Presentation Link

https://www.youtube.com/watch?v=L7zx9cpcOU4

Guardian Labs

Final Presentation

Heartbeat Sound Classification

Acknowledgement

Special thanks to Dr.Muhammad Ali Shahid DO, for helping the team manually label missing heartbeat audio data.

AGENDA

1. Introduction
2. Business Problem, Objectives, & Solution
3. Methodology
   - Data Overview
   - EDA and Data Preprocessing
   - Feature Extraction
   - Modeling Techniques
4. Results
5. Conclusion
6. Dashboard & Mobile App DEMO
7. Future Work

Introduction

WHO WE ARE

Guardian Labs is a leading healthcare technology company, focused on applying innovative data and analytics solutions to help improve clinical decision-making.

People **Protection** **Innovation** **Partnerships**

OUR TEAM

Alfred Yi
Technical Project Manager

Steven Aramony
Product Manager

Maira Shahid
Machine Learning Developer

Gurjus Singh
Machine Learning Developer

Ankita Avadhani
Data Visualization Developer

OUR CLIENT

UnitedHealthcare®

- America's largest health insurance company
- Advancing a consumer-centric, integrated, simple and safe digital health system
- $13 billion investment in bolstering software and data analytics capabilities
- Seeking opportunities to capitalize on mobile health-related data to lower costs, simplify user experience, and integrate data

Business Problem
&
Solution

KEY PROBLEMS

1. TOO COSTLY

- Heart disease is the leading cause of death for men, women, and people of most racial and ethnic groups in the United States
- Heart disease is the world's leading cause of medical claims
- Cardiovascular patients typically cost more per member than cancer patients

2. OUTDATED METHODOLOGY

- Doctors still struggle to detect (early on) abnormal heart sounds that could be indicative of heart disease or abnormalities
- The possibility of human error (e.g., fatigue, inexperience, poor technique, too much background noise) is still too high
- A more accurate, sophisticated, and faster method to detect heart diseases is necessary

3. NO INTEGRATION

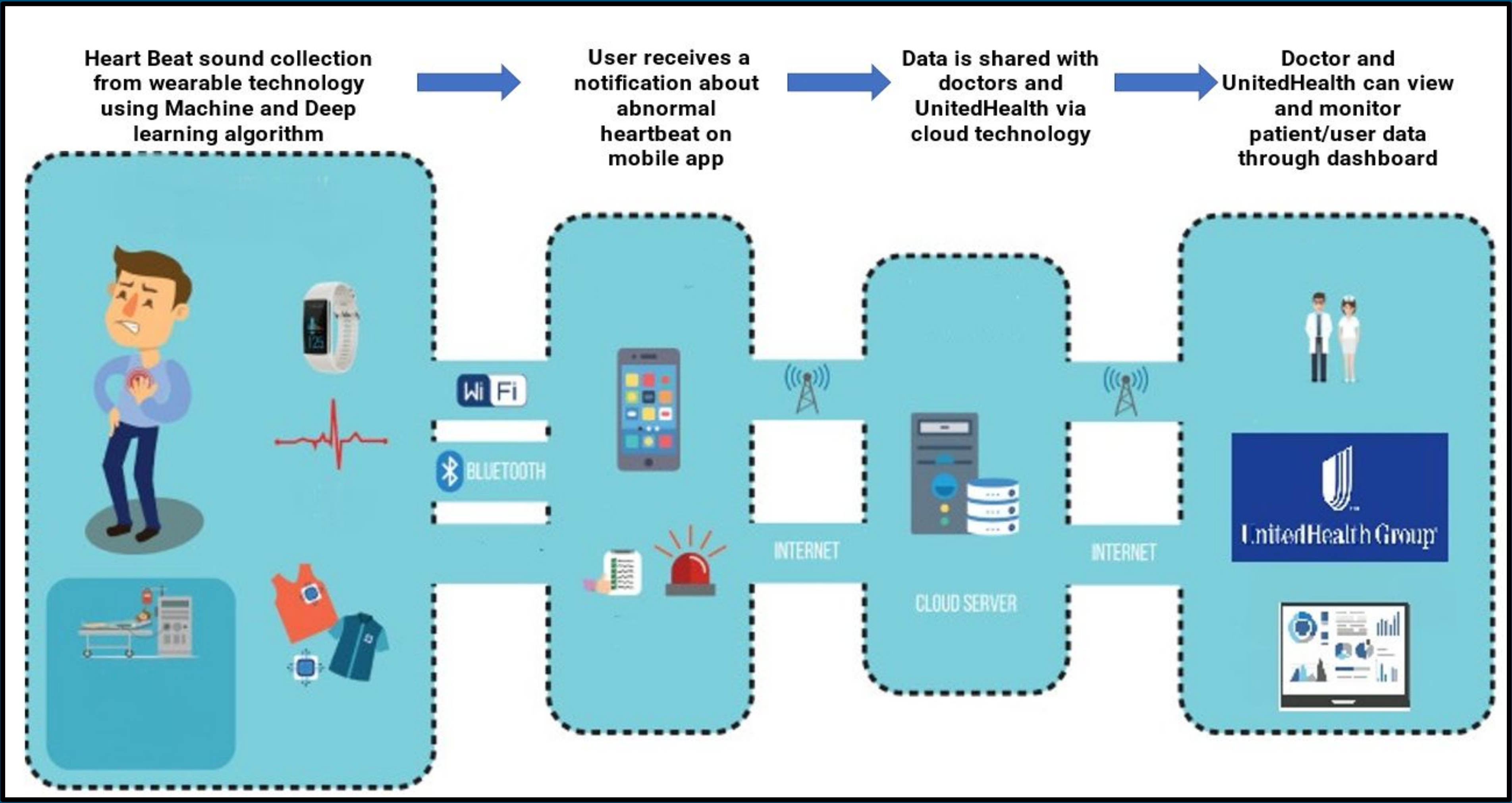
- Roughly 1 in 5 U.S. adults (21%) regularly wear a smartwatch or wearable fitness tracker
- An increasing number of insurance companies are using digital platforms to interact with customers
- The two entities—wearable tech and digital/mobile apps—are not talking

OUR SOLUTION

- Pulling wearable technology data and creating a machine learning algorithm that can predict when abnormal heartbeats exist

- Embedding our data services & algorithms in a wide range of devices, including the company's internal and external apps across its vast network of healthcare providers and patients

MOBILE HEALTH DATA WORKFLOW



BENEFITS

Reduce Cost for Stakeholders

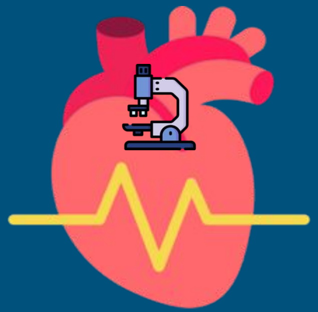
Guardian Labs is seeking to reduce UnitedHealth Group's spending on cardiovascular disease by at least 5%. Similarly, our product would enable any individual—doctor or patient—to detect heart abnormalities faster and more accurately, resulting in more affordable preventative treatment.

Enhance Marketing Capabilities

Our product will equip UnitedHealth Group and its affiliates with the precise data and insights necessary to target specific users and patients with relevant information, including customized healthcare plans and treatment options

Contribute to Heart Health & Disease Research

Our product would enable UnitedHealth Group to attract more mobile app users/participants through multiple apps, which in turn would increase the amount of data Guardian Labs could use to improve our heartbeat detection algorithms..



OUR OBJECTIVES

01 **Classify Data:** Learn to distinguish different heartbeat sounds (e.g., normal vs. abnormal heartbeats)

02 **Prep Data:** Create and extract features from audio data

03 **Build ML Algorithm:** Creation of state-of-the-art classifier for the early detection of heart disease

04 **Implement Model:** Implementation of classification model algorithm

05 **Build Dashboard:** Build interactive dashboard and mobile app that clients (e.g., medical providers and patients) can use to monitor/detect abnormal heartbeats

06 **SUPPLEMENT GOAL:** Develop strategy to expand product to wider client base

Data Overview

DATA OVERVIEW

- To make this project applicable to real world situation, Guardian Labs is utilizing a publicly available heartbeat sound dataset recorded in real life setting.
- The heartbeat dataset is primarily audio-based.
- All the heartbeat sounds are stored as WAV files that record either normal, murmur, extrasystole or artifact.
- Data is gathered in real-world situations and frequently contains background noise of every conceivable type.

DATA OVERVIEW

Data Set A

- **iPhone Data:** General public via the iStethoscope Pro iPhone app.
- Contains 176 audio files.

Data Set B

- **Medical Grade Trials:** clinical trial in hospitals using the digital stethoscope Digi Scope.
- Contains 656 audio files.

Meta Data File

- **Fname:** Name of the audio file.
- Label- Defines the heartbeat classification i.e., whether a heart beat is normal, murmur, extrasystole or artifact.

UNDERSTANDING THE HEART SOUNDS

The Project deals with classifying heart sounds into following categories.

Normal Heart Sound

lub…..dub…..lub….dub…lub…..dub……lub….dub…..lub…..dub

Murmur Heart Sound

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

OR

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

Extrasystole Heart Sound

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

OR

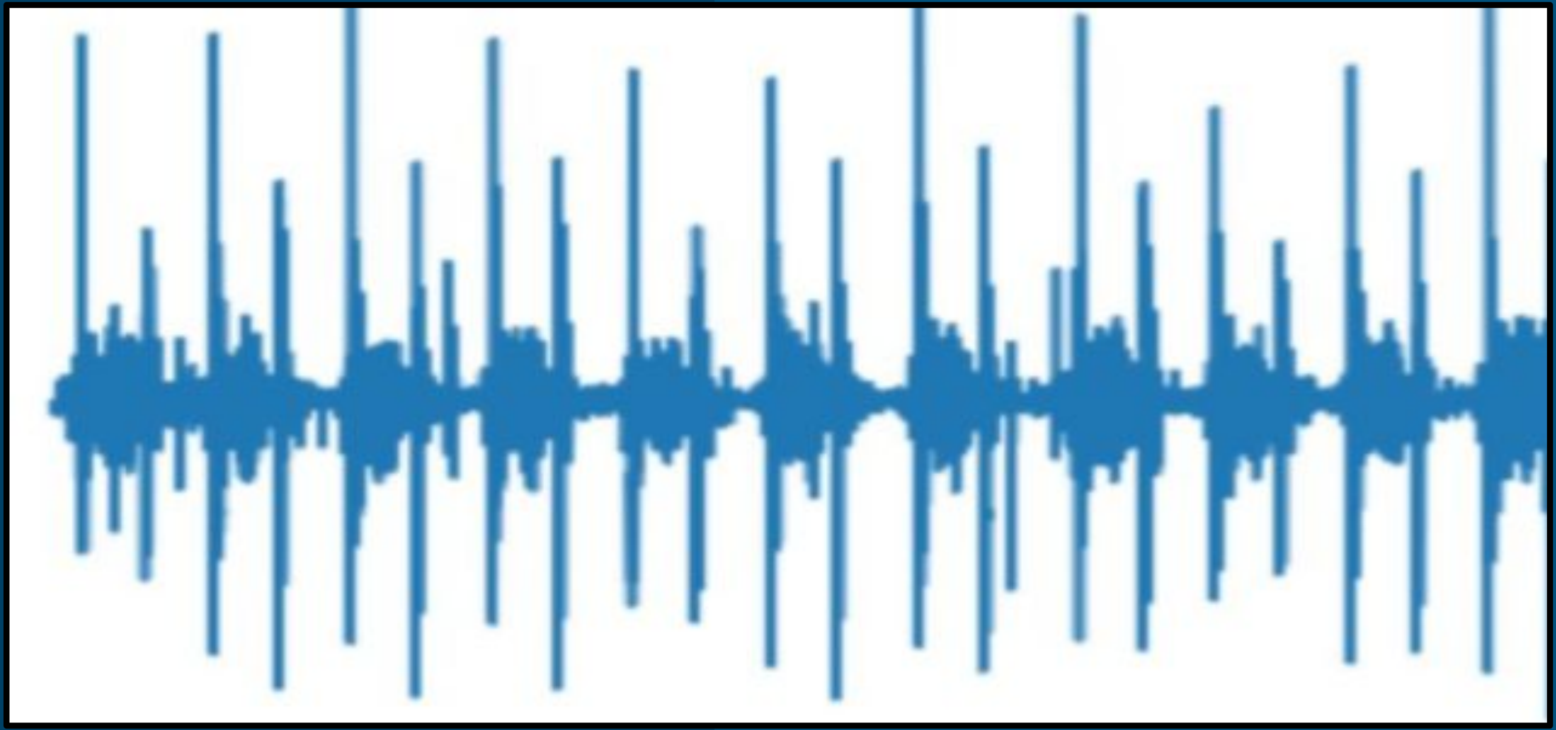
lub…..dub…..lub….dub…lub…..**dub dub**……lub….dub…..lub…..dub…lub

Artifacts

Wide range of different sounds like people speaking, music, background noise, echoes etc

Asterisk shows the location of murmur heart sound

CAN YOU GUESS THE CATEGORY ??????



EDA
&
Pre-processing

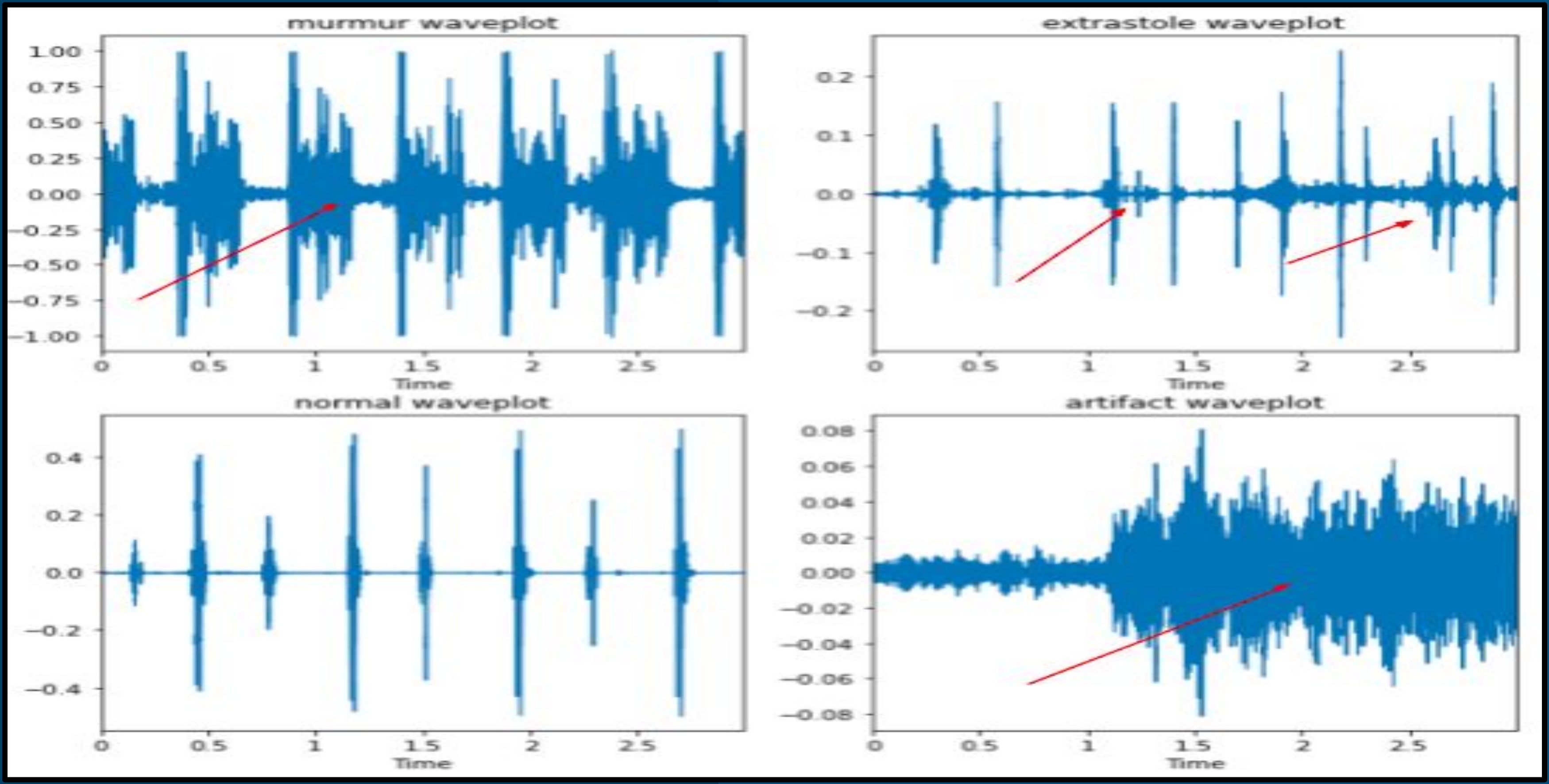
EXPLORATORY DATA ANALYSIS

- **Auditory Inspection**
  - Listened audio files of each heartbeat class using the iPython library.
- **Audio Length**
  - Audio length vary between 1 and 30 seconds
- **Sampling Rate, Signal Length and Duration**
  - All files have uniform sampling rate of 22050 HZ
  - No sampling conversion techniques was applied.

	filename	sampling rate	Signal_Length	Duration
610	/content/drive/MyDrive/Dataset/set_b/normal__1...	22050	48902	2.217778
819	/content/drive/MyDrive/Dataset/set_b/normal_no...	22050	51746	2.346757
290	/content/drive/MyDrive/Dataset/set_b/normal__1...	22050	122736	5.566259
559	/content/drive/MyDrive/Dataset/set_b/normal__1...	22050	75208	3.410794
168	/content/drive/MyDrive/Dataset/set_a/normal__2...	22050	198450	9.000000
687	/content/drive/MyDrive/Dataset/set_b/normal__2...	22050	37067	1.681043
818	/content/drive/MyDrive/Dataset/set_b/normal_no...	22050	102494	4.648254
86	/content/drive/MyDrive/Dataset/set_a/murmur__2...	22050	174979	7.935556
260	/content/drive/MyDrive/Dataset/set_b/normal__1...	22050	58554	2.655510
547	/content/drive/MyDrive/Dataset/set_b/normal__1...	22050	212408	9.633016

EXPLORATORY DATA ANALYSIS

- **Wave Plots**
  - Amplitude vs the time representation of the signal
  - Waveform plots indicate how loud an audio is at a given time.



DATA PRE-PROCESSING

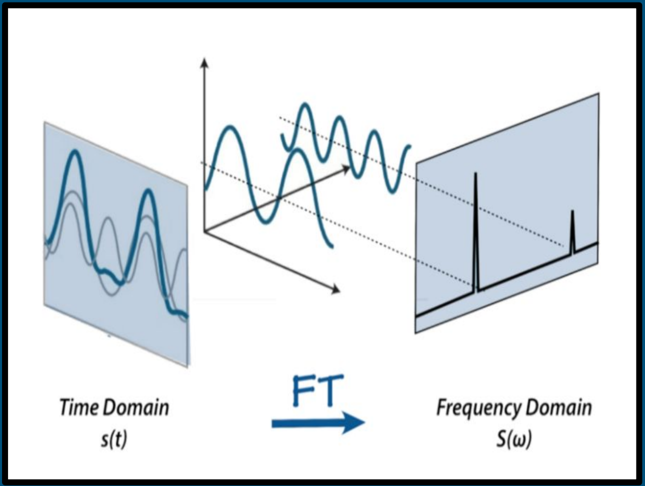
- **Missing Labels**
  - Total of 247 audio files with missing labels.
  - Dr. Muhammad Ali Shahid helped in labelling the missing records by listening to each audio file.
- **Resizing Audio Files**
  - Removed audio files with duration of fewer than 2 seconds.
  - Converted audio files into fixed length segment of 2 seconds.
- **Label Conversion**
  - All the labels were encoded from categorical to numerical
  - Artifact : 0 | Extrasystole : 1 | Murmur : 2 | Normal : 3
- **Normalization**
  - Audio files were normalized to values range from -1 to a maximum amplitude of 1.

DATA CHALLENGES

- Unlabeled Data
- Background Noise
- Limited Data
- Audio of Different Lengths
- Different Frequencies

Feature Extraction

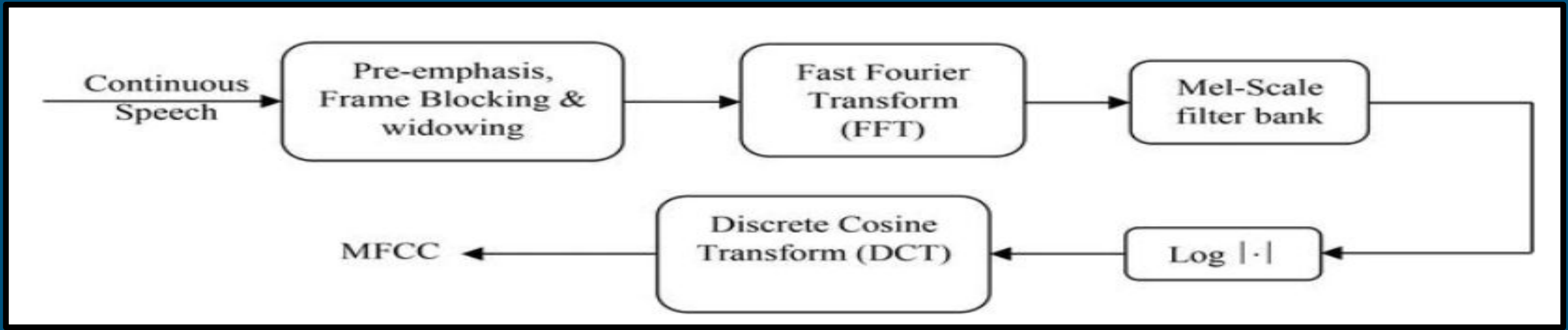
FOURIER TRANSFORM



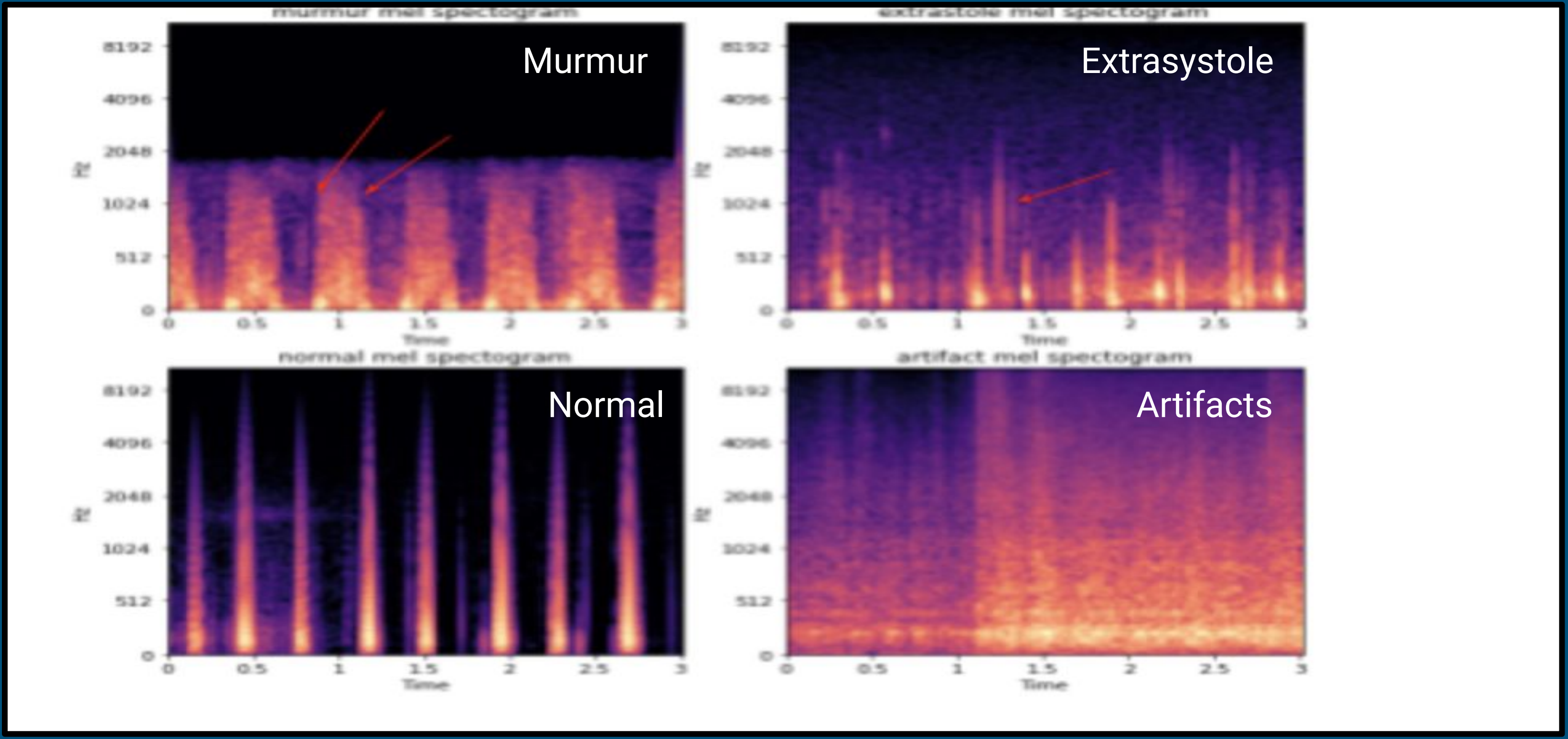
- Converted the signal from the time domain into the frequency domain using **Fourier transform.**

MEL-FREQUENCY CEPSTRAL COEFFICIENT (MFCC)

- Most important and common method to extract a feature of an audio signal
- The MFCCs of a signal are a small set of features (usually about 10–20) that extract the Cepstral Coefficients using Discrete Cosine Transform (DCT).



MEL SPECTROGRAM

- Why Need Mel Spectrogram:
  - Mel Spectrogram is a concise ‘snapshot’ of an audio wave which is used as an input for deep learning models.
- Mel Spectrogram plots Frequency (y-axis) vs Time (x-axis).
- Different colors indicate the Amplitude of each frequency.
- Murmur, Extrasystole and artifact spectrograms clearly deviate from a normal spectrogram, which has clear and consistent spikes for each heart cycle (i.e. lub dub).
- 

Modeling Techniques

MODELING TECHNIQUES

80% of the data was used for training purposes and **20%** was used for testing.

Machine Learning Models

- Random Forest
- Naive Bayes,
- Support Vector Machines
- K-Nearest Neighbors
- Gradient Boosted Trees

Deep Learning Models

- DNN
- CNN
- RNN
- LSTM

Model Performance Metrics

- Accuracy
- Precision
- Recall
- F-Score

Results

MACHINE LEARNING RESULTS

TABLE 1. PRECISION SCORES BY HEARTBEAT CLASS (%)

CLASS	Naive Bayes	SVM	Random Forest	Gradient Boosting	KNN
ARTIFACT	60	66	93	91	81
EXTRASYSTOLE	16	20	100	50	37
MURMUR	50	53	85	68	85
NORMAL	66	66	67	67	69

- Random forest with n-estimators=500 performed the best with an overall precision of 78%.
- It performed strongly on artifact, murmur, and extrasystole, but underperformed on normal heartbeats.

TABLE 2. PERFORMANCE SUMMARY RESULTS FOR MACHINE LEARNING (%)

METRICS	Naive Bayes	SVM	Random Forest	Gradient Boosting	KNN
OVERALL ACCURACY	57	57	72	69	71
PRECISION	56	59	78	69	72
RECALL	57	57	72	69	71
F-SCORE	56	57	68	67	70

DEEP LEARNING MODELS

TABLE 3. PERFORMANCE SUMMARY RESULTS FOR DENSE NEURAL NETWORK(%)

Experiment	*Model*	*Neurons*	*OVERALL ACCURACY*	*PRECISION*	*RECALL*	*F-SCORE*
Experiment 1	DNN	12	67	70	67	68
Experiment 2	DNN	32	69	75	69	71
Experiment 3	DNN	64	65	67	65	65
Experiment 4	DNN	128	68	71	68	69
Experiment 5	DNN	250	68	72	68	69

TABLE 5. PERFORMANCE SUMMARY RESULTS FOR LONG SHORT-TERM MEMORY (%)

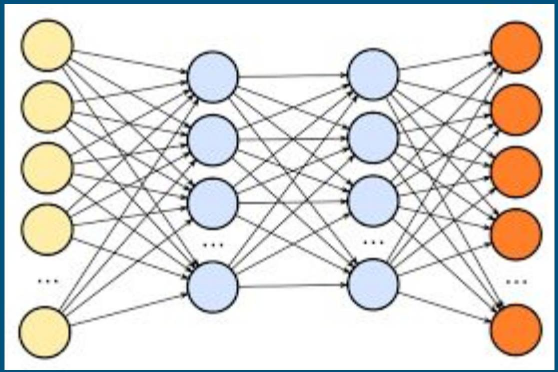
Experiment	*Model*	*Neurons*	*# of layers*	*OVERALL ACCURACY*	*PRECISION*	*RECALL*	*F-SCORE*
Experiment 1	Bi-Directional LSTM	64,32	2	60	61	60	60
Experiment 2	Simple RNN	64,32	2	45	45	45	45
Experiment 3	UniDirectional & Bidirectional LSTM	64,32	2	59	60	59	60
Experiment 4	Bi-Directional LSTM	64,128,128	3	61	62	61	61
Experiment 5	Simple RNN	128,64,64	3	49	49	49	49

TABLE 4. PERFORMANCE SUMMARY RESULTS FOR CONVOLUTIONAL NEURAL NETWORK (%)

Experiment	*Model*	*Neurons*	*# of layers*	**Dropout Layer**	*OVERALL ACCURACY*	*PRECISION*	*RECALL*	*F-SCORE*
Experiment 1	CNN	16,32,64,128	4	0.2, 0.2, 0.2, 0.5	75	81	75	76
Experiment 2	CNN	16,32,64,128	4	0.2, 0.2, 0.2	76	80	76	77
Experiment 3	CNN	16,32,64,128	4	0.5, 0.5 , 0.5	70	78	70	72
Experiment 4	CNN	16,32,64,128	4	0.2	83	86	81	82
Experiment 5	CNN	16,32,64,128	4	None	78	77	78	77

CONCLUSION

- Convolutional Neural network with following hyper parameters yielded the best heartbeat sound classification with an accuracy of 83% and precision of 86% among all machine and deep learning models.
  - 4 Hidden Layers
  - Neurons - 12, 32, 64, 128
  - Dropout Layer Ratio- 0.2



- CNN classifier performed extremely well on normal heartbeats and decently for murmur and artifacts, but was unable to perform well on extrasystole heartbeats due to imbalance of classes.

- Guardian Lab will use CNN model for classifying heart beat sounds in wearable technology.

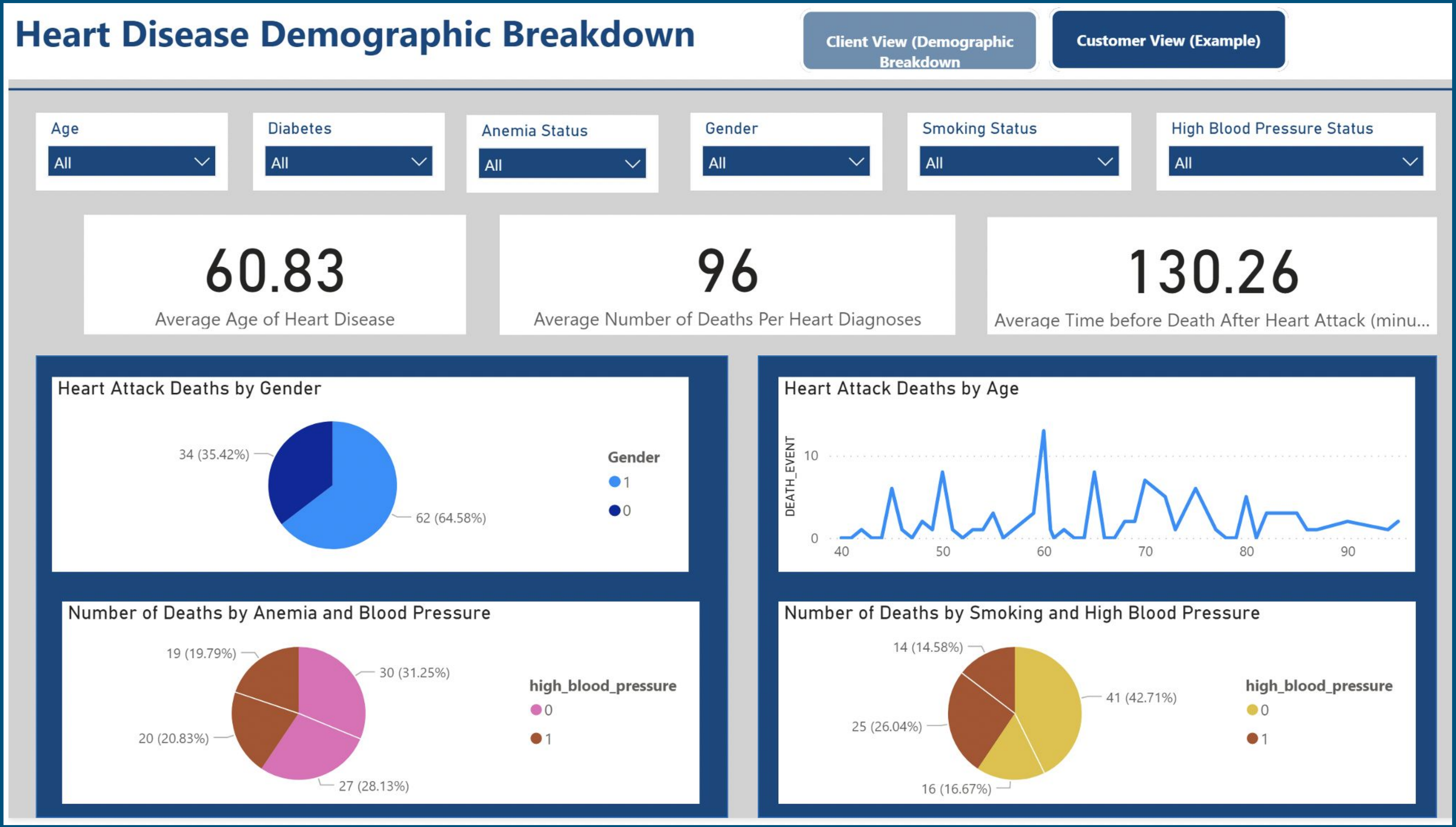
MODELING CHALLENGES

- Imbalanced Classes and Overfitting Issue
  - Dataset contains far more normal, murmur and artifacts data than extrasystole samples; hence, affecting the model's ability to distinguish between classes.
  - Overfitting normal heartbeats as murmur, extrasystole and artifacts.
  - Limited number of training and testing sets which also leads to overfitting of data.
- Synthetic Minority Oversampling Technique (SMOTE)
  - Experimented with data augmentation methods (SMOTE) to account for the imbalanced records.
  - Resulted in even lower results, suggesting that collecting more data samples in the future can mitigate this issue (i.e., increasing the training dataset).

Dashboard and Mobile App

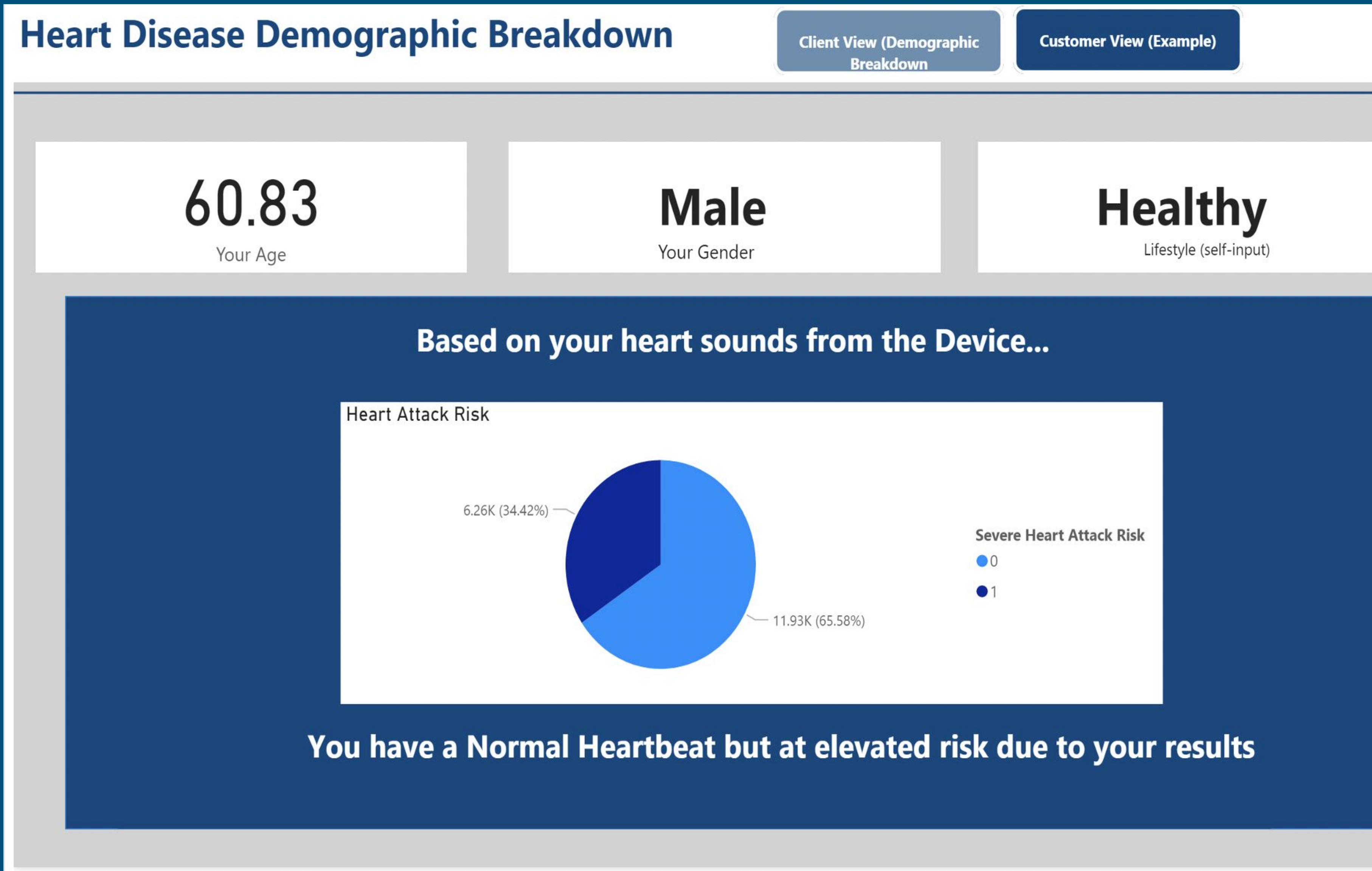
DASHBOARD PROTOTYPE

Client View



Link to live demo: https://www.youtube.com/watch?v=2Bq1Kf7Lupk

User View



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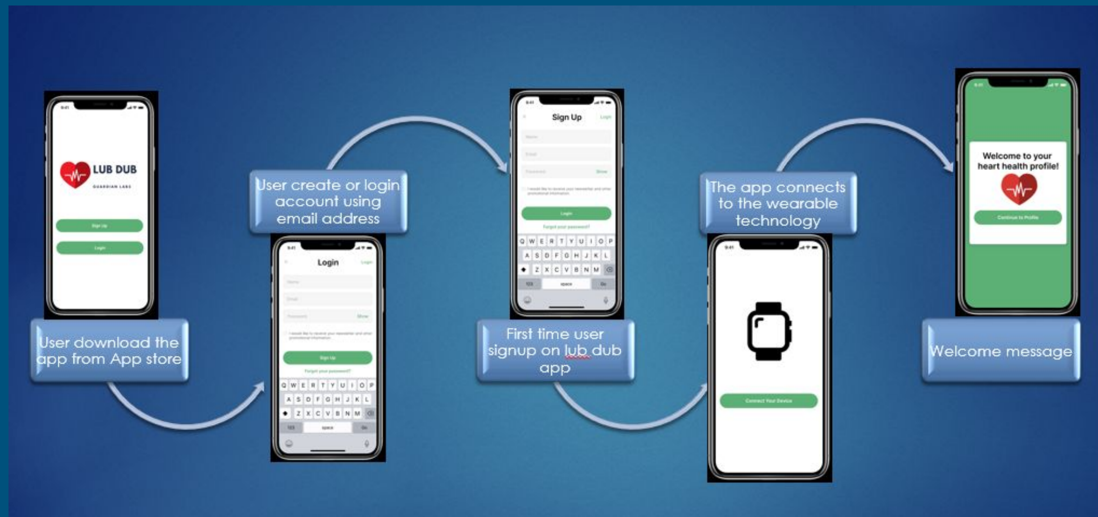
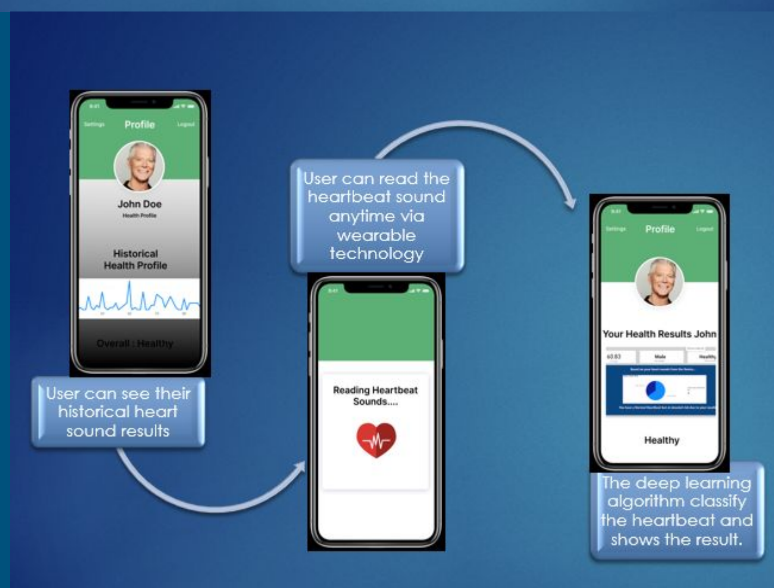
MOBILE APP PROTOTYPE

LUB DUB Mobile App





Link to live demo: https://www.youtube.com/watch?v=lbQVLWLXoDk

DEMO

FUTURE WORK

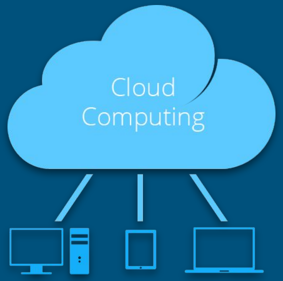
FUTURE WORK

Expand Client Base

Feature Extraction

Data Collection

Natural Language Processing



Transition to the Cloud

QUESTIONS?