3_Hazim_Pima_Indians_Diabetes_93_4_Acc,_90_3_val_Acc

February 10, 2021

1 The Pima Indians Diabetes Dataset

2 Step 1: Answering the question

2.1 Loading the Dataset

[ ]:
```
# Get the dataset by raw URL
!wget https://github.com/hazmash5/ds-projects/raw/main/Proj_05_Diabetes/data/
↪pima-indians-diabetes.csv
```

```
--2021-02-08 12:14:03--  https://github.com/hazmash5/ds-
projects/raw/main/Proj_05_Diabetes/data/pima-indians-diabetes.csv
Resolving github.com (github.com)... 140.82.113.4
Connecting to github.com (github.com)|140.82.113.4|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://raw.githubusercontent.com/hazmash5/ds-
projects/main/Proj_05_Diabetes/data/pima-indians-diabetes.csv [following]
--2021-02-08 12:14:03--  https://raw.githubusercontent.com/hazmash5/ds-
projects/main/Proj_05_Diabetes/data/pima-indians-diabetes.csv
Resolving raw.githubusercontent.com (raw.githubusercontent.com)...
151.101.0.133, 151.101.64.133, 151.101.128.133, ...
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|151.101.0.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 23278 (23K) [text/plain]
Saving to: pima-indians-diabetes.csv

pima-indians-diabet 100%[===================>]  22.73K  --.-KB/s    in 0s

2021-02-08 12:14:04 (80.7 MB/s) - pima-indians-diabetes.csv saved
[23278/23278]
```

[ ]:
```
# Create new folder and name it data
!mkdir data
```

[ ]:
```
# Moving our datasets to the data folder
!mv pima-indians-diabetes.csv data/
```

[ ]:
```
# Showing the first line of the dataset
!head -n 3 data/pima-indians-diabetes.csv
```

```
6,148,72,35,0,33.6,0.627,50,1
1,85,66,29,0,26.6,0.351,31,0
8,183,64,0,0,23.3,0.672,32,1
```

We can notes the following: 1. There is no header row so `header= None` must be used while we read the csv. 2. There is no need to use `Sep parameter` because the separation between the values is (,) as the default separation of Panda csv Sep.

[ ]:
```
# Showing the number of lines.
!cat data/pima-indians-diabetes.csv | wc -l
```

```
767
```

We have 768 of instances

2.2 Introduction

The Pima Indians Diabetes Dataset involves predicting the onset of diabetes within five years in Pima Indians given medical details. It is a binary (2-class) classification problem. Several familiar types of classification models algorithms utilized: 1. To choose the best classification algorithms and efficiently perform another appropriate comparison between the same algorithms. 2. To compare the utilized feature engineering and pre-processing methods. 3. To get a broad range of choices.

> Utilized classification models are respectively: 1. Logistic Regression 2. Linear Discriminant Analysis 3. K Neighbors Classifier 4. Decision Tree Classifier 5. Gaussian NB 6. Support Vector Classifier 7. XGBoost Classifier

2.3 Required libraries

This notebook uses several Python packages that come standard with the Google Colaboratory. The primary libraries that we'll be operating are respectively: * **NumPy**: Provides a fast numerical array structure and helper functions. * **Pandas**: Provides a DataFrame structure to store data in memory and work with it easily and efficiently. * **Scikit-learn**: The essential Machine Learning package in Python. * **XGBoost**: Optimized distributed gradient boosting library designed to be highly efficient, flexible and portable matplotlib: Basic plotting library in Python; most other Python plotting libraries are built on top of it. * **Seaborn**: Advanced statistical plotting library. * **watermark**: A Jupyter Notebook extension for printing timestamps, version numbers, and hardware information.

[ ]:
```
import pandas as pd
import numpy as np

%matplotlib inline
```

```
import matplotlib.pyplot as plt
import seaborn as sb
```

[ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from xgboost import XGBClassifier
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
models.append(('XGB', XGBClassifier()))
```

2.4 The problem domain

Our company just got funded to create a smartphone app that automatically female diabetes detection to use in remote villages in India, from simple devices for each test attribute and fill it in the smartphone, we will be building part of the data analysis pipeline for this app. We tasked by the Head of Data Science to create a machine learning model, the model takes eight attributes from the user and detects diabetes based on those attributes alone. We got a dataset from the field researchers to develop the model, which includes predicting the onset of diabetes within five years in Pima-Indians given medical details. With the following attributes: * Number of times pregnant. * Plasma glucose concentration a 2 hours in an oral glucose tolerance test. * Diastolic blood pressure (mm Hg). * Triceps skinfold thickness (mm). * 2-Hour serum insulin (mu U/ml). * Body mass index (weight kg / height m2). * Diabetes pedigree function. * Age (years). * Class variable (0 or 1).

2.5 Data analysis checklist:

The data analysis checklist: 1. **Specify the type of data analytic question (e.g. exploration, association causality) before touching the data**: We are trying to detect female diabetes tests (Positive test or Negative test) based on eight continuous attributes. 2. **Define the metric for success before beginning:** We will use the accuracy to quantify how well our model is performing. they told us that we should achieve at least 77% accuracy.

3 Step 2: EDA Exploratory Data Analysis

[ ]:
```python
df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
df.columns= ['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',␣
↪'class']
df
```

[ ]:
```
     preg  plas  pres_mm  skin_mm  insu   BMI    DPF  age  class
0       6   148       72       35     0  33.6  0.627   50      1
1       1    85       66       29     0  26.6  0.351   31      0
2       8   183       64        0     0  23.3  0.672   32      1
3       1    89       66       23    94  28.1  0.167   21      0
4       0   137       40       35   168  43.1  2.288   33      1
..    ...   ...      ...      ...   ...   ...    ...  ...    ...
763    10   101       76       48   180  32.9  0.171   63      0
764     2   122       70       27     0  36.8  0.340   27      0
765     5   121       72       23   112  26.2  0.245   30      0
766     1   126       60        0     0  30.1  0.349   47      1
767     1    93       70       31     0  30.4  0.315   23      0

[768 rows x 9 columns]
```

[ ]:
```python
# Check duplicated rows
print('The number of repeated rows= ',
      df.duplicated(keep='last').sum() )
```

```
The number of repeated rows=  0
```

There is no duplicated rows

[ ]:
```python
print('The number of null values= ',
      df.isnull().sum().sum())
```

```
The number of null values=  0
```

There is no `NaN` values.

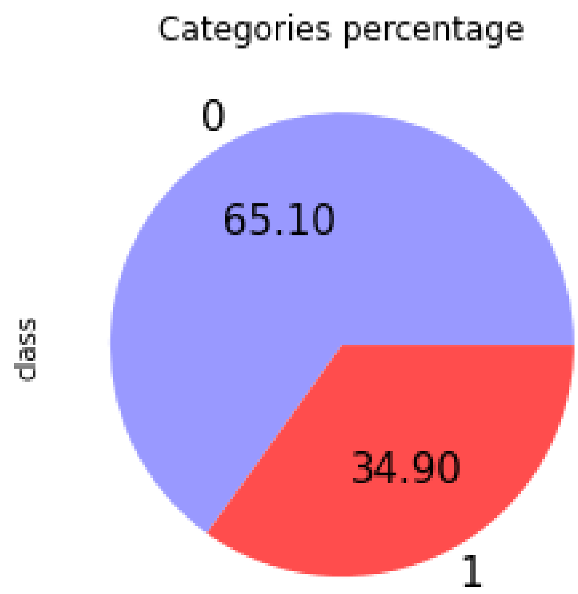
3.1 1. Using pie plot

By using a pie plot to visualize and compute the difference between the categories, we can perceive the notable difference between the numbers of categories. A balance issue must be considered.

[ ]:
```python
color= ['#9999ff','#ff4d4d']
```

[ ]:
```python
pd.value_counts(df['class']).plot(kind='pie',
                                  autopct='%.2f',fontsize=15,
                                  colors= color,
                                  title='Categories percentage')
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc14a1524a8>
```



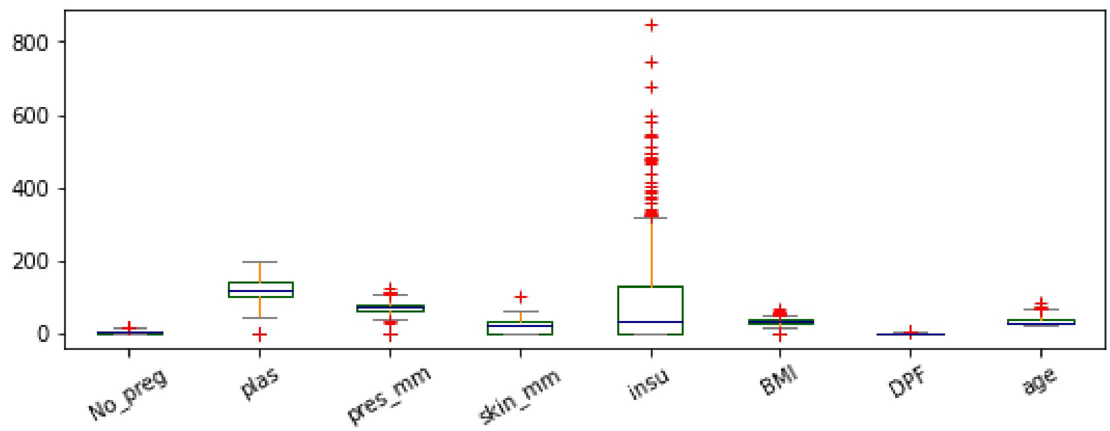
By using pie plot to visualize and compute the difference between the categories; we can notes the big difference between numbers of categories. There is an unbalance issue must be considered.

3.2 2. Using box plot

By using a box plot to receive an indication of how the values in the data are spread out, and to visualize the distribution of values within each attribute, we can notes the following: 1. All attributes values spread between 0 and 200 except insulin values, 2. The variance of values is extremely, so we must utilize preprocessing methods before training.

[ ]:
```
color = dict(boxes='DarkGreen', whiskers='DarkOrange',medians='DarkBlue',␣
 ↪caps='Gray')
df[df.columns[:-1]].plot(kind='box', color=color, sym='r+', figsize=(9,3),␣
 ↪rot=30)
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc13f6d0898>
```

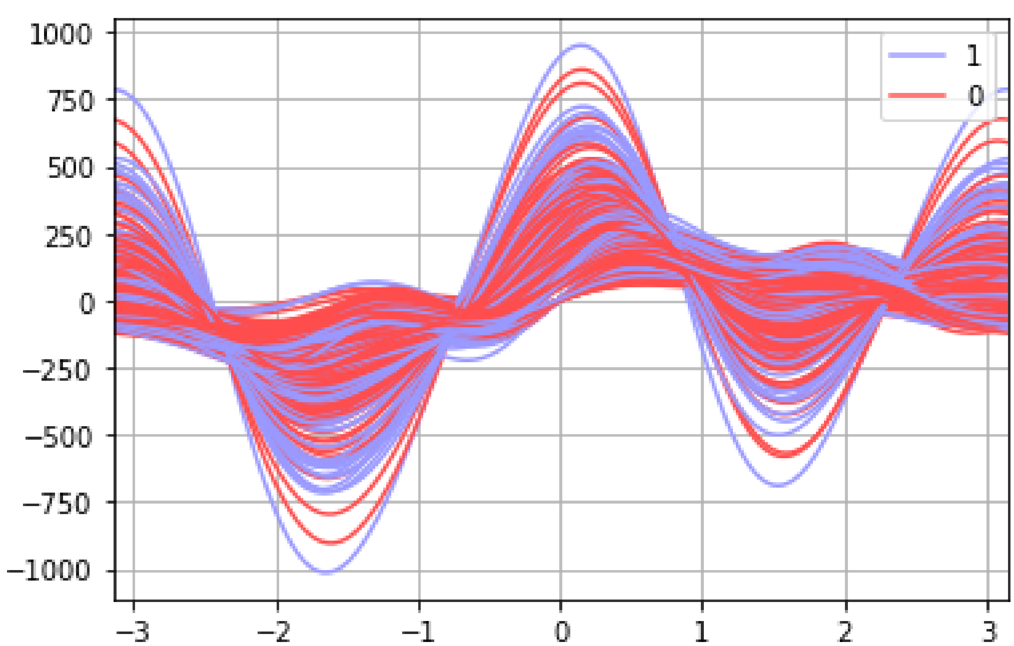


3.3 3. Using Andrews curves

By exploiting Andrew's curves plot to visualize data clustering for each class, we can notes: 1. Curves belonging to samples of a similar class aren't closer together. 2. The curves of the two classes mix together and don't define structures. 3. It is problematic to target those classes, add features must be considered.

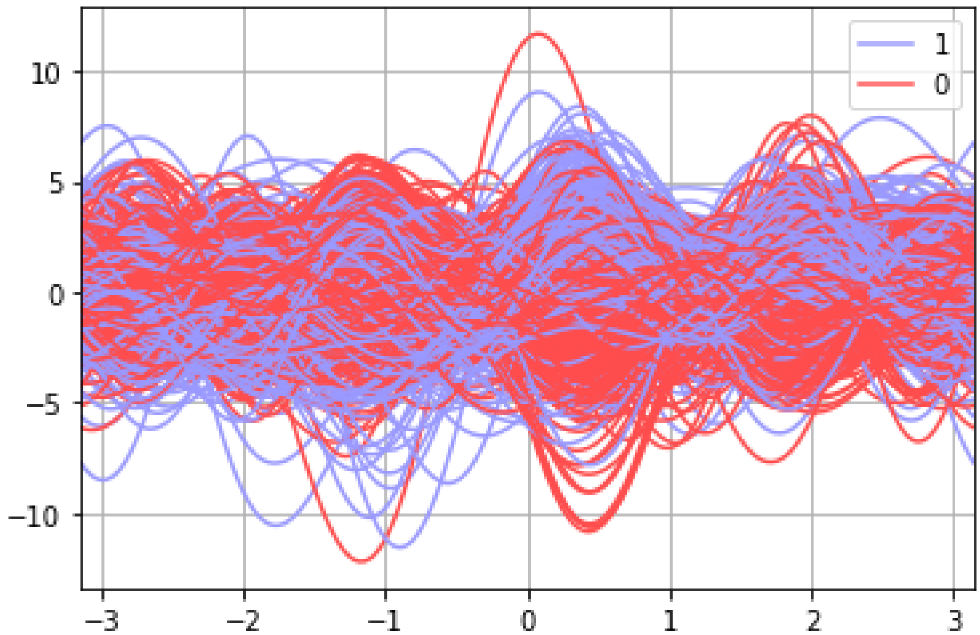
[ ]:
```
pd.plotting.andrews_curves(df, 'class', color=color)
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc14a050e10>
```



[ ]:
```
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
all_inputs = sc.fit_transform(all_inputs)
ddf= pd.DataFrame(all_inputs)
ddf['class']= all_labels
pd.plotting.andrews_curves(ddf, 'class', color=color)
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc149f502e8>

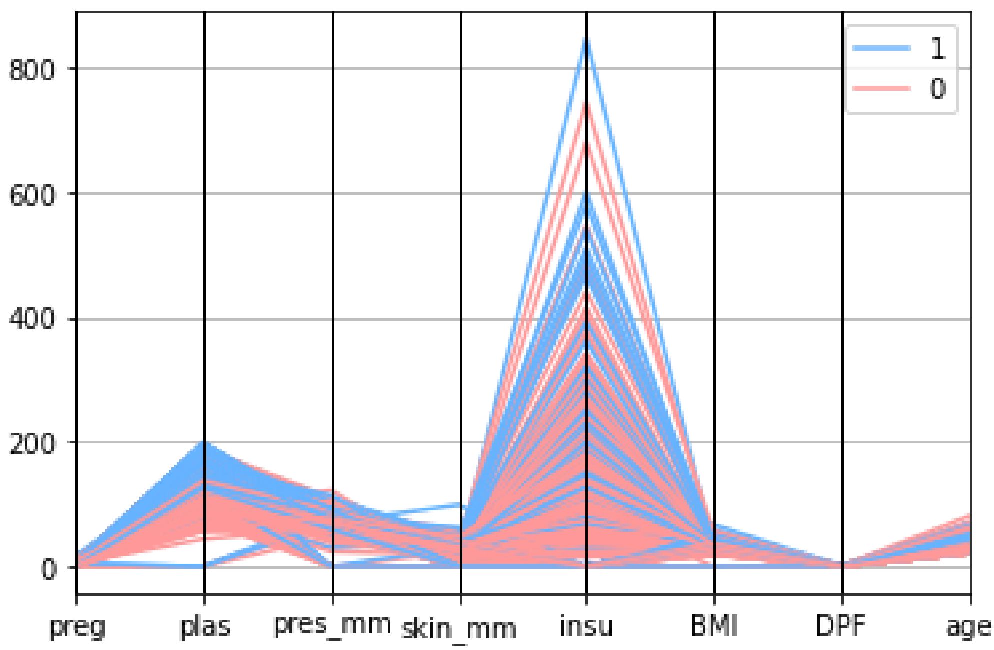


3.4 4. Using Parallel coordinates plot

By using Parallel coordinates plot to comparing variables together and observing the relationships between them, we can notes that there are no significant phenomena for each class, between the attributes.

[ ]:
```
pd.plotting.parallel_coordinates(df, 'class', color=['#66b3ff','#ff9999'])
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd10b6b4cc0>

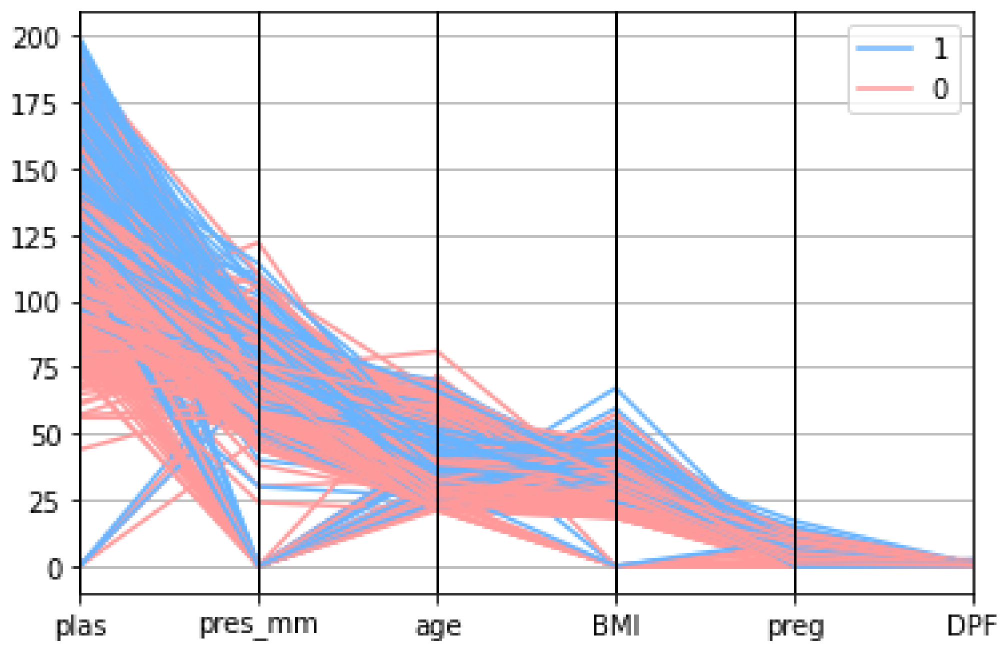


[ ]:
```
df.columns
```

[ ]:
```
Index(['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',
       'class'],
      dtype='object')
```

[ ]:
```
pd.plotting.parallel_coordinates(df[['plas', 'pres_mm','age','BMI',␣
 ↪'preg','DPF', 'class']], 'class', color=['#66b3ff','#ff9999'])
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0f41da4a8>
```

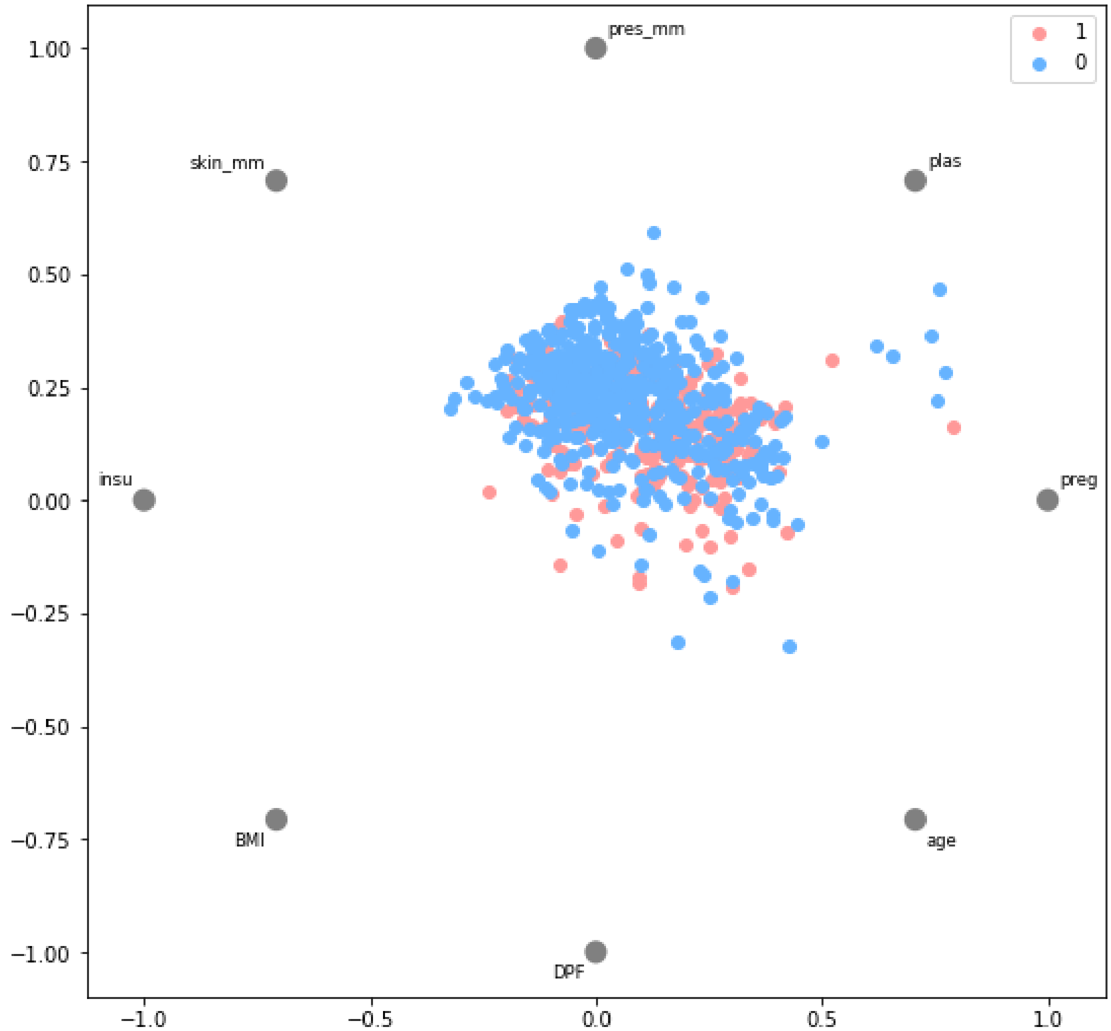


3.5 5. Using Radviz Plot

By using Radviz plotting to recognize clustering attribute for each class, we can notes the following: 1. Classes are clustering to the same attributes. 2. There are outlier instances, so outlier detection methods must be used. 3. Some attributes do not affect the categories, so feature selection methods must be used.

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler()
all_inputs = sc.fit_transform(all_inputs)
ddf= pd.DataFrame(all_inputs)
ddf.columns= df.columns[0:-1]
plt.figure(figsize=(9, 9))
ddf['class']= all_labels
pd.plotting.radviz(ddf, 'class', color=['#ff9999','#66b3ff'], )
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd10b6e2208>



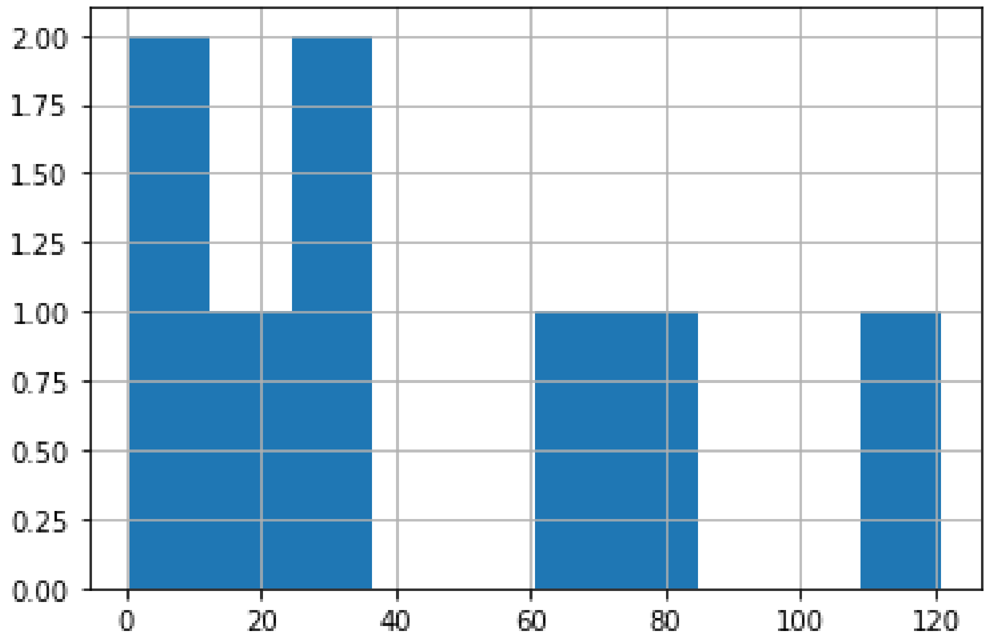
There is no clear recognize distinguished cluster for each class to attributes as we saw in the previous figures. We can see a lot of outliers corresponding to the negative tests class.

3.6 6. Using hist plot

By using histogram plots we can visualize mean, median, standard deviation, and mode for the values of the attributes.

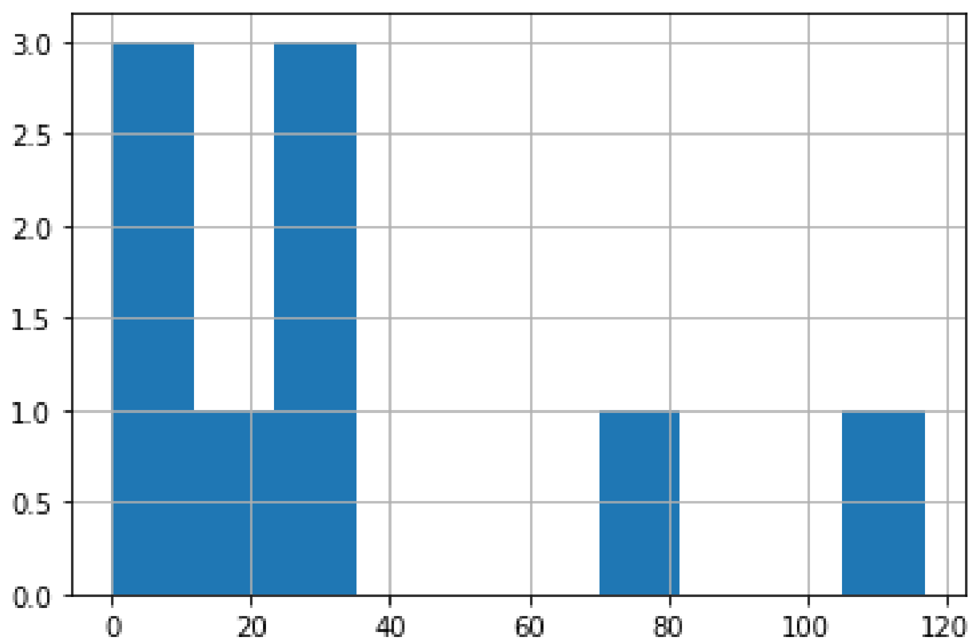
[ ]:
```
df.describe().T['mean'].hist()
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f54a417ee48>



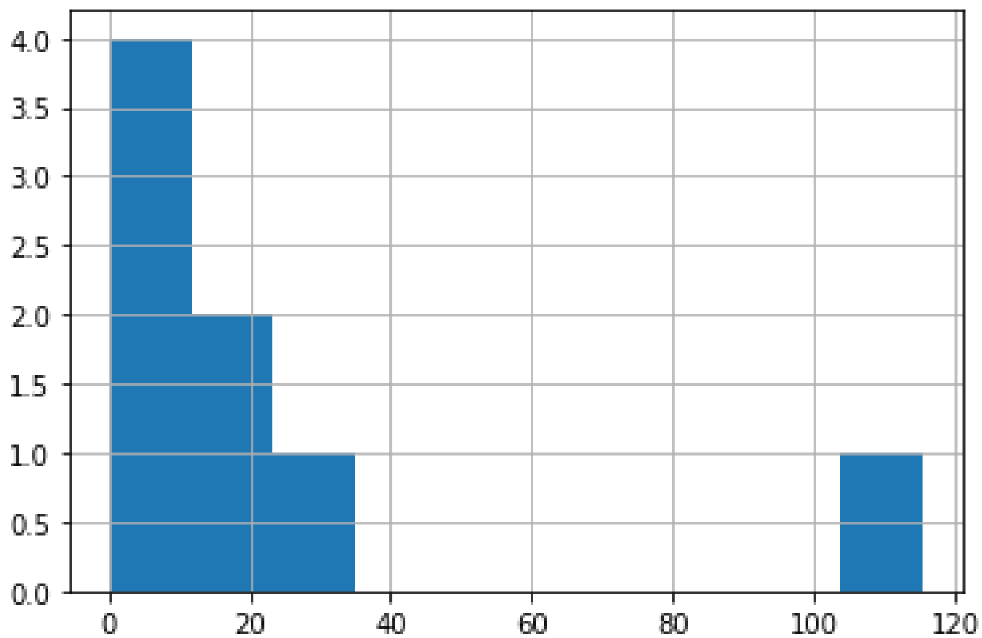
[ ]:
```
df.median().hist()
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc13eed7cf8>



[ ]:
```
df.describe().T['std'].hist()
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f54a417ecf8>

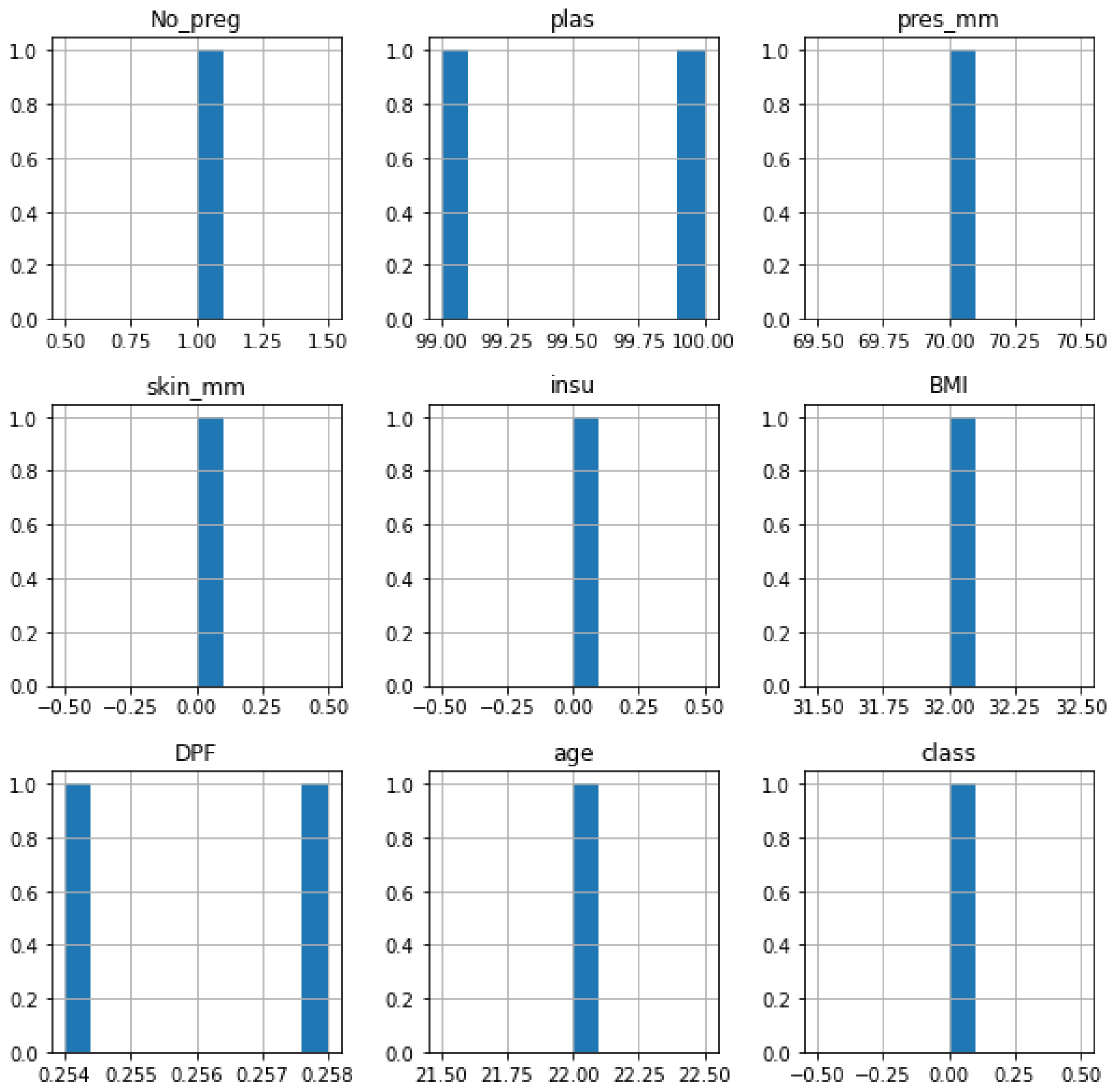


The mode is the most frequent observation

[ ]:
```
fig = plt.figure(figsize = (10,10))
ax = fig.gca()
df.mode().hist(ax=ax)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:3: UserWarning: To
output multiple subplots, the figure containing the passed axes is being cleared
  This is separate from the ipykernel package so we can avoid doing imports
until
```

[ ]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f538ef0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f4b2630>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f462898>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f494b00>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f4dbc18>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f3fd400>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f3b0668>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f366898>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fc13f366908>]],
      dtype=object)
```



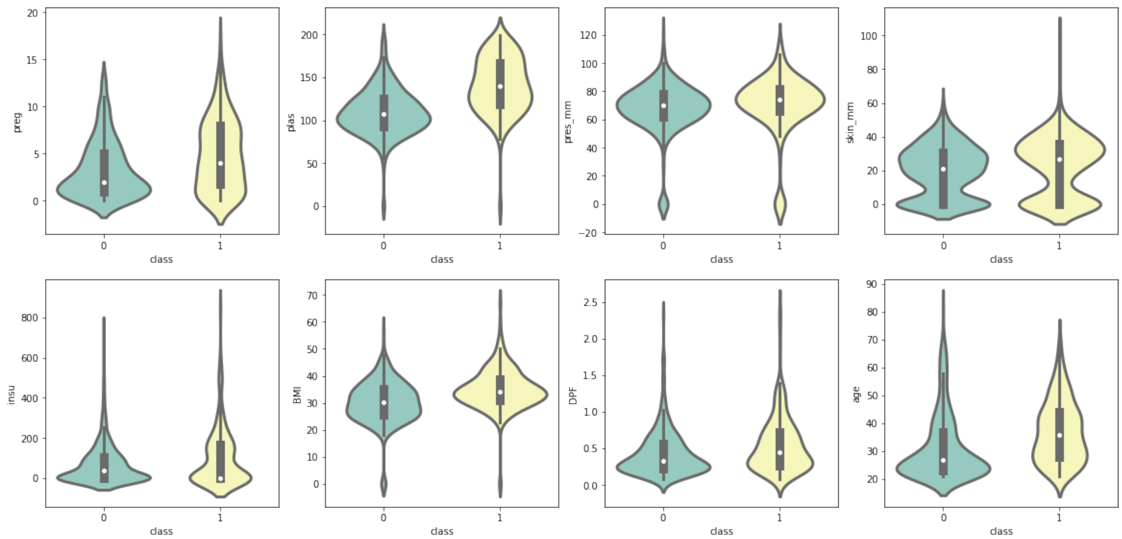
3.7 7. Using Violin plot

By using violin plot to shows the distribution of quantitative data across several levels of categorical variables such that those distributions can be compared and features a kernel density estimation of the underlying distribution we can notes

1. Many zeros values.
2. The mean values for each class are different, so we must consider this when imputing Nan values.
3. There are outlier values.

[ ]:
```
plt.figure(figsize=(20, 20))

for column_index, column in enumerate(df):
```

```
    if column == 'class':
        continue
    plt.subplot(4, 4, column_index + 1)
    sb.violinplot(x='class', y=column, data=df, inner="box", palette="Set3",␣
↪cut=2, linewidth=3)
```



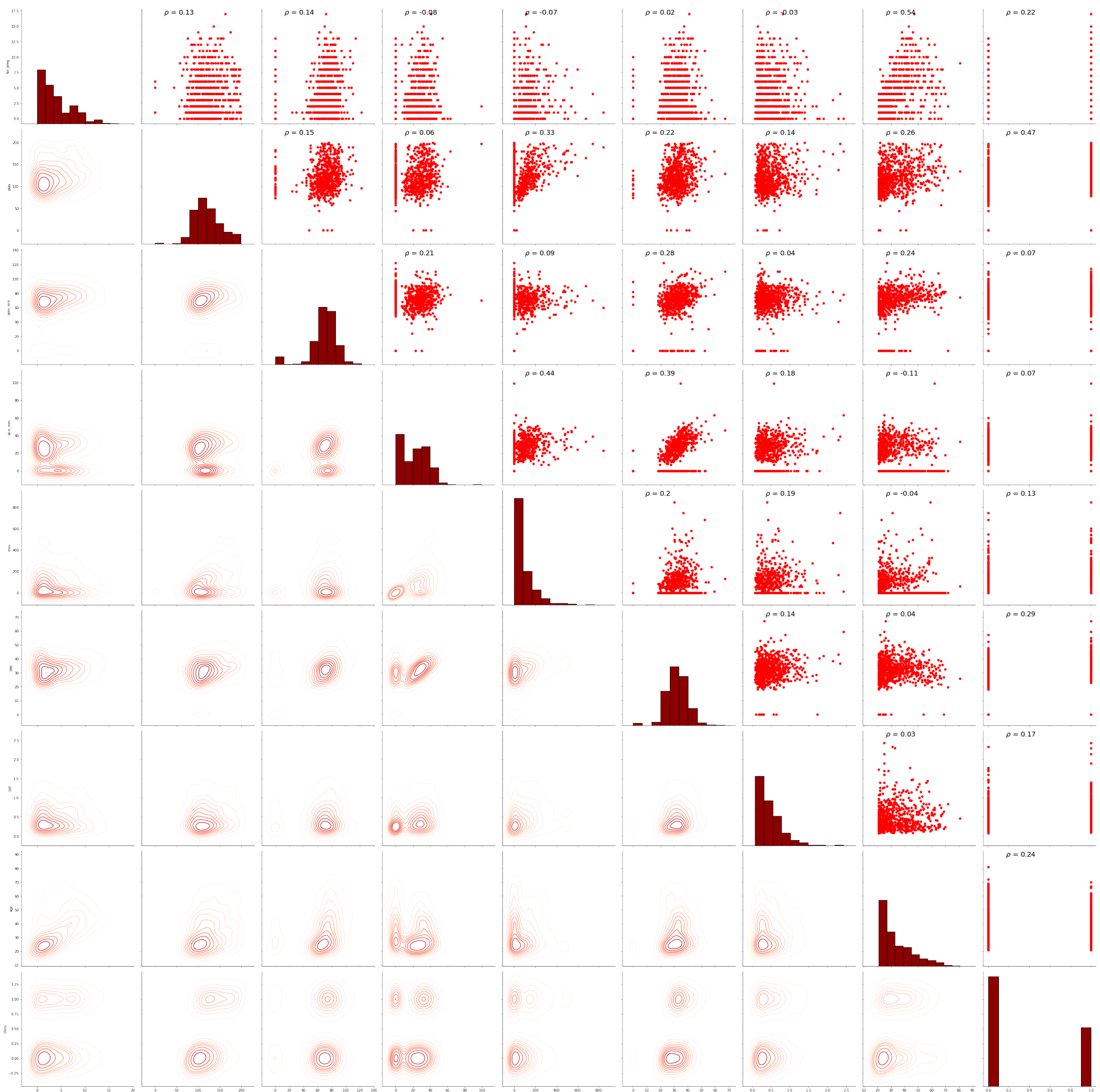
After talking with the field researchers, they fill the null values with zero so we must replace all not logical zeros values with NaN values.

3.8 8. Using Pair and KDE *Kernel Density Estimate* Plot

By using Pair and KDE plot to visualize distribution of single variables and relationships between variables we can notes 1. Relationships between some attribute, 2. A lot of zeros also, 3. Probability distributions are close and same.

[ ]:
```
# Function to calculate correlation coefficient between two arrays
def corr(x, y, **kwargs):

    # Calculate the value
    coef = np.corrcoef(x, y)[0][1]
    # Make the label
    label = r'$\rho$ = ' + str(round(coef, 2))

    # Add the label to the plot
    ax = plt.gca()
    ax.annotate(label, xy = (0.2, 0.95), size = 20, xycoords = ax.transAxes)

# Create a pair grid instance
grid = sb.PairGrid(data= df,
                   vars = ['No_preg', 'plas', 'pres_mm', 'skin_mm',
```

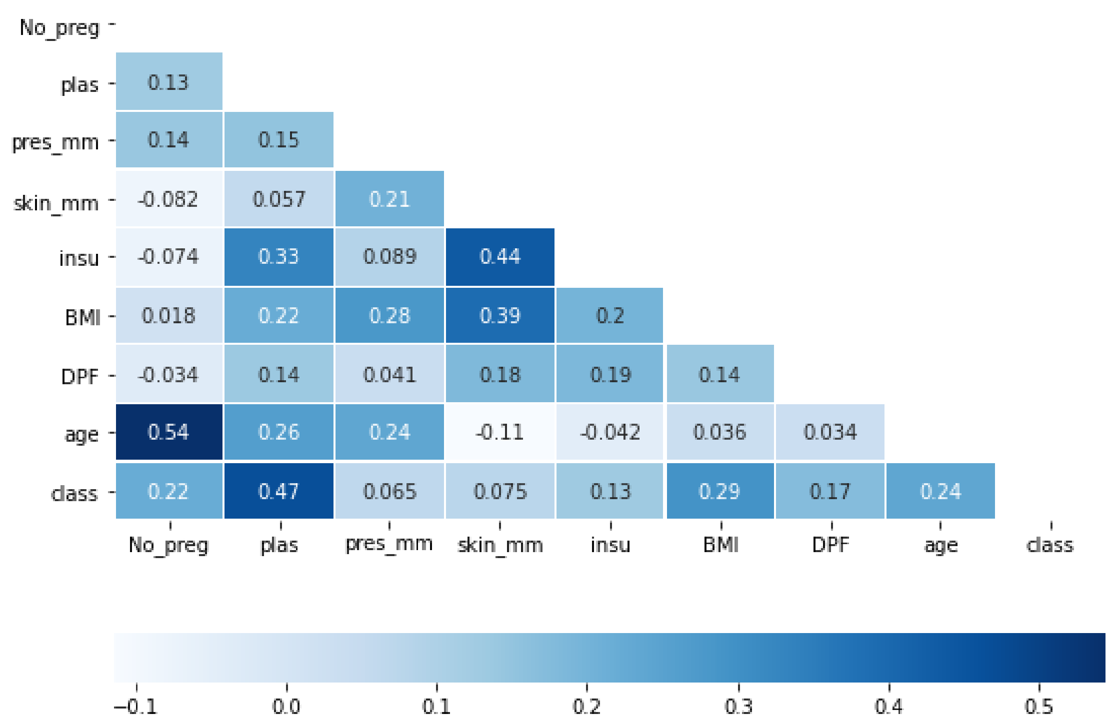
```
                              'insu', 'BMI', 'DPF', 'age', 'class'], height = 5)

# Map the plots to the locations
grid = grid.map_upper(plt.scatter, color = 'red')
grid = grid.map_upper(corr)
grid = grid.map_lower(sb.kdeplot, cmap = 'Reds',)
grid = grid.map_diag(plt.hist, bins = 10, edgecolor =  'k', color = 'darkred');
```



3.9 9. Using the Correlation Matrix Heat map

By using the Correlation Matrix Heat map (figure 2.9) to illustrate the relationship between variables, we can note no significant case of multicollinearity is observed because all of the correlation coefficients are less than 0.7.

[ ]:
```
plt.figure(figsize=(9, 7))
matrix = np.triu(df.corr())
corrMatrix = df.corr()
sb.heatmap(corrMatrix, annot=True, cmap='Blues', linewidths=0.15,
           mask=matrix, cbar_kws= {'orientation': 'horizontal'})
plt.show()
```



4 Step 3: Tidying the data

5 1. Fill NaN Methods Comparison

[ ]:
```
df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
df.columns= ['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',␣
 ↪'class']
```

[ ]:
```
df.columns
```

[ ]:
```
Index(['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',
       'class'],
      dtype='object')
```

[ ]:
```
(df['age']==0).sum()
```

[ ]:
```
0
```

```
[ ]: print('''Columns coud'nt be zero are: ''' , list(df.columns[1:6]))
```

```
Columns coud'nt be zero are:  ['plas', 'pres_mm', 'skin_mm', 'insu', 'BMI']
```

```
[ ]: # Redefining zeros into NaN values
     df[df.columns[1:6]]= df[df.columns[1:6]].replace(0, np.nan)
```

```
[ ]: df[df.columns[1:6]].isnull().sum()
```

```
[ ]: plas          5
     pres_mm      35
     skin_mm     227
     insu        374
     BMI          11
     dtype: int64
```

I will compare between 5 technique to fill NaN values

5.1 1. Remove Rows With Missing Values

```
[ ]: df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
     df.columns= ['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',␣
      ↪'class']
     df[df.columns[1:6]]= df[df.columns[1:6]].replace(0, np.nan)
```

```
[ ]: df.dropna(inplace=True)
     df.shape
```

```
[ ]: (392, 9)
```

```
[ ]: print('Percentage of dropped data=', (768-392)/768)
```

```
Percentage of dropped data= 0.4895833333333333
```

```
[ ]: all_inputs = df[df.columns[0:-1]].values
     all_labels = df['class'].values
     print(all_inputs.shape)
     from sklearn.model_selection import train_test_split
     (X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,
                                                          test_size=0.25,␣
      ↪random_state=1,)
     # Feature Scaling
     from sklearn.preprocessing import StandardScaler
     sc = StandardScaler()
     X_train = sc.fit_transform(X_train)
     X_test = sc.transform(X_test)

     results_1 = []; names = []; seed=42
     for name, model in models:
```

```
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_1 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy' )
    results_1.append(cv_results_1)
    names.append(name)
    print(f"{name}, {cv_results_1.mean()}, {cv_results_1.std()}))")
```

```
(392, 8)
LR, 0.7861904761904762, 0.12857054673418924))
LDA, 0.7897619047619047, 0.12802595931491162))
KNN, 0.7623809523809524, 0.11292744444886092))
CART, 0.6897619047619046, 0.1308464939868934))
NB, 0.7797619047619049, 0.11212111810322156))
SVM, 0.7554761904761904, 0.11571795996518176))
XGB, 0.7816666666666667, 0.11272018010217857))
```

5.2 2. Impute Missing Values (Mean Value Filling)

[ ]:
```
df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
df.columns= ['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',␣
↪'class']
df[df.columns[1:6]]= df[df.columns[1:6]].replace(0, np.nan)

df1 = df.loc[df['class'] == 1]
df2 = df.loc[df['class'] == 0]
```

[ ]:
```
df1.fillna(df1.mean(), inplace=True)
df2.fillna(df2.mean(), inplace=True)

dataframe = [df1, df2]
df = pd.concat(dataframe)
```

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
all_inputs.shape
```

[ ]:
```
(768, 8)
```

[ ]:
```
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,
                                                      test_size=0.25,␣
↪random_state=1,                                                      )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_2 = []; names = []; seed=42
for name, model in models:
```

```
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_2 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_2.append(cv_results_2)
    names.append(name)
    print(f"{name}, {cv_results_2.mean()}, {cv_results_2.std()}))")
```

```
LR, 0.7738300492610837, 0.0689196220881071))
LDA, 0.7737684729064039, 0.07106786364748625))
KNN, 0.8173645320197045, 0.07886207573510806))
CART, 0.8796798029556652, 0.06851110409920169))
NB, 0.7720443349753694, 0.0700920699840484))
SVM, 0.8349137931034484, 0.06586019332396725))
XGB, 0.8869458128078817, 0.05642168499262387))
```

5.3 3. Impute Missing Values (Median Value Filling)

[ ]:
```
df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
df.columns= ['No_preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF',␣
↪'age', 'class']
df[df.columns[1:6]]= df[df.columns[1:6]].replace(0, np.nan)

df1 = df.loc[df['class'] == 1]
df2 = df.loc[df['class'] == 0]
```

[ ]:
```
df1.fillna(df1.median(), inplace=True)
df2.fillna(df2.median(), inplace=True)

dataframe = [df1, df2]
df = pd.concat(dataframe)
```

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
all_inputs.shape
```

[ ]:
```
(768, 8)
```

[ ]:
```
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,
                                                      test_size=0.25,␣
↪random_state=1)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_3 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
```

```
    cv_results_3 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_3.append(cv_results_3)
    names.append(name)
    print(f"{name}, {cv_results_3.mean()}, {cv_results_3.std()}))")
```

```
LR, 0.7633004926108373, 0.07843541820685897))
LDA, 0.7703817733990148, 0.07992931047044209))
KNN, 0.8070812807881772, 0.07939031074825631))
CART, 0.8729064039408868, 0.048698449505117515))
NB, 0.7598522167487685, 0.08545857474403694))
SVM, 0.8504926108374384, 0.05873674193644676))
XGB, 0.888793103448276, 0.06942809765514414))
```

5.4 4. Using back Filling

[ ]:
```
df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
df.columns= ['No_preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF',␣
↪'age', 'class']
df[df.columns[1:6]]= df[df.columns[1:6]].replace(0, np.nan)

df1 = df.loc[df['class'] == 1]
df2 = df.loc[df['class'] == 0]
```

[ ]:
```
df1.fillna(method= 'backfill', inplace=True)
df2.fillna(method= 'backfill', inplace=True)

df1.fillna(df1.mean(), inplace=True)
df2.fillna(df2.mean(), inplace=True)

dataframe = [df1, df2]
df = pd.concat(dataframe)
```

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
all_inputs.shape
```

[ ]:
```
(768, 8)
```

[ ]:
```
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,
                                                      test_size=0.25,␣
↪random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_4 = []; names = []; seed=42
```

```python
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_4 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_4.append(cv_results_4)
    names.append(name)
    print(f"{name}, {cv_results_4.mean()}, {cv_results_4.std()}))")
```

```
LR, 0.7668103448275861, 0.08091636753181289))
LDA, 0.7652709359605911, 0.07755140356317015))
KNN, 0.7690270935960591, 0.0745836590047773))
CART, 0.7551724137931034, 0.07015987262294252))
NB, 0.7598522167487685, 0.07873013142757428))
SVM, 0.7686576354679804, 0.08000877623455863))
XGB, 0.7896551724137931, 0.07607369241829157))
```

5.5 5. Using forward Filling

[ ]:
```python
df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
df.columns= ['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',␣
 ↪'class']
df[df.columns[1:6]]= df[df.columns[1:6]].replace(0, np.nan)

df1 = df.loc[df['class'] == 1]
df2 = df.loc[df['class'] == 0]
```

[ ]:
```python
df1.fillna(method= 'ffill', inplace=True)
df2.fillna(method= 'ffill', inplace=True)

df1.fillna(df1.mean(), inplace=True)
df2.fillna(df2.mean(), inplace=True)

dataframe = [df1, df2]
df = pd.concat(dataframe)
```

[ ]:
```python
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
all_inputs.shape
```

[ ]:
```
(768, 8)
```

[ ]:
```python
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,
                                                       test_size=0.25,␣
 ↪random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
results_5 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_5 = cross_val_score(model, X_train, y_train, cv=kfold,
 ↪scoring='accuracy')
    results_5.append(cv_results_5)
    names.append(name)
    print(f"{name}, {cv_results_5.mean()}, {cv_results_5.std()}))")
```

```
LR, 0.7652093596059113, 0.07235394610657282))
LDA, 0.7669334975369458, 0.07328349403480619))
KNN, 0.7568965517241378, 0.0940046500259637))
CART, 0.7362068965517241, 0.053470972003503356))
NB, 0.7461206896551724, 0.06380840654648952))
SVM, 0.7600985221674877, 0.06766521362701008))
XGB, 0.7846059113300492, 0.05681452407049272))
```

5.6 Classification Comparison of Fill NaN Methods

[ ]:
```
classification_comparison= pd.DataFrame(index=[i for i in names])
```

[ ]:
```
names
```

[ ]:
```
['LR', 'LDA', 'KNN', 'CART', 'NB', 'SVM', 'XGB']
```

[ ]:
```
dfresults = pd.DataFrame(results_1)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy']= df_mean
classification_comparison['sd']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_2)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
```

```
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_2']= df_mean
classification_comparison['sd_2']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_3)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_3']= df_mean
classification_comparison['sd_3']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_4)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_4']= df_mean
classification_comparison['sd_4']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_5)
dfresults=dfresults.T
dfresults.columns=names
```

```
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_5']= df_mean
classification_comparison['sd_5']= df_sd
```

[ ]:
```
values= ['Acc', 'SD']
```

[ ]:
```
Fill_NaN_Methods=['1_Remove', '2_Mean_fill','3_Median_fill',
     '4_Back_fill', '5_Forwd_fill']
```

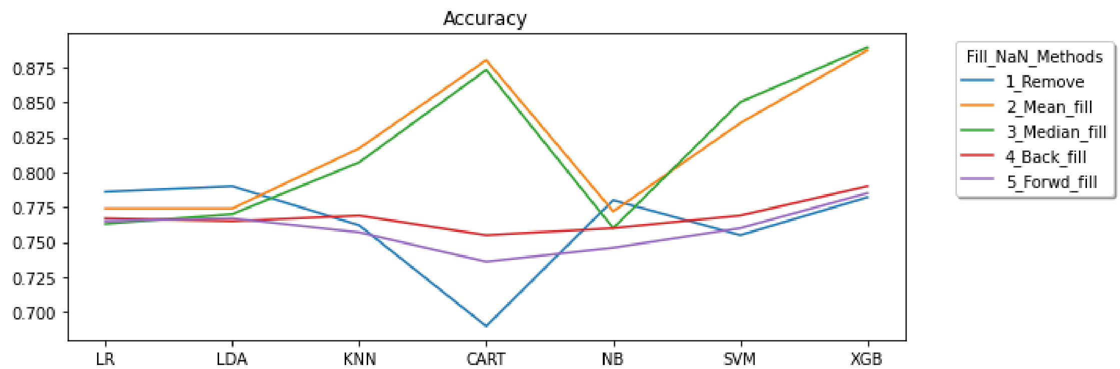
[ ]:
```
idx = pd.MultiIndex.from_product([Fill_NaN_Methods, values],
                                 names=['Fill_NaN_Methods', 'values'])

classification_comparison.columns = idx
classification_comparison
```

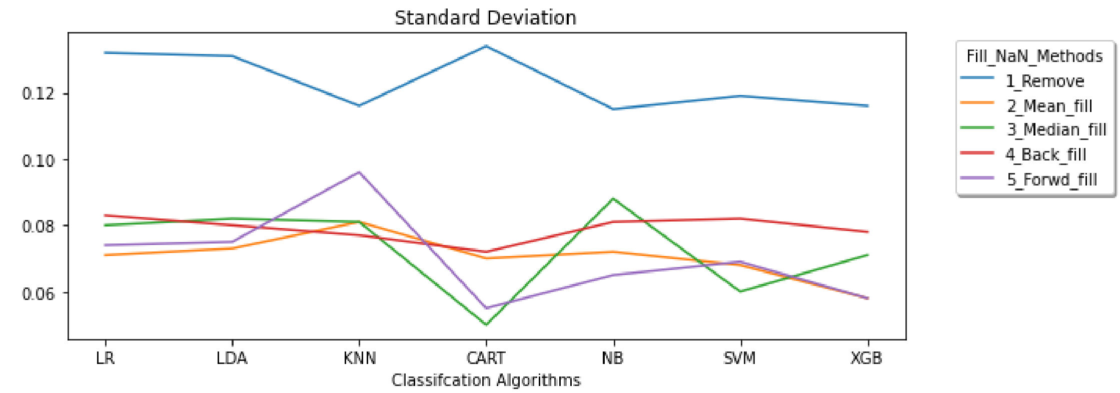
[ ]:
```
Fill_NaN_Methods 1_Remove        2_Mean_fill  ... 4_Back_fill 5_Forwd_fill
values                Acc     SD         Acc  ...          SD          Acc
SD
LR                  0.786  0.132       0.774  ...       0.083        0.765
0.074
LDA                 0.790  0.131       0.774  ...       0.080        0.767
0.075
KNN                 0.762  0.116       0.817  ...       0.077        0.757
0.096
CART                0.690  0.134       0.880  ...       0.072        0.736
0.055
NB                  0.780  0.115       0.772  ...       0.081        0.746
0.065
SVM                 0.755  0.119       0.835  ...       0.082        0.760
0.069
XGB                 0.782  0.116       0.887  ...       0.078        0.785
0.058

[7 rows x 10 columns]
```

[ ]:
```
classification_comparison.to_csv('Classification Comparison of Fill_NaN_Methods.
 ↪csv', index= False)
```

[ ]:
```
plt.figure(figsize=(10,7))
ax = plt.subplot(211)
```

```
classification_comparison.xs('Acc', axis=1, level='values').plot( ax=ax)
plt.title("Accuracy")
plt.legend(shadow=True, frameon=True, fancybox=True, title='Fill_NaN_Methods',␣
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
ax = plt.subplot(212)
classification_comparison.xs('SD', axis=1, level='values').plot( ax=ax)
plt.title("Standard Deviation")
plt.xlabel("Classifcation Algorithms")
plt.legend(shadow=True, frameon=True, fancybox=True, title='Fill_NaN_Methods',␣
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
```





[ ]:
```
#classification_comparison= classification_comparison.drop('1_Remove', axis=1,␣
 ↪level=0)
```

[ ]:
```
classification_comparison.T.max()
```

[ ]:
```
LR      0.786
LDA     0.790
KNN     0.817
CART    0.880
NB      0.780
SVM     0.850
XGB     0.889
```

```
dtype: float64
```

[ ]:
```
FIll_NaN= classification_comparison.T.max()
```

[ ]:
```
classification_comparison.T['CART']
```

[ ]:
```
Fill_NaN_Methods  values
1_Remove          Acc       0.690
                  SD        0.134
2_Mean_fill       Acc       0.880
                  SD        0.070
3_Median_fill     Acc       0.873
                  SD        0.050
4_Back_fill       Acc       0.755
                  SD        0.072
5_Forwd_fill      Acc       0.736
                  SD        0.055
Name: CART, dtype: float64
```

[ ]:
```
classification_comparison.T['XGB']
```

[ ]:
```
Fill_NaN_Methods  values
1_Remove          Acc       0.782
                  SD        0.116
2_Mean_fill       Acc       0.887
                  SD        0.058
3_Median_fill     Acc       0.889
                  SD        0.071
4_Back_fill       Acc       0.790
                  SD        0.078
5_Forwd_fill      Acc       0.785
                  SD        0.058
Name: XGB, dtype: float64
```

[ ]:
```
methods_comparison= pd.DataFrame(FIll_NaN, columns=['FIll_NaN'])
methods_comparison
```

[ ]:
```
      FIll_NaN
LR       0.786
LDA      0.790
KNN      0.817
CART     0.880
NB       0.780
SVM      0.850
XGB      0.889
```

6 Selected Fill NaN Methods

The best fill NaN method is **Median_fill**

```
[ ]: df= pd.read_csv('/content/data/pima-indians-diabetes.csv', header= None)
     df.columns= ['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',␣
      ↪'class']
     df[df.columns[1:6]]= df[df.columns[1:6]].replace(0, np.nan)

     df1 = df.loc[df['class'] == 1]
     df2 = df.loc[df['class'] == 0]
```

```
[ ]: df1.fillna(df1.median(), inplace=True)
     df2.fillna(df2.median(), inplace=True)

     dataframe = [df1, df2]
     df = pd.concat(dataframe)
```

7 2. Add features

7.1 1. Add features based on BMI classification table

BMI classification table
- BMI CLASSIFICATION - > 30 :Obese - 25-30 :Overweight - 20-25 :Healthy weight range - 20-18 :Underweight - <18 :Very Underweight

```
[ ]: Obese= []
     for i in df['BMI']:
       Obese.append(1 if i>30 else 0)
     pd.value_counts(Obese)
```

```
[ ]: 1    476
     0    292
     dtype: int64
```

```
[ ]: df['Obese']= Obese
```

```
[ ]: Overweight= []
     for i in df['BMI']:
       Overweight.append(1 if 30>i>25 else 0)
     pd.value_counts(Overweight)
```

```
[ ]: 0    595
     1    173
     dtype: int64
```

```
[ ]: df['Overweight']= Overweight
```

```
[ ]: Healthy_weight= []
     for i in df['BMI']:
       Healthy_weight.append(1 if 25>i>20 else 0)
     pd.value_counts(Healthy_weight)
```

```
[ ]: 0    676
     1     92
```

```
dtype: int64
```

[ ]:
```
df['Healthy_weight']= Healthy_weight
```

[ ]:
```
Underweight= []
for i in df['BMI']:
  Underweight.append(1 if 20>i>18 else 0)
pd.value_counts(Underweight)
```

[ ]:
```
0    755
1     13
dtype: int64
```

[ ]:
```
df['Underweight']= Underweight
```

[ ]:
```
Very_Underweight= []
for i in df['BMI']:
  Very_Underweight.append(1 if i<18 else 0)
pd.value_counts(Very_Underweight)
```

[ ]:
```
0    768
dtype: int64
```

[ ]:
```
#df['Very_Underweight']= Very_Underweight
```

7.2 2. Add features based on 2-Hour serum insulin

2-Hour serum insulin classification table
- insulin CLASSIFICATION - >140 :Normal - 140-199 :pre-diabetic - < 199 :diabetic

[ ]:
```
Normal= []
for i in df['insu']:
  Normal.append(1 if i<140 else 0)
pd.value_counts(Normal)
```

[ ]:
```
1    457
0    311
dtype: int64
```

[ ]:
```
df['Normal']= Normal
```

[ ]:
```
pre_diabetic= []
for i in df['insu']:
  pre_diabetic.append(1 if 199>i>140 else 0)
pd.value_counts(pre_diabetic)
```

[ ]:
```
0    693
1     75
dtype: int64
```

[ ]:
```
df['pre_diabetic']= pre_diabetic
```

[ ]:
```
diabetic= []
for i in df['insu']:
```

```
  diabetic.append(1 if i>199 else 0)
pd.value_counts(diabetic)
```

```
[ ]: 0    541
     1    227
     dtype: int64
```

```
[ ]: df['diabetic']= diabetic
```

7.3 3. Add features based on Plasma glucose 2-Hour in an oral glucose tolerance test

2-Hour in an oral glucose classification table
- insulin CLASSIFICATION - >100 :Normal - 100-125 :pre_diabetic - < 125 :diabetic

```
[ ]: Normal_p= []
     for i in df['plas']:
       Normal_p.append(1 if i<100 else 0)
     pd.value_counts(Normal_p)
```

```
[ ]: 0    576
     1    192
     dtype: int64
```

```
[ ]: df['Normal_p']= Normal_p
```

```
[ ]: pre_diabetic_p= []
     for i in df['plas']:
       pre_diabetic_p.append(1 if 125>i>100 else 0)
     pd.value_counts(pre_diabetic_p)
```

```
[ ]: 0    522
     1    246
     dtype: int64
```

```
[ ]: df['pre_diabetic_p']= pre_diabetic_p
```

```
[ ]: diabetic_p= []
     for i in df['plas']:
       diabetic_p.append(1 if i>125 else 0)
     pd.value_counts(diabetic_p)
```

```
[ ]: 0    469
     1    299
     dtype: int64
```

```
[ ]: df['diabetic_p']= diabetic_p
```

```
[ ]: df= df[['preg', 'plas', 'pres_mm', 'skin_mm', 'insu', 'BMI', 'DPF', 'age',
             'Obese', 'Overweight', 'Healthy_weight', 'Underweight',
             'Normal', 'pre_diabetic', 'diabetic', 'Normal_p',
            'pre_diabetic_p', 'diabetic_p', 'class']]
```

```
[ ]: all_inputs = df[df.columns[0:-1]].values
     all_labels = df['class'].values
     all_inputs.shape
```

```
[ ]: (768, 18)
```

7.4 Classification Comparison

```
[ ]: results_1 = []; names = []; seed=42
     for name, model in models:
         kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
         cv_results_1 = cross_val_score(model, X_train, y_train, cv=kfold,␣
      ↪scoring='accuracy')
         results_1.append(cv_results_1)
         names.append(name)
         print(f"{name}, {cv_results_1.mean()}, {cv_results_1.std()}))")
```

```
LR, 0.7652093596059113, 0.07235394610657282))
LDA, 0.7669334975369458, 0.07328349403480619))
KNN, 0.7568965517241378, 0.0940046500259637))
CART, 0.724076354679803, 0.06990961268480901))
NB, 0.7461206896551724, 0.06380840654648952))
SVM, 0.7600985221674877, 0.06766521362701008))
XGB, 0.7846059113300492, 0.05681452407049272))
```

```
[ ]: classification_comparison= pd.DataFrame(index=[i for i in names])
```

```
[ ]: dfresults = pd.DataFrame(results_1)
     dfresults=dfresults.T
     dfresults.columns=names
     df_mean=[]
     df_sd=[]
     for i in dfresults.columns:
       d= dfresults[i].mean()
       df_mean.append(d)
     df_mean= [round(num, 3) for num in df_mean]
     for i in dfresults.columns:
       n= dfresults[i].std()
       df_sd.append(n)
     df_sd= [round(num, 3) for num in df_sd]

     classification_comparison['Accuracy']= df_mean
     classification_comparison['sd']= df_sd
     classification_comparison
```

```
[ ]:       Accuracy     sd
     LR       0.765  0.074
     LDA      0.767  0.075
```

```
KNN      0.757  0.096
CART     0.724  0.072
NB       0.746  0.065
SVM      0.760  0.069
XGB      0.785  0.058
```

[ ]:
```
Add_F= classification_comparison.T.max()
```

[ ]:
```
methods_comparison['Add_F']= Add_F
methods_comparison
```

[ ]:
```
      FIll_NaN  Add_F
LR       0.786  0.765
LDA      0.790  0.767
KNN      0.817  0.757
CART     0.880  0.724
NB       0.780  0.746
SVM      0.850  0.760
XGB      0.889  0.785
```

8 3. Automatic Outlier Detection Algorithms Comparison

8.1 1. DBSCAN

[ ]:
```
from sklearn.cluster import DBSCAN
def remove_outliers_DBSCAN(df,eps,min_samples):
    outlier_detection = DBSCAN(eps = eps, min_samples = min_samples)
    clusters = outlier_detection.fit_predict(df.values.reshape(-1,1))
    data = pd.DataFrame()
    data['cluster'] = clusters
    return data['cluster']
```

[ ]:
```
outlier_index1=[]
for col in df.columns[0:-1]:
  clusters=remove_outliers_DBSCAN((df[col]), .2, 2)
  df_cluster=pd.DataFrame(clusters)
  outlier_index1= outlier_index1+(list(df_cluster.
 ↪index[df_cluster['cluster']==-1]))
outlier_index1=list(set(outlier_index1))
print(len(outlier_index1))

DBSCAN_df=df.drop(outlier_index1)
#DBSCAN_df.to_csv('DBSCAN_df.csv', index= False)

#!mkdir Outlier_Detection_DFs
#!mv DBSCAN_df.csv Outlier_Detection_DFs/

all_inputs = DBSCAN_df[DBSCAN_df.columns[0:-1]].values
```

```
all_labels = DBSCAN_df['class'].values

(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_1 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_1 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_1.append(cv_results_1)
    names.append(name)
    print(f"{name}, {cv_results_1.mean()}, {cv_results_1.std()}))")
```

```
136
LR, 0.8817934782608697, 0.07055194255956952))
LDA, 0.879981884057971, 0.06803706068962845))
KNN, 0.8903985507246377, 0.06055035130416818))
CART, 0.8694746376811594, 0.08009925407624391))
NB, 0.6959239130434783, 0.09377738870386135))
SVM, 0.8842391304347826, 0.062361745847078154))
XGB, 0.8971014492753623, 0.06704269346708851))
```

8.2 2. Isolation Forest

[ ]:
```
to_model_columns=df.columns[0:-1]
from sklearn.ensemble import IsolationForest
clf=IsolationForest(n_estimators=99, max_samples='auto',
                    contamination=0.2,
                        max_features=1.0 , bootstrap=False, n_jobs=-1,
                     random_state=42, verbose=0 )

clf.fit(df[to_model_columns])
pred = clf.predict(df[to_model_columns])
df['anomaly']=pred
outliers=df.loc[df['anomaly']==-1]
outlier_index2=list(outliers.index)
print(outlier_index2)
#Find the number of anomalies and normal points here points classified -1 are␣
↪anomalous
print(df['anomaly'].value_counts())
df.drop('anomaly', axis='columns', inplace=True)
```

```python
Isolation_Forest_df=df.drop(outlier_index2)
Isolation_Forest_df['class'].value_counts()
#Isolation_Forest_df.to_csv('Isolation_Forest_df.csv', index= False)
#!mv Isolation_Forest_df.csv Outlier_Detection_DFs/
all_inputs = Isolation_Forest_df[Isolation_Forest_df.columns[0:-1]].values
all_labels = Isolation_Forest_df['class'].values
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_2 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_2 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_2.append(cv_results_2)
    names.append(name)
    print(f"{name}, {cv_results_2.mean()}, {cv_results_2.std()}))")
```

```
[2, 4, 8, 13, 14, 24, 38, 39, 43, 93, 99, 114, 120, 125, 128, 129, 130, 131,
152, 159, 165, 177, 214, 218, 236, 243, 245, 254, 259, 270, 276, 284, 292, 293,
296, 298, 308, 319, 322, 323, 356, 370, 400, 408, 429, 444, 445, 476, 498, 510,
516, 539, 542, 579, 584, 588, 590, 595, 614, 618, 646, 647, 676, 689, 709, 719,
731, 740, 749, 12, 27, 28, 33, 35, 50, 51, 57, 59, 68, 90, 91, 94, 105, 106,
194, 204, 223, 228, 239, 247, 248, 258, 279, 294, 307, 311, 316, 320, 325, 330,
333, 374, 379, 382, 385, 390, 392, 395, 396, 405, 418, 420, 428, 434, 438, 452,
453, 459, 460, 464, 466, 489, 499, 507, 511, 512, 519, 526, 528, 537, 549, 582,
593, 597, 607, 609, 610, 617, 621, 633, 639, 644, 657, 668, 672, 673, 679, 688,
713, 717, 718, 733, 738, 763]
 1    614
-1    154
Name: anomaly, dtype: int64
LR, 0.8739130434782607, 0.06860753842634564))
LDA, 0.8760869565217391, 0.06341718324267313))
KNN, 0.8782608695652174, 0.0507039295203939))
CART, 0.8804347826086956, 0.04534055133611785))
NB, 0.8413043478260869, 0.07810975749226816))
SVM, 0.8739130434782607, 0.059772726455945724))
XGB, 0.8956521739130435, 0.055679341195068247))
```

8.3 3. Minimum Covariance Determinant

[ ]:
```
to_model_columns=df.columns[:-1]
from sklearn.covariance import EllipticEnvelope
ee = EllipticEnvelope(contamination=.01, )
ee.fit(df[to_model_columns])
pred = ee.predict(df[to_model_columns])
df['anomaly']=pred
outliers=df.loc[df['anomaly']==-1]
outlier_index3=list(outliers.index)
print(outlier_index3)
#Find the number of anomalies and normal points here points classified -1 are␣
↪anomalous
print(df['anomaly'].value_counts())
df.drop('anomaly', axis='columns', inplace=True)
Minimum_Covariance_Determinant_df=df.drop(outlier_index3)
Minimum_Covariance_Determinant_df['class'].value_counts()
#Minimum_Covariance_Determinant_df.to_csv('Minimum_Covariance_Determinant_df.
↪csv', index= False)
#!mv Minimum_Covariance_Determinant_df.csv Outlier_Detection_DFs/
all_inputs =␣
↪Minimum_Covariance_Determinant_df[Minimum_Covariance_Determinant_df.
↪columns[0:-1]].values
all_labels = Minimum_Covariance_Determinant_df['class'].values
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_3 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_3 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_3.append(cv_results_3)
    names.append(name)
    print(f"{name}, {cv_results_3.mean()}, {cv_results_3.std()}))")
```

```
[15, 245, 62, 217, 453, 519, 639, 745]
 1    760
-1      8
Name: anomaly, dtype: int64
LR, 0.8751847290640395, 0.061953616476605494))
LDA, 0.875, 0.06923165135030956))
```

```
KNN, 0.862807881773399, 0.06063992388560086))
CART, 0.8504310344827586, 0.06325360413847252))
NB, 0.6526477832512315, 0.08628908379926371))
SVM, 0.8573275862068966, 0.07557531190421447))
XGB, 0.8858990147783251, 0.04310569135613251))
```

8.4 4. Local Outlier Factor

[ ]:
```
to_model_columns=df.columns[0:-1]
from sklearn.neighbors import LocalOutlierFactor
lof = LocalOutlierFactor(novelty=True, n_jobs=1,
                         n_neighbors=5, contamination=0.15, leaf_size= 60 )
lof.fit(df[to_model_columns])
pred = lof.predict(df[to_model_columns])
df['anomaly']=pred
outliers=df.loc[df['anomaly']==-1]
outlier_index4=list(outliers.index)
print(outlier_index4)
#Find the number of anomalies and normal points here points classified -1 are␣
 ↪anomalous
print(df['anomaly'].value_counts())
df.drop('anomaly', axis='columns', inplace=True)
Local_Outlier_Factor_df=df.drop(outlier_index4)
Local_Outlier_Factor_df['class'].value_counts()
#Local_Outlier_Factor_df.to_csv('Local_Outlier_Factor_df.csv', index= False)
#!mv Local_Outlier_Factor_df.csv Outlier_Detection_DFs/
all_inputs = Local_Outlier_Factor_df[Local_Outlier_Factor_df.columns[0:-1]].
 ↪values
all_labels = Local_Outlier_Factor_df['class'].values
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_4 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_4 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_4.append(cv_results_4)
    names.append(name)
    print(f"{name}, {cv_results_4.mean()}, {cv_results_4.std()}))")
```

```
[13, 39, 43, 120, 125, 132, 177, 187, 193, 227, 237, 238, 242, 293, 328, 440,
444, 445, 476, 545, 579, 595, 647, 691, 693, 716, 740, 759, 18, 28, 33, 55, 57,
62, 86, 95, 106, 117, 135, 147, 150, 182, 223, 228, 244, 247, 250, 256, 277,
307, 320, 346, 362, 379, 396, 434, 456, 459, 460, 466, 511, 519, 537, 573, 575,
597, 653, 657, 658, 672, 680, 763]
 1    696
-1     72
Name: anomaly, dtype: int64
LR, 0.8618945868945869, 0.07896991242112261))
LDA, 0.8618233618233617, 0.07821148501142053))
KNN, 0.8580484330484331, 0.0758341665289647))
CART, 0.8619658119658119, 0.06257745746129312))
NB, 0.6515669515669515, 0.11241599903766386))
SVM, 0.8752849002849002, 0.056754316011546))
XGB, 0.904059829059829, 0.07256471637788393))
```

8.5 5. One-Class SVM

[ ]:
```
to_model_columns=df.columns[0:-1]
from sklearn.svm import OneClassSVM

ocs = OneClassSVM(nu=0.15, )
ocs.fit(df[to_model_columns])
pred = ocs.predict(df[to_model_columns])
df['anomaly']=pred
outliers=df.loc[df['anomaly']==-1]
outlier_index5=list(outliers.index)
print(outlier_index5)

#Find the number of anomalies and normal points here points classified -1 are␣
 ↪anomalous
print(df['anomaly'].value_counts())
df.drop('anomaly', axis='columns', inplace=True)
One_Class_SVM_df=df.drop(outlier_index5)
One_Class_SVM_df['class'].value_counts()

#One_Class_SVM_df.to_csv('One_Class_SVM_df.csv', index= False)
#!mv One_Class_SVM_df.csv Outlier_Detection_DFs/

all_inputs = One_Class_SVM_df[One_Class_SVM_df.columns[0:-1]].values
all_labels = One_Class_SVM_df['class'].values
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
```

```
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_5 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_5 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_5.append(cv_results_5)
    names.append(name)
    print(f"{name}, {cv_results_5.mean()}, {cv_results_5.std()}))")
```

```
[8, 13, 22, 43, 53, 56, 109, 111, 186, 199, 206, 220, 231, 254, 296, 319, 323,
359, 360, 370, 375, 388, 408, 409, 415, 425, 440, 445, 480, 498, 506, 561, 579,
584, 606, 612, 655, 661, 695, 715, 753, 759, 32, 40, 51, 52, 54, 62, 68, 73, 92,
103, 108, 112, 139, 144, 153, 162, 173, 174, 182, 203, 225, 228, 232, 234, 247,
248, 258, 260, 273, 279, 286, 288, 290, 302, 353, 364, 392, 395, 412, 441, 459,
462, 466, 482, 486, 487, 489, 519, 520, 534, 537, 548, 549, 553, 566, 572, 574,
597, 607, 617, 625, 639, 645, 672, 679, 680, 707, 710, 711, 713, 747, 760]
 1    654
-1    114
Name: anomaly, dtype: int64
LR, 0.8913333333333334, 0.06084954121985363))
LDA, 0.8955, 0.05515407711332157))
KNN, 0.887416666666667, 0.06921077910589103))
CART, 0.8877499999999999, 0.0630878466020904))
NB, 0.6793333333333333, 0.08945110396188523))
SVM, 0.8873333333333333, 0.06971250485625469))
XGB, 0.8915, 0.058790825058941905))
```

8.6 Comparison

[ ]:
```
classification_comparison= pd.DataFrame(index=[i for i in names])
```

[ ]:
```
dfresults = pd.DataFrame(results_1)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]
```

```
classification_comparison['Accuracy_1']= df_mean
classification_comparison['sd_1']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_2)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_2']= df_mean
classification_comparison['sd_2']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_3)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_3']= df_mean
classification_comparison['sd_3']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_4)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
```

```
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_4']= df_mean
classification_comparison['sd_4']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_5)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 3) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 3) for num in df_sd]

classification_comparison['Accuracy_5']= df_mean
classification_comparison['sd_5']= df_sd
```

[ ]:
```
classification_comparison
```

[ ]:
```
      Accuracy_1   sd_1  Accuracy_2  ...   sd_4  Accuracy_5   sd_5
LR         0.882  0.072       0.874  ...  0.081       0.891  0.062
LDA        0.880  0.070       0.876  ...  0.080       0.895  0.057
KNN        0.890  0.062       0.878  ...  0.078       0.887  0.071
CART       0.869  0.082       0.880  ...  0.064       0.888  0.065
NB         0.696  0.096       0.841  ...  0.115       0.679  0.092
SVM        0.884  0.064       0.874  ...  0.058       0.887  0.072
XGB        0.897  0.069       0.896  ...  0.074       0.892  0.060

[7 rows x 10 columns]
```

[ ]:
```
values= ['Acc', 'SD']
```

[ ]:
```
DFs=[ '1_DBSCAN_df', '2_IF_df', '3_MCD_df', '4_LOF_df','5_OCSVM_df']
```

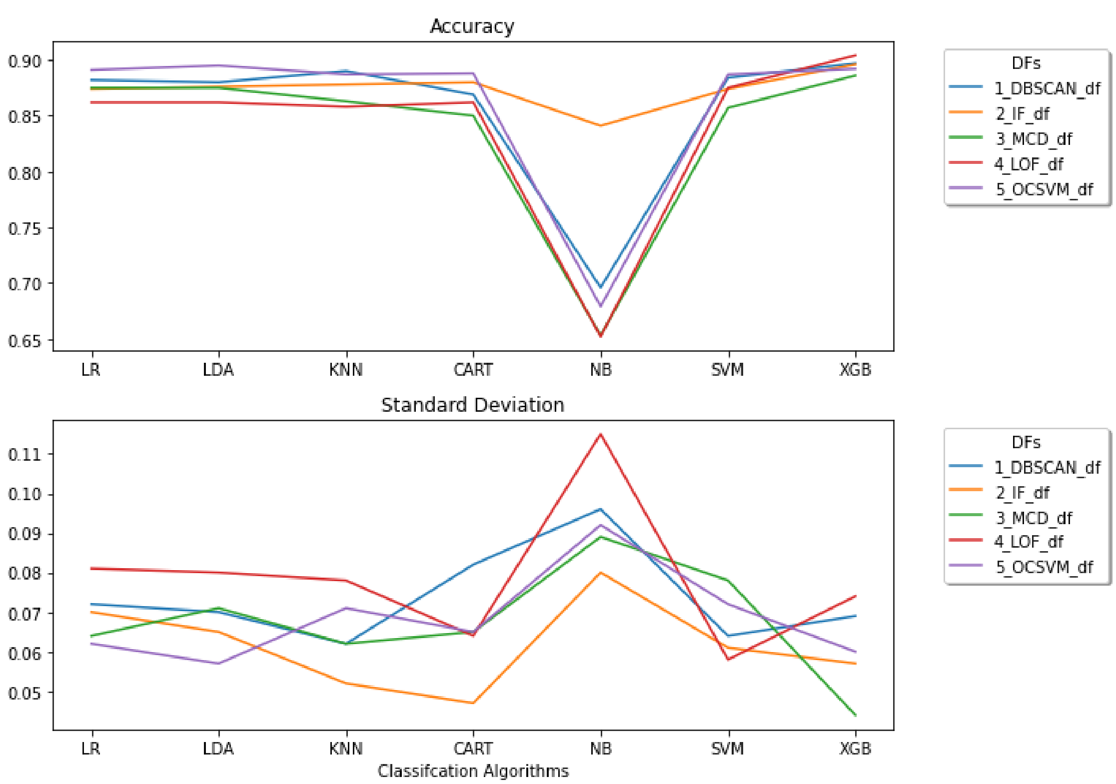
[ ]:
```
idx = pd.MultiIndex.from_product([DFs, values],
                                 names=['DFs', 'values'])

classification_comparison.columns = idx
classification_comparison
```

[ ]:
```
DFs    1_DBSCAN_df        2_IF_df        ... 4_LOF_df        5_OCSVM_df
values         Acc     SD     Acc     SD ...      Acc     SD        Acc     SD
LR           0.882  0.072   0.874  0.070 ...    0.862  0.081      0.891  0.062
```

```
LDA           0.880  0.070   0.876  0.065  ...   0.862  0.080     0.895  0.057
KNN           0.890  0.062   0.878  0.052  ...   0.858  0.078     0.887  0.071
CART          0.869  0.082   0.880  0.047  ...   0.862  0.064     0.888  0.065
NB            0.696  0.096   0.841  0.080  ...   0.652  0.115     0.679  0.092
SVM           0.884  0.064   0.874  0.061  ...   0.875  0.058     0.887  0.072
XGB           0.897  0.069   0.896  0.057  ...   0.904  0.074     0.892  0.060

[7 rows x 10 columns]
```

[ ]:
```
#classification_comparison.to_csv('classification_comparison.csv', index=
 ↪False)
```

[ ]:
```
plt.figure(figsize=(10,7))
ax = plt.subplot(211)
classification_comparison.xs('Acc', axis=1, level='values').plot( ax=ax)
plt.title("Accuracy")
plt.legend(shadow=True, frameon=True, fancybox=True, title='DFs',
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
ax = plt.subplot(212)
classification_comparison.xs('SD', axis=1, level='values').plot( ax=ax)
plt.title("Standard Deviation")
plt.xlabel("Classifcation Algorithms")
plt.legend(shadow=True, frameon=True, fancybox=True, title='DFs',
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
```



[ ]:
```
classification_comparison.T.max()
```

[ ]:
```
LR      0.891
LDA     0.895
KNN     0.890
CART    0.888
NB      0.841
SVM     0.887
XGB     0.904
dtype: float64
```

[ ]:
```
classification_comparison.T['CART']
```

[ ]:
```
DFs          values
1_DBSCAN_df  Acc       0.869
             SD        0.082
2_IF_df      Acc       0.880
             SD        0.047
3_MCD_df     Acc       0.850
             SD        0.065
4_LOF_df     Acc       0.862
             SD        0.064
5_OCSVM_df   Acc       0.888
             SD        0.065
Name: CART, dtype: float64
```

[ ]:
```
classification_comparison.T['XGB']
```

[ ]:
```
DFs          values
1_DBSCAN_df  Acc       0.897
             SD        0.069
2_IF_df      Acc       0.896
             SD        0.057
3_MCD_df     Acc       0.886
             SD        0.044
4_LOF_df     Acc       0.904
             SD        0.074
5_OCSVM_df   Acc       0.892
             SD        0.060
Name: XGB, dtype: float64
```

[ ]:
```
Outlier=classification_comparison.T.max()
```

[ ]:
```
methods_comparison['Outlier']= Outlier
methods_comparison
```

[ ]:
```
      FIll_NaN  Add_F  Outlier
LR       0.786  0.765    0.891
LDA      0.790  0.767    0.895
```

```
KNN       0.817  0.757    0.890
CART      0.880  0.724    0.888
NB        0.780  0.746    0.841
SVM       0.850  0.760    0.887
XGB       0.889  0.785    0.904
```

8.7 Selected Outlier Algorithm DF

The best Outlier Algorithm is Local Outlier Factor, so it performed on the data.

[ ]:
```
df= Local_Outlier_Factor_df
```

[ ]:
```
df['class'].value_counts()
```

[ ]:
```
0    456
1    240
Name: class, dtype: int64
```

9 4. Feature Selection Methods Comparison

9.1 1. Removing features with low variance

VarianceThreshold is a simple baseline approach to feature selection. It removes all features whose variance doesn't meet some threshold. By default, it removes all zero-variance features, i.e. features that have the same value in all samples.*italicised text*

[ ]:
```
df.var().nlargest(20)
```

[ ]:
```
insu              6739.204056
plas               882.869127
age                129.165945
pres_mm            118.224352
skin_mm             64.182265
BMI                 42.363108
preg                11.016919
Normal               0.239938
Obese                0.236796
diabetic_p           0.235070
class                0.226247
pre_diabetic_p       0.220590
diabetic             0.207492
Normal_p             0.189909
Overweight           0.178068
Healthy_weight       0.104085
DPF                  0.100794
pre_diabetic         0.084791
Underweight          0.015577
dtype: float64
```

```python
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
print(all_inputs.shape)

from sklearn.feature_selection import VarianceThreshold
sel = VarianceThreshold(threshold= 0.104085)
all_inputs = sel.fit_transform(all_inputs)
print(all_inputs.shape)
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_1 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_1 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_1.append(cv_results_1)
    names.append(name)
    print(f"{name}, {cv_results_1.mean()}, {cv_results_1.std()}))")
```

```
(696, 18)
(696, 14)
LR, 0.862037037037037, 0.06597345014640185))
LDA, 0.8618945868945869, 0.07555832044504261))
KNN, 0.8582621082621082, 0.0759855017679339))
CART, 0.8413105413105415, 0.07110445627784064))
NB, 0.8447293447293449, 0.06945960094664742))
SVM, 0.8773504273504272, 0.08218138723352486))
XGB, 0.8984330484330485, 0.06469354046681688))
```

Univariate Feature Selection

9.2 2. UFS SelectKBest Select K Best

it removes all but the highest scoring features

```python
all_inputs = df[df.columns[0:-1]].values
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler()
all_inputs = sc.fit_transform(all_inputs)
all_labels = df['class'].values
print(all_inputs.shape)
```

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

all_inputs = SelectKBest(chi2, k=15).fit_transform(all_inputs, all_labels)
print(all_inputs.shape)
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_2 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_2 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_2.append(cv_results_2)
    names.append(name)
    print(f"{name}, {cv_results_2.mean()}, {cv_results_2.std()}))")
```

```
(696, 18)
(696, 15)
LR, 0.8619658119658119, 0.06138411185508111))
LDA, 0.8734330484330485, 0.06463105191758405))
KNN, 0.8560541310541311, 0.07311658592755686))
CART, 0.861894586894587, 0.06727278674035306))
NB, 0.6435185185185184, 0.08472835202709286))
SVM, 0.8657407407407408, 0.07563804110411428))
XGB, 0.9041310541310541, 0.06387280762652076))
```

9.3 3. UFSSelectFpr‘ False Positive Rate test.

Filter: Select the p values below alpha based on a FPR test. a smaller p-value bears more significance as it can tell you that the hypothesis may not explain the observation fairly. If one or more of these probabilities turn out to be less than or equal to , the level of significance, we reject the null hypothesis. For a true null hypothesis, p can take on any value between 0 and 1 with equal likeliness. For a true alternative hypothesis, p-values likely fall closer to 0.

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
sc = MinMaxScaler()
all_inputs = sc.fit_transform(all_inputs)
all_labels = df['class'].values
from sklearn.feature_selection import SelectFpr, chi2
all_inputs = SelectFpr(chi2, alpha= 0.09
                       ).fit_transform(all_inputs, all_labels)
```

```
print(all_inputs.shape)
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_3 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_3 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_3.append(cv_results_3)
    names.append(name)
    print(f"{name}, {cv_results_3.mean()}, {cv_results_3.std()}))")
```

```
(696, 16)
LR, 0.8677350427350428, 0.05641326900643618))
LDA, 0.8733618233618234, 0.06583277504291998))
KNN, 0.8447293447293449, 0.06729619733314672))
CART, 0.8527065527065527, 0.07052418683031295))
NB, 0.6684472934472934, 0.08571531178496568))
SVM, 0.8753561253561255, 0.07497872415709027))
XGB, 0.8983618233618234, 0.06592114099112054))
```

9.4 4. Feature selection using SelectFromModel

9.4.1 L1-based feature selection

Linear models penalized with the L1 norm have sparse solutions: many of their estimated coefficients are zero. When the goal is to reduce the dimensionality of the data to use with another classifier, they can be used along with SelectFromModel to select the non-zero coefficients. In particular, sparse estimators useful for this purpose are the Lasso for regression, and of LogisticRegression and LinearSVC for classification:

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
sc = StandardScaler()
all_inputs = sc.fit_transform(all_inputs)
all_labels = df['class'].values

from sklearn.svm import LinearSVC
from sklearn.feature_selection import SelectFromModel

lsvc = LinearSVC(C=.09 , penalty="l1", dual=False).fit(all_inputs, all_labels)
model = SelectFromModel(lsvc, prefit=True)
```

```
all_inputs = model.transform(all_inputs)
print(all_inputs.shape)

from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_4 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_4 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_4.append(cv_results_4)
    names.append(name)
    print(f"{name}, {cv_results_4.mean()}, {cv_results_4.std()}))")
```

```
(696, 14)
LR, 0.8716524216524217, 0.057349054491092656))
LDA, 0.8753561253561255, 0.05958861601904569))
KNN, 0.8657407407407408, 0.06845151790492156))
CART, 0.8467948717948717, 0.06182643886679986))
NB, 0.8504985754985755, 0.07195561951720005))
SVM, 0.865883190883191, 0.07546399654292588))
XGB, 0.9061253561253562, 0.05633700530500054))
```

9.5 5. Sequential Feature Selection

(Selecting features based on importance) The features with the highest absolute coef_ value are considered the most important.

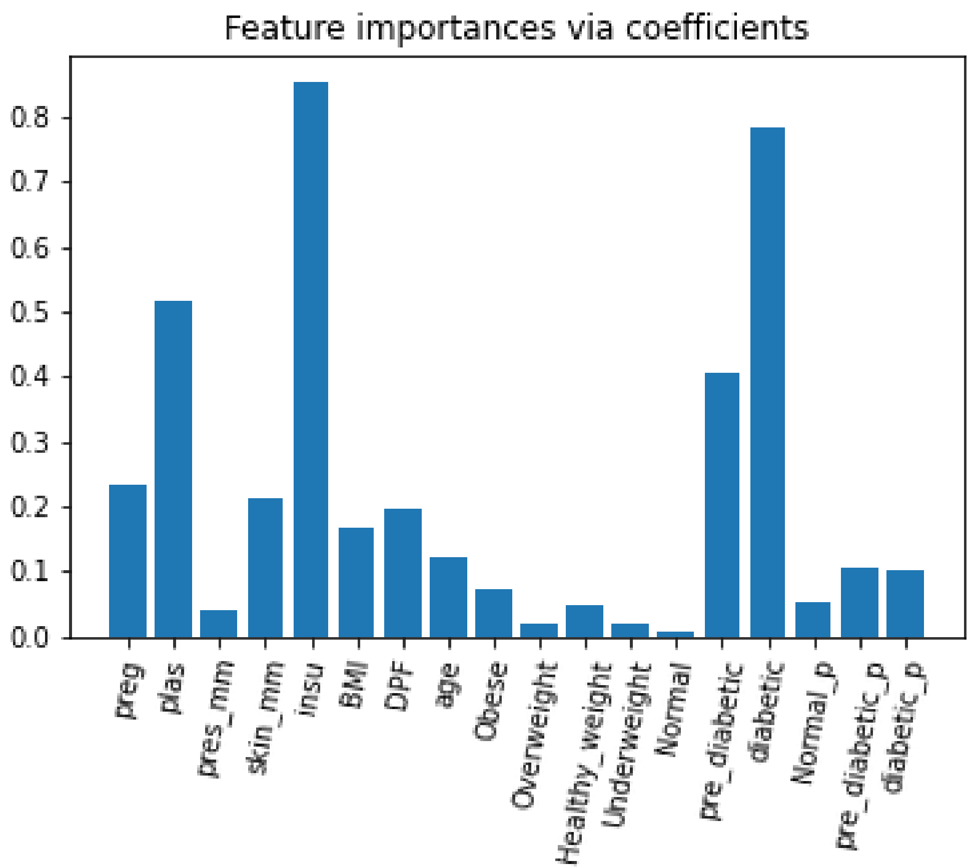
[ ]:
```
all_inputs = df[df.columns[0:-1]].values
sc = StandardScaler()
all_inputs = sc.fit_transform(all_inputs)
all_labels = df['class'].values
all_inputs.shape
```

[ ]:
```
(696, 18)
```

Feature importance from coefficients

[ ]:
```
from sklearn.linear_model import LassoCV
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler()
all_inputs = sc.fit_transform(all_inputs)
```

```
lasso = LassoCV().fit(all_inputs, all_labels)
importance = np.abs(lasso.coef_)
feature_names = np.array(all_labels)
plt.bar(height=importance, x=df.columns[0:-1])
plt.xticks(rotation=80)
plt.title("Feature importances via coefficients")
plt.show()
```



[ ]:
```
np.sort(importance)
```

[ ]:
```
array([0.00516833, 0.01704968, 0.01878721, 0.03886262, 0.04583879,
       0.05275003, 0.0706723 , 0.10114942, 0.10380875, 0.12037679,
       0.1681799 , 0.19411578, 0.21222111, 0.23328783, 0.40594585,
       0.51628021, 0.78462425, 0.85159204])
```

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
sc = MinMaxScaler()
all_inputs = sc.fit_transform(all_inputs)
all_labels = df['class'].values
print(all_inputs.shape)
```

```python
from sklearn.feature_selection import SelectFromModel

threshold = 0.03886262

sfm = SelectFromModel(lasso, threshold=threshold).fit(all_inputs, all_labels)
selected_Features = df.columns[:-1][sfm.get_support()]
print("Features selected by SelectFromModel: ",
      f"{df.columns[0:-1][sfm.get_support()]}")


all_inputs = df[selected_Features].values
all_labels = df['class'].values
print(all_inputs.shape)
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_5 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_5 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_5.append(cv_results_5)
    names.append(name)
    print(f"{name}, {cv_results_5.mean()}, {cv_results_5.std()}))")
```

```
(696, 18)
Features selected by SelectFromModel:  Index(['preg', 'plas', 'skin_mm', 'insu',
'BMI', 'DPF', 'age', 'Obese',
       'Healthy_weight', 'pre_diabetic', 'diabetic', 'Normal_p',
       'pre_diabetic_p', 'diabetic_p'],
      dtype='object')
(696, 14)
LR, 0.8735042735042736, 0.05453552591347405))
LDA, 0.8752849002849004, 0.06089218750812922))
KNN, 0.8428062678062679, 0.06207995349260721))
CART, 0.8544159544159544, 0.061490959824290425))
NB, 0.8141737891737891, 0.08181584589396765))
SVM, 0.8772079772079773, 0.07476067936357167))
XGB, 0.9061253561253559, 0.05890429657420025))
```

9.6 6. Principal Component Analysis

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
all_labels = df['class'].values
all_inputs.shape
```

[ ]: (696, 18)

[ ]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components= 12)
pca.fit(all_inputs)
```

[ ]:
```
PCA(copy=True, iterated_power='auto', n_components=12, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

[ ]:
```
print(pca.explained_variance_)
```

```
[6.99890877e+03 6.54746066e+02 1.52460758e+02 9.32832577e+01
 6.02073986e+01 2.07172485e+01 7.41590680e+00 3.10281425e-01
 2.16565656e-01 1.61184212e-01 1.22365951e-01 9.54000208e-02]
```

[ ]:
```
all_inputs = pca.transform(all_inputs)
all_inputs.shape
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_6 = []
names = []
seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_6 = cross_val_score(model, X_train, y_train, cv=kfold,           ␣
 ↪scoring='accuracy')
    results_6.append(cv_results_6)
    names.append(name)
    print(f"{name}, {cv_results_6.mean()}, {cv_results_6.std()}))")
```

```
LR, 0.8620370370370372, 0.054964854020312))
LDA, 0.8619658119658121, 0.06498115844858557))
KNN, 0.8619658119658121, 0.0725124397045091))
CART, 0.817877492877493, 0.09005764588838602))
NB, 0.8486467236467238, 0.0670679642257839))
SVM, 0.8715099715099717, 0.07539045098468716))
XGB, 0.8563390313390314, 0.08044621919946748))
```

9.7 Classification Comparison of Feature Selection Methods

```
[ ]: classification_comparison= pd.DataFrame(index=[i for i in names])
```

```
[ ]: dfresults = pd.DataFrame(results_1)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy']= df_mean
classification_comparison['sd']= df_sd
```

```
[ ]: dfresults = pd.DataFrame(results_2)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_2']= df_mean
classification_comparison['sd_2']= df_sd
```

```
[ ]: dfresults = pd.DataFrame(results_3)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
```

```
    df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_3']= df_mean
classification_comparison['sd_3']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_4)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
    d= dfresults[i].mean()
    df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
    n= dfresults[i].std()
    df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_4']= df_mean
classification_comparison['sd_4']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_5)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
    d= dfresults[i].mean()
    df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
    n= dfresults[i].std()
    df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_5']= df_mean
classification_comparison['sd_5']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_6)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
    d= dfresults[i].mean()
    df_mean.append(d)
```

```
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_6']= df_mean
classification_comparison['sd_6']= df_sd
```

[ ]:
```
values= ['Acc', 'SD']
```

[ ]:
```
FS_Methods=['1_RFLVar', '2_UFSKBest','3_UFSFpr',
     '4_FSU', '5_SFS', '6_PCA']
```

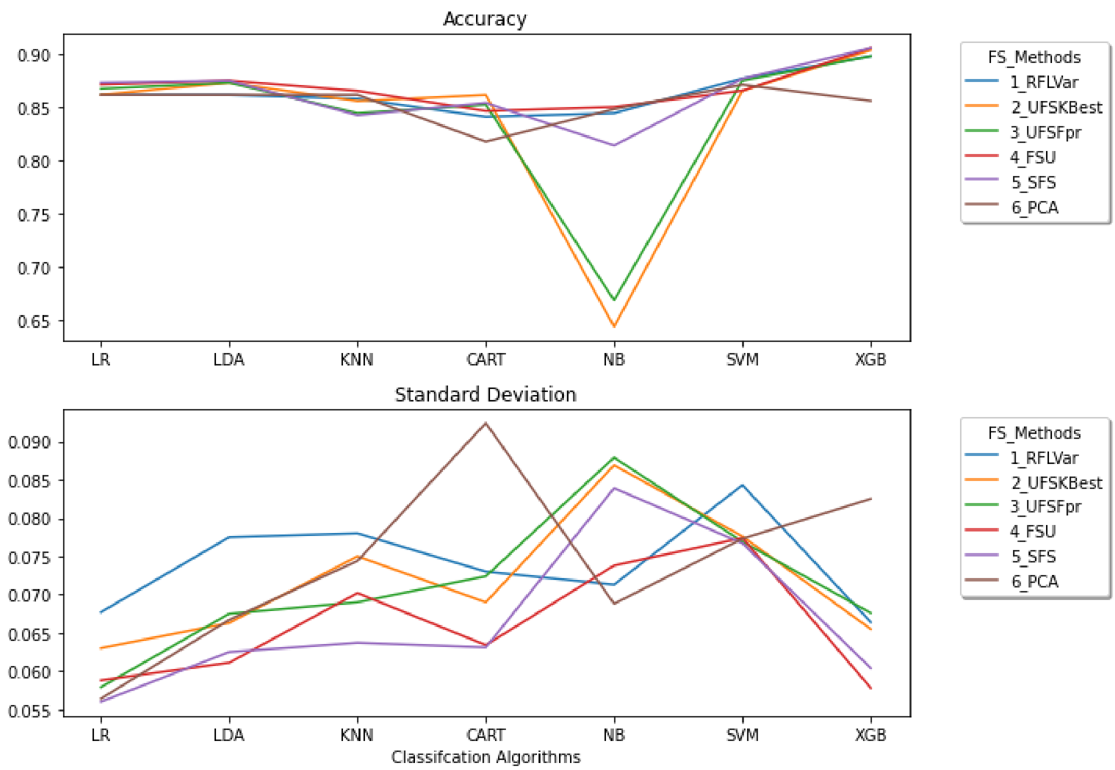
[ ]:
```
idx = pd.MultiIndex.from_product([FS_Methods, values],
                                 names=['FS_Methods', 'values'])

classification_comparison.columns = idx
classification_comparison
```

[ ]:
```
FS_Methods 1_RFLVar         2_UFSKBest          ...    5_SFS             6_PCA
values          Acc      SD        Acc      SD  ...      Acc      SD      Acc
SD
LR           0.8620  0.0677     0.8620  0.0630  ...   0.8735  0.0560   0.8620
0.0564
LDA          0.8619  0.0775     0.8734  0.0663  ...   0.8753  0.0625   0.8620
0.0667
KNN          0.8583  0.0780     0.8561  0.0750  ...   0.8428  0.0637   0.8620
0.0744
CART         0.8413  0.0730     0.8619  0.0690  ...   0.8544  0.0631   0.8179
0.0924
NB           0.8447  0.0713     0.6435  0.0869  ...   0.8142  0.0839   0.8486
0.0688
SVM          0.8774  0.0843     0.8657  0.0776  ...   0.8772  0.0767   0.8715
0.0773
XGB          0.8984  0.0664     0.9041  0.0655  ...   0.9061  0.0604   0.8563
0.0825

[7 rows x 12 columns]
```

[ ]:
```
classification_comparison.to_csv('Classification Comparison of Feature␣
 ↪Selection Methods.csv', index= False)
```

[ ]:
```
plt.figure(figsize=(10,7))
ax = plt.subplot(211)
classification_comparison.xs('Acc', axis=1, level='values').plot( ax=ax)
plt.title("Accuracy")
plt.legend(shadow=True, frameon=True, fancybox=True, title='FS_Methods',␣
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
ax = plt.subplot(212)
```

```
classification_comparison.xs('SD', axis=1, level='values').plot( ax=ax)
plt.title("Standard Deviation")
plt.xlabel("Classifcation Algorithms")
plt.legend(shadow=True, frameon=True, fancybox=True, title='FS_Methods',␣
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
```



[ ]:
```
classification_comparison.T.max()
```

[ ]:
```
LR      0.8735
LDA     0.8754
KNN     0.8657
CART    0.8619
NB      0.8505
SVM     0.8774
XGB     0.9061
dtype: float64
```

[ ]:
```
Feature =classification_comparison.T.max()
```

[ ]:
```
classification_comparison.T['XGB']
```

[ ]:
```
FS_Methods  values
1_RFLVar    Acc       0.8984
            SD        0.0664
```

```
2_UFSKBest  Acc       0.9041
            SD        0.0655
3_UFSFpr    Acc       0.8984
            SD        0.0676
4_FSU       Acc       0.9061
            SD        0.0578
5_SFS       Acc       0.9061
            SD        0.0604
6_PCA       Acc       0.8563
            SD        0.0825
Name: XGB, dtype: float64
```

[ ]:
```
classification_comparison.T['CART']
```

[ ]:
```
FS_Methods  values
1_RFLVar    Acc       0.8413
            SD        0.0730
2_UFSKBest  Acc       0.8619
            SD        0.0690
3_UFSFpr    Acc       0.8527
            SD        0.0724
4_FSU       Acc       0.8468
            SD        0.0634
5_SFS       Acc       0.8544
            SD        0.0631
6_PCA       Acc       0.8179
            SD        0.0924
Name: CART, dtype: float64
```

[ ]:
```
methods_comparison['Feature']= Feature
methods_comparison
```

[ ]:
```
      FIll_NaN  Add_F  Outlier  Feature
LR       0.786  0.765    0.891   0.8735
LDA      0.790  0.767    0.895   0.8754
KNN      0.817  0.757    0.890   0.8657
CART     0.880  0.724    0.888   0.8619
NB       0.780  0.746    0.841   0.8505
SVM      0.850  0.760    0.887   0.8774
XGB      0.889  0.785    0.904   0.9061
```

The max accuracy was by using Select From Model

9.8 Selected Feature

[ ]:
```
all_inputs = df[df.columns[0:-1]].values
sc = StandardScaler()
all_inputs = sc.fit_transform(all_inputs)
all_labels = df['class'].values
```

```
from sklearn.svm import LinearSVC
from sklearn.feature_selection import SelectFromModel

lsvc = LinearSVC(C=.09 , penalty="l1", dual=False).fit(all_inputs, all_labels)
model = SelectFromModel(lsvc, prefit=True)
all_inputs = model.transform(all_inputs)
print(all_inputs.shape)

from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1)
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_4 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_4 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_4.append(cv_results_4)
    names.append(name)
    print(f"{name}, {cv_results_4.mean()}, {cv_results_4.std()}))")
```

```
(696, 14)
LR, 0.8716524216524217, 0.05734905449109265 6))
LDA, 0.8753561253561255, 0.05958861601904569))
KNN, 0.8657407407407408, 0.06845151790492156))
CART, 0.8467948717948717, 0.06182643886679986))
NB, 0.8504985754985755, 0.07195561951720005))
SVM, 0.865883190883191, 0.07546399654292588))
XGB, 0.9061253561253562, 0.05633700530500054))
```

[ ]:
```
df.shape
```

[ ]:
```
(696, 15)
```

10 5. Imbalanced Correction Methods

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
pd.value_counts(df['class'])
```

[ ]:
```
0    456
1    240
```

```
Name: class, dtype: int64
```

```
[ ]: all_inputs.shape
```

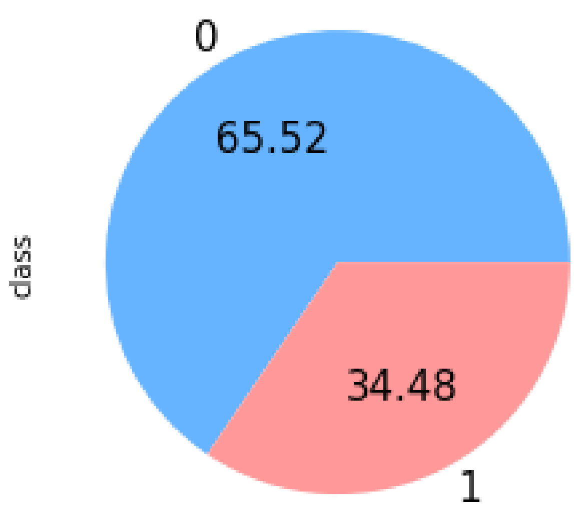
```
[ ]: (696, 14)
```

```
[ ]: from sklearn.utils.class_weight import compute_class_weight
     class_weights = compute_class_weight('balanced', np.unique(all_labels),␣
      ↪all_labels)
     print(class_weights)
```

```
[0.76315789 1.45      ]
```

```
[ ]: pd.value_counts(df['class']).plot(kind='pie', autopct='%.2f',fontsize=15,␣
      ↪colors= ['#66b3ff','#ff9999'])
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fcadb549550>
```



10.1 1. SMOTE

```
[ ]: all_inputs = df[df.columns[:-1]].values
     all_labels = df['class'].values
     pd.value_counts(df['class'])
```

```
[ ]: 0    456
     1    240
     Name: class, dtype: int64
```

[ ]:
```python
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
all_inputs, all_labels = oversample.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/externals/six.py:31:
FutureWarning: The module is deprecated in version 0.21 and will be removed in
version 0.23 since we've dropped support for Python 2.7. Please rely on the
official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:144:
FutureWarning: The sklearn.neighbors.base module is  deprecated in version 0.22
and will be removed in version 0.24. The corresponding classes / functions
should instead be imported from sklearn.neighbors. Anything that cannot be
imported from sklearn.neighbors is now part of the private API.
  warnings.warn(message, FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
1    456
0    456
dtype: int64
```

[ ]:
```python
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_1 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_1 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_1.append(cv_results_1)
    names.append(name)
    print(f"{name}, {cv_results_1.mean()}, {cv_results_1.std()}))")
```

```
LR, 0.864327731092437, 0.07061647844343612))
LDA, 0.852563025210084, 0.07573870608521982))
KNN, 0.8803781512605042, 0.0689722359962584))
CART, 0.8847058823529412, 0.04496434416635351))
```

```
NB, 0.8264285714285714, 0.0796771941301821))
SVM, 0.8571428571428571, 0.08050885058768605))
XGB, 0.9139075630252099, 0.05052403517213921))
```

10.2 2. Border line SMOTE

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
pd.value_counts(df['class'])
```

[ ]:
```
0    456
1    240
Name: class, dtype: int64
```

[ ]:
```
from imblearn.over_sampling import BorderlineSMOTE
oversample = BorderlineSMOTE()
all_inputs, all_labels = oversample.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
1    456
0    456
dtype: int64
```

[ ]:
```
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_2 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
```

```
    cv_results_2 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_2.append(cv_results_2)
    names.append(name)
    print(f"{name}, {cv_results_2.mean()}, {cv_results_2.std()}))")
```

```
LR, 0.8405882352941176, 0.06742518025605315))
LDA, 0.8333613445378152, 0.06235107247647126 6))
KNN, 0.8538655462184874, 0.07252003465854545))
CART, 0.8775630252100839, 0.0659260166576104))
NB, 0.8189495798319328, 0.06368865097025407))
SVM, 0.8744117647058822, 0.05982666568734233))
XGB, 0.9270588235294115, 0.03943281228312503))
```

10.3 3. SVM SMOTE

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
pd.value_counts(all_labels)
```

[ ]:
```
0    456
1    240
dtype: int64
```

[ ]:
```
from imblearn.over_sampling import SVMSMOTE
oversample = SVMSMOTE()
all_inputs, all_labels = oversample.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
```

```
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
1    456
0    456
dtype: int64
```

[ ]:
```
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_3 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_3 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_3.append(cv_results_3)
    names.append(name)
    print(f"{name}, {cv_results_3.mean()}, {cv_results_3.std()}))")
```

```
LR, 0.8568487394957984, 0.0632914683906705))
LDA, 0.8466386554621849, 0.052723642715918145))
KNN, 0.8670168067226891, 0.05101184696196572))
CART, 0.8876050420168067, 0.04973474942606156))
NB, 0.8190336134453782, 0.07572276088325611))
SVM, 0.8656302521008403, 0.06492808078200309))
XGB, 0.9227310924369746, 0.049563075789801826))
```

10.4 4. Adaptive Synthetic Sampling (ADASYN)

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
pd.value_counts(all_labels)
```

[ ]:
```
0    456
1    240
dtype: int64
```

[ ]:
```
from imblearn.over_sampling import ADASYN
oversample = ADASYN(random_state=42)
all_inputs, all_labels = oversample.fit_resample(all_inputs, all_labels)
```

```
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
1    463
0    456
dtype: int64
```

[ ]:
```
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_4 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_4 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_4.append(cv_results_4)
    names.append(name)
    print(f"{name}, {cv_results_4.mean()}, {cv_results_4.std()}))")
```

```
LR, 0.8057142857142857, 0.060236100684876004))
LDA, 0.7881512605042017, 0.05399177647682829))
KNN, 0.8735714285714286, 0.059343128313607926))
CART, 0.8809663865546218, 0.04492795274422015))
NB, 0.7763025210084035, 0.0543214753298728))
SVM, 0.8603361344537817, 0.05325013223997295))
XGB, 0.9173949579831933, 0.04475537476515333))
```

10.5 5. Random Over Sampler

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
pd.value_counts(all_labels)
```

[ ]:
```
0    456
1    240
dtype: int64
```

```python
from imblearn.over_sampling import RandomOverSampler
oversample = RandomOverSampler(sampling_strategy='minority')
all_inputs, all_labels = oversample.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

```
1    456
0    456
dtype: int64
```

```python
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels, test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_5 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_5 = cross_val_score(model, X_train, y_train, cv=kfold, scoring='accuracy')
    results_5.append(cv_results_5)
    names.append(name)
    print(f"{name}, {cv_results_5.mean()}, {cv_results_5.std()}))")
```

```
LR, 0.8773949579831932, 0.05463988066938839))
LDA, 0.8729831932773108, 0.0561532418364705455))
KNN, 0.8641596638655462, 0.06511888006068071))
CART, 0.9124369747899159, 0.04493213739132524))
NB, 0.8277731092436975, 0.06759065188336488))
SVM, 0.8788655462184873, 0.05422237569869624))
XGB, 0.9372268907563024, 0.05165921533119705))
```

10.6 6. Random Under Sampler

```python
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
pd.value_counts(all_labels)
```

```
0    456
1    240
```

```
dtype: int64
```

[ ]:
```
from imblearn.under_sampling import RandomUnderSampler
undersample = RandomUnderSampler()
all_inputs, all_labels = undersample.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
1    240
0    240
dtype: int64
```

[ ]:
```
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler( )
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_6 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_6 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_6.append(cv_results_6)
    names.append(name)
    print(f"{name}, {cv_results_6.mean()}, {cv_results_6.std()}))")
```

```
LR, 0.8388888888888889, 0.08940820521906158))
LDA, 0.8388888888888889, 0.09606453592105879))
KNN, 0.8194444444444444, 0.08216777476527243))
CART, 0.8416666666666668, 0.09005313931915183))
NB, 0.8111111111111111, 0.09196080754026026))
SVM, 0.8472222222222223, 0.07632573146685602))
XGB, 0.8694444444444445, 0.07301910793386061))
```

10.7 7. Combining Random Oversampling and Undersampling

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
pd.value_counts(all_labels)
```

[ ]:
```
0    456
1    240
dtype: int64
```

[ ]:
```
under = RandomUnderSampler(sampling_strategy=.7)
all_inputs, all_labels = under.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
0    342
1    240
dtype: int64
```

[ ]:
```
over = RandomOverSampler()
all_inputs, all_labels = over.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
1    342
0    342
dtype: int64
```

[ ]:
```
from sklearn.model_selection import train_test_split
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1, stratify= all_labels  )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

results_7 = []; names = []; seed=42
for name, model in models:
    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    cv_results_7 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_7.append(cv_results_7)
    names.append(name)
    print(f"{name}, {cv_results_7.mean()}, {cv_results_7.std()}))")
```

```
LR, 0.8576923076923076, 0.07534300264349224))
LDA, 0.8537692307692308, 0.07913508037997789))
KNN, 0.8261538461538462, 0.07429670248402684))
CART, 0.8772307692307691, 0.06310055842362079))
NB, 0.8206153846153846, 0.08142139637086955))
SVM, 0.8516923076923077, 0.07258604361590905))
XGB, 0.8944615384615385, 0.07443896669966349))
```

10.8 Classification Comparison of Feature Selection Methods

[ ]:
```
classification_comparison= pd.DataFrame(index=[i for i in names])
```

[ ]:
```
dfresults = pd.DataFrame(results_1)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy']= df_mean
classification_comparison['sd']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_2)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_2']= df_mean
classification_comparison['sd_2']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_3)
dfresults=dfresults.T
```

```
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_3']= df_mean
classification_comparison['sd_3']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_4)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_4']= df_mean
classification_comparison['sd_4']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_5)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_5']= df_mean
classification_comparison['sd_5']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_6)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_6']= df_mean
classification_comparison['sd_6']= df_sd
```

[ ]:
```
dfresults = pd.DataFrame(results_7)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy_7']= df_mean
classification_comparison['sd_7']= df_sd
```

[ ]:
```
values= ['Acc', 'SD']
```

[ ]:
```
FS_Methods=['1_SMOTE', '2_BL-SMOTE','3_SVM-SMOTE',
     '4_ADASYN', '5_ROS', '6_RUS', '7_CR(O-U)S']
```

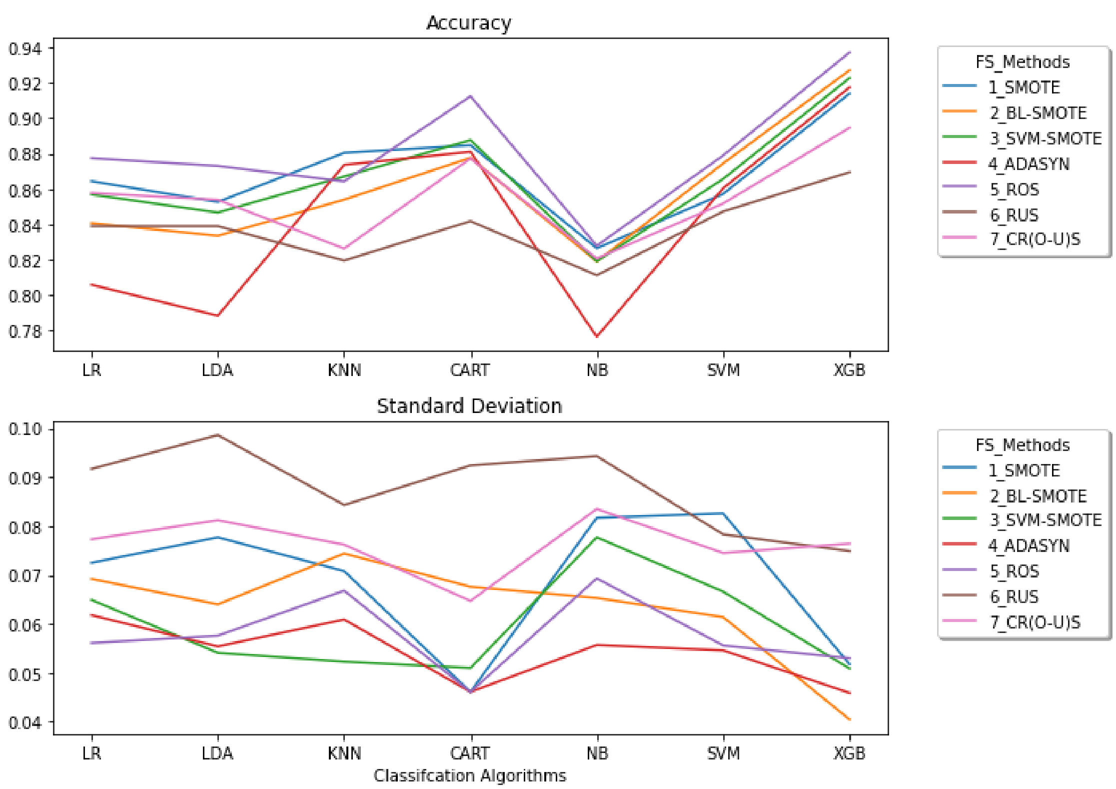
[ ]:
```
idx = pd.MultiIndex.from_product([FS_Methods, values],
                                  names=['FS_Methods', 'values'])

classification_comparison.columns = idx
classification_comparison
```

[ ]:
```
FS_Methods 1_SMOTE         2_BL-SMOTE  ...   6_RUS 7_CR(O-U)S
values         Acc      SD        Acc  ...      SD        Acc      SD
LR          0.8643  0.0725     0.8406  ...  0.0917     0.8577  0.0773
LDA         0.8526  0.0777     0.8334  ...  0.0986     0.8538  0.0812
```

```
KNN        0.8804  0.0708    0.8539  ...  0.0843    0.8262  0.0762
CART       0.8847  0.0461    0.8776  ...  0.0924    0.8772  0.0647
NB         0.8264  0.0817    0.8189  ...  0.0943    0.8206  0.0835
SVM        0.8571  0.0826    0.8744  ...  0.0783    0.8517  0.0745
XGB        0.9139  0.0518    0.9271  ...  0.0749    0.8945  0.0764

[7 rows x 14 columns]
```

[ ]:
```
classification_comparison.to_csv('Classification Comparison of Feature␣
 ↪Selection Methods.csv', index= False)
```

[ ]:
```
plt.figure(figsize=(10,7))
ax = plt.subplot(211)
classification_comparison.xs('Acc', axis=1, level='values').plot( ax=ax)
plt.title("Accuracy")
plt.legend(shadow=True, frameon=True, fancybox=True, title='FS_Methods',␣
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
ax = plt.subplot(212)
classification_comparison.xs('SD', axis=1, level='values').plot( ax=ax)
plt.title("Standard Deviation")
plt.xlabel("Classifcation Algorithms")
plt.legend(shadow=True, frameon=True, fancybox=True, title='FS_Methods',␣
 ↪bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
```



[ ]:
```
classification_comparison.T.max()
```

[ ]:
```
LR      0.8774
LDA     0.8730
KNN     0.8804
CART    0.9124
NB      0.8278
SVM     0.8789
XGB     0.9372
dtype: float64
```

[ ]:
```
Imbalance= classification_comparison.T.max()
```

[ ]:
```
classification_comparison.T['CART']
```

[ ]:
```
FS_Methods   values
1_SMOTE      Acc       0.8847
             SD        0.0461
2_BL-SMOTE   Acc       0.8776
             SD        0.0676
3_SVM-SMOTE  Acc       0.8876
             SD        0.0510
4_ADASYN     Acc       0.8810
             SD        0.0461
5_ROS        Acc       0.9124
             SD        0.0461
6_RUS        Acc       0.8417
             SD        0.0924
7_CR(O-U)S   Acc       0.8772
             SD        0.0647
Name: CART, dtype: float64
```

[ ]:
```
classification_comparison.T['XGB']
```

[ ]:
```
FS_Methods   values
1_SMOTE      Acc       0.9139
             SD        0.0518
2_BL-SMOTE   Acc       0.9271
             SD        0.0405
3_SVM-SMOTE  Acc       0.9227
             SD        0.0509
4_ADASYN     Acc       0.9174
             SD        0.0459
5_ROS        Acc       0.9372
             SD        0.0530
6_RUS        Acc       0.8694
             SD        0.0749
7_CR(O-U)S   Acc       0.8945
             SD        0.0764
```

```
Name: XGB, dtype: float64
```

[ ]:
```
methods_comparison['Imbalance']= Imbalance
methods_comparison
```

[ ]:

	FIll_NaN	Add_F	Outlier	Feature	Imbalance
LR	0.786	0.765	0.891	0.8735	0.8774
LDA	0.790	0.767	0.895	0.8754	0.8730
KNN	0.817	0.757	0.890	0.8657	0.8804
CART	0.880	0.724	0.888	0.8619	0.9124
NB	0.780	0.746	0.841	0.8505	0.8278
SVM	0.850	0.760	0.887	0.8774	0.8789
XGB	0.889	0.785	0.904	0.9061	0.9372

10.9 Selected imbalance mehods

The max accuracy was by using Random Over Sampler

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values
all_inputs.shape
```

[ ]:
```
(696, 14)
```

[ ]:
```
from imblearn.over_sampling import BorderlineSMOTE
oversample = BorderlineSMOTE()
all_inputs, all_labels = oversample.fit_resample(all_inputs, all_labels)
pd.value_counts(all_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
1    456
0    456
dtype: int64
```

11 Step 5: Building the classifier

11.1 1. XGBoost Classifier

11.1.1 Hyperparameter Randomized Search CV

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import StratifiedKFold

params = {
        'min_child_weight': [1, 5, 10],
        'gamma': [0.5, 1, 1.5, 2, 5],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [3, 4, 5]
        }
xgb = XGBClassifier(learning_rate=0.02, n_estimators=600, objective='binary:
 ↪logistic',
                    silent=True, nthread=1)

folds = 3
param_comb = 5

skf = StratifiedKFold(n_splits=folds, shuffle = True, random_state = 1001)

random_search = RandomizedSearchCV(xgb, param_distributions=params,
                                   n_iter=param_comb, scoring='roc_auc',
                                   n_jobs=4, cv=skf.
 ↪split(all_inputs,all_labels),
                                   verbose=3, random_state=1001 )
random_search.fit(all_inputs,all_labels)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  15 out of  15 | elapsed:    6.6s finished
```

[ ]:
```
RandomizedSearchCV(cv=<generator object _BaseKFold.split at 0x7fcad356cba0>,
                   error_score=nan,
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.02, max_delta_step=0,
                                           max_depth=3, min_child_weight=1,
                                           missing=None, n_estimators=600,
                                           n_jobs=1, nthread=1,
```

```
                                objective='binary:logist...
                                reg_lambda=1, scale_pos_weight=1,
                                seed=None, silent=True, subsample=1,
                                verbosity=1),
                   iid='deprecated', n_iter=5, n_jobs=4,
                   param_distributions={'colsample_bytree': [0.6, 0.8, 1.0],
                                        'gamma': [0.5, 1, 1.5, 2, 5],
                                        'max_depth': [3, 4, 5],
                                        'min_child_weight': [1, 5, 10],
                                        'subsample': [0.6, 0.8, 1.0]},
                   pre_dispatch='2*n_jobs', random_state=1001, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=3)
```

[ ]:
```
print('\n Best estimator:')
print(random_search.best_estimator_)
print('\n Best normalized gini score for %d-fold search with %d parameter␣
 ↪combinations:' % (folds, param_comb))
print(random_search.best_score_ * 2 - 1)
print('\n Best hyperparameters:')
print(random_search.best_params_)
results = pd.DataFrame(random_search.cv_results_)
results.to_csv('xgb-random-grid-search-results-01.csv', index=False)
```

```
 Best estimator:
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
              learning_rate=0.02, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=None, n_estimators=600, n_jobs=1,
              nthread=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=True, subsample=0.6, verbosity=1)

 Best normalized gini score for 3-fold search with 5 parameter combinations:
0.92321675900277

 Best hyperparameters:
{'subsample': 0.6, 'min_child_weight': 1, 'max_depth': 5, 'gamma': 1.5,
'colsample_bytree': 0.8}
```

11.1.2 Confusion Matrix & Tuning

[ ]:
```
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1)
from sklearn.preprocessing import RobustScaler
sc = RobustScaler()
X_train = sc.fit_transform(X_train)
```

```python
X_test = sc.transform(X_test)

cls = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                    colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
                    learning_rate=0.02, max_delta_step=0, max_depth=5,
                    min_child_weight=1, missing=None, n_estimators=600,␣
 ↪n_jobs=1,
                    nthread=1, objective='binary:logistic', random_state=0,
                    reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                    silent=True, subsample=0.6, verbosity=1)
cls.fit(X_train,y_train)
y_pred = cls.predict(X_test)
print("------- Accuracy --------\n")
print(accuracy_score(y_test,y_pred))
print('---------------------------------------------------------')
print("------- Confusion Matrix --------\n")
print(confusion_matrix(y_test,y_pred))
print("------- Classifcation Report-------- \n")
print(classification_report(y_test,y_pred))
print('---------------------------------------------------------')
```

```
------- Accuracy --------

0.9342105263157895
---------------------------------------------------------
------- Confusion Matrix --------

[[100   6]
 [  9 113]]
------- Classifcation Report--------

              precision    recall  f1-score   support

           0       0.92      0.94      0.93       106
           1       0.95      0.93      0.94       122

    accuracy                           0.93       228
   macro avg       0.93      0.93      0.93       228
weighted avg       0.93      0.93      0.93       228

---------------------------------------------------------
```

[ ]:
```python
XGB=[]
XGB.append(0.934)
```

11.1.3 Preprocessing Methods Comparison

1. Standard Scaler
2. Min Max Scaler
3. Max Abs Scaler
4. Robust Scaler
5. Power Transformer
6. Quantile Transformer (uniform output)
7. Quantile Transformer (Gaussian output)
8. Normalizer

[ ]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import MaxAbsScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import PowerTransformer
from sklearn.preprocessing import QuantileTransformer
from sklearn.preprocessing import Normalizer
scalers = []
scalers.append(('1.SS', StandardScaler()))
scalers.append(('2.MMS', MinMaxScaler()))
scalers.append(('3.MAS', MaxAbsScaler()))
scalers.append(('4.RPS', RobustScaler()))
scalers.append(('5.PT', PowerTransformer()))
scalers.append(('6.QTG', QuantileTransformer()))
scalers.append(('7.QTN', QuantileTransformer(output_distribution='normal')))
scalers.append(('8.NRM', Normalizer()))
```

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values

results_1 = []; names = []; seed=42
for name, scaler in scalers:

    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    model = cls
    cv_results_1 = cross_val_score(model, X_train, y_train, cv=kfold,␣
↪scoring='accuracy')
    results_1.append(cv_results_1)
    names.append(name)
    print(f"{name}, {cv_results_1.mean()}, {cv_results_1.std()}))")
```

```
1.SS, 0.925546218487395, 0.041576176955314443))
2.MMS, 0.927016806722689, 0.040529364721187754))
3.MAS, 0.927016806722689, 0.040529364721187754))
```

```
4.RPS, 0.925546218487395, 0.04157617695531443))
5.PT, 0.927016806722689, 0.040529364721187754))

/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/_data.py:2357:
UserWarning: n_quantiles (1000) is greater than the total number of samples
(684). n_quantiles is set to n_samples.
  % (self.n_quantiles, n_samples))

6.QTG, 0.9299579831932773, 0.039297081894647666))

/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/_data.py:2357:
UserWarning: n_quantiles (1000) is greater than the total number of samples
(684). n_quantiles is set to n_samples.
  % (self.n_quantiles, n_samples))

7.QTN, 0.9299579831932773, 0.039297081894647666))
8.NRM, 0.9197478991596638, 0.05022616738997399))
```

[ ]:

```
classification_comparison= pd.DataFrame(index=[i for i in names])
dfresults = pd.DataFrame(results_1)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy']= df_mean
classification_comparison['sd']= df_sd

classification_comparison
```

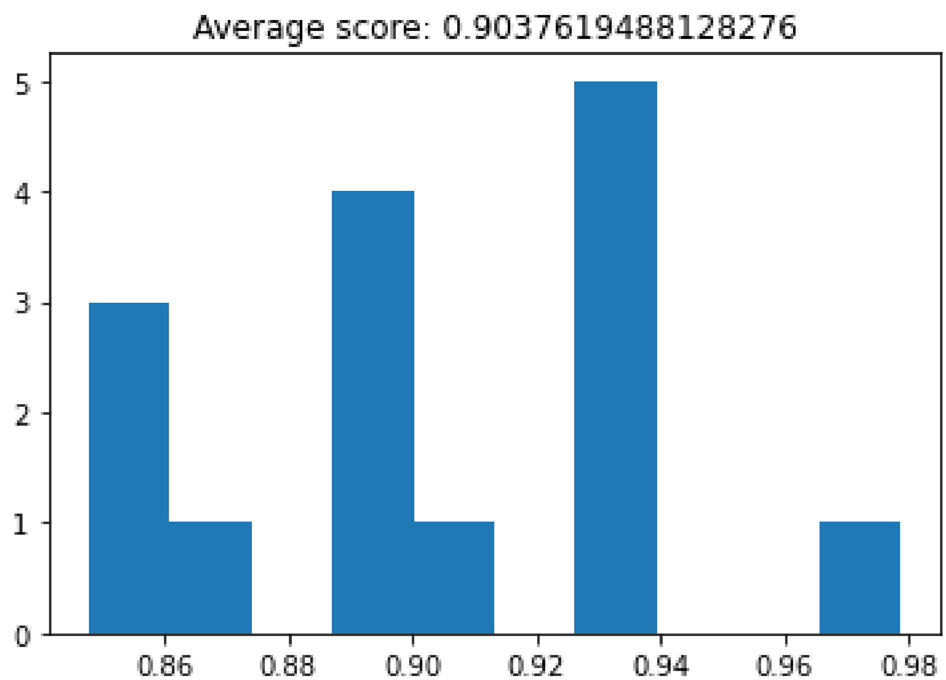
[ ]:

	Accuracy	sd
1.SS	0.9255	0.0427
2.MMS	0.9270	0.0416
3.MAS	0.9270	0.0416
4.RPS	0.9255	0.0427
5.PT	0.9270	0.0416
6.QTG	0.9300	0.0403
7.QTN	0.9300	0.0403
8.NRM	0.9197	0.0515

11.1.4 Cross-validation

[ ]:
```
from sklearn.model_selection import cross_val_score

# cross_val_score returns a list of the scores, which we can visualize
# to get a reasonable estimate of our classifier's performance
cv_scores = cross_val_score(cls, all_inputs, all_labels, cv=15)
plt.hist(cv_scores)
plt.title('Average score: {}'.format(np.mean(cv_scores)))
;
```

[ ]:
```
''
```



[ ]:
```
XGB.append(np.mean(cv_scores).round(3))
XGB
```

[ ]:
```
[0.934, 0.904]
```

11.2 2. Extra Trees Classifier

[ ]:
```
from sklearn.ensemble import ExtraTreesClassifier
```

[ ]:
```
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV

ETC = ExtraTreesClassifier(max_features=13,n_estimators= 520)
```

```
parameter_grid = {

                  'max_leaf_nodes' : [5000,700]}

cross_validation = StratifiedKFold(n_splits=10)

grid_search = GridSearchCV(ETC,
                           param_grid=parameter_grid,
                           cv=cross_validation, n_jobs=4, )

grid_search.fit(all_inputs, all_labels)
print('Best score: {}'.format(grid_search.best_score_))
print('Best parameters: {}'.format(grid_search.best_params_))
```

```
Best score: 0.8907660455486542
Best parameters: {'max_leaf_nodes': 700}
```

11.2.1 Hyperparameter Randomized Search CV

11.2.2 Confusion Matrix

[ ]:
```
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1)
from sklearn.preprocessing import RobustScaler
sc = RobustScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

cls = ExtraTreesClassifier(n_estimators=9, max_features=13,
                           criterion= 'entropy',
                           min_samples_split=3,
                           max_samples= .5, n_jobs=100)
cls.fit(X_train,y_train)
y_pred = cls.predict(X_test)
print("------- Accuracy --------\n")
print(accuracy_score(y_test,y_pred))
print('--------------------------------------------------------')
print("------- Confusion Matrix --------\n")
print(confusion_matrix(y_test,y_pred))
print("------- Classifcation Report-------- \n")
print(classification_report(y_test,y_pred))
print('--------------------------------------------------------')
```

```
------- Accuracy --------

0.8735632183908046
--------------------------------------------------------
```

```
------- Confusion Matrix --------

[[101   9]
 [ 13  51]]
------- Classifcation Report--------

              precision    recall  f1-score   support

           0       0.89      0.92      0.90       110
           1       0.85      0.80      0.82        64

    accuracy                           0.87       174
   macro avg       0.87      0.86      0.86       174
weighted avg       0.87      0.87      0.87       174

--------------------------------------------------------
```

[ ]:
```
ETsC=[]
ETsC.append(0.873)
```

11.2.3 Preprocessing Methods Comparison

1. Standard Scaler
2. Min Max Scaler
3. Max Abs Scaler
4. Robust Scaler
5. Power Transformer
6. Quantile Transformer (uniform output)
7. Quantile Transformer (Gaussian output)
8. Normalizer

[ ]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import MaxAbsScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import PowerTransformer
from sklearn.preprocessing import QuantileTransformer
from sklearn.preprocessing import Normalizer
scalers = []
scalers.append(('1.SS', StandardScaler()))
scalers.append(('2.MMS', MinMaxScaler()))
scalers.append(('3.MAS', MaxAbsScaler()))
scalers.append(('4.RPS', RobustScaler()))
scalers.append(('5.PT', PowerTransformer()))
scalers.append(('6.QTG', QuantileTransformer()))
scalers.append(('7.QTN', QuantileTransformer(output_distribution='normal')))
scalers.append(('8.NRM', Normalizer()))
```

[ ]:
```
all_inputs = df[df.columns[:-1]].values
all_labels = df['class'].values

results_1 = []; names = []; seed=42
for name, scaler in scalers:

    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    kfold = KFold(n_splits=20, random_state=seed, shuffle=True)
    model = cls
    cv_results_1 = cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    results_1.append(cv_results_1)
    names.append(name)
    print(f"{name}, {cv_results_1.mean()}, {cv_results_1.std()}))")
```

```
1.SS, 0.8562678062678064, 0.06428574649529842))
2.MMS, 0.8792735042735043, 0.057460359946266484))
3.MAS, 0.8792735042735043, 0.06472454657741178))
4.RPS, 0.8907407407407406, 0.06121230307312289))
5.PT, 0.8619658119658121, 0.061471651767881295))

/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/_data.py:2357:
UserWarning: n_quantiles (1000) is greater than the total number of samples
(522). n_quantiles is set to n_samples.
  % (self.n_quantiles, n_samples))

6.QTG, 0.8735042735042736, 0.07213746100838564))

/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/_data.py:2357:
UserWarning: n_quantiles (1000) is greater than the total number of samples
(522). n_quantiles is set to n_samples.
  % (self.n_quantiles, n_samples))

7.QTN, 0.8698005698005697, 0.07904943336596147))
8.NRM, 0.8619658119658119, 0.06383276556156207))
```

[ ]:
```
classification_comparison= pd.DataFrame(index=[i for i in names])
dfresults = pd.DataFrame(results_1)
dfresults=dfresults.T
dfresults.columns=names
df_mean=[]
df_sd=[]
for i in dfresults.columns:
  d= dfresults[i].mean()
  df_mean.append(d)
df_mean= [round(num, 4) for num in df_mean]
```

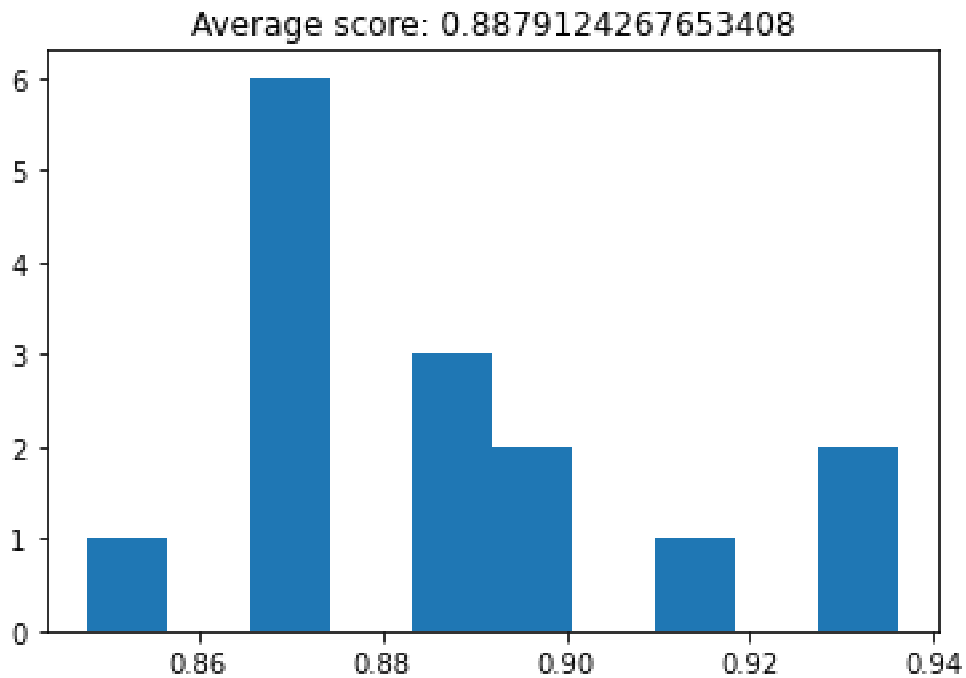
```python
for i in dfresults.columns:
  n= dfresults[i].std()
  df_sd.append(n)
df_sd= [round(num, 4) for num in df_sd]

classification_comparison['Accuracy']= df_mean
classification_comparison['sd']= df_sd

classification_comparison
```

[ ]:
```
        Accuracy      sd
1.SS      0.8563  0.0660
2.MMS     0.8793  0.0590
3.MAS     0.8793  0.0664
4.RPS     0.8907  0.0628
5.PT      0.8620  0.0631
6.QTG     0.8735  0.0740
7.QTN     0.8698  0.0811
8.NRM     0.8620  0.0655
```

11.2.4 Cross-validation

[ ]:
```python
from sklearn.model_selection import cross_val_score

# cross_val_score returns a list of the scores, which we can visualize
# to get a reasonable estimate of our classifier's performance
cv_scores = cross_val_score(cls, all_inputs, all_labels, cv=15)
plt.hist(cv_scores)
plt.title('Average score: {}'.format(np.mean(cv_scores)))
;
```

[ ]: ''



[ ]:
```
ETsC.append(np.mean(cv_scores).round(3))
ETsC
```

[ ]: [0.873, 0.888]

11.3 3. LGBM Classifier

11.3.1 Confusion Matrix & Tuning

[ ]:
```
from lightgbm import LGBMClassifier
```

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV
import lightgbm as lgb

rs_params = {

        'bagging_fraction': (0.5, 0.8),
        'bagging_frequency': (5, 8),

        'feature_fraction': (0.5, 0.8),
        'max_depth': (10, 13),
        'min_data_in_leaf': (90, 120),
        'num_leaves': (1200, 1550)


}
```

```python
lgb = LGBMClassifier()

folds = 3
param_comb = 5

skf = StratifiedKFold(n_splits=folds, shuffle = True, random_state = 1001)

random_search = RandomizedSearchCV(lgb, param_distributions=params,
                                   n_iter=param_comb, scoring='roc_auc',
                                   n_jobs=4, cv=skf.
 ↪split(all_inputs,all_labels),
                                   verbose=3, random_state=1001 )
random_search.fit(all_inputs,all_labels)
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  15 out of  15 | elapsed:    2.9s finished
```

[ ]:
```
RandomizedSearchCV(cv=<generator object _BaseKFold.split at 0x7fcad3744678>,
                   error_score=nan,
                   estimator=LGBMClassifier(boosting_type='gbdt',
                                            class_weight=None,
                                            colsample_bytree=1.0,
                                            importance_type='split',
                                            learning_rate=0.1, max_depth=-1,
                                            min_child_samples=20,
                                            min_child_weight=0.001,
                                            min_split_gain=0.0,
                                            n_estimators=100, n_jobs=-1,
                                            num_leaves=31, objective=None,
                                            ran...
                                            subsample=1.0,
                                            subsample_for_bin=200000,
                                            subsample_freq=0),
                   iid='deprecated', n_iter=5, n_jobs=4,
                   param_distributions={'ccp_alpha': [0.1, 0.5, 0.9],
                                        'colsample_bytree': [0.6, 0.8, 0.1],
                                        'max_depth': [3, 4, 5],
                                        'min_samples_split': [2, 3, 5, 8],
                                        'verbose': [0.5, 1, 1.5, 2, 5]},
                   pre_dispatch='2*n_jobs', random_state=1001, refit=True,
                   return_train_score=False, scoring='roc_auc', verbose=3)
```

[ ]:
```python
print('\n Best estimator:')
print(random_search.best_estimator_)
print('\n Best normalized gini score for %d-fold search with %d parameter␣
 ↪combinations:' % (folds, param_comb))
```

```python
print(random_search.best_score_ * 2 - 1)
print('\n Best hyperparameters:')
print(random_search.best_params_)
results = pd.DataFrame(random_search.cv_results_)
results.to_csv('xgb-random-grid-search-results-01.csv', index=False)
```

```
 Best estimator:
LGBMClassifier(boosting_type='gbdt', ccp_alpha=0.5, class_weight=None,
               colsample_bytree=0.6, importance_type='split', learning_rate=0.1,
               max_depth=3, min_child_samples=20, min_child_weight=0.001,
               min_samples_split=3, min_split_gain=0.0, n_estimators=100,
               n_jobs=-1, num_leaves=31, objective=None, random_state=None,
               reg_alpha=0.0, reg_lambda=0.0, silent=True, subsample=1.0,
               subsample_for_bin=200000, subsample_freq=0, verbose=5)

 Best normalized gini score for 3-fold search with 5 parameter combinations:
0.9081688596491226

 Best hyperparameters:
{'verbose': 5, 'min_samples_split': 3, 'max_depth': 3, 'colsample_bytree': 0.6,
'ccp_alpha': 0.5}
```

[ ]:
```python
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

cls = LGBMClassifier(num_leaves= 55,
                     learning_rate  = .3,
                     subsample_for_bin  = 233,
                     importance_type  ='gain')
cls.fit(X_train,y_train)
y_pred = cls.predict(X_test)
print("------- Accuracy --------\n")
print(accuracy_score(y_test,y_pred))
print('--------------------------------------------------------')
print("------- Confusion Matrix --------\n")
print(confusion_matrix(y_test,y_pred))
print("------- Classifcation Report-------- \n")
print(classification_report(y_test,y_pred))
print('--------------------------------------------------------')
```

```
------- Accuracy --------
```

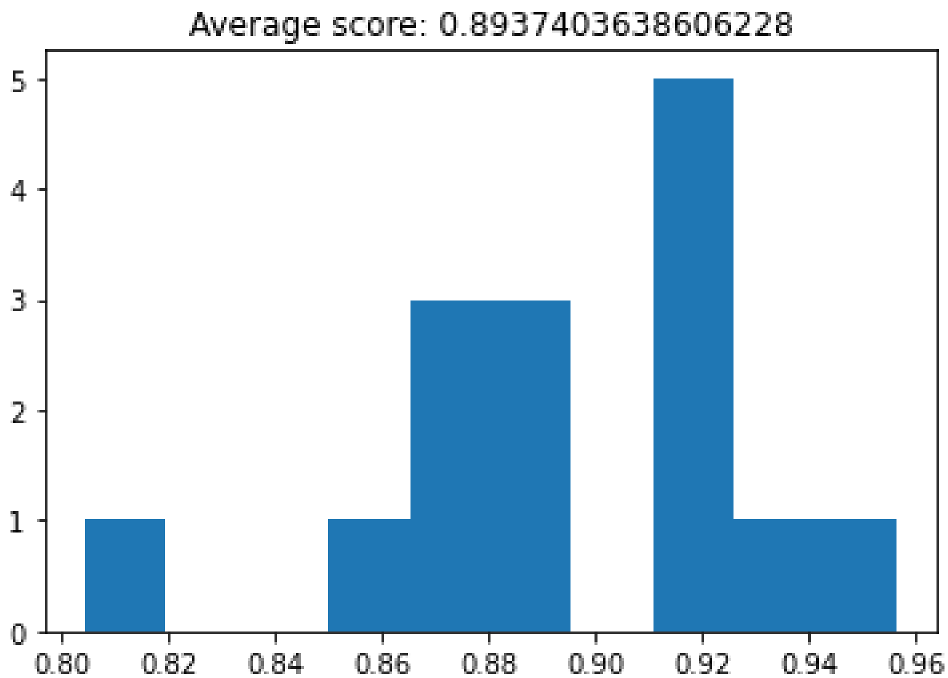
```
0.9022988505747126
--------------------------------------------------------
------- Confusion Matrix --------

[[102   8]
 [  9  55]]
------- Classifcation Report--------

              precision    recall  f1-score   support

           0       0.92      0.93      0.92       110
           1       0.87      0.86      0.87        64

    accuracy                           0.90       174
   macro avg       0.90      0.89      0.89       174
weighted avg       0.90      0.90      0.90       174

--------------------------------------------------------
```

[ ]:
```python
LGBM=[]
LGBM.append(0.902)
```

11.3.2 Cross-validation

[ ]:
```python
from sklearn.model_selection import cross_val_score

# cross_val_score returns a list of the scores, which we can visualize
# to get a reasonable estimate of our classifier's performance
cv_scores = cross_val_score(cls, all_inputs, all_labels, cv=15)
plt.hist(cv_scores)
plt.title('Average score: {}'.format(np.mean(cv_scores)))
;
```

[ ]: ''



[ ]:
```
LGBM.append(np.mean(cv_scores).round(3))
LGBM
```

[ ]: [0.902, 0.894]

11.4 4. Decision Tree Classifier

11.4.1 Confusion Matrix & Tuning

[ ]:
```
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV

decision_tree_classifier = DecisionTreeClassifier()

parameter_grid = {'criterion': ['gini', 'entropy'],
                  'splitter': ['best', 'random'],
                  'max_depth': list(range(21,55,2)),
                  'max_features': list(range(1,14))}

cross_validation = StratifiedKFold(n_splits=10)

grid_search = GridSearchCV(decision_tree_classifier,
                           param_grid=parameter_grid,
                           cv=cross_validation)
```

```
grid_search.fit(all_inputs, all_labels)
print('Best score: {}'.format(grid_search.best_score_))
print('Best parameters: {}'.format(grid_search.best_params_))
```

```
Best score: 0.8863975155279503
Best parameters: {'criterion': 'gini', 'max_depth': 47, 'max_features': 11,
'splitter': 'best'}
```

[ ]:
```
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,␣
 ↪test_size=0.25, random_state=1)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

cls = DecisionTreeClassifier(criterion='entropy',
                             max_depth=21,
                             max_features=11,
                             splitter='best')
cls.fit(X_train,y_train)
y_pred = cls.predict(X_test)
print("------- Accuracy --------\n")
print(accuracy_score(y_test,y_pred))
print('--------------------------------------------------------')
print("------- Confusion Matrix --------\n")
print(confusion_matrix(y_test,y_pred))
print("------- Classifcation Report-------- \n")
print(classification_report(y_test,y_pred))
print('--------------------------------------------------------')
```

```
------- Accuracy --------

0.9022988505747126
--------------------------------------------------------
------- Confusion Matrix --------

[[102   8]
 [  9  55]]
------- Classifcation Report--------

              precision    recall  f1-score   support

           0       0.92      0.93      0.92       110
           1       0.87      0.86      0.87        64

    accuracy                           0.90       174
   macro avg       0.90      0.89      0.89       174
```

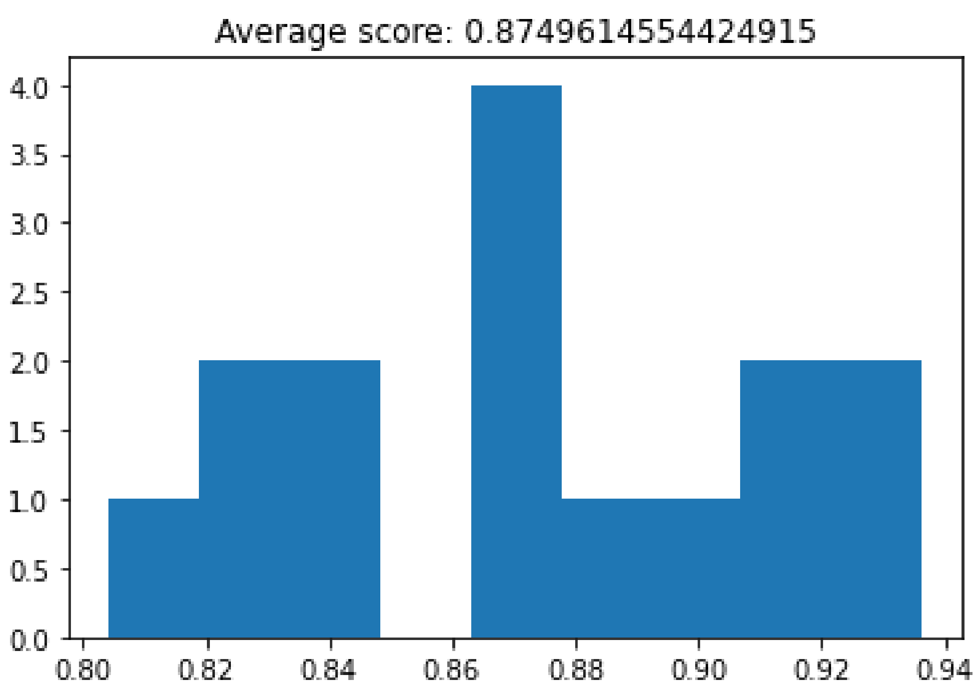
```
weighted avg       0.90      0.90      0.90       174

--------------------------------------------------------
```

[ ]:
```
DTC=[]
DTC.append(0.902)
```

11.4.2 Cross-validation

[ ]:
```
from sklearn.model_selection import cross_val_score

# cross_val_score returns a list of the scores, which we can visualize
# to get a reasonable estimate of our classifier's performance
cv_scores = cross_val_score(cls, all_inputs, all_labels, cv=15)
plt.hist(cv_scores,bins=9, stacked=True)
plt.title('Average score: {}'.format(np.mean(cv_scores)))
;
```

[ ]:
```
''
```



[ ]:
```
DTC.append(np.mean(cv_scores).round(3))
DTC
```

[ ]:
```
[0.902, 0.875]
```

11.5 Comparison

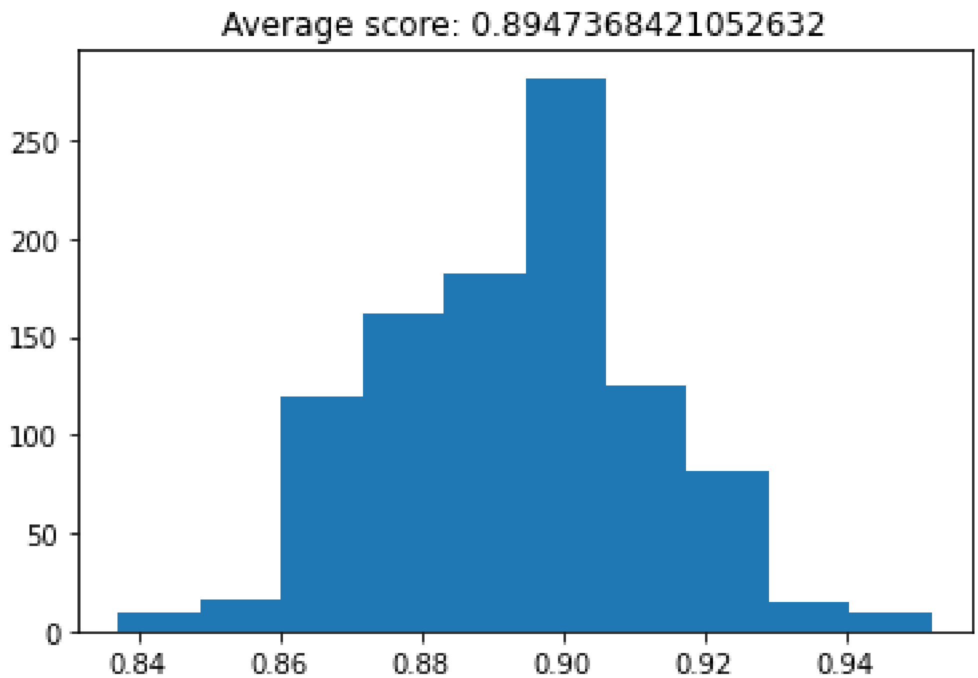
```
[ ]: compile= pd.DataFrame(ETsC, index=['Acc','Val_acc'], columns=['ETsC'])
compile['XGB']= XGB
compile['LGBM']= LGBM
compile['DTC']= DTC
compile= compile.T
compile
```

```
[ ]:        Acc  Val_acc
ETsC  0.873    0.888
XGB   0.934    0.904
LGBM  0.902    0.894
DTC   0.902    0.875
```

12 Selected model

```
[ ]: cls = XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                    colsample_bynode=1, colsample_bytree=0.8, gamma=1.5,
                    learning_rate=0.02, max_delta_step=0, max_depth=5,
                    min_child_weight=1, missing=None, n_estimators=600,␣
 ↪n_jobs=1,
                    nthread=1, objective='binary:logistic', random_state=0,
                    reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                    silent=True, subsample=0.6, verbosity=1)
model_accuracies = []

for repetition in range(1000):
    (training_inputs,
     testing_inputs,
     training_classes,
     testing_classes) = train_test_split(all_inputs, all_labels, test_size=0.30)

    cls.fit(training_inputs, training_classes)
    classifier_accuracy = cls.score(testing_inputs, testing_classes)
    model_accuracies.append(classifier_accuracy)

plt.hist(model_accuracies)
plt.title('Average score: {}'.format(np.mean(classifier_accuracy)))

;
```

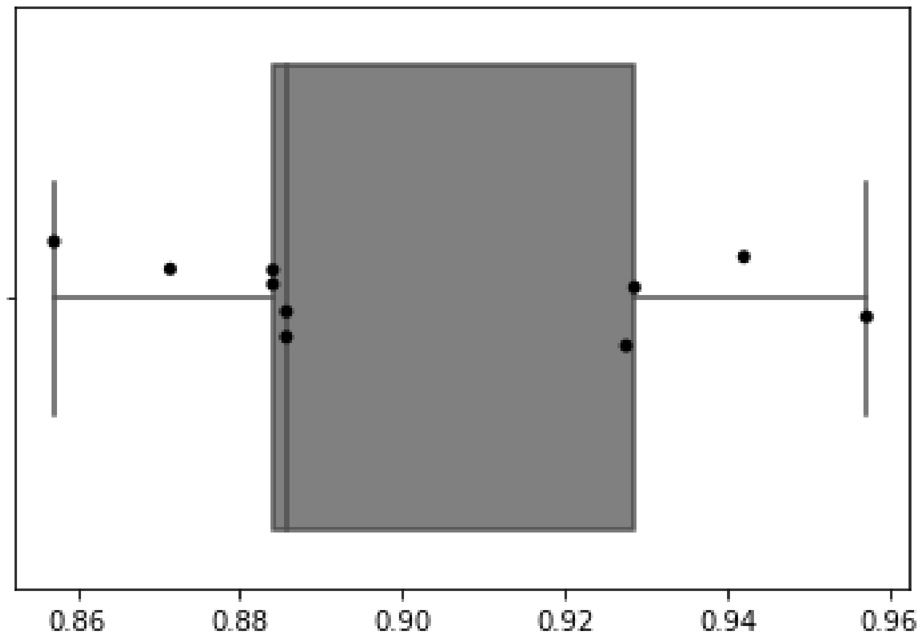
```
[ ]: ''
```



[ ]:
```
dt_scores = cross_val_score(cls, all_inputs, all_labels, cv=10)

sb.boxplot(dt_scores, color='gray', )
sb.stripplot(dt_scores, jitter=True, color='black')
;
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

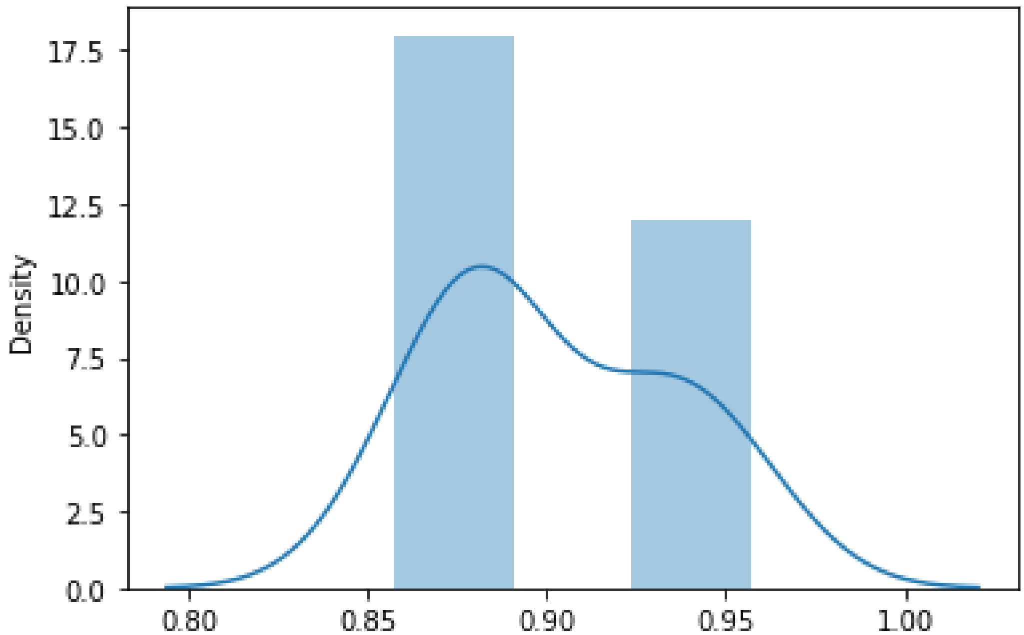
[ ]: ''



[ ]:
```
sb.distplot(dt_scores)
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

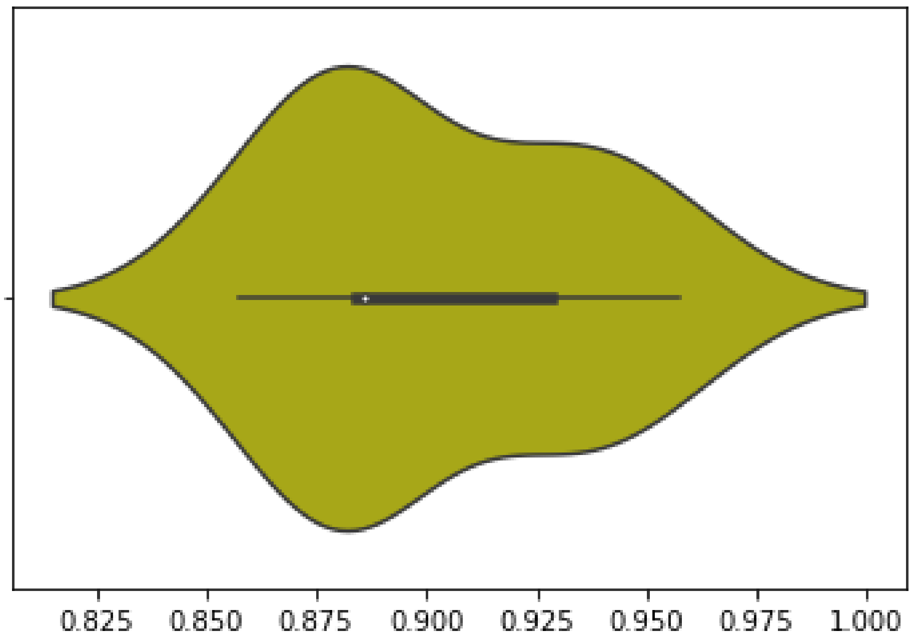
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fcadb5abd30>



[ ]:
```
sb.violinplot(dt_scores, color='y')
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcadd11b400>
```



13 Using Neural Networks

[ ]:
```
import tensorflow as tf
(X_train, X_test, y_train, y_test) = train_test_split(all_inputs, all_labels,
                                                      test_size=0.2,␣
 ↪random_state=1,
                                                      stratify= all_labels )
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

[ ]:
```
def build_model():
    model = tf.keras.Sequential([
    tf.keras.layers.Dense(14, activation='relu', input_shape=[14]),
    tf.keras.layers.Dense(4, activation='relu'),
    tf.keras.layers.Dense(1,activation='sigmoid')
  ])

    optimizer = tf.keras.optimizers.RMSprop(0.01)

    model.compile(loss='binary_crossentropy', optimizer=optimizer,␣
 ↪metrics=['accuracy'])
    return model
```

```
model = build_model()
```

[ ]:
```
del model
```

[ ]:
```
Epochs = 75
history = model.fit(X_train, y_train,epochs=Epochs,
                    validation_split=0.2,)
```

```
Epoch 1/75
14/14 [==============================] - 1s 15ms/step - loss: 0.7363 - accuracy:
0.5698 - val_loss: 0.6165 - val_accuracy: 0.8036
Epoch 2/75
14/14 [==============================] - 0s 4ms/step - loss: 0.5889 - accuracy:
0.8301 - val_loss: 0.5116 - val_accuracy: 0.8571
Epoch 3/75
14/14 [==============================] - 0s 4ms/step - loss: 0.4434 - accuracy:
0.8499 - val_loss: 0.4022 - val_accuracy: 0.8661
Epoch 4/75
14/14 [==============================] - 0s 4ms/step - loss: 0.3221 - accuracy:
0.8853 - val_loss: 0.3796 - val_accuracy: 0.8839
Epoch 5/75
14/14 [==============================] - 0s 4ms/step - loss: 0.3168 - accuracy:
0.8904 - val_loss: 0.3835 - val_accuracy: 0.8571
Epoch 6/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2661 - accuracy:
0.8838 - val_loss: 0.3870 - val_accuracy: 0.8571
Epoch 7/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2607 - accuracy:
0.8998 - val_loss: 0.4030 - val_accuracy: 0.8661
Epoch 8/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2512 - accuracy:
0.9153 - val_loss: 0.4117 - val_accuracy: 0.8750
Epoch 9/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2173 - accuracy:
0.9236 - val_loss: 0.4176 - val_accuracy: 0.8571
Epoch 10/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2542 - accuracy:
0.8982 - val_loss: 0.4247 - val_accuracy: 0.8482
Epoch 11/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2214 - accuracy:
0.9120 - val_loss: 0.4622 - val_accuracy: 0.8482
Epoch 12/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1829 - accuracy:
0.9294 - val_loss: 0.4446 - val_accuracy: 0.8482
Epoch 13/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1818 - accuracy:
0.9441 - val_loss: 0.4274 - val_accuracy: 0.8482
```

```
Epoch 14/75
14/14 [==============================] - 0s 17ms/step - loss: 0.2083 - accuracy:
0.9051 - val_loss: 0.4668 - val_accuracy: 0.8482
Epoch 15/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2039 - accuracy:
0.9206 - val_loss: 0.4463 - val_accuracy: 0.8661
Epoch 16/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2078 - accuracy:
0.9237 - val_loss: 0.4705 - val_accuracy: 0.8482
Epoch 17/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2120 - accuracy:
0.9124 - val_loss: 0.4740 - val_accuracy: 0.8304
Epoch 18/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1867 - accuracy:
0.9286 - val_loss: 0.4473 - val_accuracy: 0.8393
Epoch 19/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2027 - accuracy:
0.9306 - val_loss: 0.4712 - val_accuracy: 0.8393
Epoch 20/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1701 - accuracy:
0.9365 - val_loss: 0.4676 - val_accuracy: 0.8393
Epoch 21/75
14/14 [==============================] - 0s 4ms/step - loss: 0.2039 - accuracy:
0.8971 - val_loss: 0.4978 - val_accuracy: 0.8482
Epoch 22/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1922 - accuracy:
0.9220 - val_loss: 0.4740 - val_accuracy: 0.8214
Epoch 23/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1739 - accuracy:
0.9378 - val_loss: 0.5477 - val_accuracy: 0.8304
Epoch 24/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1701 - accuracy:
0.9473 - val_loss: 0.5498 - val_accuracy: 0.8661
Epoch 25/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1994 - accuracy:
0.9387 - val_loss: 0.5139 - val_accuracy: 0.8304
Epoch 26/75
14/14 [==============================] - 0s 5ms/step - loss: 0.1665 - accuracy:
0.9347 - val_loss: 0.5298 - val_accuracy: 0.8304
Epoch 27/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1556 - accuracy:
0.9456 - val_loss: 0.5018 - val_accuracy: 0.8304
Epoch 28/75
14/14 [==============================] - 0s 5ms/step - loss: 0.1420 - accuracy:
0.9409 - val_loss: 0.5326 - val_accuracy: 0.8214
Epoch 29/75
14/14 [==============================] - 0s 5ms/step - loss: 0.1637 - accuracy:
0.9346 - val_loss: 0.5236 - val_accuracy: 0.8393
```

```
Epoch 30/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1896 - accuracy:
0.9303 - val_loss: 0.4957 - val_accuracy: 0.8482
Epoch 31/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1337 - accuracy:
0.9644 - val_loss: 0.5546 - val_accuracy: 0.8393
Epoch 32/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1699 - accuracy:
0.9397 - val_loss: 0.5585 - val_accuracy: 0.8214
Epoch 33/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1574 - accuracy:
0.9406 - val_loss: 0.5259 - val_accuracy: 0.8393
Epoch 34/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1597 - accuracy:
0.9335 - val_loss: 0.5181 - val_accuracy: 0.8393
Epoch 35/75
14/14 [==============================] - 0s 5ms/step - loss: 0.1235 - accuracy:
0.9549 - val_loss: 0.5721 - val_accuracy: 0.8482
Epoch 36/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1232 - accuracy:
0.9466 - val_loss: 0.5770 - val_accuracy: 0.8393
Epoch 37/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1449 - accuracy:
0.9309 - val_loss: 0.5766 - val_accuracy: 0.8482
Epoch 38/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1376 - accuracy:
0.9497 - val_loss: 0.5506 - val_accuracy: 0.8571
Epoch 39/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1226 - accuracy:
0.9436 - val_loss: 0.5997 - val_accuracy: 0.8482
Epoch 40/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1654 - accuracy:
0.9313 - val_loss: 0.5790 - val_accuracy: 0.8482
Epoch 41/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1431 - accuracy:
0.9521 - val_loss: 0.6055 - val_accuracy: 0.8482
Epoch 42/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1230 - accuracy:
0.9469 - val_loss: 0.5923 - val_accuracy: 0.8482
Epoch 43/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1026 - accuracy:
0.9500 - val_loss: 0.6488 - val_accuracy: 0.8393
Epoch 44/75
14/14 [==============================] - 0s 15ms/step - loss: 0.1124 - accuracy:
0.9460 - val_loss: 0.6342 - val_accuracy: 0.8482
Epoch 45/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1037 - accuracy:
0.9615 - val_loss: 0.6603 - val_accuracy: 0.8304
```

```
Epoch 46/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1153 - accuracy:
0.9576 - val_loss: 0.6443 - val_accuracy: 0.8393
Epoch 47/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0979 - accuracy:
0.9671 - val_loss: 0.6694 - val_accuracy: 0.8571
Epoch 48/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0890 - accuracy:
0.9657 - val_loss: 0.6707 - val_accuracy: 0.8393
Epoch 49/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0930 - accuracy:
0.9748 - val_loss: 0.6537 - val_accuracy: 0.8304
Epoch 50/75
14/14 [==============================] - 0s 5ms/step - loss: 0.1113 - accuracy:
0.9600 - val_loss: 0.6483 - val_accuracy: 0.8482
Epoch 51/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0931 - accuracy:
0.9636 - val_loss: 0.6393 - val_accuracy: 0.8482
Epoch 52/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0871 - accuracy:
0.9611 - val_loss: 0.6828 - val_accuracy: 0.8482
Epoch 53/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1029 - accuracy:
0.9557 - val_loss: 0.7635 - val_accuracy: 0.8393
Epoch 54/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0819 - accuracy:
0.9716 - val_loss: 0.8066 - val_accuracy: 0.8304
Epoch 55/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0999 - accuracy:
0.9548 - val_loss: 0.7401 - val_accuracy: 0.8571
Epoch 56/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0921 - accuracy:
0.9555 - val_loss: 0.7453 - val_accuracy: 0.8393
Epoch 57/75
14/14 [==============================] - 0s 5ms/step - loss: 0.1081 - accuracy:
0.9558 - val_loss: 0.7492 - val_accuracy: 0.8482
Epoch 58/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0944 - accuracy:
0.9598 - val_loss: 0.7757 - val_accuracy: 0.8482
Epoch 59/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1053 - accuracy:
0.9609 - val_loss: 0.8660 - val_accuracy: 0.8393
Epoch 60/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1051 - accuracy:
0.9492 - val_loss: 0.8125 - val_accuracy: 0.8482
Epoch 61/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0812 - accuracy:
0.9766 - val_loss: 0.7916 - val_accuracy: 0.8482
```

```
Epoch 62/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0870 - accuracy:
0.9601 - val_loss: 0.8041 - val_accuracy: 0.8571
Epoch 63/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0835 - accuracy:
0.9647 - val_loss: 0.8099 - val_accuracy: 0.8482
Epoch 64/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0963 - accuracy:
0.9639 - val_loss: 0.8542 - val_accuracy: 0.8482
Epoch 65/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0626 - accuracy:
0.9793 - val_loss: 0.8070 - val_accuracy: 0.8304
Epoch 66/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0732 - accuracy:
0.9657 - val_loss: 0.8366 - val_accuracy: 0.8482
Epoch 67/75
14/14 [==============================] - 0s 5ms/step - loss: 0.0623 - accuracy:
0.9800 - val_loss: 0.8704 - val_accuracy: 0.8482
Epoch 68/75
14/14 [==============================] - 0s 4ms/step - loss: 0.1131 - accuracy:
0.9484 - val_loss: 0.8432 - val_accuracy: 0.8482
Epoch 69/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0841 - accuracy:
0.9647 - val_loss: 0.8692 - val_accuracy: 0.8482
Epoch 70/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0869 - accuracy:
0.9696 - val_loss: 0.8658 - val_accuracy: 0.8393
Epoch 71/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0691 - accuracy:
0.9737 - val_loss: 0.8994 - val_accuracy: 0.8304
Epoch 72/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0608 - accuracy:
0.9781 - val_loss: 0.9170 - val_accuracy: 0.8482
Epoch 73/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0627 - accuracy:
0.9796 - val_loss: 0.8816 - val_accuracy: 0.8482
Epoch 74/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0850 - accuracy:
0.9749 - val_loss: 0.9836 - val_accuracy: 0.8304
Epoch 75/75
14/14 [==============================] - 0s 4ms/step - loss: 0.0940 - accuracy:
0.9472 - val_loss: 0.9276 - val_accuracy: 0.8304
```

[ ]:
```
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
hist.tail()
```

[ ]:

	loss	accuracy	val_loss	val_accuracy	epoch
70	0.083450	0.963964	0.899368	0.830357	70
71	0.080079	0.970721	0.917036	0.848214	71
72	0.079431	0.968468	0.881565	0.848214	72
73	0.072801	0.970721	0.983648	0.830357	73
74	0.081346	0.961712	0.927632	0.830357	74

[ ]:

```
acc = (hist['accuracy'].tail().sum())*100/5
val_acc = (hist['val_accuracy'].tail().sum())*100/5

print("Training Accuracy = {}% and Validation Accuracy= {}%".
 ↪format(acc,val_acc))
```

```
Training Accuracy = 96.71171188354492% and Validation Accuracy=
83.7499988079071%
```

[ ]:

```
y_pred = model.predict_classes(X_test)
print("------- Accuracy --------\n")
print(accuracy_score(y_test,y_pred))
print('--------------------------------------------------------')
print("------- Confusion Matrix --------\n")
print(confusion_matrix(y_test,y_pred))
print("------- Classifcation Report-------- \n")
print(classification_report(y_test,y_pred))
print('--------------------------------------------------------')
```

```
------- Accuracy --------

0.7571428571428571
--------------------------------------------------------
------- Confusion Matrix --------

[[70 22]
 [12 36]]
------- Classifcation Report--------

              precision    recall  f1-score   support

           0       0.85      0.76      0.80        92
           1       0.62      0.75      0.68        48

    accuracy                           0.76       140
   macro avg       0.74      0.76      0.74       140
weighted avg       0.77      0.76      0.76       140

--------------------------------------------------------

/usr/local/lib/python3.6/dist-
packages/tensorflow/python/keras/engine/sequential.py:450: UserWarning:
```

```
`model.predict_classes()` is deprecated and will be removed after 2021-01-01.
Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model
does multi-class classification   (e.g. if it uses a `softmax` last-layer
activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does
binary classification   (e.g. if it uses a `sigmoid` last-layer activation).
  warnings.warn('`model.predict_classes()` is deprecated and '
```

14 Conclusion

Best accuracy was by using **XGboost Classifier** with 93.4% accuracy, and an excellent validation accuracy (89.5 %). The accuracy achieved by using: 1. Forward filling the NaN, 2. without using the extracted feature, 3. DBSCAN Density-Based Spatial Clustering of Applications for outlier detection, 4. Random over sampler to balance the classes

15 Step 6: Reproducibility

[ ]:
```
!pip install watermark
```

```
Collecting watermark
  Downloading https://files.pythonhosted.org/packages/60/fe/3ed83b6122e70dce6fe2
69dfd763103c333f168bf91037add73ea4fe81c2/watermark-2.0.2-py2.py3-none-any.whl
Requirement already satisfied: ipython in /usr/local/lib/python3.6/dist-packages
(from watermark) (5.5.0)
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/python3.6
/dist-packages (from ipython->watermark) (0.8.1)
Requirement already satisfied: decorator in /usr/local/lib/python3.6/dist-
packages (from ipython->watermark) (4.4.2)
Requirement already satisfied: pygments in /usr/local/lib/python3.6/dist-
packages (from ipython->watermark) (2.6.1)
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.6/dist-
packages (from ipython->watermark) (4.3.3)
Requirement already satisfied: pexpect; sys_platform != "win32" in
/usr/local/lib/python3.6/dist-packages (from ipython->watermark) (4.8.0)
Requirement already satisfied: prompt-toolkit<2.0.0,>=1.0.4 in
/usr/local/lib/python3.6/dist-packages (from ipython->watermark) (1.0.18)
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.6
/dist-packages (from ipython->watermark) (51.0.0)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.6/dist-
packages (from ipython->watermark) (0.7.5)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages
(from traitlets>=4.2->ipython->watermark) (1.15.0)
Requirement already satisfied: ipython-genutils in /usr/local/lib/python3.6
/dist-packages (from traitlets>=4.2->ipython->watermark) (0.2.0)
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.6/dist-
packages (from pexpect; sys_platform != "win32"->ipython->watermark) (0.6.0)
```

```
Requirement already satisfied: wcwidth in /usr/local/lib/python3.6/dist-packages
(from prompt-toolkit<2.0.0,>=1.0.4->ipython->watermark) (0.2.5)
Installing collected packages: watermark
Successfully installed watermark-2.0.2
```

[ ]:
```
%load_ext watermark
```

[ ]:
```
%watermark -a 'Hazim' -nmv --packages numpy,pandas,sklearn,matplotlib,seaborn
```

```
Hazim Tue Dec 29 2020

CPython 3.6.9
IPython 5.5.0

numpy 1.19.4
pandas 1.1.5
sklearn 0.0
matplotlib 3.2.2
seaborn 0.11.0

compiler   : GCC 8.4.0
system     : Linux
release    : 4.19.112+
machine    : x86_64
processor  : x86_64
CPU cores  : 2
interpreter: 64bit
```