Capstone Project: Titanic Survivors Prediction

Problem Statement

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing numerous passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships. One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class. In this, we ask you to complete the analysis of what sorts of people were likely to survive. In particular, we ask you to apply the tools of machine learning to predict which passengers survived the tragedy.

Data Dictionary Variables:

1. survived: Survival (0 = No, 1 = Yes)
2. Pclass: Ticket class (1 = 1st, 2 = 2nd, 3 = 3rd)
3. Sex: Gender (Male or Female)
4. Age: Age in years
5. Sibsp: # of siblings / spouses aboard the Titanic
6. Parch: # of parents / children aboard the Titanic
7. Ticket: Ticket number
8. Fare: Passenger fare
9. Cabin: Cabin number
10. embarked: Port of Embarkation (C= Cherbourg, Q = Queenstown, S =Southampton)

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import  mean_squared_error
from sklearn.preprocessing import StandardScaler
import scipy
import matplotlib.pyplot
import statistics
from   pylab import rcParams
import warnings
from matplotlib.pyplot import figure
warnings.filterwarnings("ignore")
```

```
df=pd.read_csv('train.csv')
df.sample(5)
```

```
     PassengerId  Survived  Pclass                                    Name
Sex  \
```

```
593          594         0       3            Bourke, Miss. Mary
female
136          137         1       1  Newsom, Miss. Helen Monypeny
female
29            30         0       3           Todoroff, Mr. Lalio
male
868          869         0       3   van Melkebeke, Mr. Philemon
male
196          197         0       3           Mernagh, Mr. Robert
male

      Age  SibSp  Parch  Ticket     Fare Cabin Embarked
593   NaN      0      2  364848   7.7500   NaN        Q
136  19.0      0      2   11752  26.2833   D47        S
29    NaN      0      0  349216   7.8958   NaN        S
868   NaN      0      0  345777   9.5000   NaN        S
196   NaN      0      0  368703   7.7500   NaN        Q
```

```
print('The number of rows (observations) is',df.shape[0],'\n''The
number of columns (variables) is',df.shape[1],'\n''Total values in
dataset:',df.size)
```

```
The number of rows (observations) is 891
The number of columns (variables) is 12
Total values in dataset: 10692
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

```
pd.DataFrame(data={'# Missing Values':df.isna().sum(),
                '% of Missing
```

```
Values':round(df.isnull().sum()/df.isnull().count()*100,2)}).sort_valu
es(by='# Missing Values',ascending=False)
```

```
             # Missing Values  % of Missing Values
Cabin                     687                77.10
Age                       177                19.87
Embarked                    2                 0.22
PassengerId                 0                 0.00
Survived                    0                 0.00
Pclass                      0                 0.00
Name                        0                 0.00
Sex                         0                 0.00
SibSp                       0                 0.00
Parch                       0                 0.00
Ticket                      0                 0.00
Fare                        0                 0.00
```

```
df.describe()
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

Imputing Missing Values

```
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace = True)
pd.DataFrame(data={'# Missing Values':df.isna().sum(),
                '% of Missing
Values':round(df.isnull().sum()/df.isnull().count()*100,2)}).sort_valu
es(by='# Missing Values',ascending=False)
```

```
             # Missing Values  % of Missing Values
Cabin                     687                77.10
Age                       177                19.87
PassengerId                 0                 0.00
Survived                    0                 0.00
```

```
Pclass                         0                   0.00
Name                           0                   0.00
Sex                            0                   0.00
SibSp                          0                   0.00
Parch                          0                   0.00
Ticket                         0                   0.00
Fare                           0                   0.00
Embarked                       0                   0.00
```

```
from sklearn.impute import KNNImputer

dfB = pd.DataFrame(df.Age)

imputer = KNNImputer(n_neighbors=10)
dfA = pd.DataFrame(imputer.fit_transform(dfB), columns=['Age'])
dfA.Age=dfA.Age.round()
df.Age=dfA.Age
df
```

```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           ...       ...     ...
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex   Age
SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0
1
1    Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                               Heikkinen, Miss. Laina  female  26.0
0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                             Allen, Mr. William Henry    male  35.0
0
..                                                 ...     ...   ...
...
886                              Montvila, Rev. Juozas    male  27.0
0
887                       Graham, Miss. Margaret Edith  female  19.0
0
```

```
888           Johnston, Miss. Catherine Helen "Carrie"  female  30.0
1
889                              Behr, Mr. Karl Howell    male  26.0
0
890                                Dooley, Mr. Patrick    male  32.0
0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     ...               ...      ...   ...      ...
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

```
df.to_csv('new.csv')
```

```
pd.DataFrame(data={'# Missing Values':df.isna().sum(),
                '% of Missing
Values':round(df.isnull().sum()/df.isnull().count()*100,2)}).sort_valu
es(by='# Missing Values',ascending=False)
```

```
             # Missing Values  % of Missing Values
Cabin                     687                 77.1
PassengerId                 0                  0.0
Survived                    0                  0.0
Pclass                      0                  0.0
Name                        0                  0.0
Sex                         0                  0.0
Age                         0                  0.0
SibSp                       0                  0.0
Parch                       0                  0.0
Ticket                      0                  0.0
Fare                        0                  0.0
Embarked                    0                  0.0
```

```
df1=df.copy()
```

```
df1.Age=df1.Age.astype('int64')
```

```
df1.drop(['PassengerId','Cabin','Name','Ticket'],axis=1,inplace=True)
df1=
df1[['Sex','Age','SibSp','Parch','Pclass','Fare','Embarked','Survived'
```

```
]]
df1.sample(10)
```

```
        Sex  Age  SibSp  Parch  Pclass      Fare Embarked  Survived
870    male   26      0      0       3    7.8958        S         0
550    male   17      0      2       1  110.8833        C         1
660    male   50      2      0       1  133.6500        S         1
848    male   28      0      1       2   33.0000        S         0
351    male   30      0      0       1   35.0000        S         0
734    male   23      0      0       2   13.0000        S         0
20     male   35      0      0       2   26.0000        S         0
412  female   33      1      0       1   90.0000        Q         1
64     male   30      0      0       1   27.7208        C         0
203    male   46      0      0       3    7.2250        C         0
```

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Sex       891 non-null    object 
 1   Age       891 non-null    int64  
 2   SibSp     891 non-null    int64  
 3   Parch     891 non-null    int64  
 4   Pclass    891 non-null    int64  
 5   Fare      891 non-null    float64
 6   Embarked  891 non-null    object 
 7   Survived  891 non-null    int64  
dtypes: float64(1), int64(5), object(2)
memory usage: 55.8+ KB
```

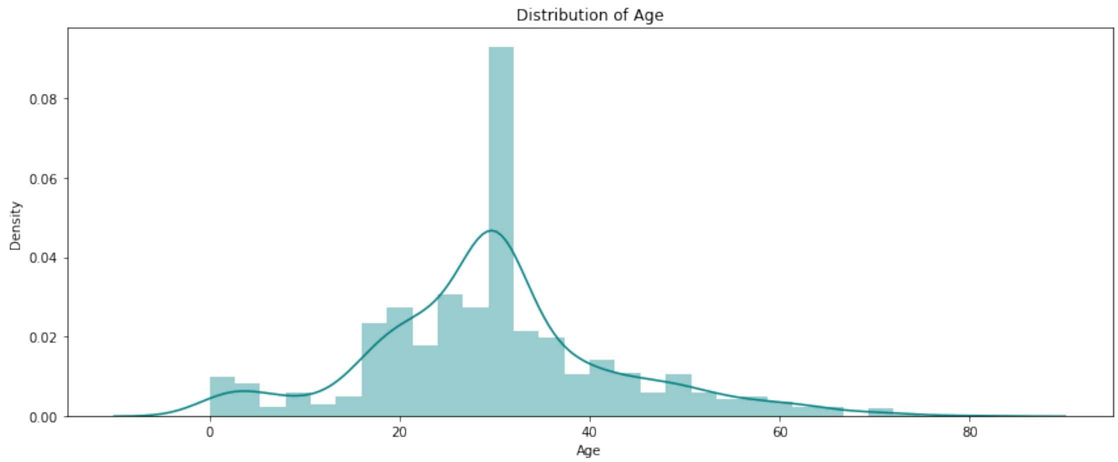
```
print('The number of rows (observations) is',df1.shape[0],'\n''The number of columns (variables) is',df1.shape[1],'\n''Total values in dataset:',df1.size)
df_eda=df1.copy()
```

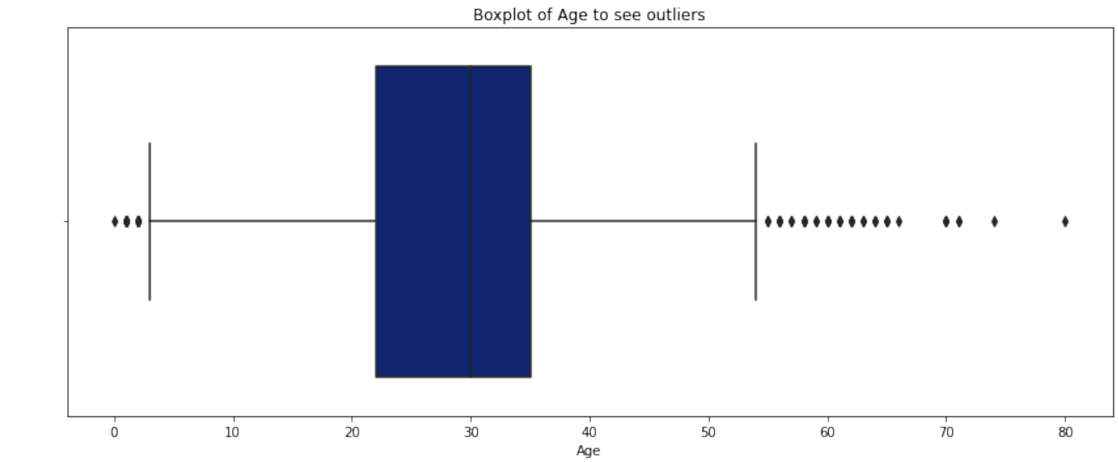
```
The number of rows (observations) is 891
The number of columns (variables) is 8
Total values in dataset: 7128
```

EDA

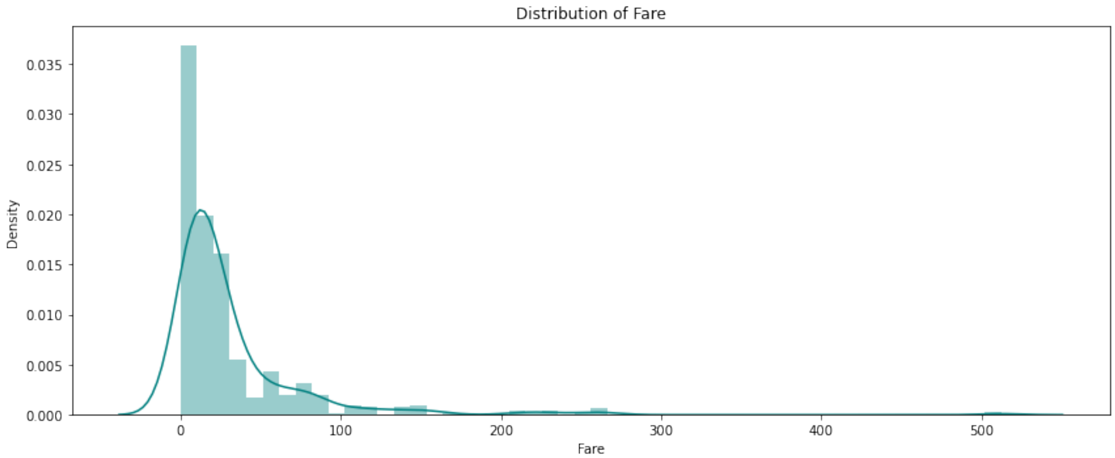
```
def uniplot(x):
    fig,axs = plt.subplots(2,figsize=(12,10))
    axs[0].set_title('Distribution of '+x)
    sns.distplot(df_eda[x],ax=axs[0],color='teal')
    axs[1].set_title('Boxplot of '+x+' to see outliers')
    sns.boxplot(df_eda[x],ax=axs[1],palette='dark')
    plt.tight_layout()
    plt.show()
```

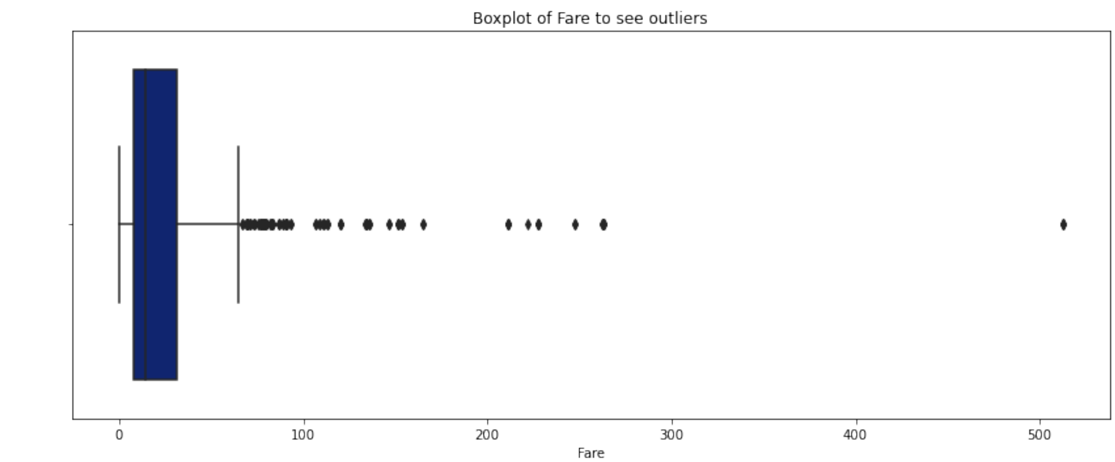
```
uniplot('Age')
```






```
uniplot('Fare')
```





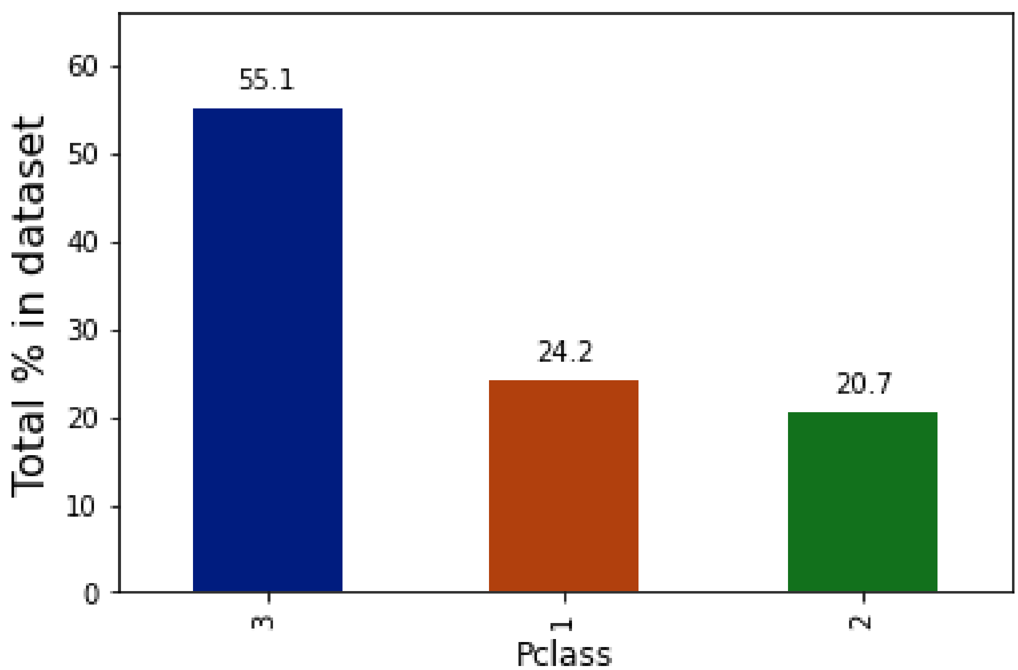

```
# Survived
print(df_eda.Survived.value_counts())
srate = round((sum(df_eda[df_eda['Survived']==1]
['Survived'])/len(df_eda['Survived'].index))*100,2)
print('Survival Rate : ',srate,'%')
```

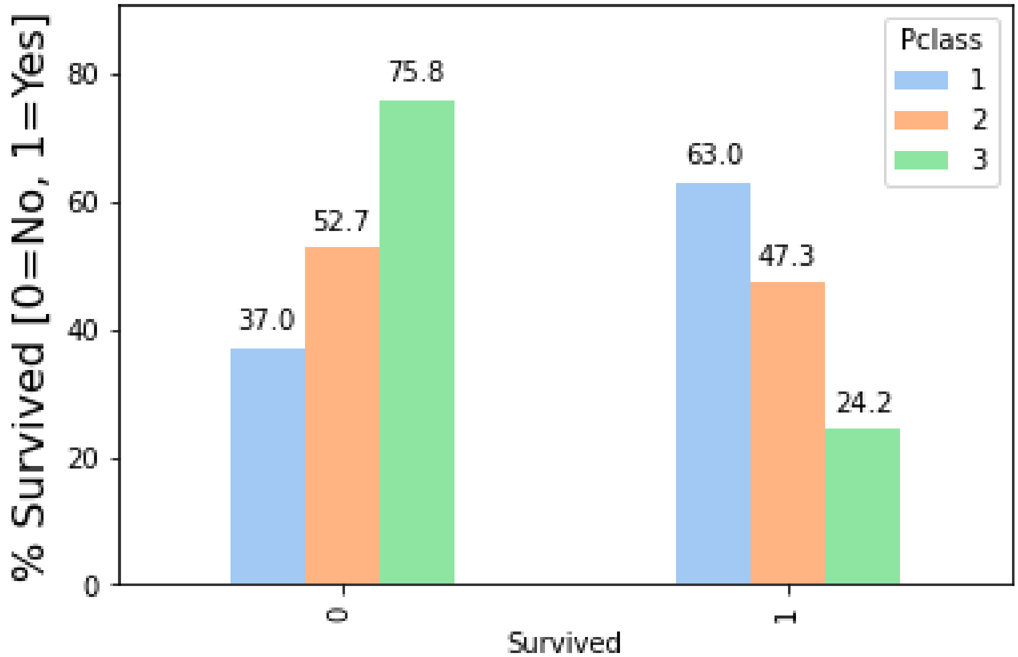
```
0    549
1    342
Name: Survived, dtype: int64
Survival Rate :  38.38 %
```

```
# Functions for visualization and beautifications

## Wonderful solution to show labels in bar plots - copied from
https://stackoverflow.com/a/48372659 and edited
def showLabels(ax, d=None):
    plt.margins(0.2, 0.2)
    rects = ax.patches
    i = 0
    locs, labels = plt.xticks()
    counts = {}
    if not d is None:
```

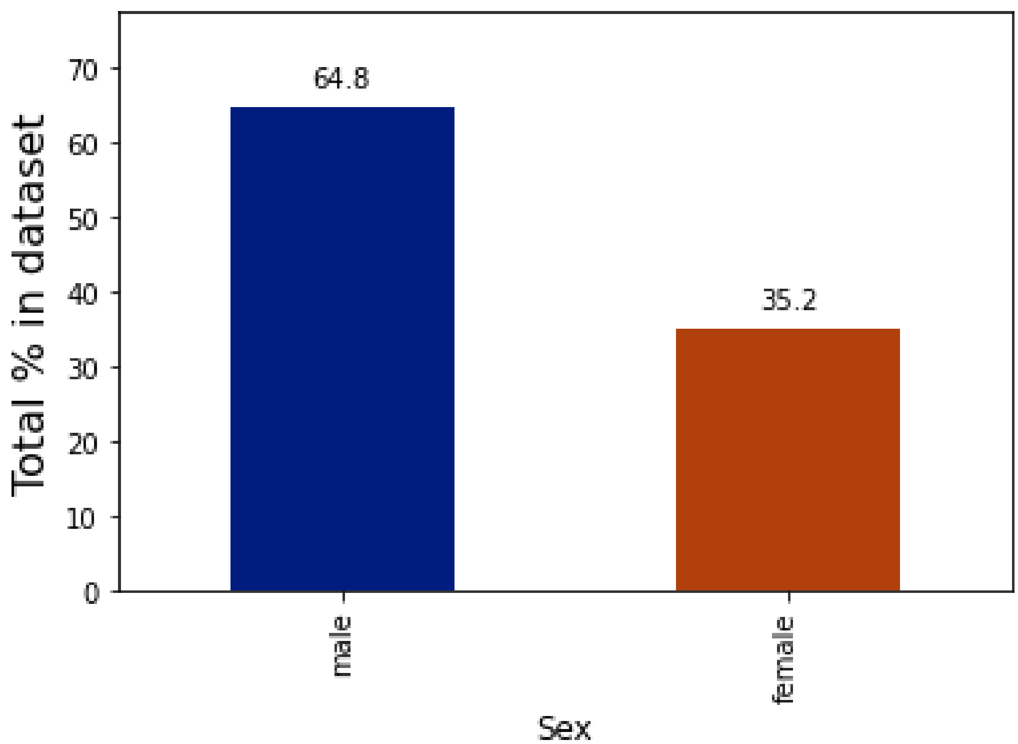
```
        for key, value in d.items():
            counts[str(key)] = value

    # For each bar: Place a label
    for rect in rects:
        # Get X and Y placement of label from rect.
        y_value = rect.get_height()
        x_value = rect.get_x() + rect.get_width() / 2

        # Number of points between bar and label. Change to your
liking.
        space = 5
        # Vertical alignment for positive values
        va = 'bottom'

        # If value of bar is negative: Place label below bar
        if y_value < 0:
            # Invert space to place label below
            space *= -1
            # Vertically align label at top
            va = 'top'

        # Use Y value as label and format number with one decimal
place
        if d is None:
            label = "{:.1f}".format(y_value)
        else:
            try:
                label = "{:.1f}%".format(y_value) + "\nof " +
str(counts[str(labels[i].get_text())])
            except:
                label = "{:.1f}%".format(y_value)

        i = i+1

        # Create annotation
        plt.annotate(
            label,                      # Use `label` as label
            (x_value, y_value),         # Place label at end of the
bar
            xytext=(0, space),          # Vertically shift label by
`space`
            textcoords="offset points", # Interpret `xytext` as offset
in points
            ha='center',                # Horizontally center label
            va=va)                      # Vertically align label
differently for
                                        # positive and negative
values.
```

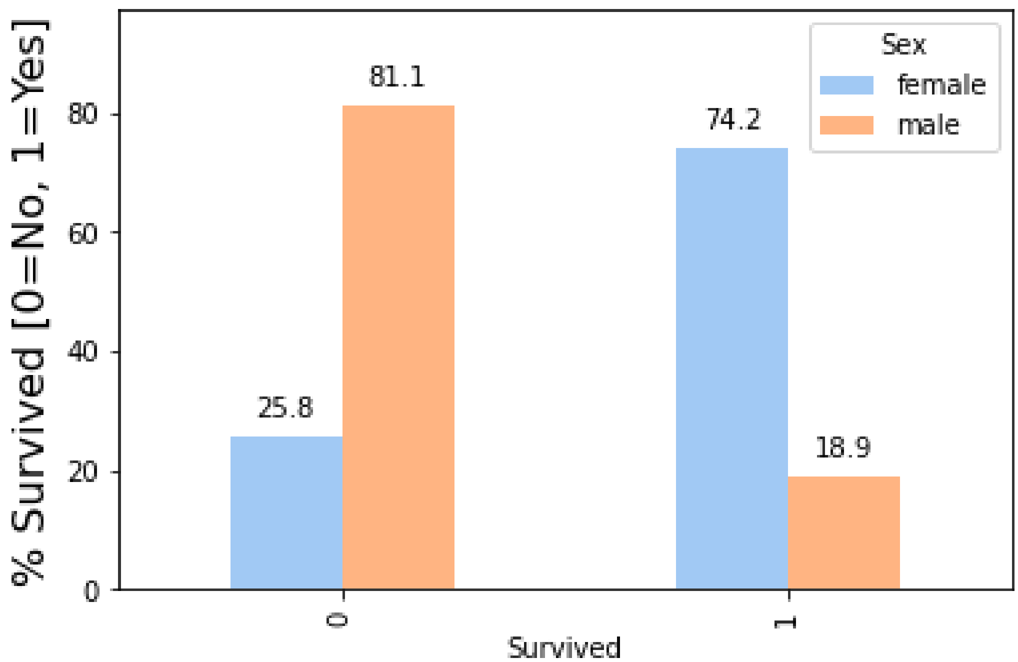
```python
def plot_percentages(dataframe, by, sortbyindex=False):
    #plt.subplot(1, 2, 1)
    values = (dataframe[by].value_counts(normalize=True)*100)
    if sortbyindex:
        values = values.sort_index()
    ax = values.plot.bar(color=sns.color_palette('dark',16))
    ax.set_ylabel('Total % in dataset', fontsize=16)
    ax.set_xlabel(by, fontsize=12)
    showLabels(ax)

    grp = dataframe.groupby(['Survived',by])[by].count()
    cnt = dataframe.groupby(by)[by].count()

    percentages = grp.unstack() * 100 / cnt.T

    ax = percentages.plot.bar(color=sns.color_palette('pastel', 16))
    ax.set_ylabel('% Survived [0=No, 1=Yes]', fontsize=16)
    showLabels(ax)

# Pclass
plot_percentages(df_eda,'Pclass')
plt.show()
```



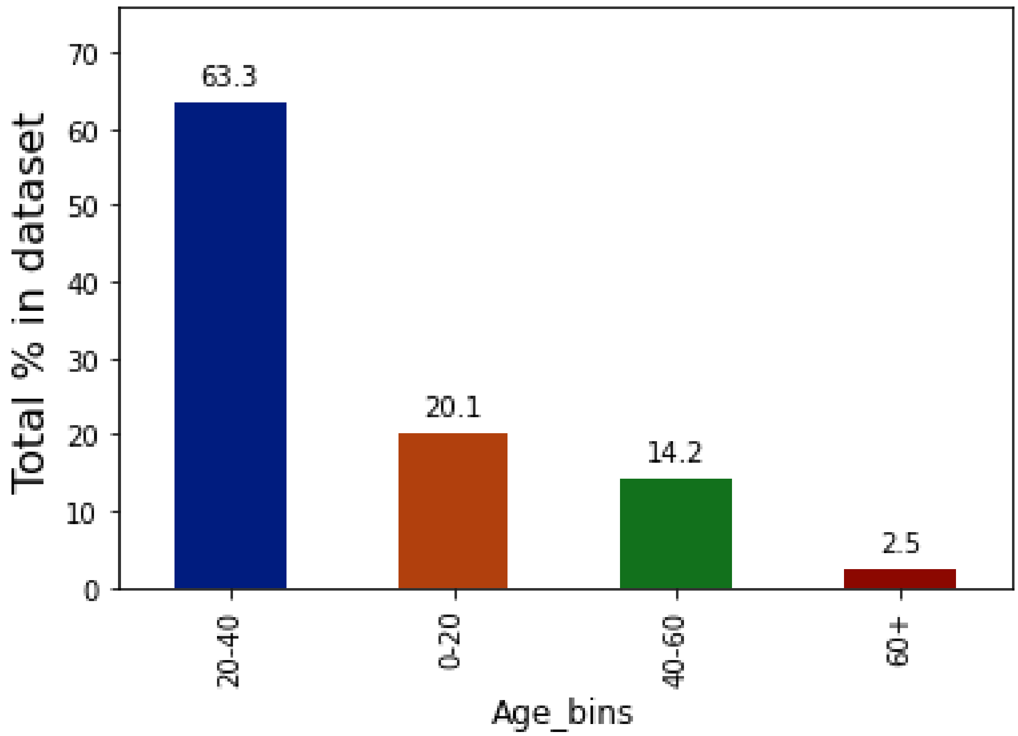


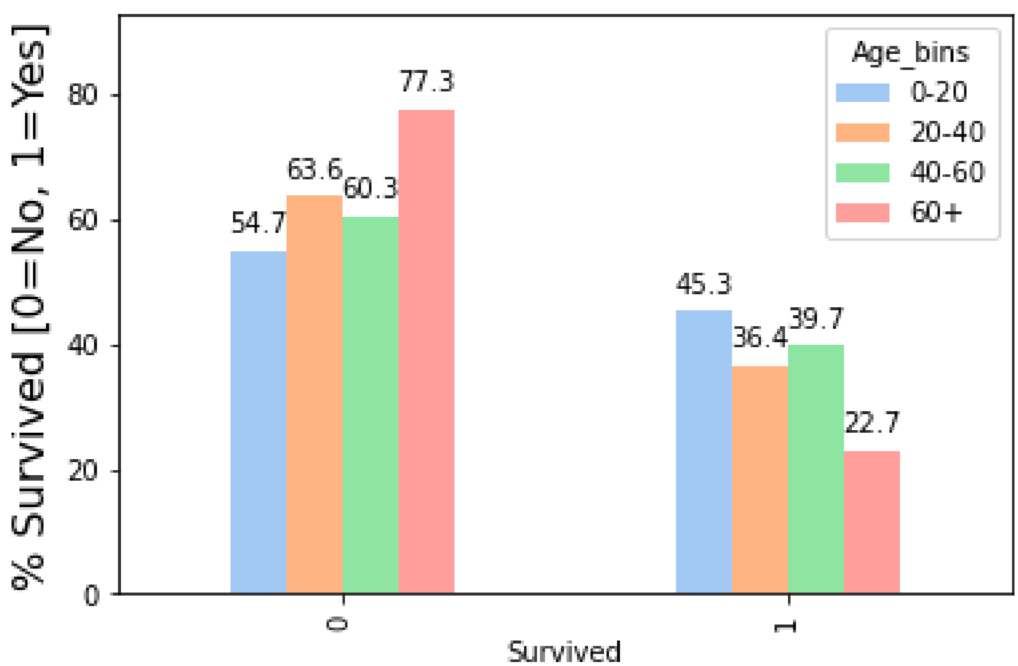

```
# Sex
plot_percentages(df_eda,'Sex')
plt.show()
```



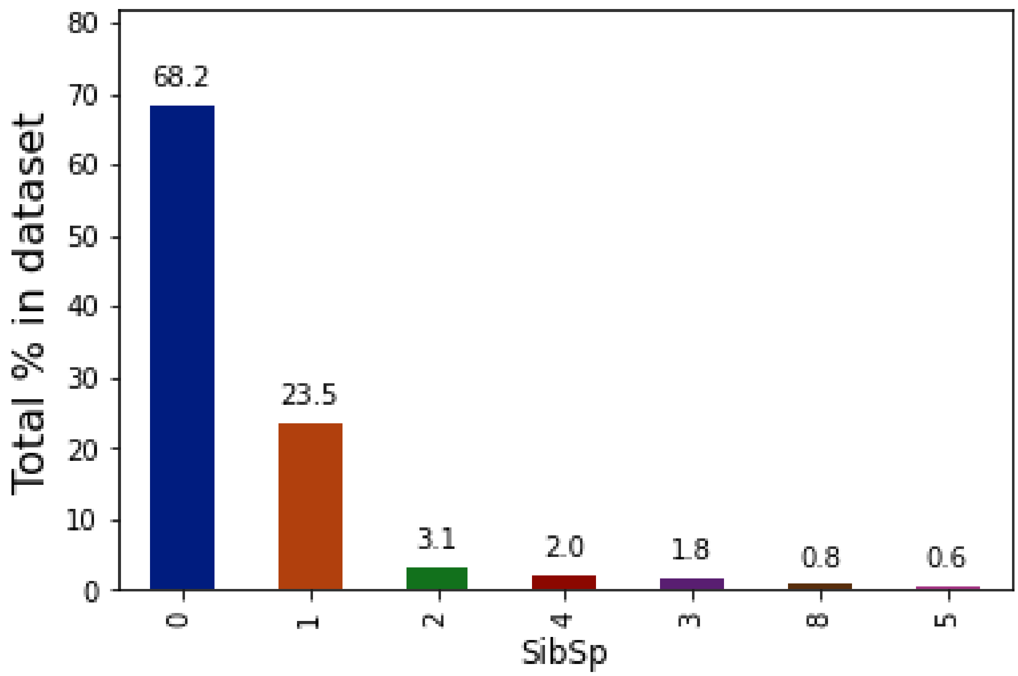


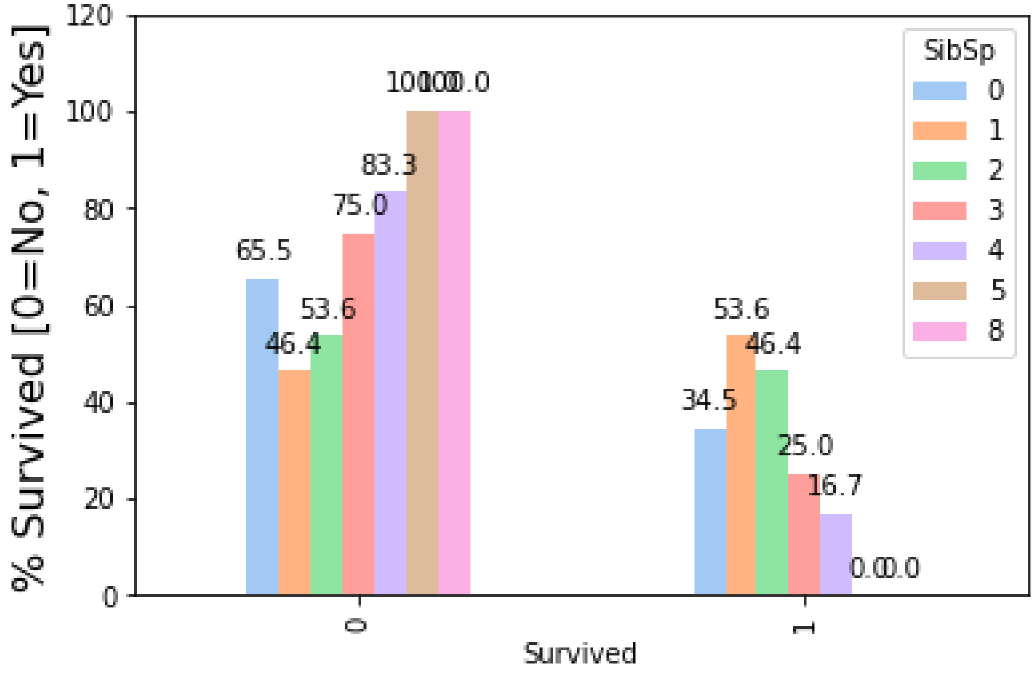

```
# Age
bins = [0,20,40,60,np.inf]
labels = ['0-20','20-40','40-60','60+']
age_bins = pd.cut(df1.Age, bins, labels=labels)
df1['Age_bins'] = age_bins

plot_percentages(df1,'Age_bins')
```



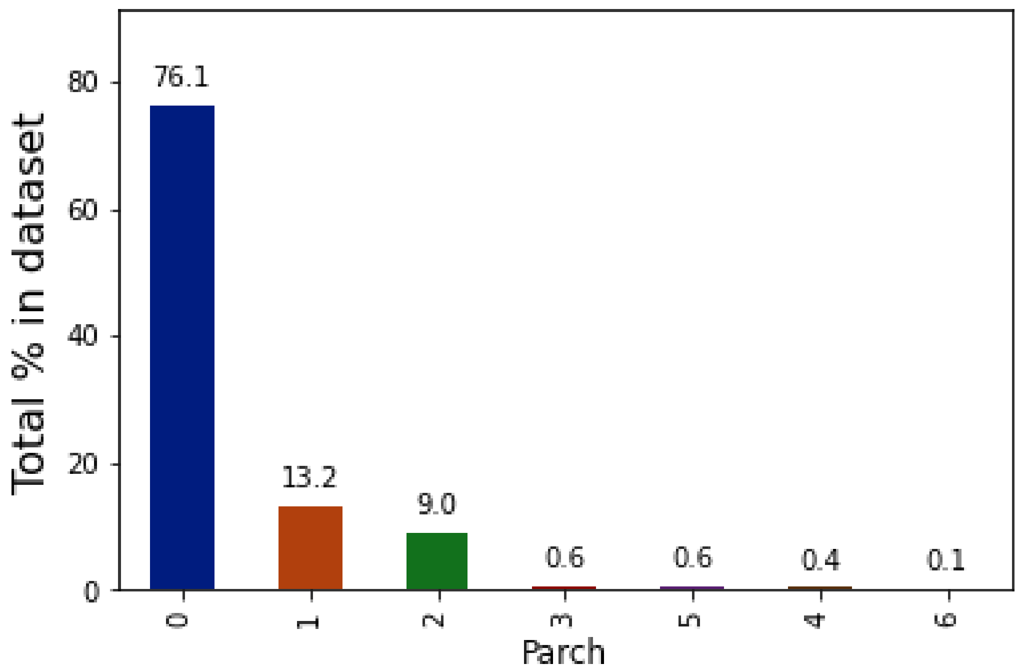


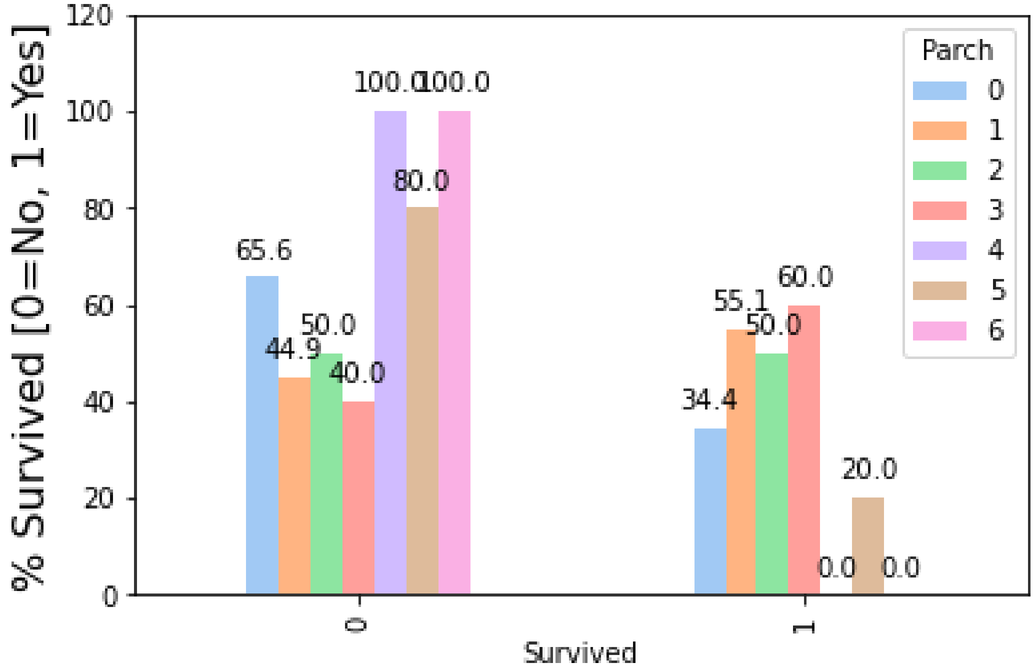

```
# SibSp
plot_percentages(df_eda,'SibSp')
plt.show()
```



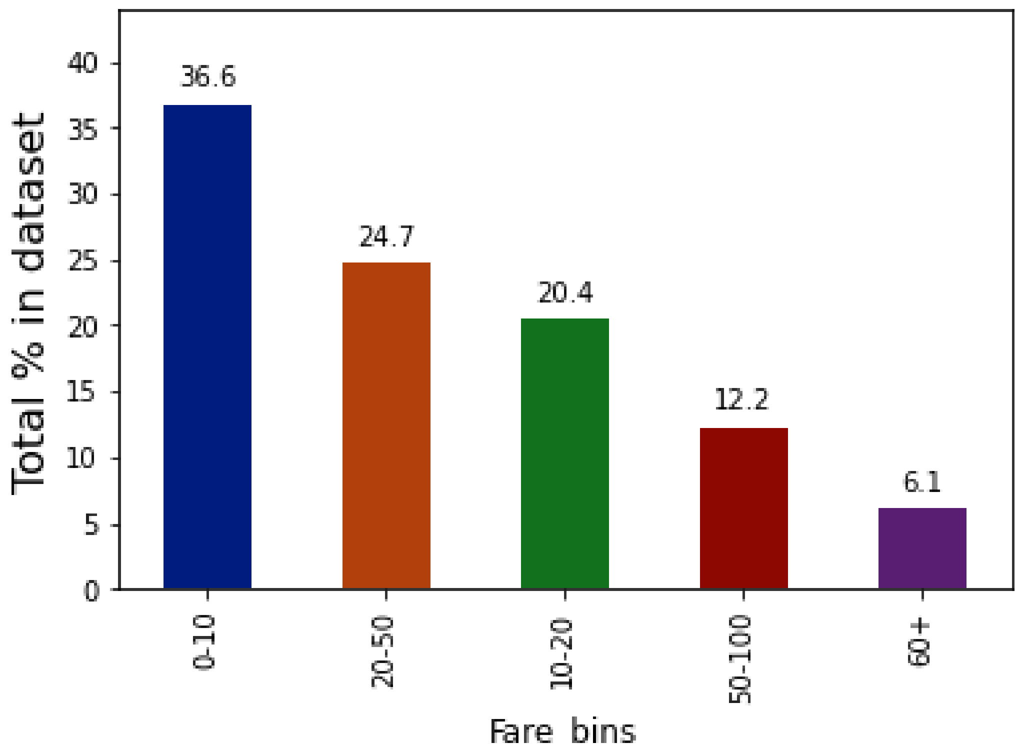


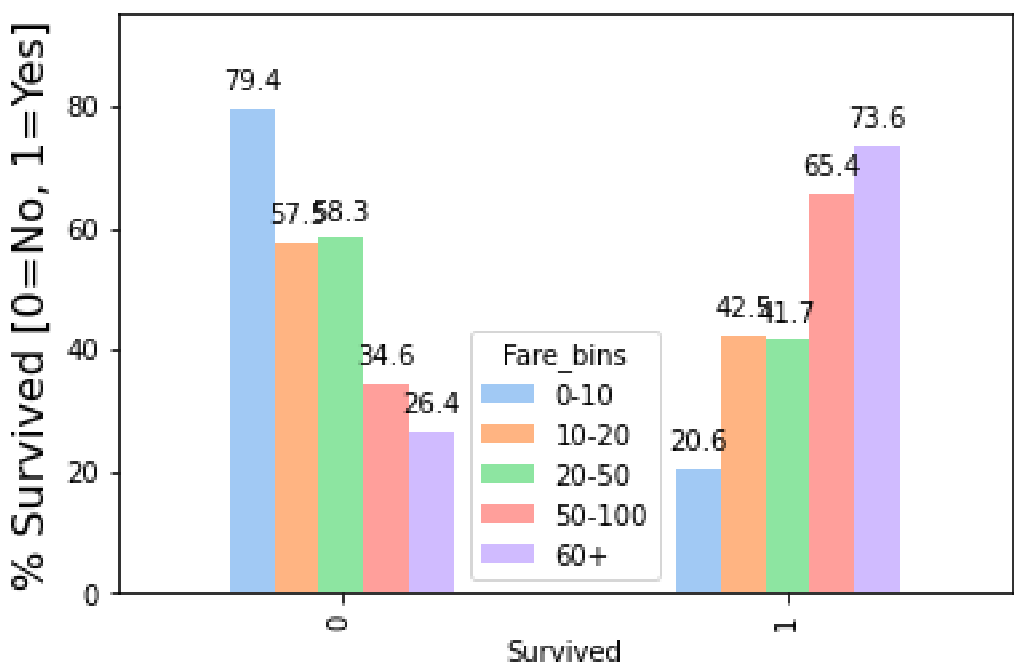

```
# Parch
plot_percentages(df_eda,'Parch')
plt.show()
```



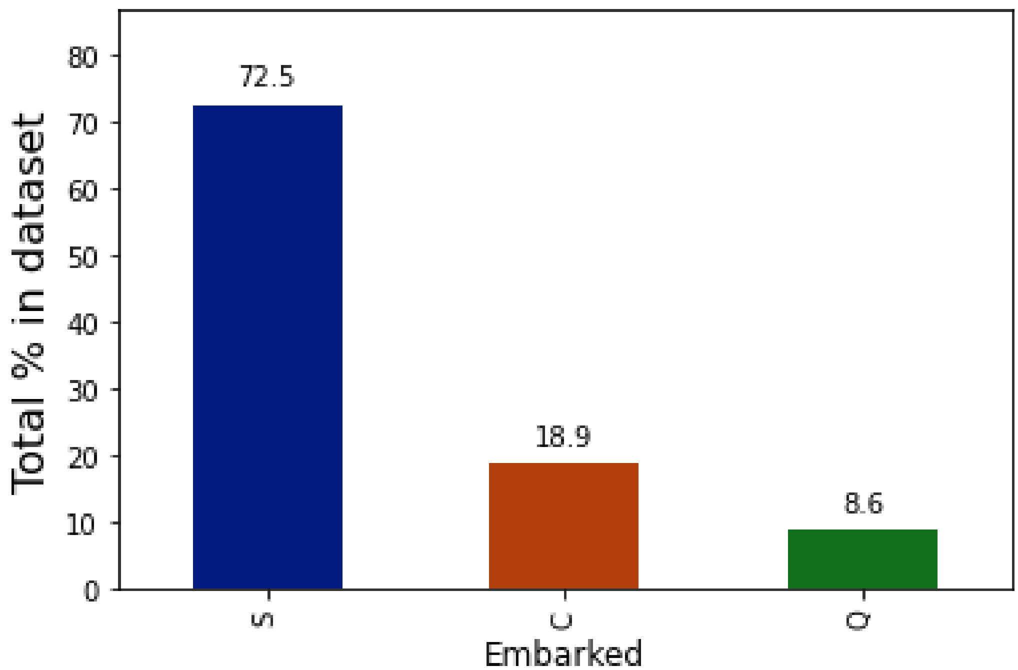


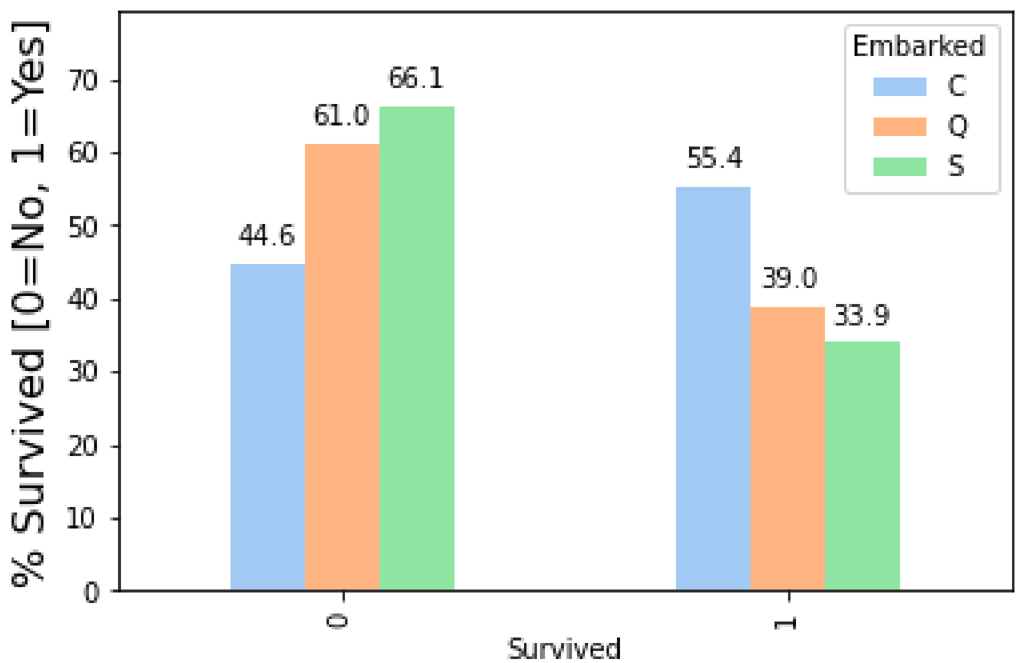

```
# Fare
bins = [0,10,20,50,100,np.inf]
labels = ['0-10','10-20','20-50','50-100','60+']
fare_bins = pd.cut(df1.Fare, bins, labels=labels)
df1['Fare_bins'] = fare_bins

plot_percentages(df1,'Fare_bins')
```






```
# Embark
plot_percentages(df_eda,'Embarked')
plt.show()
```

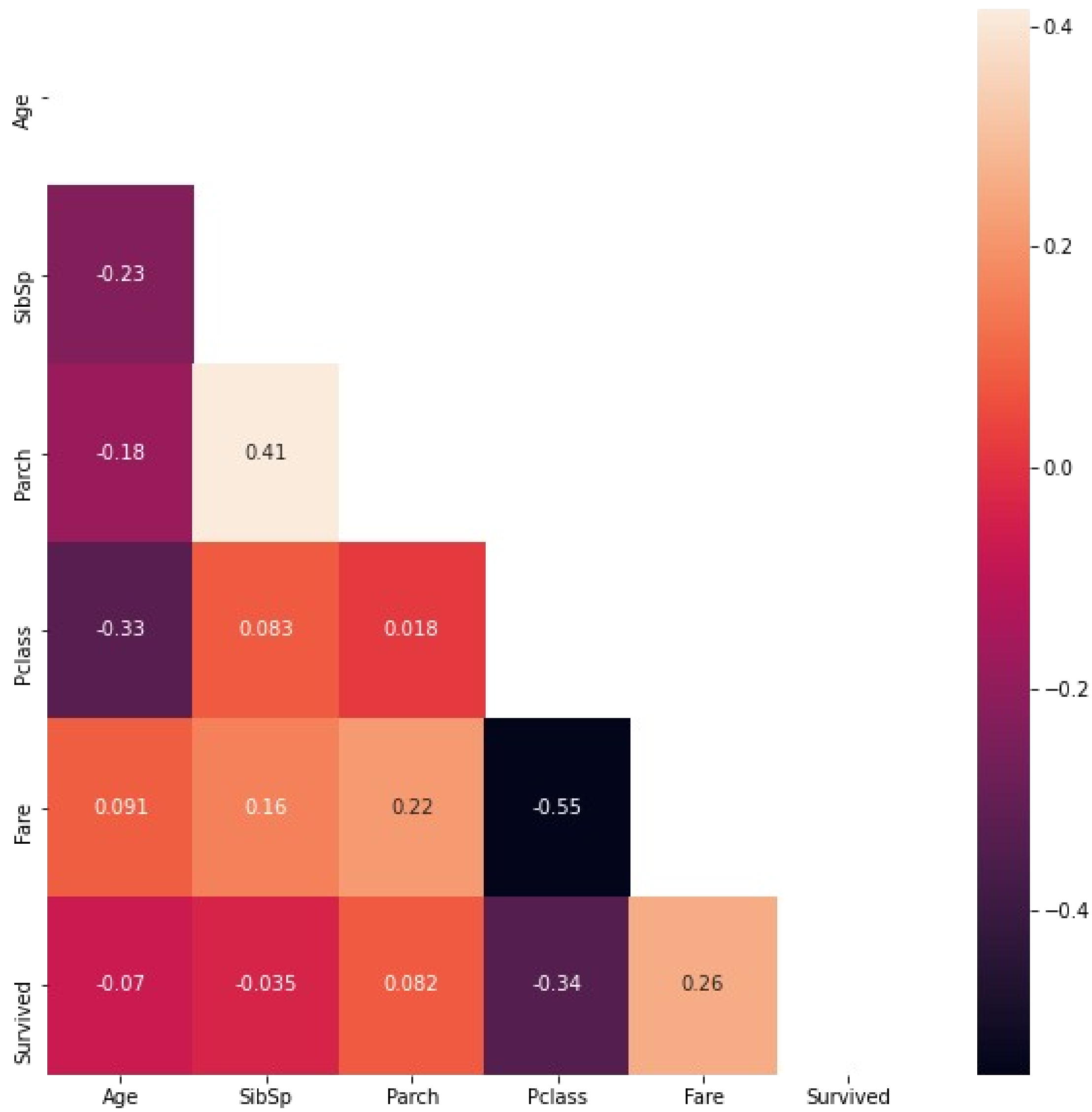




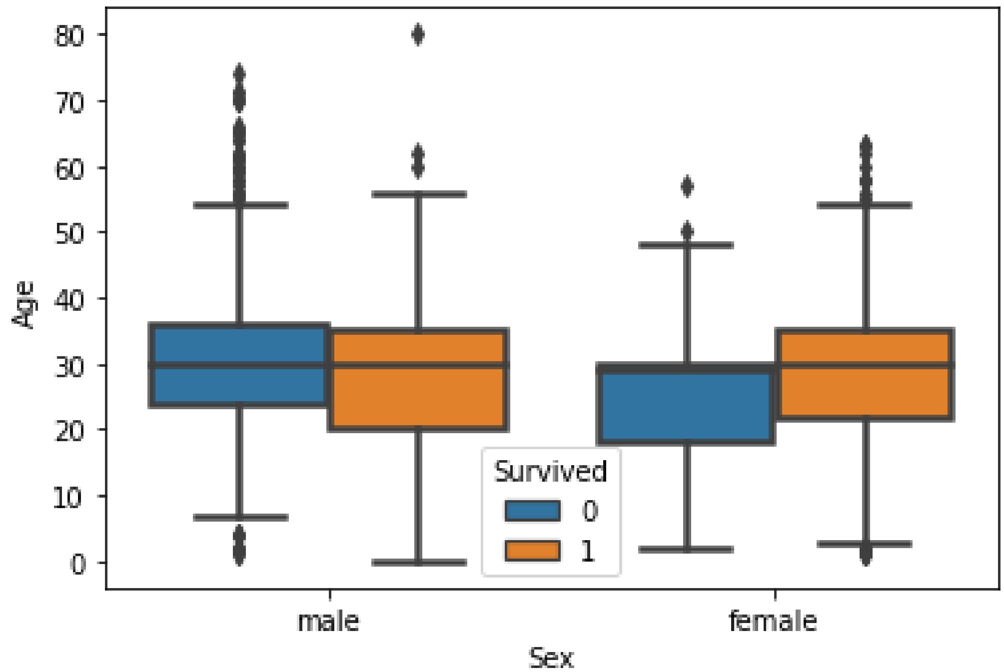

```
# Tickets, Cabins and Names

print('There are {} unique Tickets values in the provided
data'.format(len(df.Ticket.unique())))
print('\nThere are {} unique Cabin values excluding the nulls in the
provided data'.format(len(df.Cabin.unique())))
print('\nThere are {} Unique passanger
names'.format(len(df.Name.unique())))
```

```
There are 681 unique Tickets values in the provided data

There are 148 unique Cabin values excluding the nulls in the provided
data

There are 891 Unique passanger names
```

```
corr = df1.corr()
mask = np.triu(np.ones_like(corr, dtype=np.bool)) #masks upper
triangle
fig = plt.subplots(figsize=(10, 10))
sns.heatmap(corr, annot=True,mask=mask)
plt.show()
```




```
ax = sns.boxplot(x="Sex", y="Age", hue="Survived",data=df1,
linewidth=2.5)
```



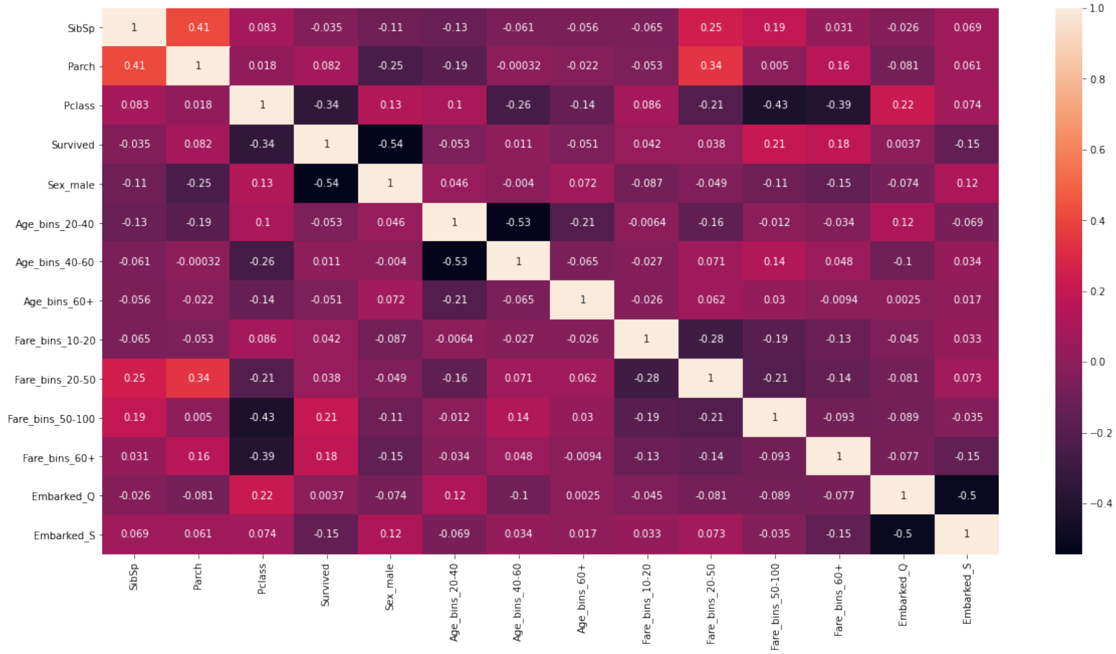

```
#df1.drop(['Age','Fare'],axis=1,inplace=True)
df1=
df1[['Sex','Age_bins','SibSp','Parch','Pclass','Fare_bins','Embarked',
'Survived']]
df1.sample(5)

        Sex Age_bins  SibSp  Parch  Pclass Fare_bins Embarked
Survived
287    male    20-40      0      0       3      0-10        S
0
657  female    20-40      1      1       3     10-20        Q
0
179    male    20-40      0      0       3       NaN        S
0
762    male     0-20      0      0       3      0-10        C
1
472  female    20-40      1      2       2     20-50        S
1

dummy=pd.get_dummies(df1,drop_first=True)
dummy.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   SibSp            891 non-null    int64
 1   Parch            891 non-null    int64
 2   Pclass           891 non-null    int64
```

```
 3   Survived          891 non-null    int64
 4   Sex_male          891 non-null    uint8
 5   Age_bins_20-40    891 non-null    uint8
 6   Age_bins_40-60    891 non-null    uint8
 7   Age_bins_60+      891 non-null    uint8
 8   Fare_bins_10-20   891 non-null    uint8
 9   Fare_bins_20-50   891 non-null    uint8
 10  Fare_bins_50-100  891 non-null    uint8
 11  Fare_bins_60+     891 non-null    uint8
 12  Embarked_Q        891 non-null    uint8
 13  Embarked_S        891 non-null    uint8
dtypes: int64(4), uint8(10)
memory usage: 36.7 KB
```

```
dummy.sample(5)
```

```
     SibSp  Parch  Pclass  Survived  Sex_male  Age_bins_20-40
Age_bins_40-60  \
315      0      0       3         1         0               1
0
214      1      0       3         0         1               1
0
445      0      2       1         1         1               0
0
602      0      0       1         0         1               1
0
622      1      1       3         1         1               0
0

     Age_bins_60+  Fare_bins_10-20  Fare_bins_20-50  Fare_bins_50-100
\
315             0                0                0                 0

214             0                0                0                 0

445             0                0                0                 1

602             0                0                1                 0

622             0                1                0                 0


     Fare_bins_60+  Embarked_Q  Embarked_S
315              0           0           1
214              0           1           0
445              0           0           1
602              0           0           1
622              0           0           0
```

```
plt.figure(figsize = (20,10))        # Size of the figure
sns.heatmap(dummy.corr(),annot = True)
plt.show()
```




```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

X= dummy.drop('Survived', axis =1) #features
Y= dummy.pop ('Survived') #target

Xtrain, Xtest, Ytrain, Ytest = train_test_split(X, Y, test_size=0.3,
random_state=50)
Xtrain.shape
```

```
(623, 13)
```

Logistic Regression

```
#Method 1- Default Parameters
from sklearn.linear_model import LogisticRegression
from sklearn import metrics,model_selection
from sklearn.metrics import
roc_auc_score,roc_curve,classification_report,confusion_matrix,plot_co
nfusion_matrix

model = LogisticRegression()
model.fit(Xtrain, Ytrain)

LR_Ytrain_predict = model.predict(Xtrain)
LR_Ytest_predict = model.predict(Xtest)
```

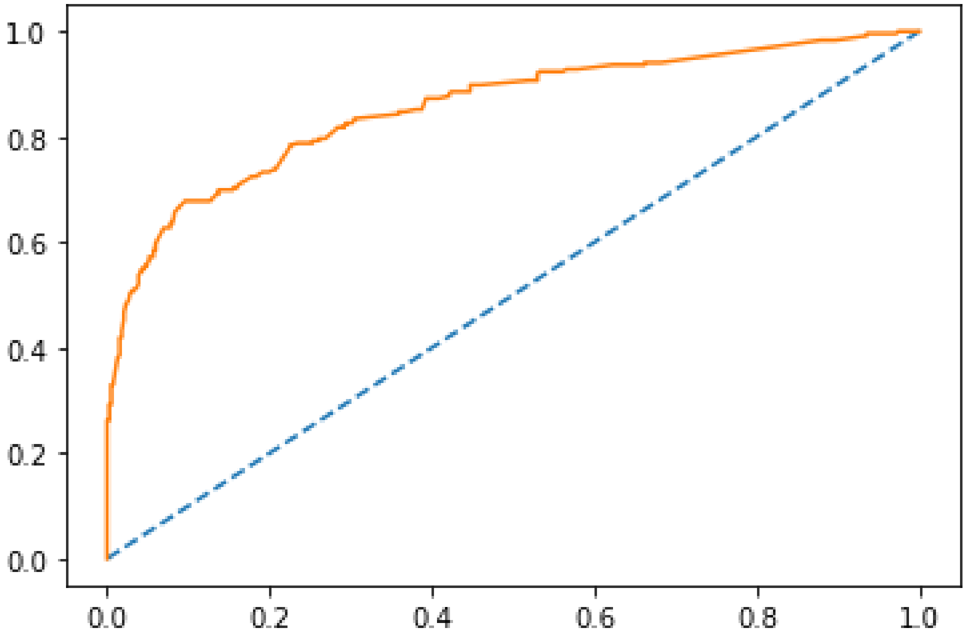
```
print('Train Set Accuracy:-',model.score(Xtrain, Ytrain))
print('Test Set Accuracy:-',model.score(Xtest, Ytest))
print('\nConfusion Matrix for Train Set:-\n',confusion_matrix(Ytrain,
LR_Ytrain_predict))
print('\nClassification Report for Train Set:-\
n',classification_report(Ytrain, LR_Ytrain_predict))
print('\nConfusion Matrix for Test Set:-\n',confusion_matrix(Ytest,
LR_Ytest_predict))
print('\nClassification Report for Test Set:-\
n',classification_report(Ytest, LR_Ytest_predict))
```

```
Train Set Accuracy:- 0.8041733547351525
Test Set Accuracy:- 0.8059701492537313

Confusion Matrix for Train Set:-
 [[341  46]
 [ 76 160]]

Classification Report for Train Set:-
               precision    recall  f1-score   support

           0       0.82      0.88      0.85       387
           1       0.78      0.68      0.72       236

    accuracy                           0.80       623
   macro avg       0.80      0.78      0.79       623
weighted avg       0.80      0.80      0.80       623


Confusion Matrix for Test Set:-
 [[143  19]
 [ 33  73]]

Classification Report for Test Set:-
               precision    recall  f1-score   support

           0       0.81      0.88      0.85       162
           1       0.79      0.69      0.74       106

    accuracy                           0.81       268
   macro avg       0.80      0.79      0.79       268
weighted avg       0.80      0.81      0.80       268
```

```
#AUC and ROC for train data wrt LR
probs = model.predict_proba(Xtrain)
probs = probs[:, 1]
LRbasic_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % LRbasic_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
```

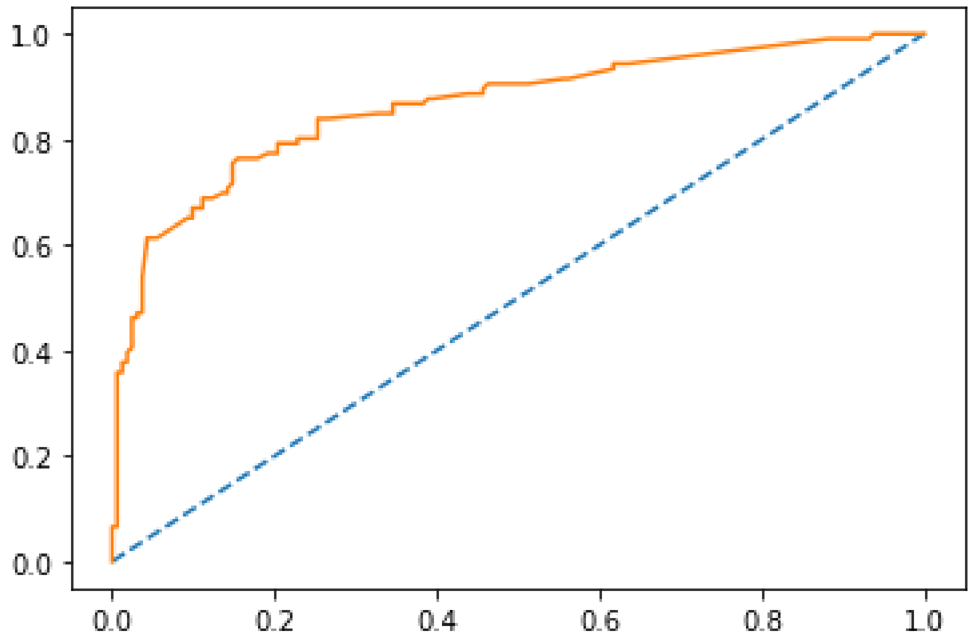
```
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

AUC: 0.855




```
#AUC and ROC for test data wrt LR
probs = model.predict_proba(Xtest)
probs = probs[:, 1]
LRbasic_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % LRbasic_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

AUC: 0.863




```
#Method 2- Grid Search Logistic Regression
grid={'penalty':['l2','none'],
      'solver':['liblinear','lbfgs','saga'],
      'tol':[0.001,0.00001]}

LR = LogisticRegression(max_iter=1000,n_jobs=2)
grid_search = GridSearchCV(estimator = LR, param_grid = grid, cv =
3,scoring='f1')
grid_search.fit(Xtrain, Ytrain)
```

```
GridSearchCV(cv=3, estimator=LogisticRegression(max_iter=1000,
n_jobs=2),
             param_grid={'penalty': ['l2', 'none'],
                         'solver': ['liblinear', 'lbfgs', 'saga'],
                         'tol': [0.001, 1e-05]},
             scoring='f1')
```

```
print(grid_search.best_params_,'\n')
print(grid_search.best_estimator_)
```

```
{'penalty': 'l2', 'solver': 'liblinear', 'tol': 0.001}

LogisticRegression(max_iter=1000, n_jobs=2, solver='liblinear',
tol=0.001)
```

```
bestmodel = grid_search.best_estimator_
```

```
LRM_Ytrain_predict = bestmodel.predict(Xtrain)
LRM_train_score = bestmodel.score(Xtrain, Ytrain)
print('Train Set Accuracy:',LRM_train_score)
print('Confusion Matrix:-\n',confusion_matrix(Ytrain,
```

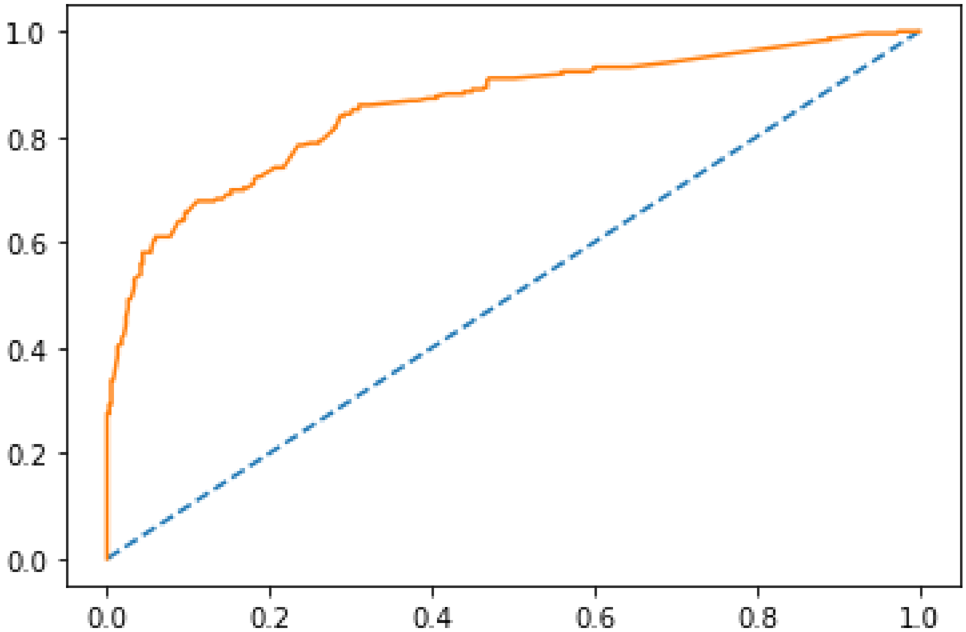
```
LRM_Ytrain_predict))
print('\nClassification Report:-\n',classification_report(Ytrain,
LRM_Ytrain_predict))

LRM_Ytest_predict = bestmodel.predict(Xtest)
LRM_test_score = bestmodel.score(Xtest, Ytest)
print('Test Set Accuracy:',LRM_test_score)
print('Confusion Matrix:-\n',confusion_matrix(Ytest,
LRM_Ytest_predict))
print('\nClassification Report:-\n',classification_report(Ytest,
LRM_Ytest_predict))
```

```
Train Set Accuracy: 0.8025682182985554
Confusion Matrix:-
 [[340  47]
 [ 76 160]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.82      0.88      0.85       387
           1       0.77      0.68      0.72       236

    accuracy                           0.80       623
   macro avg       0.80      0.78      0.78       623
weighted avg       0.80      0.80      0.80       623

Test Set Accuracy: 0.8022388059701493
Confusion Matrix:-
 [[143  19]
 [ 34  72]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.81      0.88      0.84       162
           1       0.79      0.68      0.73       106

    accuracy                           0.80       268
   macro avg       0.80      0.78      0.79       268
weighted avg       0.80      0.80      0.80       268
```

```
#AUC and ROC for train data wrt LRM
probs = bestmodel.predict_proba(Xtrain)
probs = probs[:, 1]
LR_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % LR_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
```

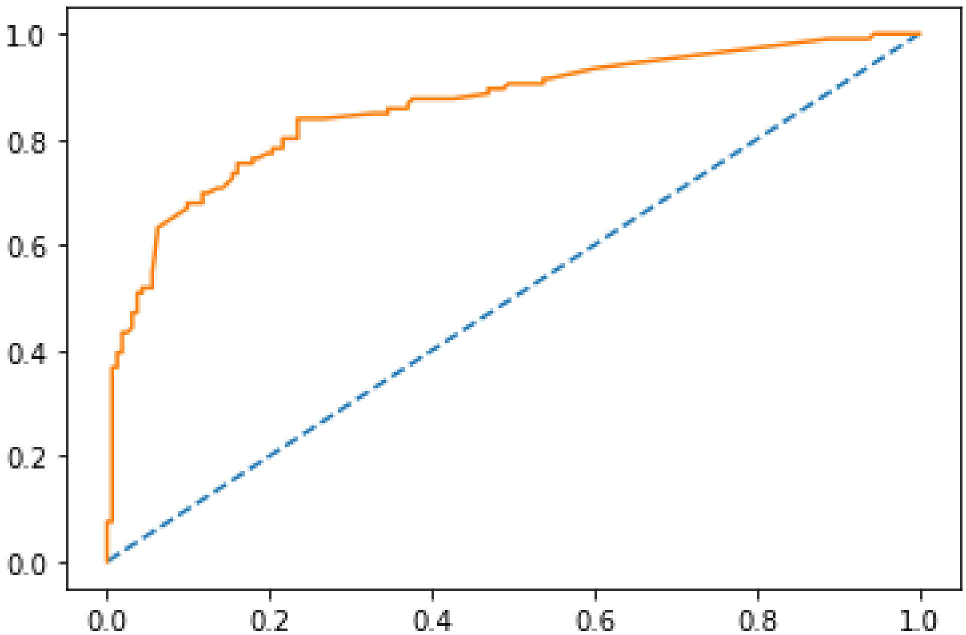
```
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

```
AUC: 0.855
```




```
#AUC and ROC for test data wrt LRM
probs = bestmodel.predict_proba(Xtest)
probs = probs[:, 1]
LR_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % LR_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

```
AUC: 0.862
```



KNN

```
from sklearn.neighbors import KNeighborsClassifier

KNN=KNeighborsClassifier()
KNN.fit(Xtrain,Ytrain)
```

```
KNeighborsClassifier()
```

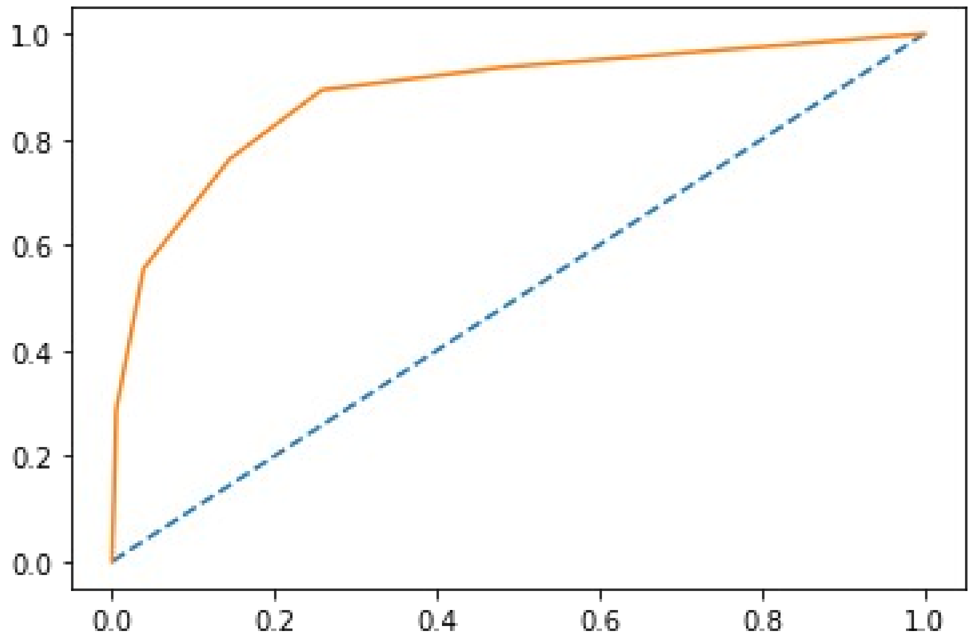
```
#Performance on Train Dataset wrt KNN
KNN_Ytrain_predict = KNN.predict(Xtrain)
KNN_train_score = KNN.score(Xtrain, Ytrain)
print('Train Data Accuracy:-',KNN_train_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytrain,
KNN_Ytrain_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytrain, KNN_Ytrain_predict))

#Performance on Test Dataset wrt KNN
KNN_Ytest_predict = KNN.predict(Xtest)
KNN_test_score = KNN.score(Xtest, Ytest)
print('Test Data Accuracy:-',KNN_test_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytest,
KNN_Ytest_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytest, KNN_Ytest_predict))
```

```
Train Data Accuracy:- 0.8202247191011236

Confusion Matrix:-
 [[331  56]
```

```
 [ 56 180]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.86      0.86      0.86       387
           1       0.76      0.76      0.76       236

    accuracy                           0.82       623
   macro avg       0.81      0.81      0.81       623
weighted avg       0.82      0.82      0.82       623

Test Data Accuracy:- 0.7798507462686567

Confusion Matrix:-
 [[141  21]
 [ 38  68]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.79      0.87      0.83       162
           1       0.76      0.64      0.70       106

    accuracy                           0.78       268
   macro avg       0.78      0.76      0.76       268
weighted avg       0.78      0.78      0.78       268
```

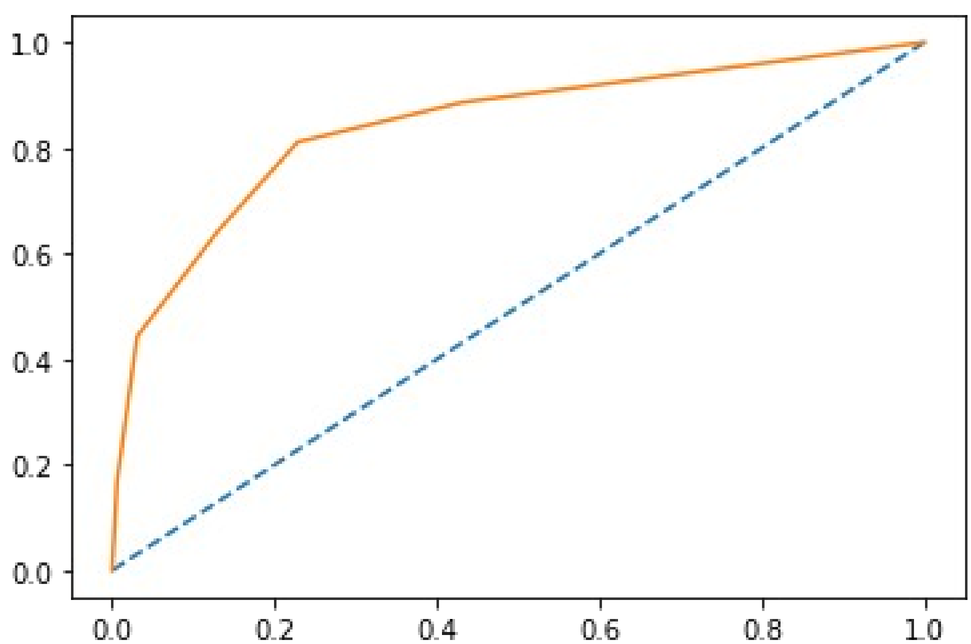
```
#AUC and ROC for train data wrt KNN
probs = KNN.predict_proba(Xtrain)
probs = probs[:, 1]
KNN_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % KNN_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

```
AUC: 0.885
```




```
#AUC and ROC for test data wrt KNN
probs = KNN.predict_proba(Xtest)
probs = probs[:, 1]
KNN_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % KNN_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

AUC: 0.842



```
KNN = KNeighborsClassifier(n_jobs=-1)
params = {'n_neighbors':[3,5,7,9],
          'leaf_size':[5,10,15],
          'weights':['uniform', 'distance'],
          'algorithm':['auto', 'ball_tree','kd_tree','brute'],
          'n_jobs':[-1]}
gridKNN = GridSearchCV(KNN, param_grid=params, n_jobs=1)
gridKNN.fit(Xtrain,Ytrain)
```

```
GridSearchCV(estimator=KNeighborsClassifier(n_jobs=-1), n_jobs=1,
             param_grid={'algorithm': ['auto', 'ball_tree', 'kd_tree',
'brute'],
                         'leaf_size': [5, 10, 15], 'n_jobs': [-1],
                         'n_neighbors': [3, 5, 7, 9],
                         'weights': ['uniform', 'distance']})
```

```
print(gridKNN.best_params_,'\n')
print(gridKNN.best_estimator_)
```

```
{'algorithm': 'ball_tree', 'leaf_size': 10, 'n_jobs': -1,
'n_neighbors': 9, 'weights': 'distance'}

KNeighborsClassifier(algorithm='ball_tree', leaf_size=10, n_jobs=-1,
                     n_neighbors=9, weights='distance')
```

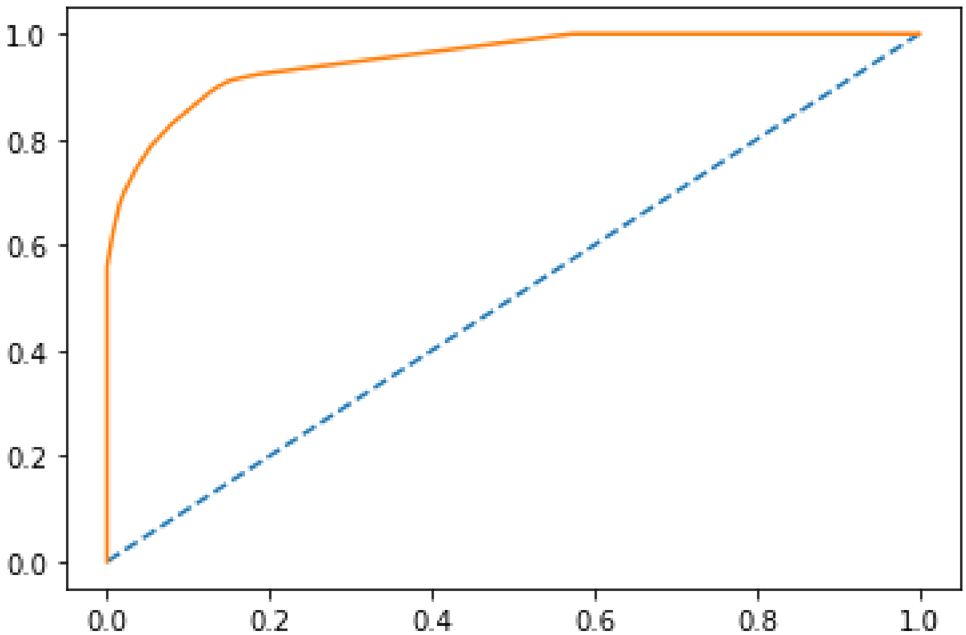
```
bestmodelKNN = gridKNN.best_estimator_

KNNM_Ytrain_predict = bestmodelKNN.predict(Xtrain)
KNNM_train_score = bestmodelKNN.score(Xtrain, Ytrain)
print('Train Set Accuracy:',KNNM_train_score)
print('Confusion Matrix:-\n',confusion_matrix(Ytrain,
KNNM_Ytrain_predict))
print('\nClassification Report:-\n',classification_report(Ytrain,
KNNM_Ytrain_predict))

KNNM_Ytest_predict = bestmodelKNN.predict(Xtest)
KNNM_test_score = bestmodelKNN.score(Xtest, Ytest)
print('Test Set Accuracy:',KNNM_test_score)
print('Confusion Matrix:-\n',confusion_matrix(Ytest,
KNNM_Ytest_predict))
print('\nClassification Report:-\n',classification_report(Ytest,
KNNM_Ytest_predict))
```

```
Train Set Accuracy: 0.8860353130016051
Confusion Matrix:-
 [[366  21]
 [ 50 186]]

Classification Report:-
```

```
              precision    recall  f1-score   support

           0       0.88      0.95      0.91       387
           1       0.90      0.79      0.84       236

    accuracy                           0.89       623
   macro avg       0.89      0.87      0.88       623
weighted avg       0.89      0.89      0.88       623

Test Set Accuracy: 0.8097014925373134
Confusion Matrix:-
 [[150  12]
 [ 39  67]]

Classification Report:-
              precision    recall  f1-score   support

           0       0.79      0.93      0.85       162
           1       0.85      0.63      0.72       106

    accuracy                           0.81       268
   macro avg       0.82      0.78      0.79       268
weighted avg       0.82      0.81      0.80       268
```

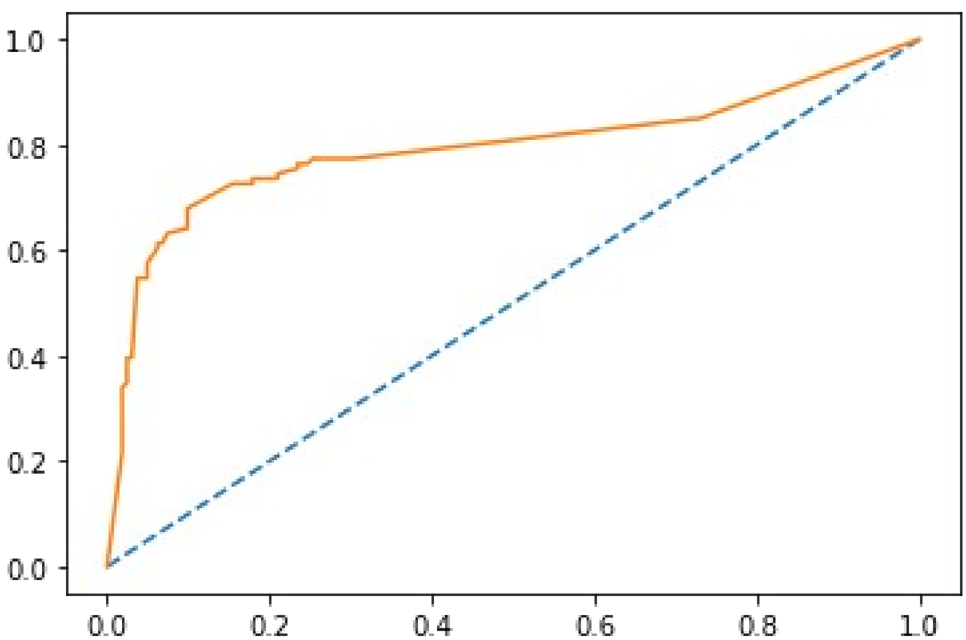
```
#AUC and ROC for train data wrt KNN-M
probs = bestmodelKNN.predict_proba(Xtrain)
probs = probs[:, 1]
KNNM_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % KNNM_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

```
AUC: 0.953
```




```
#AUC and ROC for test data wrt KNN-M
probs = bestmodelKNN.predict_proba(Xtest)
probs = probs[:, 1]
KNNM_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % KNNM_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

```
AUC: 0.794
```



AdaBoost

```python
from sklearn.ensemble import AdaBoostClassifier

ADaBo = AdaBoostClassifier(n_estimators=100,random_state=1)
ADaBo.fit(Xtrain,Ytrain)
```

```
AdaBoostClassifier(n_estimators=100, random_state=1)
```

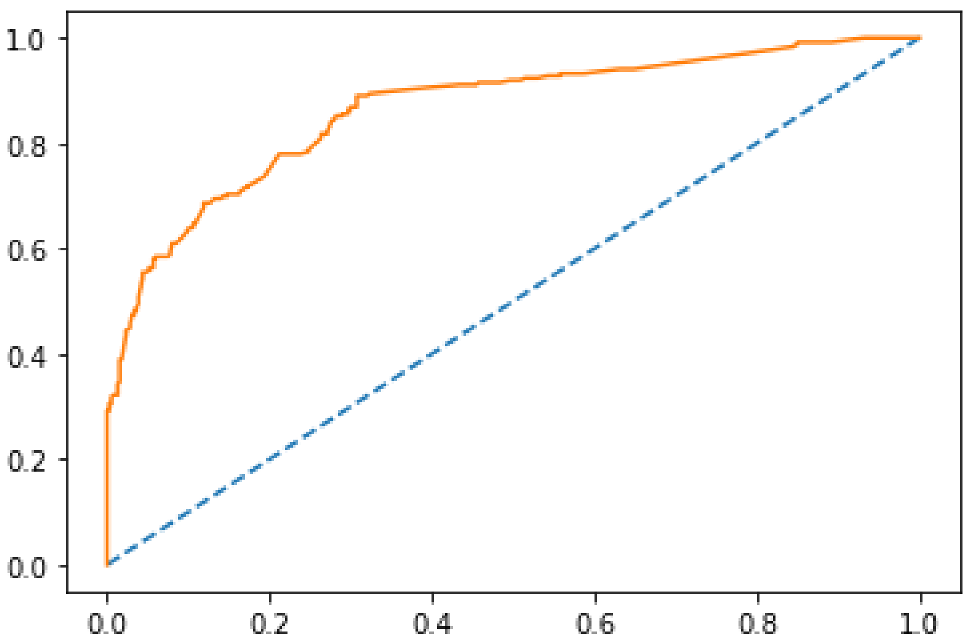
```python
## Performance Matrix on train data set
ADaBo_Ytrain_predict = ADaBo.predict(Xtrain)
ADaBo_train_score = ADaBo.score(Xtrain, Ytrain)
print('Train Data Accuracy:-',ADaBo_train_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytrain,
ADaBo_Ytrain_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytrain, ADaBo_Ytrain_predict))

## Performance Matrix on test data set
ADaBo_Ytest_predict = ADaBo.predict(Xtest)
ADaBo_test_score = ADaBo.score(Xtest, Ytest)
print('Test Data Accuracy:-',ADaBo_test_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytest,
ADaBo_Ytest_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytest, ADaBo_Ytest_predict))
```

```
Train Data Accuracy:- 0.7961476725521669

Confusion Matrix:-
 [[330  57]
 [ 70 166]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.82      0.85      0.84       387
           1       0.74      0.70      0.72       236

    accuracy                           0.80       623
   macro avg       0.78      0.78      0.78       623
weighted avg       0.79      0.80      0.79       623

Test Data Accuracy:- 0.7947761194029851

Confusion Matrix:-
 [[136  26]
 [ 29  77]]

Classification Report:-
               precision    recall  f1-score   support
```

```
           0       0.82      0.84      0.83       162
           1       0.75      0.73      0.74       106

    accuracy                           0.79       268
   macro avg       0.79      0.78      0.78       268
weighted avg       0.79      0.79      0.79       268
```

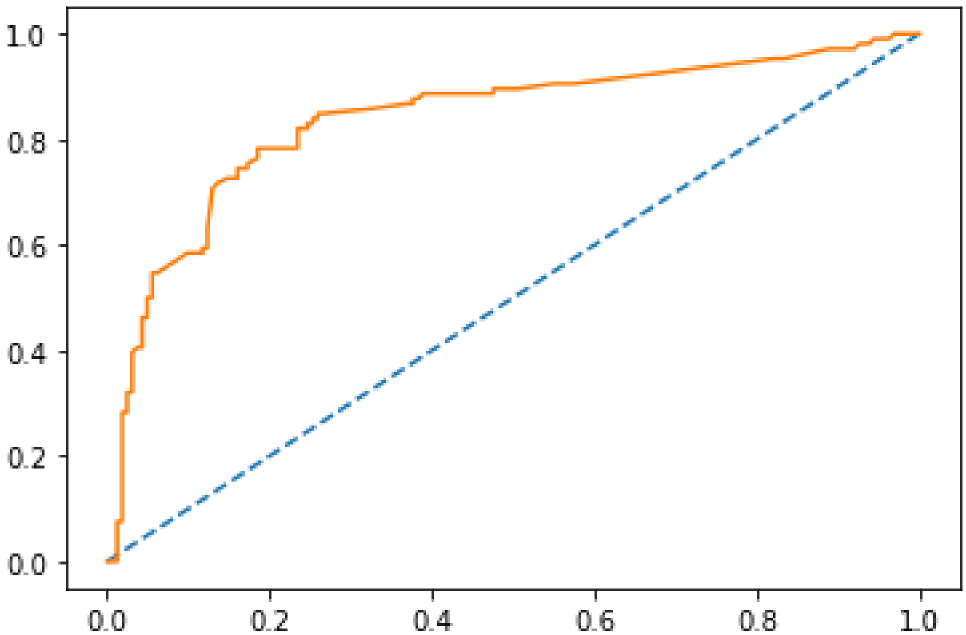
```
#AUC and ROC for train data wrt AdaBoost
probs = ADaBo.predict_proba(Xtrain)
probs = probs[:, 1]
ADaBo_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % ADaBo_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

AUC: 0.864




```
#AUC and ROC for test data wrt AdaBoost
probs = ADaBo.predict_proba(Xtest)
probs = probs[:, 1]
ADaBo_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % ADaBo_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

AUC: 0.839



GradientBoost

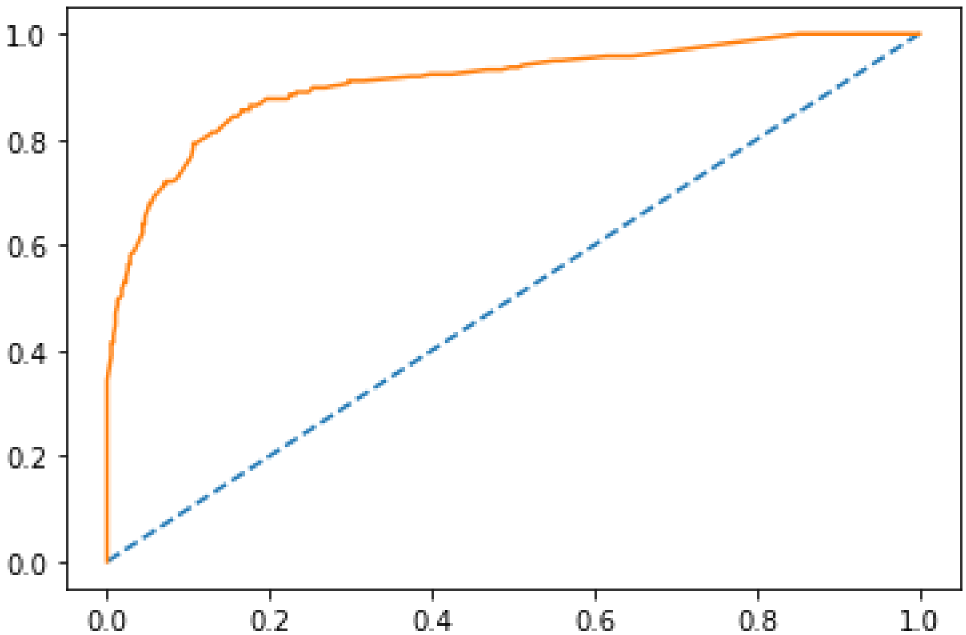
```
from sklearn.ensemble import GradientBoostingClassifier
GBo = GradientBoostingClassifier(random_state=1)
GBo = GBo.fit(Xtrain, Ytrain)

## Performance Matrix on train data set
GBo_Ytrain_predict = GBo.predict(Xtrain)
GBo_train_score = GBo.score(Xtrain, Ytrain)
print('Train Data Accuracy',GBo_train_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytrain, 
GBo_Ytrain_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytrain, GBo_Ytrain_predict))

## Performance Matrix on test data set
GBo_Ytest_predict = GBo.predict(Xtest)
GBo_test_score = GBo.score(Xtest, Ytest)
print('Test Data Accuracy',GBo_test_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytest, 
GBo_Ytest_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytest, GBo_Ytest_predict))
```

```
Train Data Accuracy 0.8475120385232745

Confusion Matrix:-
 [[360  27]
 [ 68 168]]

Classification Report:-
```

```
              precision    recall  f1-score   support

           0       0.84      0.93      0.88       387
           1       0.86      0.71      0.78       236

    accuracy                           0.85       623
   macro avg       0.85      0.82      0.83       623
weighted avg       0.85      0.85      0.84       623

Test Data Accuracy 0.8171641791044776

Confusion Matrix:-
 [[151  11]
 [ 38  68]]

Classification Report:-
              precision    recall  f1-score   support

           0       0.80      0.93      0.86       162
           1       0.86      0.64      0.74       106

    accuracy                           0.82       268
   macro avg       0.83      0.79      0.80       268
weighted avg       0.82      0.82      0.81       268
```

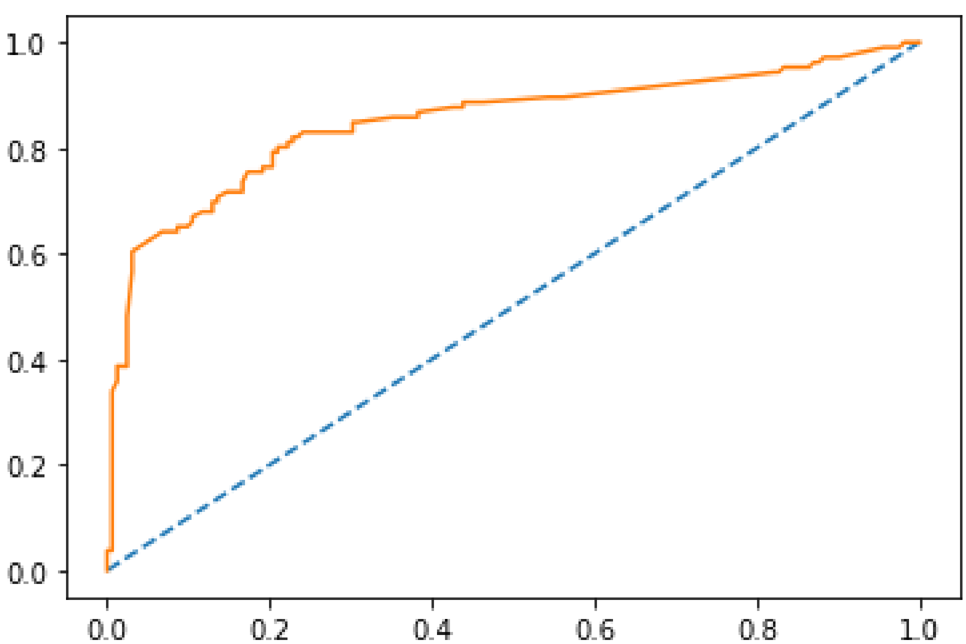
```
#AUC and ROC for train data wrt GradientBoost
probs = GBo.predict_proba(Xtrain)
probs = probs[:, 1]
GBo_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % GBo_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

```
AUC: 0.908
```




```
#AUC and ROC for test data wrt GradientBoost
probs = GBo.predict_proba(Xtest)
probs = probs[:, 1]
GBo_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % GBo_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

```
AUC: 0.850
```



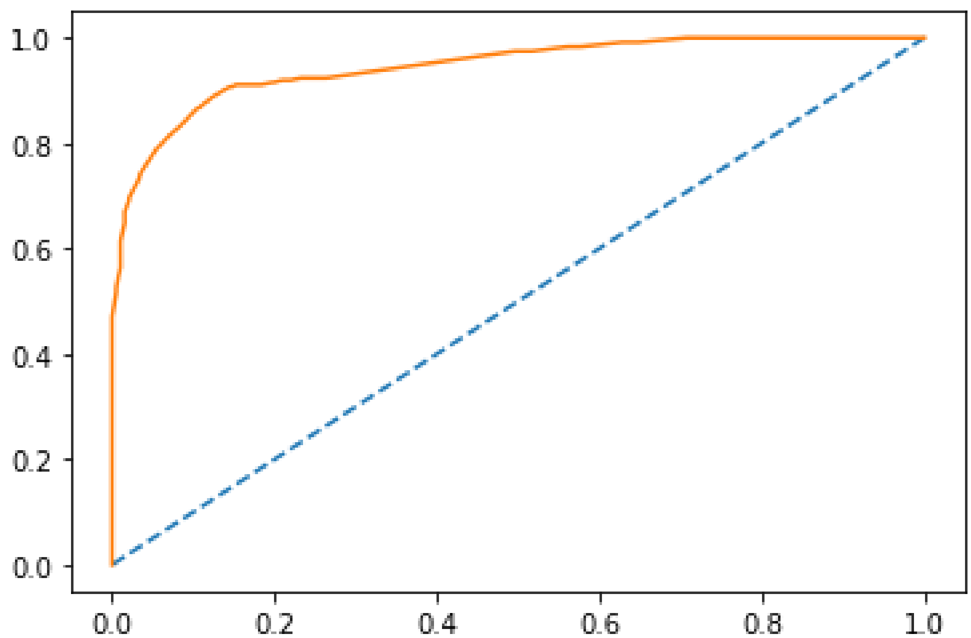
Random Forest

```
from sklearn.ensemble import RandomForestClassifier

RF=RandomForestClassifier(n_estimators=100,random_state=1)
RF.fit(Xtrain, Ytrain)

RandomForestClassifier(random_state=1)

## Performance Matrix on train data set
RF_Ytrain_predict = RF.predict(Xtrain)
RF_train_score =RF.score(Xtrain, Ytrain)
print('Train Data Accuracy:-',RF_train_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytrain,
RF_Ytrain_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytrain, RF_Ytrain_predict))

## Performance Matrix on test data set
RF_Ytest_predict = RF.predict(Xtest)
RF_test_score = RF.score(Xtest, Ytest)
print('Test Data Accuracy:-',RF_test_score)
print('\nConfusion Matrix:-\n',metrics.confusion_matrix(Ytest,
RF_Ytest_predict))
print('\nClassification Report:-\
n',metrics.classification_report(Ytest, RF_Ytest_predict))

Train Data Accuracy:- 0.8860353130016051

Confusion Matrix:-
 [[360  27]
 [ 44 192]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.89      0.93      0.91       387
           1       0.88      0.81      0.84       236

    accuracy                           0.89       623
   macro avg       0.88      0.87      0.88       623
weighted avg       0.89      0.89      0.89       623

Test Data Accuracy:- 0.8171641791044776

Confusion Matrix:-
 [[147  15]
 [ 34  72]]

Classification Report:-
               precision    recall  f1-score   support
```

```
              0       0.81      0.91      0.86       162
              1       0.83      0.68      0.75       106

       accuracy                           0.82       268
      macro avg       0.82      0.79      0.80       268
   weighted avg       0.82      0.82      0.81       268
```

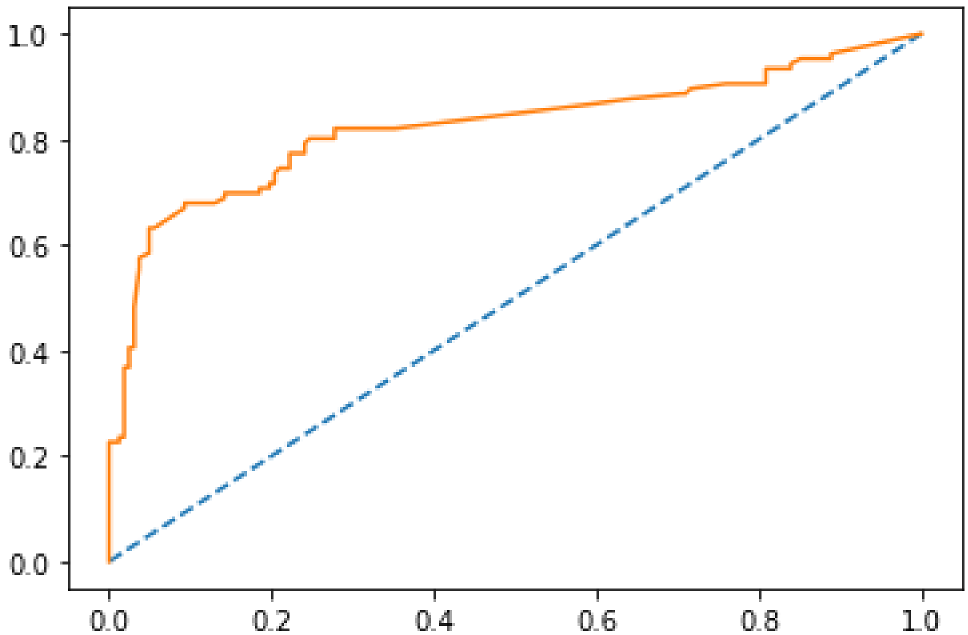
```
#AUC and ROC for train data wrt RandomForest
probs = RF.predict_proba(Xtrain)
probs = probs[:, 1]
RF_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % RF_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

```
AUC: 0.945
```




```
#AUC and ROC for test data wrt Random Forest
probs = RF.predict_proba(Xtest)
probs = probs[:, 1]
RF_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % RF_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

```
AUC: 0.823
```



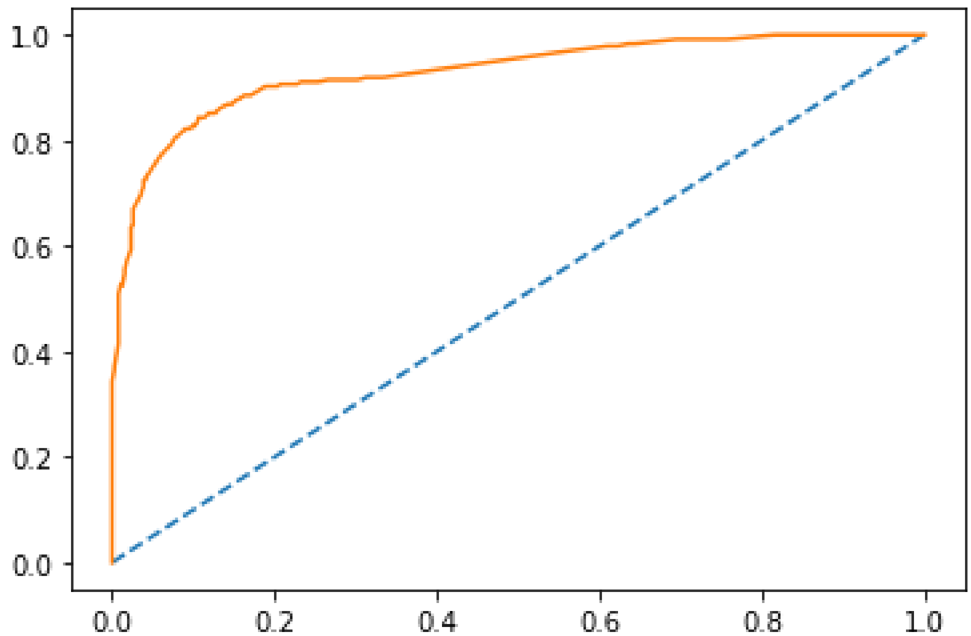

```
params = {'n_estimators': [15,25,30],
              'criterion': ['gini','entropy'],
              'max_depth': [3,7,None],
              'min_samples_split': [5,10,],
              'min_samples_leaf': [1,3,5],
              'max_features': [2,'auto'],
             }

gridRF = GridSearchCV(RF, param_grid=params, n_jobs=1)
gridRF.fit(Xtrain,Ytrain)

GridSearchCV(estimator=RandomForestClassifier(random_state=1),
n_jobs=1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [3, 7, None], 'max_features':
[2, 'auto'],
                         'min_samples_leaf': [1, 3, 5],
                         'min_samples_split': [5, 10],
                         'n_estimators': [15, 25, 30]})

print(gridRF.best_params_,'\n')
print(gridRF.best_estimator_)

{'criterion': 'gini', 'max_depth': None, 'max_features': 2,
'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 30}

RandomForestClassifier(max_features=2, min_samples_split=5,
n_estimators=30,
                       random_state=1)
```

```python
bestmodelRF = gridRF.best_estimator_

RFM_Ytrain_predict = bestmodelRF.predict(Xtrain)
RFM_train_score = bestmodelRF.score(Xtrain, Ytrain)
print('Train Set Accuracy:',RFM_train_score)
print('Confusion Matrix:-\n',confusion_matrix(Ytrain,
RFM_Ytrain_predict))
print('\nClassification Report:-\n',classification_report(Ytrain,
RFM_Ytrain_predict))

RFM_Ytest_predict = bestmodelRF.predict(Xtest)
RFM_test_score = bestmodelRF.score(Xtest, Ytest)
print('Test Set Accuracy:',RFM_test_score)
print('Confusion Matrix:-\n',confusion_matrix(Ytest,
RFM_Ytest_predict))
print('\nClassification Report:-\n',classification_report(Ytest,
RFM_Ytest_predict))
```

```
Train Set Accuracy: 0.8731942215088283
Confusion Matrix:-
 [[348  39]
 [ 40 196]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.90      0.90      0.90       387
           1       0.83      0.83      0.83       236

    accuracy                           0.87       623
   macro avg       0.87      0.86      0.87       623
weighted avg       0.87      0.87      0.87       623

Test Set Accuracy: 0.8022388059701493
Confusion Matrix:-
 [[143  19]
 [ 34  72]]

Classification Report:-
               precision    recall  f1-score   support

           0       0.81      0.88      0.84       162
           1       0.79      0.68      0.73       106

    accuracy                           0.80       268
   macro avg       0.80      0.78      0.79       268
weighted avg       0.80      0.80      0.80       268
```

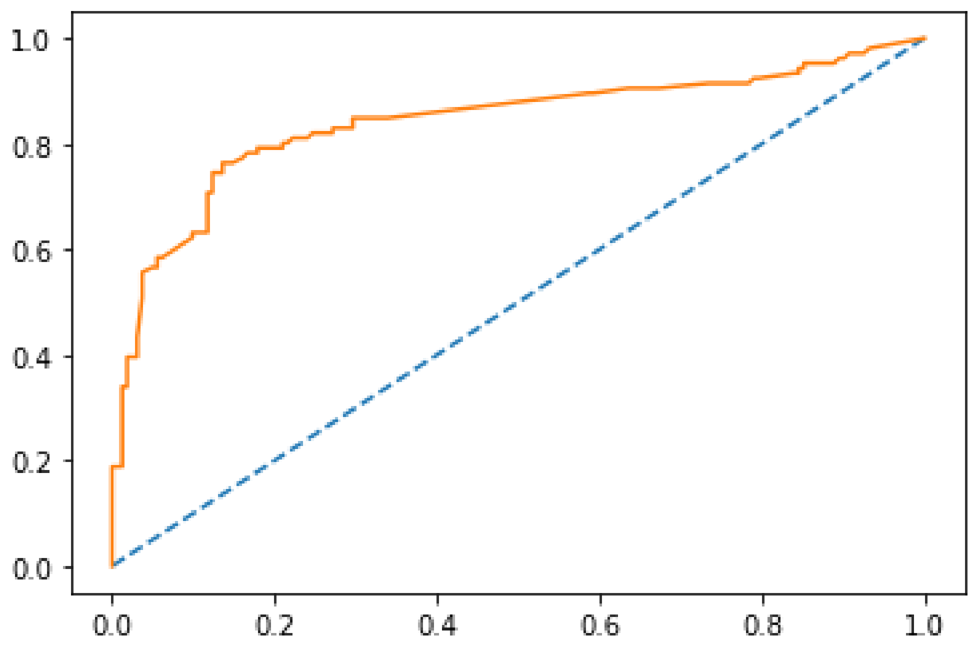
```python
#AUC and ROC for train data wrt RF-M
probs = bestmodelRF.predict_proba(Xtrain)
probs = probs[:, 1]
RFM_train_auc = roc_auc_score(Ytrain, probs)
print('AUC: %.3f' % RFM_train_auc)
train_fpr, train_tpr, train_thresholds = roc_curve(Ytrain, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(train_fpr, train_tpr);
```

```
AUC: 0.930
```




```python
#AUC and ROC for test data wrt RF-M
probs = bestmodelRF.predict_proba(Xtest)
probs = probs[:, 1]
RFM_test_auc = roc_auc_score(Ytest, probs)
print('AUC: %.3f' % RFM_test_auc)
test_fpr, test_tpr, test_thresholds = roc_curve(Ytest, probs)
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(test_fpr, test_tpr);
```

```
AUC: 0.842
```



So, we can predict around 88% values in train set and 82% in test set using Random Forest model.