Listen to your Heart:
Heartbeat Sound Segmentation & Classification

September 11, 2019

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Agenda

- Introduction
- Objectives
- Background
  - Heartbeat Sounds Categories
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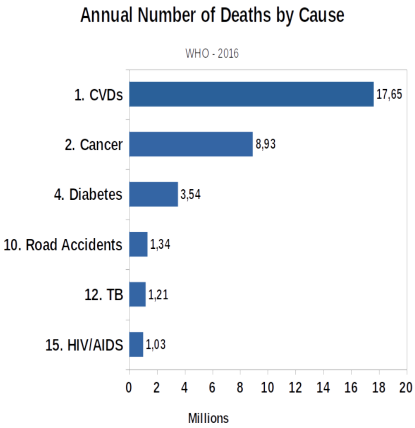
  - Classification
- Testing & Results
- Future Work
- User Interface
- Work Division

Introduction

- CVDs are the leading causes of deaths globally - WHO.



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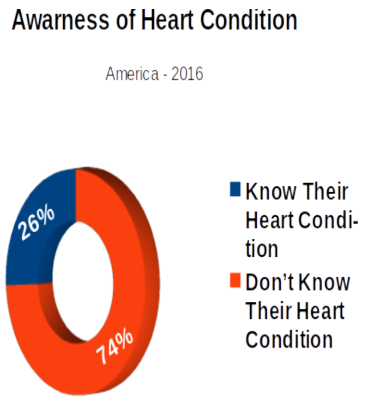
Correct diagnosis using CA in USA, Canada & UK respectively.

Introduction

- CVDs are the leading causes of deaths globally - WHO.
- Currently used method to check for CVDs is Cardiac Auscultation (CA).
- CA is a difficult skill to acquire.
- People are not aware of their heart conditions.

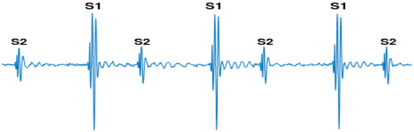


Introduction

Easily accessible & reliable heart diagnosis systems would help reduce deaths due to CVDs.

Objectives

- To segment Heartbeat sounds (HSs) based on the location of S1 (lub) S2 (dub) in Normal HSs.



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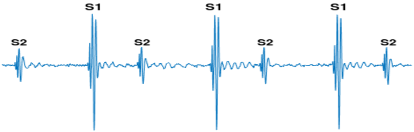
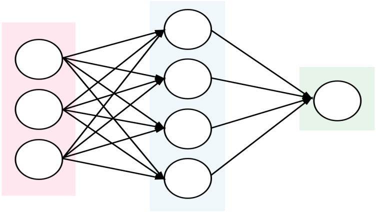


- Create models that will enable preliminary screening of CVDs



Background

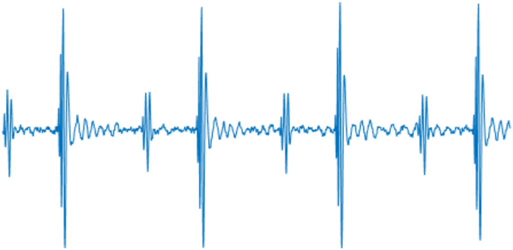
Heartbeat Sounds Categories

This project deals with classifying HSs into the following categories:

1. Normal HSs
2. Murmur HSs
3. Extra Heartsounds
4. Exrasystole HSs
5. Artifact

Normal HSs

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

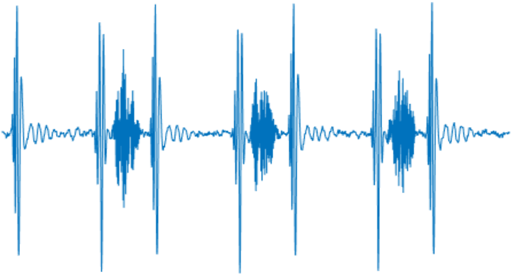


Murmur HSs

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

or

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

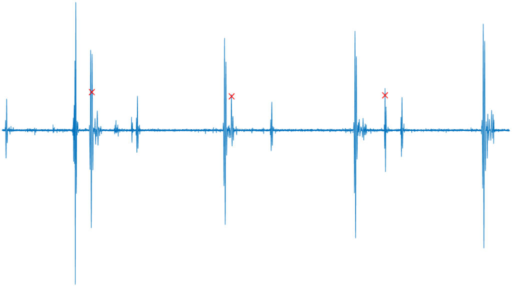


Extra HS

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

or

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

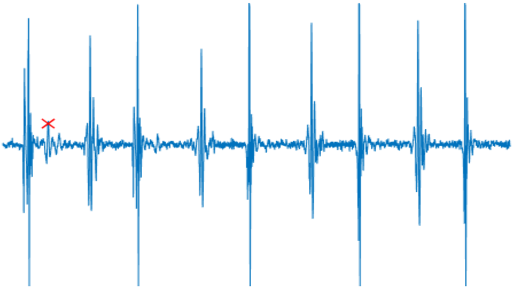


Extrasytole HSs

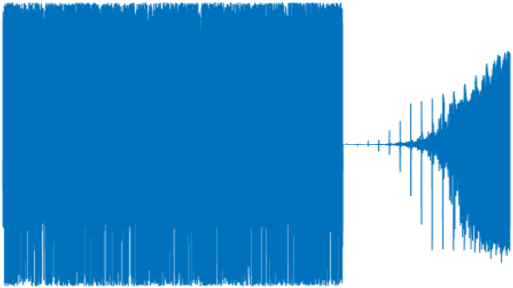
lub....dub......lub.lub...dub.....lub....

or

lub....dub.dub.....lub...dub......lub....



Artifact Sound
Not an actual HSs.

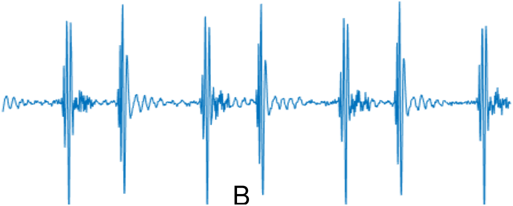


Background

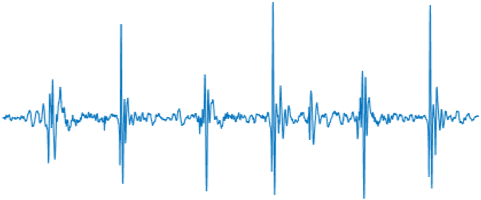
Heartbeat Sounds Categories

Can you guess the categories?

A



B



Background
Related Work

Strunic's attempt to classify HSs with ANN.

85±7.4%

Accuracy when classifying simulated HSs with no noise.

48±12.7%

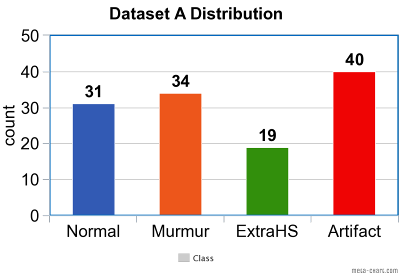
Accuracy when classifying real life HSs with noise.

Background

Project Setting

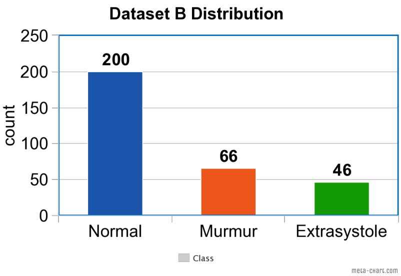
To make this project applicable to real world situations, two datasets recorded in real life settings will be used. Both datasets contain excessive background noise.

Dataset A



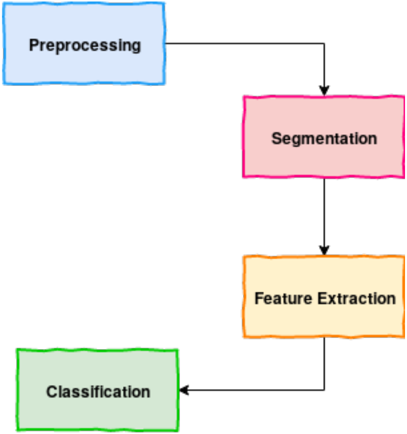
- Recorded by the general public
- Device - iStethoscope Pro Iphone app
- Sampling Freq - 44100Hz
- Contains excessive background noise

Dataset B



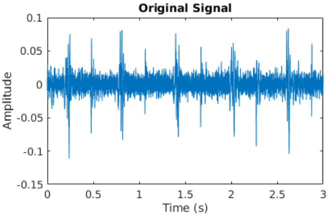
- Recorded from a hospital by Medical Practitioners
- Device - Digital Stethoscope
- Sampling Freq - 4000Hz
- Contains background noise

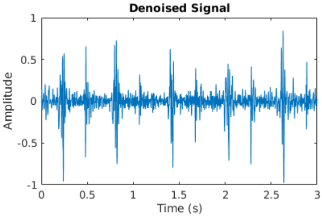
Methodology
System Overview



Methodology
Preprocessing

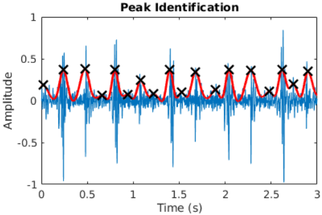
1. Downsample to 2kHz
2. Bandpass Chebyshev filter [30Hz-195Hz]
3. Normalization [-1 1]
4. Wavelet Decomposition (db7 level 5)
5. Refilter with LPF [195Hz]

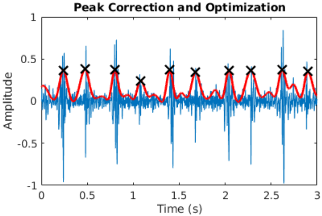




Methodology
Segmentation

1. Envelope Detection
2. Peak Detection
3. Extra Peak Rejection
4. Peak Correction & Optimization
5. Location of S1 and S2



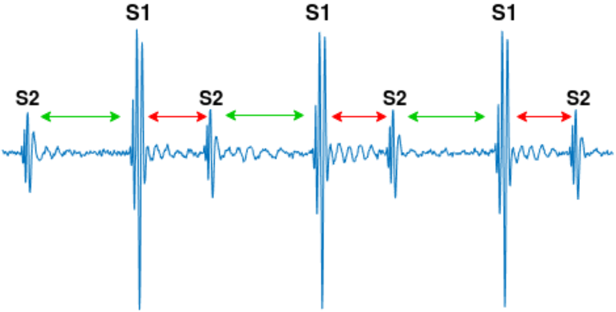


Methodology

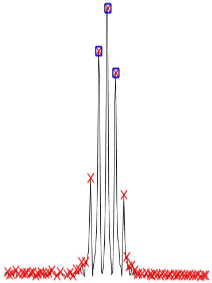
Feature Extraction

1. Time Domain
2. Frequency Domain
3. Wavelet
4. Ceptrum

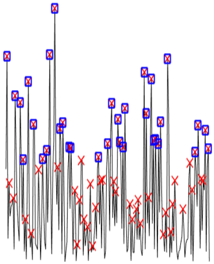
Time Domain Features



Frequency Domain Features

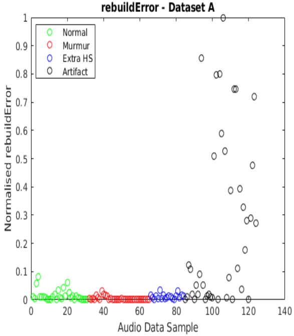


FFTSHA of Murmur HSs at [180 190] Hz band

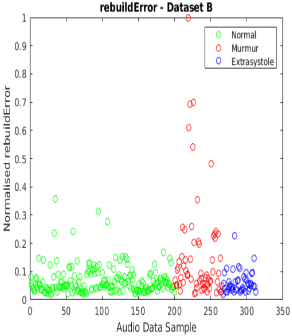


FFTSHA of Normal HS at [180 190] Hz band

Wavelet Features

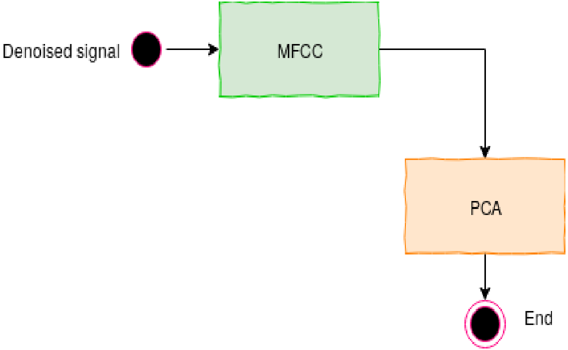


Rebuild error of Dataset A



Rebuild error of Dataset B

Cepstrum Features



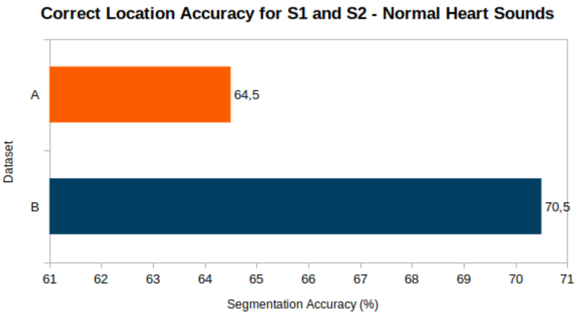
Cepstrum Feature Extraction

Methodology
Classification

1. ANN (Artificial Neural Network)
2. SVM (Support Vector Machine)
3. XGBoost (XGradient Boost)

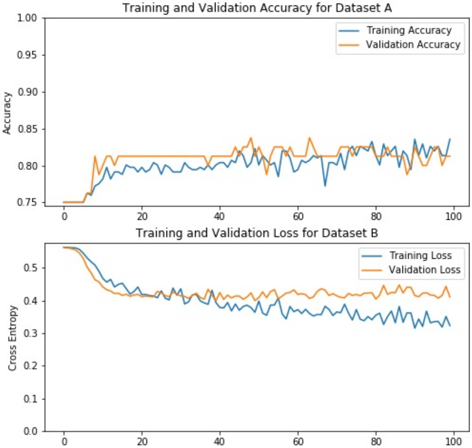
Testing & Results

Segmentation



Testing & Results

Dataset A - ANN Performance



Testing & Results

Dataset B - ANN Performance

Classification

Table: Classification Performance Dataset-A

Class (A)	ANN (%)	SVM (%)	XGB (%)	Literature (%)
Normal	27	80	71	45
Murmur	88	78	86	31
ExtraHS	67	25	57	11
Artifact	100	57	50	58
Overall Accuracy	**81**	**64**	**68**	**46**

Testing & Results

Classification

Table: Classification Performance Dataset-B

Class (B)	ANN (%)	SVM (%)	XGB (%)	Literature (%)
Normal	80	77	89	78
Murmur	90	87	75	37
Extrasys	15	0	17	17
Overall Accuracy	**80**	**78**	**79**	**77**

Improvements and Future Work

- Increase dataset

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- Increase dataset
- Use equally distributed dataset

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- Improve recording techniques

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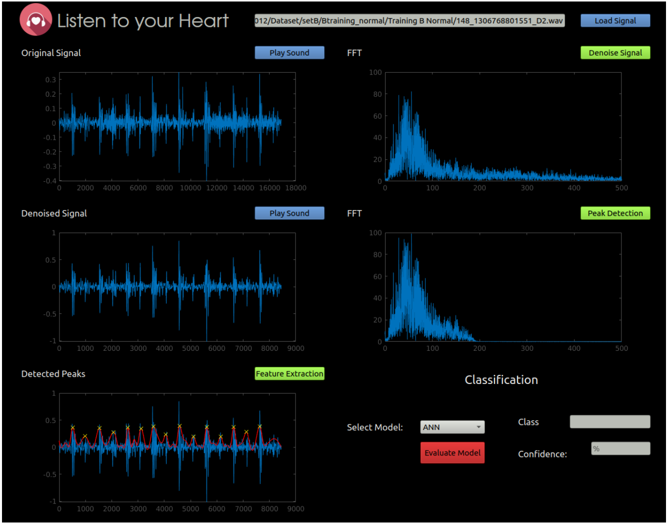
- Improve location of S1 and S2

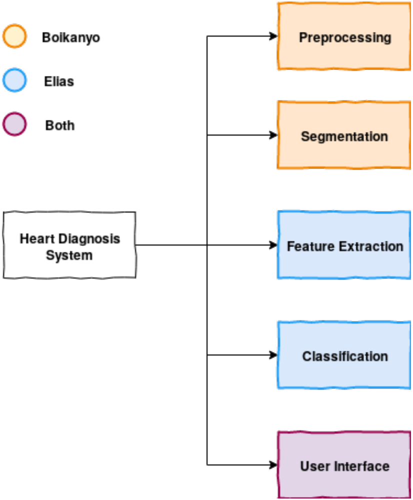
Improvements and Future Work

- Increase dataset
- Use equally distributed dataset
- Improve recording techniques
- Improve location of S1 and S2
- Distinguishing features between Extra HS and Extrasystole

User Interface



Work Division



Conclusion

- A method to segment and classify heart sounds into normal and diseased categories has been successfully developed and implemented.
- An accuracy of over 80% and above is achieved for normal heart sounds classification
- More work is required to improve the classification of Extrasystole HSs

Thank you!

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