DETECTION OF ATRIAL FIBRILLATION IN SEGMENTS OF ECG SIGNALS USING DEEP NEURAL NETWORKS

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Trabajo de Grado para optar al título de
Ingeniero Electrónico

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DEDICATORIA

Este trabajo viene dedicado para todas aquellas personas que apoyaron el desarrollo y ejecución de este trabajo de grado.

En especial reconocemos la permanente presencia de Dios en el camino de nuestras vidas.

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Jeyson Arley Castillo Bohórquez.

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RESUMEN

TÍTULO: DETECCIÓN DE FIBRILACIÓN AURICULAR EN SEGMENTOS DE SEÑALES ELECTROCARDIOGRÁFICAS USANDO REDES NEURONALES [*]

AUTOR: JEYSON A. CASTILLO, YENNY C. GRANADOS [**]

PALABRAS CLAVE: DETECCION, ECG, FIBRILACION AURICULAR, REDES NEURONALES PROFUNDAS.

DESCRIPCIÓN:
La fibrilación auricular (FA) es la arritmia cardíaca más común en todo el mundo. Se asocia con la reducción en la calidad de vida y aumenta el riesgo de accidente cerebrovascular e infarto de miocardio. Lamentablemente, muchos casos de FA son asintomáticos y no diagnosticados a tiempo, lo que aumenta el riesgo para los pacientes. La detección de FA exige un monitoreo a largo plazo debido a su naturaleza paroxística y tal acción es lenta, costosa y, a veces, su valoración puede ser subjetiva. Este proyecto es la primera etapa de un proyecto macro que tiene como objetivo desarrollar un dispositivo portátil para la detección de FA, que se basará en una red neuronal convolucional (CNN). Los datos para el proceso de entrenamiento y validación son Atrial Fibrillation Database, un recurso público de MIT-BIH[1]. Nuestro objetivo es encontrar un modelo CNN adecuado, que posteriormente podría llegar a implementarse en hardware. Aplicamos diversas técnicas para mejorar la respuesta con respecto a la precisión, sensibilidad, especificidad y precisión. El modelo final logra una precisión del 97,44 %, una especificidad del 97,76 %, una sensibilidad del 96,97 % y una precisión del 96,80 %. Además, seleccionando un optimizador adecuado se realiza la mejora en la sensibilidad del modelo, a un menor costo computacional. Los resultados de estos trabajos se utilizarán como marco para el trabajo futuro centrado en la implementación del dispositivo portátil basado en CNN para la detección automática de FA.

[*] Trabajo de grado

[**] Facultad de Ingenierías Físico-Mecánicas. Escuela de Ingenierías Eléctrica, Electrónica y telecomunicaciones. Director: Carlos A. Fajardo.

[1] Goldberger AL. “The MIT-BIH Atrial Fibrillation Database”. En: (2000). Accessed: 2019-01-26.

ABSTRACT

TITLE: DETECTION OF ATRIAL FIBRILLATION IN SEGMENTS OF ECG SIGNALS USING DEEP NEURAL NETWORKS *

AUTHOR: JEYSON A. CASTILLO, YENNY C. GRANADOS **

KEYWORDS: ATRIAL FIBRILLATION, DEEP NEURAL NETWORKS, DETECTION, ECG.

DESCRIPTION:

Atrial Fibrillation (AF) is the most common cardiac arrhythmia worldwide. It is associated with reduced quality of life and increases the risk of stroke and myocardial infarction. Lamentably, many cases of AF are asymptomatic and undiagnosed, which increases the risk for the patients. The detection of AF demands long-term monitoring because of its paroxysmal nature and is time-consuming, expensive, and sometimes it could be subjective. This project is the first stage in a macro project that aims to develop a portable device for the detection of AF, which will be based in a Convolutional Neural Network (CNN). The data for the train and validation process is the Atrial Fibrillation database, a public resource from MIT-BIH[1]. We aim to find a suitable CNN model, which later could be implemented in hardware. We apply diverse techniques to improve the answer regarding accuracy, sensitivity, specificity, and precision. The final model achieves an accuracy of 97.44 %, a specificity of 97.76 %, a sensitivity of 96.97 % and a precision of 96.80 %. Besides the optimizer selected performs the best sensitivity at a lower computational cost. The results of this works will be used as framework for the future work focused on the implementation of the CNN-based portable device for automatic detection of AF.

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* Bachelor Thesis

** Faculty of Physico-Mechanical Engeenering. School of Electronics and Electrical engineering and Telecommunications. Advisor: Carlos A. Fajardo.

1 AL, ver n. 1.

INTRODUCTION

Atrial Fibrillation (AF) is the most common cardiac arrhythmia in clinical practice. Its global prevalence is around 2 % in the community, around 5 % in patients older than 60 years and 10 % in people over 80 years old. The AF is associated with reduced quality of life and also increases the risk of stroke and myocardial infarction. In Colombia, some studies show that the incidence and mortality of AF have increased especially in people over the age of 70[2,3].

AF is caused due to various health complications. During an episode of AF, the contraction of the atria is asynchronous because of the fast firing of electrical impulses. The main characteristics of an episode of AF are: the absence of a sinus p wave, irregular and fast ventricular contraction, presence of a variable and abnormal RR interval, atrial heart rate variable between 350 to 600 beats per minute (bpm) and narrow QRS complexes ($< 120 milliseconds$)[4].

By using electrodes placed on the skin is possible to record the electrical activity of the heart. A graph of voltage versus time is known as an electrocardiogram (ECG signal). These electrical changes are a consequence of cardiac muscle depolarization followed by repolarization during each cardiac cycle (heartbeat). The ECG morphology contains important information about the conditions of the heart. Thus, the ECG signals are used to detect abnormalities in heart activity[5].

The ECG signals are interpreted manually by cardiologists in order to detect cardiac abnor-

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[2] Julián Eduardo Forero-Gómez y col. "Fibrilación auricular: Enfoque para el médico no cardiólogo". En: *Iatreia* 30.4 (2017), págs. 404-422.

[3] Martín Romero y Diana Chávez. "Carga de enfermedad atribuible a fibrilación auricular en Colombia (2000-2009)". En: *Revista Colombiana de Cardiología* 21.6 (2014), págs. 374-381.

[4] Forero-Gómez y col., ver n. 2.

[5] U. Rajendra Acharya y col. "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network". En: *Information Sciences* 405 (2017), págs. 81 -90. DOI: https://doi.org/10.1016/j.ins.2017.04.012.

malities. The detection of AF demands to analyze long recordings because of its paroxysmal nature. These analyses are time-consuming, expensive, and some times could be subjective. Figure 1 shows typical ECG signals. The first one is a normal ECG signal and the second one is an Atrial Fibrillation ECG.

The FA generally is asymptomatic or present nonspecific symptoms[6]. However, several medical reports call attention to the importance of early diagnosis in order to start an early treatment[7]. However, these early diagnostics are quite difficult in countries like Colombia, where there is an inadequate distribution of cardiologists by geographical regions and economically. For example, more than 80 % of cardiologists are localized only in seven of the main cities in Colombia Artemo L Pérez C, Bllanco M, Toledo D. "Cardiólogos en Colombia". En: *Educación en Cardiología* 10.6 (2003), págs. 378-385. Thus, the intermediate cities, small towns, and rural zones have not the possibility to have access to an early cardiology service.

Convolution Neural Networks (CNN) have recently used to detect cardiac arrhythmias. In[8] a 1-D CNN approach is used, which classifies the ECG signal for the detection of ventricular ectopic beats and supraventricular ectopic beats with very high accuracy.

In[9] has developed a CNN approach to detect AF. In this work, the cardiac signals are recorded by a Pulsatile photoplethysmographic sensor. The approach uses a Wavelet Transform before

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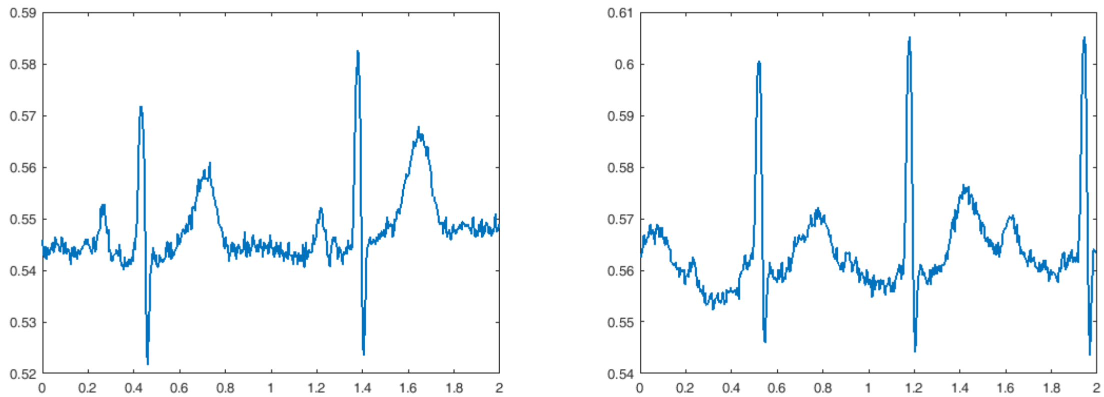
6 Himani V. Bhatt y Gregory W. Fischer. "Atrial Fibrillation: Pathophysiology and Therapeutic Options". En: *Journal of Cardiothoracic and Vascular Anesthesia* 29.5 (2015), págs. 1333-1340.

7 Paulus Kirchhof y col. "2016 ESC Guidelines for the management of atrial fibrillation developed in collaboration with EACTS". En: *European journal of cardio-thoracic surgery* 50.5 (2016), e1-e88; José Kelvin Galvez-Olortegui y col. "Current clinical practice guidelines in atrial fibrillation: a review". En: *Medwave* 16.01 (2016).

8 S. Kiranyaz, T. Ince y M. Gabbouj. "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks". En: *IEEE Transactions on Biomedical Engineering* 63.3 (2016), págs. 664-675. DOI: 10.1109/TBME.2015.2468589.

9 Supreeth Prajwal Shashikumar y col. "A deep learning approach to monitoring and detecting atrial fibrillation using wearable technology". En: *2017 IEEE EMBS International Conference on Biomedical and Health Informatics, BHI 2017* (2017), págs. 141-144.

Figura 1. a) Normal ECG , b) Atrial Fibrillation ECG.



fed the CNN. Finally, a multinomial regression is used to establish the presence or not of an episode of AF. This approach obtained an accuracy of 91.8 %. In[10] signal quality index SQI technique was combined with CNN following by a post-processing feature-based to classify AF. The accuracy for the PhysioNet/CinC database was of 80 %.

This work is part of a macro project that seeks to develop a medical device, which is based on artificial intelligence. The macro project aims to offer an alternative for diagnosis in areas where there is no cardiology service. The aim is to find a suitable CNN model, which later could be implemented in hardware. We apply diverse techniques regarding batch, learning rate, and optimizer function in order to improve the accuracy, sensitivity, specificity, and precision of the network. We proposed a model, which achieves an accuracy of 97.44 %, a specificity of 97.76 %, a sensitivity of 96.97 % and a precision of 96.80 %. Besides the proposed model performs the best sensitivity at a lower computational cost.

The rest of this paper is organized as follows: Section 2 shows a description of the database. Section 3 introduces the convolutional neural networks. In Section 4, we develop the training

[10] Jonathan Rubin y col. “Densely Connected Convolutional Networks and Signal Quality Analysis to Detect Atrial Fibrillation Using Short Single-Lead ECG Recordings”. En: *Computing in Cardiology* 44 (2017), págs. 2-5.

methodology and realized tests for different topologies regarding optimization techniques. In Section 5 are summarized the results. Finally, the conclusions close the article.

1. DATABASE

We use ECG signals from a free public arrhythmia database called MIT BIH Atrial Fibrillation Database[11]. The database includes 25 long-term ECG recordings, which were sampled at 250 samples per second with a resolution of 12 bits in a range of $\pm 10[mV]$. The recordings were made at Beth Israel Hospital in Boston of people with atrial fibrillation (AF), which include more than 300 episodes of AF.

The database has non-numerical annotations, which are given according to a convention. An A indicates an episode of the AF and a N indicates a normal episode. The moment in which the annotations were made was when there was a change of state, either from A to N or vice versa.

A pre-label function was created to label 500-samples segments. Then, each segment was normalized from 0 to 1. Finally, the normalized segments were randomized to guarantee the performance of the algorithm.

[11] AL, ver n. 1.

2. CONVOLUTIONAL NEURAL NETWORKS (CNN)

To the best of our knowledge, Japanese scientist Kunihiko Fukushima published the first CNN model in 1980[12]. Then, the French scientist Yann LeCun improved this first model in 1988[13]. The LeCun model uses three types of layers: Convolutional, sub-sampling and fully connected layers.Convolutional layers extract features from the input image.Sub-sampling layers reduce both spatial size and computational complexity. Finally, the Fully connected layers classify the data. CNN has been implemented in various applications such as: object

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12 Kunihiko Fukushima. "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position". En: *Biological cybernetics* 36 (feb. de 1980), págs. 193-202. DOI: 10.1007/BF00344251.

13 "Gradient-based learning applied to document recognition". En: *Proceedings of the IEEE* 86.11 (1998), págs. 2278-2324. DOI: 10.1109/5.726791.

recognition[14][15], handwriting classification[16][17] and image classification[18][19][20], to name a few. Recently some works have used the CNNs as a diagnostic tool of diseases such as heart attacks[21], colon cancer[22], melanoma[23], Alzheimer[24], cardiac arrhythmia's[25] and hemorrhage

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[14] S. Hayat y col. "A Deep Learning Framework Using Convolutional Neural Network for Multi-Class Object Recognition". En: *2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC)*. 2018, págs. 194-198. DOI: `10.1109/ICIVC.2018.8492777`.

[15] T. Ishii y col. "Surface object recognition with CNN and SVM in Landsat 8 images". En: *2015 14th IAPR International Conference on Machine Vision Applications (MVA)*. 2015, págs. 341-344. DOI: `10.1109/MVA.2015.7153200`.

[16] N. Yu, P. Jiao e Y. Zheng. "Handwritten digits recognition base on improved LeNet5". En: *The 27th Chinese Control and Decision Conference (2015 CCDC)*. 2015, págs. 4871-4875. DOI: `10.1109/CCDC.2015.7162796`.

[17] S. Pan y col. "A discriminative cascade CNN model for offline handwritten digit recognition". En: *2015 14th IAPR International Conference on Machine Vision Applications (MVA)*. 2015, págs. 501-504. DOI: `10.1109/MVA.2015.7153240`.

[18] K. Sirinukunwattana y col. "Locality Sensitive Deep Learning for Detection and Classification of Nuclei in Routine Colon Cancer Histology Images". En: *IEEE Transactions on Medical Imaging* 35.5 (2016), págs. 1196-1206. DOI: `10.1109/TMI.2016.2525803`.

[19] M. J. J. P. van Grinsven y col. "Fast Convolutional Neural Network Training Using Selective Data Sampling: Application to Hemorrhage Detection in Color Fundus Images". En: *IEEE Transactions on Medical Imaging* 35.5 (2016), págs. 1273-1284. DOI: `10.1109/TMI.2016.2526689`.

[20] Acharya y col., ver n. 5.

[21] Z. Liu y col. "Automatic Identification of Abnormalities in 12-Lead ECGs Using Expert Features and Convolutional Neural Networks". En: *2018 International Conference on Sensor Networks and Signal Processing (SNSP)*. 2018, págs. 163-167. DOI: `10.1109/SNSP.2018.00038`.

[22] Sirinukunwattana y col., ver n. 18.

[23] A. Namozov e Y. I. Cho. "Convolutional Neural Network Algorithm with Parameterized Activation Function for Melanoma Classification". En: *2018 International Conference on Information and Communication Technology Convergence (ICTC)*. 2018, págs. 417-419. DOI: `10.1109/ICTC.2018.8539451`.

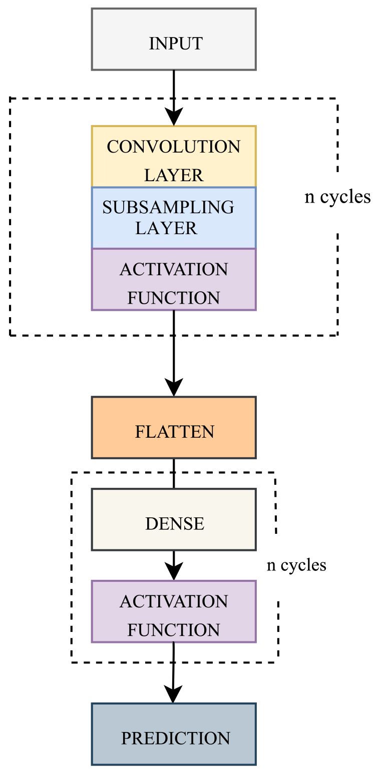
[24] B. Khagi, C. G. Lee y G. Kwon. "Alzheimer?s disease Classification from Brain MRI based on transfer learning from CNN". En: *2018 11th Biomedical Engineering International Conference (BMEiCON)*. 2018, págs. 1-4. DOI: `10.1109/BMEiCON.2018.8609974`.

[25] Acharya y col., ver n. 5.

detection[26].

Figure2 shows the basic configuration of a convolutional neural network. Note that every layer of convolution are coupled with a subsampling layer and an activation function.

Figura 2. Basic configuration of CNN



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[26] van Grinsven y col., ver n. 19.

3. SELECTING THE CNN ARCHITECTURE

For the training process, we use an Intel Core i5 with 2.9 GHz, and 8 Gb of RAM memory. The description language used was Python 3.5 in the Jupyter notebook application. Python environment was created using Anaconda Navigator with Tensor Flow Back-end and the Keras libraries for AI.

We developed three CNN architectures, which were implemented from low complexity to high complexity, in order to establish better results at low complexity possible.

Figura 3. Architecture 1

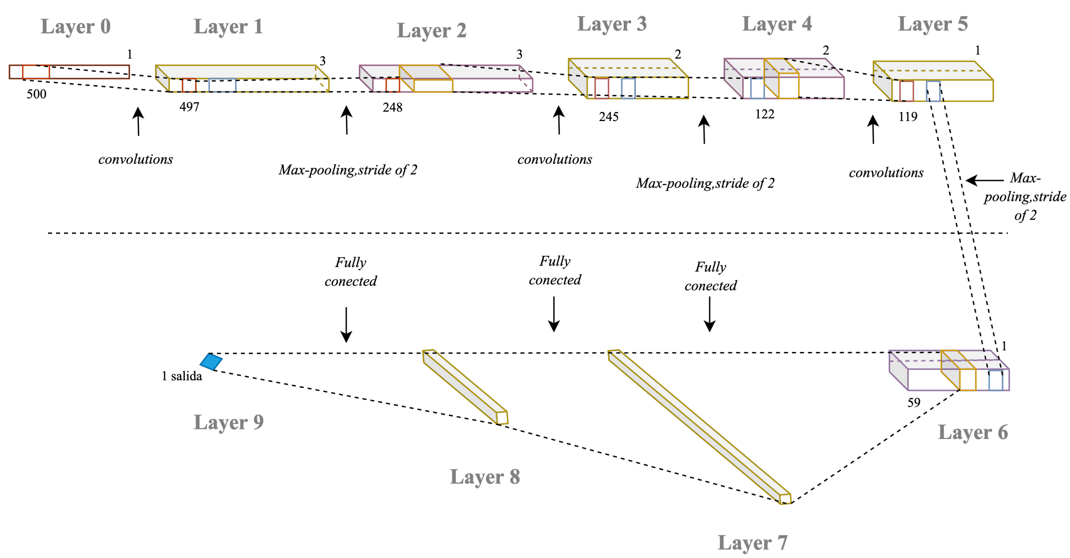


Figure 3 shows the architecture 1, which consists of 9 layers distributed as follows:

- Convolutional layer, with 3 kernels of size 4.
- Max-pooling layers of with stride = 2
- Convolutional layer, with 2 kernels of size 4.
- Max-pooling layers of with stride = 2

- Convolutional layer, with 1 kernel of size 4.
- Max-pooling layers of with stride = 2
- Flatten layer fully connected
- Fully connected layer with 10 neurons
- Fully connected layer with 1 neuron
- RELU activation function, used for the convolutional layers and middle fully connected layer.
- SIGMOID activation function, used for the output layer.

The architecture 2 consists of 9 layers in total, which are distributed as follows:

- Convolutional layer, with 3 kernels of size 15.
- Max-pooling layers of with stride = 2
- Convolutional layer, with 5 kernels of size 10.
- Max-pooling layers of with stride = 2
- Convolutional layer, with 10 kernels of size 10.
- Max-pooling layers of with stride = 2
- Flatten layer fully connected
- Fully connected layer with 10 neurons
- Fully connected layer with 1 neuron
- RELU activation function, used for the convolutional layers and middle fully connected layer.

- SIGMOID activation function, used for the output layer.

The the architecture 3. It consists of 11 layers in total, which are distributed as follows:

- Convolutional layer, with 3 kernels of size 27.
- Max-pooling layers of with stride = 2
- Convolutional layer, with 10 kernels of size 14.
- Max-pooling layers of with stride = 2
- Convolutional layer, with 10 kernels of size 3.
- Max-pooling layers of with stride = 2
- Convolutional layer, with 10 kernels of size 4.
- Max-pooling layers of with stride = 2
- Flatten layer fully connected
- Fully connected layer with 10 neurons
- Fully connected layer with 1 neuron
- RELU activation function, used for the convolutional layers and the two middle fully connected layer.
- SIGMOID activation function, used for the output layer.

Table 1 summarizes the composition of layers and their trainable parameters. This table indicates the size of the output feature maps of each layer. Note that, Max-pooling (sub-sampling) layers do not have trainable parameters.

Tabla 1. Architectures comparison

	architecture 1			architecture 2			architecture 3		
	layer type	output shape	# parameters	layer type	output shape	# parameters	layer type	output shape	# parameters
0	in	(500,1)	0	in	(500,1)	0	in	(500,1)	0
1	convolutional	(497,3)	15	convolutional	(486,3)	48	convolutional	(474,3)	84
2	max pooling	(248,3)	0	max pooling	(243,3)	0	max pooling	(273,3)	0
3	convolutional	(245,2)	26	convolutional	(234,5)	155	convolutional	(224,10)	430
4	max pooling	(122,2)	0	max pooling	(117,5)	0	max pooling	(112,10)	0
5	convolutional	(119,1)	9	convolutional	(108,10)	510	convolutional	(110,10)	310
6	max pooling	(59,1)	0	max pooling	(54,10)	0	max pooling	(55,10)	0
7	flatten	59	0	flatten	59	0	convolutional	(52,10)	410
8	dense	10	600	dense	10	5410	max pooling	(26,10)	0
9	dense	1	11	dense	1	11	flatten	59	0
10							dense	10	7830
11							dense	1	11

3.1. TRAINING THE ARCHITECTURES

We trained architecture 1 with the following algorithm:

- Optimization method: SGD
- Loss evaluation method: Mean Squared Error
- Activation's function of the middle layers: Relu
- Activation's function of the final layer: Sigmoid
- Epochs: 40

Figures 4, 5 and 6 show the accuracy results for training (orange line) and validation (blue) processes of the architectures 1, 2 and 3 respectively.

Figura 4. Training and validation process for Architecture 1

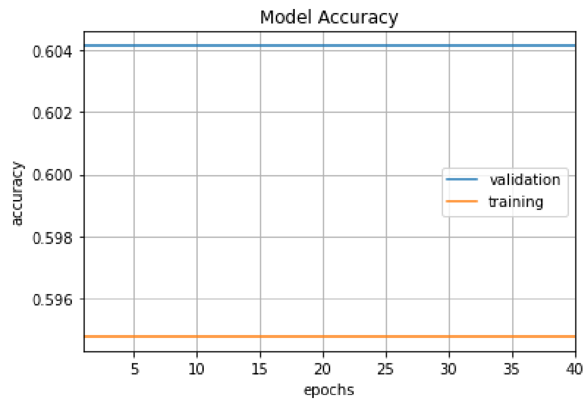
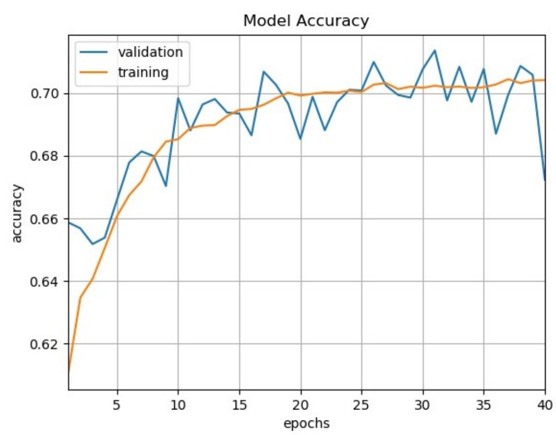


Figura 5. Training and validation process for Architecture 2



Architecture 1 does not increase accuracy during the training process. The constant behavior of the accuracy is due to the few amounts of parameters. Besides, there is high bias and high variance. In the other hand, architecture 2 achieves better accuracy than architecture 1. However, during the validation process, a high variance and noise validation are observed. Finally, architecture 3 achieves better accuracy levels. However, a high variance is still observed in this architecture, which demands to apply additional techniques to reduce this variance.

Figura 6. Training and validation process for Architecture 3

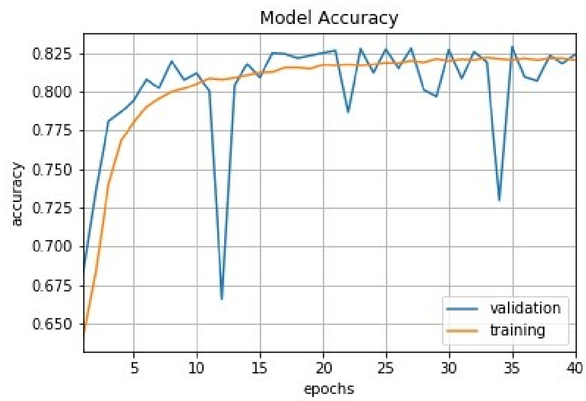


Table 2 summarizes accuracy results for the three architectures. Besides, this table also shows the number of trainable parameters, which are related to the amount of memory required during the inference process.

Tabla 2. Architecture's trainable parameters VS Train Accuracy

	architecture		
	1	2	3
trainable parameters	661	6134	9385
train accuracy	61.58 %	80.58 %	83.01 %

3.2. TESTING DIFFERENT BATCH VALUES

We performed a test with different batch values for architecture 3, which achieved better accuracy in the previous test. The batch values used were 10, 15, 20, 25, 50, 100 and 200. For each one of these batch values, it was performed a training and testing processes with the following parameters:

- Optimization method: SGD
- Loss evaluation method: binary cross entropy
- Activation's function of the middle layers: Relu
- Activation's function of the final layer: Sigmoid
- Epochs: 40

Figura 7. Accuracy results for different batch values.

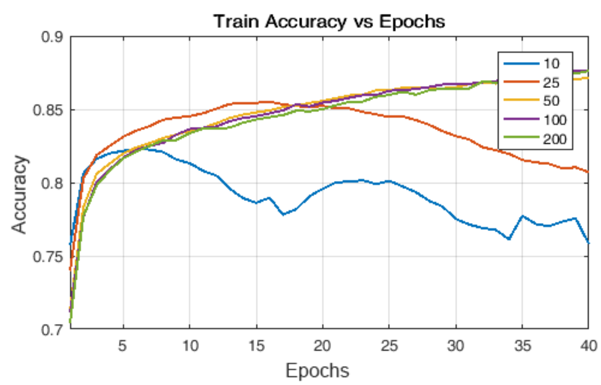
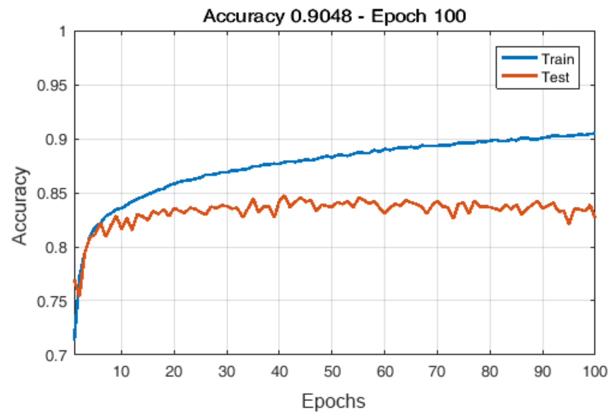


Figure 7 shows the results for the training accuracy for different batch values. Note that, for values over 50, the learning process is stable.

Figure 8 shows the results of training and validation accuracy for a batch value of 100. Note that, there is an improvement in the training process, however, the validation process stops the generalization since epoch 10.

Figura 8. Accuracy for a batch = 100.



3.3. TESTING DIFFERENT LEARNING RATE VALUES

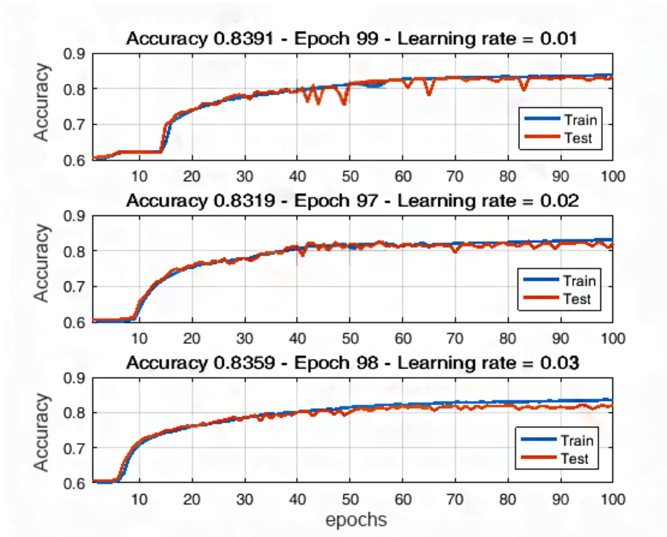
For improving the response regarding learning rate values, it was made a test using SGD optimizer.

The training and testing parameters used were:

- Optimization method: SGD
- Loss evaluation method: binary cross entropy
- Activation's function of the middle layers: Relu
- Activation's function of the final layer: Sigmoid
- Epochs: 100

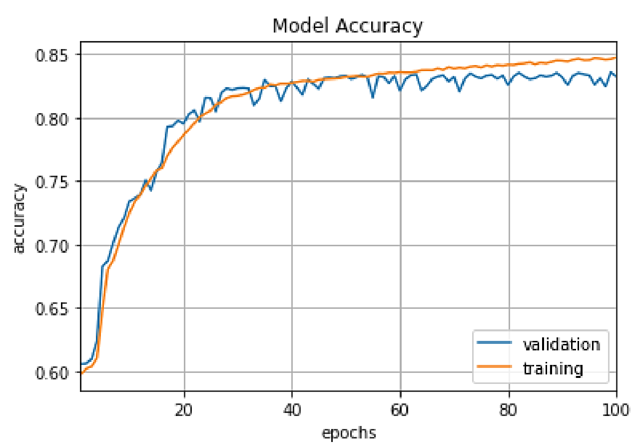
Figure 9 shows the training and validation processes for learning rate values of 0.1, 0.2 and 0.3. Note that, for values of 0.1 and 0.2 the learning process takes more epochs but evidences a lower variance. On the other hand, for a learning rate of 0.3, the training process takes fewer epochs but a higher variance. Thus, a learning rate value of 0.1 was selected.

Figura 9. Training and validation accuracy for different Learning rate values test



A new test was performed with the learning rate value selected. This test was performed with the calculated parameters in the previous tests. In this case, we change the learning rate epoch by epoch with a constant decay factor. Figure 10 summarizes the results of this test. Note that, the accuracy reached is similar to the previous test but it takes a few numbers of epochs. However, the variance is increased when the number of epochs is over 60.

Figura 10. Accuracy for constant Decay Learning rate



3.4. TESTING DIFFERENT OPTIMIZERS

We tested 3 different optimizers. The tests keep the learning rate and batch values as were calculated in the previous test. Figure 11 shows the training process using a SGD Optimizer. Note that, the training process takes a lot of epochs to begin the learning process, which means more computational cost.

Figura 11. Accuracy for SGD optimizer - 20 epochs

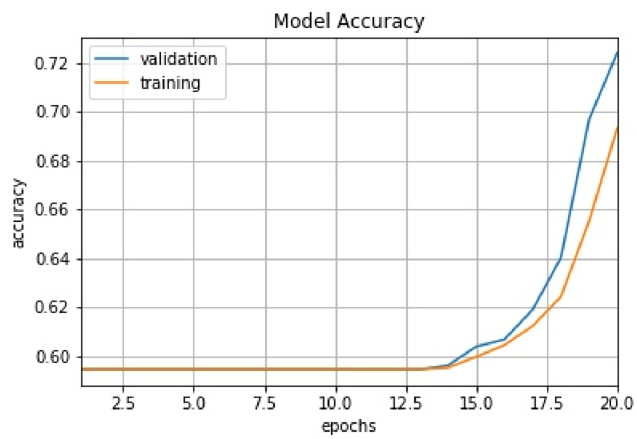


Figura 12. Accuracy for RMSPROP optimizer - 20 epochs

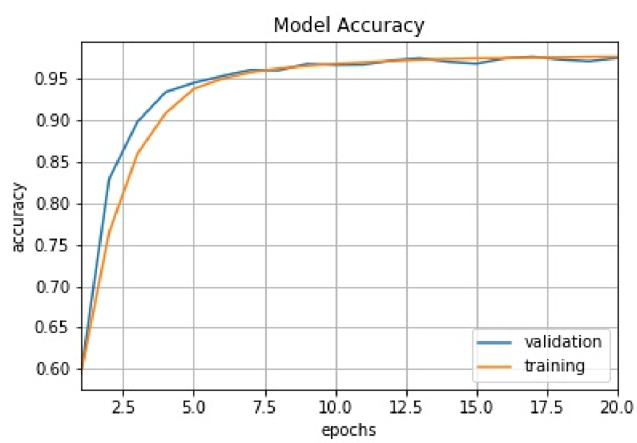


Figure 12 shows the training process using a RMSPROP Optimizer. In this case, the training process takes fewer epochs, and reaches stability since 10 epochs, with low variance (less than 0.36 %). In spite of the similarity of the SGD and RMSPROP algorithms, Figure 12 shows the advantages of the RMSPROP regarding the modification of the velocity function produced by the hyperparameter β. Figure 13 shows the training using ADAM Optimizer. The training process increases faster than in SGD and RMSPROP, and the accuracy that is achieved is similar to RMSPROP. Besides, the trend for both RMSPROP and ADAM optimizers are similar.

Figura 13. Accuracy for ADAM optimizer - 20 epochs

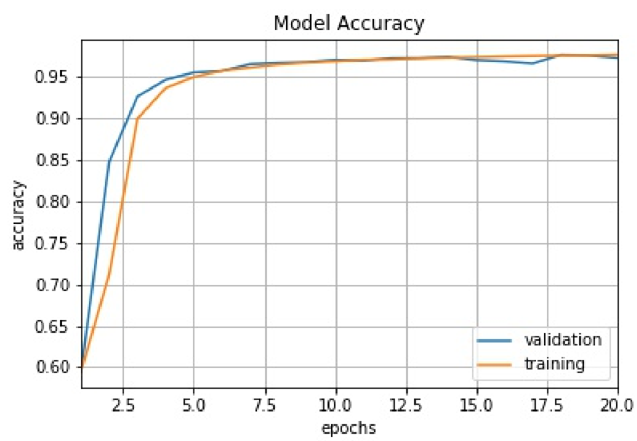


Table 3 summarizes the accuracy achieved by each optimizer, for both train and validation processes.

Tabla 3. Comparison3opt

	optimizer		
	SGD	RMSPROP	ADAM
train accuracy	72.97 %	97.58 %	97.57 %
validation accuracy	69.33 %	97.22 %	97.43 %

4. RESULTS

In the context of supervised learning, the confusion matrix (or error matrix), is a table layout that allows the visualization of the performance of learning algorithms. Figure 14 shows the confusion matrix for the RMSPROP-based learning algorithm. In this matrix is showed: the normal signal well and wrongly classified, fibrillated signals well and wrongly classified, the accuracy, the specificity, the sensitivity, true positives, true negatives, false positives, false negatives and precision.

In this case, the sensitivity is measured when all the input signals are fibrillated (positive condition). The value of sensitivity is the rate between the number of fibrillated signals well classified over the total of input signals. The specificity is as the sensitivity case but for normal signals (negative condition).

The Positive predicted values (PPV) are the rate between the true positives (True Fibrillated signals), and the number of predicted as positives. The negative Predicted Values (NPV) are the rate similar to PPV, but with the negative (Normal signals). The False Positives Value are the rate between the false positive (Normal signals predicted as Fibrillated) and the number of condition negative signals (True normal signals). The false Negative Value is the rate between the false negative signals (Fibrillated predicted as normal) and the total of true positives conditions.

Figura 14. Confusion matrix for RMSPROP test

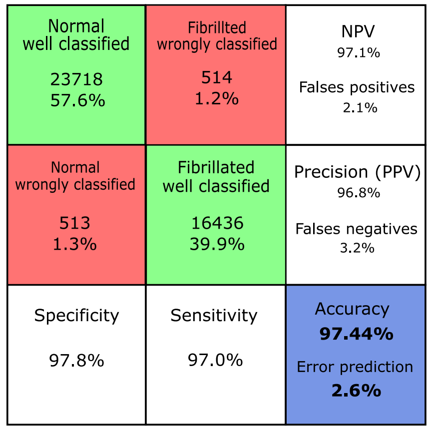


Table 4 summarizes the main results for the confusion matrix for the three optimizers used. Note that, the ADAM reaches the best specificity (negative condition - normal signals). On the other hand, the RMSPROP achieves the best values for accuracy, sensitivity, and precision. It is important to note that in the case of diseases diagnosis, one of the more important statistical value is the sensitivity (positive condition - fibrillated signals).

Tabla 4. Matrix of predictive parameters

Positive and negative predictive values			
Parameter	ADAM	RMSPROP	SGD
Accuracy	97.22 %	97.44 %	66.33 %
Specificity	98.13 %	97.76 %	64.69 %
Sensitivity	95.92 %	**96.97** %	68.69 %
Precision	95.92 %	96.80 %	57.61 %

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5. CONCLUSIONS

We have developed a CNN model to automatically identify AF from 2 seconds ECG-signals (500 samples). We tested several batch and learning rate values and three different optimizers. Our results suggest that a batch and learning rate of 100 and 0.1 respectively improve the validation accuracy. On the other hand, the RMSPROP is the better optimizer in this case, because of its matrix confusion results and for its low computational cost. We aim to use this model in future work, which will focus on the implementation of a CNN-based portable device for automatic detection of AF in Colombia. However, our work clearly has a limitation related to the database used, which is not from Colombia, and thus the generalization capability of the proposed model may vary.

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