DeepCardio—Cardiac Arrhythmia Detection with a Neural Network

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Monitoring cardiac arrhythmias over long periods of time is a resource-intensive task as a specialist needs to review ECG signals. Methods for automatic detection can help to reduce the time needed to review the data by selecting interesting segments. However, these methods need to be accurate to avoid erroneous detections. We trained a neural network model to detect arrhythmias from a single-lead ECG signal and applied it to data collected with a smart vest previously developed at CSEM. The results are promising for screening cardiac arrhythmias in large populations.

Heart arrhythmias are caused by irregular electrical conduction in cardiac tissue. Atrial fibrillation (AF), which affects 1–2% of the population [1], is the most common one. Furthermore, its prevalence increases with age, from < 0.5% at 40-50 years to 5-15% at 80 years. While not directly life-threatening, it can lead to serious complications [2]. Typical symptoms include heart palpitations, shortness of breath, and fainting. However, about one third of the cases are asymptomatic which prevents early diagnosis. This, in turn, precludes early therapies which might protect the patient from the consequences of AF but also from its progression. Indeed, AF causes electrical and structural remodeling of the atria which facilitates its further development.

The gold standard for diagnosing AF and other heart arrhythmias is the 12-lead electrocardiogram (ECG). A trained electro-physiologist can select the most appropriate treatment after reviewing ECG signals and the patient history. This is, however, a time-consuming task, especially for long recordings. To alleviate this task, several approaches have been proposed to detect arrhythmias from ECG signals. Even without perfect detection accuracy, these approaches are useful as they facilitate reviewing ECG by selecting relevant signal excerpts. Recently, neural networks (NNs) have shown impressive performance in various classification and regression tasks. In particular, several architectures have been proposed to detect and classify heart arrhythmias from ECG signals [3].

Based on the promising results obtained with NNs, we developed an architecture to tackle the issue of early detection of cardiac arrhythmias. Our architecture takes as input a sequence of sliding windows extracted from a single-lead ECG signal. It combines convolutional layers to extract high-level features from the windows, a recurrent layer to take into account sequences with different lengths, and a softmax layer to output class probabilities. The network includes seven convolutional layers and each layer is composed of a 1D convolution, a ReLU activation, and a max pooling operation. The recurrent layer is a long short-term memory (LSTM) layer that aggregates the features extracted by the convolutional layer over sliding windows.

We trained this network on the dataset used for the challenge of Computing in Cardiology 2017 [4]. This dataset includes 8528 single-lead ECG records with durations ranging from 9 to 60 seconds. Each record is labeled with one of the following four classes: normal rhythm, AF, other rhythm, and noise. We divided the dataset into two subsets stratified by label: a training set with 7000 records and a test set with 1528 records. To limit overfitting, we applied dropout to the LSTM layer and used data augmentation strategies. The accuracy of the trained NN was 92.64% on the training set and 87.50% on the test set. In addition, it achieved a score of 0.8495 on the test set when evaluated with the metric used to rank participants of the challenge (the mean of the F1 scores for normal rhythm, AF, and other rhythm). This is comparable to the scores obtained by the winning entries.

After training and validating the NN, we applied it to ECG data collected with the Sense smart vest developed at CSEM to classify cardiac rhythms. This smart vest uses two dry stainless steel bi-electrodes to record a single-lead ECG signal. An example of arrhythmia detection is shown in Figure 1. In this example, the NN correctly identified premature ventricular contractions. These results suggest that combining a NN model with a smart vest could be helpful for long-term monitoring of heart arrhythmias in large populations.

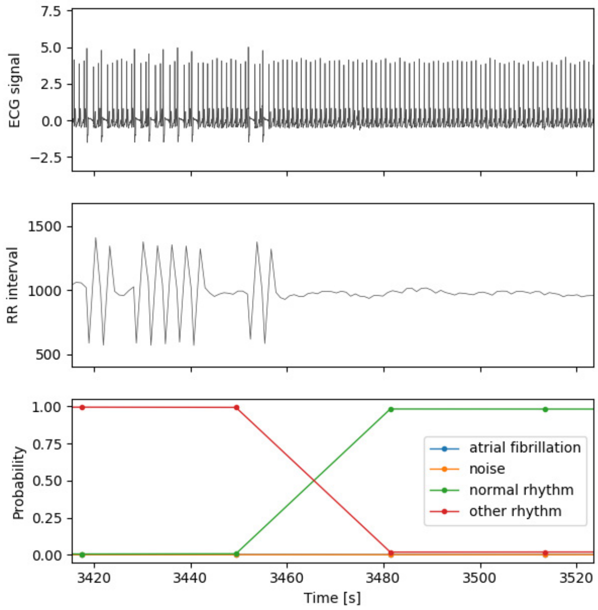

Figure 1: Cardiac rhythm classification from an ECG signal recorded with the smart vest. The ECG signal (top) includes premature ventricular contractions which are visible in the RR intervals (middle). The NN correctly identifies this segment of the signal as reflected by the class probabilities (bottom).

[1] Camm, *et al.*, "Guidelines for the management of atrial fibrillation: the Task Force for the Management of Atrial Fibrillation of the ESC." European Heart Journal 31.19 (2010): 2369-2429.

[2] January, *et al.*, "2014 AHA/ACC/HRS guideline for the management of patients with atrial fibrillation: a report of the ACC/AHA Task Force on Practice Guidelines and the HRS." Journal of the American College of Cardiology 64.21 (2014): e1-e76.

[3] Rajpurkar, *et al.*, "Cardiologist-level arrhythmia detection with convolutional neural networks." arXiv preprint arXiv:1707.01836 (2017).

[4] Clifford, *et al.*, "AF Classification from a short single lead ECG recording: the PhysioNet/Computing in Cardiology Challenge 2017." Computing in Cardiology. IEEE, 2017.