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A CASE-STUDY VISION

1D neural network design to detect cardiac arrhythmias

Diseño de red neuronal 1D para detectar arritmias cardiacas

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ABSTRACT

This article shows a neuronal network for deep learning focused on recognizing and classification five types of cardiac signals (Sinus, Ventricular Tachycardia, Ventricular Fibrillation, Atrial Flutter, and Atrial Fibrillation). The final objective is to obtain an architecture that can be implemented in an embedded system as a pre-diagnostic device linked to a Holter monitoring system. The network was designed using the Keras API programmed in Python, where it is possible to obtain a comparison of different types of networks that vary the presence of a residual block, with the result that the network with said block obtains the best response (100% success rate) and a model loss of approximately 0.15%. On the other hand, a validation by means of confusion matrices was carried out to verify the existence of false positives in the network results and evidence what type of arrhythmia can be presented according to the network output against an input signal through the console.

RESUMEN

El presente artículo muestra el diseño de una red neuronal para aprendizaje profundo enfocado al reconocimiento y clasificación de cinco tipos de señales cardiacas (Sinusal, taquicardia ventricular, fibrilación ventricular, flutter atrial y fibrilación atrial). El objetivo es obtener una arquitectura que pueda ser implementada en un sistema embebido como un dispositivo de prediagnóstico que se pueda vincular a un sistema de monitorización de un holter. La red fue diseñada por medio de la API de Keras programada en Python, en donde se logra obtener una comparación de diferentes tipos de redes que varían la presencia de un bloque residual, teniendo como resultado que la red con dicho bloque obtiene la mejor respuesta (porcentaje de aciertos de 100%) y una pérdida del modelo aproximadamente del 0.15%. Por otro lado, se realizó una validación mediante matrices de confusión para verificar la existencia de falsos positivos en los resultados otorgados por la red y adicionalmente evidenciar que tipo de arritmia se puede presentar conforme la salida de la red frente a una señal de entrada por medio de la consola.

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1. Introduction

The electrocardiographic signal (ECG) is a graphic representation in the time domain, which by mathematical methods can be represented in the frequency domain [1] of the electrical stimulus produced in the heart by the excitations in the cardiac muscles [2], it can be divided into fundamental characteristics such as P-waves, QRS complex, T-wave, U-wave, PR interval, ST interval and RR interval [3]. The main function of this signal is to detect anomalies or cardiac pathologies such as heart attacks, arrhythmias, and fibrillations, among others, by reading it and identifying certain characteristics such as the amplitude of the QRS complex, the duration of certain intervals, or the morphology of different types of waves [1]. The rhythms that will be considered for this research are:

1.1. Sinus rhythm: "Sinus rhythm is characterized by a rate between 60 and 100 beats per minute. Each QRS complex must last between 80 and 100 ms and is preceded by a P wave, which must be followed by a QRS" [3].

1.2 Ventricular tachycardia: This is defined as an arrhythmia, like ventricular fibrillation, and has an ECG tracing, which can be diagnosed by the same heart rate and wide QRS complexes (greater than 120 beats per minute) [3].

1.3 Ventricular fibrillation: This is an arrhythmia in which he ventricular fibres' contractions are asynchronous, causing the muscle fibres located in the ventricles to shake instead of making a coordinated contraction [3].

1.4 Atrial fibrillation: Characterized by completely irregular R-R intervals that do not follow any pattern. Besides, since there is a chaotic atrial stimulation, there are no P waves [3].

1.5 Atrial flutter: Atrial flutter is a supraventricular arrhythmia, which generates P-wave-like patterns along with the intervals between the R-R peaks.

For the detection of heart rhythms mentioned above, it must be implemented a method of characterization and recognition of them automatically, for this different techniques are used, some are detection algorithms and others use the concept of deep learning or machine learning [4] to execute such classification, an example of this is the use of convolutional neural networks, which are a computer algorithm that attempts to mimic the functioning of the human brain for specific tasks, where, through layers containing artificial neurons are achieved to perform tasks such as multiclass classification, binary classification, image reconstruction among other functions. Convolutional networks are an example of a specialized neural network architecture, which employs knowledge about the invariance of two-dimensional shapes using local connection patterns among other parameters. They also present a multilayer architecture, which indicates that each layer comprises of a certain number of convolutions with non-linear mathematical functions. They are characterized by determining a mathematical representation for each neuron by assigning a convolutional operation [5] (the signal convolution is based on a mathematical process that "fuses" two signals to transform them into a new signal, which can extract characteristics from it [6]), in order to generate an artificial intelligence algorithm, which requires a good signal processing that allows extracting characteristics from it, such as frequency response, the wallet transforms among others [7-8]. However, in some cases have been designed multichannel pattern networks (MART) that allow more than one input of the processed signal [9].

Some studies seek to classify rhythms that have an almost defined pattern with symmetry functions to extract patterns [10] or characteristics of the ECG signal such as duration, amplitude, gradients, among others [11], also seeking the classification of sinus arrhythmias or ventricular arrhythmias from individual analysis [12-13], however, other networks seek to establish a significant difference between a specific wave compared to normal waves (sinus rhythms), such as efficiently detecting a blockage or ischemic episodes [14-15] and premature ventricular and atrial onset [16]; The most common rhythm is atrial fibrillation and therefore it is considered important to establish classification and prediction algorithms for it [17] as Artis, Mark and Moody did, using the Markov model for the implementation of a neural network based on the Back-Propagation algorithm and trained with signals obtained from the MIT-BIH database, present in Physionet® [18-19].

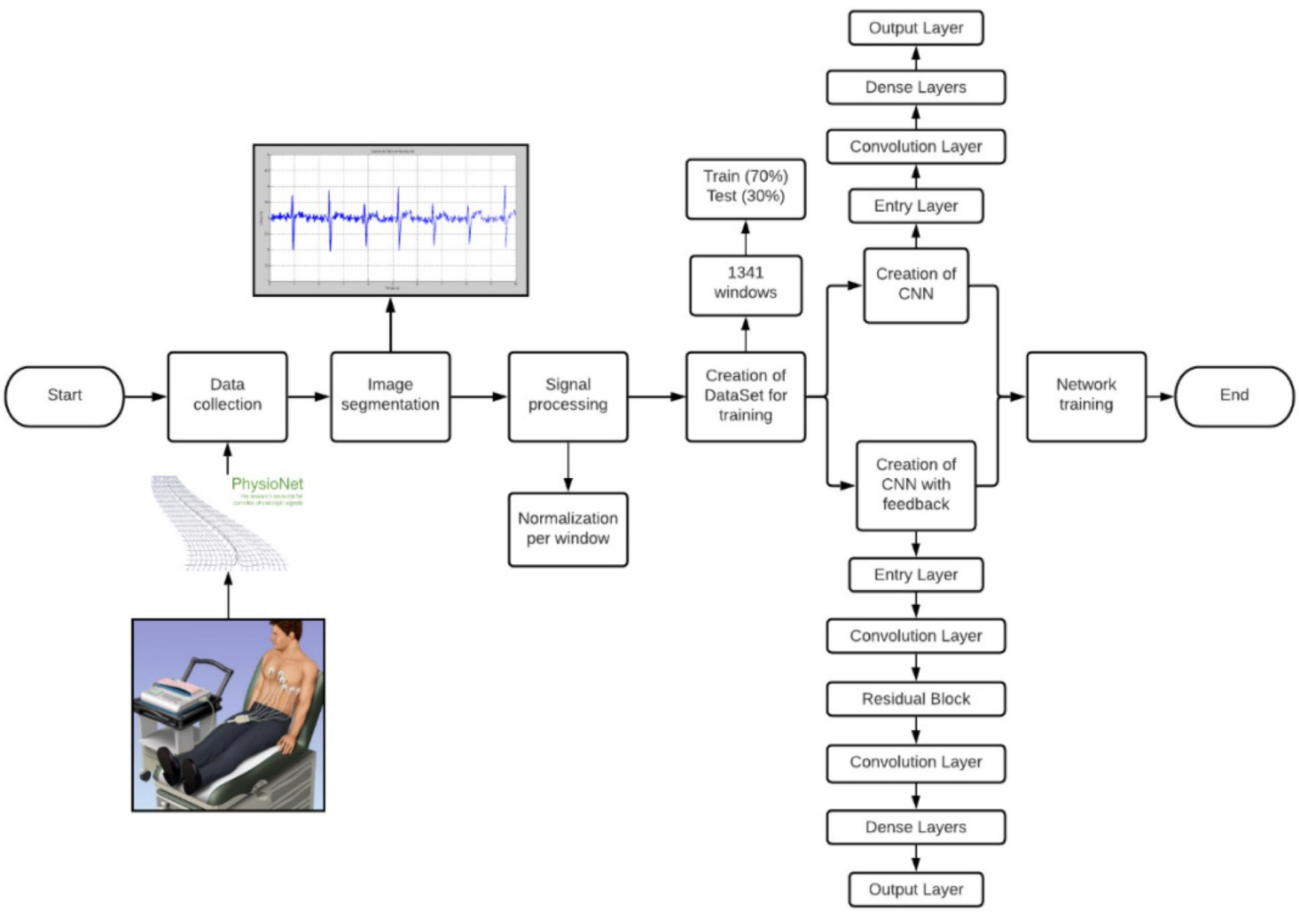
On the other hand, it is important to highlight the efficiency of different types of networks, as indicated above, the percentage of success that a simple neuronal network can provide compared to a proximate neuronal network (KNN) can be tested to obtain a relationship between network complexity/efficiency [20]. Networks based on the feedforward backpropagation method and the logistic regression variable selection method have also been used with the objective of reducing a variable of the ECG signal beat by improving the classification providing more speed and avoiding situations of over-adjustment [19]. Also, three-layer neuronal networks with an optimized BPN-4-3-2 topology have been used, which work with four input parameters for the main layer, characteristic of the signal such as the amplitude of the QRS complex, the RR interval, the ST segment amplitude, among others, having as a result after its implementation, data that agree with the clinical diagnosis of the analyzed disease [21].

In accordance with the above, we propose to design a convolutional neuronal network that can be connected to an ECG device that has the DII derivation, where we want to build a model that allows classifying the waves: Ventricular tachycardia, atrial fibrillation, ventricular fibrillation, sinus rhythm and atrial flutter. The purpose is to propose an embedded network that can be used in a portable Holter that can perform real-time classification of these waves, with the long-term goal of incorporating an alarm system when these waves are presented (except for sinus rhythm) and expand the database of waves that are being classified, this project will be designed in python with the help of the keras API.

2. Methodology

To present the methodological part, a block diagram was made with the main components used in the research, show the figure 1.

Figure 1. Block diagram of the methodological process



Source: own.

2.1. Data collection and segmentation

Sampling was done by collecting data through the Physionet® database, which was specifically searched in the Physionet® arrhythmia data base V1.0 and Malignant Ventricular tachycardia [22] and were extracted by means of the wdfd libraries provided by the database in Matlab. However, at that point, the signals whose entries will have records of the cardiac signals mentioned above were considered, and additionally, the signals that did not belong to the DI or DII derivatives were omitted, since the aim is to build a single-channel neuronal network.

Once the necessary data for the research were known, the signals were separated into .mat files, corresponding to each classification, it means one file per signal. On the other hand, sampling frequencies were considered, and signal lengths were obtained in total time scale as shown in Table 1.

Table 1. Duration of cardiac signals.

Signal	Time (minutes)	Label
Sinus Rhythm	20	0
Atrial Fibrillation	30	1
Flutter Auricular	17	2
Ventricular Tachycardia	23	3
Ventricular Fibrillation	26	4

Source: own.

2.2. Signal processing and DataSet creation

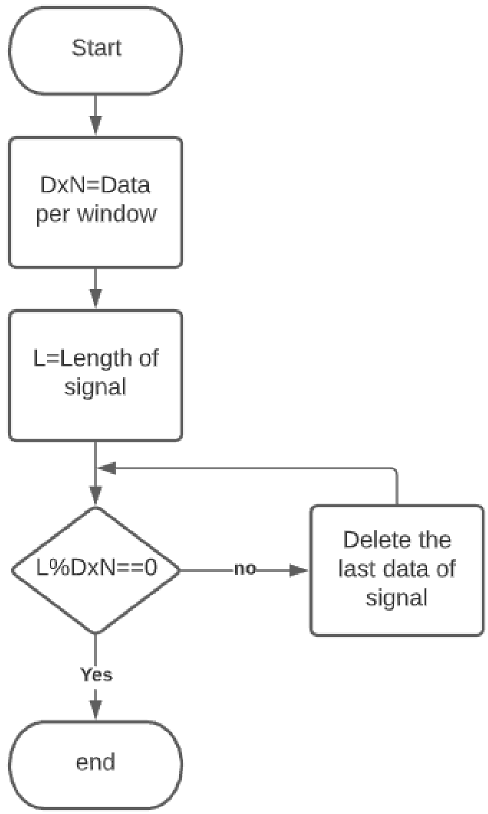
In some signals of the databases the sampling frequency was different from each other, which means that a portion of the data was sampled at 360 Hz while the other was at 250 Hz, so it was necessary to remove data from the signals more frequently, this was done by the "resample" function incorporated in Matlab. Knowing an identical sampling frequency for all data, a "reshape" is performed, considering a fixed window time, that is, following equation 1, it is possible to know the number of total windows per signal (1250), however, in some cases the division can be rational, so the algorithm of Figure 2 is implemented to avoid this problem.

$$Fs * Time_{window} = \text{Amount of data} \tag{1}$$

To complete the processing, signal normalization is performed for each of the windows, since there are points that are extremely positive in a signal and affect the amplitudes of signals that handle low voltages at some points, such as ventricular fibrillation; normalization per window is performed with equation 2.

$$Data = \frac{Data - min(Data)}{max\,(Data - min(Data))} \tag{2}$$

Figure 2. Algorithm to reduce the length of the windows.



Source: own.

On the other hand, to create the DataSet all the signals are unified in one, which means that a concatenation is made, and as the data are connected, also is their respective classification, where the training magnitudes are decided in 70% of the collected data and 30% of the model validation data thus having a total of 939 training data and 402 validation data.

2.3. Development of the deep learning algorithm

To make a comparison between two convolutional neural networks in 1D, a model with a residual block and one without was used (Check Table 2).

Table 2. Neural network with residual block

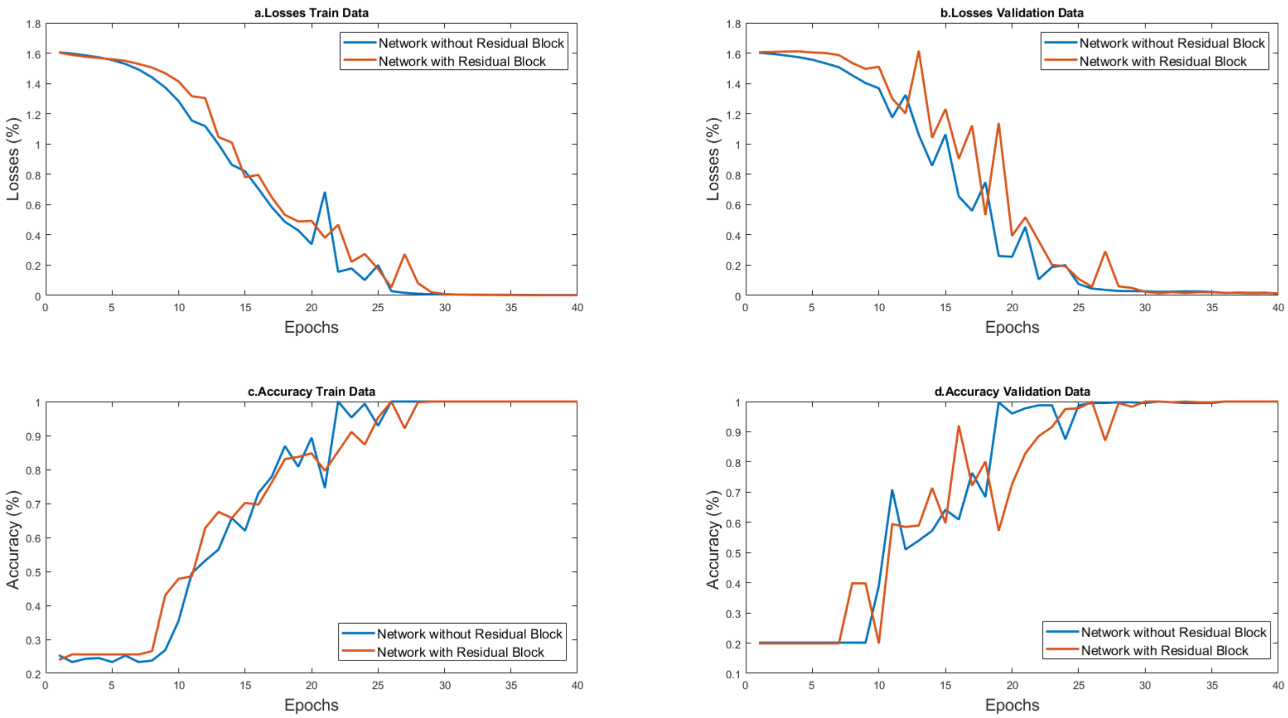
Model	Layer	Output size	#parameters
Network without residual block	Entry layer	1250 x 1	0
	Convolution layer 1	1245 x 16	112
	Max Pooling layer 1	1244 x 16	0
	Convolution layer 2	1233 x 32	6176
	Convolution layer 3	1222 x 32	12320
	Convolution layer 4	1199 x 32	24608
	Max Pooling layer 2	11998 x 32	0
	Dense layer	38336	0
	Dense layer 1	64	2453568
	Dense layer 2	16	1040
	Dense layer 3 (output)	5	85
Network with residual block	Entry layer	1250 x 1	0
	Convolution layer 1	1245 x 16	112
	Convolution layer 2	1245 x 16	1552
	Activation layer 1 (Relu)	1245 x 16	0
	Convolution layer 3	1245 x 16	1552
	Convolution layer 4	1245 x 16	112
	Residual block	1245 x 16	0
	Activation layer 2 (Relu)	1245 x 16	0
	Convolution layer 5	1240 x 16	1552
	Max Pooling layer 1	1239 x 16	0
	Convolution layer 6	1228 x 32	6176
	Convolution layer 7	1217 x 32	12320
	Convolution layer 8	1194 x 32	24608
	Max Pooling layer 2	1193 x 32	0
	Flatten layer	38176	0
	Dense layer 1	64	244332
	Dense layer 2	16	1040
	Dense layer 3	5	85

Source: own.

3. Results

The results are the curves obtained from the respective trainings of each one of the neural networks, where the value of model losses of the training data (figure 3-a), losses in the validation data (figure 3-b), hits of the model with training data (figure 3-c), and finally hits with the validation data (figure 3-d) are illustrated. In all the figures a faster response is observed by the convolutional network without residual block, since it reaches a period of stability in fewer times compared to the neural network with residual block; likewise, both networks manage to reach the same percentage of precision but with a different percentage of losses (table 3).

Figure 3. Training results.



Source: own.

Table 3. Results obtained when implementing the neural networks.

Model	Epoch of stabilization	Accuracy [%]	Losses [%]
Network with residual block	28	100	0.15
Network without residual block	26	100	0.27

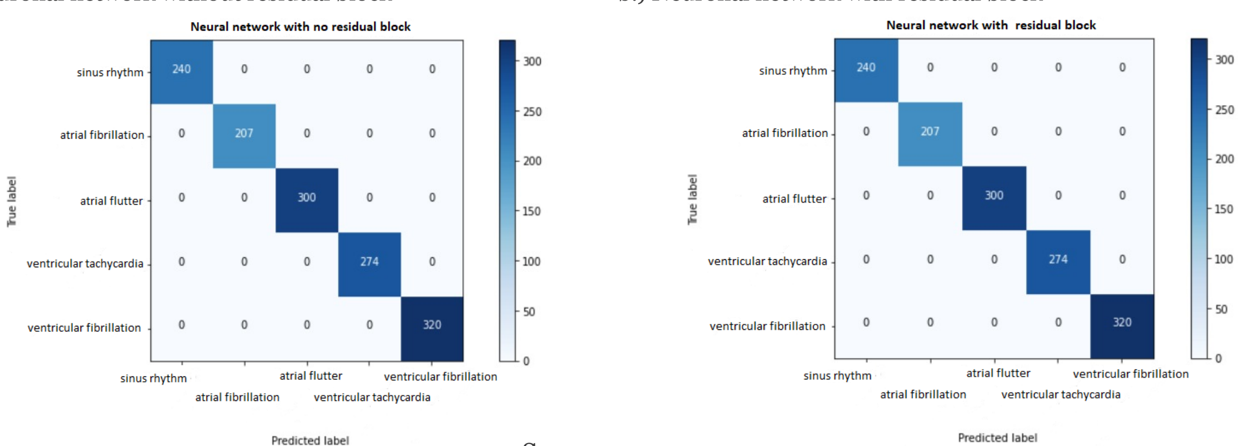
Source: own.

On the other hand, in order to validate the model, a confusion matrix was made with the entire DataSet (See Figure 4-a and 4-b), which showed that no errors in classification occur (false positives). Additionally, in figure 5 the response by the neuronal network console can be seen, demonstrating that the result of the model's prediction is correct when a random heart rhythm is taken as the input to the data set. By knowing the label of each signal according to Table 1, a console print can be generated indicating the presence of the rhythm presented in the input signal.

Figure 4. Confusion Matrices.

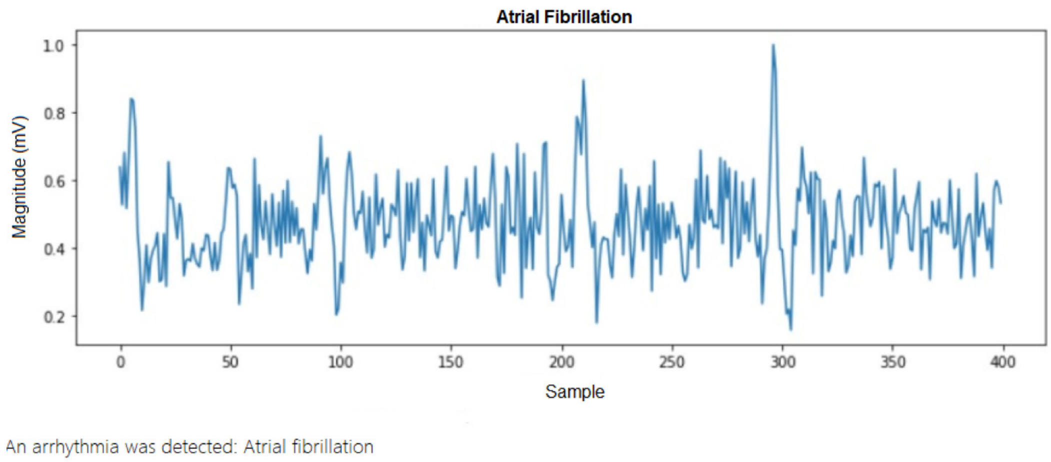
a.) Neuronal network without residual block

b.) Neuronal network with residual block



Source: own.

Figure 5. Neural network output by console.



Source: own.

4. Discussion

When observing the curves obtained in the figures exposed in the previous section, it can be inferred that there is a better response from the neural network that does not have a residual block, since according to table 2, more parameters must be trained and therefore a difference in the stabilization period is identified, given that the network without a residual block reaches 100% success in a smaller number of times, However, the models carried out indicate that the convolutional network with a residual layer has a lower percentage of losses (0.15%), compared to the simple convolutional neural network (0.27%), the cause of this phenomenon may be due to the back-propagation of the network by the same phenomenon of the number of trainable parameters.

It should be noted that the training was done with a batch size of 128, that is, 128 data were presented in the iteration of each cycle (epoch) and no dropout layers were used, which indicates that neurons were not deactivated in a random way for the training, since when implementing these layers in the comparison process, this begins to depend on the randomness that is present in the deactivation, affecting the results of the curves obtained.

Finally, at the time of training the network, the residual block was tested with different kernel sizes in the convolutional layers that integrate it, which gave positive effects in the process, since the network was capable of extracting more relevant characteristics in a group of data, determining that the greater the kernel size, the more characteristics per wave increased (in the development a kernel size of 6 was established), because in signals such as ventricular fibrillation, atrial fibrillation and atrial flutter where a perfect isoelectric line cannot be visualized, in the R-R intervals, relevant information can continue to be rescued in the convolution layers, therefore it is determined that in the result obtained, the capacity of the network to generate a classification without significant losses of the model is observed.

5. Conclusions

A DataSet was created based on databases belonging to the Physionet® domain, where the corresponding processing and adaptation was carried out to introduce them into a convolutional neural network with 100% pressure in each network.

Two convolutional neural networks were implemented with the presence/absence of a residual block, which oversees generating "feedback" to the network to obtain a greater number of characteristics by multiplying the convolutions obtained by the initial layer, evidencing that both networks have losses that are close to 0%.

It was possible to make the comparison between a neuronal network with the residual blockade in front and without it, and it was found the possible variables that contribute to the cause of this phenomenon, these are the kernel size, the lack of dropout layers, and the number of parameters that exist in the network.

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