PART-2: Training a model to classify an ECG with AF

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Null Values Handling

The data is checked for any Null values and if found are replaced by the mean of the respective feature/column as shown below.

Null value report:

| FEATURE | NULL VALUE COUNT |
|---------------|------------------|
| bpm | 23 |
| ibi | 23 |
| sdnn | 23 |
| sdsd | 106 |
| rmssd | 106 |
| pnn20 | 106 |
| pnn50 | 106 |
| hr_mad | 23 |
| sd1 | 106 |
| sd2 | 106 |
| S | 106 |
| sd1/sd2 | 161 |
| breathingrate | 115 |

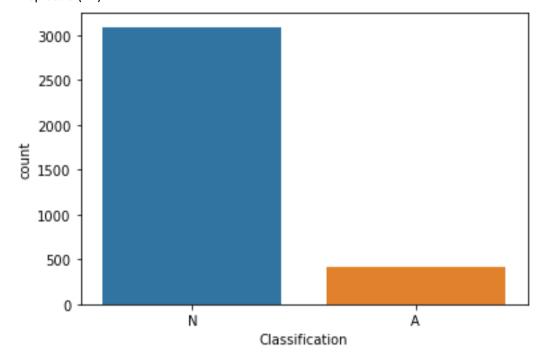
The null values are replaced with mean using the below code:

Data Analysing & Outlier Detection

The data is analysed to check the skewness and detect outliers.

Count Plot for the Output/Predicted variable with two possible outputs that are:

- Normal (N)
- AF episode (AF)



The count plot shows that the data having normal reading is a lot higher than the data dealing with AF episode.

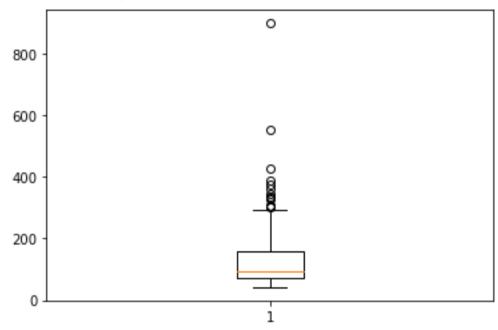
The skewness of data is checked as below:

```
# Checking Skewness of features
 3
   for column in xx_noise.columns[:-1]:
        print(column, 'skewness:',xx_noise[column].skew())
bpm skewness: 1.7225403355998257
ibi skewness: 0.18061994491252278
sdnn skewness: 0.14470856318984826
sdsd skewness: 0.5673517267619748
rmssd skewness: 0.4729273752227066
pnn20 skewness: -0.48056216436576576
pnn50 skewness: 0.006890443533169791
hr mad skewness: 0.9123081957165963
sd1 skewness: 0.5134504333916752
sd2 skewness: 0.6805479653622352
s skewness: 0.8826475613133172
sd1/sd2 skewness: 15.283806168391749
breathingrate skewness: 3.6419024221751273
```

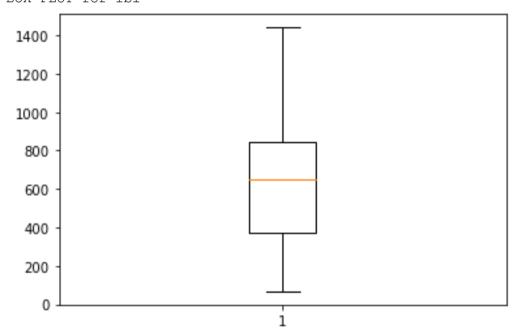
This skewness is a lot higher for 'sd1/sd2' feature.

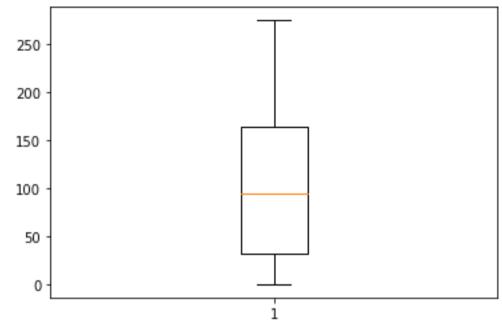
Checking outliers using the box plot graph as shown below.

BOX PLOT for bpm

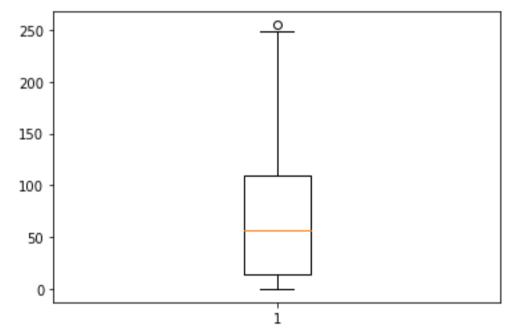


BOX PLOT for ibi

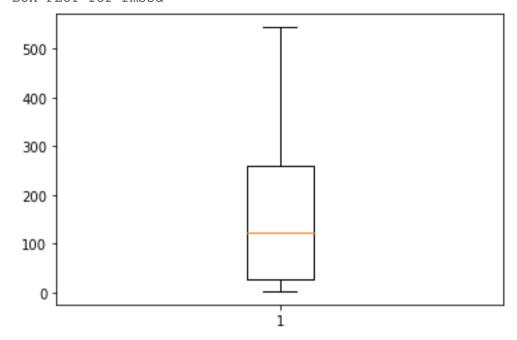




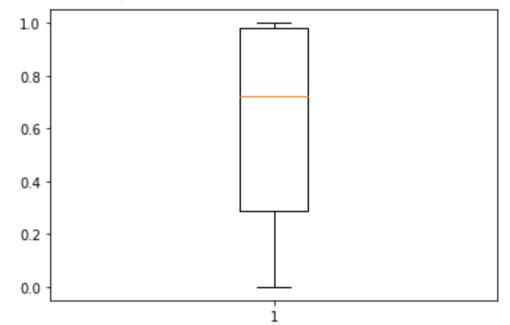
BOX PLOT for sdsd



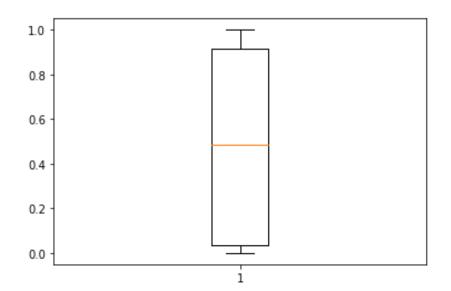
BOX PLOT for rmssd



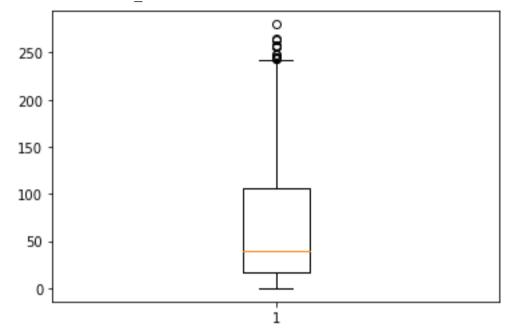
BOX PLOT for pnn20



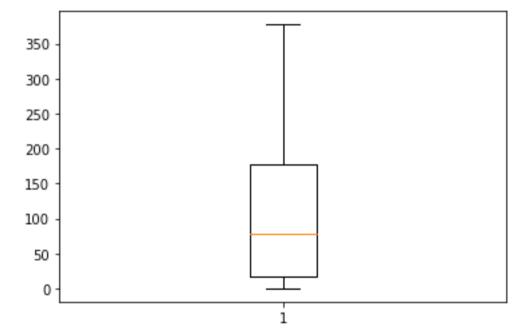
BOX PLOT for pnn50

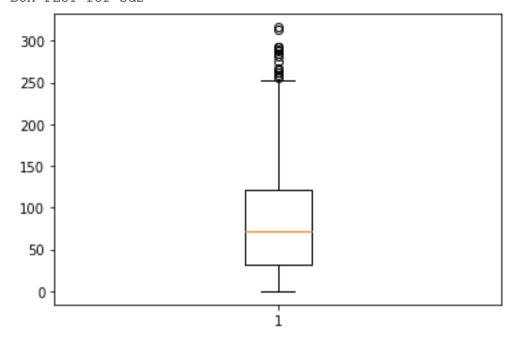


BOX PLOT for hr_mad

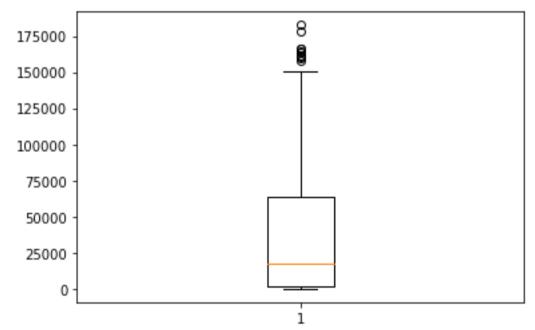


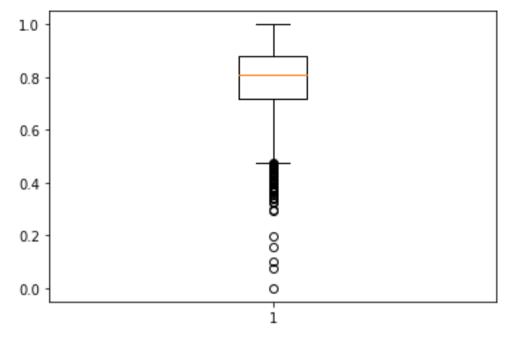
BOX PLOT for sdl

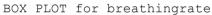


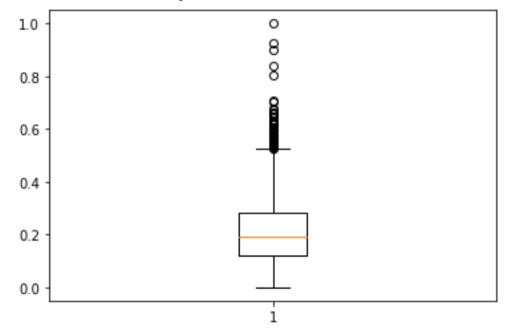












Data Transformation

As observed from the analysis the data is skewed and has outliers. We can perform log transformation to reduce the skewness and data normalisation using L1 regularization (Lasso regression) with a penalty function to transform the data in a range of 0 to 1.

```
from sklearn.preprocessing import Normalizer
Data_normalizer = Normalizer(norm='l1').fit(xx_noise.iloc[:,:13])
Data_normalized = Data_normalizer.transform(xx_noise.iloc[:,:13])
```

The above piece of code is used to normalize the data using L1 regularization technique. Now that the data is transformed we have to split it into test and train variables using below code.

```
# Data splitting into train and test with 80:20 split 
x_train,x_test,y_train,y_test=train_test_split(Data_normalized,y,test_size=0.2)
```

Now we can perform feature selection method using **ANOVA** (Analysis of Variance) to check the relation between features and understand it. Then with the understanding of the data ANOVA can transform the data to give more accuracy as shown below.

```
# configure to select all features
fs = SelectKBest(score_func=f_classif, k='all')
# learn relationship from training data
fs.fit(x_train, y_train)
# transform train input data
X_train_fs = fs.transform(x_train)
# transform test input data
X_test_fs = fs.transform(x_test)
```

```
2 # what are scores for the features
 3 for i in range(len(fs.scores_)):
      print('Feature %s: %f' % (fields[i], fs.scores_[i]))
 5 # plot the scores
 6 plt.bar([fields[i] for i in range(len(fs.scores_))], fs.scores_)
 7 plt.show()
Feature bpm: 94.418302
Feature ibi: 161.422435
Feature sdnn: 26.929492
Feature sdsd: 11.346253
Feature rmssd: 7.110362
Feature pnn20: 19.999804
Feature pnn50: 0.838868
Feature hr_mad: 28.252391
Feature sd1: 29.413127
Feature sd2: 123.773385
Feature s: 159.903890
Feature sd1/sd2: 131.737579
Feature breathingrate: 116.195230
 160
 140
 120
 100
  80
  60
  40
  20
```

The Scores of the features can be observed above.

bpm ibi sdnnsdsdmssphn2pnn9p maddl sd2 s sdbr/sabbingrate

The target variable/ predicted variable is label encoded by replacing values of 'N' with '0' and values of 'A' with '1'.

Model Building

Now that the data is transformed, we are going to train the K nearest neighbour classifier model. This can be observed below.

```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()
knn.fit(x_train, y_train)

# evaluate the model

yhat = knn.predict(x_test)

# evaluate predictions

accuracy = accuracy_score(y_test, yhat)

print('Accuracy: %.2f' % (accuracy*100))

y_pred=knn.predict(x_test)

print('MSE:',np.sqrt(mean_squared_error(y_test,y_pred)))

print('f1_score:',f1_score(y_test,y_pred))

Accuracy: 90.71

MSE: 0.304724700110022

f1_score: 0.5962732919254659
```

As we can see the model's accuracy is 90.71% but it varies when trained at different times. The highest accuracy achieved was 93% and the f1_score ranged from 0.5 to 0.61.

Model Analysis

```
--->CLASSIFICATION REPORT=>
            precision recall f1-score
                                      support
         0
               0.93 0.96
                              0.95
                                         623
               0.60
                       0.43
                                0.50
                                         77
                                0.91
                                         700
   accuracy
              0.77 0.70
                              0.72
                                         700
  macro avg
weighted avg
               0.90
                       0.91
                               0.90
                                         700
--->CONFUSION MATRIX=>
[[601 22]
[ 44 33]]
```

In the classification report the class values '0' and '1' stand for 'N' normal reading and 'A' AF episode respectively. Due to imbalance of the data we can observe low 'f1_score 'for class 'A' i.e., AF episode.

Saving the KNN Model, L1 Normalizer, ANOVA Transformer

The KNN Model, L1 Normalizer, ANOVA Transformer models can be saved using pickle module as shown.

```
import pickle as pkl
pkl.dump(knn,open('knn_model.pkl','wb'))
pkl.dump(Data_normalizer,open('normalizer.pkl','wb'))
pkl.dump(fs,open('ANOVA.pkl','wb'))
```

Evaluation Script

The following script can be used to evaluate the model using three pre-trained model files which are:

- KNN model saved as Pickle file
- L1 normaliser saved as Pickle file
- ANOVA transformer saved as Pickle file

The code for the evaluation can be observed below.

```
import pickle
import pandas as pd
import numpy as np
from sklearn.metrics import accuracy score,f1 score
# loading model and normalizer
model = pickle.load(open('knn model.pkl','rb'))
normalizer = pickle.load(open('normalizer.pkl','rb'))
fs = pickle.load(open('ANOVA.pkl','rb'))
# loading dataset
try:
    df = pd.read_csv('ECG_testing.csv')
    print('Dataset Loaded')
except:
    print('Check File/ path')
x = xx noise.iloc[:,:13]
y = xx_noise.iloc[:,-1:]
# Label encoding
y = y.replace('N',0)
y = y.replace('A',1)
# Data Normalization
normalized_data = normalizer.transform(x)
# ANOVA Transformation
anova_data = fs.transform(normalized_data)
# Predicting values
y_pred = model.predict(anova_data)
# checking scores
print('F1_score is :',f1_score(y.values,y_pred))
print('accuracy is:',accuracy_score(y.values,y_pred)*100)
```

Output is the f1 score of the model with test data and the accuracy score.