Applied AI in Biomedicine - Workshop Report

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I. Context

The goal of this project is to build a classification model that properly annotates each peaks as Normal, PAC (supraventricular beats) or PVC (ventricular beats). The available dataset is composed of 2-lead ECG signal and R peaks position of 105 patient recordings.

II. Introduction

Electrocardiogram (ECG) signals records the electrical activity of the human hearts and consist of several waveforms (P, QRS, and T). The duration and shape of each waveform and the distances between different peaks are used to diagnose cardiovascular heart diseases (CVD). Premature atrial contractions (PAC) and premature ventricular contractions (PVC) are among the most common forms of arrhythmias; the first results from premature electrical activation originating in the atria of the heart, while the second one is caused by a premature electrical activation originating in the ventricles. As the presence of frequent PACs and PVCs are associated with a higher risk of unfavorable prognosis[1][2], the accurate recognition of these abnormal beats is strictly required. The aim of the this work is to design a deep-learning ensemble model that properly classifies all the peaks in a recording, without requiring the extraction of ECG features. The History-Time-Frequency Classifier analyzes each samples in both the time and frequency domain, and take as input also the labels assigned to the previous two samples. The miss-classification error on the test set was around 3%, highlighting the potential of our classifier.

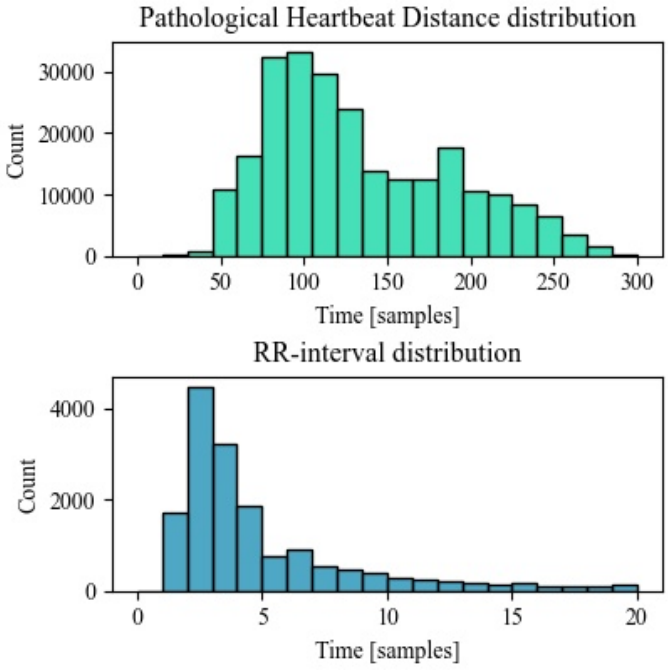
A. Dataset

The dataset consists of ECGs recorded from 105 patients

III. Data Preprocessing

The available raw dataset undergoes a pre-processing phase necessary for the optimal interfacing between the data and the model.

A. Exploratory Data Analysis



B. Signal Windowing

The heartbeat-by-heartbeat classification that the model performs implies the necessity of splitting the 30 minutes recording of each patient in windows, each one to be processed separately by the network: choosing the proper width and the optimal windowing approach is key in obtaining the best model performance. Three different approaches have been taken into consideration when splitting the windows, which are graphically compared in *Figure* **??**.

C. Class imbalance

IV. The H.T.F. Model

1. Parlare del class imbalance? Undersampling? 2. Mettere il graphviz del modello?

A. H as History

During a first inspection phase, an analysis on the distribution of pathological beats has been performed. In fig. 1a, the histogram reports the abnormal interpeak distances computed over all the recordings, confirming that PACs and PVCs often occurs in repeated patterns[3][4]. For these reasons, the involvement of the labels assigned to the previous peak could help in predicting more precisely the current peak. Considering the interpeak distances distributions, in this classifier the

two previous labels has been added as further inputs of the ensemble model

B. T as Time

C. F as Frequency

The last branch of this model consists in a frequency-domain classifier by a proper Fourier Transformation of the inputs. In order to apply the Fourier Transform, the stationarity hypothesis has been assumed for each window. This is not an heavy assumption, since the inputs length is very short and most part of the window consists in the peak recorded. The classifier consist of multiple CNN-ReLU-MaxPooling stacks. A low filter size has been chosen to get useful features in afew amount of samples at a time. After the application of the FFT on the input signal, the output of the CNN layer is concatenated with the two history-labels as in the time model. Finally, a dense layer with a softmax AF provides the probability assigned to the three labels.

V. Results

VI. Discussion

VII. Conclusions