

SMALL CONVOLUTIONAL NETWORK FOR ARRHYTHMIA CLASSIFICATION IN ELECTROCARDIOGRAM SIGNALS

Jorge Torres¹, Julio David Buldain²



Instituto Universitario de Investigación
en Ingeniería de Aragón
Universidad Zaragoza

¹Accenture

²Department of Electronic and Communication Engineering, University of Zaragoza

INTRODUCTION

Electrocardiograms (ECG) are electrical signals that have been widely extended due to being a noninvasive technique that can record valuable information about heart activity. These signals can be recorded using wearable devices, but their limitations make them incapable of executing large neural networks to perform on-device analysis tasks.

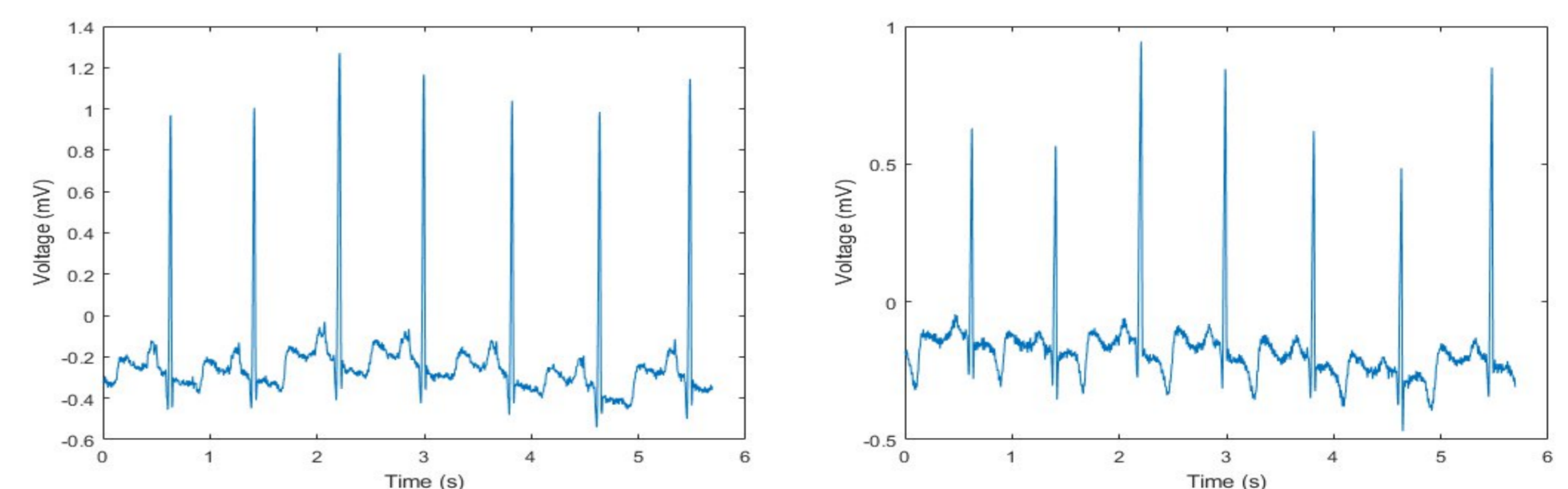
Several studies [1] have shown that new architectures, such as separable layers, can reduce neural networks complexity and their processing requirements. Using these layers, EEGNet [2] achieved state-of-the-art results in electroencephalogram classification with a very few number of parameters. Inspired by this study, we tried to generate a small convolutional model capable of classifying ECG segments and suitable for running on wearable devices.

METHODOLOGY

We normalized each signal from the MIT-BIH database [3], and then we resampled the signals from 360Hz to 512Hz. We extracted segments of 1.5 seconds duration from both derivations and we stacked both samples to create signals with size 2x768.

We generated sets for training, validation and test models. Once the models were trained, we calculated their ROC curves using predicted values from the test samples. Then, we obtained the optimal cut-point, and we used this value as baseline to classify segments between arrhythmic and not arrhythmic.

IMAGES



The left image shows an ECG segment obtained from the first derivation of a MIT-BIH database sample, and the right image plots a segment from its second derivation. We stacked both derivations to obtain a two channel signal used as input for the neural network.

ARCHITECTURE

EEGNet model is composed by a convolutional layer, which uses a 64 channel signal as input, and followed by a depthwise convolutional layer and a separable layer. Then, a dense layer performs the EEG classification. We tried to adapt this architecture to ECG characteristics, using a 2 channel signal as input. Also, we modified the size of filters according to the ECG time characteristics, applied selu as layer activation and added a second fully connected layer.

We trained several models and we calculated their ROC curve, reporting 90% AUC along all models. Using their cut-point as baseline, we calculated the classification accuracy in test batches, where the smallest model only used 4.8k parameters and obtained a 78% accuracy.

As second experiment, we tested if stacking separable layers could improve the classification accuracy, so we added three separable layers to the previous model. Also, we used strides instead of average pooling layers to decrease the output size. This model improved the previous results and reached an 82% accuracy in arrhythmia classification with only 15k parameters.

CONCLUSIONS

We have trained small neural networks that are able to classify electrocardiogram segments between arrhythmic and not arrhythmic with 82% accuracy. These models are suitable for being used in small devices such as wearables with low processing power due to their small size and the reduced number of convolutions to perform. Our next steps are focused on training and exploring different architectures that can improve the classifying accuracy without increasing the size or complexity of the network.

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