

Heart Sound Classification - High Level Design Document

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1 Introduction

The High Level Design document aims to give a brief idea on well defined problem statement, software strategy, evaluation mechanism, data sources etc

2 Problem Statement

The Human heart generates a lub dub sound under its normal operating conditions. But it gives rise to many variations of the normal sounds when recorded from unhealthy subjects. Hence with an increase in the number of smart devices capable of listening to heart sounds, there is a need to conceptualize and prototype algorithms capable of automatically detecting normal v/s abnormal heart sounds.

3 Physionet Challenge 2016

Physionet is basically an online resource platform offering complex physiologic signals and other related open source software. It is managed by members of MIT's Lab of Computational Physiology. In the year 2016, they launched a challenge aiming to create an automated way to distinguish between normal/abnormal heart sounds utilizing machine learning techniques.

3.1 Challenge Data

As part of the challenge, the physionet have put forward a training dataset of consisting of almost 3K heart sound wave files ranging from 5sec to 120 sec in duration. This is an unbalanced dataset with more number of Normal sounds compared to abnormal sounds. They have provided a validation set of data consisting of the 20

4 Software Strategy

As part of the project implementation, we have broadly divided the efforts into two halves as Feature Engineering and Data modeling

4.1 Feature Engineering

The data is presented in the form of waveform(.wav format) and hence the feature engineering and extraction becomes a crucial pre-processing step. The clinical method of normal vs abnormal classifications are done in a acoustic manner by the doctor. Hence we are planning to extract acoustically motivated features like MFCC, STFT, CQT etc.

4.2 Data modeling

Once the acoustic features are extracted for every waveform in the dataset, the next step is to apply classification algorithms on top the data. Since this is a binary classification problem, we are giving preference to usage of SVM, Random Forest, Gradient boosting trees and their ensemble combinations

5 Evaluation

As per the original challenge, the evaluation is carried out by measuring the sensitivity, specificity and the overall score. the mathematical relation to find these are as below

$$\text{Sensitivity, } Se = w_1(A_{n1}/(A_{n1}+A_{q1}+A_{n1}))+w_2((A_{n2}+A_{q2})/(A_{n2}+A_{q2}+A_{n2})) \quad (1)$$

$$\text{Specificity, } Sp = w_1(N_{n1}/(N_{n1}+N_{q1}+N_{n1}))+w_2((N_{n2}+N_{q2})/(N_{n2}+N_{q2}+N_{n2})) \quad (2)$$

$$\text{OverallScore} = (Se + Sp)/2 \quad (3)$$

N_{n1} = Normal heat sound in Normal clean record
 N_{g1} = Uncertain heat sound in Normal clean record
 N_{a1} = Abnormal heat sound in Normal clean record
 N_{n2} = Normal heat sound in Normal noisy record
 N_{g2} = Uncertain heat sound in Normal noisy record
 N_{a2} = Abnormal heat sound in Normal noisy record

An1 = Normal heat sound in Abnormal clean record
Ag1 = Uncertain heat sound in Abnormal clean record
Aa1 = Abnormal heat sound in Abnormal clean record
An2 = Normal heat sound in Abnormal noisy record
Ag2 = Uncertain heat sound in Abnormal noisy record
Aa2 = Abnormal heat sound in Abnormal noisy record

wa1 = clean abnormal records/total abnormal record
wa2 = noisy abnormal records/total abnormal record
wn1 = clean normal records/total normal record
wn2 = noisy normal records/total normal record