

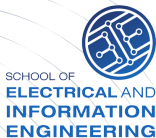
# Listen to your Heart:

## Heartbeat Sound Segmentation & Classification

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# Agenda



Introduction

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- Heartbeat Sounds Categories

- Related Work

- Project Setting

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- System Overview

- Preprocessing

- Segmentation

- Feature Extraction

- Feature Extraction

- Classification

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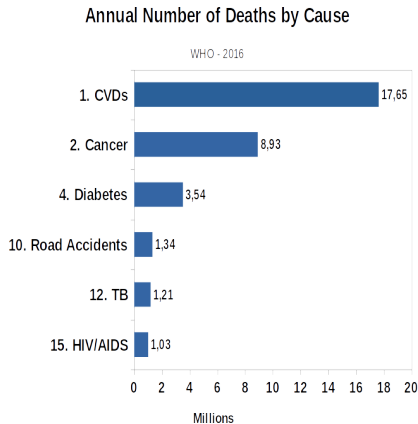
User Interface

Work Division

# Introduction



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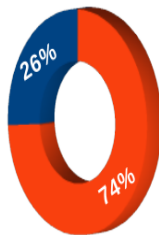
Correct diagnosis using CA in USA, Canada & UK respectively.



## Awareness of Heart Condition

America - 2016

- ▶ 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.



- Know Their Heart Condition
- Don't Know Their Heart Condition

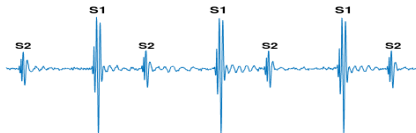


Easily accessible & reliable heart diagnosis systems would help reduce deaths due to CVDs.

# Objectives



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

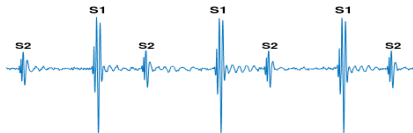




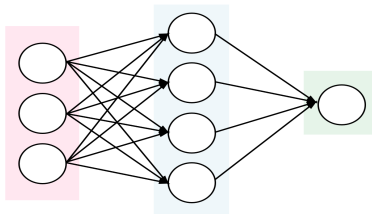
# Objectives



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



- Create models that will enable preliminary screening of CVDs





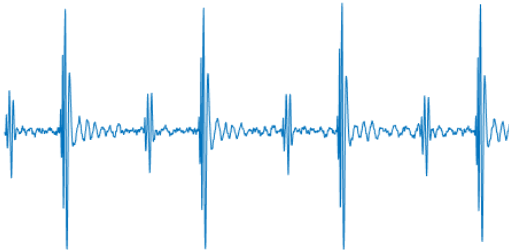
This project deals with classifying HSs into the following categories:

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



## Normal HSs

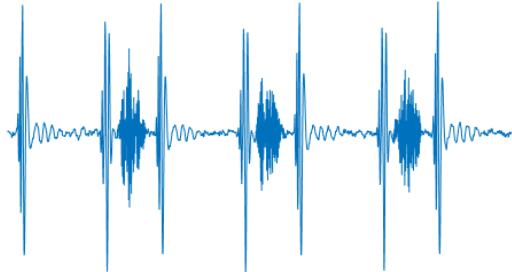
lub...dub.....lub...dub.....





## Murmur HSs

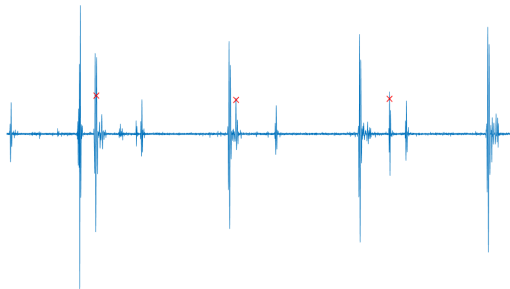
lub...\*\*\*..dub.....lub...\*\*\*..dub.....  
or  
lub....dub...\*\*\*...lub....dub...\*\*\*...





## Extra HS

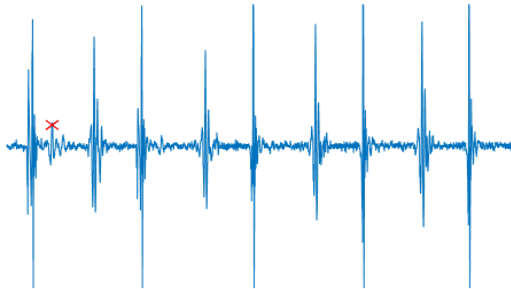
lub.lub...dub....lub.lub...dub....  
or  
lub...dub.dub....lub...dub.dub....





## Extrasystole HSs

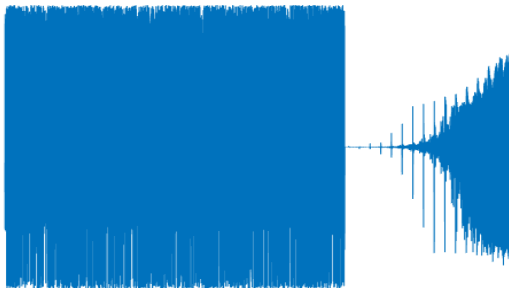
lub....dub.....lub.lub...dub.....lub....  
or  
lub....dub.dub.....lub...dub.....lub....





## Artifact Sound

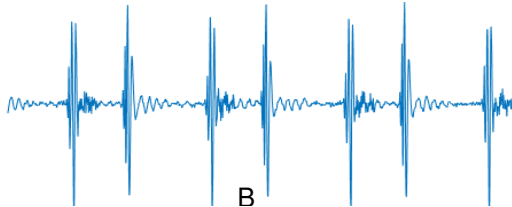
Not an actual HSs.



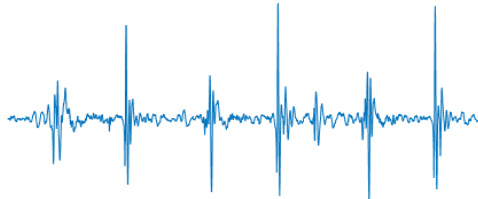


Can you guess the categories?

A



B







Strunic's attempt to classify HSs with ANN.

**85±7.4%**

Accuracy when classifying simulated HSs with no noise.

**48±12.7%**

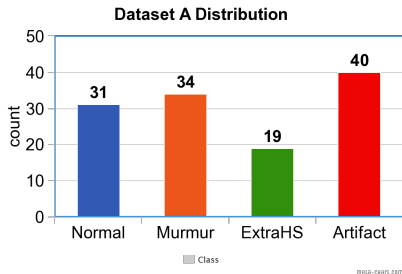
Accuracy when classifying real life HSs with noise.



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.



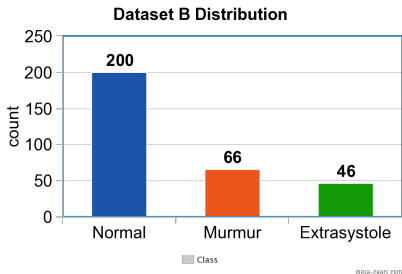
## Dataset A



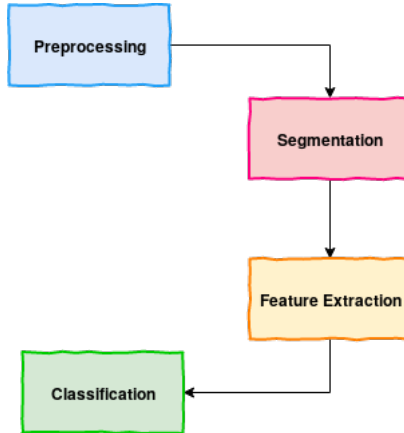
- ▶ Recorded by the general public
- ▶ Device - iStethoscope Pro Iphone app
- ▶ Sampling Freq - 44100Hz
- ▶ Contains excessive background noise



## Dataset B

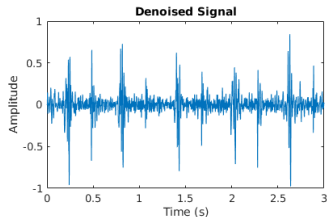
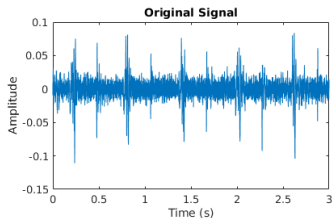


- ▶ Recorded from a hospital by Medical Practitioners
- ▶ Device - Digital Stethoscope
- ▶ Sampling Freq - 4000Hz
- ▶ Contains background noise



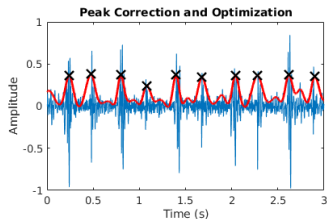
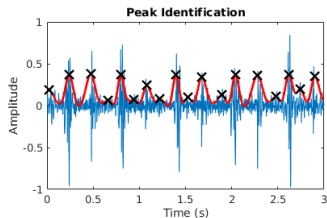


1. Downsample to 2kHz
2. Bandpass Chebyshev filter [30Hz-195Hz]
3. Normalization [-1 1]
4. Wavelet Decomposition (db7 level 5)
5. Refilter with LPF [195Hz]





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



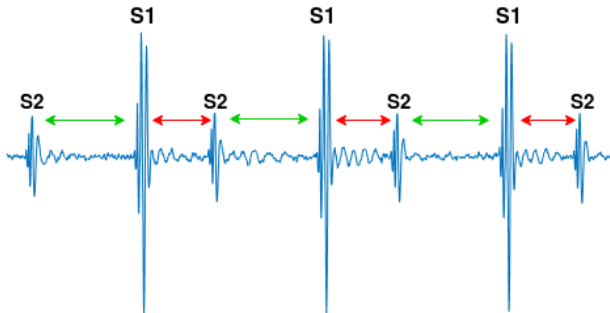


1. Time Domain
2. Frequency Domain
3. Wavelet
4. Ceptrum



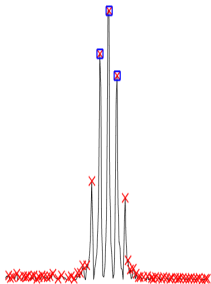


## Time Domain Features

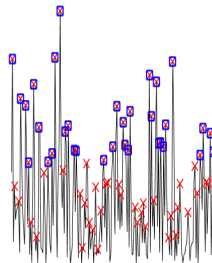




## Frequency Domain Features



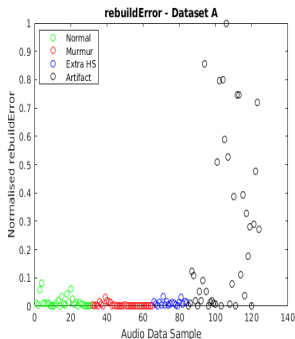
FFTSHA of Murmur HSs at [180 190]  
Hz band



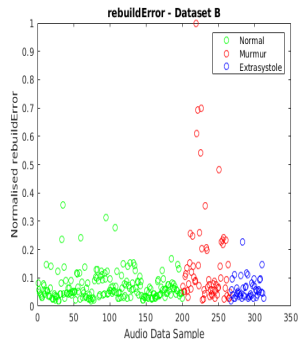
FFTSHA of Normal HS at [180 190]  
Hz band



## Wavelet Features



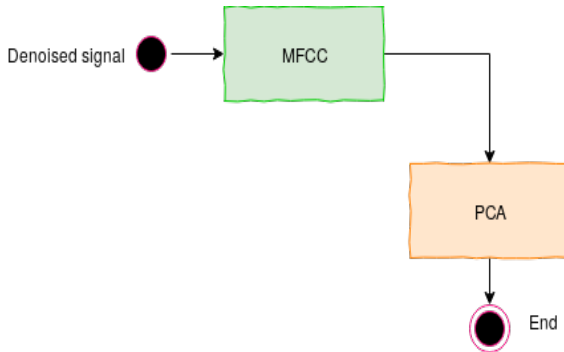
Rebuild error of Dataset A



Rebuild error of Dataset B



## Cepstrum Features



## Cepstrum Feature Extraction

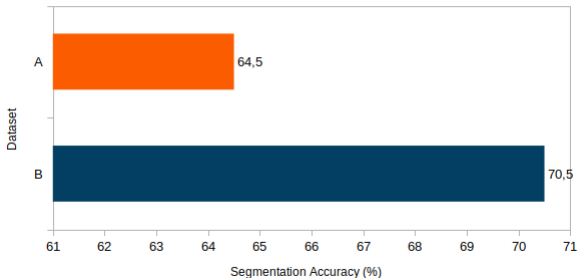


1. ANN (Artificial Neural Network)
2. SVM (Support Vector Machine)
3. XGBoost (XGradient Boost)



## Segmentation

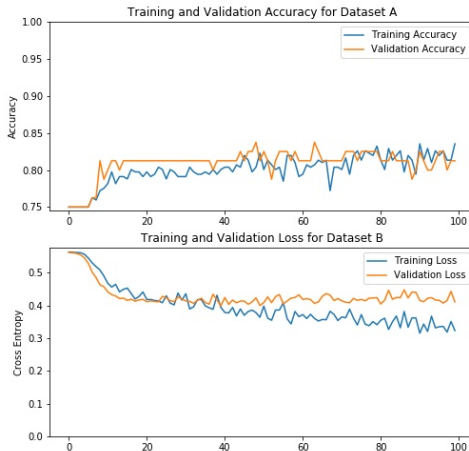
**Correct Location Accuracy for S1 and S2 - Normal Heart Sounds**



# Testing & Results



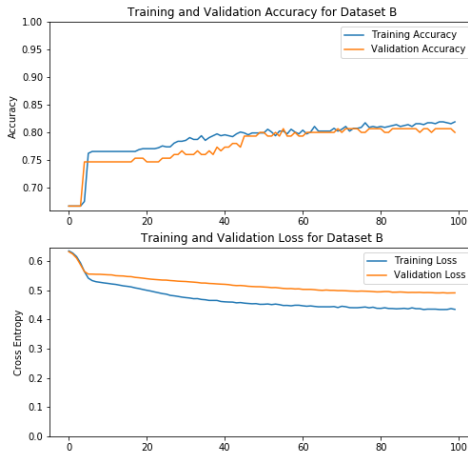
## Dataset A - ANN Performance



# Testing & Results



## Dataset B - ANN Performance







## Classification

Table: Classification Performance Dataset-A

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



## Classification

Table: Classification Performance Dataset-B

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

# Improvements and Future Work



- ▶ Increase dataset

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- ▶ Increase dataset
- ▶ Use equally distributed dataset

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- ▶ Increase dataset
- ▶ Use equally distributed dataset
- ▶ Improve recording techniques
- ▶ Improve location of S1 and S2



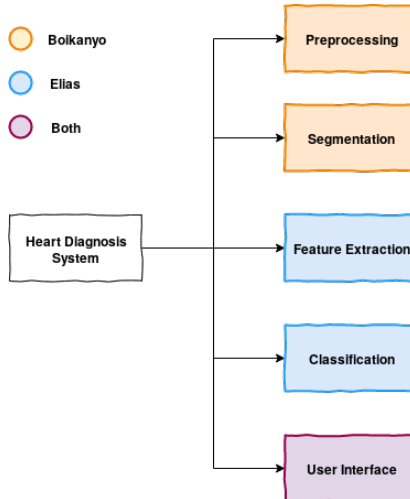
- ▶ Increase dataset
- ▶ Use equally distributed dataset
- ▶ Improve recording techniques
- ▶ Improve location of S1 and S2
- ▶ Distinguishing features between Extra HS and Extrasystole

# User Interface





# Work Division





- ▶ 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!

