

**REVIEW**

**CAPSTONE PROJECT**

**ECM4099**

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(Deemed to be University under section 3 of UGC Act, 1956)  
CHENNAI

# **CARDIAC HEALTH MONITORING SYSTEM Using Machine Learning**

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**ASSISTANT PROFESSOR**

**SENSE, VIT CHENNAI**

# Motivation:

Why we choose this topic ?

- Use ML/DL Tools efficiently for Developing Product that can function independently without the need of human interference.
- With increase in heart related problems in humans enabling every individual to know about their cardiac health at their convenience
- Have a broad understanding of Artificial Intelligence
- Apply Exploratory Data Analysis techniques to analyze complex data sets.
- Implement Unsupervised and Supervised Learning techniques
- Understand how to design and train Deep Neural Networks.

# OBJECTIVE

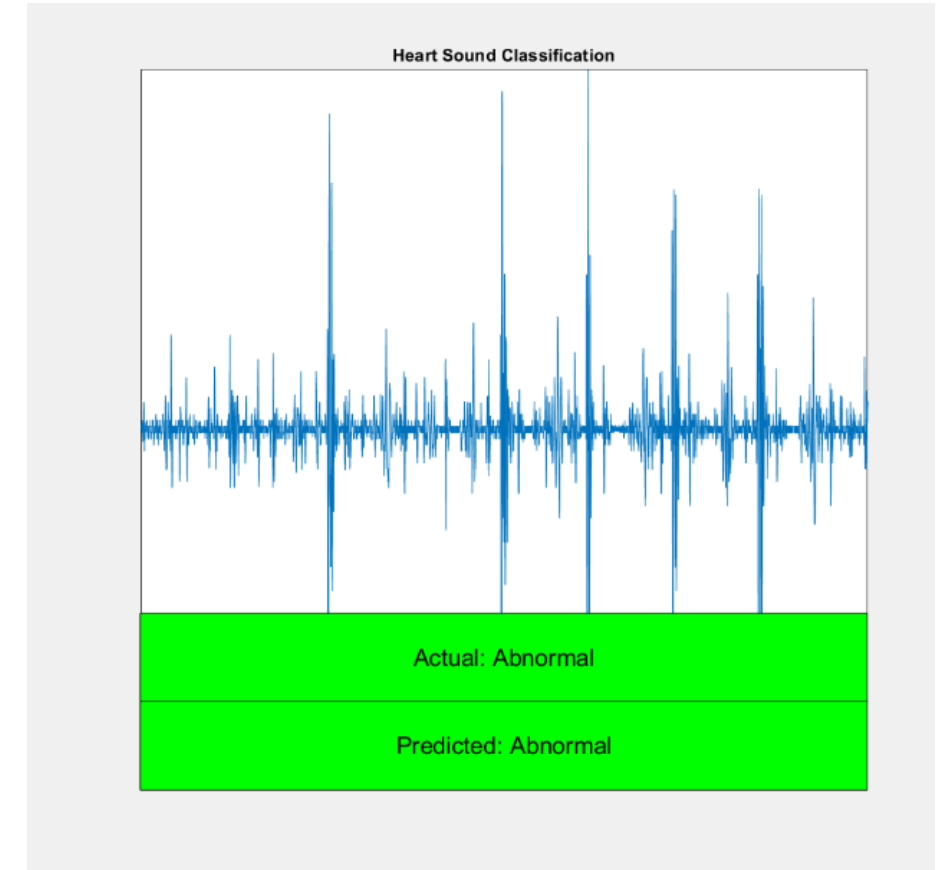
## CAPSTONE PROJECT

- We will be making a cardiac health monitoring system using Machine Learning and hence we will be training a model using a dataset to classify/predict the heartbeats of individuals as normal and abnormal using various features in the dataset
- Heart sounds classifier
  - Using a heart sounds classifier to understand the complete workflow for developing a real-world machine learning application, from loading data to deploying a trained model
  - Compared with the linear models, non-linear models satisfy more effectively the classification.

# Heart sounds classifier

## About the Project

- The number of people suffering from cardiac health issues around the globe are in lakhs and the number of accidents happening due to them getting no sign of warning or signal is appalling, so that's why fitness bands and smartwatches are being used more and more so that people can keep track of their heart rates.
- The project aims to find an ideal real-time solution to the problem which can analyze the live/recorded heart sounds through a hardware setup and yield an output that corresponds to the data plots made in the feed, thereby, providing a cost-effective and comprehensive system to the people. This ultimately empowers people and provides a way to interact with machines and if used with devices like fitness bands and smartwatches.
- The proposed model is based on KNN Classifier which is trained and used to classify the normal from abnormal heart sounds and is implemented using MATLAB.



# LITERATURE REVIEW

PUBLICATION/YEAR	TITLE	OVERVIEW	POSITIVE ASPECTS	LIMITATIONS
Front Physics / 2019	A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection.	In this work, it has been proposed an ensemble of Echo State Networks (ESNs) as the classifier method, using the raw ECG waveforms and time intervals between the heartbeats as the input features.	Uses ESN technique to evaluate the signals. The idea is based on Reservoir Computing which uses Recurrent Neural Networks. This gives good accuracy; hence this model can be used as standard.	The model works very well on long duration recordings but does not give the same results when implemented for short duration recordings.
IEEE / 2020	Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation	The work aims to provide accurate results for smaller datasets. The model uses Deep Learning based CNN which classifies whether the person has Arrhythmia.	The model provides accurate results for small datasets and provides reliable findings in that direction.	If the dataset contains signals with a lot of noise, then the model's noise removal part fails and the results lose accuracy.
Elsevier / 2020	A review on deep learning methods for ECG arrhythmia classification	The paper aims to provide deep learning algorithms which are suitable for classification and also provide datasets which can be used for analysis.	The algorithms provided are simple to use and can also provide accurate results.	The datasets listed are generic and require lots of pre-processing.
ISTAC/ 2008	Unsupervised learning-based feature points detection in ECG	The paper aims to use existing algorithms to extract features out of ECG signals so that the classification is more accurate and is also faster.	The algorithms give good results and can extract features well out of the signals.	The only problem being that the algorithms are biased towards some features and will mostly look for them in the signal.

# Design Methodology

## About the Project

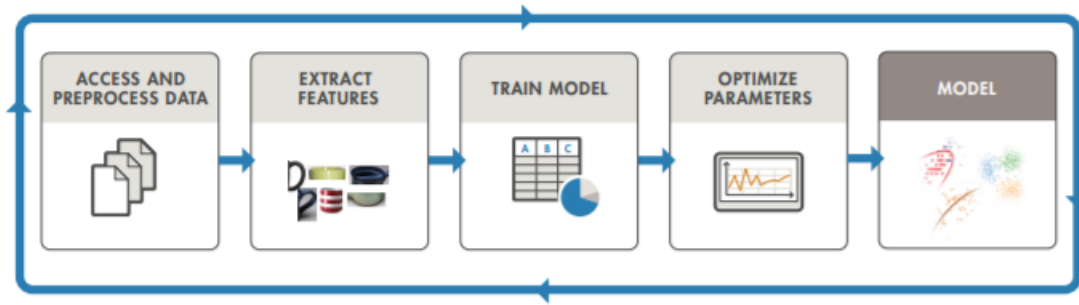
Heart sounds are a rich source of information for early diagnosis of cardiac pathologies. Distinguishing normal from abnormal heart sounds requires a specially trained clinician. Our goal is to develop a machine learning application that can identify abnormal heart sounds. Using a heart sounds monitoring application, regular medical staff could screen for heart conditions when no specialist is available, and patients could monitor themselves. In developing this application, we'll follow these steps:

- 1. Access and explore the data.
- 2. Preprocess the data and extract features.
- 3. Develop predictive models.
- 4. Optimize the model.
- 5. Deploy analytics to a production system.

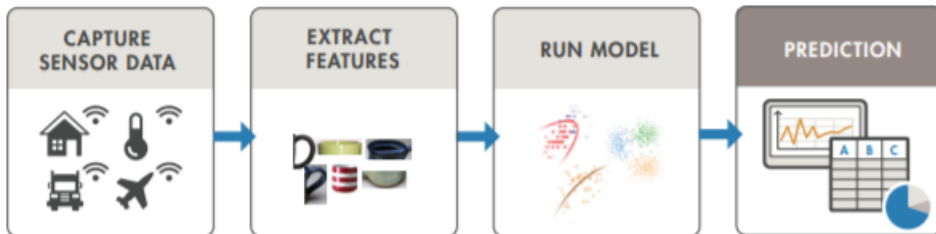
# Design Methodology

Steps that we will be following

**TRAIN:** Iterate until you achieve satisfactory performance.



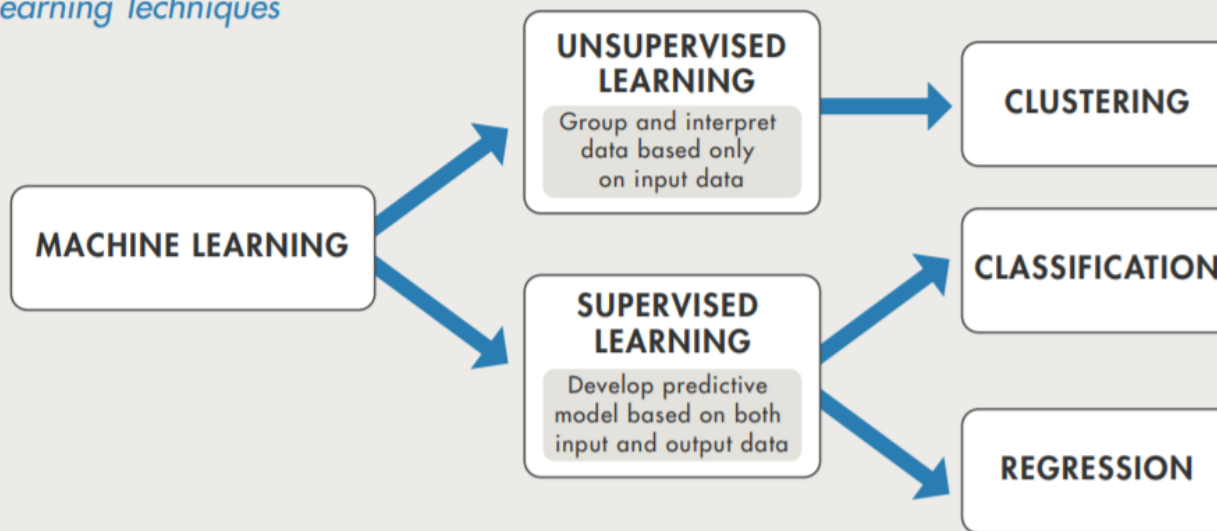
**PREDICT:** Integrate trained models into applications.



# How Machine Learning Works

- Machine learning uses two types of techniques: supervised learning, which trains a model on known input and output data so that it can predict future outputs, and unsupervised learning, which finds hidden patterns structures in input data.

## *Machine Learning Techniques*

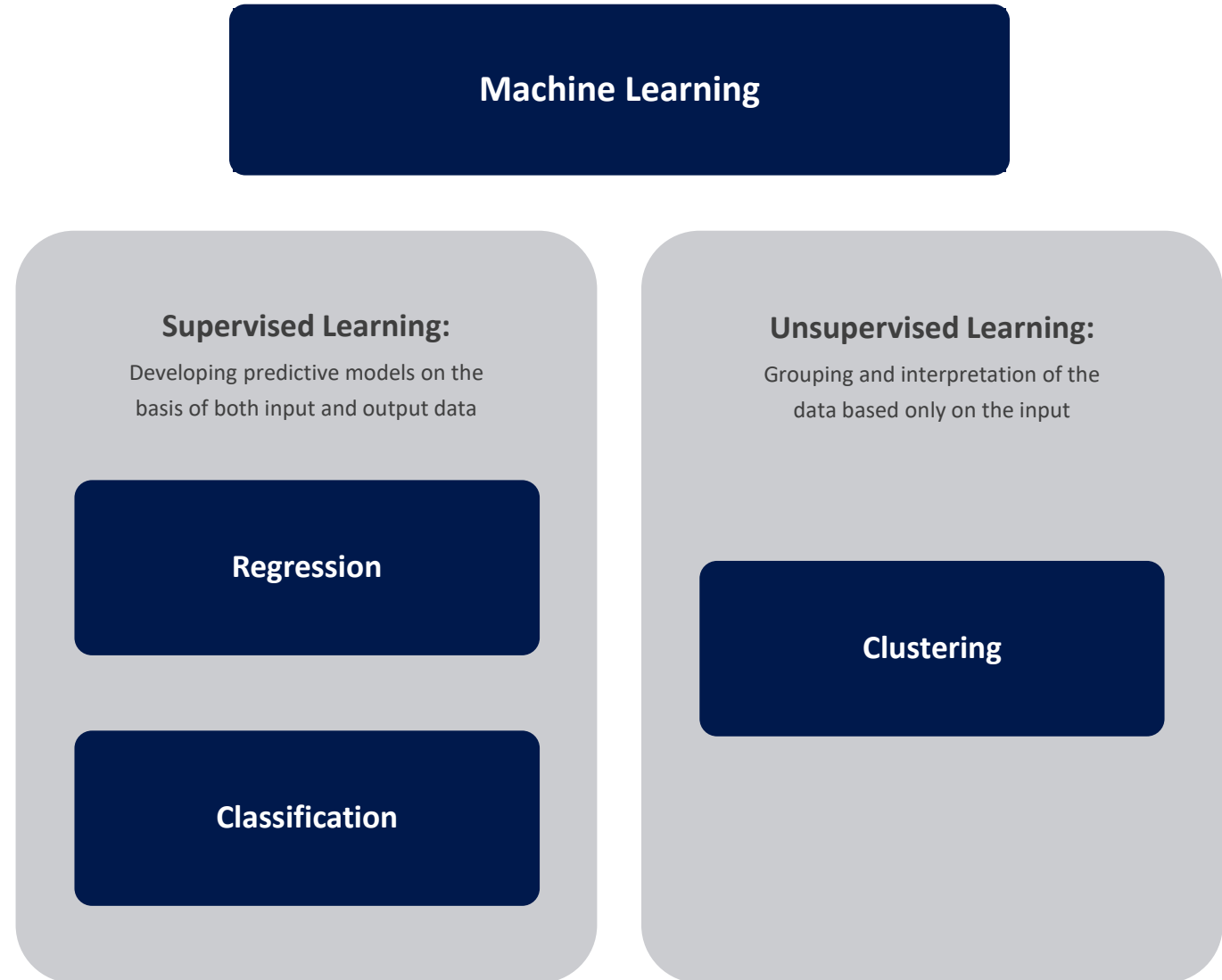




# Design Methodology

(BLOCK DIAGRAM)

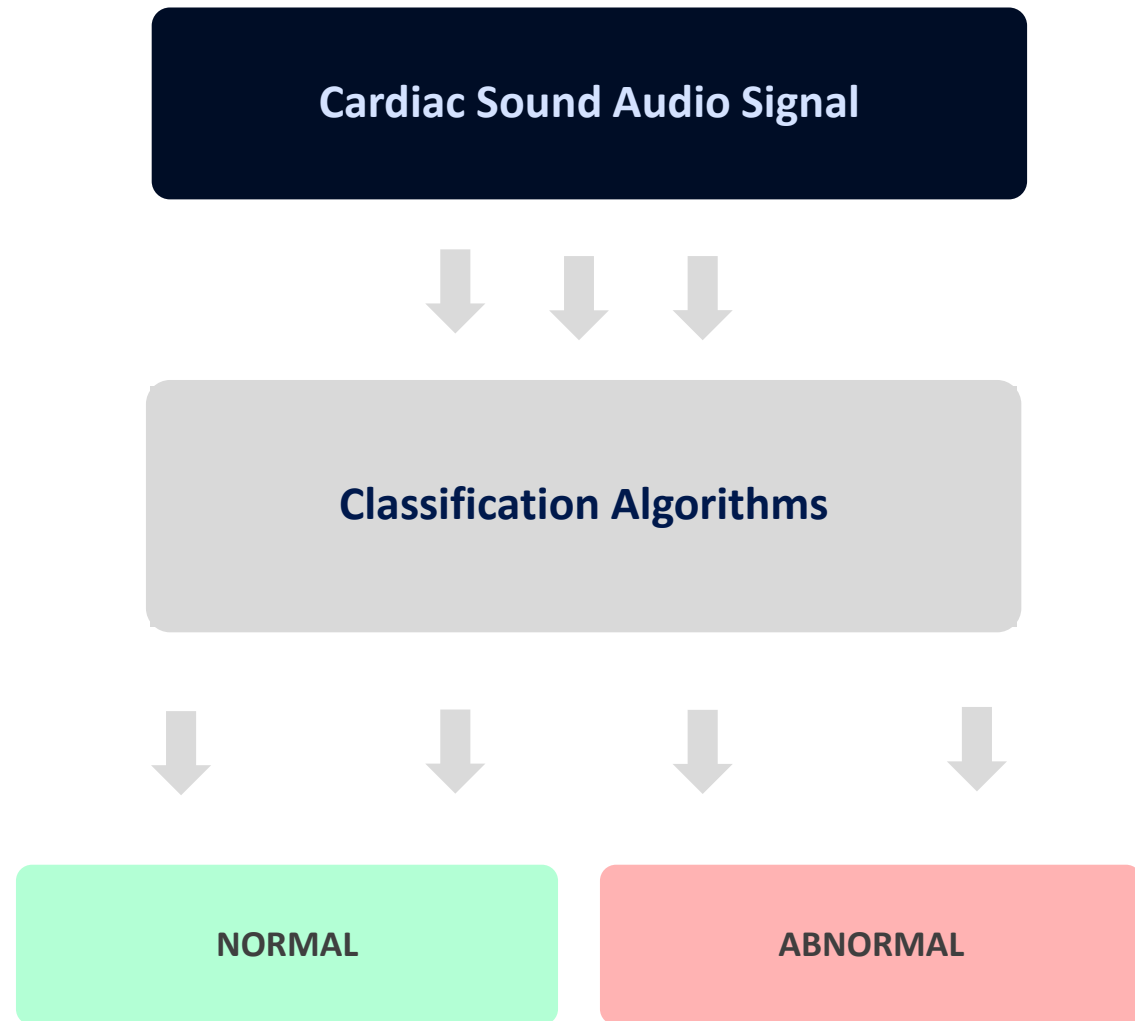
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# Design Methodology

(BLOCK DIAGRAM)

Building a Heart Sounds  
Classification Application



# Technical Specifications

- We won't be using any Hardware in this project except computing systems to run our project
- Software to be used are :
  - PYHTON
  - MATLAB

## MATLAB TOOL BOX USED

- MATLAB Coder
- Signal Processing Toolbox
- Statistics and Machine Learning Toolbox
- Wavelet Toolbox

## STANDARDS USED

- Automated machine
- Data exploration
- Live script
- Machine learning
- Signal processing
- Wavelets

# DATASET STUDY: Three questions

More Data, More Questions, Better Answers

- What kind of data are you working with?
- What insights do you want to get from it?
- How and where will those insights be applied?

## About the DATASET

The dataset from the **2016 PhysioNet** and Computing in Cardiology challenge, which consists of thousands of recorded heart sounds ranging in length from 5 seconds to 120 seconds. The dataset includes 3240 recordings for model training and 301 recordings for model validation. After downloading the data, we store the training and validation sets in separate folders—a standard procedure in machine learning.

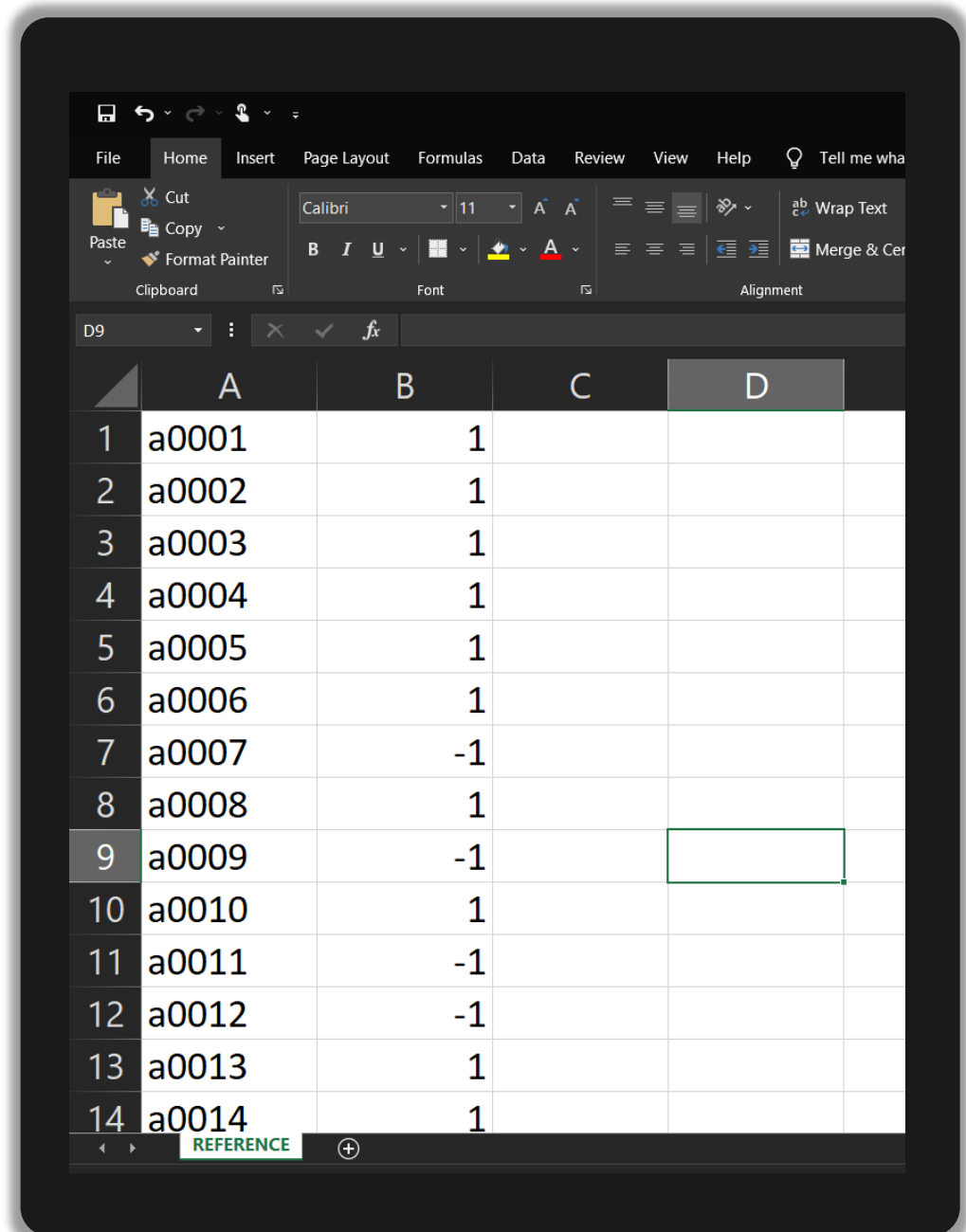
# Codes and Standards

## About the DATASET

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**ABNORMAL: -1 | NORMAL: 1**

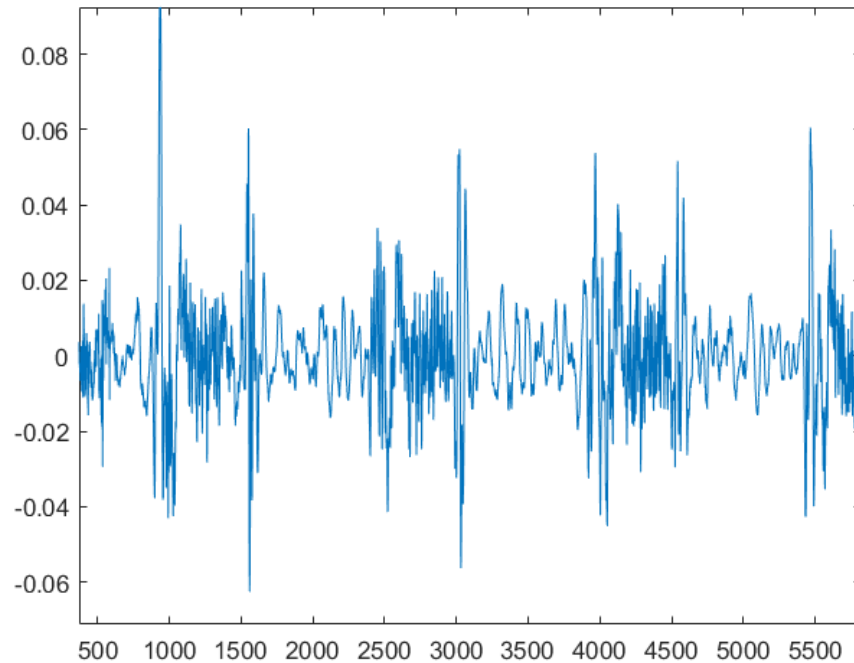


	A	B	C	D
1	a0001	1		
2	a0002	1		
3	a0003	1		
4	a0004	1		
5	a0005	1		
6	a0006	1		
7	a0007	-1		
8	a0008	1		
9	a0009	-1		
10	a0010	1		
11	a0011	-1		
12	a0012	-1		
13	a0013	1		
14	a0014	1		

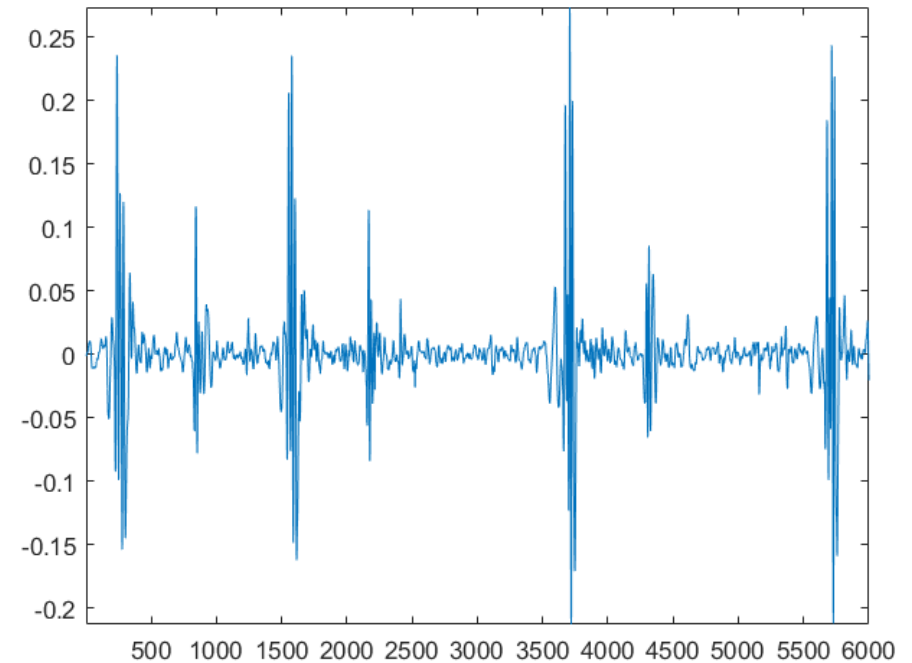
# Results and Discussions:

Analysis of Sample Duration:

**SAMPLE DURATION: 3 Seconds**



**ABNORMAL**

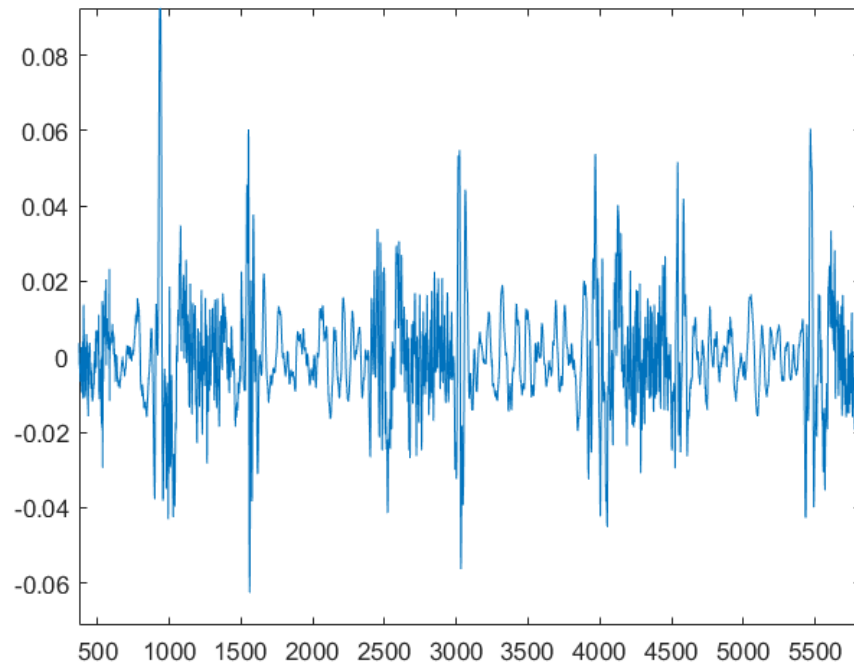


**NORMAL**

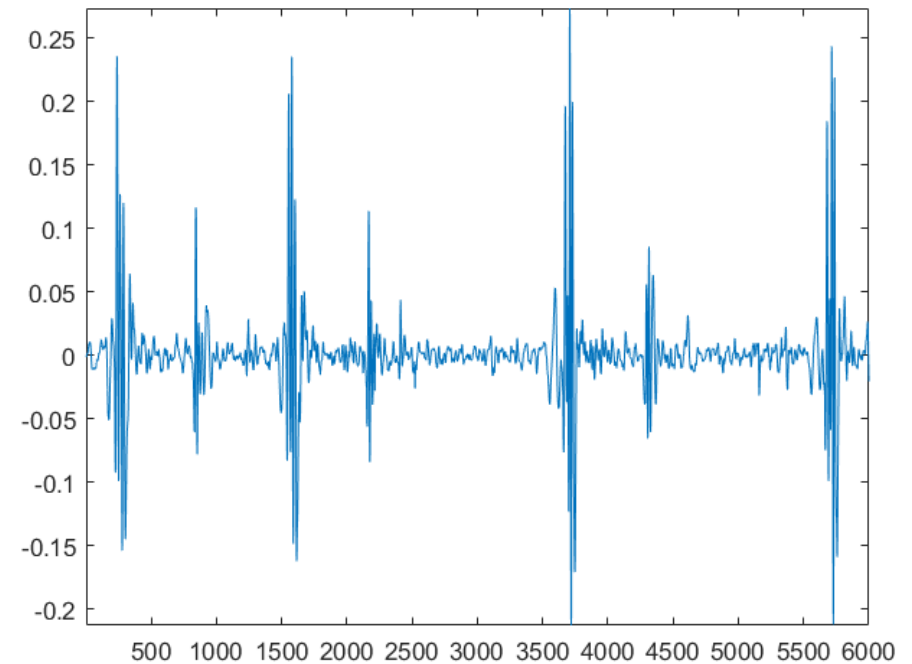
# Results and Discussions:

Analysis of Sample Duration:

**SAMPLE DURATION: 3 Seconds**



**ABNORMAL**

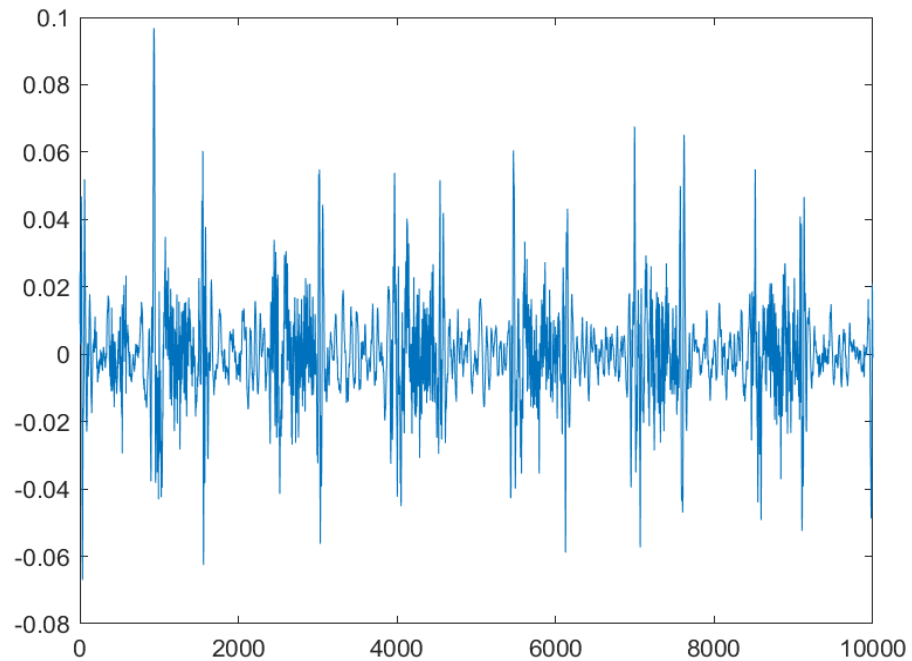


**NORMAL**

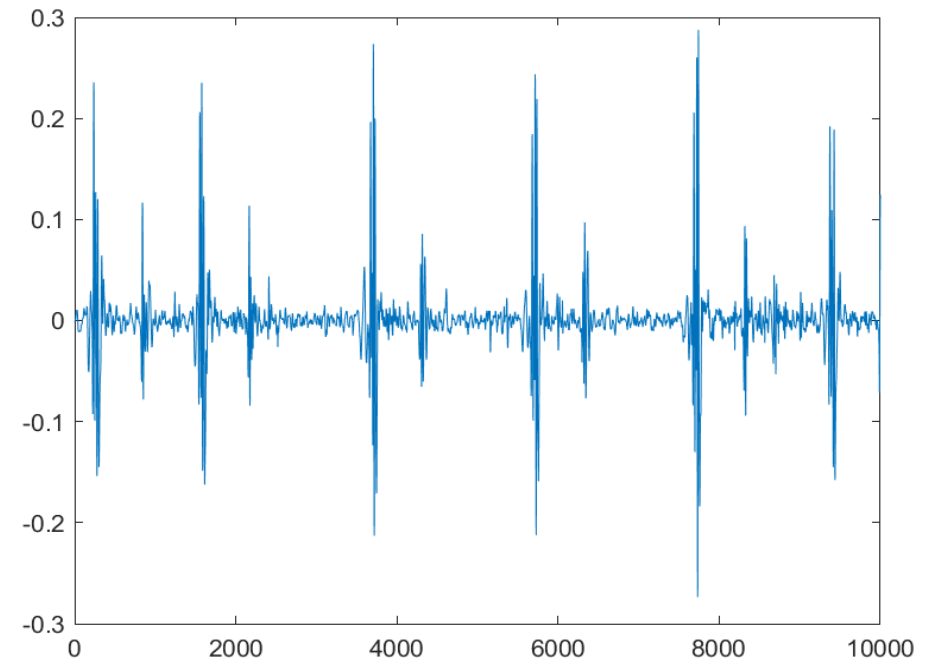
# Results and Discussions:

Analysis of Sample Duration:

**SAMPLE DURATION: 5 Seconds**



**ABNORMAL**



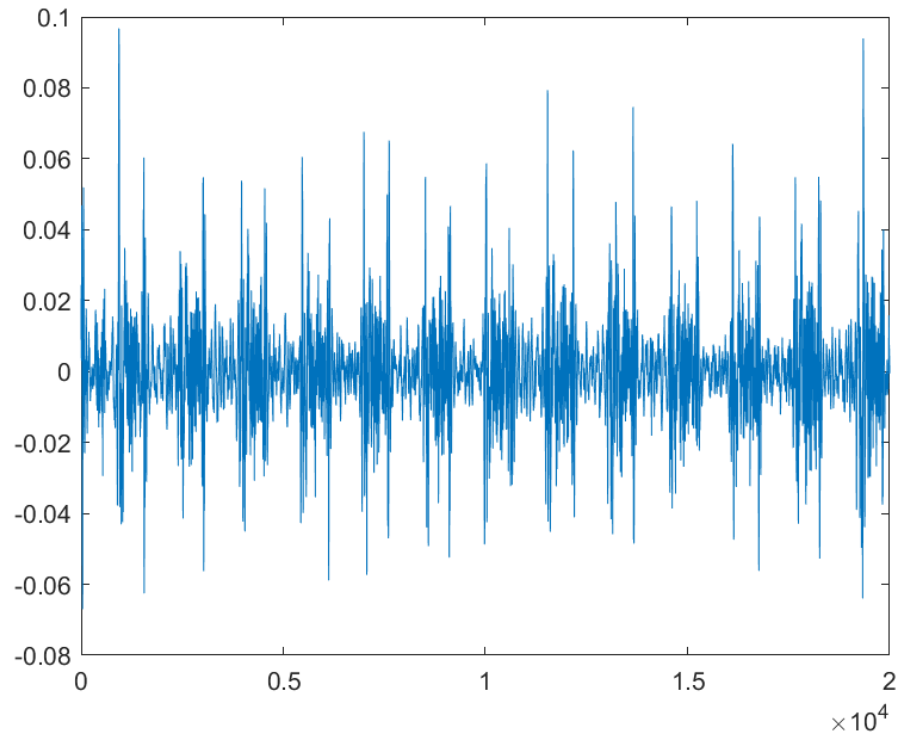
**NORMAL**



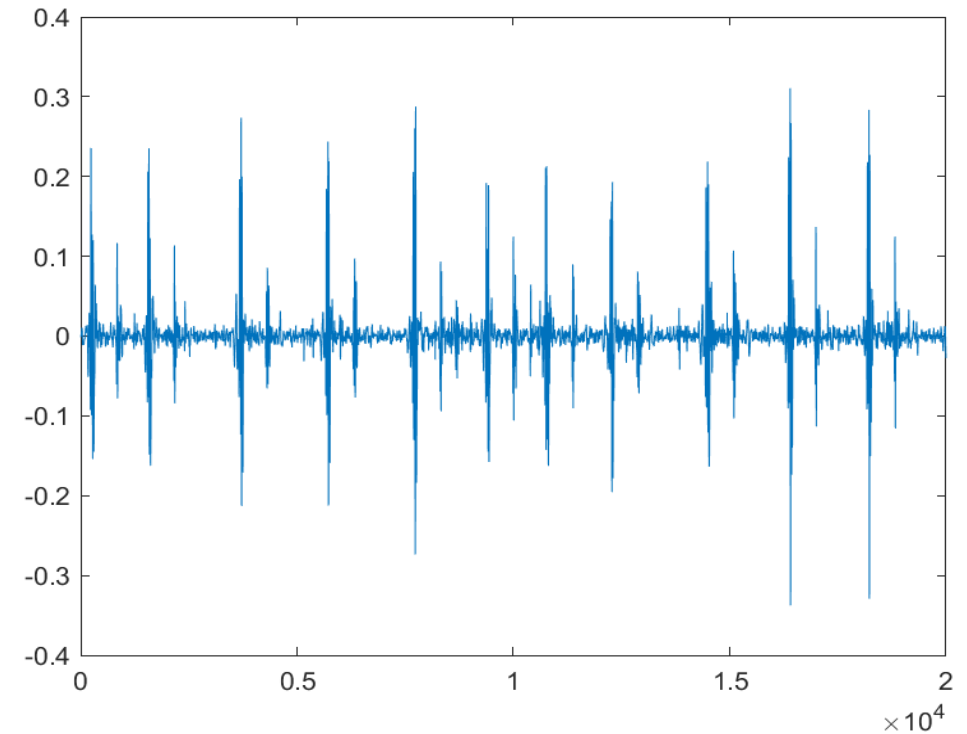
# Results and Discussions:

Analysis of Sample Duration:

**SAMPLE DURATION: 10 Seconds**



**ABNORMAL**

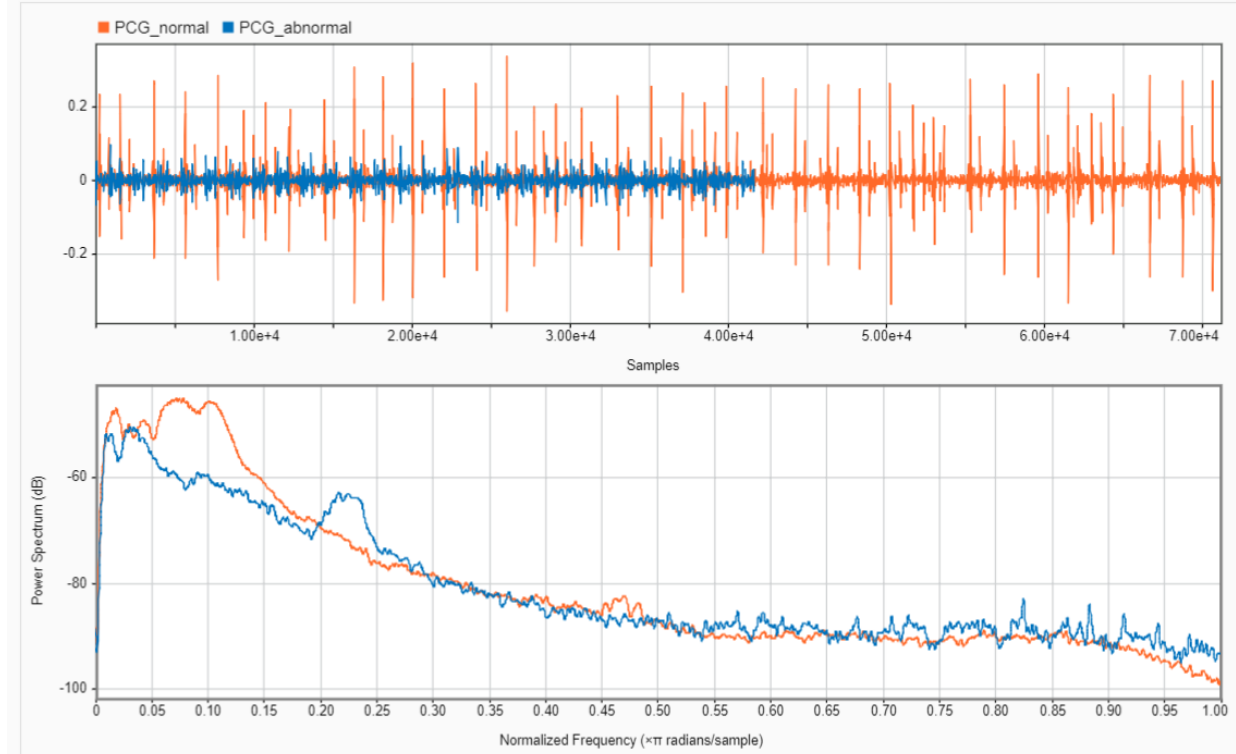
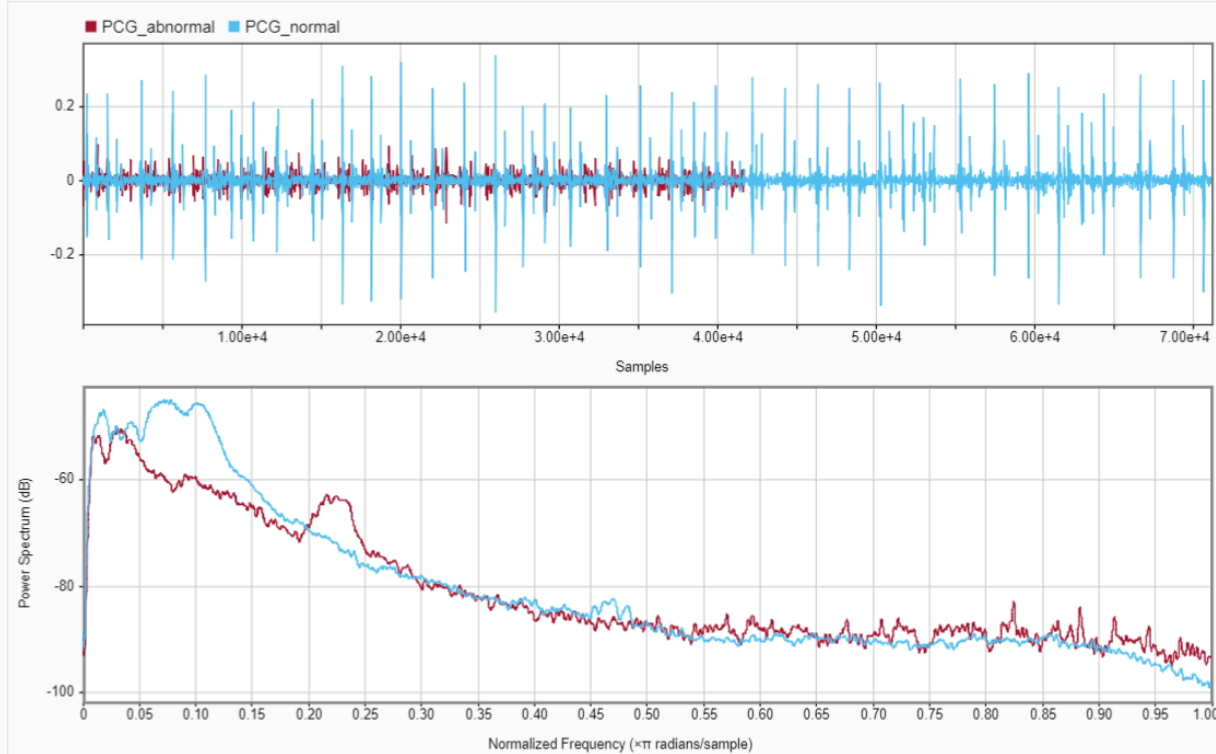


**NORMAL**

# Results and Discussions:

What do the signals look like in the frequency domain?

**CONCLUSION:** Sample rate doesn't affect the frequency distribution.



# Results and Discussions:

Feature extraction using statistical analysis

**CONCLUSION:** 27 features were extracted.

sampleSkewness	sampleKurtosis	signalEntropy	spectralEntropy	dominantFrequencyValue	dominantFrequencyMagnitude
1.4484	21.147	-2.7659	0.28682	17.098	0.066932
0.59825	16.507	-2.7017	0.29779	15.633	0.051741
1.039	14.776	-2.6434	0.23184	26.38	0.090545
0.78882	13.674	-2.716	0.25299	24.915	0.065139
1.2829	21.825	-2.7703	0.27842	30.288	0.051823

meanValue	medianValue	standardDeviation	meanAbsoluteDeviation	quantile25	quantile75	signalIQR
-2.7121e-05	0.00015259	0.02033	0.01228	-0.0083771	0.0082092	0.016586
-4.3304e-06	6.1035e-05	0.021358	0.012943	-0.0079041	0.0081482	0.016052
1.6452e-05	0.00036621	0.021588	0.013572	-0.0092163	0.0085297	0.017746
-7.8979e-05	-0.00015259	0.019643	0.012688	-0.0090179	0.008606	0.017624
4.4342e-06	0.00048828	0.023276	0.012722	-0.0072021	0.0073853	0.014587

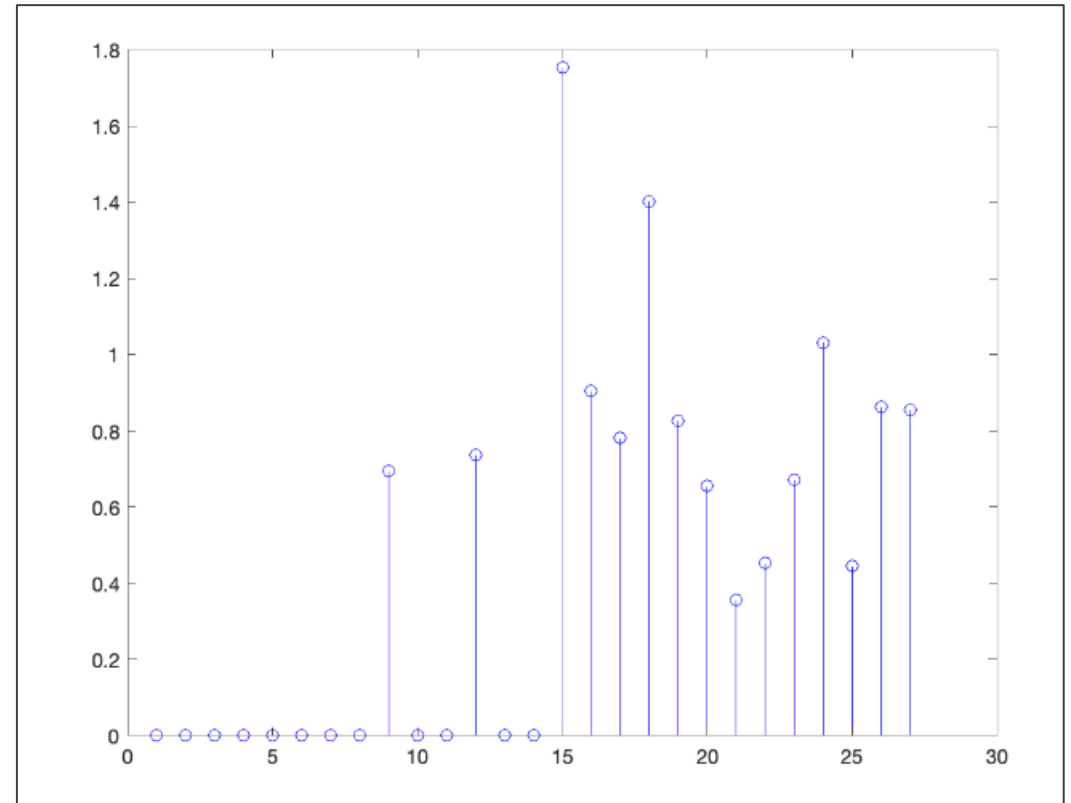
CC4	MFCC5	MFCC6	MFCC7	MFCC8	MFCC9	MFCC10	MFCC11	MFCC12	MFCC13	class
51239	-2.5149	-3.143	-1.9638	-0.11315	-0.28488	1.6218	-0.53338	-1.6926	-2.0239	{'Abnormal'}
33812	-1.7421	-4.6783	-2.7332	2.394	0.10001	2.9168	-1.3413	-0.90557	-1.4914	{'Abnormal'}
.2183	-0.55386	-1.3512	-2.2507	1.1322	-0.42672	2.3943	1.5946	-2.0933	-1.3693	{'Abnormal'}
73843	-0.74028	-4.1818	-2.0782	1.8257	0.865	2.4926	-0.91656	-0.55254	-2.2298	{'Abnormal'}
85403	-0.82052	-5.8922	-2.0241	1.5196	-0.64708	3.923	-0.5634	-1.7582	-0.4827	{'Abnormal'}

dominantFrequencyRatio	MFCC1	MFCC2	MFCC3	MFCC4	MFCC5	MFCC6	MFCC7	MFCC8	MFCC9
0.22436	88.196	7.3405	6.4674	-0.051239	-2.5149	-3.143	-1.9638	-0.11315	-0.2848
0.16802	88.048	7.9407	6.6784	-0.33812	-1.7421	-4.6783	-2.7332	2.394	0.1000
0.38065	90.012	8.0685	1.5072	-2.2183	-0.55386	-1.3512	-2.2507	1.1322	-0.4267
0.4354	87.303	7.4797	7.4607	-0.73843	-0.74028	-4.1818	-2.0782	1.8257	0.86
0.34453	88.171	7.8968	6.8715	0.85403	-0.82052	-5.8922	-2.0241	1.5196	-0.6470

Feature Reduction using NCA

# Results and Discussions:

**CONCLUSION:** 15 features were extracted.

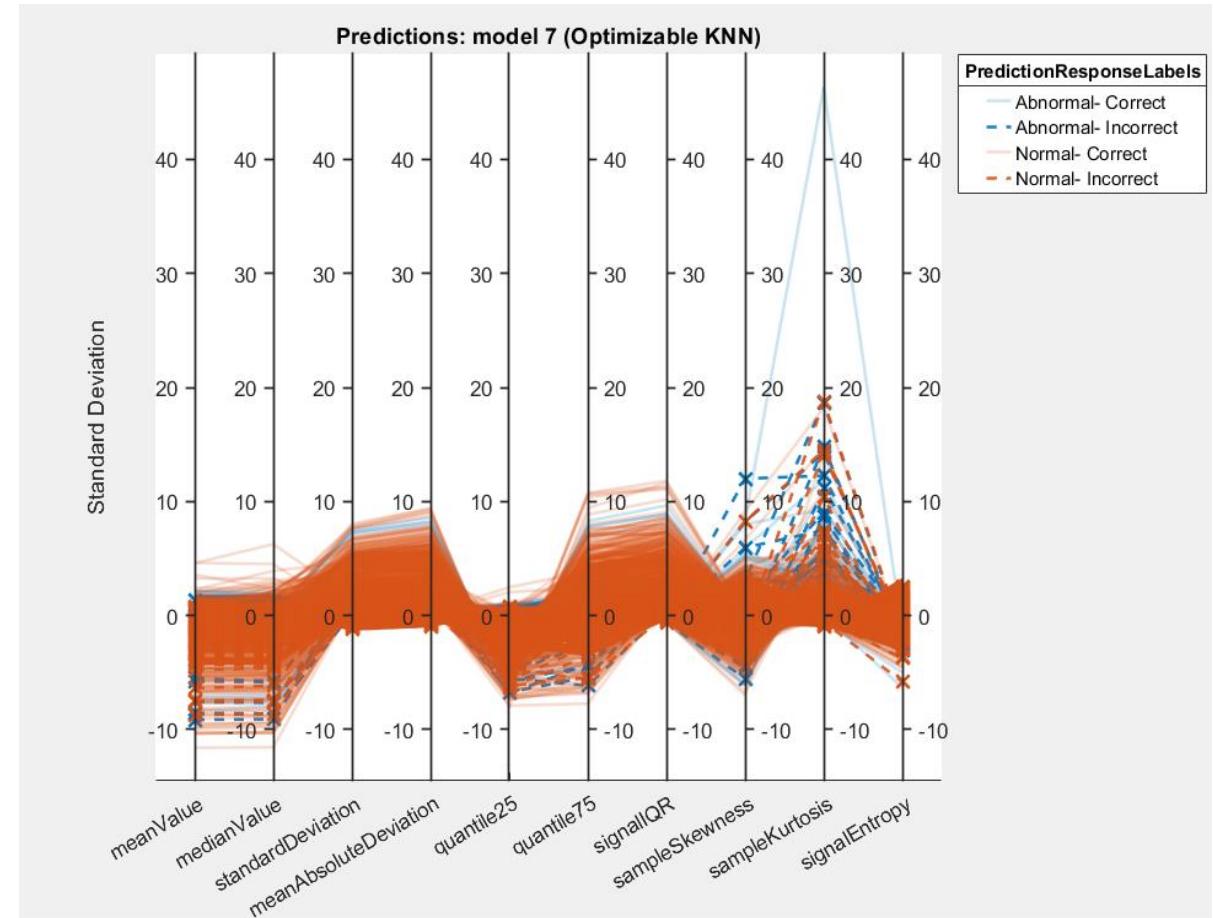


*'sampleKurtosis' , 'dominantFrequency...' , 'MFCC1' , 'MFCC2' , 'MFCC3'  
'MFCC4' , 'MFCC5' , 'MFCC6' , 'MFCC7' , 'MFCC8' , 'MFCC9' , 'MFCC10'  
'MFCC11' , 'MFCC12' , 'MFCC13'*

Feature Reduction using NCA

# Results and Discussions:

**CONCLUSION:** 15 features were extracted.



# Results and Discussions:

## Analysis of Sample Duration: Models Tested

### SAMPLE DURATION: 5 Seconds

▼ History		
1 ☆ Tree	Accuracy: 90.0%	
Last change: Disabled PCA 27/27 features		
2 ☆ Linear Discriminant	Accuracy: 85.7%	
Last change: Linear Discriminant 27/27 features		
3 ☆ Quadratic Discriminant		Failed
Last change: Quadratic Discriminant 27/27 features		
4 ☆ Optimizable Discriminant	Accuracy: 85.6%	
Last change: Optimizable Discriminant 27/27 features		
5 ☆ KNN	Accuracy: 94.5%	
Last change: Fine KNN 27/27 features		
6 ☆ KNN	Accuracy: 92.0%	
Last change: Cosine KNN 27/27 features		
7 ☆ KNN	Accuracy: <b>94.6%</b>	
Last change: Optimizable KNN 27/27 features		

### SAMPLE DURATION: 10 Seconds

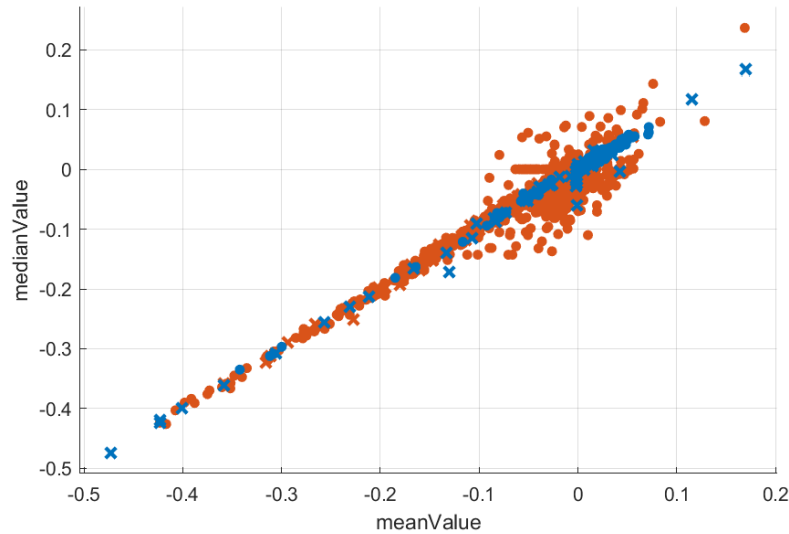
Data Browser		
▼ History		
1 ☆ Tree	Accuracy: 89.7%	
Last change: Disabled PCA 27/27 features		
2 ☆ Linear Discriminant	Accuracy: 85.7%	
Last change: Linear Discriminant 27/27 features		
3 ☆ Logistic Regression	Accuracy: 86.1%	
Last change: Logistic Regression 27/27 features		
4 ☆ Optimizable Discriminant	Accuracy: 85.6%	
Last change: Optimizable Discriminant 27/27 features		
5 ☆ KNN	Accuracy: 94.7%	
Last change: Fine KNN 27/27 features		
6 ☆ KNN	Accuracy: 92.0%	
Last change: Cosine KNN 27/27 features		
7 ☆ KNN	Accuracy: <b>95.2%</b>	
Last change: Optimizable KNN 27/27 features		

# Results and Discussions:

Analysis of Sample Duration: Models Tested

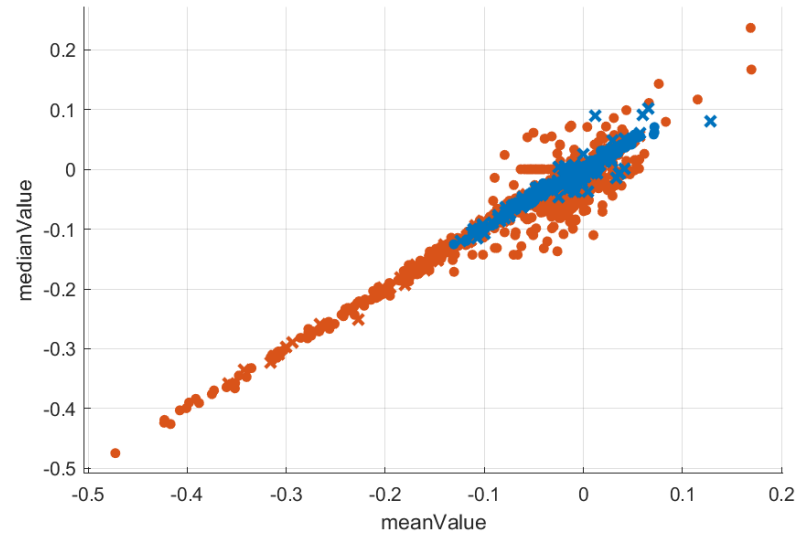
**SAMPLE DURATION: 5 Seconds**

Predictions: model 1



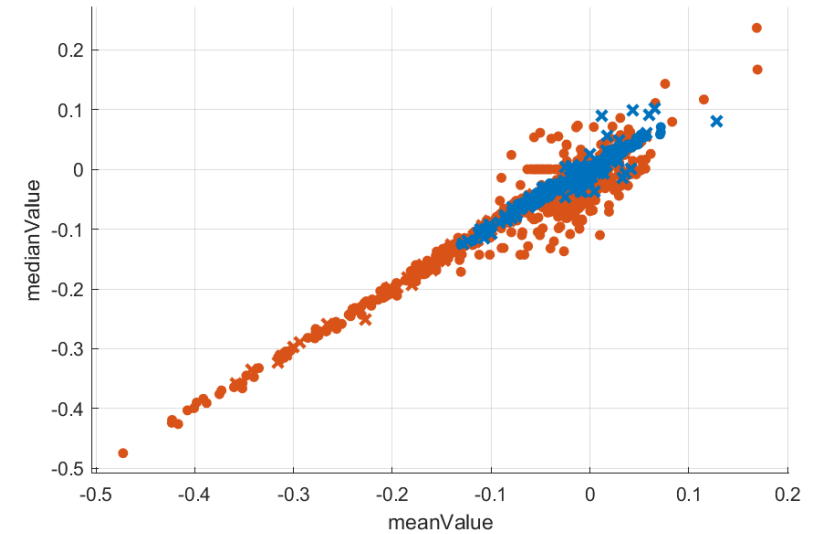
**Tree:**

Predictions: model 2



**Linear Discriminant:**

Predictions: model 4



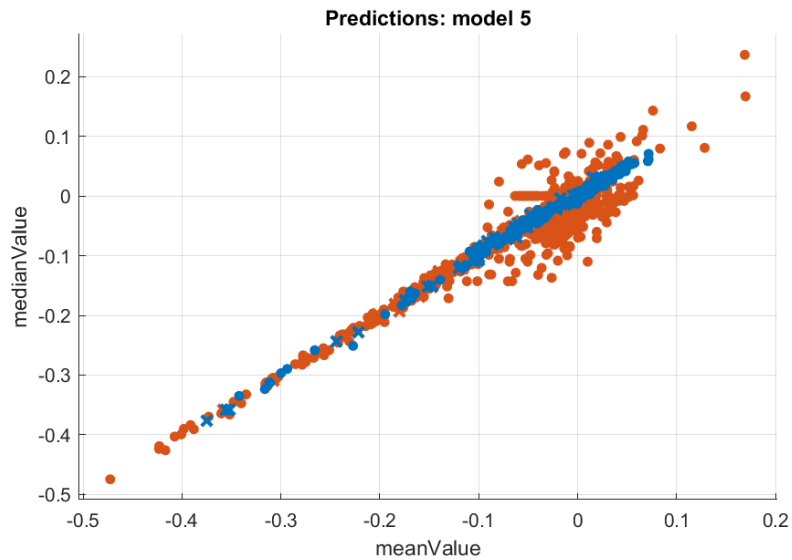
**Optimised Discriminant Analysis:**

# Results and Discussions:

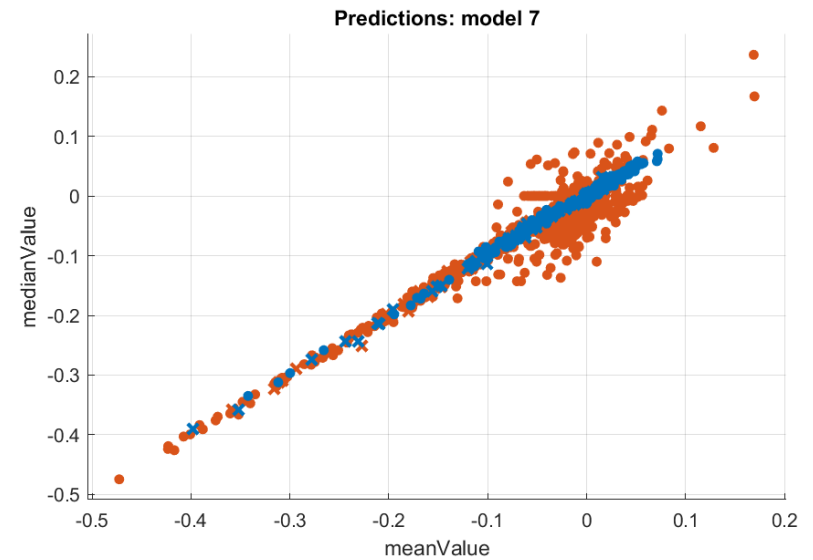
Analysis of Sample Duration : Models Tested

**SAMPLE RATE: 5 Seconds**

Principle Used: **Hyperparameter Optimization in Classification Learner App**



**KNN:**



**Optimised KNN: (BEST MODEL)**

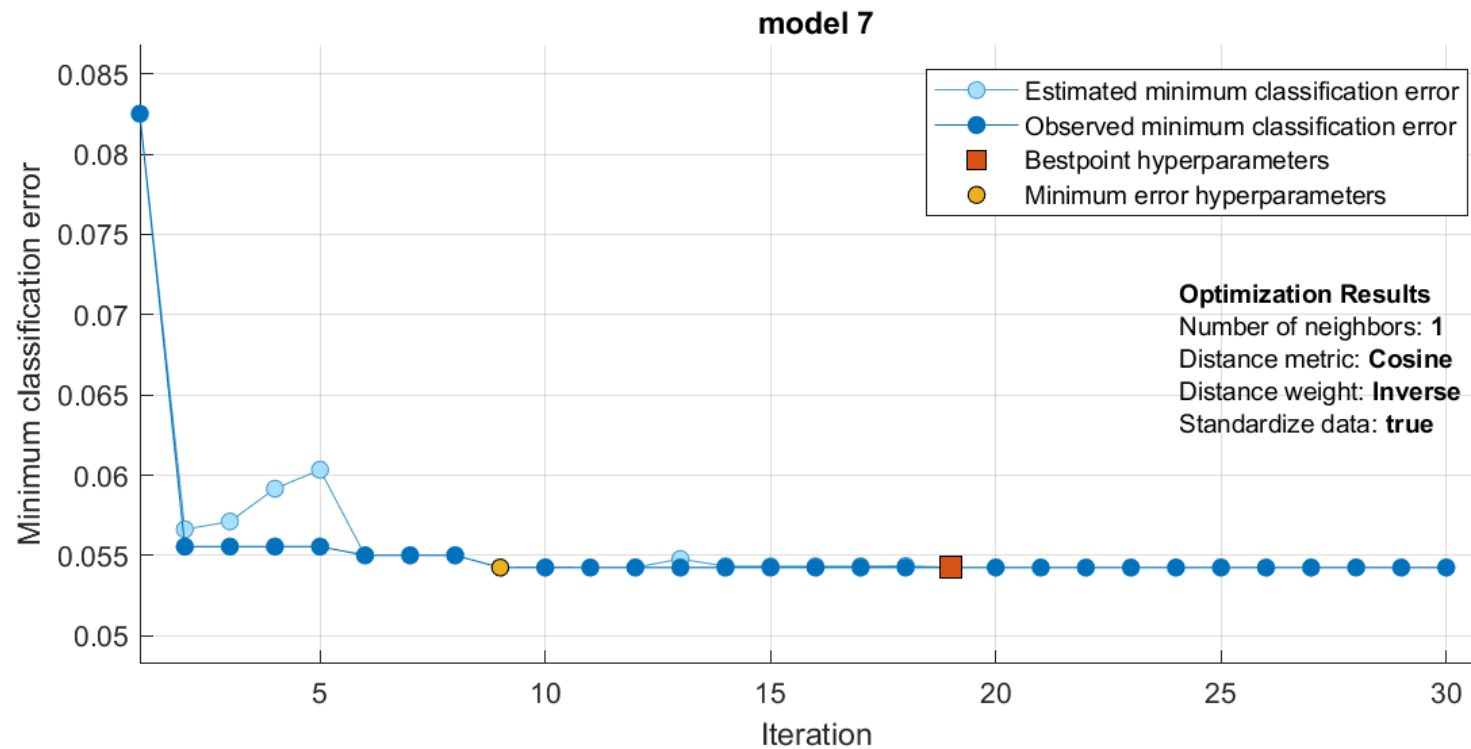


# Work Analysis:

Analysis of Sample Duration : Models Tested

**SAMPLE DURATION: 5 Seconds**

## Minimum Classification Error Plot

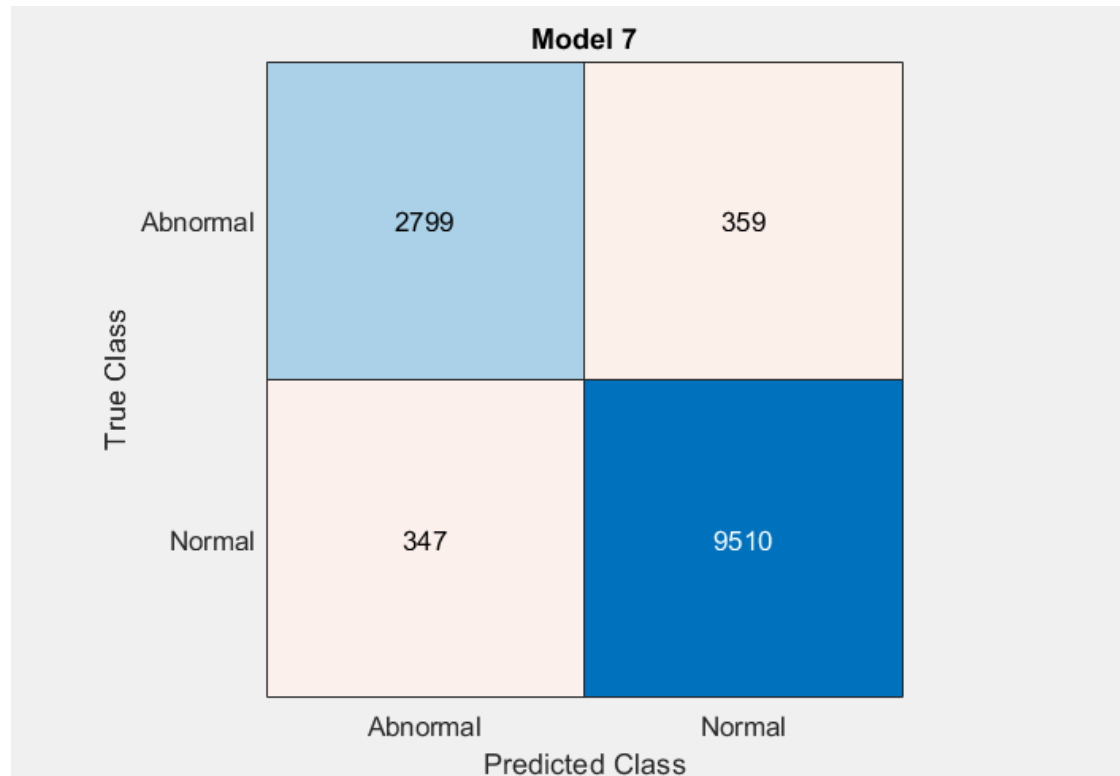


# Work Analysis:

Analysis of Sample Duration : Models Tested

**SAMPLE DURATION: 5 Seconds**

## Confusion Matrix And ROC Curve

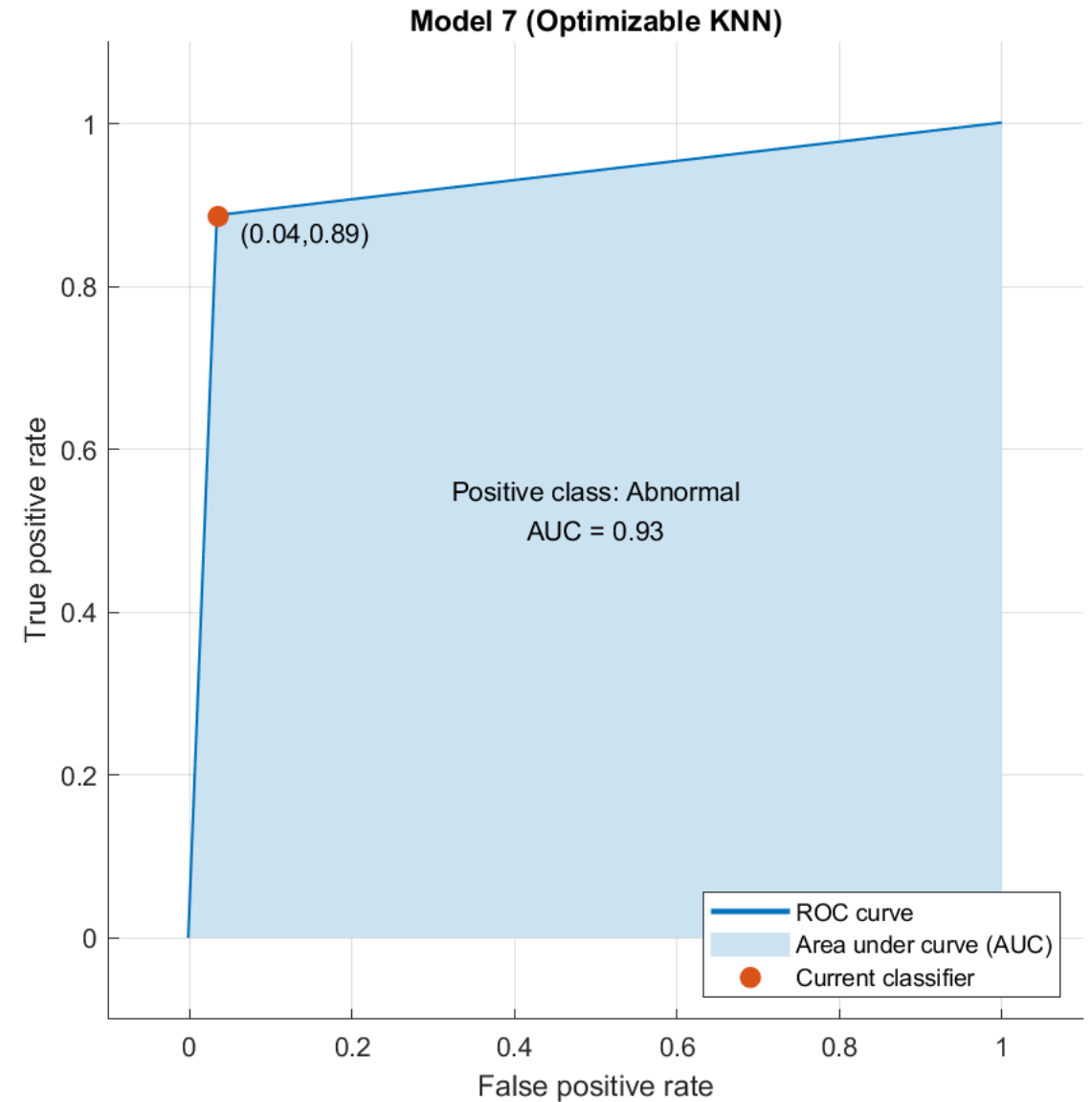


# Work Analysis:

Sample Duration : Models Tested

**SAMPLE DURATION: 5 Seconds**

## Confusion Matrix And ROC Curve

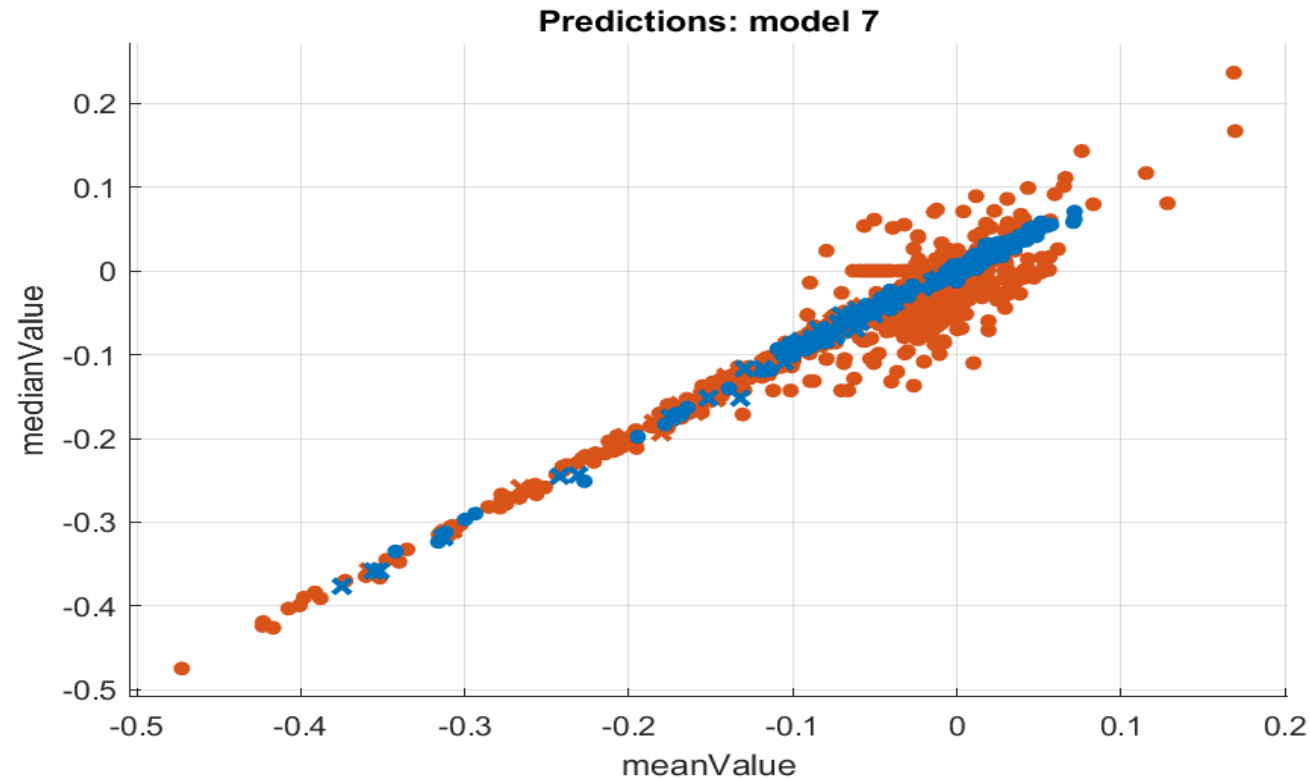


# Work Analysis:

Analysis of Sample Duration : Models Tested

**SAMPLE RATE: 10 Seconds**

Principle Used: **Hyperparameter Optimization in Classification Learner App**



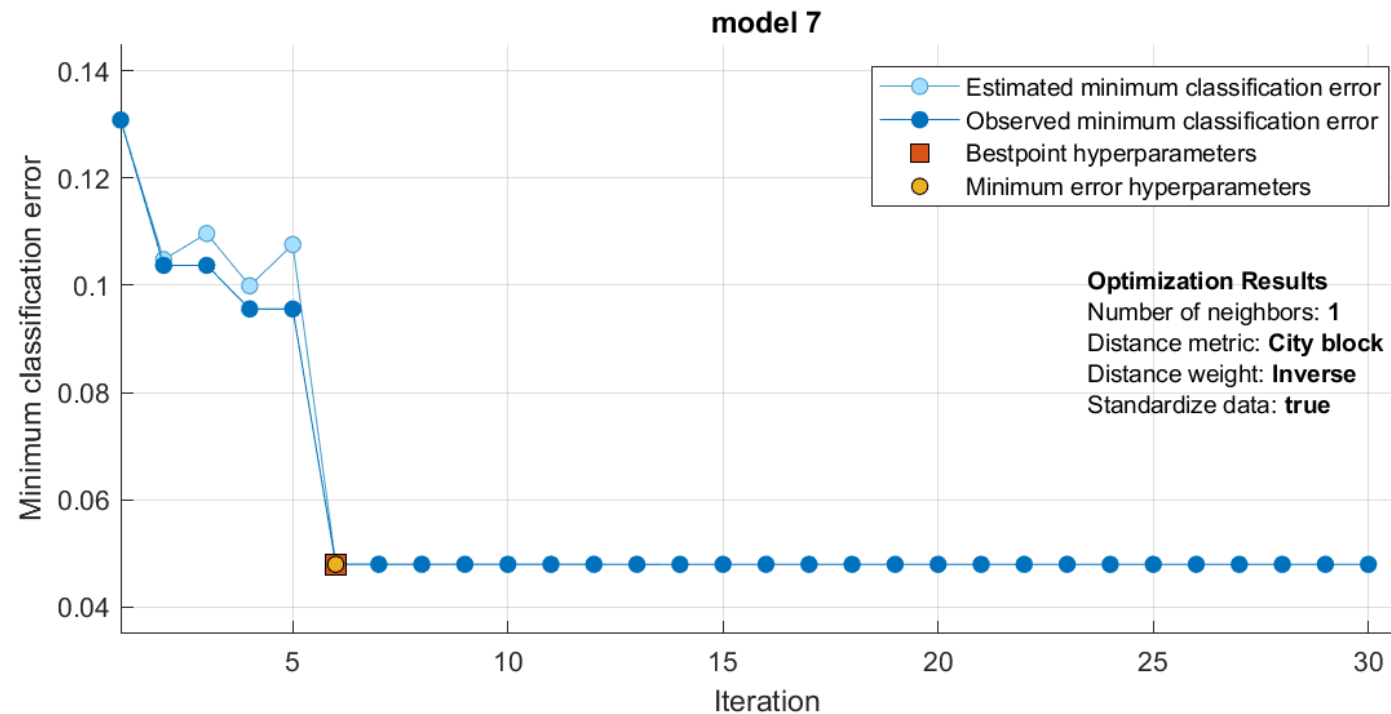
**Optimised KNN (Highest accuracy):**

# Work Analysis:

Analysis of Sample Duration : Models Tested

**SAMPLE DURATION: 5 Seconds**

## Minimum Classification Error Plot

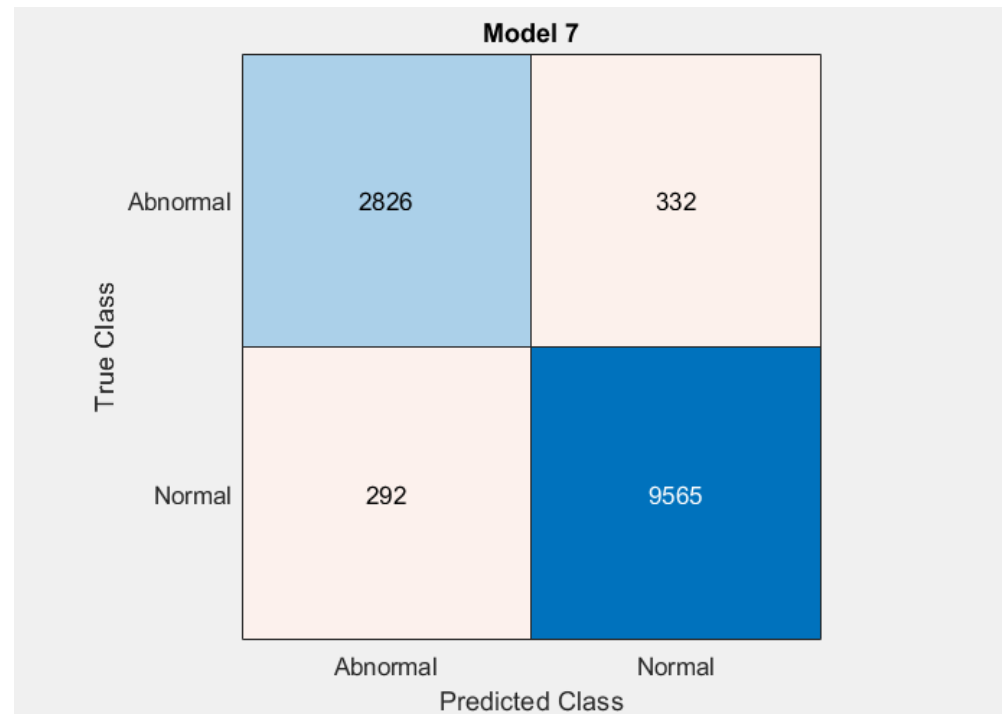


# Work Analysis:

Analysis of Sample Duration : Models Tested

**SAMPLE DURATION: 5 Seconds**

## Confusion Matrix And ROC Curve

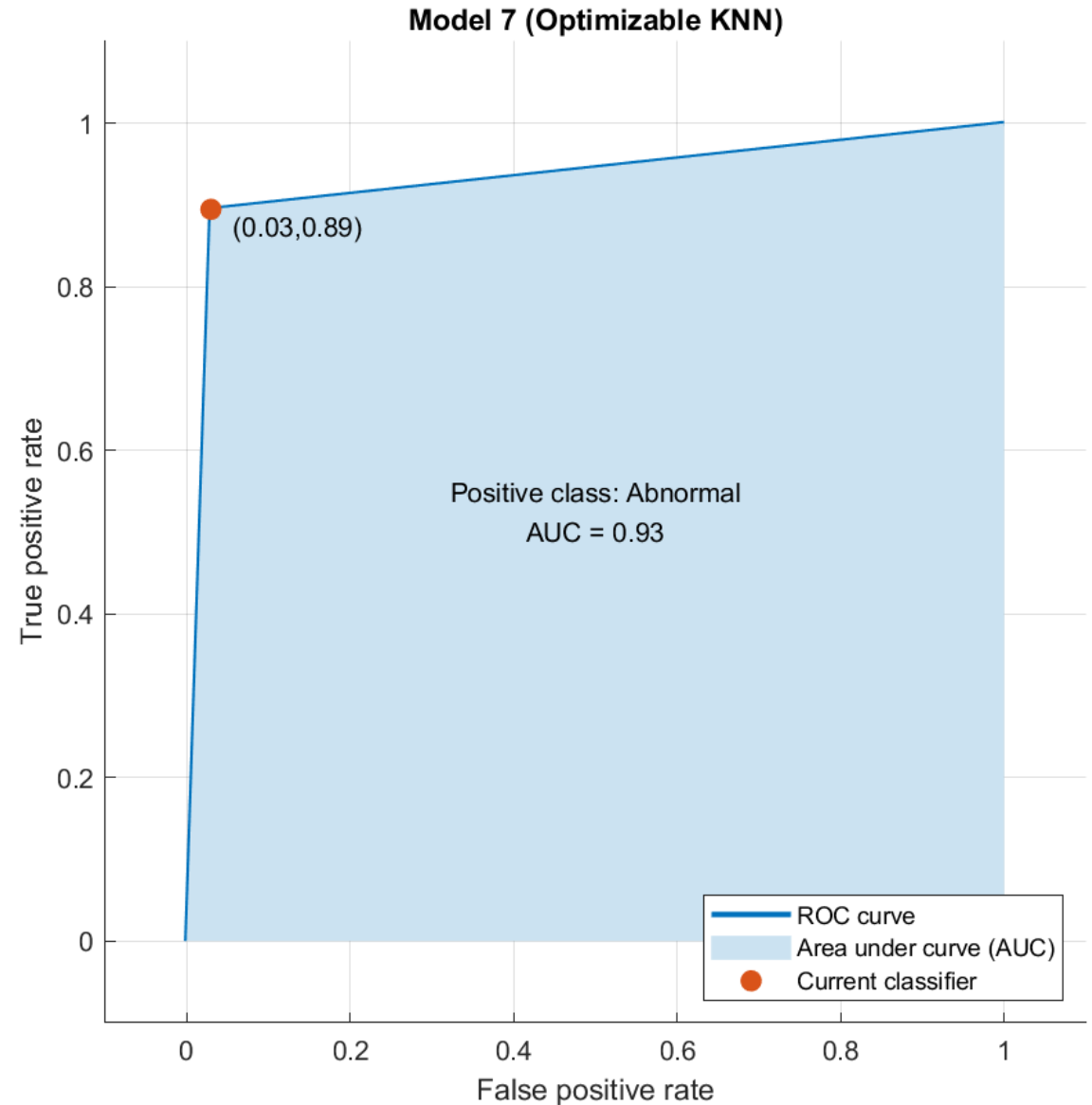


# Work Analysis:

Sample Duration : Models Tested

**SAMPLE DURATION:** 10 Seconds

## Confusion Matrix And ROC Curve



# Discussion of Results Obtained

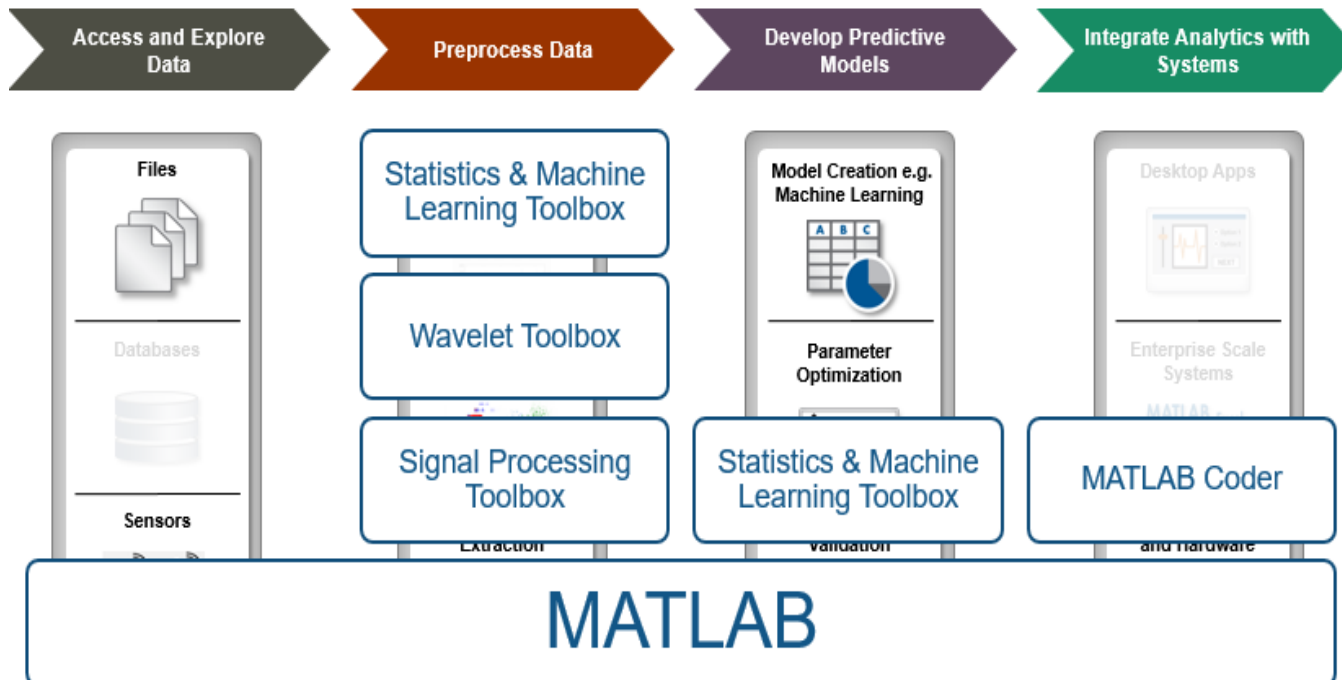
MACHINE LEARNING ALGORITHMS to be used

Algorithm	Prediction Speed	Training Speed	Memory Usage	Required Tuning
Logistic Regression	Fast	Fast	Small	Minimal
Decision Trees	Fast	Fast	Small	Some
Non-Linear SVM	Slow	Slow	Medium	Some
KNN	Moderate	Minimal	Medium	Minimal
Naïve Bayes	Fast	Fast	Medium	Some
Ensembles	Moderate	Slow	Varies	Some
Neural Networks	Moderate	Slow	Medium	Lots



# Codes and Standards

## Heart Sound Classification – Workflow



# Codes and Standards

## Analysis of Sample Duration:

What does an **abnormal** heart sound like?

**X** is the sample rate

```
[PCG_abnormal, fs] = audioread('a0002.wav');  
p_abnormal = audioplayer(PCG_abnormal, fs);  
play(p_abnormal, [1 (get(p_abnormal, 'SampleRate') * X)]);
```

```
% Plot the sound waveform  
plot(PCG_abnormal(1:fs*X))
```

What does a **normal** heart sound like?

```
[PCG_normal, fs] = audioread('a0011.wav');  
p_normal = audioplayer(PCG_normal, fs);  
play(p_normal, [1 (get(p_normal, 'SampleRate') * X)]);
```

```
% Plot the sound waveform  
plot(PCG_normal(1:fs*X))
```

# Codes and Standards

## Analysis of Sample Rate:

### Extract features from raw heart sound signals

We extracted features from the raw recordings. We used statistical and signal processing functions available in MATLAB to process and extract features from the raw heart sound signal. The following section extracts some 26 features for each recording, and splits each recording into windows consisting of 5 seconds of heart sound.

The preprocessing of all 3000+ recordings may take a while, even though the code below leverages the Parallel Computing toolbox to execute on multiple cores.

#### Code:

```
runExtraction = false;
if runExtraction | ~exist('FeatureTable.mat')
    win_len = 5;
    win_overlap = 0;
    feature_table = table();
    n_parts = numpartitions(training_fds, gcp);
    parfor ipart = 1:n_parts
        subds = partition(training_fds, n_parts, ipart);
        [feature_win, sampleN] = extractFeatures(subds, win_len, win_overlap,
            reference_table);
        feature_table = [feature_table; feature_win];
        disp(['Part ' num2str(ipart) ' done.'])
    end
    save('FeatureTable', 'feature_table');

else load('FeatureTable.mat');
end

disp(feature_table(1:5,:))
```

# Codes and Standards

## Analysis of Sample Rate:

### Split data into training and testing sets

Holding out 30% of the data for testing

#### Code:

```
[training_set, test_set] = splitDataSets(feature_table,0.3);
```

### Train, compare and select classifier

Having an initial set of features, we can proceed to the next phase of the machine learning workflow, the training of various predictive models. We used the Classification Learner App to interactively train, compare and select classifiers.

#### Code:

```
classificationLearner;  
  
predicted_class_featsel = predict(trained_model_featsel,  
test_set(:,selected_feature_idx));  
conf_mat_featsel = confusionmat(test_set.class, predicted_class_featsel);  
conf_mat_per_featsel = conf_mat_featsel*100./sum(conf_mat_featsel, 2);  
labels = {'Abnormal', 'Normal'};  
  
heatmap(labels,labels,conf_mat_per_featsel, 'Colormap', winter,  
'ColorbarVisible','off');
```

# Constraints, Alternatives and Trade offs

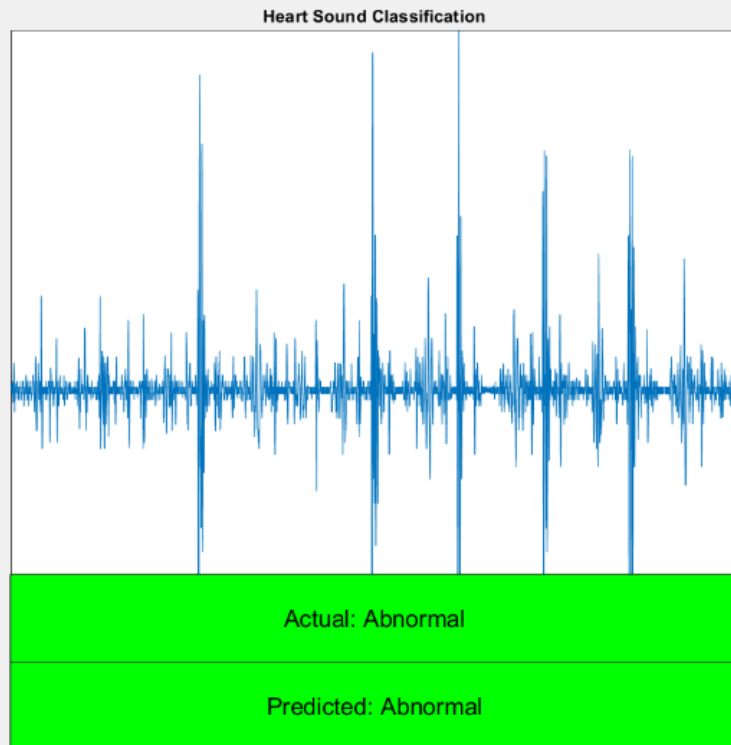
- The model works very well on long duration recordings but does not give the same results when implemented for short duration recordings.
- If the dataset contains signals with a lot of noise, then the model's noise removal part fails and the results lose accuracy.
- The datasets listed are generic and require lots of pre-processing.
- The only problem being that the algorithms are biased towards some features and will mostly look for them in the signal.
- MATLAB is not support all cloud services.
- The model is trained based on the data collected by a specific set of hardware setup and the model may produced varied results when exposed to different dataset and the accuracy may reduce significantly.
- **ALTERNATIVES: Using unsupervised learning techniques or deep learning may improve the adaptability**

# Cost Analysis

Particulars	Cost
MATLAB Academic Use License	₹ 28,500 Only/Free for VIT
Signal Processing Toolbox- MATLAB	₹ 2,500 Only
DATA SET	₹ 0.00 Only
AWS SERVER	₹ 10,000 Only
<b>Total:</b>	<b>₹ 41,000 Only/₹12,500</b>

# Work Done so Far:

## WORKING MODEL



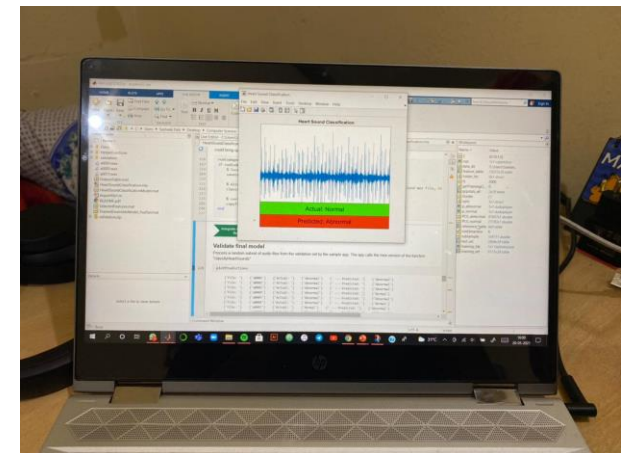
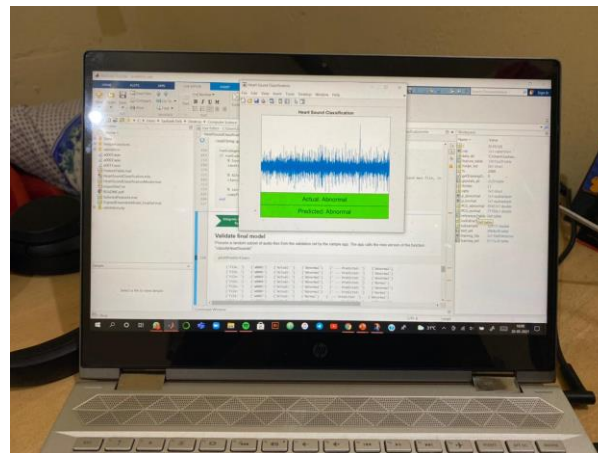
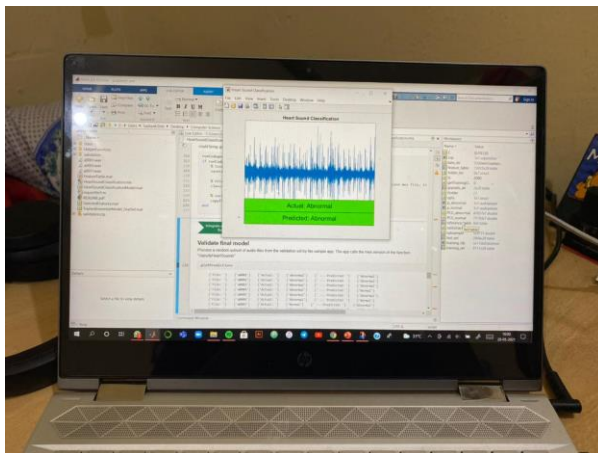
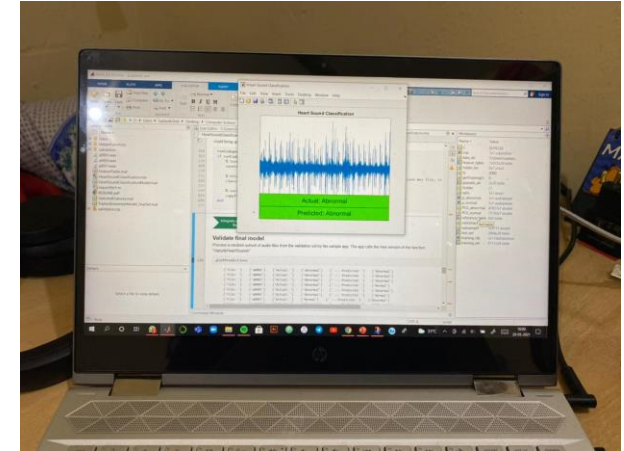
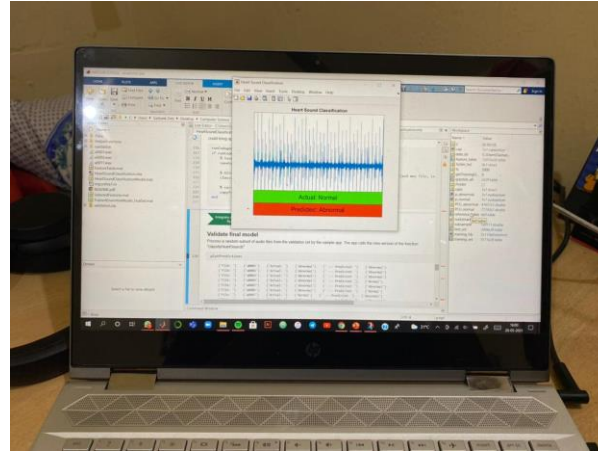
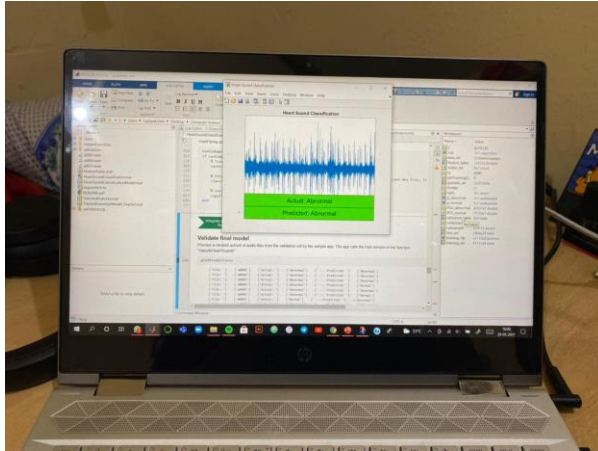
## PLOT PREDICTIONS

plotPredictions

{'File: '}	{'a0001'}	{'Actual: '}	{'Abnormal'}	{' --- Predicted: '}	{'Abnormal'}
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{'File: '}	{'a0003'}	{'Actual: '}	{'Abnormal'}	{' --- Predicted: '}	{'Abnormal'}
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{'File: '}	{'a0008'}	{'Actual: '}	{'Abnormal'}	{' --- Predicted: '}	{'Abnormal'}
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# Work Done so Far:

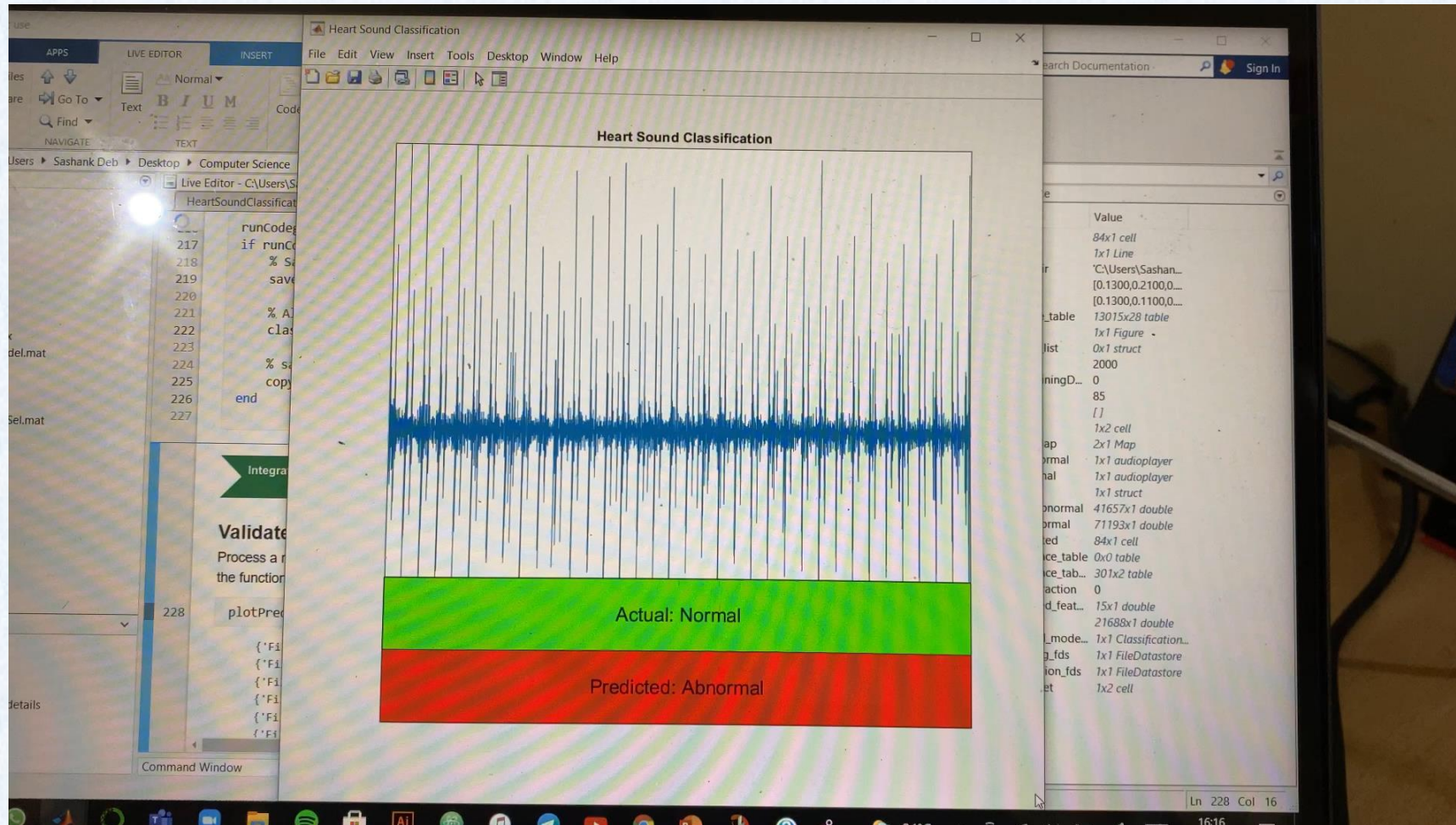
WORKING MODEL REAL TIME PHOTOS





# Work Done so Far:

WORKING MODEL



# Conclusion

## About the Project

- The model provides accurate results for datasets and provides reliable findings in that direction.
- The algorithms provided are simple to use and can also provide accurate results.
- The algorithms give good results and can extract features well out of the signals.
- Can be a revolutionary model in the field of Cardiac Health infrastructure.
- Can be used by ordinary people if they have the hardware to collect PCG signals
- Can help in early diagnosis of Cardiac Health issues and accordingly consult a doctor

# References ( IEEE Format)

## For the Project

1. W. Ping, W. Jin-Gang, S. Xiao-Bo, and H. Wei, “The research of telemedicine system based on embedded computer,” in *Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society (IEEE-EMBS '05)*, pp. 114–117, IEEE, Shanghai, China, January 2006.
2. H. S. Ng, M. L. Sim, C. M. Tan, and C. C. Wong, “Wireless technologies for telemedicine,” *BT Technology Journal*, vol. 24, no. 2, pp. 130–137, 2006.
3. Sarkar, T. (2020, May 1). *AI and machine learning for healthcare - Towards Data Science*. Medium.
4. C. Takenga, R. Berndt, O. Musongya et al., “An ICT-based diabetes management system tested for health care delivery in the african context,” *International Journal of Telemedicine and Applications*, vol. 2014, Article ID 437307, 10 pages, 2014.
5. G. Bobrie, N. Postel-Vinay, J. Delonca, and P. Corvol, “Self-measurement and self-titration in hypertension: a pilot telemedicine study,” *American Journal of Hypertension*, vol. 20, no. 12, pp. 1314–1320, 2007.

# CARDIAC HEALTH MONITORING SYSTEM Using ML

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## ABSTRACT:

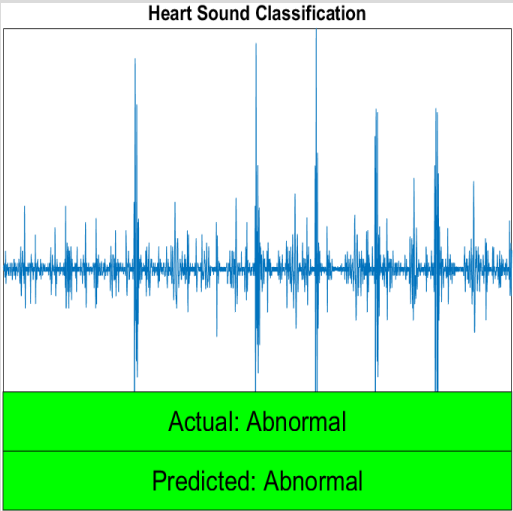
Based on the heart sound recordings of the Physio Net 2016, a model is developed that classifies heart sounds into normal vs abnormal, and deployed in a prototype (heart) screening application.

The Project demonstrates signal processing, wavelets and statistics to interactively train, compare and optimize classifiers  
The project aims to automatically extract features that outperform manually engineered ones

## OBJECTIVE AND SCOPE:

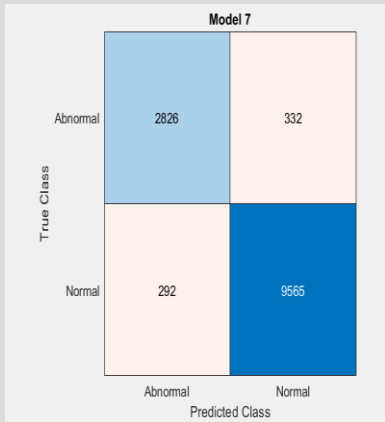
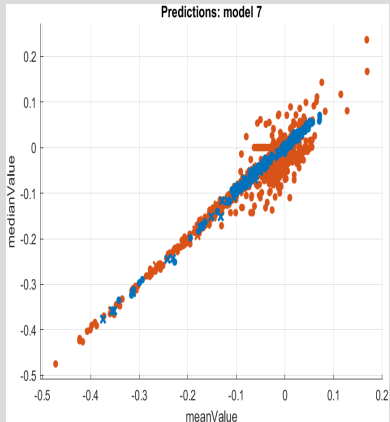
We have made a cardiac health monitoring system using ML/DL and hence will we training a model using a dataset to classify/predict the heartbeats of individuals as normal and abnormal using various features in the dataset

## BASIC OPERATION:



## ALGORITHM:

Optimised KNN (Highest accuracy): Principle Used is Hyperparameter Optimization in Classification Learner App



## METHODOLOGY:

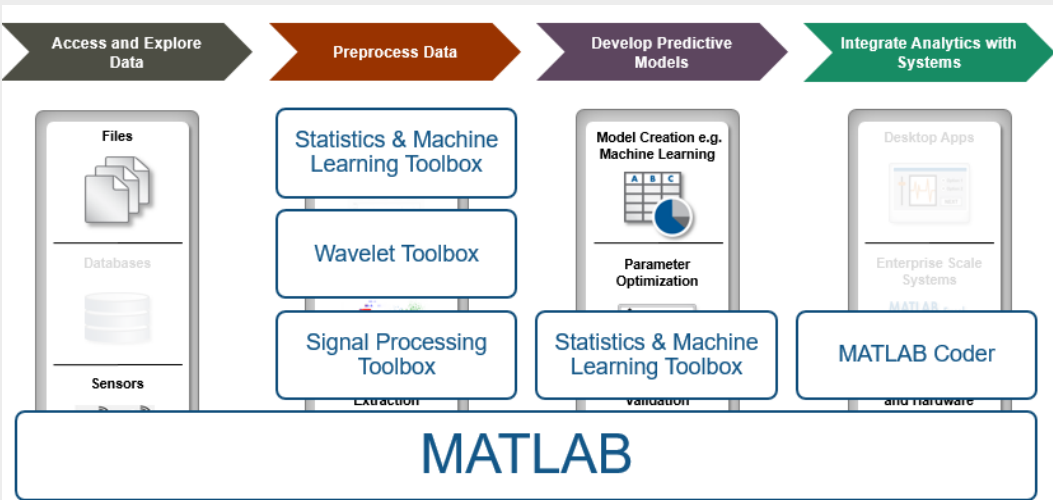
The project is structured according to the four phases of the typical machine learning workflow:

Access and Explore Data

Preprocess Data

Develop Predictive Models

Integrate Models with Systems



## CONCLUSION:

The model provides accurate results for datasets and provides reliable findings in that direction. The algorithms can extract features well out of the signals and can be used by ordinary people if they have the hardware to collect PCG signals. Useful in early diagnosis of Cardiac Health issues and accordingly consult a doctor.

## REFERENCE:

W. Ping, W. Jinn-Gang, S. Xiao-Bo, and H. Wei, "The research of telemedicine system based on embedded computer," in Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society (IEEE-EMBS '05)



# ECM4099

CAPSTONE PROJECT

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**Thank You.**