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ECG Classification Using Artificial Neural Networks

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Abstract. We propose two Artificial Neural Networks (ANN) architectures for classification of electrocardiogram (ECG) signals to compare effectiveness between them. The atrial fibrillation (AF) classification data set provided by PhysioNet/CinC Challenge 2017 was used. The ANNs proposed are a feed forward neural network (FFNN) and a convolutional neural network (CNN). In order to train the convolutional neural network we transformed the ECG signals to images. The convolutional neural network overcomes the other by reaching an average accuracy of 97.6% in prediction set.

1. Introduction

ECG analysis arises from the necessity to efficiently diagnose heart diseases. AF is one of the most preoccupying heart abnormalities affecting 1-2% of the entire population and is likely to increase in the next decades [1]. The prevalence of AF increases with age, from less than 0.5% at 40-50 years of age, to 5-15% at 80 years [2]. The incidence of AF appears to be increasing as high as 13% in the past decades [3].

A promising tool to improve diagnosis is machine learning and more recently deep learning, despite the fact that there are other methods of AF classification which are not based on deep neural networks [4]. Currently AF and other various heart abnormalities detection are having trouble generalizing to new data. In order to improve this, some efforts have been done, for instance, the Physionet/CinC Challenge 2017 [5] encourage the development of algorithms to classify ECG lead signals and hence improve the disease detection. In this endeavour we try to classify ECG data with two simple machine learning methods, with the purpose to explore the way they behave with this type of data and to find the best approach by comparing the performance of a FFNN and CNN. Convolutional neural networks are specifically applied to images and had shown the powerful tool they are when classifying and recognizing patterns. Previous works classified ECG transforming the signals to images with the Logarithmic Spectrogram which increased the classification accuracy [6].

After training the neural networks with the training data set provided by The Physionet/CinC Challenge 2017 we test the final networks with the prediction set (i.e. a set not presented to the network while training). The measure of the performance of both architectures is reported computing the mean accuracy over the training and prediction set.

The structure of the article is the following: In section 2 we describe the data used and the structure of the networks, in section 3 we discuss the comparison among the networks and the work we plan to do in the near future. Finally in section 4 we present the conclusions.

2. ECG data and NN Architectures

The input data consisted on ECG signals taken from the Phyisionet database CinC 2017 challenge [5]. The training set contains 8,528 single lead recordings and the prediction set contains 300 single lead recordings. The recordings are of different duration in time and were sampled with a frequency of 300 Hz. There are 4 different classes in this set, normal rhythm, AF rhythm, other rhythm and noisy. Preprocess was applied in order to have the signal normalized and to have the same length in each sample, namely, the first 1,212 input nodes of each signal, this allows to speed up training. Figure 1 shows an example of a normalized ECG signal. In addition, a downsampling was made over the ECG signal, taking as sample every 4 points and dropping out the rest, generating final signals of 303-points long. In the case of the convolutional neural network an extra step was taken, the input elements were converted to 303 by 303 images using the GASF matrix [7] and reduced to 50 by 50 images by means of the resize Matlab function, the final image is shown in figure 2.

Both neural networks were programmed in python3 language, for the FFNN Numpy [8] library was used and TFlearn [9] library for the CNN. The structures of the neural networks were chosen using a rule of thumb along with trial and error. Starting by the simplest structure and adjusting the hyperparameters after assessing the net.

2.1. FFNN Architecture

The feed forward neural network structure was programmed from scratch and comprises of two layers, the input 303-neurons layer and the 300-neurons hidden layer, a learning rate of 0.7, the whole training set as the training batch, the sigmoid activation function and using the gradient descent method for training. The cost or error function considered in this structure was the mean squared error (MSE). The Net was trained for 220 cycles.

The MSE function is defined as

$$E = \sum_{i,\mu} \left(O_i^{\mu} - y_i^{\mu}\right)^2, \tag{1}$$

where the μ superscript denotes the sample and the i subscript denotes the component of the neuron in both the output O layer and label y of the sample.

The training is based on the well-known delta rule or gradient descent were the weight values are slightly corrected at each cycle with the following expression

$$\begin{aligned} w_{j,k}^{new} &= w_{j,k}^{old} - \eta \Delta w_{j,k} \\ &= w_{j,k}^{old} - \eta \frac{\partial E}{\partial w_{j,k}}, \end{aligned} \tag{2}$$

where $\Delta w_{j,k}$ is computed with the gradient of the cost function respect to the weight values of each layer and the j and k indices select the corresponding value of the weights between the layers.

2.2. CNN Architecture
The convolutional neural network architecture was programmed using the TFlearn library [9]. It comprises of two convolutional layers each with 64 and 32 filters respectively of size 2 by 2, strides of 1, a fully connected layer with 100 neurons and a Max pooling layer between each layer of size 2 by 2 and stride of 2. The ReLu was used as activation function except in the output layer where the Softmax function was utilized, a learning rate of 0.001, the categorical cross entropy (CCE) cost function, an Adam optimizer for learning, batch size of 64 and a dropout node probability of 0.2 to prevent overfitting.

The CCE function is defined as

$$E_c = -\sum_{i,\mu} y_i^{\mu} \log(O_i^{\mu}), \tag{3}$$

where the μ superscript denotes the sample and the i subscript denotes the component of the neuron in both the output O layer and label y of the sample.

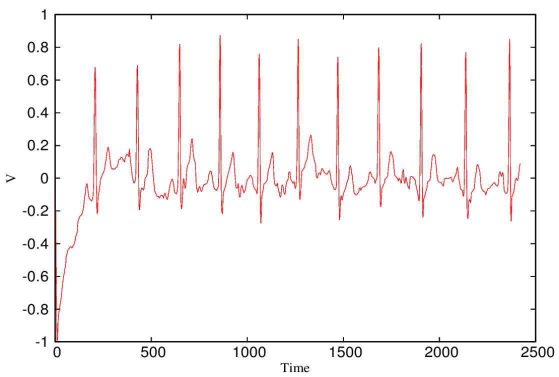

Figure 1. Normalized time series of an ECG signal sample.

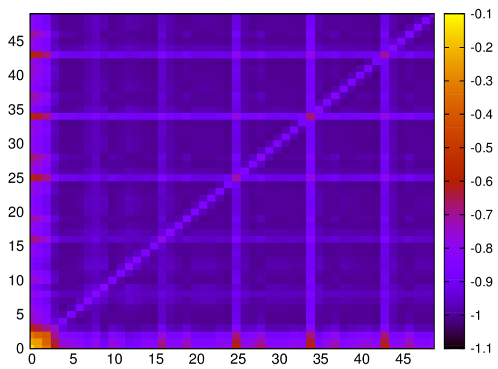

Figure 2. GASF transformation [2] of the normalized ECG signal sample.

3. Results, Comparison & Future Work
In this section we present and discuss the outcome of both neural network structures, namely, the FFNN and the CNN which were described in section 2. The ECG signals were given as an input to both nets after pre-processing and in the case of the CNN after applying the GASF transformation. The results enlighten how much a classification problem can be improved by means of CCN compared to the standard feed forward neural net. The performance of the nets was assessed by executing the whole training process 10 times and testing after the net was completely trained. In this sense we are able to estimate the mean value of the final performance of each neural network.

3.1. Feed Forward Neural Network Results
After 10 runs of the complete training, the neural net got an average accuracy of 86.4% on the prediction set. Table 1 (Left Structure) shows the accuracy of both training and prediction sets in each run.

The best accuracy reached was 89.3% in prediction set. Figure 3 and Figure 4 show the training set MSE and accuracy, respectively, through the 220 cycles of training of the run with the best accuracy. It can be observed that the neural network had learnt with a good rate until the last cycles where it ceased to learn.

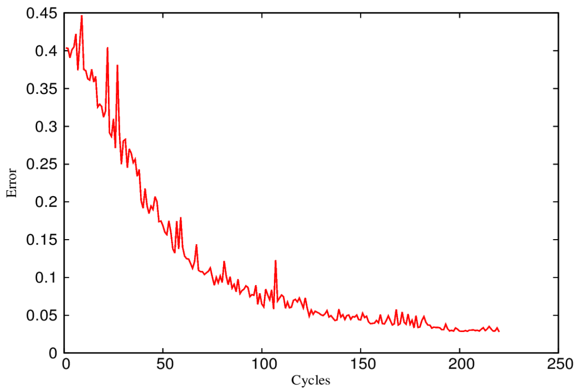

Figure 3. MSE of the training set of the feed forward neural network

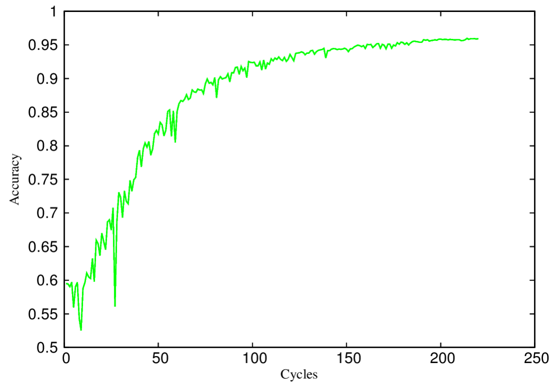

Figure 4. Accuracy of the training set of the feed forward neural network.

3.2. Convolutional Neural Network Results

In the same way, after the 10 runs we got an average accuracy of 97.6% with this structure on the prediction set. Table 1(Right structure) shows the accuracy of both training and prediction sets in each run.

The best accuracy on the prediction set produced by this neural net was 99%. Figure 5 and Figure 6 show the training set CCE error and accuracy, respectively, through the 150 cycles of training of the run with the best prediction accuracy.

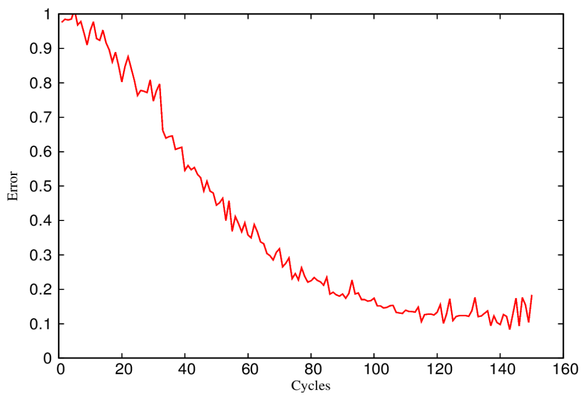

Figure 5. CCE error of the training set of the convolutional neural network.

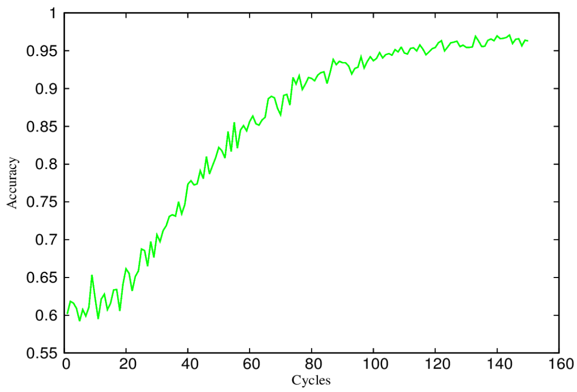

Figure 6. Accuracy of the training set of the convolutional neural network.

The performance of this structure overcomes by far the latter structure. Although the performance of the CNN is much higher than the previous one, after the 140th cycle the net stopped learning, moreover it started to forget what it had learnt and the error started to oscillate abruptly instead of diminishing, which forces us to stop the training.

Table 1. Accuracies of the provided standard neural network and convolutional neural network on each run and its mean value.

	FFNN		**CNN**	
Run	**Training (%)**	**Prediction (%)**	**Training (%)**	**Prediction (%)**
1	94.2	85.6	92.7	97.0
2	95.4	87.0	96.1	98.3
3	95.4	87.3	93.9	98.3
4	95.4	87.0	96.2	99.0
5	95.5	86.0	96.3	99.0
6	95.7	89.0	96.1	97.6
7	95.4	83.3	93.9	97.6
8	95.3	84.6	92.6	96.3
9	95.9	89.3	94.2	96.3
10	95.0	85.3	95.1	97.3
Mean	**95.3**	**86.4**	**94.7**	**97.6**

3.3. Comparison and Future work

The fact that we transformed the ECG signals to images clearly enhanced the classification performance which suggests that this type of transformation amplifies the features of each signal making it easier to detect differences between them, being aware that cost function and optimizers had an effect on accuracy as well. A better experiment can be done once the hidden test set of the CinC challenge is released considering that this set includes 3,658 ECG recordings.

Future work heads towards experiments between smaller sizes of images so as to make the training faster without losing accuracy. Also, introduce at least a third method of classification to compare would give a wider analysis to find the best approach to the problem, for instance support vector machines is a great candidate, in as much as it has been applied in previous works and result in a useful tool for myocardial infarction detection [10].

4. Conclusion

We developed and assessed two artificial neural network architectures for ECG signal classification. The neural networks were fed with input signals in time series format for the FFNN and in image format for the CNN. The image for the CNN was obtained proposing the GASF transformation. Clearly the first method shows having problems generalizing what it learnt, in contrast, the second method generalized pretty well, getting an accuracy of 99.0% in the best run.

Acknowledgments

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References

[1] Lip GY, Fauchier L, Freedman S B, Van Gelder I, Natale A, Gianni C, Nattel S, Potpara T, Rienstra M, Tse H F and Lane D A 2016 Atrial fibrillation *Nat. Rev.* D P **2** 16016

[2] Naccarelli G V, Varker H, Lin J and Schulman K L 2009 Increasing prevalence of atrial fibrillation and flutter in the United States *Am. J. Cardiol.* **104** 1534–9

[3] Camm A J, Kirchhof P, Lip G Y, Schotten U, Savelieva I, Ernst S, Van Gelder I C, Al-Attar N, Hindricks G, Prendergast B, Heidbuchel H, Alfieri O, Angelini A, Atar D, Colonna P, De Caterina R, De Sutter J, Goette A, Gorenek B, Heldal M, Hohloser S H, Kolh P, Le Heuzey JY, Ponikowski P, Rutten F H and ESC Committee for Practice Guidelines 2010 Guidelines for the management of atrial fibrillation: the Task Force for the Management of Atrial Fibrillation of the European Society of Cardiology (ESC) *Europace.* **12** 1360–420

[4] Larburu N, Lopetegi T and Romero I 2011 Comparative study of algorithms for atrial fibrillation detection *Comput. Cardiol. (2011)* 265–8

[5] Clifford G D, Liu C, Moody B, Lehman L H, Silva I, Li Q, Johnson A E and Mark R G 2017 AF classification from a short single lead ECG recording: The Physionet/Computing in Cardiology Challenge 2017 *Comput. Cardiol. (2010)* **44** 065–469

[6] Zihlmann M, Perekrestenko D and Tschannen M 2017 Convolutional recurrent neural networks for electrocardiogram classification 2017 *Comput. Cardiol. (2017)* 070-060 (*Preprint* arXiv:1710.06122 [cs.LG])

[7] Wang Z and Oates T 2015 Imaging Time-Series to Improve Classification and Imputation *Preprint* arXiv:1506.00327 [cs.LG]

[8] Oliphant T E 2006 *A guide to NumPy* (Trelgol Publishing)

[9] Damien A 2016 TFlearn Github

[10] Kumar A D,Kumar V and Kumar R 2017 Detection of myocardial infarction in 12 lead ECG using support vector machine *Appl. Soft Comp.* **64** 138–47