Listen to your Heart:

Heartbeat Sound Segmentation & Classification

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Feature Extraction

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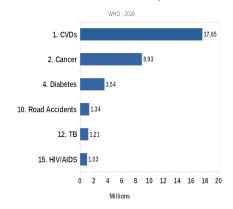
User Interface

Work Division



 CVDs are the leading causes of deaths globally - WHO.

Annual Number of Deaths by Cause





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- Currently used method to check for CVDs is Cardiac Auscultation (CA).





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- CA is a difficult skill to acquire.



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



- 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.

Awarness of Heart Condition

America - 2016



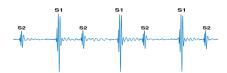
- Know Their Heart Condition
- Don't Know Their Heart Condition



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.

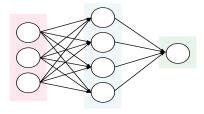


Objectives

➤ 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
- 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.....
```





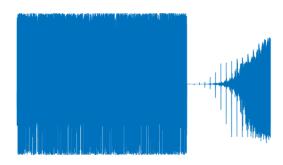
Extrasytole HSs



Background Heartbeat Sounds Categories



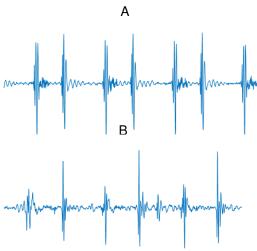
Artifact Sound Not an actual HSs.



Background Heartbeat Sounds Categories



Can you guess the categories?





Strunic's attempt to classify HSs with ANN.

85±7.4%

Accuracy when classifying simulated HSs with no noise.



Accuracy when classifying real life HSs with noise.

Background Project Setting

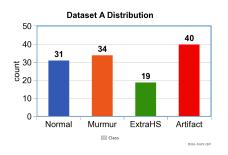


To make this project applicable to real world situations, two datasets recorded in real life settings will be used. Both datasets contain excessive background noise.

Methodology Data Acquisition



Dataset A

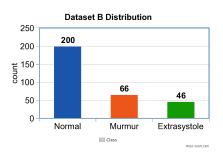


- Recorded by the general public
- Device iStethoscope Pro lphone app
- ► Sampling Freq 44100Hz
- Contains excessive background noise

Methodology Data Acquisition



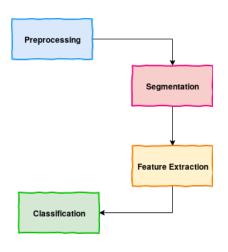
Dataset B



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

Methodology System Overview

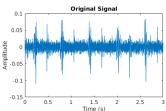


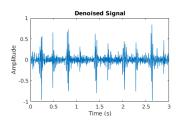


Methodology Preprocessing



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

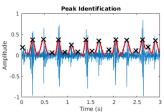


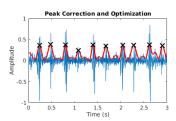


Methodology Segmentation



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





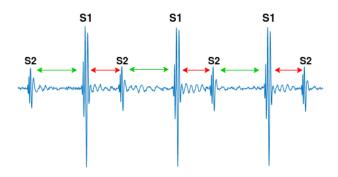
Methodology Feature Extraction



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



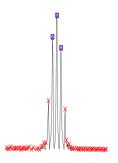
Time Domain Features



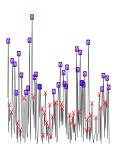
Methodology Feature Extraction



Frequency Domain Features



FFTSHA of Murmur HSs at [180 190] Hz band

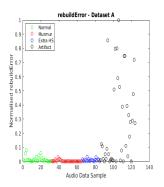


FFTSHA of Normal HS at [180 190] Hz band

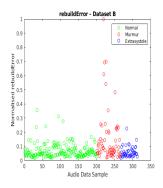
Methodology Feature Extraction



Wavelet Features



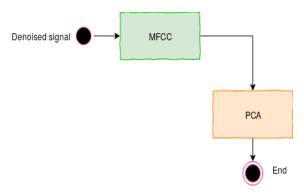
Rebuild error of Dataset A



Rebuild error of Dataset B



Cepstrum Features



Cepstrum Feature Extraction

Methodology Classification

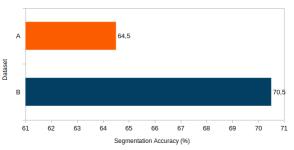


- 1. ANN (Artificial Neural Network)
- 2. SVM (Support Vector Machine)
- 3. XGBoost (XGradient Boost)



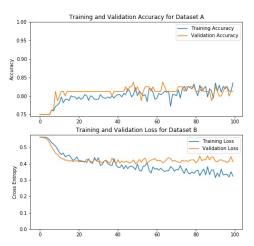
Segmentation

Correct Location Accuracy for S1 and S2 - Normal Heart Sounds



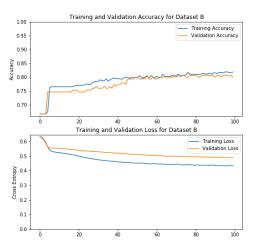


Dataset A - ANN Performance





Dataset B - ANN Performance



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Classification

Table: Classification Performance Dataset-A

Class	ANN	SVM	XGB	Literature
(A)	(%)	(%)	(%)	(%)
Normal	27	80	71	45
Murmur	88	78	86	31
ExtraHS	67	25	57	11
Artifact	100	57	50	58
Overall	81	64	68	46
Accuracy	01	04	08	40



Classification

Table: Classification Performance Dataset-B

Class	ANN	SVM	XGB	Literature
(B)	(%)	(%)	(%)	(%)
Normal	80	77	89	78
Murmur	90	87	75	37
Extrasys	15	0	17	17
Overall	80	78	79	77
Accuracy		70	19	,,,



► Increase dataset



- ▶ Increase dataset
- ► Use equally distributed dataset



- ▶ Increase dataset
- Use equally distributed dataset
- ► Improve recording techniques

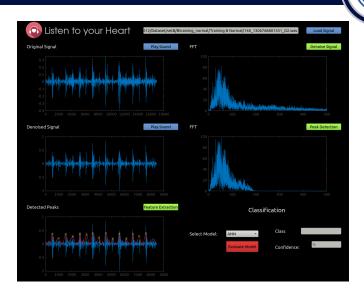


- ▶ Increase dataset
- ► Use equally distributed dataset
- ► Improve recording techniques
- ► Improve location of S1 and S2



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

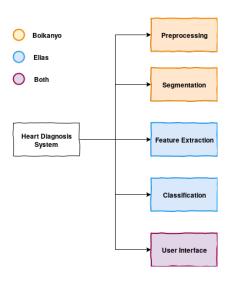
User Interface



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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!

