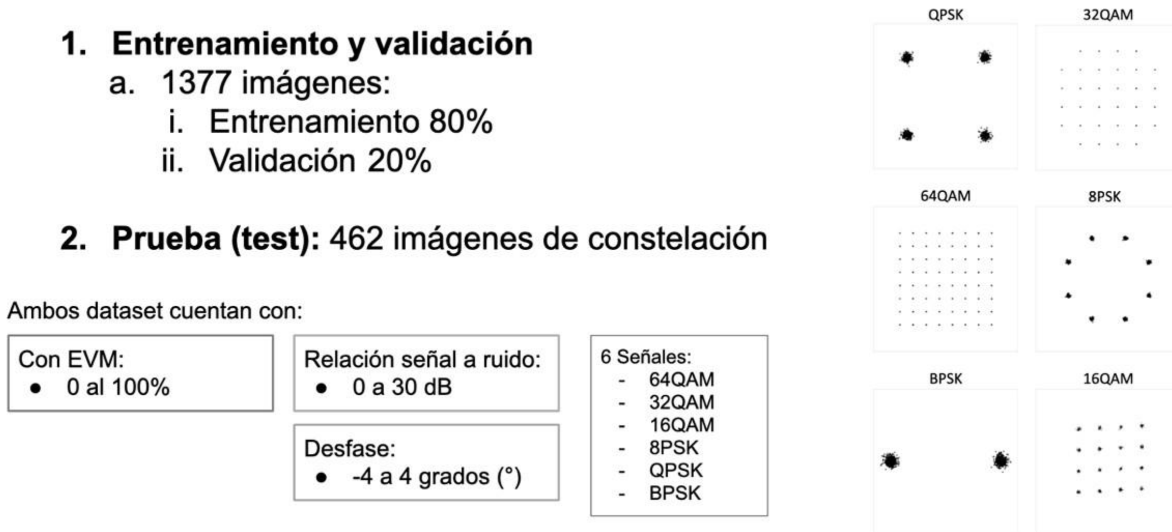
The dataset must be composed of at least two parts: training and test. For training of 1839, 1377 images are destined, corresponding to 75% and 462 for testing, which will be organized in folders labeled with the name of the corresponding modulation scheme, thus obtaining the complete dataset for this project. The dataset is made up of images in PNG format of the constellation diagrams of 6 types of digital modulations with a size of 600x600 pixels, which are divided to form a dataset for the training phase and another one for the testing phase. It should be noted that the training dataset is divided in the training phase by means of code to obtain 20% of its distribution for validation without the need to create a new dataset. Table 1 shows the distribution of images of the training dataset for each type of modulation selected for this research. In the test dataset there are 77 images per modulation giving a total of 462 images.

Table 1. Distribution of images by dataset and modulation.

Modulation Scheme	Training Dataset
BPSK	228
QPSK	227
8PSK	226
16QAM	236
32QAM	232
64QAM	228
Total	1377

Source: Own.

Figure 5. Dataset and image characteristics



Source: Own.

Dataset characteristics such as EVM range, SNR and phase shift can be seen in Figure 5 along with evidence of the constellation diagram of each modulation. The dataset entitled "Digital Modulation Constellation Images" can be downloaded from [24].

2.1.4. Model selection

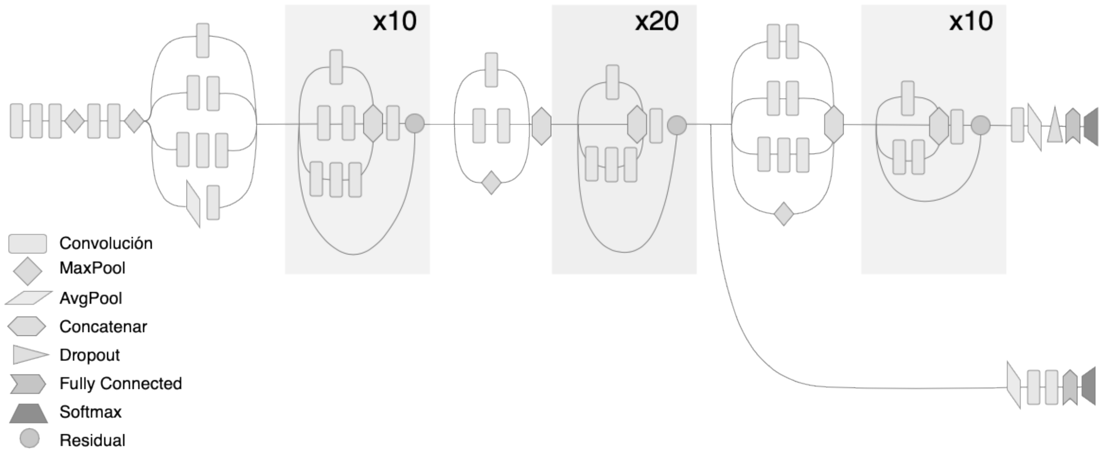
Convolutional neural networks are ideal for solving classification problems with images, it is true that they can cover a wide variety of applications, however, it is necessary to have some power in image processing as there is a wide difference in the time it takes to train the network when it is done only in the central processing unit (CPU) compared to the graphics processing unit (GPU), for this reason, using the online tool Google Colab training and testing of the neural network is performed without the need for a computer with GPU.

For this case, the InceptionResNetv2 network [25] was used as a reference, where the combination of the Inception networks, which seek to have shallow models to improve the amount of processed load, and the residual ResNet networks, known for being deep and of high computational cost, is exposed. Both bring with them a problem, inception being computationally light, its performance when classifying is not the best and ResNet being very deep, the optimization becomes more complex in order to avoid overfitting, a drawback produced in neural networks when they become very good at classifying images similar to the training ones, but not very good when trying to catalog images with some differences to the training ones. For this reason, InceptionResNetv2 being a combination of power and optimization, becomes a test candidate in modulation classification as occurs in [16] demonstrating its effectiveness. An example of this is shown in Figure 6 [26].

2.1.5. Evaluation metrics

Considering that parameters must be measured to define how good the network is at predicting, the confusion matrix and the accuracy percentage are used. The confusion matrix shows the number of predictions of the network by category versus the actual category, Figure 7 shows an example of a confusion matrix where the horizontal axis corresponds to the network prediction and the vertical axis to the true category, the light color shows that there are more images

Figure 6. Dataset and image characteristics



Source: Improving Inception and Image Classification in TensorFlow [26].

Figure 7. Confusion matrix

Source: Own.

classified in that category than in the dark colors so a diagonal line is to be expected as shown in Figure 7 when the results are ideal, it is also accompanied by a numerical indicator that quantifies the number of images in that section.

The percentage error and accuracy metrics are obtained from the confusion matrix, equation (1) and equation (2), where the percentage error and accuracy are calculated as follows according to how many are correctly classified, the variables VP(True Positive), VN (True Negative), FP(False Positive), FN (False Negative). On the other hand, the neural network is also able to calculate these metrics with the keras error algorithm "Sparce categorical crossentropy" which performs a comparison between the actual value labels with the predictions of each category, this can lead to higher error rates [27].

$$Error = \frac{FP+FN}{VP+VN+FP+FN} * 100 \quad (1)$$

$$Precisión = \frac{VP+VN}{VP+VN+FP+FN} * 100 \quad (2)$$

Table 2 Percentage error and accuracy for the InceptionResNetV2 model

Percentage of error (%)	Accuracy percentage (%)
18.18	81.81

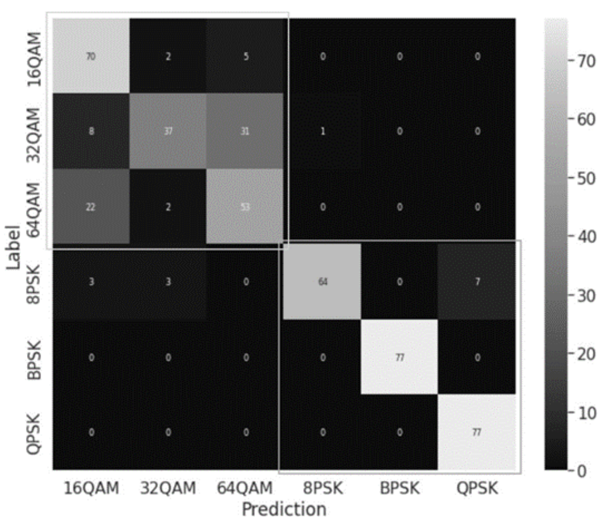
Source:Own.

3. Analysis of results

By training the InceptionResNetV2 network with the dataset created in section 2.1.3, the classification accuracy can be tested with the test dataset. In this test 77 images are classified by digital modulation and resulting in the confusion matrix shown in Figure 8.

As can be seen in Figure 8, the network presents confusion in classifying 32QAM and 64QAM modulations; however, it is able to classify at least 64 or more constellations in the other categories. The classification accuracy and error of the whole network can be calculated using equation (1) and equation (2) presented in section 2.1.5. Table 2 shows the results of percentage error and percentage accuracy for the matrix in Figure 8.

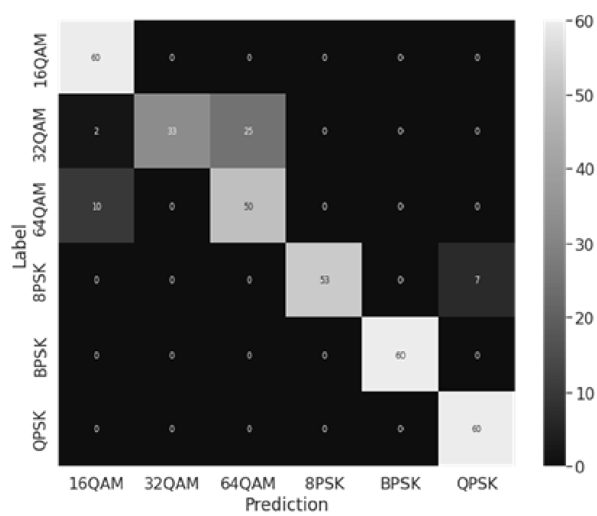
Figure 8. Confusion matrix of the InceptionResNetV2 model.

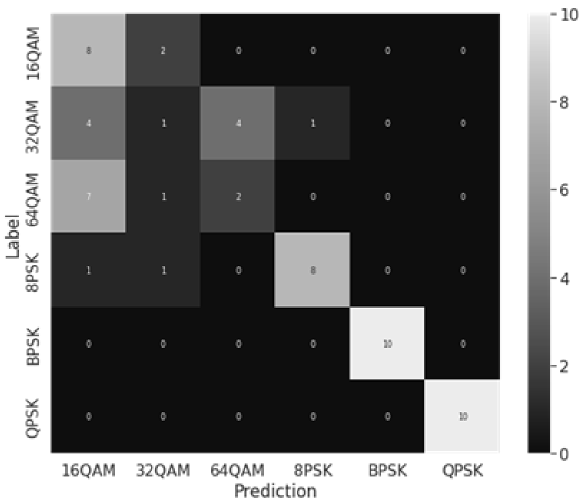


Source: Own.

Once the network has been evaluated, an accuracy percentage above 81% is obtained for all EVM levels. It is not possible to deduce if at higher EVM levels this accuracy increases or decreases, this leads to segment the test dataset in 4 ranges according to the EVM of the signals, performing 4 tests to find the effectiveness of the network to classify at different EVM levels. Figure 9 shows the confusion matrix in the EVM range between 0% and 25% on the left side and on the right side for the range between 25% and 50%, from similarly, Figure 10 shows the confusion matrix for the range between 50% and 75% on the left side and on the right side for the range between 75% and 100%.

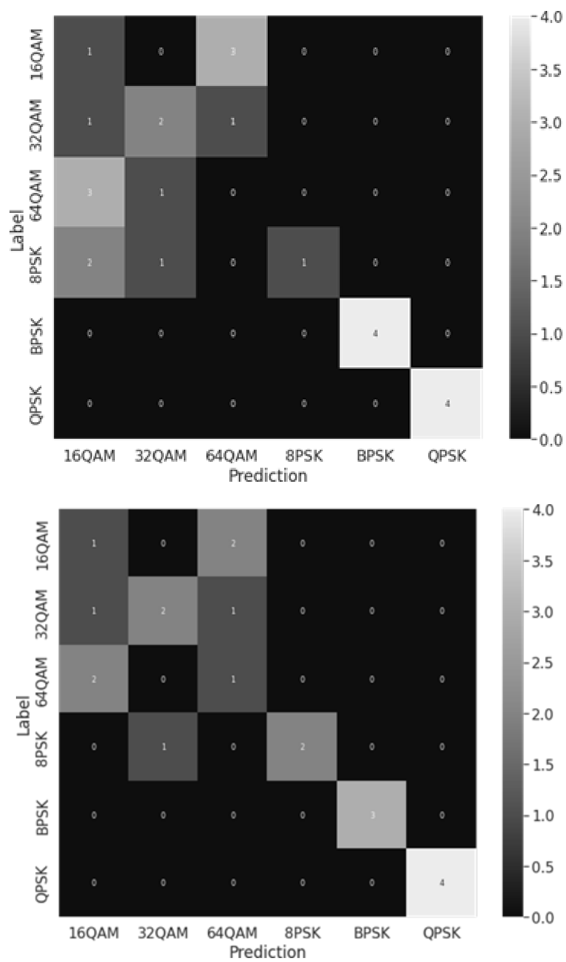
Figure 9. Confusion matrix in the EVM range from 0% to 25% (left) and from 25% to 50% (right).





Source: Own.

Figure 10. **Confusion matrix in the EVM range from 50% to 75% (left) and from 75% to 100% (right).**



Source: Own

Thanks to the confusion matrix it is possible to calculate the error and precision with equation 1 and 2, the results are shown in table 3.

Table 3 **Percent error and accuracy for the InceptionResNetV2 model**

InceptionResNetV2 Model		
EVM Range	Percentage of error (%)	Accuracy percentage (%)
Full range	18.18	81.81
0% - 25%	12.22	87.77
25% - 50%	35.00	65.00
50% - 75%	50.00	50.00
75% - 100%	45.83	54.16

Source: Own.

The results obtained show a decrease in the classification accuracy when the EVM increases, this is due to the fact that at higher EVM levels the signal contains high levels of noise and the constellation points are so dispersed that it is not possible to distinguish which type of modulation it belongs to, likewise, when EVM levels are below 25% the classification accuracy exceeds 87%, which is above the general classification percentage of all signals.

4. Conclusions

Within the different types of digital modulations studied in this research, it is identified that there is ease in classification for BPSK, QPSK, 8PSK and 16QAM modulation schemes versus 32QAM and 64QAM, which leaves open for future research the search for new models and processes capable of improving the general indiscriminate classification of digital modulation schemes using constellation diagram images.

Signals present at EVM levels between 25% and 100% present a challenge for digital modulation classification since in a real environment signals can be in this range due to noise or other factors that can decrease signal quality.

The creation of a dataset with unique parameters leaves the door open to the contribution of new datasets containing a larger number of images and possibly a larger number of digital modulation schemes in order to provide sufficient information for training and classification with convolutional neural networks for application in cognitive radio.

Convolutional neural networks can be adapted to the required application, being the case of the InceptionResNetV2 model that was not designed for the application in digital modulation classification, demonstrating the versatility they have and the possibility of coupling to the required needs oriented to cognitive radio. After this research remains as future work the exploration of other models capable of classifying different digital modulation schemes with greater accuracy for QAM modulation schemes, high levels of EVM and make a comparison between their metrics.

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References

[1] A. M. Wyglinski, M. Nekovee, and Y. T. Hou, Cognitive Radio Communications and Networks: Principles and Practice. 2009.

[2] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," IEEE Pers. Commun., vol. 6, no. 4, pp. 13-18, 1999. https://doi.org/10.1109/98.788210

[3] J. H. Aguilar Rentería and A. Navarro Cadavid, "Cognitive radio - State of the Art," Sist. y Telemática, vol. 9, no. 16, p. 31, 2011. https://doi.org/10.18046/syt.v9i16.1028

[4] G. Arulampalam, V. Ramakonar, A. Bouzerdoum, and D. Habibi, "Classification of digital modulation schemes using neural networks," ISSPA 1999 - Proc. 5th Int. Symp. Signal Process. Its Appl., vol. 2, pp. 649-652, 1999. https://doi.org/10.1109/ISSPA.1999.815756

[5] A. K. Nandi and E. E. Azzouz, "Modulation recognition using artificial neural networks," Signal Processing, vol. 56, no. 2, pp. 165-175, 1997. https://doi.org/10.1016/S0165-1684(96)00165-X

[6] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, "Survey of automatic modulation classification techniques: Classical approaches and new trends," IET Commun., vol. 1, no. 2, pp. 137-156, 2007. https://doi.org/10.1049/iet-com:20050176

[7] A. Ali, F. Yangyu, and S. Liu, "Automatic modulation classification of digital modulation signals with stacked autoencoders," Digit. Signal Process. A Rev. J., vol. 71, pp. 108-116, 2017. https://doi.org/10.1016/j.dsp.2017.09.005

[8] Y. Tevfik and A. Huseyin, "A survey of spectrum sensing algorithms for cognitive radio applications," IEEE Commun. Surv. Tutorials, vol. 11, no. 1, pp. 116-130, 2009. https://doi.org/10.1109/SURV.2009.090109

[9] T. J. O'Shea, J. Corgan, and T. C. Clancy, "Convolutional radio modulation recognition networks," Commun. Comput. Inf. Sci., vol. 629, pp. 213-226, 2016. https://doi.org/10.1007/978-3-319-44188-7_16

[10] S. Ramjee, S. Ju, D. Yang, X. Liu, A. El Gamal, and Y. C. Eldar, "Fast Deep Learning for Automatic Modulation Classification," no. 108818, 2019. http://arxiv.org/abs/1901.05850

[11] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-Air Deep Learning Based Radio Signal Classification," IEEE J. Sel. Top. Signal Process., vol. 12, no. 1, pp. 168-179, 2018. https://doi.org/10.1109/JSTSP.2018.2797022

[12] T. Huynh-The, C. H. Hua, J. W. Kim, S. H. Kim, and D. S. Kim, "Exploiting a low-cost CNN with skip connection for robust automatic modulation classification," IEEE Wirel. Commun. Netw. Conf. WCNC, vol. 2020-May, 2020. https://doi.org/10.1109/WCNC45663.2020.9120667

[13] 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. https://doi.org/10.1109/ACCESS.2021.3091421

[14] P. Ghasemzadeh, S. Banerjee, M. Hempel, and H. Sharif, "A Novel Deep Learning and Polar Transformation Framework for an Adaptive Automatic Modulation Classification," IEEE Trans. Veh. Technol., vol. 69, no. 11, pp. 13243-13258, 2020. https://doi.org/10.1109/TVT.2020.3022394

[15] S. Peng et al., "Modulation Classification Based on Signal Constellation Diagrams and Deep Learning," IEEE Trans. Neural Networks Learn. Syst., vol. 30, no. 3, pp. 718-727, 2019. https://doi.org/10.1109/TNNLS.2018.2850703

[16] K. Jiang, J. Zhang, H. Wu, and A. Wang, "applied sciences Based on Deep Convolutional Neural Network," pp. 1-14, 2020.

[17] N. Daldal, Z. Cömert, and K. Polat, "Automatic determination of digital modulation types with different noises using Convolutional Neural Network based on time-frequency information," Appl. Soft Comput. J., vol. 86, , p. 105834, 2020. https://doi.org/10.1016/j.asoc.2019.105834

[18] W. Wang, "A Brief Survey on Cognitive Radio," in Cognitive Radio Systems, China: InTech, 2009. https://doi.org/10.5772/7842

[19] Y. Arjoune and N. Kaabouch, "A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions," Sensors (Switzerland), vol. 19, no. 1, Jan. 2019. https://doi.org/10.3390/s19010126

[20] S. Haykin and P. Setoodeh, "Cognitive Radio Networks: The Spectrum Supply Chain Paradigm," IEEE Trans. Cogn. Commun. Netw., vol. 1, no. 1, pp. 3-28, 2015. https://doi.org/10.1109/TCCN.2015.2488627

[21] R. G. Nair and K. Narayanan, "Cooperative spectrum sensing in cognitive radio networks using machine learning techniques," Appl. Nanosci., vol. 31, no. 11, pp. 2209-2221, 2022. https://doi.org/10.1007/s13204-021-02261-0

[22] GNU Radio, "About GNU Radio · GNU Radio." https://www.gnuradio.org/about/

[23] Mathworks, "What Is MATLAB? - MATLAB & Simulink." https://www.mathworks.com/discovery/what-is-matlab.html

[24] C. Ballesteros, E. P. Estupinan Cuesta, and J. C. Martinez Quintero, "Digital Modulation Constellation Images," vol. 1, 2022. https://doi.org/10.17632/WG2GN8D5G9.1

[25] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-ResNet and the impact of residual connections on learning," 31st AAAI Conf. Artif. Intell. AAAI 2017, pp. 4278-4284, 2017. https://doi.org/10.1609/aaai.v31i1.11231

[26] A. Alemi, "Improving Inception and Image Classification in TensorFlow - Google AI Blog," 2016. https://ai.googleblog.com/2016/08/improving-inception-and-image.html

[27] Tensorflow, "tf.keras.losses.SparseCategorical Crossentropy | TensorFlow Core v2.9.1." https://www.tensorflow.org/api_docs/python/tf/keras/losses/SparseCategoricalCrossentropy