**REPORT – CAPSTONE PROJECT I**

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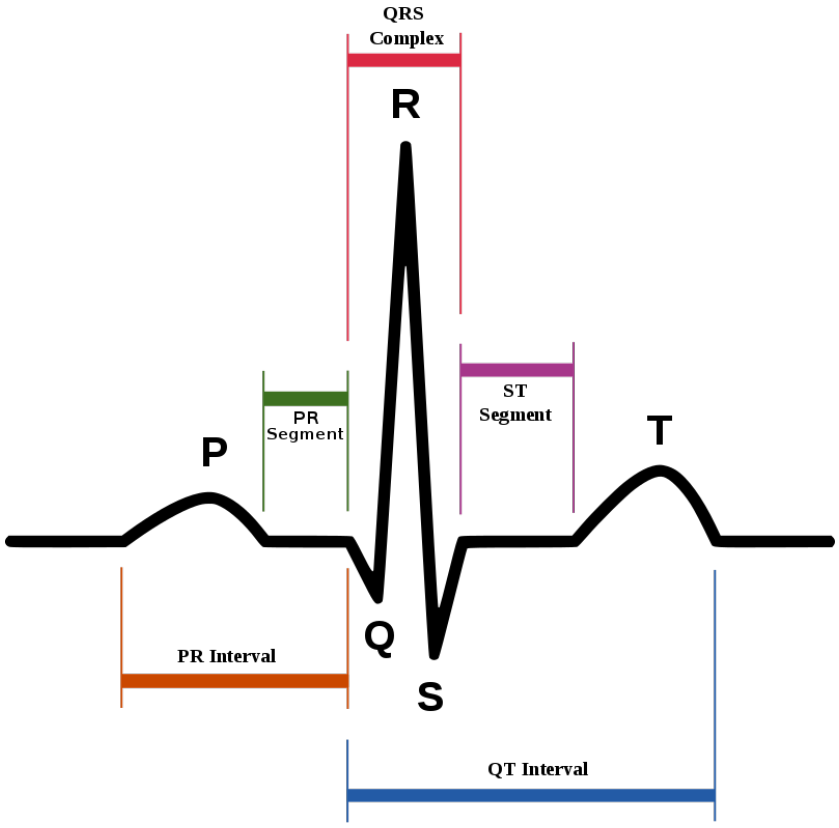
# 1. PROBLEM

Prediction and Classification of Cardiac Arrhythmia.

## a. Introduction:

Arrhythmia can be diagnosed by measuring the heart activity using an instrument called Electrocardiogram (ECG) and then analyzing the recorded data. The ECG is an established technique in cardiology for the analysis of cardiac condition of the patients. In its basic definition, ECG is the electrical representation of the contractile activity of the heart, and can be recorded fairly easily by using surface electrodes on the limbs or chest of the patient. The ECG is one of the most recognized and used biomedical signal in the field of medicine. The rhythm of the heart in terms of beats per minute (bpm) can be easily calculated by counting the R peaks of the ECG wave during one minute of recording.

Below is a schematic sample of a normal ECG.



Irregularity in heart beat may be life threatening. Hence both accurate detection of presence as well as classification of arrhythmia are important.

Different parameter values can be extracted from the ECG waveforms and can be used along with other information about the patient like age, medical history, etc to detect arrhythmia. However, sometimes it may be difficult for a doctor to look at these long duration ECG recordings and find minute irregularities. Therefore, using machine learning for automating arrhythmia diagnosis can be very helpful.

This project aims using different machine learning algorithms for predicting and classifying arrhythmia into different categories.

# 2. DATA WRANGLING

## a. Examining the Features and Samples

### Features:

| F.Nu. | Name | Explanation | Lin./Nom. |
|---|---|---|---|
| 1 | Age | Age in years | Linear |
| 2 | Sex | 0 = male; 1 = female | nominal |
| 3 | Height | Height in centimeters | Linear |
| 4 | Weight | Weight in kilograms | Linear |
| 5 | QRS duration | Average of QRS duration in msec. | Linear |
| 6 | P-R interval | Average duration between onset of P and Q waves in msec. | linear |
| 7 | Q-T interval | Average duration between onset of Q and offset of T waves in msec. | Linear |
| 8 | T interval | Average duration of T wave in msec. | Linear |

| | | | |
|---|---|---|---|
| 9 | P interval | Average duration of P wave in msec. | linear |
| | Vector angles in degrees on front plane of: | | |
| 10 | QRS | | linear |
| 11 | T | | linear |
| 12 | P | | linear |
| 13 | QRST | | linear |
| 14 | J | | linear |
| 15 | Heart rate | Number of heart beats per minute | Linear |
| | Of channel DI:<br>Average width, in msec. | | |
| 16 | Q wave | | linear |
| 17 | R wave | | linear |
| 18 | S wave | | linear |
| 19 | R' wave | small peak just after R | linear |
| 20 | S' wave | | linear |
| 21 | Number of intrinsic deflections | | linear |
| 22 | Existence of ragged R wave | | nominal |
| 23 | Existence of diphasic derivation of R wave | | nominal |
| 24 | Existence of ragged P wave | | Nominal |
| 25 | Existence of diphasic derivation of P wave | | nominal |
| 26 | Existence of ragged T wave | | nominal |
| 27 | Existence of diphasic derivation of T wave | | nominal |
| 28 .. 39 | Of channel DII | (similar to 16 .. 27 of channel DI) | |
| 40 .. 51 | Of channels DIII | | |
| 52 .. 63 | Of channel AVR | | |
| 64 .. 75 | Of channel AVL | | |
| 76 .. 87 | Of channel AVF | | |
| 88 .. 99 | Of channel V1 | | |
| 100..111 | Of channel V2 | | |
| 112..123 | Of channel V3 | | |
| 124..135 | Of channel V4 | | |

| | | | |
|---|---|---|---|
| 136..147 | Of channel V5 | | |
| 148..159 | Of channel V6 | | |
| | Of channel DI | Amplitude , * 0.1 milivolt, of | |
| 160 | | JJ wave | Linear |
| 161 | | Q wave | Linear |
| 162 | | R wave | Linear |
| 163 | | S wave | Linear |
| 164 | | R' wave | Linear |
| 165 | | S' wave | linear |
| 166 | | P wave | linear |
| 167 | | T wave | linear |
| 168 | QRSA | Sum of areas of all segments divided by 10,( Area= width * height / 2 ) | linear |
| 169 | QRSTA | QRSTA = QRSA + 0.5 * width of T wave * 0.1 * height of T wave. (If T is diphasic then the bigger segment is considered) | Linear |
| 170..179 | Of channel DII | | |
| 180..189 | Of channel DIII | | |
| 190..199 | Of channel AVR | | |
| 200..209 | Of channel AVL | | |
| 210..219 | Of channel AVF | | |
| 220..229 | Of channel V1 | | |
| 230..239 | Of channel V2 | | |
| 240..249 | Of channel V3 | | |
| 250..259 | Of channel V4 | | |
| 260..269 | Of channel V5 | | |
| 270..279 | Of channel V6 | | |

**b. Class Distribution:**

| Class code | Class | Number of instances |
|---|---|---|
| 01 | Normal | 245 |

| | | |
|---|---|---|
| 02 | Ischemic changes (Coronary Artery Disease) | 44 |
| 03 | Old Anterior Myocardial Infarction | 15 |
| 04 | Old Inferior Myocardial Infarction | 15 |
| 05 | Sinus tachycardy | 13 |
| 06 | Sinus bradycardy | 25 |
| 07 | Ventricular Premature Contraction (PVC) | 3 |
| 08 | Supraventricular Premature Contraction | 2 |
| 09 | Left bundle branch block | 9 |
| 10 | Right bundle branch block | 50 |
| 11 | 1. degree AtrioVentricular block | 0 |
| 12 | 2. degree AV block | 0 |
| 13 | 3. degree AV block | 0 |
| 14 | Left ventricule hypertrophy | 4 |
| 15 | Atrial Fibrillation or Flutter | 5 |
| 16 | Others | 22 |

There are (452) rows, each representing medical record of a different patient. There are 279 attributes like age, weight and patient's ECG related data.

The data set is labeled with 16 different classes. Classes 2 to 15 correspond to different types of arrhythmia. Class 1 corresponds to normal ECG with no arrhythmia and class 16 refers to unlabeled patient.

The data set is heavily biased towards the no arrhythmia case with 245 instances belonging to class 1 and 185 instances being split among the 14 arrhythmia classes and the rest 22 are unclassified.

The main challenges in processing this data set are the limited number of training examples compared to the number of features, heavy bias towards the case of normal ECG, missing feature values and feature values belonging to both continuous and categorical types.

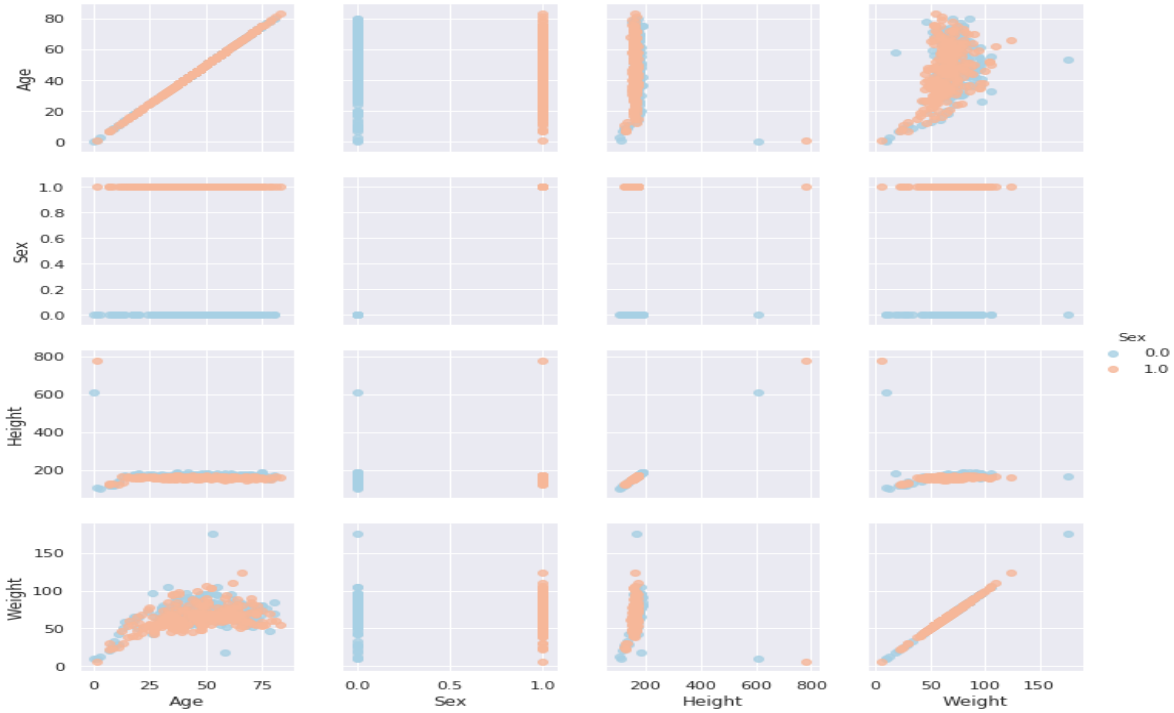
### c. Evaluation Strategy

I chose "WEIGHTED RECALL" as evaluation strategy because we are predicting Cardiac Arrhythmia, which is serious medical condition.

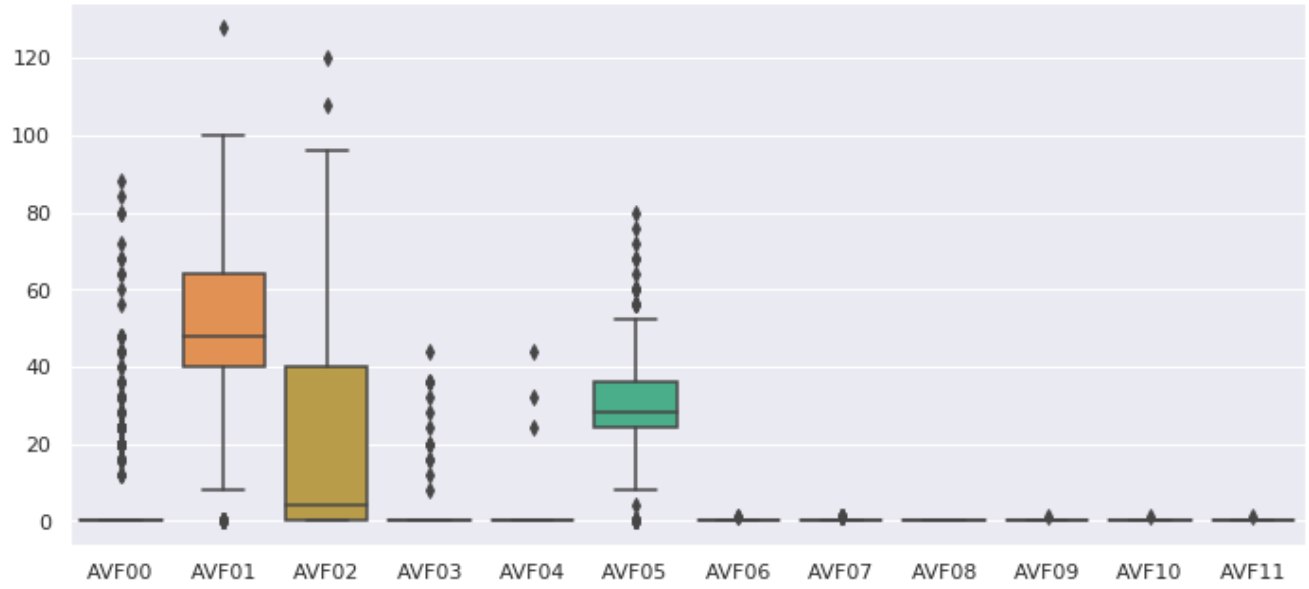
No one wants to mis-classify someone having arrhythmia as normal. It is even lot bigger risk than classifying someone normal as having arrhythmia. So I want to maximize true positive rate i.e. Recall.

Weighted recall is used instead of normal recall because it accounts for label imbalance present in data.

## 3. EXPLORATORY DATA ANALYSIS




With some nice plots, it’s becoming much more simple to notice outliers.




I modified some outliers which I can estimate (i.e. weight/heights) but haven't adjusted anything in ECG values due to the high bias of my data as mentioned above.

## 4. MACHINE LEARNING MODELS

I've tried 13 different models (7 ML models and 6 of them repeated after PCA).

Tried bagging and boosting methods but they generally raised the average training accuracy of the models but the test accuracy got reduced.

PCA generally provided better results.

Train and test accuracy scores of the models listed below.

| | Train Recall Score | Test Recall Score |
|---|---|---|
| **KNN Clasification** | 0.669271 | 0.647059 |
| **Logistic Regression** | 0.841146 | 0.676471 |
| **Linear SVM** | 0.783854 | 0.720588 |
| **Kernelized SVM** | 0.976562 | 0.676471 |
| **Naive Bayes** | 0.760417 | 0.632353 |
| **Decision Tree** | 0.750000 | 0.661765 |
| **Random Forest** | 0.940104 | 0.750000 |
| **KNN Classification with PCA** | 0.677083 | 0.647059 |
| **Logistic Regression with PCA** | 0.825521 | 0.676471 |
| **Linear SVM with PCA** | 0.776042 | 0.735294 |
| **Kernalised SVM with PCA** | 0.968750 | 0.676471 |
| **Decision Trees with PCA** | 0.674479 | 0.573529 |
| **Random Forest with PCA** | 0.966146 | 0.632353 |

With most of the models we can see large difference between train and test scores which is because of overfitting.

The most preferable model looks like Linear SVM with PCA.