INSTRUCTIONS AND STYLE GUIDELINES FOR THE PREPARATION OF FINAL YEAR LABORATORY PROJECT PAPERS : 2005 VERSION

Elias Sepuru (1386807)

School of Electrical & Information Engineering, University of the Witwatersrand, Private Bag 3, 2050, Johannesburg, South Africa

Abstract: The purpose of this document is to provide an easy-to-use template/style sheet to enable authors to prepare papers in the correct format and style for the final year laboratory project. This document may be downloaded from the School of Electrical and Information Engineering web site and can be used as a template. To ensure conformity of appearance it is essential that these instructions are followed. The abstract should be limited to 50-200 words, which should concisely summarise the paper.

Key words: Four to six key words in alphabetical order, separated by commas.

1. INTRODUCTION

As it stands, one of the most important, cost-effective and widely used techniques for one to get screened for cardiovascular diseases (CVDs) is through cardiac auscultation by a clinical physician [1, 2]. For rural populations, screening for CVDs hardly occurs due to lack of clinical physicians and health care avoidance [3, 4]. World Health Organisation (WHO) reports CVDs as the leading cause of deaths globally, with an estimated 31% of the deaths in 2016 caused by CVDs [5]. Methods to detect early signs of CVDs could prove to be very helpful in lowering the mortality rate due to CVDs, especially in disadvantaged communities [4].

This paper presents a project, that aims create an application using machine learning techniques. The application will enable first level screening of CVDs for personal use by individuals on their smartphones and will aid clinical physicians with cardiac auscultation. To train the machine learning (ML) models, heartbeat sounds, in a form of a Phonocardiogram (PCG) signal, from two sources are used. The sources are a smartphone and a digital stethoscope. Prior training, the PCG signals are segmented and used to generate features to feed the ML models. A total of 24 features, including non-time-domain features, are extracted. The ML models (ANN, SVM & XGB) trained on these features are then compared in their ability to diagnose CVDs.

2. BACKGROUND

Through cardiac auscultation clinical physicians are able to tell whether an individual has CVDs or not. They use the heart's lub (S1) and dub (S2) sounds to help them identify irregularities in ones heartbeat sounds. S1 and S2 are known as the fundamental heart sounds (FHs) [6]. The intervals between S1-S2 and S2-S1 are known as the systolic and diastolic periods respectively. For a relaxed heartbeat the diastolic period is larger than the systolic period [7]. In a normal heartbeat sound, S1 is followed by S2 in a continuous cycle.

Abnormalities occur when there are irregularities in the cycle of S1 and S2, these irregularities are what makes CVDs.

As mentioned in section 1. , the heartbeat audio data is from two sources, a smartphone (Dataset A) and a digital stethoscope (Dataset B). Dataset A has four classes: Normal, Murmur, Extra Heart Sound (HS) and Artifact. Dataset B has has three classes: Normal, Murmur and Extrasystole.

Murmurs are produced when there is a turbulent blood flow between either systolic or diastolic periods [8]. The turbulence often cause a "whooshing" sound in between S1 and S2. Extra HS are produced when there is either an extra S2 or S1 after either S2 or S1 has occurred. This repeats regularly throughout the entire heart cycle in this manner: S1-S2-S2-S1 or S1-S1-S2-S1-S1. Extrasystole occur in a similar manner as Extra HS, but they do not occur regularly [9]. See Appendix A, for a clearer explanation of the distinctions between the different classes and an explanation of the Artifact class.

2.1 PROJECT FRAMEWORK

2.1.1 Project Specifications and Requirements

The ultimate aim of the project is create an application using ML techniques that will aid patients and clinical physicians in early detection of CVDs. The application is to accept raw audio data as input and return diagnosis results as an output.

This will be carried out using data from Dataset A and Dataset B. Dataset A is recorded by the general public using the iStethoscope Pro app on an iPhone, whilst Dataset B is recorded in a more professional manner by clinical physicians using a digital stethoscope. They both differ by two categories as mentioned in the opening paragraphs of section 2. and both have excessive background noise as they are recorded in real-life settings.

Due to the excessive background noise, it is required

that processing techniques capable of denoising the audio data be implemented before segmentation can occur. Following denoising, a method to locate S1 and S2 HS as well as a method to segment the Normal PCGs from both datasets is required. After successful segmentation, it is required that features be generated from the results of segmenting the PCG signals. Lastly, it is required that ML models be built and trained using the generated features.

2.1.2 Assumptions

The project is to be conducted under the following assumptions:

- The audio data range will be 30 seconds or less.
- Dataset A has only four classes (Normal, Murmur, Extra HS and Artifact). Dataset B has only three classes (Normal, Murmur & Extrasystole)
- Both datasets have integrity and are correctly labelled.

2.1.3 Constraints

The following are the constraints imposed on the project:

- Segmentation is based only on S1 and S2 sounds.
- Only the dataset from reference [9] is to be used due to ethics clearance attached in Appendix **??**.
- Only the Normal audio data will be used as a basis for the location of S1 and S2 and as a basis for segmentation.
- The audio data is only available in `.wav` and `.aif` formats.

2.1.4 Success Criteria

The project is deemed successful if all requirements in section 2.1.1 have been met, whilst adhering to the set constraints in section 2.1.3. Existing solutions have an accuracy of upto 77% for classifying Normals of Dataset B and an accuracy of up to 46% for Dataset A. With that said an accuracy of 77% or higher in classifying Normals of Dataset B and an accuracy of 46% or higher in classifying Normals of Dataset A would be highly desirable.

3. CONCLUSION

A conclusion may review the main points of the paper, but do not replicate the abstract as the conclusion.

REFERENCES

[1] A. Gavrovska, G. Zajić, V. Bogdanović, I. Reljin, and B. Reljin. "Identification of S1 and S2 Heart Sound Patterns Based on Fractal Theory and Shape Context." *Complexity*, vol. 2017, 2017.

[2] M. R. Montinari and S. Minelli. "The first 200 years of cardiac auscultation and future perspec-
tives." *Journal of multidisciplinary healthcare*, vol. 12, p. 183, 2019.

[3] M. Robinson. "SA needs Rural Doctors." `http://www.rudasa.org.za/news/article-listing/69-sa-needs-rural-doctors-opinion-piece`. Last Accessed: 2019-09-04.

[4] A. M. Spleen, E. J. Lengerich, F. T. Camacho, and R. C. Vanderpool. "Health care avoidance among rural populations: Results from a nationally representative survey." *The journal of rural health*, vol. 30, no. 1, pp. 79–88, 2014.

[5] WHO. "Cardiovascular diseases (CVDs)." `https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)`. Last Accessed: 2019-09-04.

[6] W. Zhang, J. Han, and S. Deng. "Heart sound classification based on scaled spectrogram and partial least squares regression." *Biomedical Signal Processing and Control*, vol. 32, pp. 20–28, 2017.

[7] J. M. Orient and J. D. Sapira. *Sapira's art & science of bedside diagnosis*. Lippincott Williams & Wilkins, 2010.

[8] S. Al Bugami. "Heart murmurs." *parkhurst exchange*, 08 2007.

[9] P. Bentley, G. Nordehn, M. Coimbra, and S. Mannor. "The PASCAL Classifying Heart Sounds Challenge 2011 (CHSC2011) Results." `http://www.peterjbentley.com/heartchallenge/index.html`.

Appendix

A Heart Sound Classes

The Normal Class

The Normal class consists of normal, healthy and regular HS. A Normal HS has a clear *"lub dub, lub dub"* or S1-S2-S1-S2. The illustration above shows the *"lub, dub"* of a Normal HS over time [9].

```
lub...dub......lub...dub.....
```

Figure 1 illustrates a typical PCG of a Normal HS.
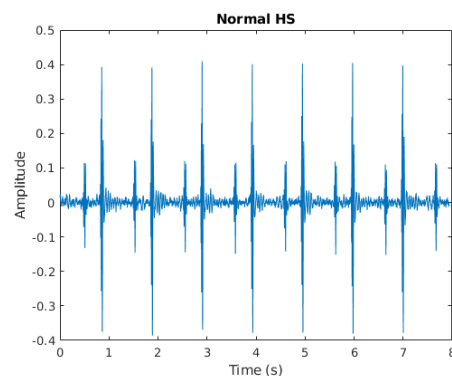

Figure 1 : PCG of a Normal HS

The Murmur Class

The Murmur class consists of pathological HS. Murmurs are produced when there is a turbulent blood flow between either systolic or diastolic periods [8]. The turbulence often cause a "whooshing" sound in between S1 and S2 or in between S2 and S1. The illustration above shows the "lub, dub" of a Murmur HS over time [9].

```
lub..***..dub......lub..***..dub.....
```

or

```
lub...dub...***...lub...dub..***...
```

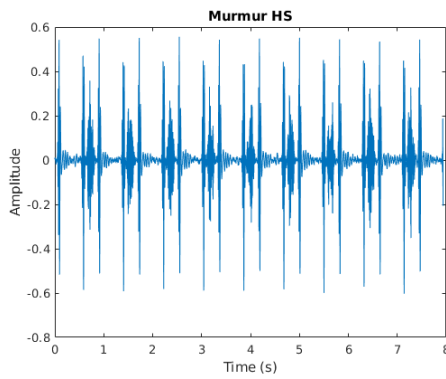Figure 2 illustrates a typical PCG of a Murmur HS.

Figure 2 : PCG of a Murmur HS

From figure 2 it can clearly be seen that there are are extra disturbances in between S1 and S2 as compared to figure 1.

The Extra HS Class

The Extra HS class does not necessarily consists of pathological HS, however sometimes it could be a sign of a disease. Extra HS are produced when there is either an extra S2 or S1 after either S2 or S1 has occurred. This repeats regularly throughout the entire heart cycle in this manner S1-S2-S2-S1 or S1-S1-S2-S1-S1. The illustration above shows the "lub, dub" of a Extra HS over time [9].

```
lub.lub...dub......lub.lub...dub.....
```

or

```
lub...dub.dub.....lub...dub.dub.....
```

Figure 3 illustrates a typical PCG of an Extra HS.

From figure 3 it can clearly be seen that there are extra peak in between S1 and S2 as compared to figure 1.
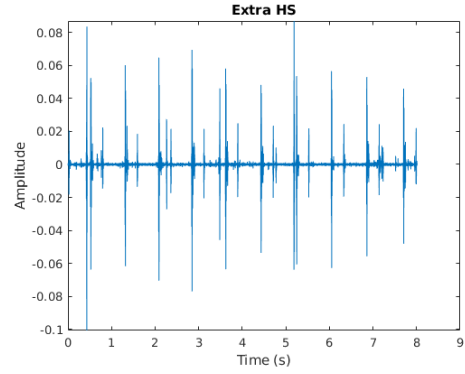

Figure 3 : PCG of an Extra HS

The Extrasystole HS Class

The Extrasystole class, similar to the Extra HS class, does not necessarily consists of pathological HS, however sometimes it could be a sign of a disease. Extrasystole HS occur in a similar manner as Extra HS, but they do not occur regularly. They are commonly identified by HS that are out of place, with a HS either repeated or skipped. The illustration above shows the "lub, dub" of a Extrasystole HS over time [9].

```
lub....dub......lub.lub...dub.....lub....
```

or

```
lub....dub.dub.....lub...dub......lub....
```

Figure 4 illustrates a typical PCG of an Extrasystole HS.
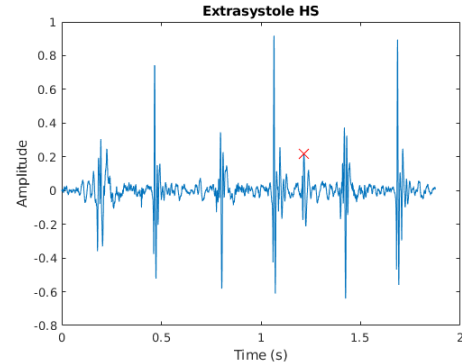

Figure 4 : PCG of an Extrasystole HS

From figure 4 it can clearly be seen that there is a single extra peak in between S1 and S2, marked with a red cross, as compared to figure 1 and figure 3.

The Artifact Class

The Artifact class does not consist of any HS. These are recordings of random sounds. The class is to help the developed models to differentiate between a HS

and just pure noise [9].

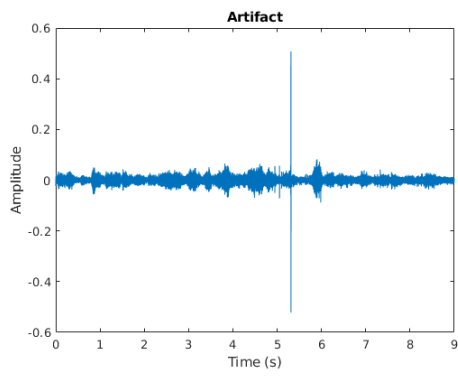Figure 5 illustrates a typical of an Artifact.

Figure 5 : Artifact Class signal

From figure 5, it can be seen that there is no sense of
normal periodicity within the signal.