By Sreehari Ram Mohan

Introduction: Heart Arrhythmias occur when the electrical impulses that coordinate your heartbeats don't work properly causing your heart to beat too fast, too slow or irregularly. Heart Arrhythmias may not cause any signs or symptoms at all, and medical examinations by a doctor have been the typical way this disease has been diagnosed.

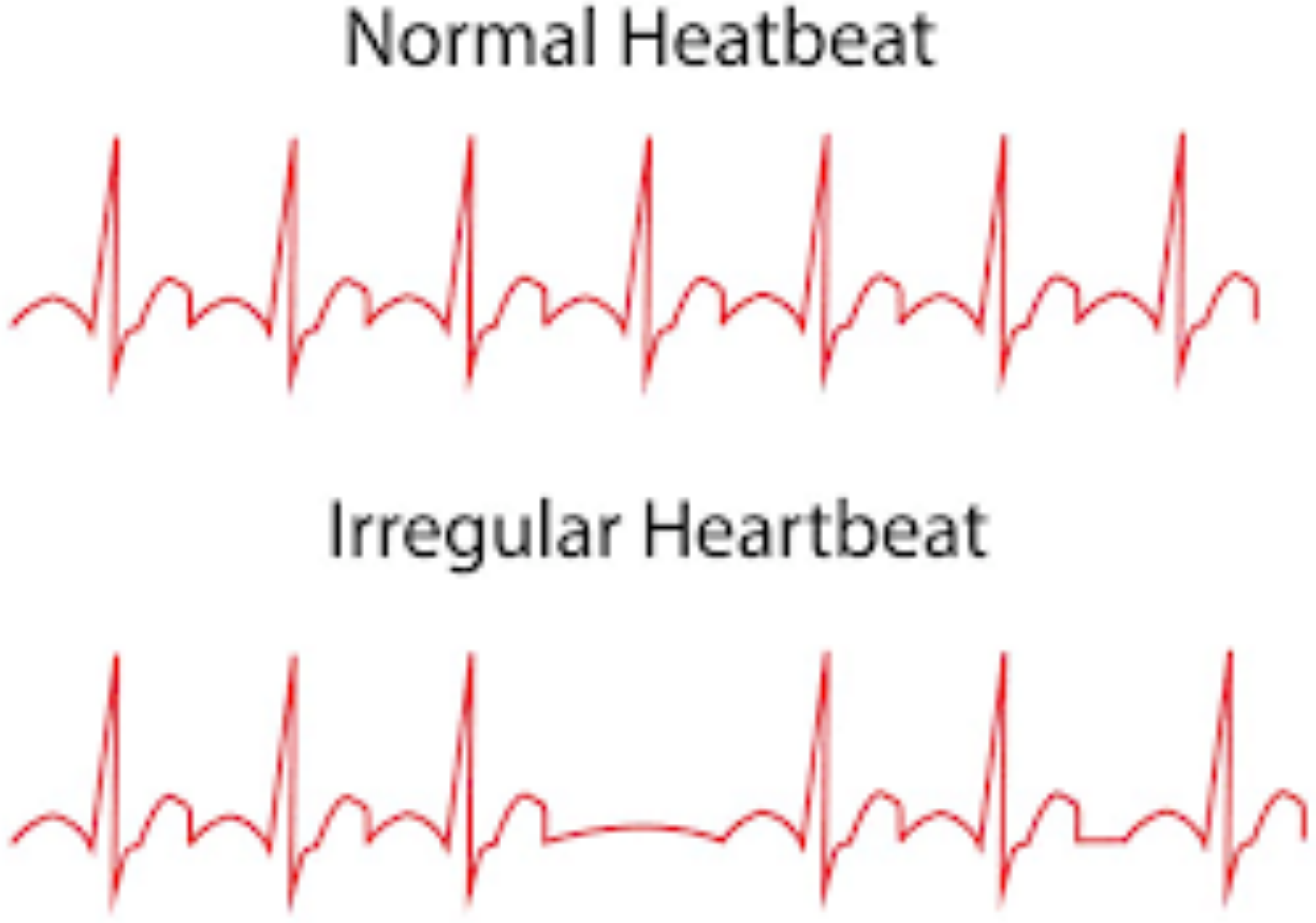
<u>Arrhythmia Classification:</u>

- **Tachycardia** - A fast heartbeat with a resting rate of over 100 beats/min
- **Bradycardia** - A slow heartbeat with a resting rate of under 60 beats/min

<u>Specific Arrhythmias</u>

- **Ventricular Fibrillation** - A deadly arrhythmia which occurs when the heart beats with rapid, erratic electrical impulses. Causes ventricles to quiver uselessly instead of pumping blood. A person with Ventricular Fibrillation will collapse within seconds.
- **Atrial Fibrillation** – Rapid heart rate caused by chaotic electrical impulse in the atria. Results in rapid, uncoordinated, weak contractions of the atria.
- **Conduction Block** – A block of your heart's electrical pathways can cause the impulses between the upper and lower halves of your heart to be slowed or blocked causing slow heartbeat.

Electrocardiograph (EKG)of Normal and Abnormal Heartbeat.



- In the irregular heartbeat shown on the bottom left, a beat has been skipped (Known as **Tachycardia)**. This can be caused from faulty electrical connections to the heart.

The Problem

Less than 40%

of heart sounds heard through cardiac auscultation are recognized by medical professionals.

17.1 Million Deaths

from cardiovascular diseases in 2004

1 in 4

global deaths are due to cardiac conditions.

400 Million

People do not have access to essential health services such as the medical examinations performed by doctors to detect heart arrhythmias.

Purpose

- Create a low-cost, effective early-warning system for patients to use to preempt onset of fatal heart conditions.
- To use Deep Learning to accurately diagnose life threatening heart abnormalities. This involves designing a machine learning model which can determine whether a patient has life-threatening abnormalities at cardiologist level accuracy.
- The hardware goal is to create a device which can take accurate heart recordings at an affordable price, and then diagnose whether the patient has a heart condition on the spot (within 1 minute).

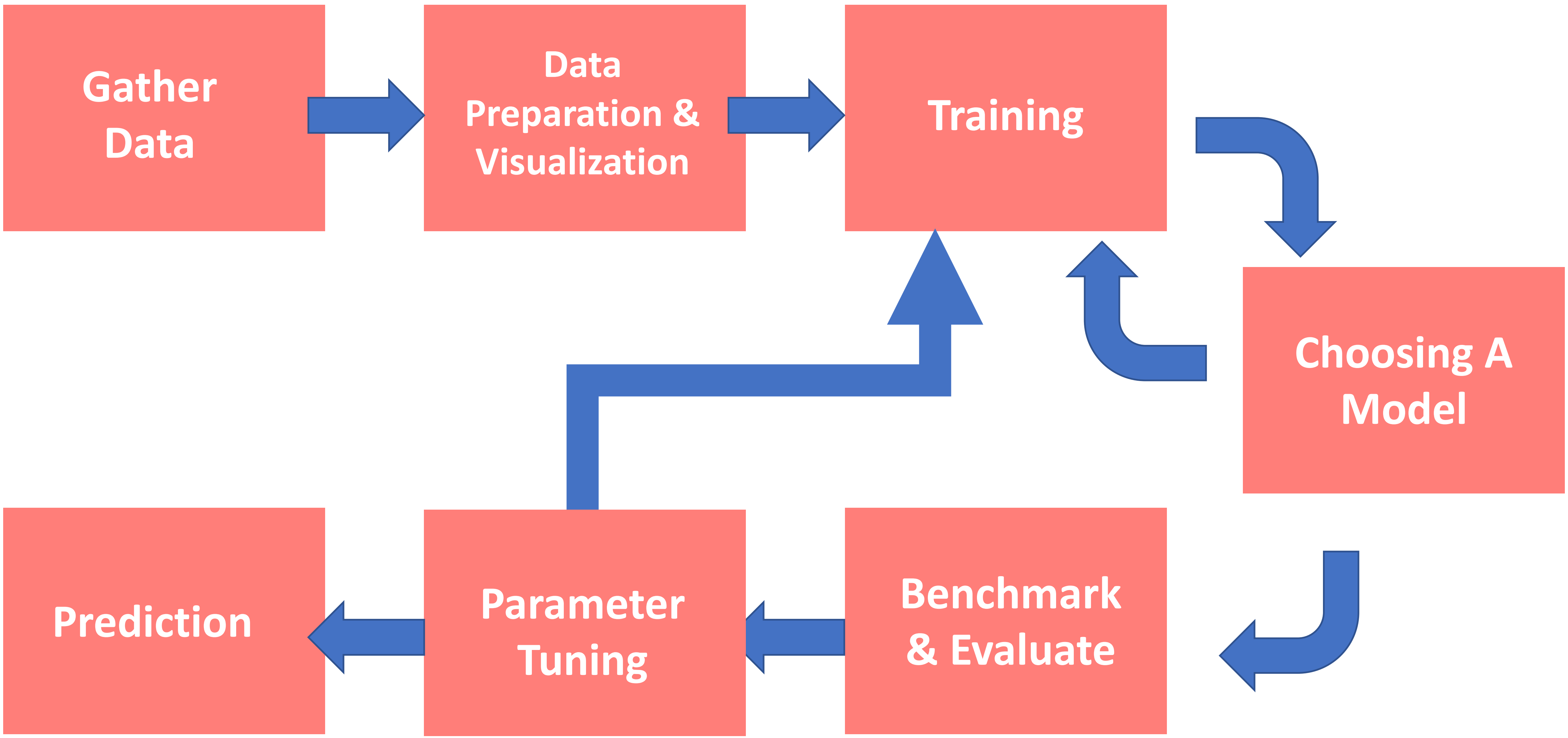
Background/Literature Search

- So far, the main way cardiac diseases are diagnosed is through a medical exam when you visits a doctor's office. A doctor will use a stethoscope to hear your heartbeat; the sounds the doctor hears can allow him/her to assess the health of your heart and its valves. Additionally, an Aneroid Monitor is used by a nurse to figure out your systolic, and diastolic blood pressure. This information is then used by a doctor to give a diagnosis.
- The crux of solving this problem lies with translating the heartbeat sound into a form that a computer can easily interpret. After reading about how Daniel Nouri, turned a whale-sound detection problem into image recognition problem by converting the sound clips to spectrograms I was inspired to do something similar.
- In the past, researchers have tried to segment a heartbeat clip into the S1 (lub) and S2 (dub) sounds to get the exact location from the audio files. However the differences between these two sounds is non-trivial and the different heart sounds can be very subtle and requires extremely robust classifiers. Despite the medical significance that a breakthrough in this field could have, it has been relatively unexplored by machine learning researchers.

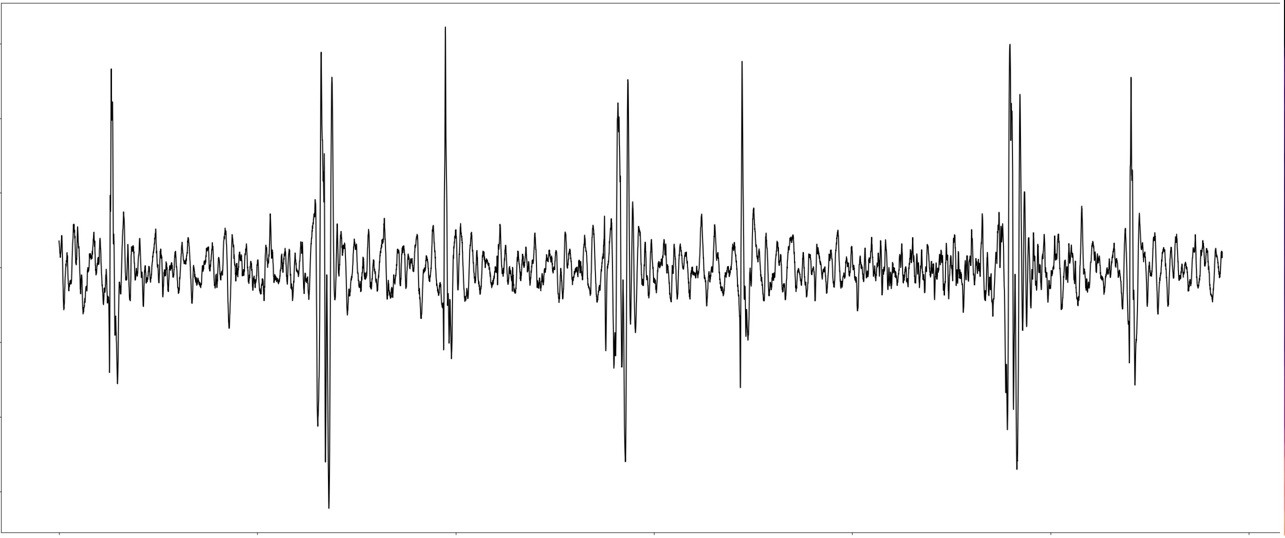
Engineering Goals

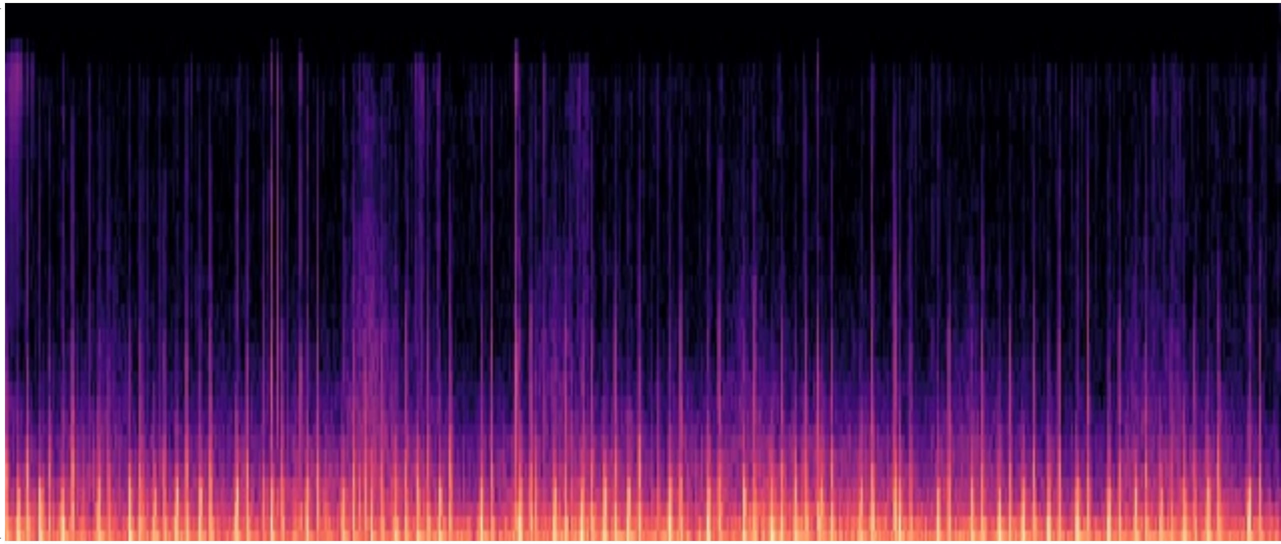
- Durable; should withstand drops from waist height.
- Ability to record audio to send to medical professionals for further analysis.
- Operate on low power; with battery installed, operational for at least 4-6 hours giving diagnoses every 1-3 minutes.
- Patient data should be safely stored, and can be sent to medical professional for further analysis.
- Low cost; less than $75 for the hardware
- Small form factor; fits in the hand of a healthcare worker
- Lightweight; weighs 0.5 kilograms, easy to carry and transport.
- The CPU intensive software must be able to run on a Rasberry Pi 3 ARM processor using the Raspbian Operating System Environment.

Project Stages



Feature Extraction

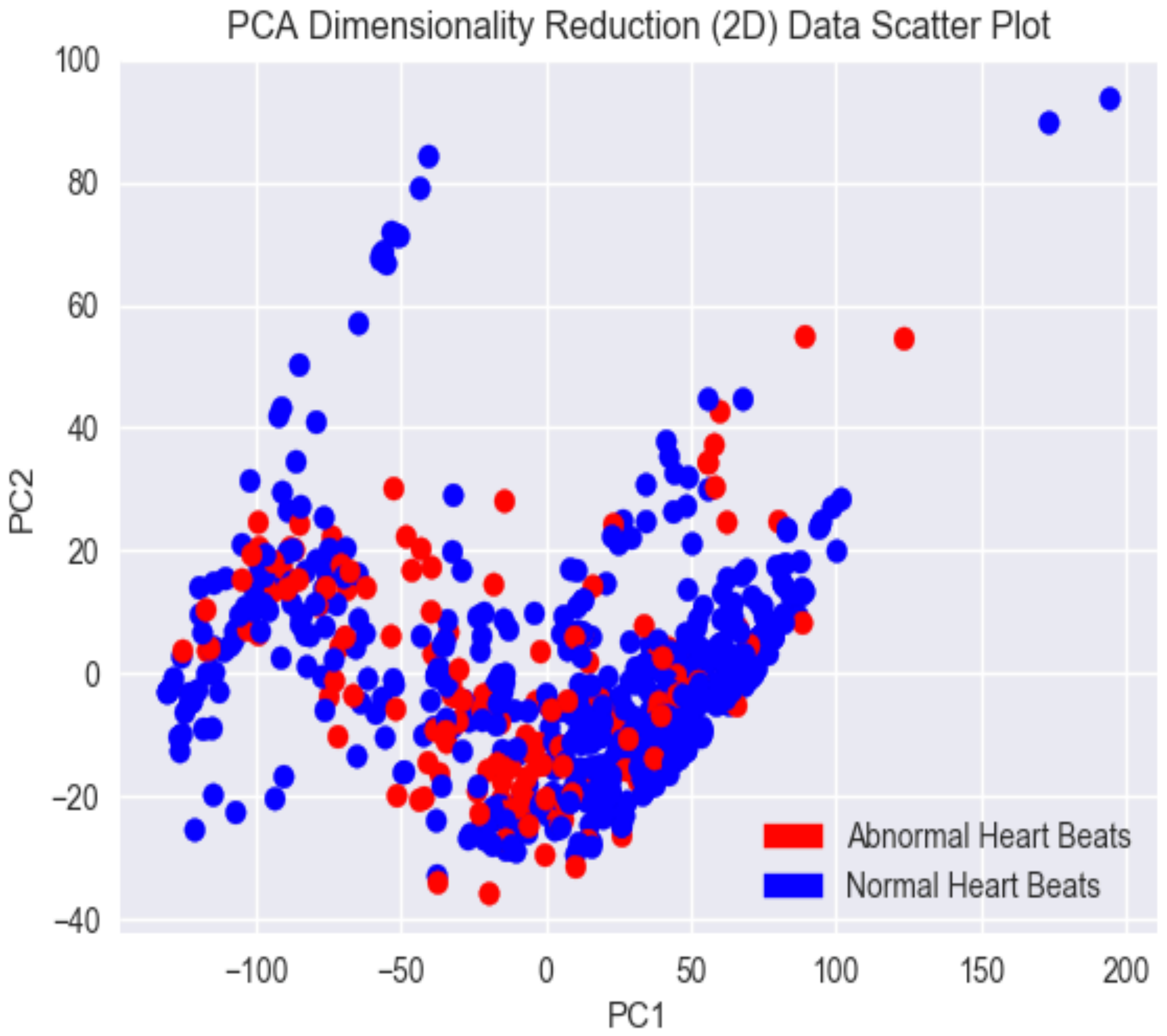




Data is recorded in waveform as a spectrogram

Fourier Transform

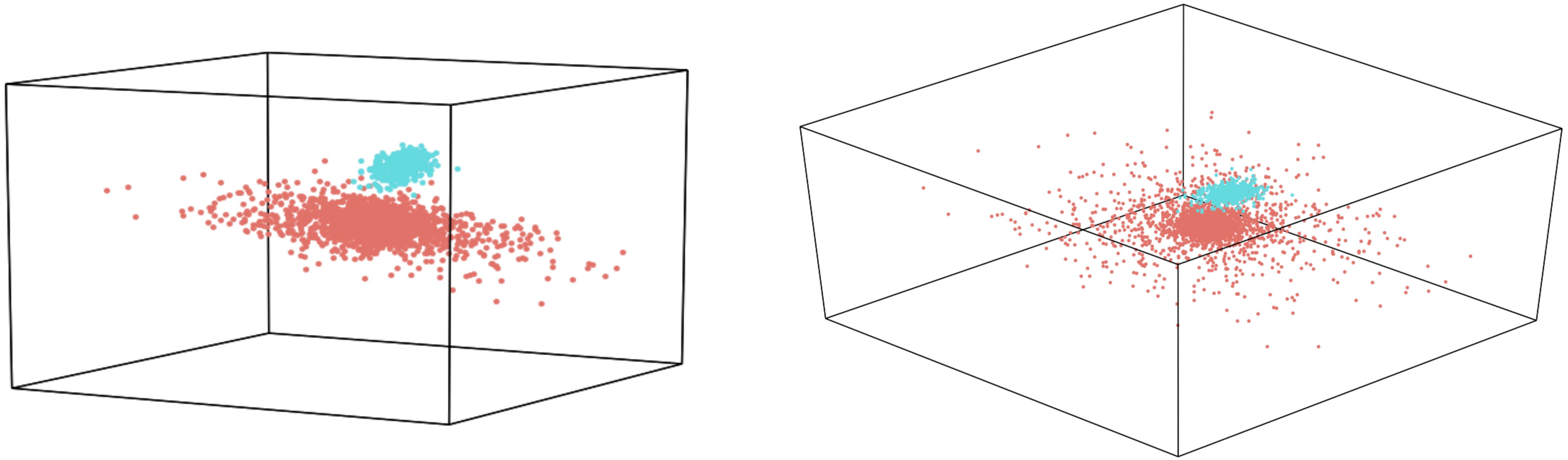
Mel Frequency Spectrogram Computed



2D Data Visualization After PCA

Dimensionality Reduction Techniques (Mainly PCA) were used to visualize the dataset and ensure that their truly was a relationship between the MFCC data and the heartbeat diagnosis.

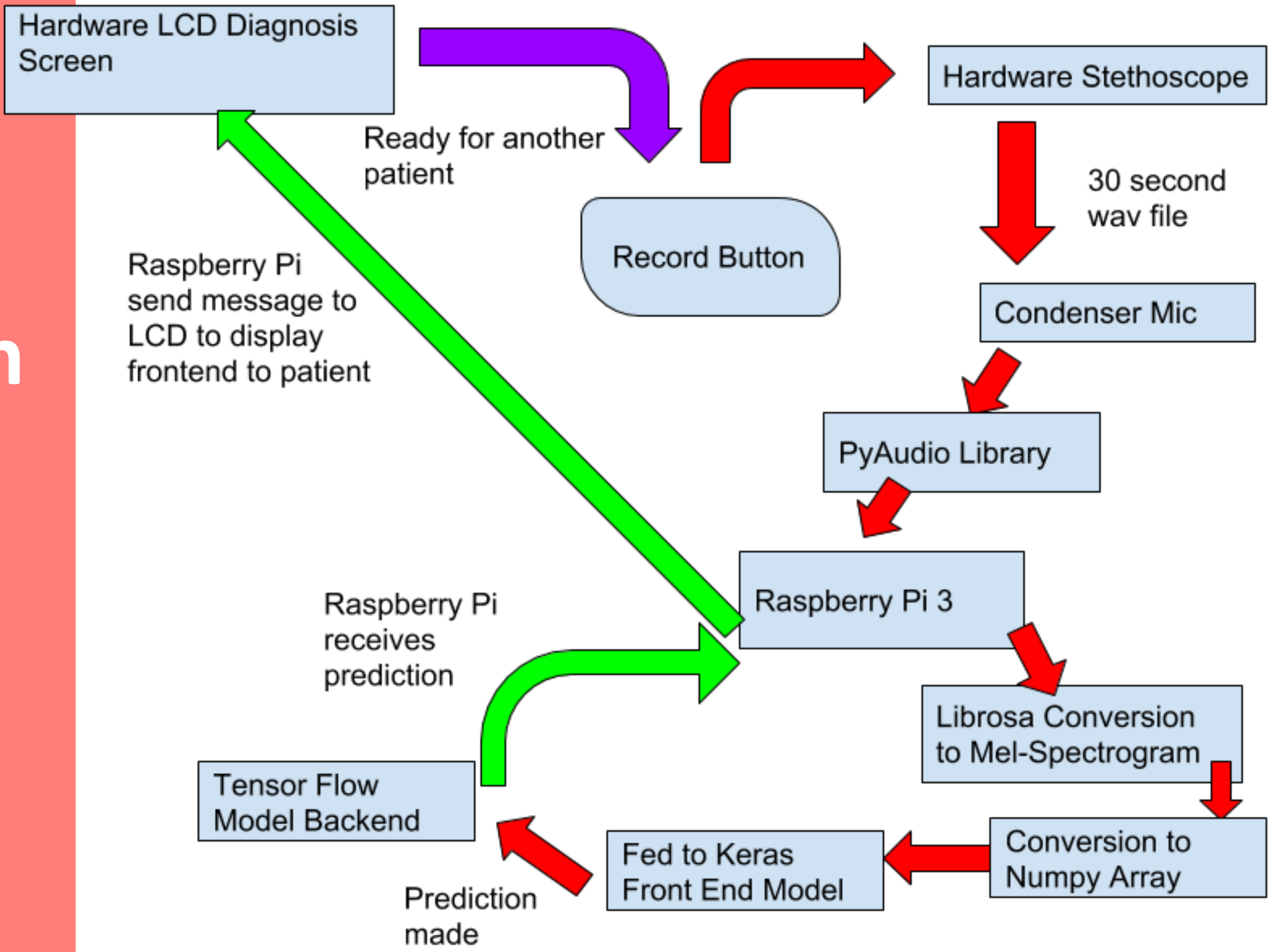
The newly augmented dataset had an **explained variance ratio of 59.417258%** which means that the 2D data accounted for approximately 60% of the variance. While a relationship is forming between the MFCC and the diagnosis, the data should be reduced to 3 dimensions (+ 1 Dimension) to increase the variance ratio and make the relationship more evident.



3 Dimensional PCA Visualization

Layers of Abstraction

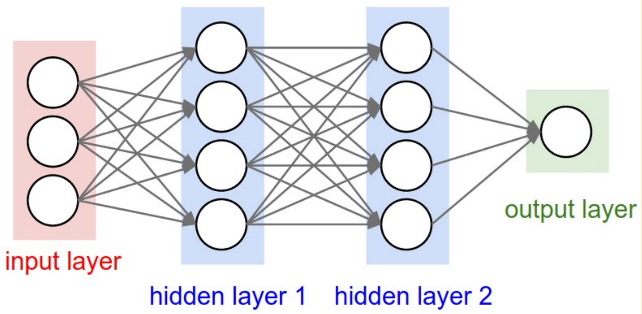
Displays the overall series of calls which occur when the device gives a diagnosis

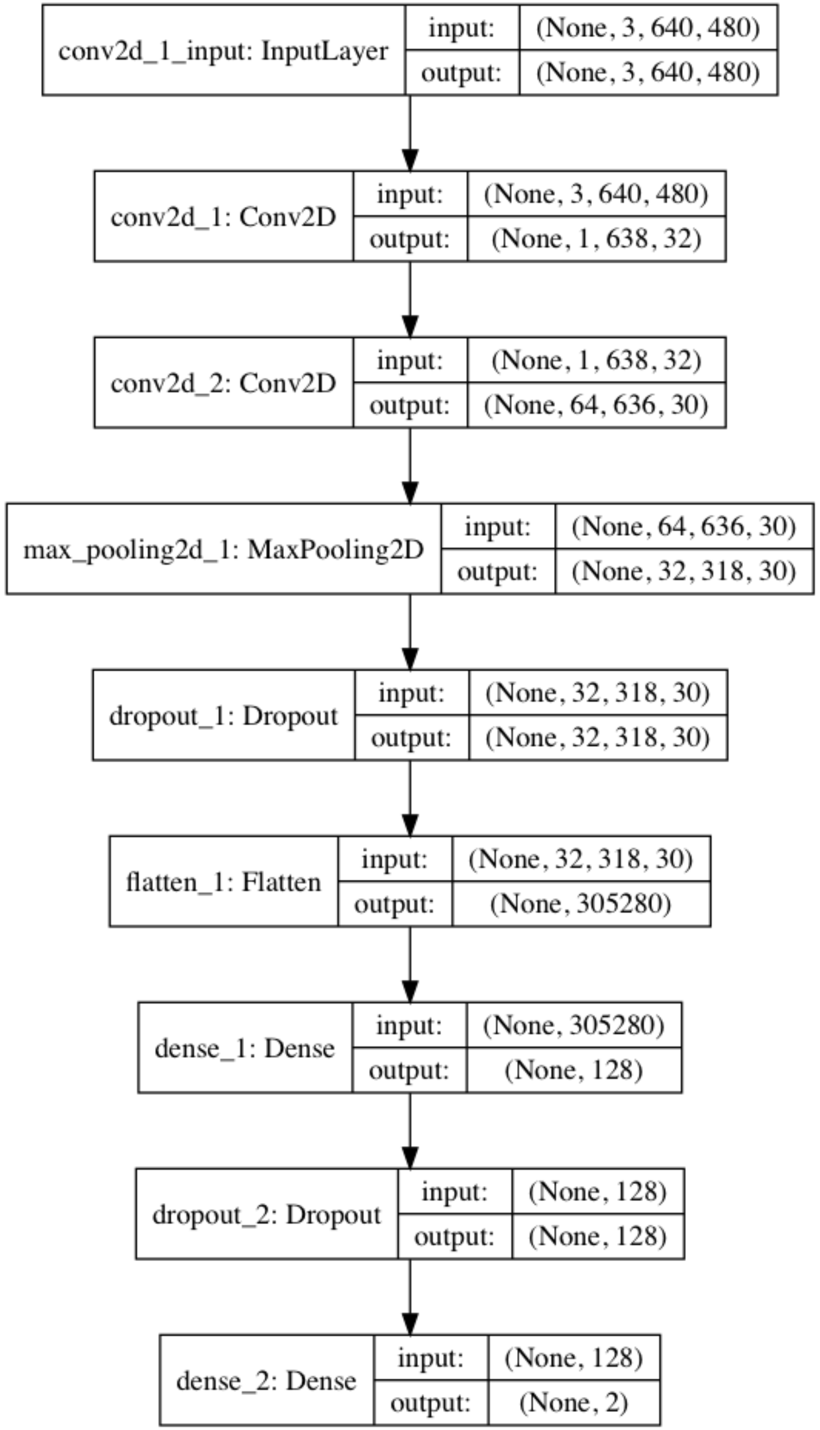


Model Architecture

Neural Networks receive an input (an image matrix), and transform it through a series of *hidden layers* to get an output value.

A Convolutional Neural Network was chosen because unlike a regular neural network it scales up well with images due to the fact that the neurons in a layer are only connected to a small region of the layer before it.



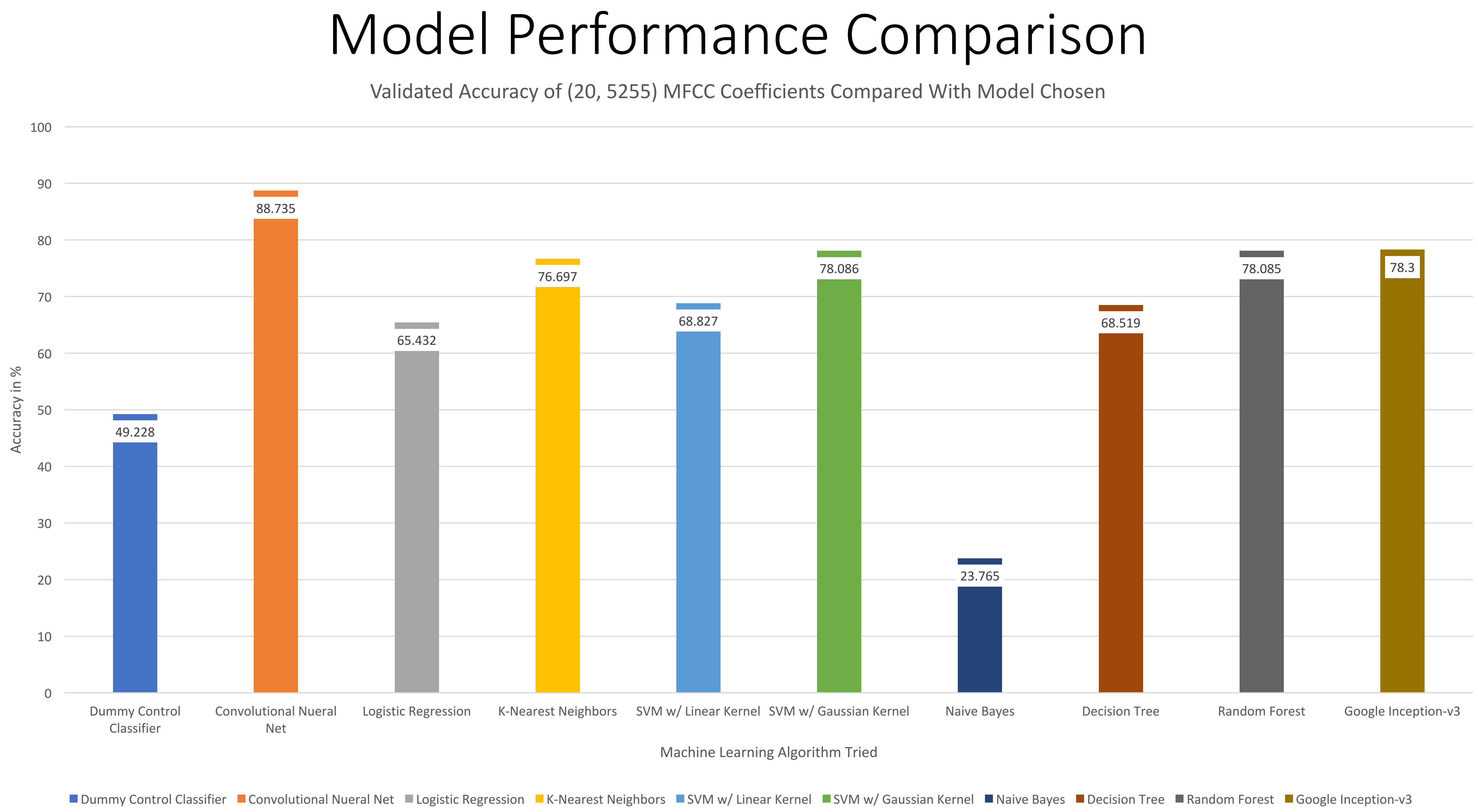


Basic Layers of a CNN and what they do

Convolution Layer – Extracts features from the image passed in. A filter slides over the input image (convolution operation) to produce a feature map, the CNN learns the values of these filters on its own during the training process.

Pooling Layer – Reduces the dimensionality of each feature map but retains the most important information. In MAX_POOLING we define a spatial neighborhood (2 * 2 window) and take the largest element from the feature map. We then slide over the 2 * 2 window over by 1 stride.

Fully Connected Layer – Every neuron in the previous layer is connected to every neuron on the next layer.



Model Performance Comparison
Validated Accuracy of (20, 5255) MFCC Coefficients Compared With Model Chosen
Accuracy in %
100
90
80
70
60
50
40
30
20
10
0
49.228
88.735
65.432
76.697
68.827
78.086
23.765
68.519
78.085
78.3
Dummy Control Classifier
Convolutional Nueral Net
Logistic Regression
K-Nearest Neighbors
SVM w/ Linear Kernel
SVM w/ Gaussian Kernel
Naive Bayes
Decision Tree
Random Forest
Google Inception-v3
Machine Learning Algorithm Tried
Dummy Control Classifier
Convolutional Nueral Net
Logistic Regression
K-Nearest Neighbors
SVM w/ Linear Kernel
SVM w/ Gaussian Kernel
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Decision Tree
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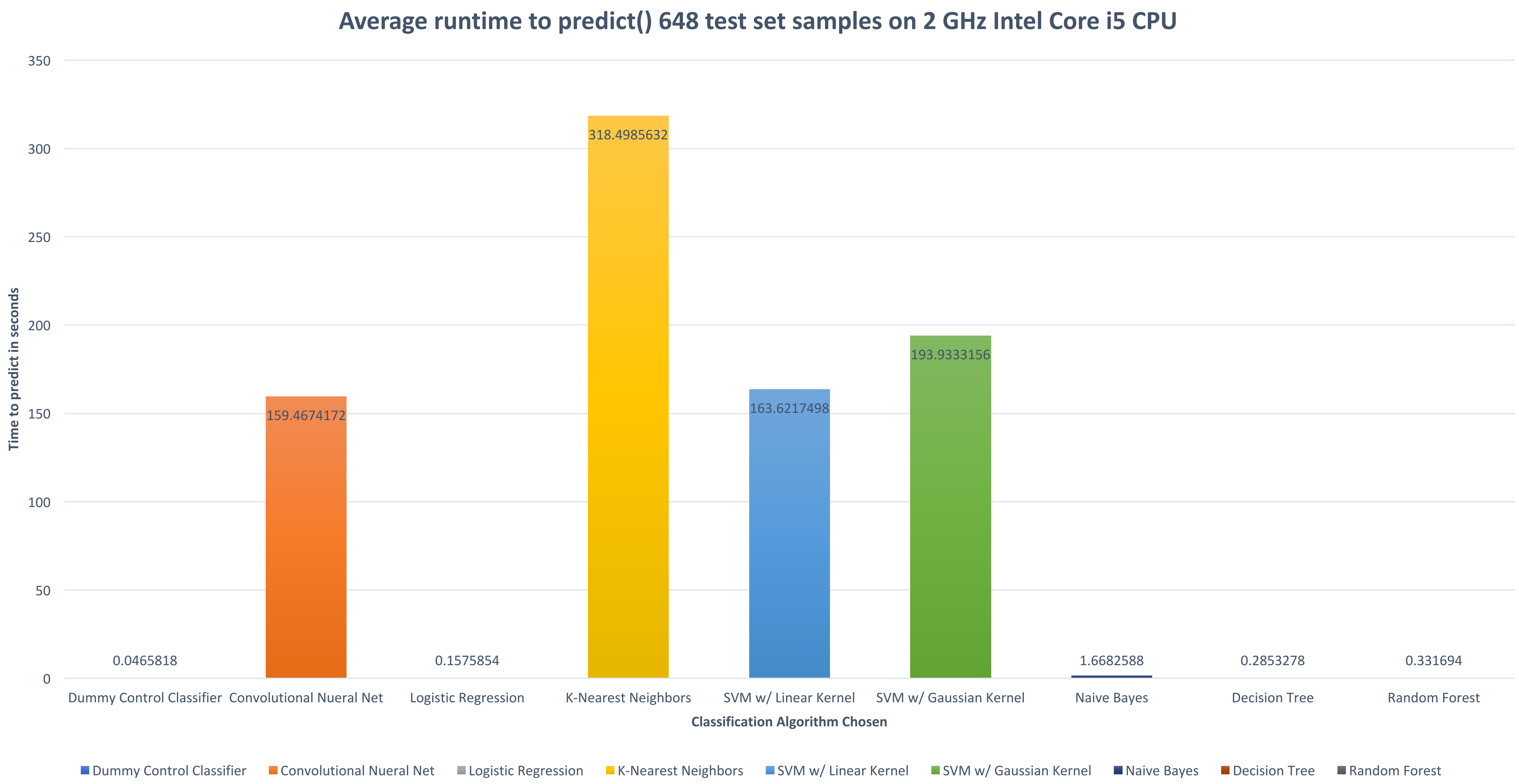
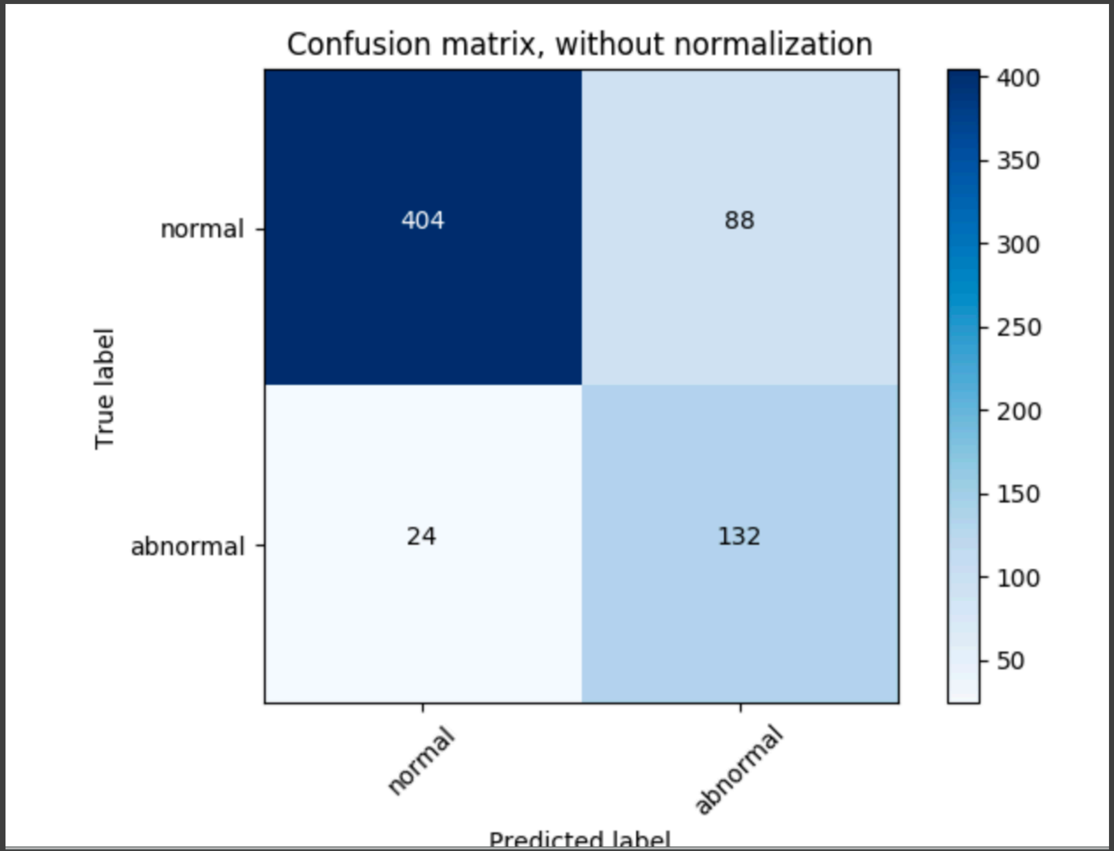
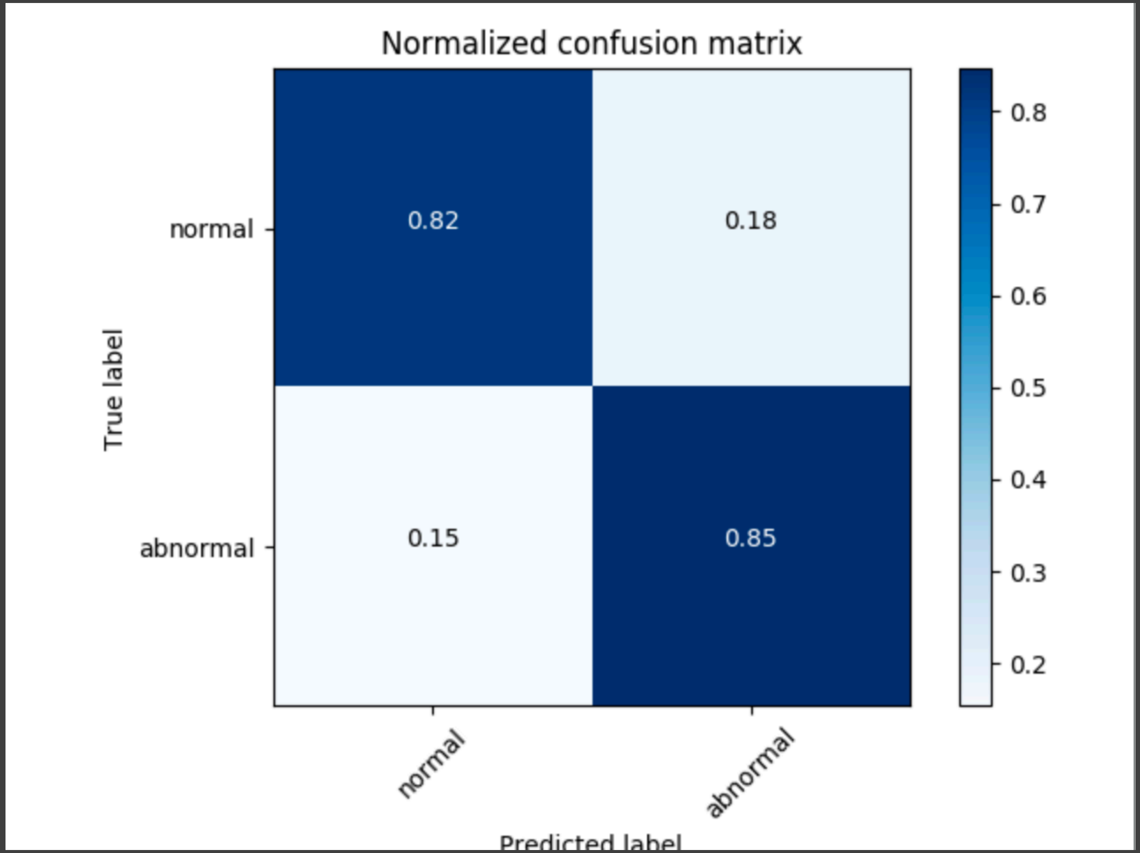
Google Inception-v3

Model Prediction Time Comparison



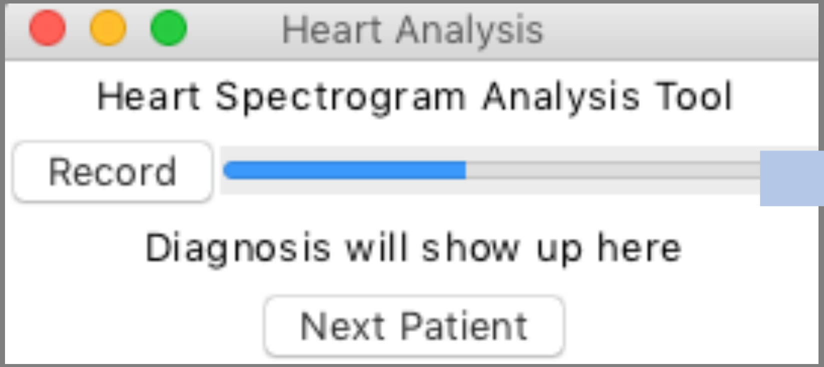


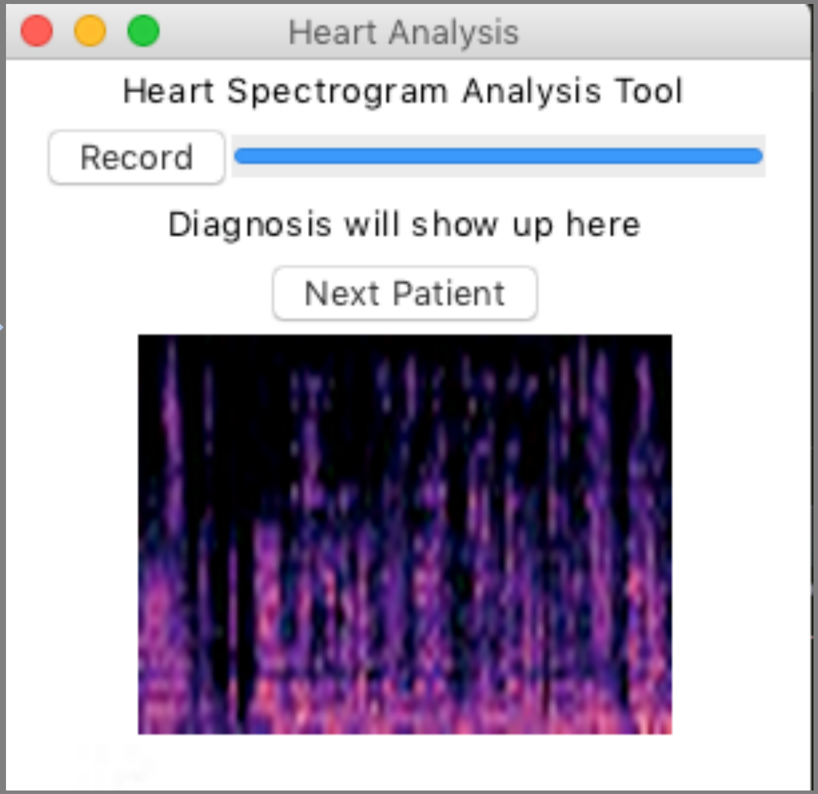


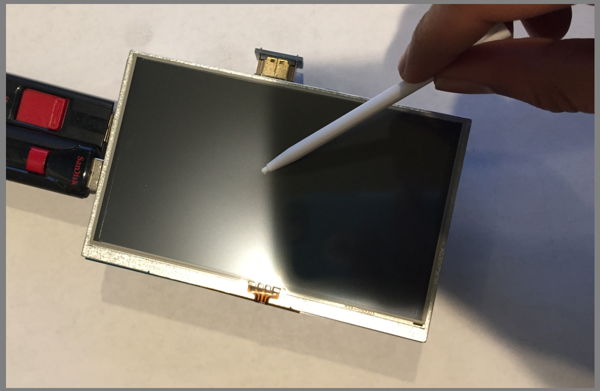
Confusion Matrix for the Convolutional Neural Net

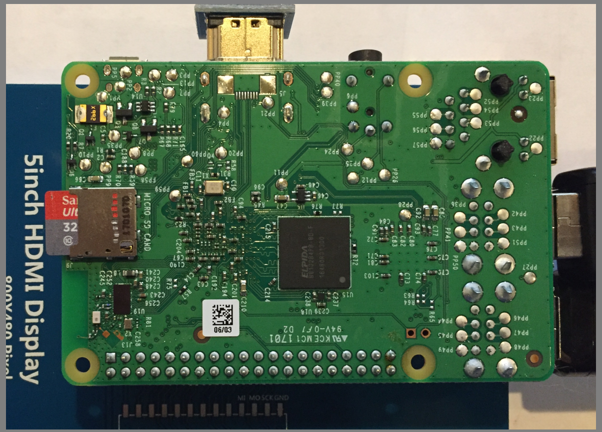
User Interface & Device Design

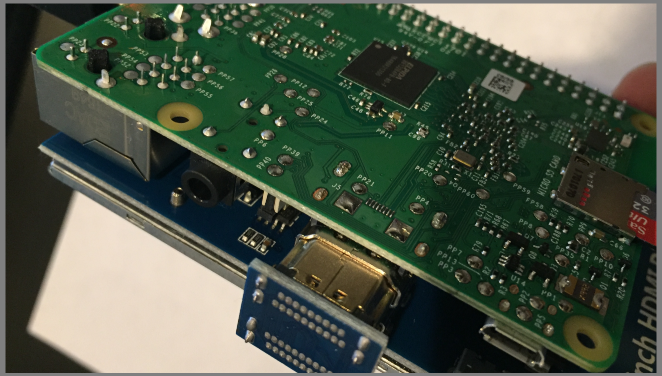
The Program & Device the patient will interact with (created with Tkinter)











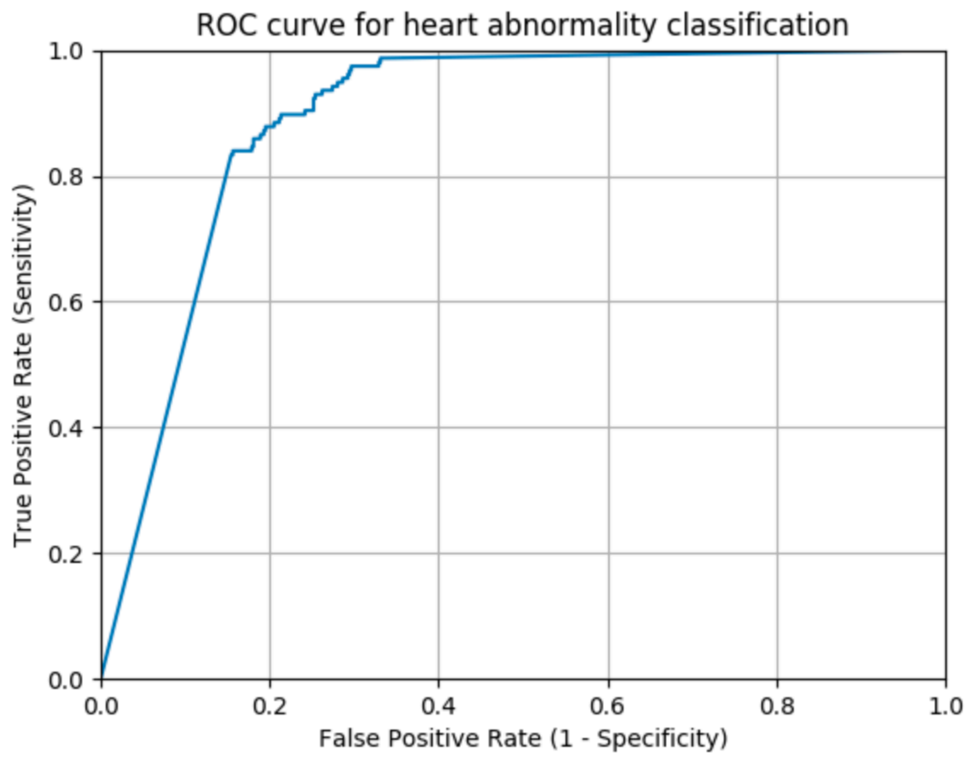
Analysis of Results

Sensitivity- how good the model is at detecting the positives.

Specificity - how good the model is at avoiding false alarms.

- The ROC (Receiver Operating Characteristic Curve) is a plot of the **true positive rate** against the **false positive rate** for different cutoffs.
  - It shows the **tradeoff** between **sensitivity** and **specificity** (any increase in sensitivity will be accompanied by a decrease in specificity).
  - The **closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test.**
  - The area under the curve is a **measure of test accuracy.**

ROC Curve & AUC



AUC = 0.88984

The area under the curve is the percentage of randomly drawn pairs for which the model correctly identifies the "normal" and "abnormal" heartbeat.

1 Tail Hypothesis Test for Difference in Accuracy

- Is the model accuracy of 88% significantly greater than Health Workers using Handheld Instruments who have an 82% (2014 Study in JACC Cardiovascular Imaging) chance of recognizing heart abnormalities?

1. α = 0.01 Significance Threshold

Let P_M represent the model accuracy of 88%

Let P_B represent the baseline cardiologist accuracy of 82%

2. H_o: $P_B \geq P_M$

H_A: $P_B < P_M$

3. Formula: The test statistic for testing the difference in two population proportions below:

$$p = \frac{p_B * n_B + p_M * n_M}{n_B + n_M}$$

$$Z = \frac{p_B - p_M}{\sqrt{p\,(1-p)(\frac{1}{n_B}+\frac{1}{n_M})}}$$

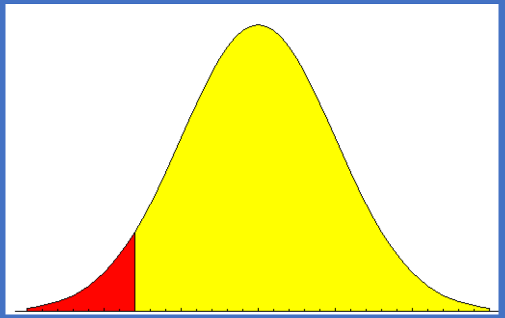
4. p = (0.88 * 648 + 0.82 * 648)/(648 + 648) = 0.85

$$Z = \frac{0.82 - 0.88}{\sqrt{(0.85)(1-0.85)(\frac{2}{648})}} = -3.02465$$

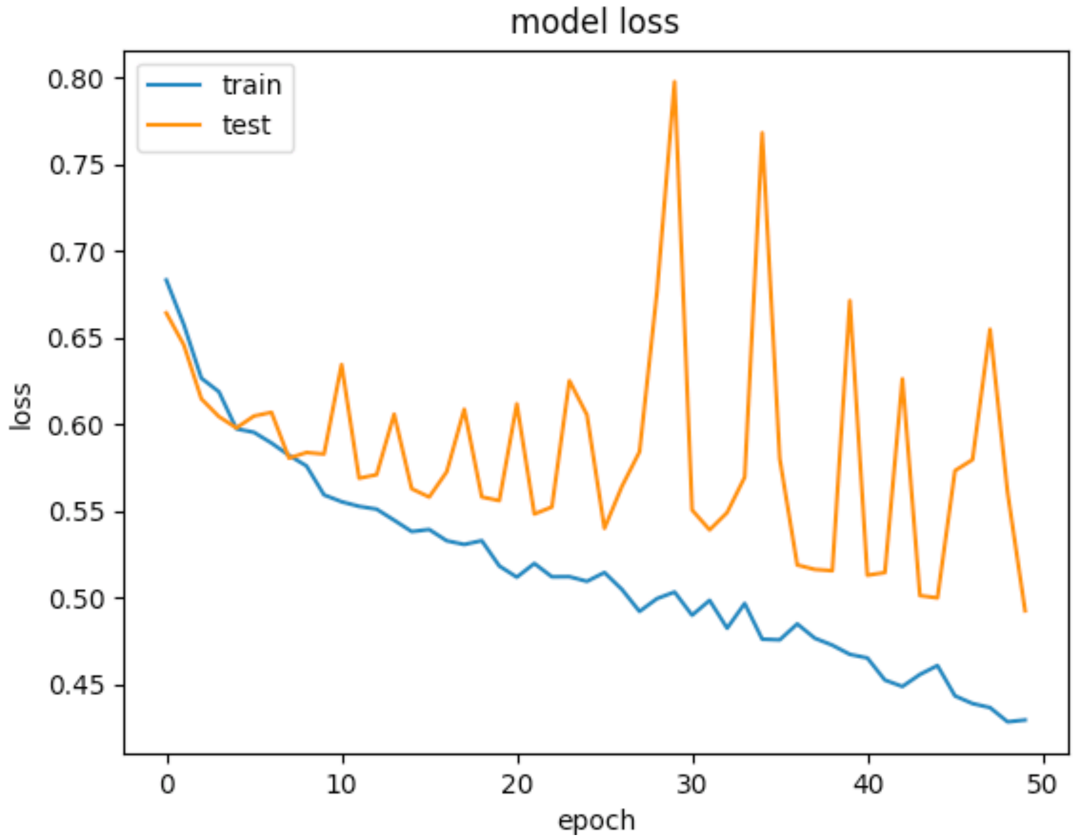
What is the area under the standard normal distribution from -∞ $to\ -3.02465$

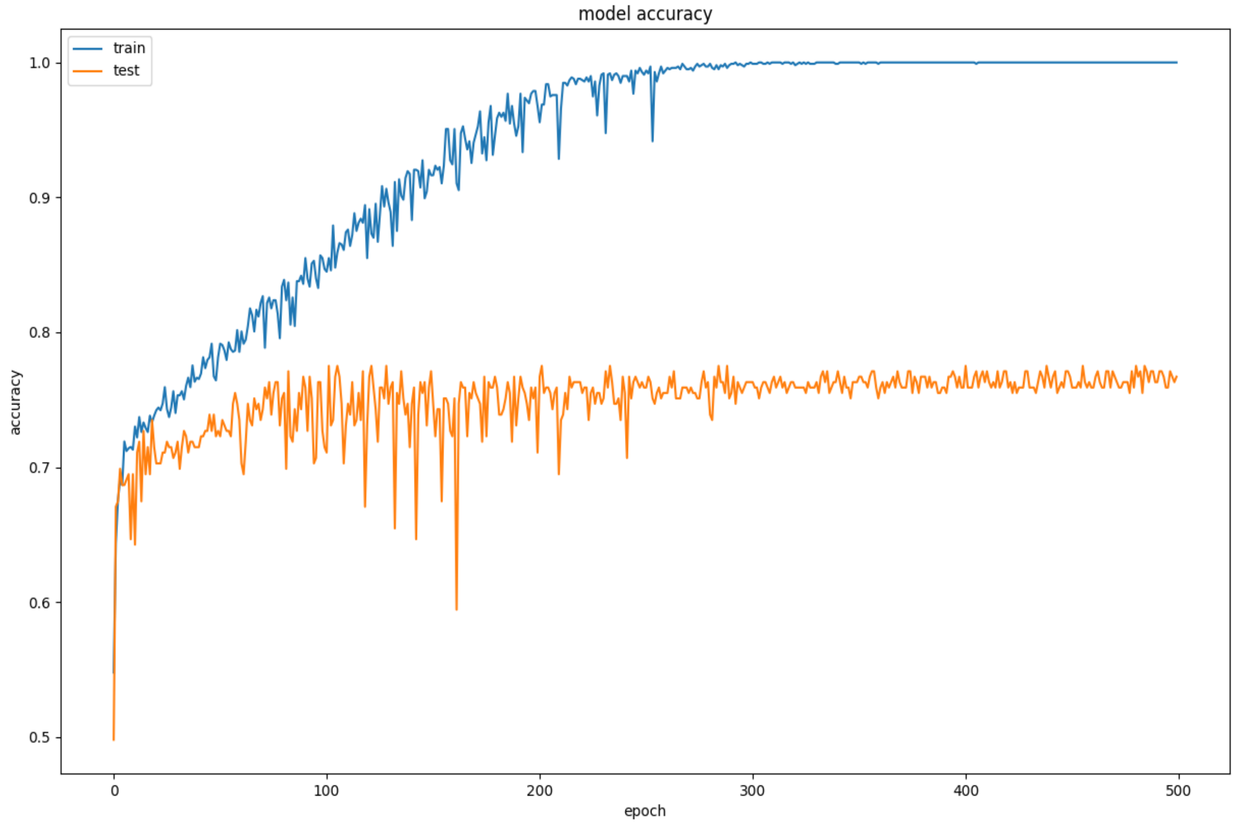
normalcdf(-∞, -3.02465, 0, 1) ≅ 0.0013499672

Therefore, we can reject H_o with a 99.99% confidence level.
We can conclude that the model performs better than the doctors in the 2014 study



Results





In general, as the number of epochs (1 epoch = 1 full run through of the data) increased, the model loss and model accuracy increased before plateauing at around an 88.8% validated accuracy, and around a 3% false negative rate. With more data, a deeper network, and a set dedicated GPUs the accuracy and loss will be reduced even further.

Results (Continued)

- After Training 10 different classifiers, the Convolutional Neural Network model is deemed favorable due to its high validation accuracy, high specificity, and low prediction time.
- The results are very encouraging because the model was able to achieve an AUC score of 0.88 and an accuracy of over 82%. These results are better than the ability of a medical professional or healthcare workers to detect Cardiac Abnormalities.
- Furthermore, this device can make a diagnosis in under 30 seconds, whereas it would take a healthcare worker or doctor at least 10-20 minutes to perform a full examination before he/she would be able to deliver a diagnosis.
- The model was able to outperform Google's Inception V3 Image Recognition Model.
- These results suggest that machine learning can aid in diagnosis of cardiac arrhythmias, I am confident that with more data and greater training time (with dedicated GPUs) the accuracy and precision of the model can be increased.
- While even an 88% test accuracy may not appear impressive when compared to the accuracy and precision required in the medical field, taking into account the little data used and simplicity of the model, these results are promising.

Software / Hardware Used

Software

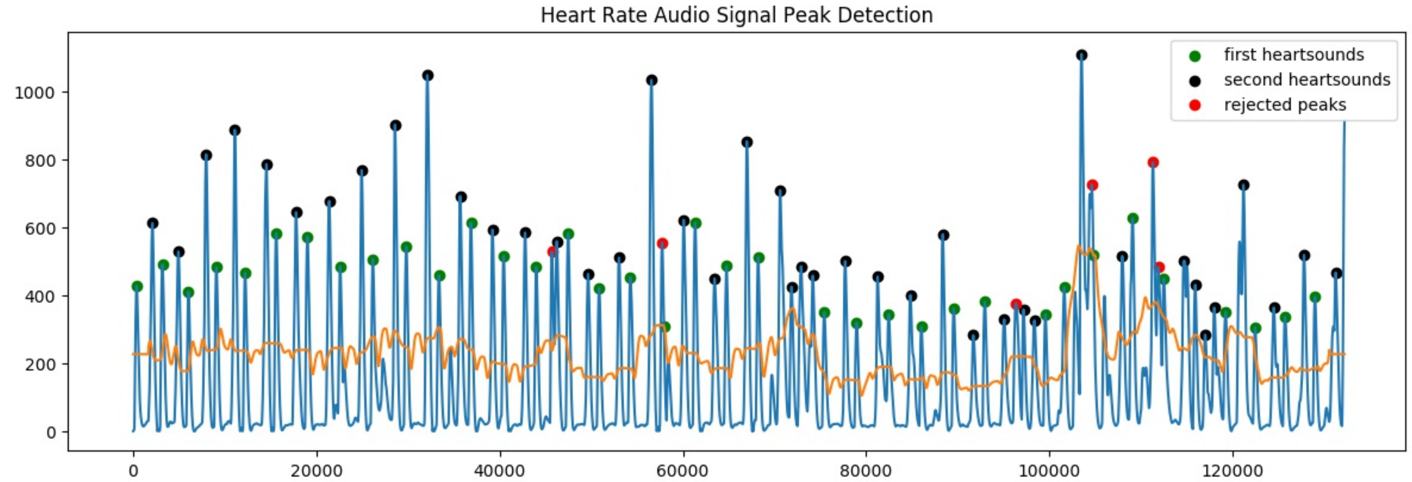
- Python 3.6.1
- Tensorflow (Backend)
- Keras
- Numpy / Scipy
- Librosa
- Scikit-Learn
- H5PY
- Matplotlib
- Pickle
- PyAudio

Hardware

- Raspberry Pi 3
- Dual Head Stethoscope
- Omnidirectional Condenser Microphone
- 5’’ Touchscreen LCD
- USB External Storage (for swap space)

Future Work

- In the future, I want to train my data on **Tachycardia, Bradycardia, Supraventricular, Ventricular, and Bradyarrhythmias arrhythmia sounds** so that it can discern the specific kind of arrhythmia a patient has.
- Work on creating a mobile app (with **TensorFlow Lite**) that utilizes this deep learning model to diagnose anyone, anywhere on the go.
- Create **Ensemble Voting Classifier** which uses the top 5 Machine Learning Models found in this project and makes a prediction based on the majority vote.
- Increase the reliability of the **Heart Rate Peak Detection Algorithm**, so that the software can more accurately tell a patient what their resting heart rate is.



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