HEALTHCARE CAPSTONE PROJECT

February 19, 2023

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```python
df=pd.read_csv('health care diabetes.csv')
df.head()
```

[2]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

According to problem statement, a value of zero in the following columns indicates missing value:

Glucose BloodPressure

SkinThickness

Insulin

BMI

We will replace zeros in these columns with null values.

[3]:
```python
cols_with_null_as_zero = ['Glucose', 'BloodPressure', 'SkinThickness',␣
↪'Insulin', 'BMI']
df[cols_with_null_as_zero] = df[cols_with_null_as_zero].replace(0, np.NaN)
```

[4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   763 non-null    float64
 2   BloodPressure             733 non-null    float64
 3   SkinThickness             541 non-null    float64
 4   Insulin                   394 non-null    float64
 5   BMI                       757 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(6), int64(3)
memory usage: 54.1 KB
```

[5]:
```
df.shape
```

[5]:
```
(768, 9)
```

[6]:
```
df.isna().sum()
```

[6]:
```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
dtype: int64
```

[7]:
```
df.describe()
```

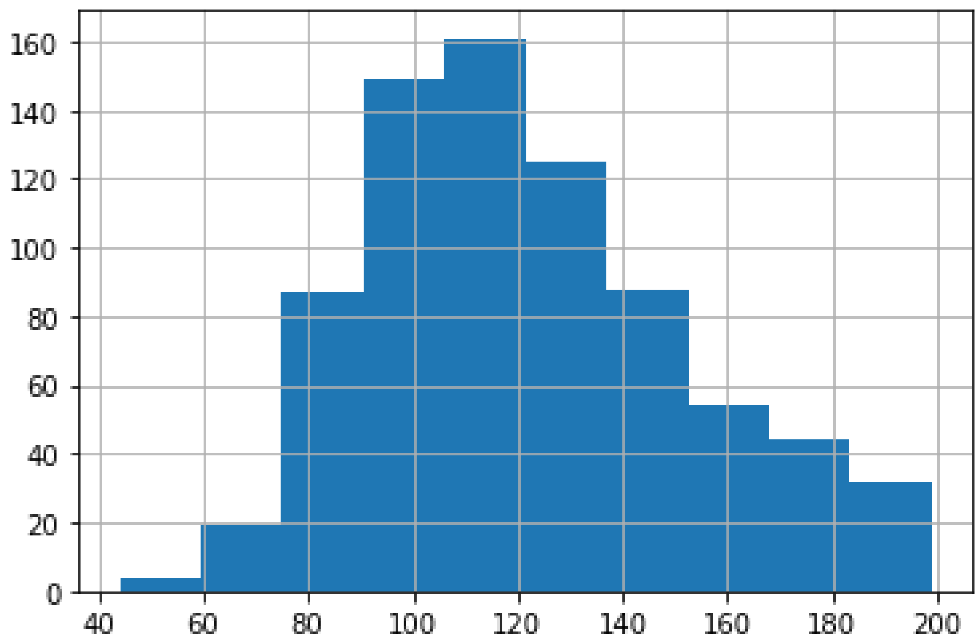
[7]:
```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  763.000000     733.000000     541.000000  394.000000
mean      3.845052  121.686763      72.405184      29.153420  155.548223
std       3.369578   30.535641      12.382158      10.476982  118.775855
min       0.000000   44.000000      24.000000       7.000000   14.000000
25%       1.000000   99.000000      64.000000      22.000000   76.250000
50%       3.000000  117.000000      72.000000      29.000000  125.000000
75%       6.000000  141.000000      80.000000      36.000000  190.000000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
```

count	757.000000	768.000000	768.000000	768.000000
mean	32.457464	0.471876	33.240885	0.348958
std	6.924988	0.331329	11.760232	0.476951
min	18.200000	0.078000	21.000000	0.000000
25%	27.500000	0.243750	24.000000	0.000000
50%	32.300000	0.372500	29.000000	0.000000
75%	36.600000	0.626250	41.000000	1.000000
max	67.100000	2.420000	81.000000	1.000000

Exploring these variables using histograms and treating the missing values accordingly:

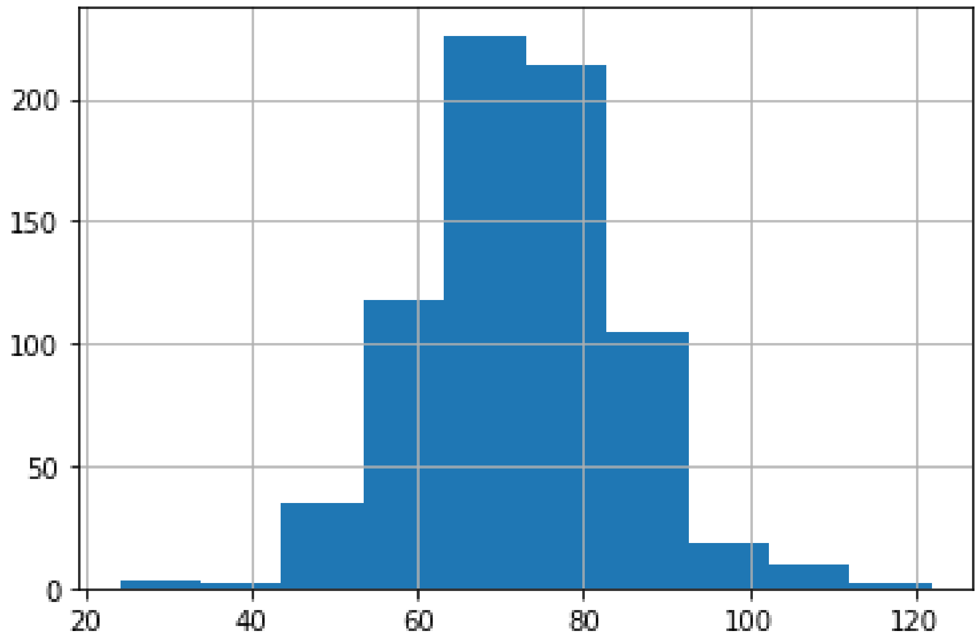
[8]:
```
df['Glucose'].hist()
```

[8]: <AxesSubplot:>



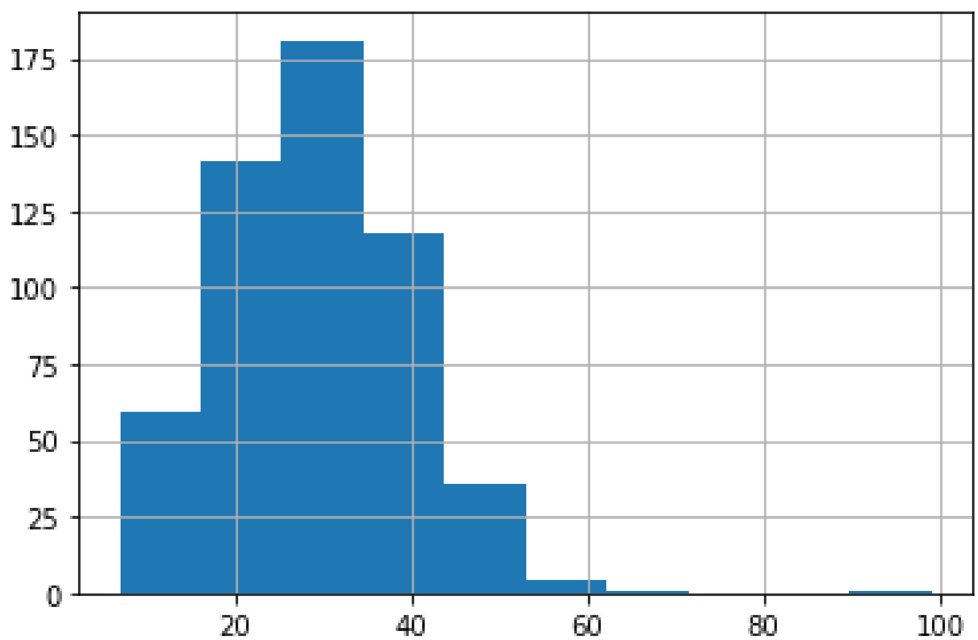
[9]:
```
df['BloodPressure'].hist()
```

[9]: <AxesSubplot:>



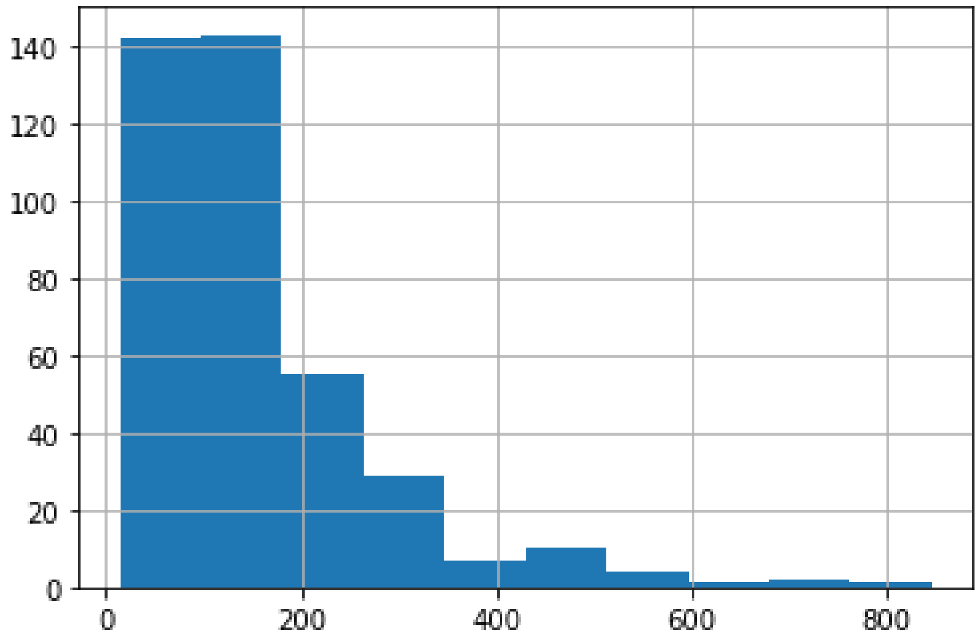

```
[10]: df['SkinThickness'].hist()
```

[10]: <AxesSubplot:>



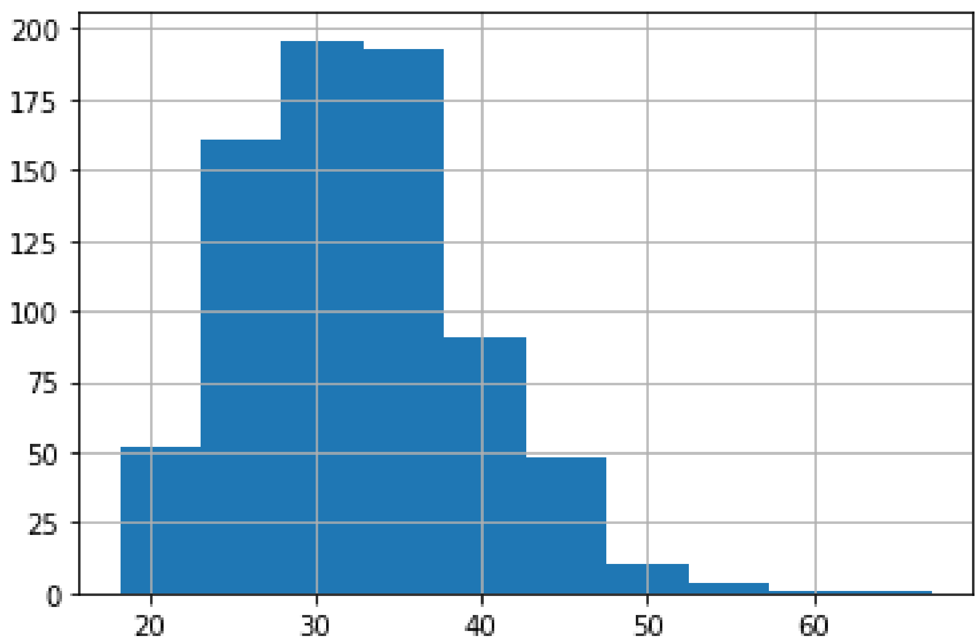
[11]:
```
df['Insulin'].hist()
```

[11]: <AxesSubplot:>



[12]:
```
df['BMI'].hist()
```

[12]: <AxesSubplot:>



From above histograms, it is clear that Insulin has highly skewed data distribution and remaining 4 variables have relatively balanced data distribution therefore we will treat missing values in these 5 variables as below:-

Glucose - replace missing values with mean of values.

BloodPressure - replace missing values with mean of values.

SkinThickness - replace missing values with mean of values.

Insulin - replace missing values with median of values.

BMI - replace missing values with mean of values.

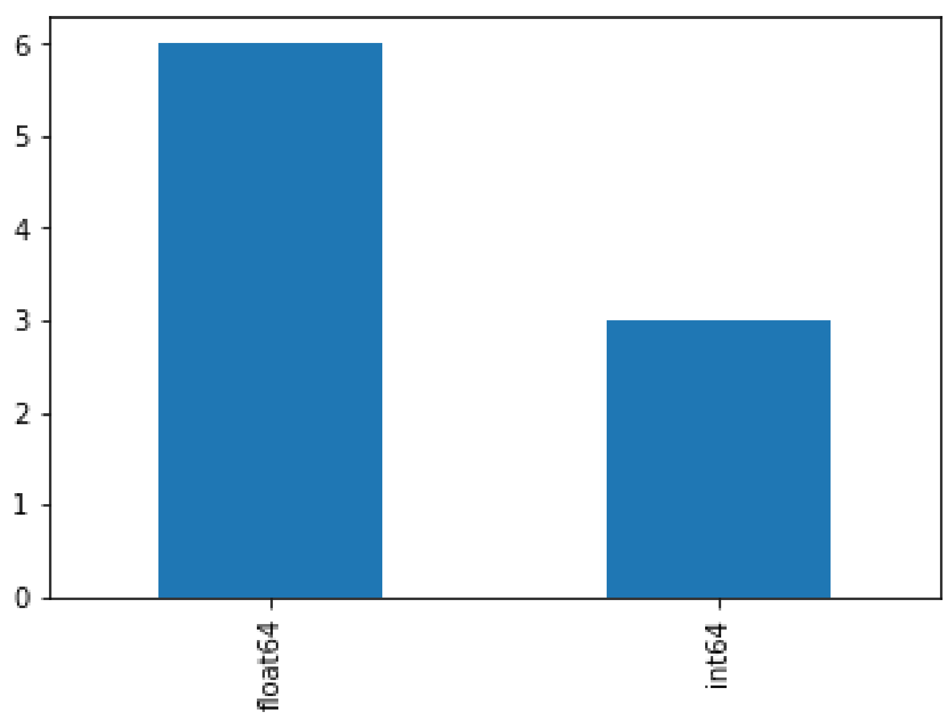
[13]:
```
df['Insulin'] = df['Insulin'].fillna(df['Insulin'].median())
```

[14]:
```
cols_mean_for_null = ['Glucose', 'BloodPressure', 'SkinThickness', 'BMI']
df[cols_mean_for_null] = df[cols_mean_for_null].fillna(df[cols_mean_for_null].
 ↪mean())
```

(3) Createing a count (frequency) plot describing the data types and the count of variables:

[15]:
```
df.dtypes.value_counts().plot(kind='bar')
```

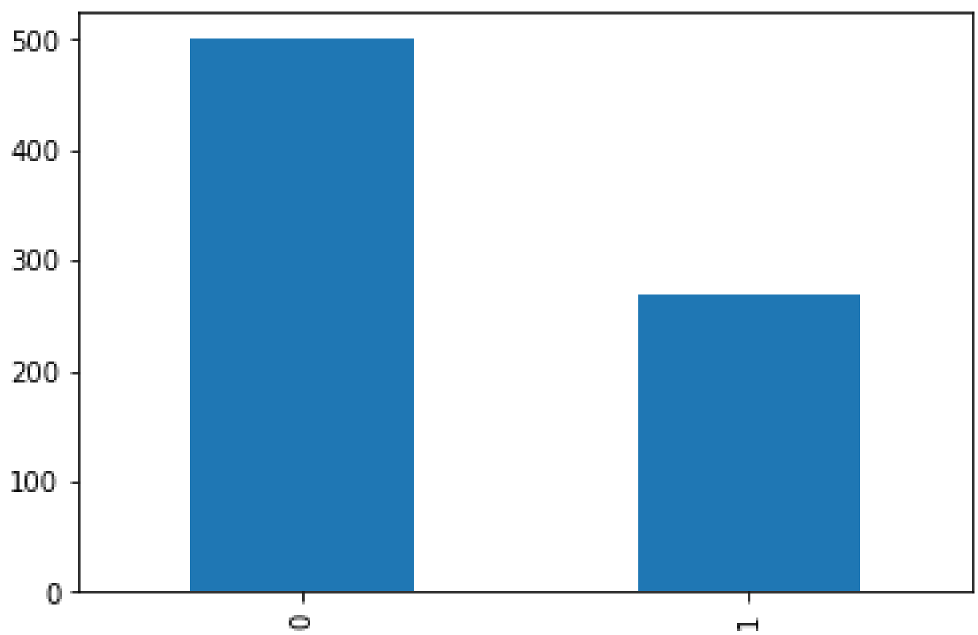
[15]: <AxesSubplot:>



Check the balance of the data by plotting the count of outcomes by their value. Describe your findings and plan future course of action:

[16]:
```
df['Outcome'].value_counts().plot(kind='bar')
df['Outcome'].value_counts()
```

[16]:
```
0    500
1    268
Name: Outcome, dtype: int64
```



Since classes in Outcome is little skewed so we will generate new samples using SMOTE (Synthetic Minority Oversampling Technique) for the class '1' which is under-represented in our data. We will use SMOTE out of many other techniques available since:

It generates new samples by interpolation.

It doesn't duplicate data.

[17]:
```
df_X = df.drop('Outcome', axis=1)
df_y = df['Outcome']
print(df_X.shape, df_y.shape)
```

```
(768, 8) (768,)
```

[18]:
```
!pip install imblearn
```

```
Requirement already satisfied: imblearn in c:\users\91940\anaconda\lib\site-
packages (0.0)
Requirement already satisfied: imbalanced-learn in
c:\users\91940\anaconda\lib\site-packages (from imblearn) (0.10.1)
Requirement already satisfied: numpy>=1.17.3 in
c:\users\91940\anaconda\lib\site-packages (from imbalanced-learn->imblearn)
(1.21.5)
Requirement already satisfied: threadpoolctl>=2.0.0 in
c:\users\91940\anaconda\lib\site-packages (from imbalanced-learn->imblearn)
(2.2.0)
Requirement already satisfied: scikit-learn>=1.0.2 in
c:\users\91940\anaconda\lib\site-packages (from imbalanced-learn->imblearn)
(1.0.2)
Requirement already satisfied: joblib>=1.1.1 in
c:\users\91940\anaconda\lib\site-packages (from imbalanced-learn->imblearn)
(1.2.0)
Requirement already satisfied: scipy>=1.3.2 in c:\users\91940\anaconda\lib\site-
packages (from imbalanced-learn->imblearn) (1.7.3)
```

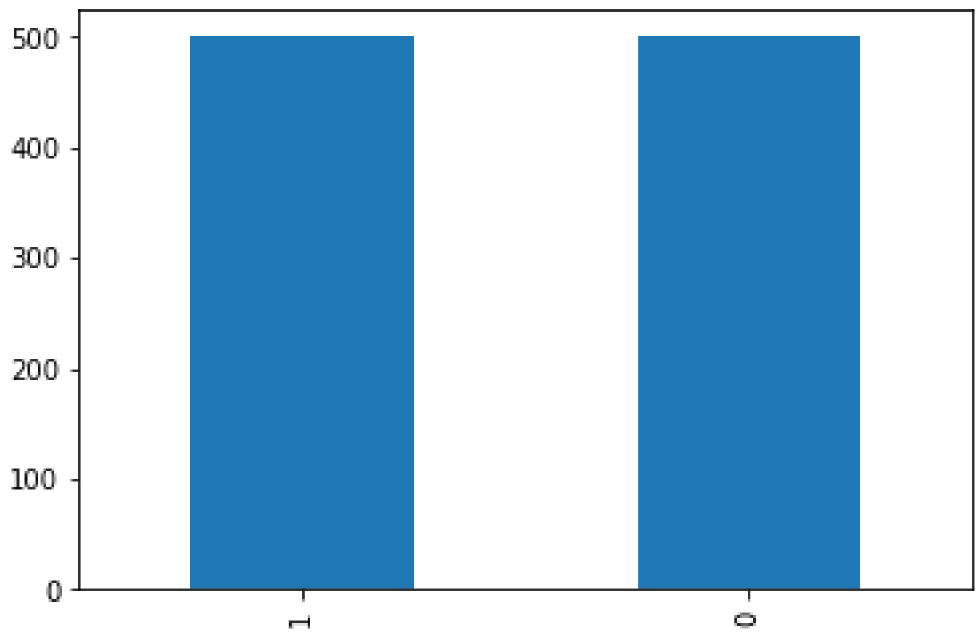
[19]:
```python
from imblearn.over_sampling import SMOTE
```

[20]:
```python
df_X_resampled, df_y_resampled = SMOTE(random_state=100).fit_resample(df_X,␣
 ↪df_y)
print(df_X_resampled.shape, df_y_resampled.shape)
```

```
(1000, 8) (1000,)
```

[21]:
```python
df_y_resampled.value_counts().plot(kind='bar')
df_y_resampled.value_counts()
```

[21]:
```
1    500
0    500
Name: Outcome, dtype: int64
```



Creating scatter charts between the pair of variables to understand the relationships:

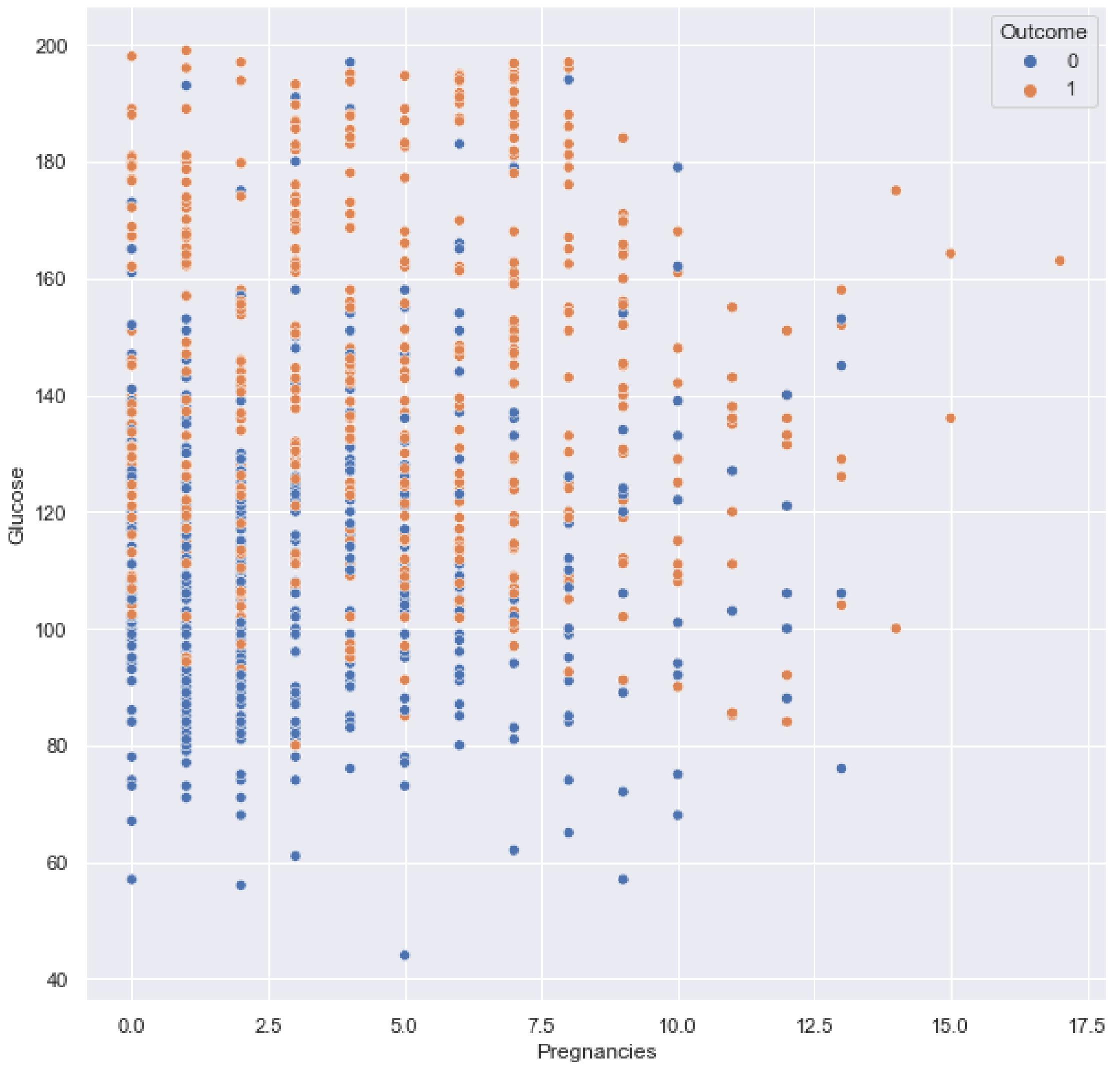
[22]:
```
df_resampled = pd.concat([df_X_resampled, df_y_resampled], axis=1)
df_resampled
```

[22]:
```
     Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
0              6  148.000000      72.000000      35.000000  125.000000
1              1   85.000000      66.000000      29.000000  125.000000
2              8  183.000000      64.000000      29.153420  125.000000
3              1   89.000000      66.000000      23.000000   94.000000
4              0  137.000000      40.000000      35.000000  168.000000
..           …           …            …            …           …
995            1  164.045192      54.128280      25.935860  621.406727
996            2  122.788919      70.728218      22.771383  125.000000
997            5  148.139351      84.512270      29.071365  125.534838
998            9  159.943751      95.858327      29.153420  125.000000
999            5  151.213781      83.803445      27.803445  288.381460

           BMI  DiabetesPedigreeFunction  Age  Outcome
0    33.600000                  0.627000   50        1
1    26.600000                  0.351000   31        0
2    23.300000                  0.672000   32        1
3    28.100000                  0.167000   21        0
4    43.100000                  2.288000   33        1
..         …                      …   …      …
995  36.412099                  0.282034   34        1
```

```
996   28.187203                   0.232503   36         1
997   33.339351                   0.620830   57         1
998   34.589789                   0.197392   45         1
999   32.383232                   0.455381   58         1

[1000 rows x 9 columns]
```

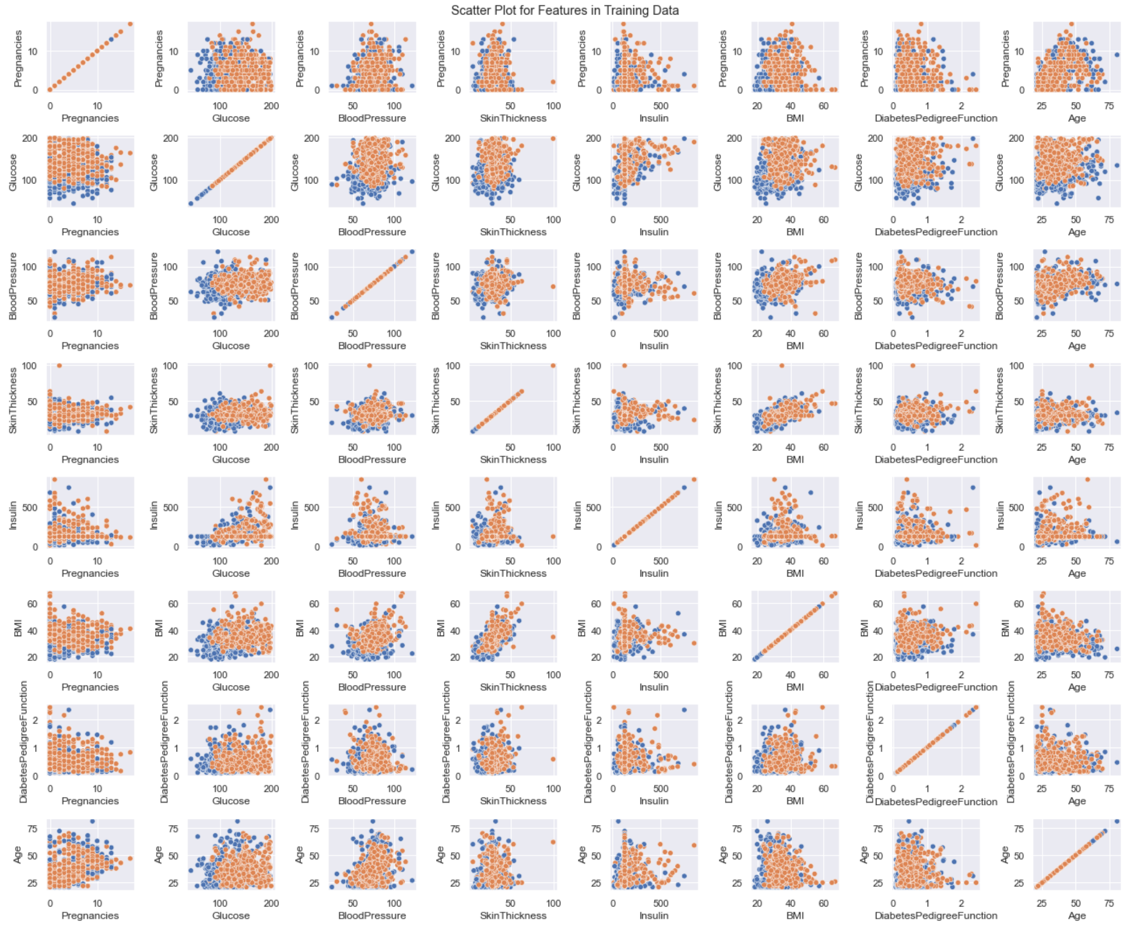
[23]:
```
sns.set(rc={'figure.figsize':(10,10)})
sns.scatterplot(x="Pregnancies", y="Glucose", data=df_resampled, hue="Outcome")
```

[23]:
```
<AxesSubplot:xlabel='Pregnancies', ylabel='Glucose'>
```



[24]:
```
fig, axes = plt.subplots(8, 8, figsize=(18, 15))
fig.suptitle('Scatter Plot for Features in Training Data')
```

```
for i, col_y in enumerate(df_X_resampled.columns):
    for j, col_x in enumerate(df_X_resampled.columns):
        sns.scatterplot(ax=axes[i, j], x=col_x, y=col_y, data=df_resampled,␣
 ↪hue="Outcome", legend = False)

plt.tight_layout()
```



We have some interesting observations from above scatter plot of pairs of features:

Glucose alone is impressively good to distinguish between the Outcome classes.

Age alone is also able to distinguish between classes to some extent.

It seems none of pairs in the dataset is able to clealry distinguish between the Outcome classes.

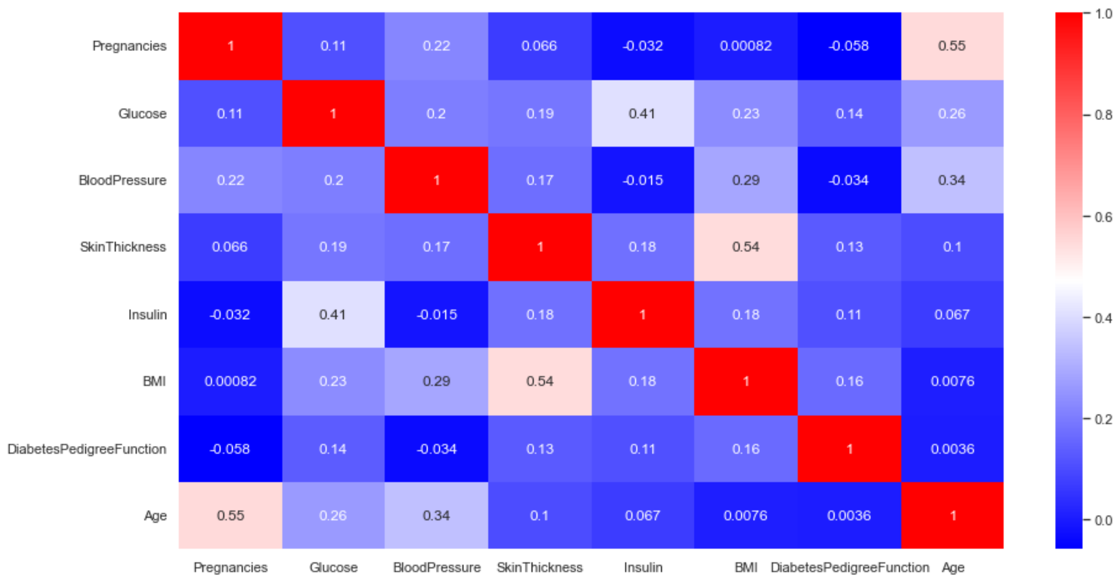
We need to use combination of features to build model for prediction of classes in Outcome.

Performing correlation analysis. Visually explore it using a heat map:

[25]:
```
df_X_resampled.corr()
```

[25]:
```
                          Pregnancies   Glucose  BloodPressure  SkinThickness  \
Pregnancies                  1.000000  0.111418       0.220954       0.066416
Glucose                      0.111418  1.000000       0.204605       0.189634
BloodPressure                0.220954  0.204605       1.000000       0.172867
SkinThickness                0.066416  0.189634       0.172867       1.000000
Insulin                     -0.031587  0.407390      -0.015417       0.176551
BMI                          0.000818  0.234148       0.285529       0.544061
DiabetesPedigreeFunction    -0.057957  0.135250      -0.033525       0.128655
Age                          0.545885  0.260517       0.339041       0.099714

                           Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies              -0.031587  0.000818                 -0.057957
Glucose                   0.407390  0.234148                  0.135250
BloodPressure            -0.015417  0.285529                 -0.033525
SkinThickness             0.176551  0.544061                  0.128655
Insulin                   1.000000  0.181248                  0.109770
BMI                       0.181248  1.000000                  0.162648
DiabetesPedigreeFunction  0.109770  0.162648                  1.000000
Age                       0.066907  0.007608                  0.003585

                               Age
Pregnancies               0.545885
Glucose                   0.260517
BloodPressure             0.339041
SkinThickness             0.099714
Insulin                   0.066907
BMI                       0.007608
DiabetesPedigreeFunction  0.003585
Age                       1.000000
```

[26]:
```python
plt.figure(figsize=(15,8))
sns.heatmap(df_X_resampled.corr(), cmap='bwr', annot=True);
```



It appears from correlation matrix and heatmap that there exists significant correlation between some pairs such as -

Age-Pregnancies

BMI-SkinThickness

Devising strategies for model building. It is important to decide the right validation framework.

Since this is a classification problem, we will be building all popular classification models for our training data and then compare performance of each model on test data to accurately predict target variable (Outcome):

1) Logistic Regression
2) Decision Tree
3) RandomForest Classifier
4) K-Nearest Neighbour (KNN)
5) Support Vector Machine (SVM)
6) Naive Bayes
7) Ensemble Learning -> Boosting -> Adaptive Boosting
8) Ensemble Learning -> Boosting -> Gradient Boosting (XGBClassifier)

We will use use GridSearchCV with Cross Validation (CV) = 5 for training and testing model which will give us insight about model performance on versatile data. It helps to loop through predefined hyperparameters and fit model on training set. GridSearchCV performs hyper parameter tuning which will give us optimal hyper parameters for each of the model. We will again train model with these optimized hyper parameters and then predict test data to get metrics for comparing all models.

Performing Train - Test split on input data (To train and test model without Cross Validation and Hyper Parameter Tuning):

[27]:
```
from sklearn.model_selection import train_test_split, KFold, RandomizedSearchCV
from sklearn.metrics import accuracy_score, average_precision_score, f1_score,␣
↪confusion_matrix, classification_report, auc, roc_curve, roc_auc_score
```

[28]:
```
X_train, X_test, y_train, y_test = train_test_split(df_X_resampled,␣
↪df_y_resampled, test_size=0.15, random_state =100)
```

Appling an appropriate classification algorithm to build a model. Comparing various models with the results from KNN algorithm.

1) Logistic Regression:'

[237]:
```
models = []
model_accuracy = []
model_f1 = []
model_auc = []
```

[238]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(max_iter=300)
```

[239]:
```
lr.fit(X_train,y_train)
```

[239]:
```
LogisticRegression(max_iter=300)
```

[240]:
```
lr.score(X_train,y_train)
```

[240]:
```
0.76
```

[241]:
```
lr.score(X_test, y_test)
```

[241]:
```
0.76
```

Performance evaluation and optimizing parameters using GridSearchCV: Logistic regression does not really have any critical hyperparameters to tune. However we will try to optimize one of its parameters 'C' with the help of GridSearchCV. So we have set this parameter as a list of values form which GridSearchCV will select the best value of parameter.

[242]:
```
from sklearn.model_selection import GridSearchCV, cross_val_score
```

[243]:
```
parameters = {'C':np.logspace(-5, 5, 50)}
```

[244]:
```
gs_lr = GridSearchCV(lr, param_grid = parameters, cv=5, verbose=0)
gs_lr.fit(df_X_resampled, df_y_resampled)
```

[244]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(max_iter=300),
             param_grid={'C': array([1.00000000e-05, 1.59985872e-05,
2.55954792e-05, 4.09491506e-05,
       6.55128557e-05, 1.04811313e-04, 1.67683294e-04, 2.68269580e-04,
```

```
        4.29193426e-04, 6.86648845e-04, 1.09854114e-03, 1.75751062e-03,
        2.81176870e-03, 4.49843267e-03, 7.19685673e-03, 1.15139540e-02,
        1.84206997e-02, 2.94705170e…
        7.90604321e-01, 1.26485522e+00, 2.02358965e+00, 3.23745754e+00,
        5.17947468e+00, 8.28642773e+00, 1.32571137e+01, 2.12095089e+01,
        3.39322177e+01, 5.42867544e+01, 8.68511374e+01, 1.38949549e+02,
        2.22299648e+02, 3.55648031e+02, 5.68986603e+02, 9.10298178e+02,
        1.45634848e+03, 2.32995181e+03, 3.72759372e+03, 5.96362332e+03,
        9.54095476e+03, 1.52641797e+04, 2.44205309e+04, 3.90693994e+04,
        6.25055193e+04, 1.00000000e+05])})
```

[245]:
```
gs_lr.best_params_
```

[245]:
```
{'C': 13.257113655901108}
```

[246]:
```
gs_lr.best_score_
```

[246]:
```
0.751
```

[247]:
```
lr2 = LogisticRegression(C=13.257113655901108, max_iter=300)
```

[248]:
```
lr2.fit(X_train,y_train)
```

[248]:
```
LogisticRegression(C=13.257113655901108, max_iter=300)
```

[249]:
```
lr2.score(X_train,y_train)
```

[249]:
```
0.7611764705882353
```

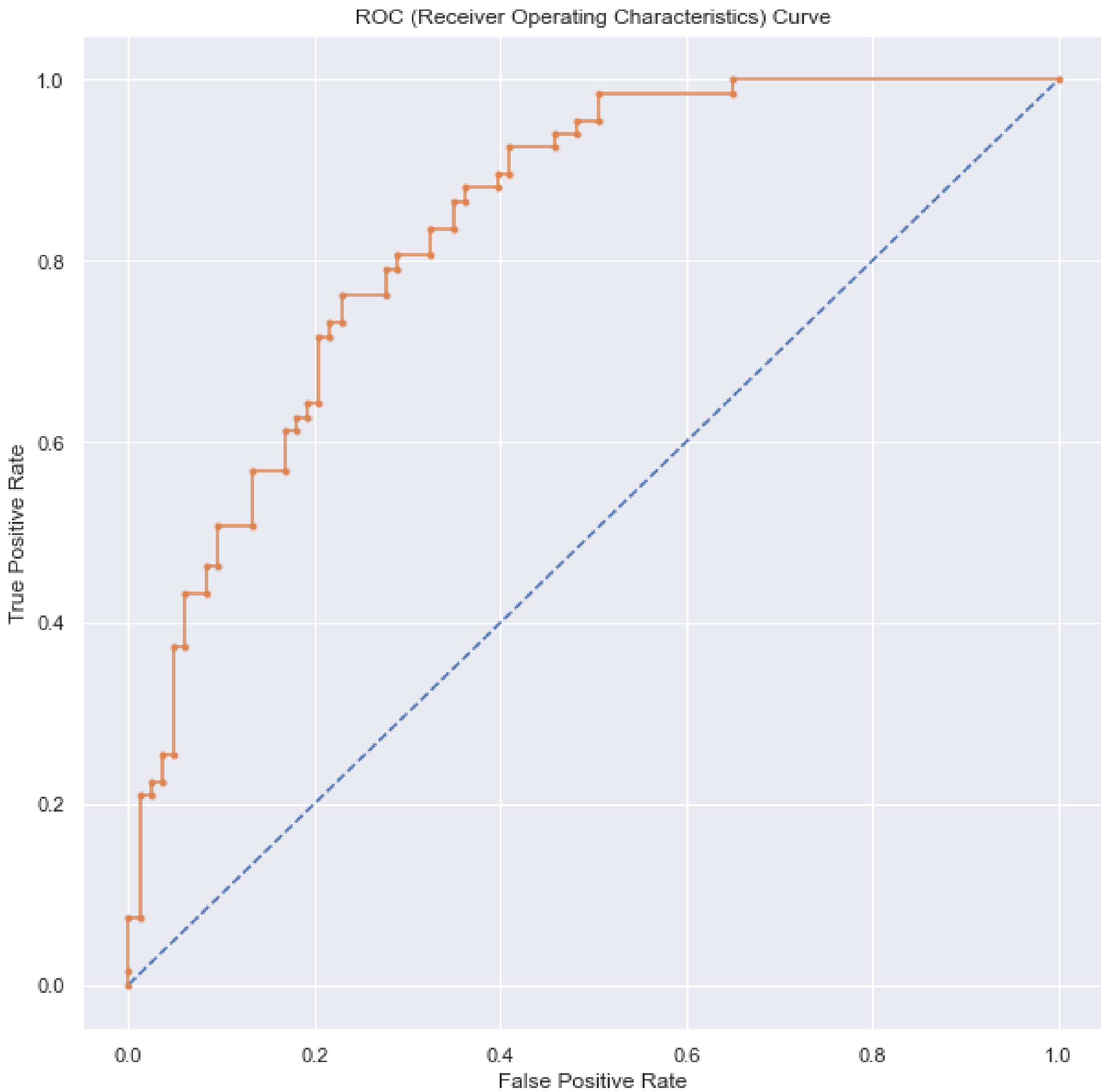
[250]:
```
lr2.score(X_test, y_test)
```

[250]:
```
0.76
```

[251]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = lr2.predict_proba(X_test)                # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the␣
 ↪positive outcome only

auc_lr = roc_auc_score(y_test, probs)            # calculate AUC
print('AUC: %.3f' %auc_lr)
fpr, tpr, thresholds = roc_curve(y_test, probs)  # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')         # plot no skill
plt.plot(fpr, tpr, marker='.')                   # plot the roc curve for the␣
 ↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
```

```
plt.title("ROC (Receiver Operating Characteristics) Curve");
```

AUC: 0.839

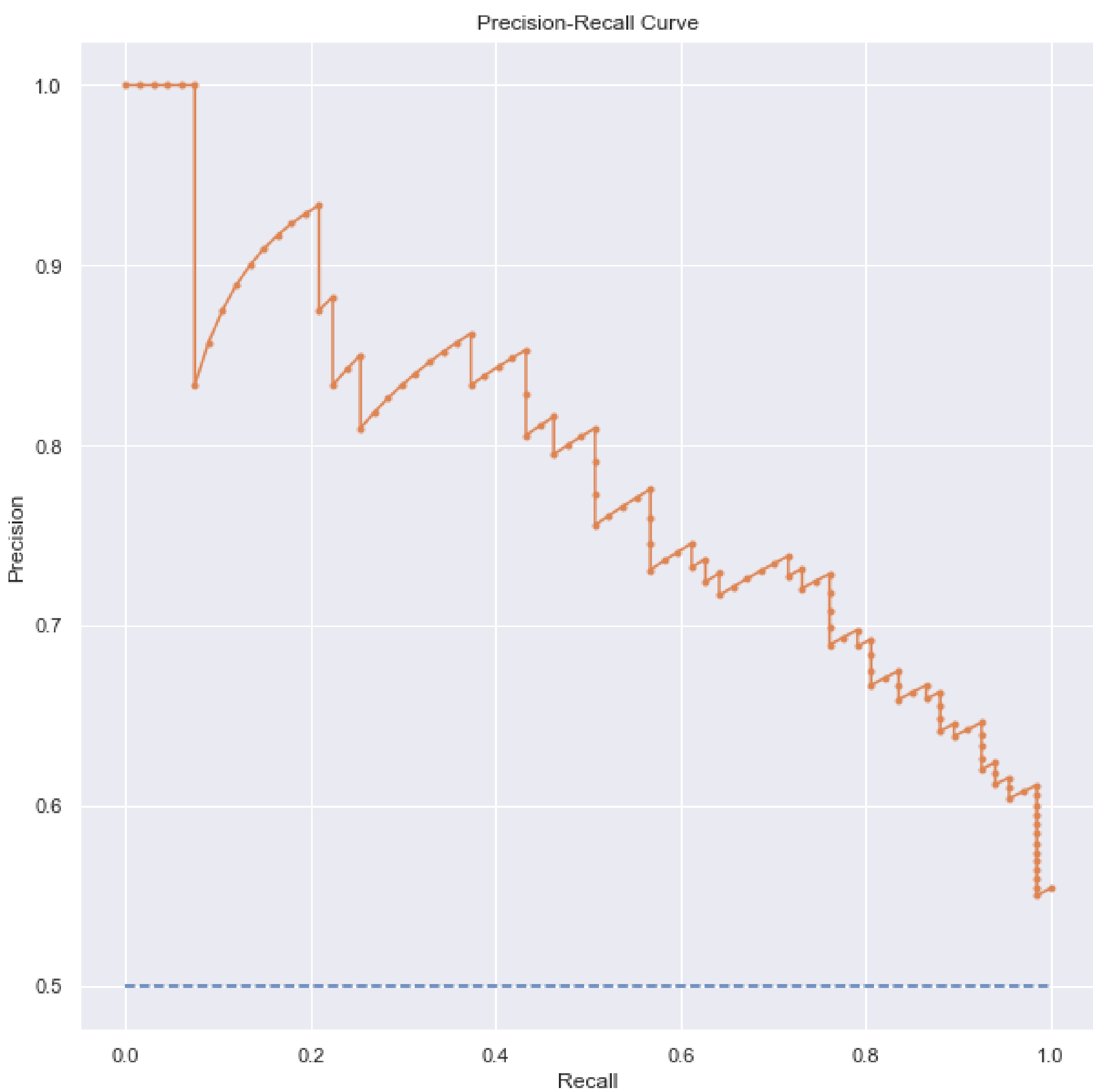


[252]:
```
from sklearn.metrics import precision_recall_curve
pred_y_test = lr2.predict(X_test)                                         # predict␣
 ↪class values
precision, recall, thresholds = precision_recall_curve(y_test, probs) #␣
 ↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                        #␣
 ↪calculate F1 score
auc_lr_pr = auc(recall, precision)                                        #␣
 ↪calculate precision-recall AUC
```

```
ap = average_precision_score(y_test, probs)                    #␣
↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_lr_pr, ap))
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                   # plot no␣
↪skill
plt.plot(recall, precision, marker='.')                        # plot␣
↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.731 auc_pr=0.786 ap=0.788
```

[252]: Text(0.5, 1.0, 'Precision-Recall Curve')



[253]:
```
models.append('LR')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_lr)
```

2) Decision Tree:

[254]:
```
from sklearn.tree import DecisionTreeClassifier
dt1 = DecisionTreeClassifier(random_state=0)
```

[255]:
```
dt1.fit(X_train,y_train)
```

[255]:
```
DecisionTreeClassifier(random_state=0)
```

[256]:
```
dt1.score(X_train,y_train)          # Decision Tree always 100% accuracy over␣
 ↪train data
```

[256]:
```
1.0
```

[257]:
```
dt1.score(X_test, y_test)
```

[257]:
```
0.7266666666666667
```

Performance evaluation and optimizing parameters using GridSearchCV:

[258]:
```
parameters = {
    'max_depth':[1,2,3,4,5,None]
}
```

[259]:
```
gs_dt = GridSearchCV(dt1, param_grid = parameters, cv=5, verbose=0)
gs_dt.fit(df_X_resampled, df_y_resampled)
```

[259]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=0),
             param_grid={'max_depth': [1, 2, 3, 4, 5, None]})
```

[260]:
```
gs_dt.best_params_
```

[260]:
```
{'max_depth': 5}
```

[261]:
```
gs_dt.best_score_
```

[261]:
```
0.762
```

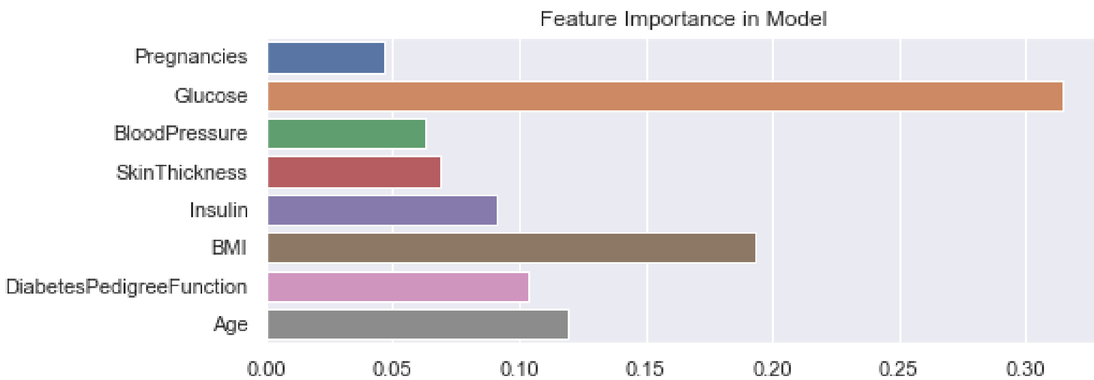
[262]:
```
dt1.feature_importances_
```

[262]: array([0.04671456, 0.31456843, 0.06275534, 0.06904818, 0.0913995 ,
        0.19291867, 0.10348904, 0.11910628])

[263]:
```
X_train.columns
```

[263]: Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age'],
      dtype='object')

[264]:
```
plt.figure(figsize=(8,3))
sns.barplot(y=X_train.columns, x=dt1.feature_importances_)
plt.title("Feature Importance in Model");
```



[265]:
```
dt2 = DecisionTreeClassifier(max_depth=5)
```

[266]:
```
dt2.fit(X_train,y_train)
```

[266]: DecisionTreeClassifier(max_depth=5)

[267]:
```
dt2.score(X_train,y_train)
```

[267]: 0.8164705882352942

[268]:
```
dt2.score(X_test,y_test)
```

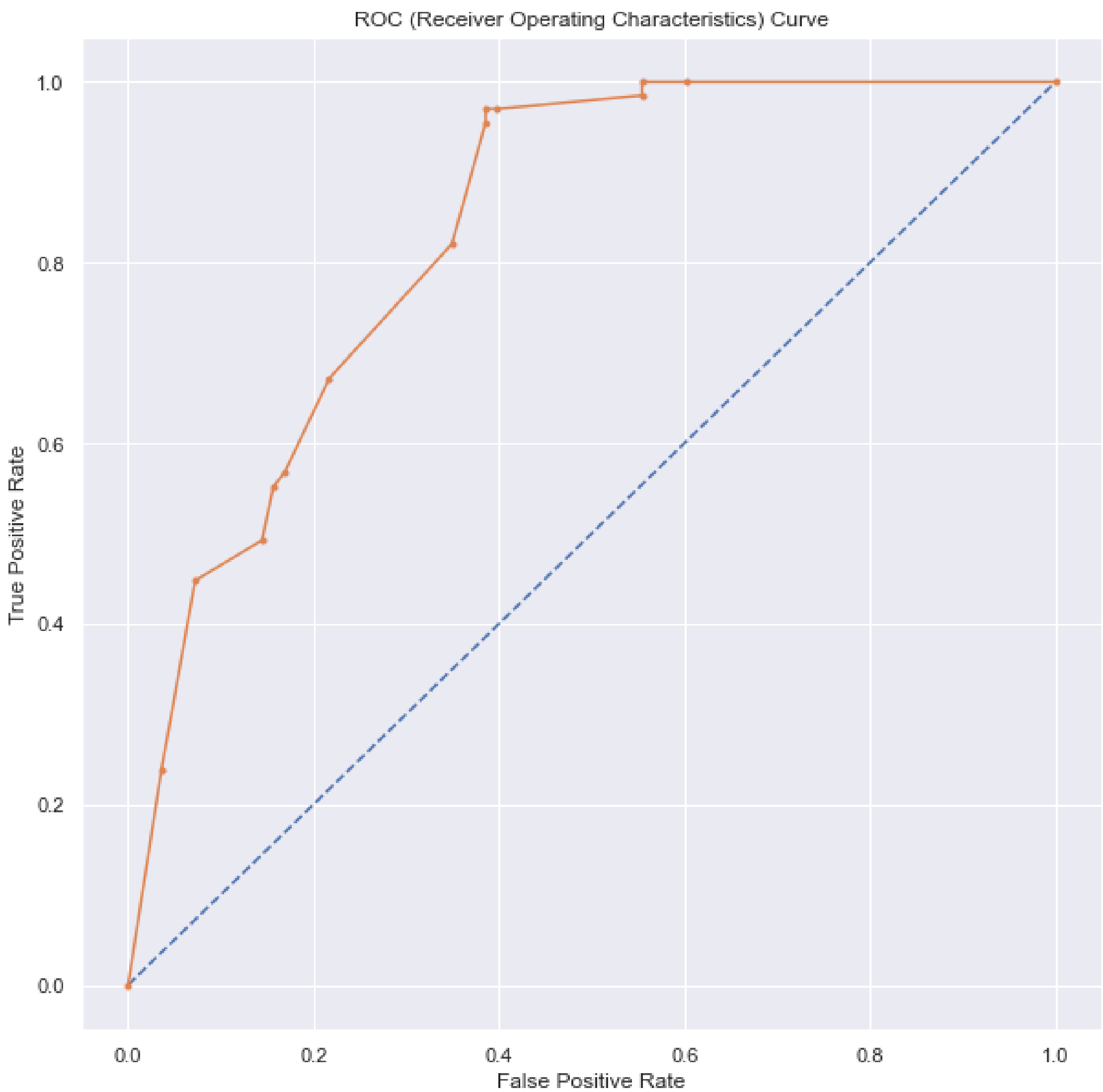
[268]: 0.7266666666666667

[269]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = dt2.predict_proba(X_test)                # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the␣
 ↪positive outcome only
```

```
auc_dt = roc_auc_score(y_test, probs)            # calculate AUC
print('AUC: %.3f' %auc_dt)
fpr, tpr, thresholds = roc_curve(y_test, probs)  # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')         # plot no skill
plt.plot(fpr, tpr, marker='.')                   # plot the roc curve for the␣
 ↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC (Receiver Operating Characteristics) Curve")
```

```
AUC: 0.835
```

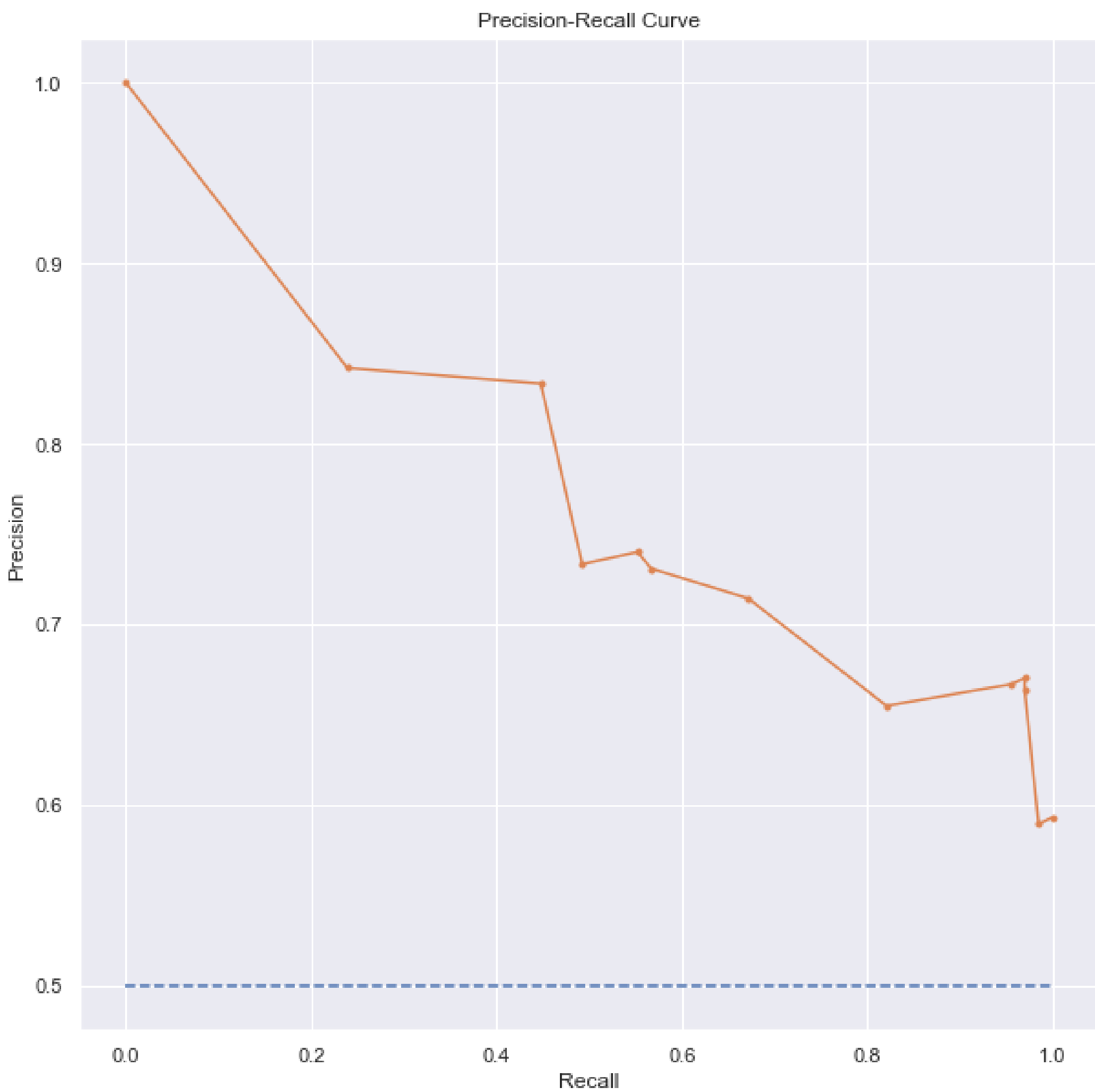
[269]:
```
Text(0.5, 1.0, 'ROC (Receiver Operating Characteristics) Curve')
```



[270]:
```
# Precision Recall Curve

pred_y_test = dt2.predict(X_test)                                                 # predict␣
 ↪class values
precision, recall, thresholds = precision_recall_curve(y_test, probs) #␣
 ↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                                #␣
 ↪calculate F1 score
auc_dt_pr = auc(recall, precision)                                                #␣
 ↪calculate precision-recall AUC
ap = average_precision_score(y_test, probs)                                       #␣
 ↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_dt_pr, ap))
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                                      # plot no␣
 ↪skill
plt.plot(recall, precision, marker='.')                                           # plot␣
 ↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.728 auc_pr=0.780 ap=0.753
```

[270]: Text(0.5, 1.0, 'Precision-Recall Curve')



[271]:
```
models.append('DT')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_dt)
```

3)RandomForest Classifier

[272]:
```
from sklearn.ensemble import RandomForestClassifier
rf1 = RandomForestClassifier()
```

[273]:
```
rf1 = RandomForestClassifier(random_state=0)
```

[274]:
```
rf1.fit(X_train, y_train)
```

[274]: RandomForestClassifier(random_state=0)

[275]:
```
rf1.score(X_train, y_train)           # Random Forest also 100% accuracy over␣
↪train data always
```

[275]: 1.0

[276]:
```
rf1.score(X_test, y_test)
```

[276]: 0.8466666666666667

Performance evaluation and optimizing parameters using GridSearchCV:

[277]:
```
parameters = {
    'n_estimators': [50,100,150],
    'max_depth': [None,1,3,5,7],
    'min_samples_leaf': [1,3,5]
}
```

[278]:
```
gs_rf = GridSearchCV(estimator=rf1, param_grid=parameters, cv=5, verbose=0)
gs_rf.fit(df_X_resampled, df_y_resampled)
```

[278]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=0),
             param_grid={'max_depth': [None, 1, 3, 5, 7],
                         'min_samples_leaf': [1, 3, 5],
                         'n_estimators': [50, 100, 150]})
```

[279]:
```
gs_rf.best_params_
```

[279]: {'max_depth': None, 'min_samples_leaf': 1, 'n_estimators': 150}

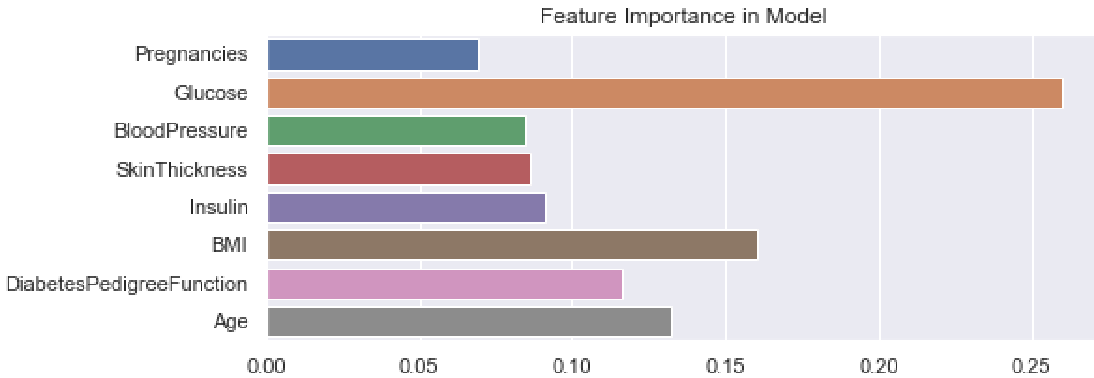
[280]:
```
gs_rf.best_score_
```

[280]: 0.825

[281]:
```
rf1.feature_importances_
```

[281]:
```
array([0.06903437, 0.26001362, 0.08444339, 0.08625883, 0.09126198,
       0.1604058 , 0.11654588, 0.13203613])
```

[282]:
```
plt.figure(figsize=(8,3))
sns.barplot(y=X_train.columns, x=rf1.feature_importances_);
plt.title("Feature Importance in Model");
```



[283]:
```
rf2 = RandomForestClassifier(max_depth=None, min_samples_leaf=1,␣
↪n_estimators=150)
```

[284]:
```
rf2.fit(X_train,y_train)
```

[284]: RandomForestClassifier(n_estimators=150)

[285]:
```
rf2.score(X_train,y_train)
```

[285]: 1.0

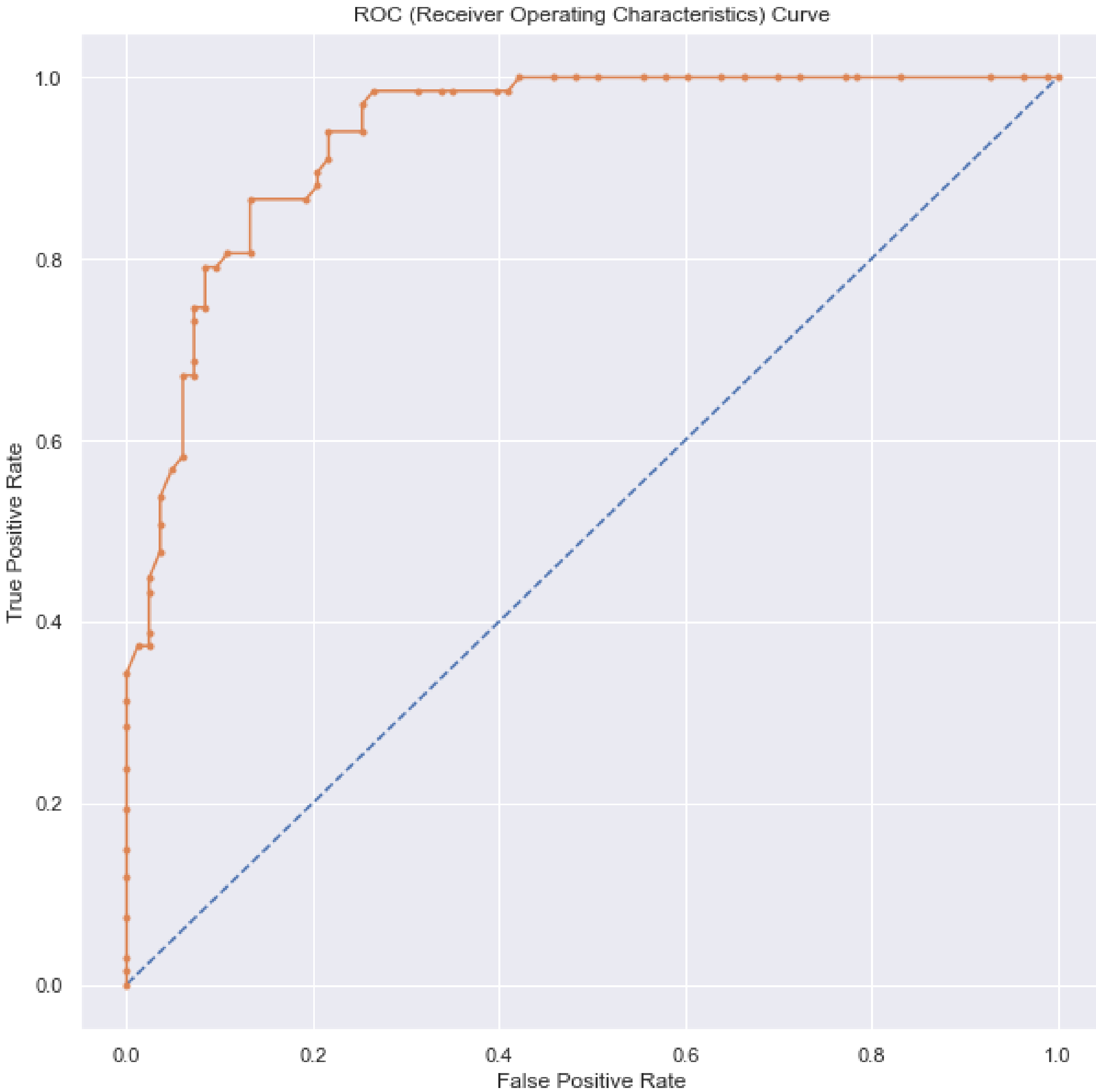
[286]:
```
rf2.score(X_test, y_test)
```

[286]: 0.8466666666666667

[287]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = rf2.predict_proba(X_test)                # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the␣
↪positive outcome only

auc_rf = roc_auc_score(y_test, probs)            # calculate AUC
print('AUC: %.3f' %auc_rf)
fpr, tpr, thresholds = roc_curve(y_test, probs)  # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')         # plot no skill
plt.plot(fpr, tpr, marker='.')                   # plot the roc curve for the␣
↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC (Receiver Operating Characteristics) Curve")
```

AUC: 0.936

[287]: Text(0.5, 1.0, 'ROC (Receiver Operating Characteristics) Curve')

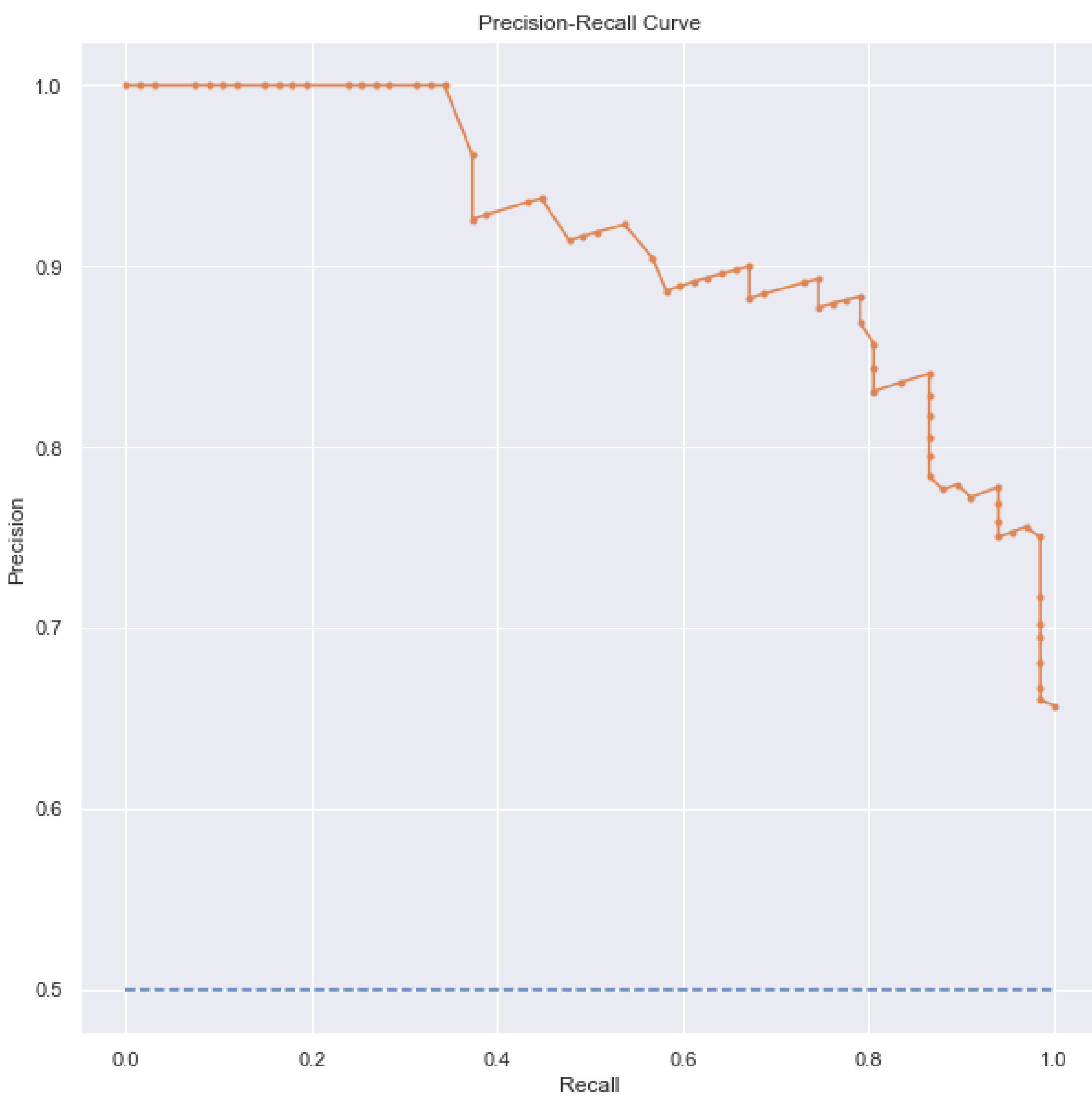


[288]:
```
# Precision Recall Curve

pred_y_test = rf2.predict(X_test)                                        # predict␣
 ↪class values
precision, recall, thresholds = precision_recall_curve(y_test, probs) #␣
 ↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                    #␣
 ↪calculate F1 score
auc_rf_pr = auc(recall, precision)                                    #␣
 ↪calculate precision-recall AUC
```

```
ap = average_precision_score(y_test, probs)                              #␣
 ↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_rf_pr, ap))
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                             # plot no␣
 ↪skill
plt.plot(recall, precision, marker='.')                                  # plot␣
 ↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.835 auc_pr=0.915 ap=0.915
```

[288]: Text(0.5, 1.0, 'Precision-Recall Curve')



[289]:
```
models.append('RF')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_dt)
```

4) K-Nearest Neighbour (KNN) Classification:

[290]:
```
from sklearn.neighbors import KNeighborsClassifier
knn1 = KNeighborsClassifier(n_neighbors=3)
```

[291]:
```
knn1.fit(X_train, y_train)
```

[291]:
```
KNeighborsClassifier(n_neighbors=3)
```

[292]:
```
knn1.score(X_train,y_train)
```

[292]:
```
0.8682352941176471
```

[293]:
```
knn1.score(X_test,y_test)
```

[293]:
```
0.78
```

Performance evaluation and optimizing parameters using GridSearchCV:

[294]:
```
knn_neighbors = [i for i in range(2,16)]
parameters = {
    'n_neighbors': knn_neighbors
}
```

[295]:
```
gs_knn = GridSearchCV(estimator=knn1, param_grid=parameters, cv=5, verbose=0)
gs_knn.fit(df_X_resampled, df_y_resampled)
```

[295]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(n_neighbors=3),
             param_grid={'n_neighbors': [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,
                                         14, 15]})
```

[296]:
```
gs_knn.best_params_
```

[296]:
```
{'n_neighbors': 3}
```

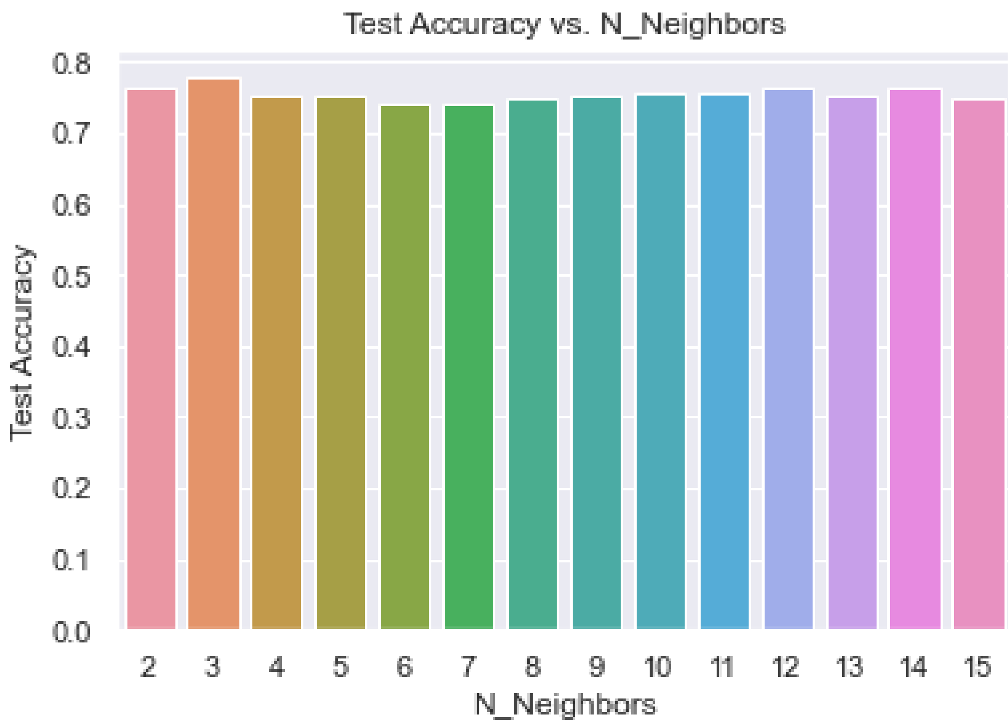
[297]:
```
gs_knn.best_score_
```

[297]:
```
0.7779999999999999
```

[298]:
```
# gs_knn.cv_results_
gs_knn.cv_results_['mean_test_score']
```

[298]: array([0.764, 0.778, 0.751, 0.752, 0.742, 0.74 , 0.749, 0.753, 0.757,
        0.758, 0.763, 0.753, 0.762, 0.747])

[299]:
```
plt.figure(figsize=(6,4))
sns.barplot(x=knn_neighbors, y=gs_knn.cv_results_['mean_test_score'])
plt.xlabel("N_Neighbors")
plt.ylabel("Test Accuracy")
plt.title("Test Accuracy vs. N_Neighbors");
```



[300]:
```
knn2 = KNeighborsClassifier(n_neighbors=3)
```

[301]:
```
knn2.fit(X_train, y_train)
```

[301]: KNeighborsClassifier(n_neighbors=3)

[302]:
```
knn2.score(X_train,y_train)
```

[302]: 0.8682352941176471

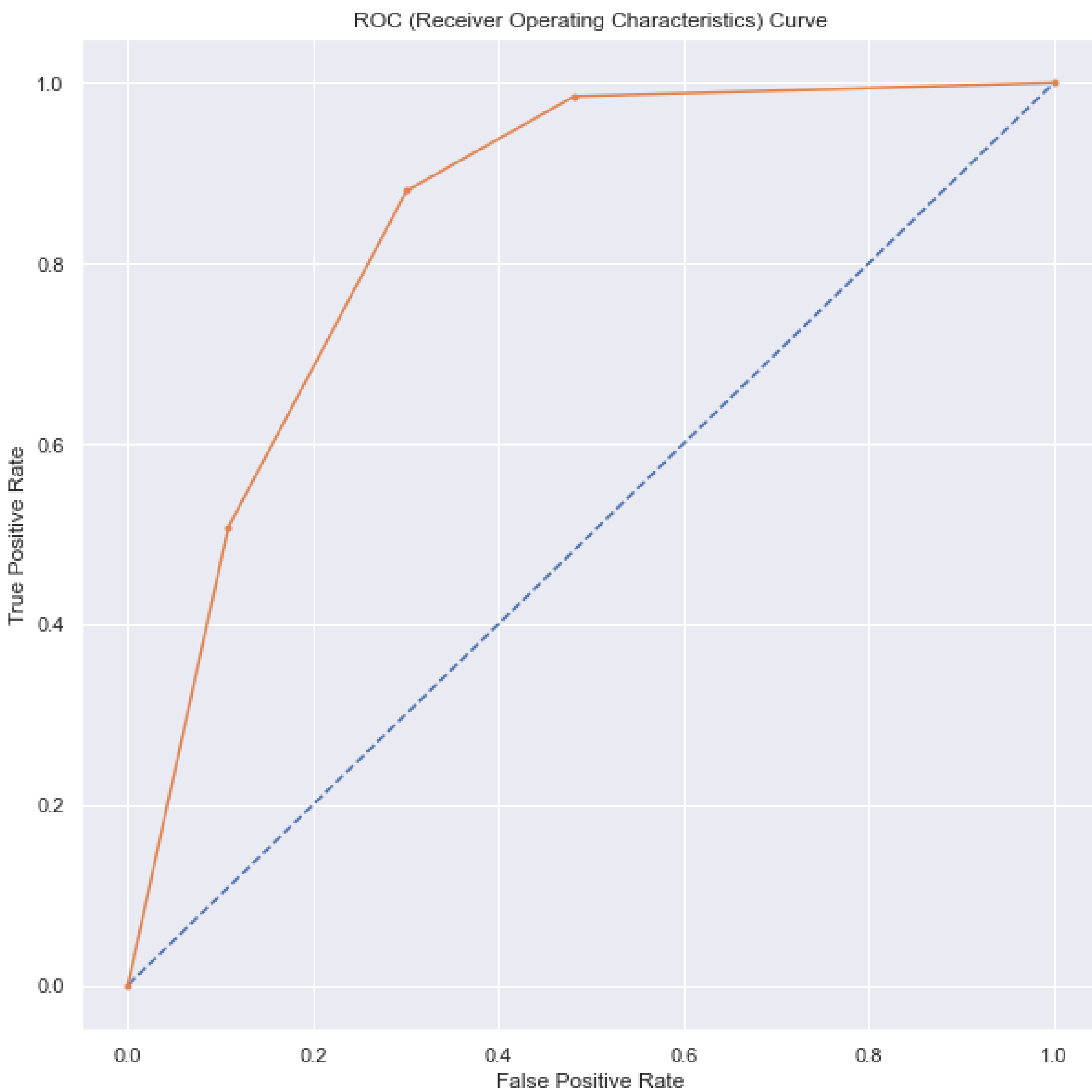
[303]:
```
knn2.score(X_test,y_test)
```

[303]: 0.78

[304]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = knn2.predict_proba(X_test)                 # predict probabilities
probs = probs[:, 1]                                # keep probabilities for the␣
 ↪positive outcome only

auc_knn = roc_auc_score(y_test, probs)             # calculate AUC
print('AUC: %.3f' %auc_knn)
fpr, tpr, thresholds = roc_curve(y_test, probs)  # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')           # plot no skill
plt.plot(fpr, tpr, marker='.')                     # plot the roc curve for the␣
 ↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC (Receiver Operating Characteristics) Curve")
```

```
AUC: 0.844
```

[304]:
```
Text(0.5, 1.0, 'ROC (Receiver Operating Characteristics) Curve')
```

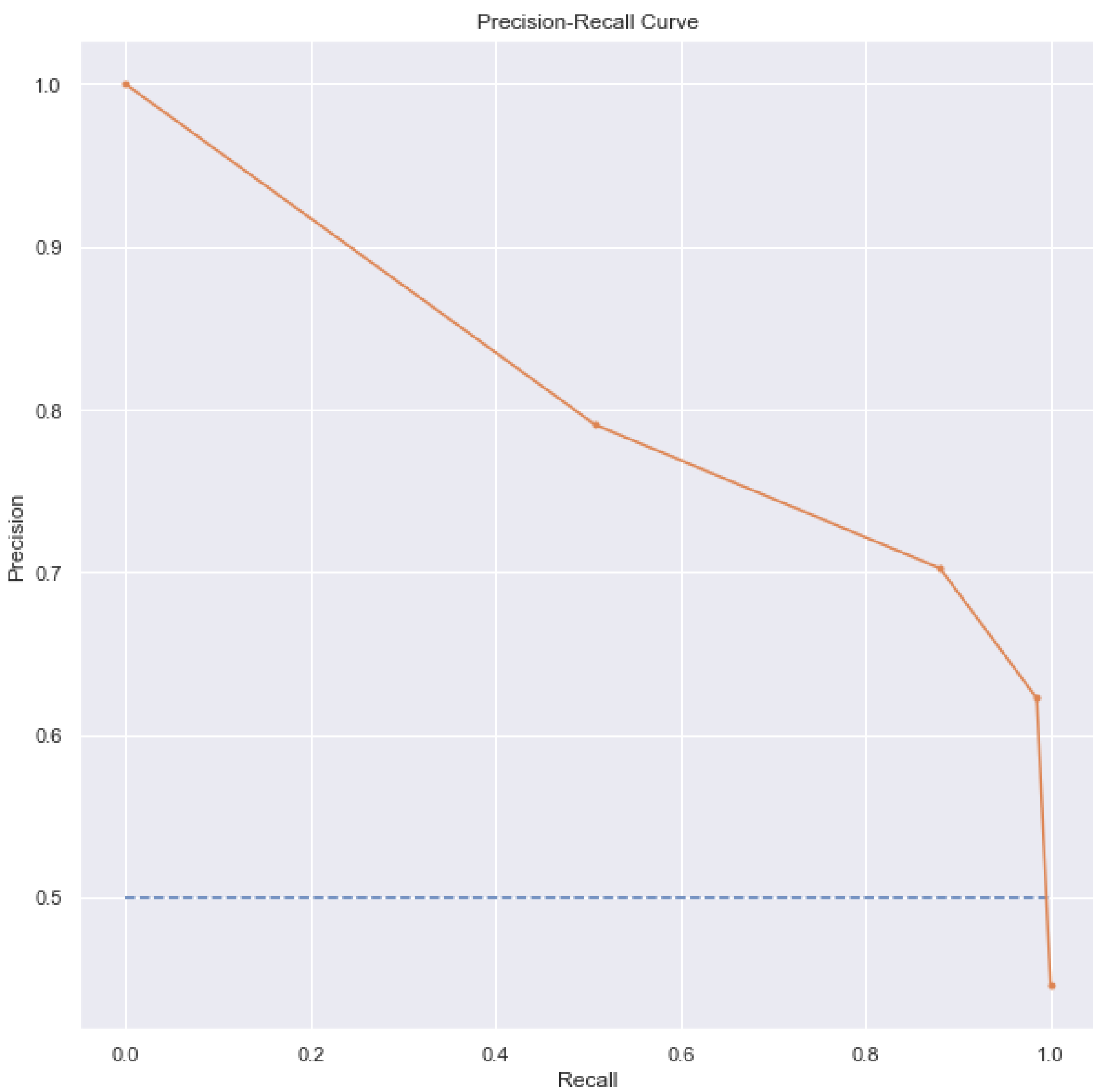


[305]:
```
# Precision Recall Curve

pred_y_test = knn2.predict(X_test)                                          #␣
 ↪predict class values
precision, recall, thresholds = precision_recall_curve(y_test, probs) #␣
 ↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                         #␣
 ↪calculate F1 score
auc_knn_pr = auc(recall, precision)                                         #␣
 ↪calculate precision-recall AUC
ap = average_precision_score(y_test, probs)                                #␣
 ↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_knn_pr, ap))
```

```
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                         # plot no␣
↪skill
plt.plot(recall, precision, marker='.')                              # plot␣
↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.781 auc_pr=0.810 ap=0.735
```

[305]: Text(0.5, 1.0, 'Precision-Recall Curve')



[306]:
```
models.append('KNN')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_knn)
```

5) Support Vector Machine (SVM) Algorithm:

[307]:
```
from sklearn.svm import SVC
svm1 = SVC(kernel='rbf')
```

[308]:
```
svm1.fit(X_train, y_train)
```

[308]:
```
SVC()
```

[309]:
```
svm1.score(X_train, y_train)
```

[309]:
```
0.74
```

[310]:
```
svm1.score(X_test, y_test)
```

[310]:
```
0.74
```

Performance evaluation and optimizing parameters using GridSearchCV:

[311]:
```
parameters = {
    'C':[1, 5, 10, 15, 20, 25],
    'gamma':[0.001, 0.005, 0.0001, 0.00001]
}
```

[312]:
```
gs_svm = GridSearchCV(estimator=svm1, param_grid=parameters, cv=5, verbose=0)
gs_svm.fit(df_X_resampled, df_y_resampled)
```

[312]:
```
GridSearchCV(cv=5, estimator=SVC(),
             param_grid={'C': [1, 5, 10, 15, 20, 25],
                         'gamma': [0.001, 0.005, 0.0001, 1e-05]})
```

[313]:
```
gs_svm.best_params_
```

[313]:
```
{'C': 20, 'gamma': 0.005}
```

[314]:
```
gs_svm.best_score_
```

[314]:
```
0.7929999999999999
```

[315]:
```
svm2 = SVC(kernel='rbf', C=20, gamma=0.005, probability=True)
```

[316]:
```
svm2.fit(X_train, y_train)
```

[316]: SVC(C=20, gamma=0.005, probability=True)

[317]:
```
svm2.score(X_train, y_train)
```

[317]: 0.9976470588235294

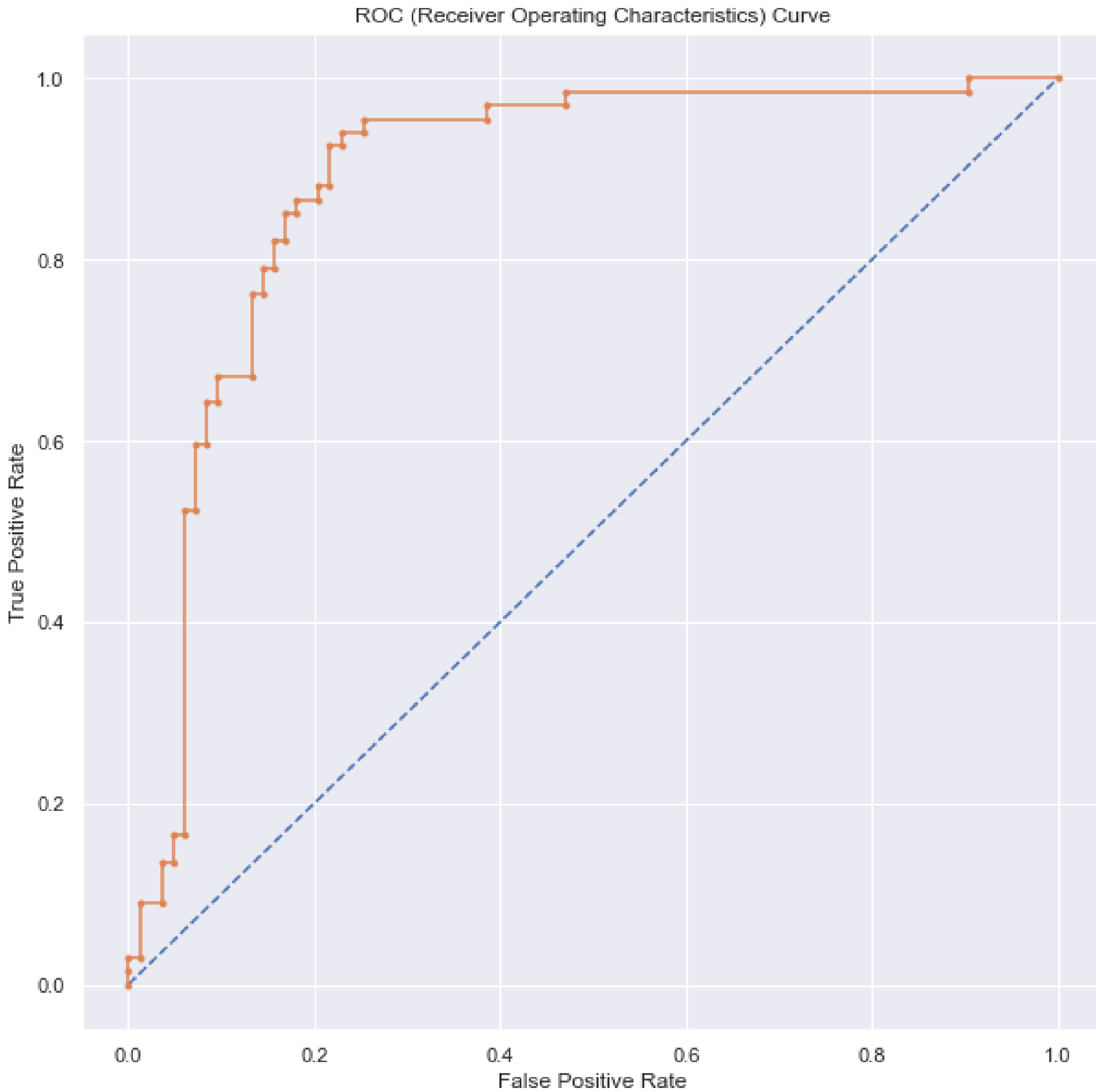
[318]:
```
svm2.score(X_test, y_test)
```

[318]: 0.8266666666666667

[319]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = svm2.predict_proba(X_test)               # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the
 ↪positive outcome only

auc_svm = roc_auc_score(y_test, probs)           # calculate AUC
print('AUC: %.3f' %auc_svm)
fpr, tpr, thresholds = roc_curve(y_test, probs)  # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')         # plot no skill
plt.plot(fpr, tpr, marker='.')                   # plot the roc curve for the
 ↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC (Receiver Operating Characteristics) Curve")
```

```
AUC: 0.888
```

[319]: Text(0.5, 1.0, 'ROC (Receiver Operating Characteristics) Curve')

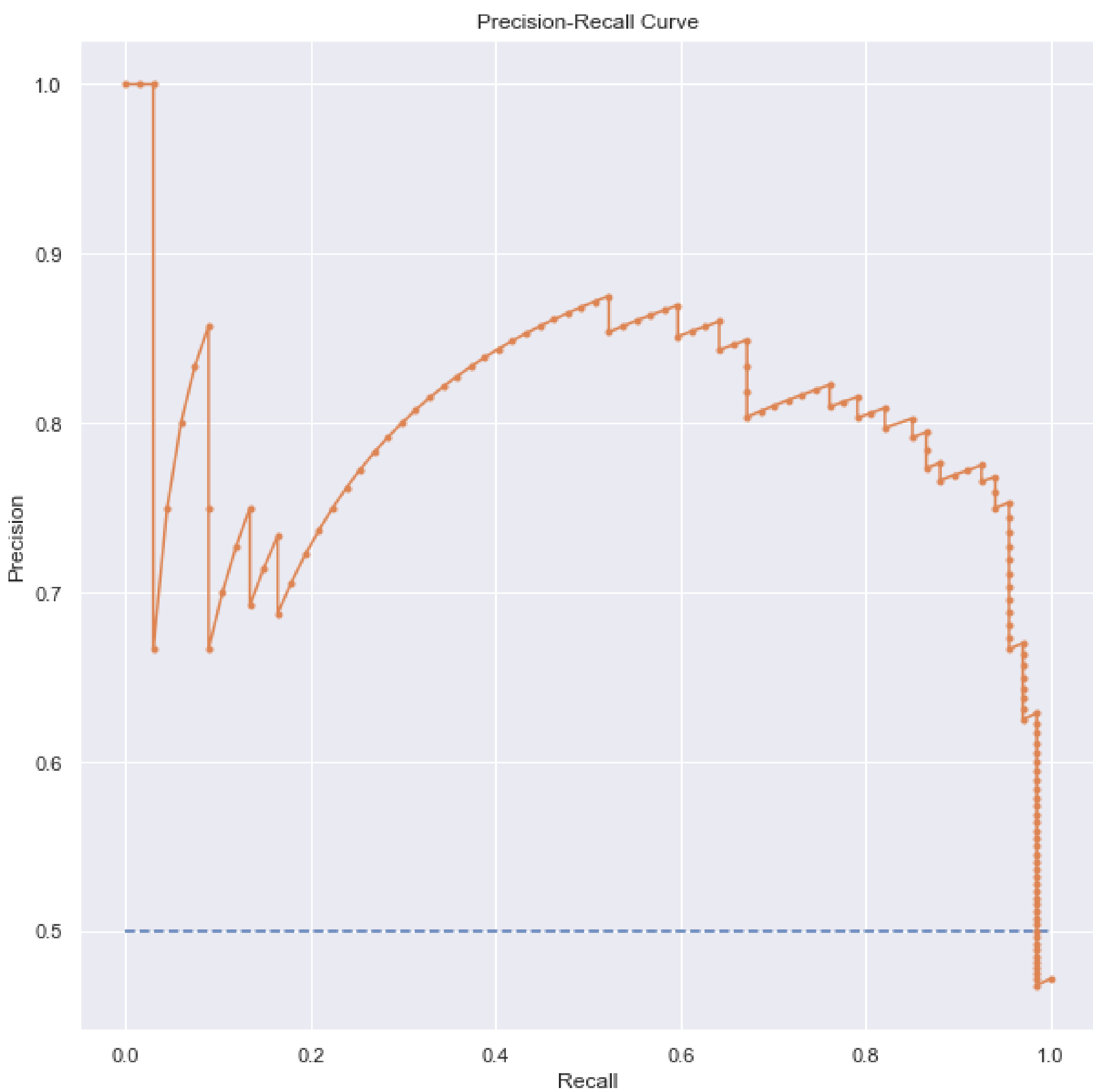


[320]:
```
# Precision Recall Curve

pred_y_test = svm2.predict(X_test)                                          # predict␣
 ↪class values
precision, recall, thresholds = precision_recall_curve(y_test, probs)  #␣
 ↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                      #␣
 ↪calculate F1 score
auc_svm_pr = auc(recall, precision)                                     #␣
 ↪calculate precision-recall AUC
ap = average_precision_score(y_test, probs)                             #␣
 ↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_svm_pr, ap))
```

```
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                              # plot no␣
 ↪skill
plt.plot(recall, precision, marker='.')                                   # plot␣
 ↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.817 auc_pr=0.800 ap=0.804
```

[320]:
```
Text(0.5, 1.0, 'Precision-Recall Curve')
```



[321]:
```
models.append('SVM')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_svm)
```

6) Naive Bayes Algorithm:

[322]:
```
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
gnb = GaussianNB()
```

[323]:
```
gnb.fit(X_train, y_train)
```

[323]:
```
GaussianNB()
```

[324]:
```
gnb.score(X_train, y_train)
```

[324]:
```
0.7223529411764706
```

[325]:
```
gnb.score(X_test, y_test)
```

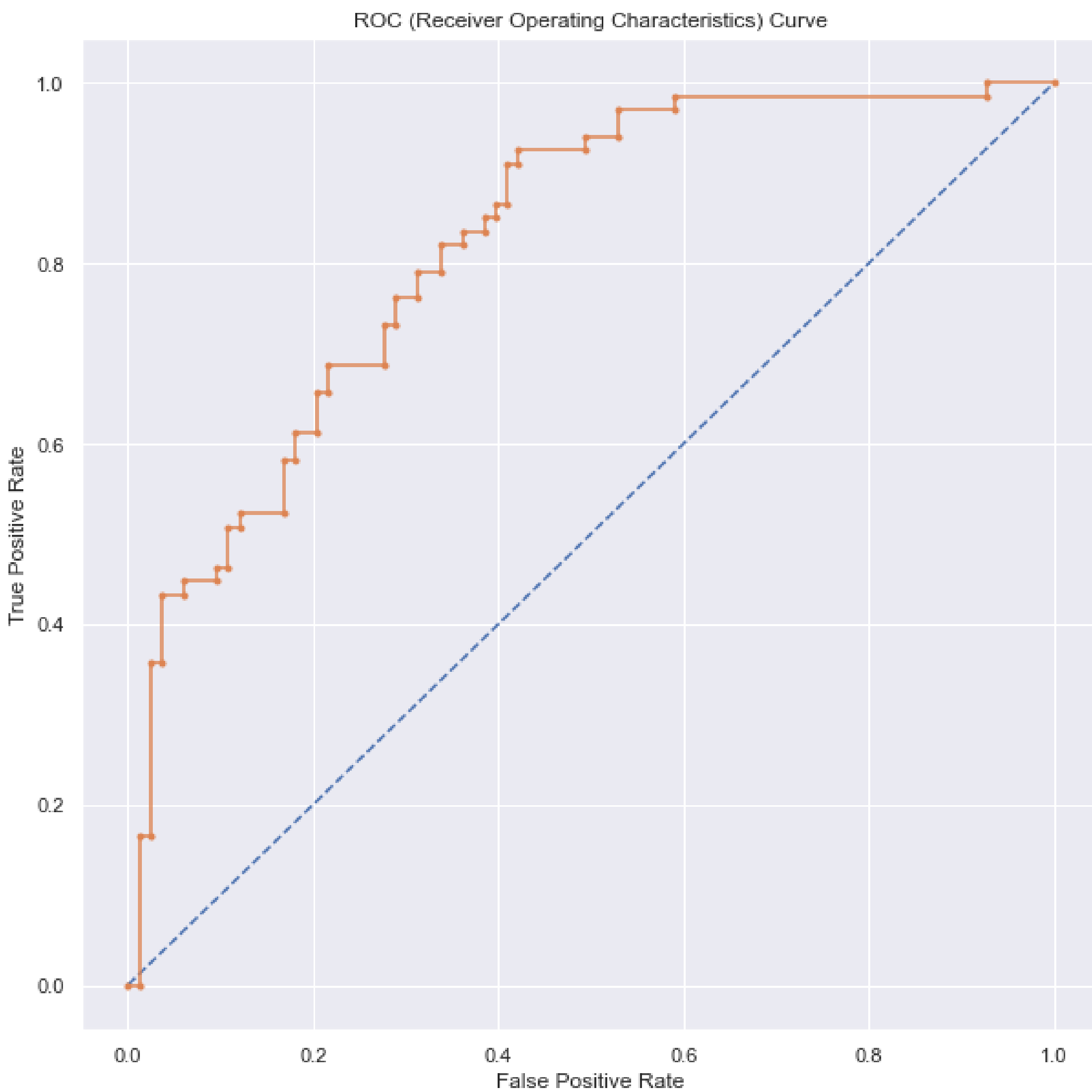
[325]:
```
0.72
```

Naive Bayes has almost no hyperparameters to tune, so it usually generalizes well.

[326]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = gnb.predict_proba(X_test)                    # predict probabilities
probs = probs[:, 1]                                  # keep probabilities for the␣
↪positive outcome only

auc_gnb = roc_auc_score(y_test, probs)                # calculate AUC
print('AUC: %.3f' %auc_gnb)
fpr, tpr, thresholds = roc_curve(y_test, probs)  # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')         # plot no skill
plt.plot(fpr, tpr, marker='.')                   # plot the roc curve for the␣
↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC (Receiver Operating Characteristics) Curve")
```

```
AUC: 0.823
```

[326]:
```
Text(0.5, 1.0, 'ROC (Receiver Operating Characteristics) Curve')
```

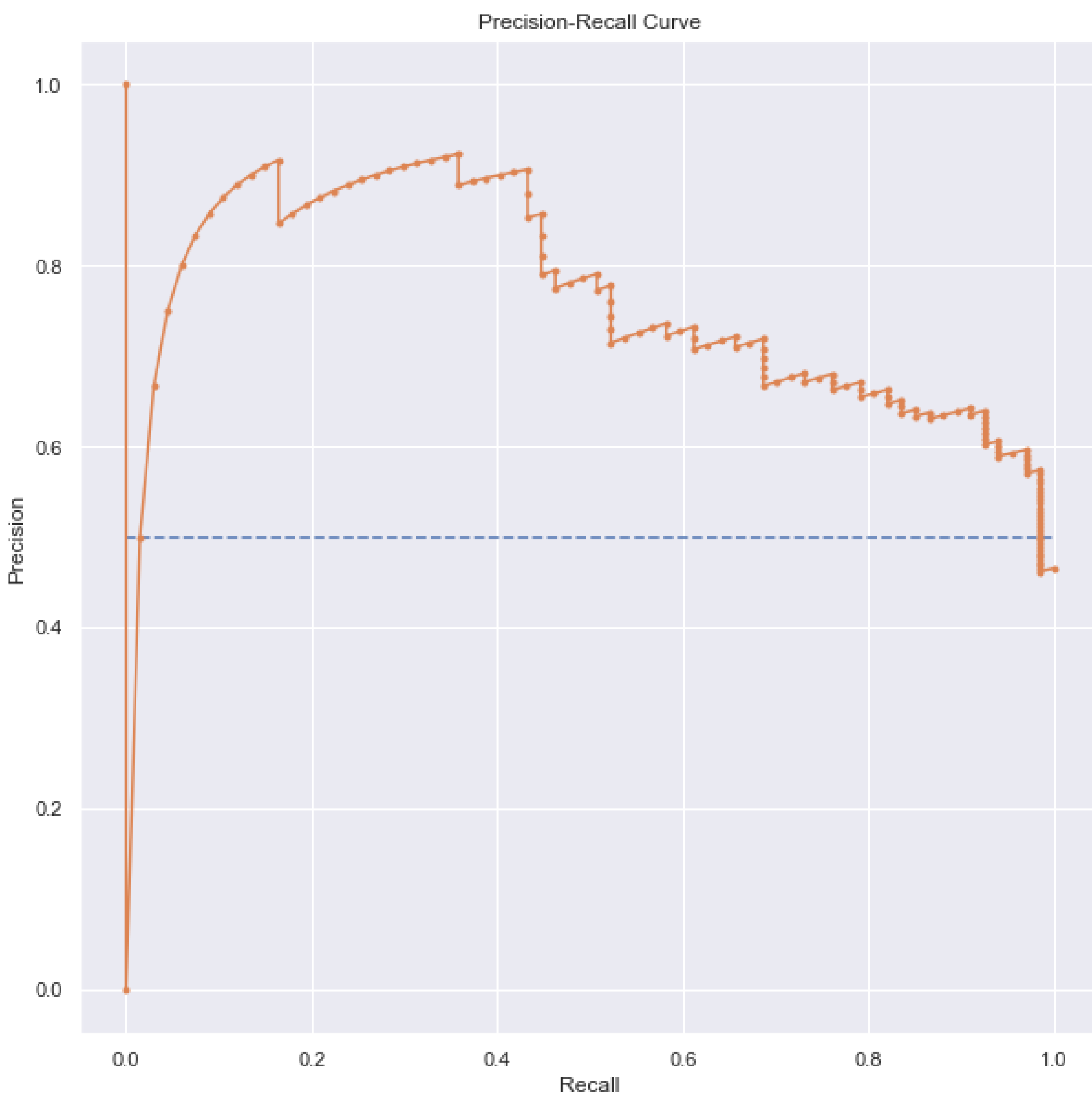


[327]:
```
# Precision Recall Curve

pred_y_test = gnb.predict(X_test)                                  # predict␣
 ↪class values
precision, recall, thresholds = precision_recall_curve(y_test, probs) #␣
 ↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                  #␣
 ↪calculate F1 score
auc_gnb_pr = auc(recall, precision)                                  #␣
 ↪calculate precision-recall AUC
ap = average_precision_score(y_test, probs)                          #␣
 ↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_gnb_pr, ap))
```

```
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                      # plot no␣
↪skill
plt.plot(recall, precision, marker='.')                            # plot␣
↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.656 auc_pr=0.755 ap=0.763
```

[327]: Text(0.5, 1.0, 'Precision-Recall Curve')



[328]:
```python
models.append('GNB')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_gnb)
```

7) Ensemble Learning --> Boosting --> Adaptive Boosting:

[329]:
```python
from sklearn.ensemble import AdaBoostClassifier
ada1 = AdaBoostClassifier(n_estimators=100)
```

[330]:
```python
ada1.fit(X_train,y_train)
```

[330]:
```
AdaBoostClassifier(n_estimators=100)
```

[331]:
```python
ada1.score(X_train,y_train)
```

[331]:
```
0.8341176470588235
```

[332]:
```python
ada1.score(X_test, y_test)
```

[332]:
```
0.7533333333333333
```

Performance evaluation and optimizing parameters using cross_val_score:

[333]:
```python
parameters = {'n_estimators': [100,200,300,400,500,700,1000]}
```

[334]:
```python
gs_ada = GridSearchCV(ada1, param_grid = parameters, cv=5, verbose=0)
gs_ada.fit(df_X_resampled, df_y_resampled)
```

[334]:
```
GridSearchCV(cv=5, estimator=AdaBoostClassifier(n_estimators=100),
             param_grid={'n_estimators': [100, 200, 300, 400, 500, 700, 1000]})
```

[335]:
```python
gs_ada.best_params_
```

[335]:
```
{'n_estimators': 200}
```

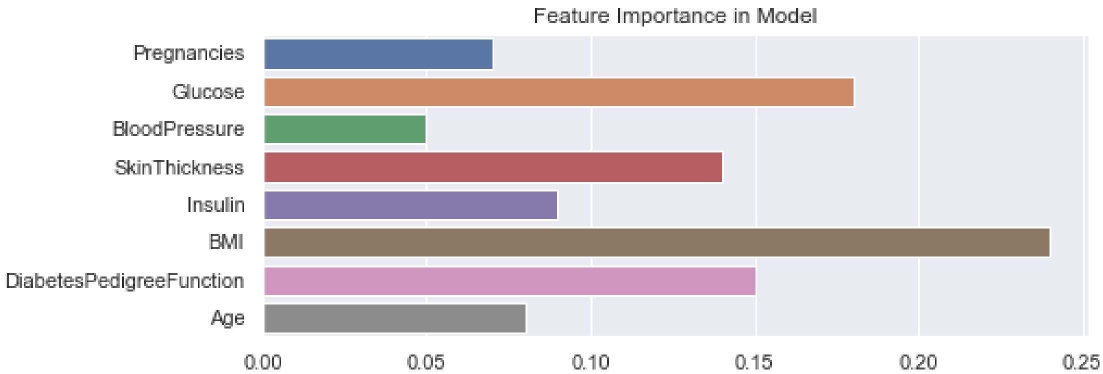
[336]:
```python
gs_ada.best_score_
```

[336]:
```
0.773
```

[337]:
```python
ada1.feature_importances_
```

[337]:
```
array([0.07, 0.18, 0.05, 0.14, 0.09, 0.24, 0.15, 0.08])
```

[338]:
```python
plt.figure(figsize=(8,3))
sns.barplot(y=X_train.columns, x=ada1.feature_importances_)
plt.title("Feature Importance in Model");
```



[339]:
```
ada2 = AdaBoostClassifier(n_estimators=200)
```

[340]:
```
ada2.fit(X_train,y_train)
```

[340]: AdaBoostClassifier(n_estimators=200)

[341]:
```
ada2.score(X_train,y_train)
```

[341]: 0.8588235294117647

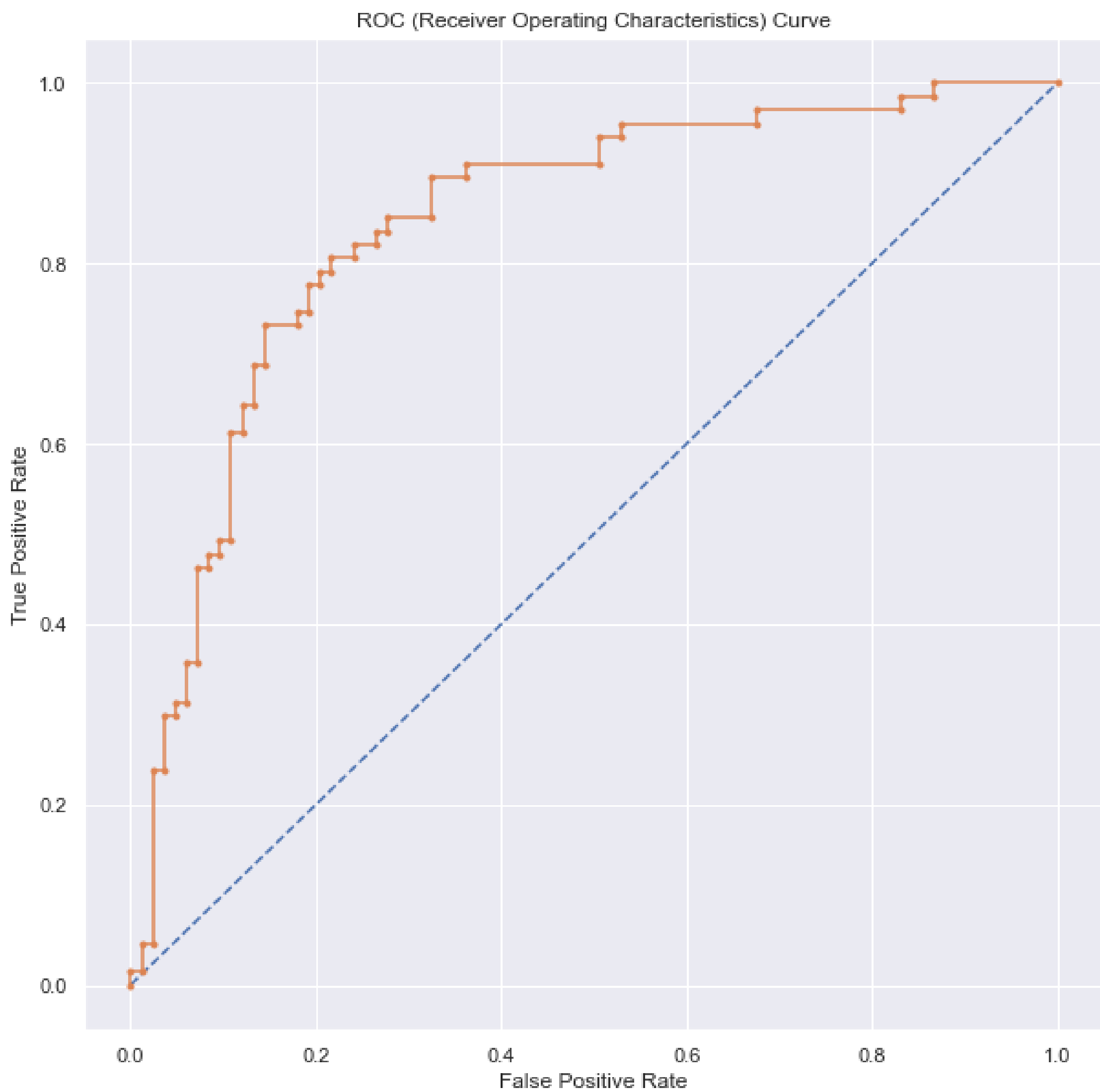
[342]:
```
ada2.score(X_test, y_test)
```

[342]: 0.78

[343]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = ada2.predict_proba(X_test)              # predict probabilities
probs = probs[:, 1]                             # keep probabilities for the␣
 ↪positive outcome only

auc_ada = roc_auc_score(y_test, probs)          # calculate AUC
print('AUC: %.3f' %auc_ada)
fpr, tpr, thresholds = roc_curve(y_test, probs)  # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')        # plot no skill
plt.plot(fpr, tpr, marker='.')                  # plot the roc curve for the␣
 ↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC (Receiver Operating Characteristics) Curve")
```

```
AUC: 0.845
```

[343]: Text(0.5, 1.0, 'ROC (Receiver Operating Characteristics) Curve')

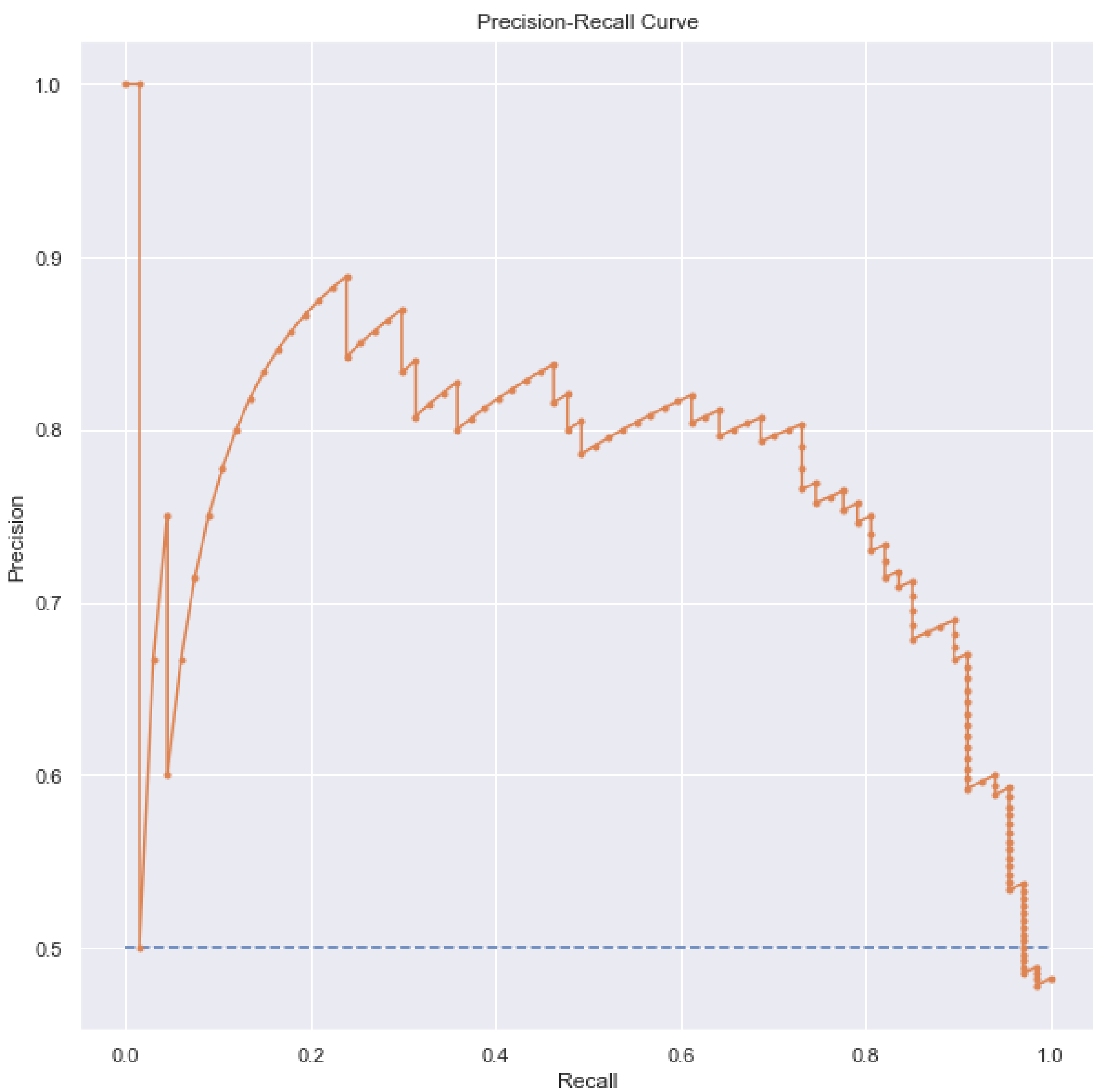


[344]:
```
# Precision Recall Curve

pred_y_test = ada2.predict(X_test)                                        # predict␣
 ↪class values
precision, recall, thresholds = precision_recall_curve(y_test, probs)  #␣
 ↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                       #␣
 ↪calculate F1 score
auc_ada_pr = auc(recall, precision)                                      #␣
 ↪calculate precision-recall AUC
ap = average_precision_score(y_test, probs)                              #␣
 ↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_ada_pr, ap))
```

```
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                              # plot no␣
 ↪skill
plt.plot(recall, precision, marker='.')                                   # plot␣
 ↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.769 auc_pr=0.770 ap=0.776
```

[344]: Text(0.5, 1.0, 'Precision-Recall Curve')



[345]:
```
models.append('ADA')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_ada)
```

8) Ensemble Learning --> Boosting --> Gradient Boosting (XGBClassifier):

[346]:
```
from xgboost import XGBClassifier
xgb1 = XGBClassifier(use_label_encoder=False, objective = 'binary:logistic',␣
↪nthread=4, seed=10)
```

```
C:\Users\91940\anaconda\lib\site-packages\xgboost\sklearn.py:1421: UserWarning:
`use_label_encoder` is deprecated in 1.7.0.
  warnings.warn("`use_label_encoder` is deprecated in 1.7.0.")
```

[347]:
```
xgb1.fit(X_train, y_train)
```

[347]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_bin=256, max_cat_threshold=64, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=4, nthread=4, num_parallel_tree=1, predictor='auto', …)
```

[348]:
```
xgb1.score(X_train, y_train)
```

[348]: 1.0

[349]:
```
xgb1.score(X_test, y_test)
```

[349]: 0.82

[350]:
```
parameters = {
    'max_depth': range (2, 10, 1),
    'n_estimators': range(60, 220, 40),
    'learning_rate': [0.1, 0.01, 0.05]
}
```

[351]:
```
gs_xgb = GridSearchCV(xgb1, param_grid = parameters, scoring = 'roc_auc',␣
↪n_jobs = 10, cv=5, verbose=0)
gs_xgb.fit(df_X_resampled, df_y_resampled)
```

```
C:\Users\91940\anaconda\lib\site-packages\xgboost\sklearn.py:1421: UserWarning:
`use_label_encoder` is deprecated in 1.7.0.
```

```
  warnings.warn("`use_label_encoder` is deprecated in 1.7.0.")
C:\Users\91940\anaconda\lib\site-packages\xgboost\sklearn.py:1421: UserWarning:
`use_label_encoder` is deprecated in 1.7.0.
  warnings.warn("`use_label_encoder` is deprecated in 1.7.0.")
```

[351]:
```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     callbacks=None, colsample_bylevel=1,
                                     colsample_bynode=1, colsample_bytree=1,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=None,
                                     feature_types=None, gamma=0, gpu_id=-1,
                                     grow_policy='depthwise',
                                     importance_type=None,
                                     interaction_constraints='',
                                     learning_rate=0.300000012…56,
                                     max_cat_threshold=64, max_cat_to_onehot=4,
                                     max_delta_step=0, max_depth=6,
                                     max_leaves=0, min_child_weight=1,
                                     missing=nan, monotone_constraints='()',
                                     n_estimators=100, n_jobs=4, nthread=4,
                                     num_parallel_tree=1, predictor='auto',
…),
             n_jobs=10,
             param_grid={'learning_rate': [0.1, 0.01, 0.05],
                         'max_depth': range(2, 10),
                         'n_estimators': range(60, 220, 40)},
             scoring='roc_auc')
```

[352]:
```
gs_xgb.best_params_
```

[352]:
```
{'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 140}
```

[353]:
```
gs_xgb.best_score_
```

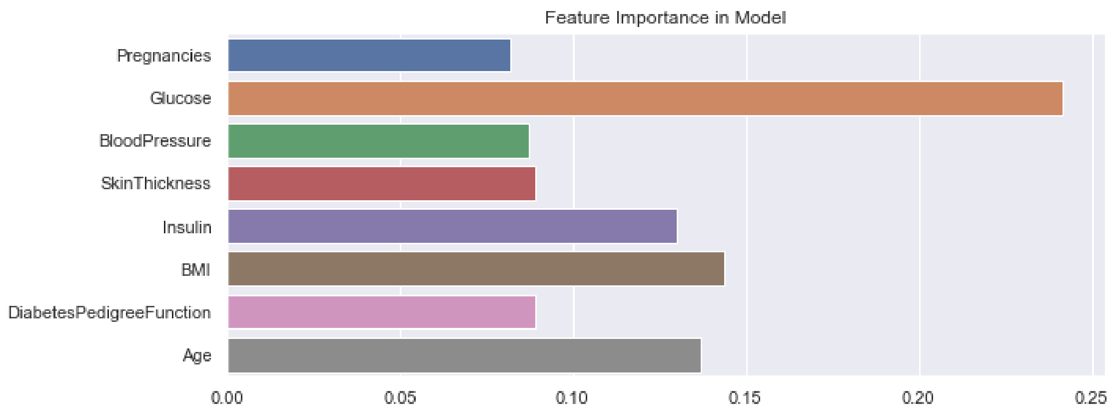
[353]:
```
0.8833400000000001
```

[354]:
```
xgb1.feature_importances_
```

[354]:
```
array([0.08192869, 0.24167173, 0.08726668, 0.08915504, 0.12994848,
       0.1436588 , 0.08942464, 0.13694592], dtype=float32)
```

[355]:
```
plt.figure(figsize=(10,4))
sns.barplot(y=X_train.columns, x=xgb1.feature_importances_)
plt.title("Feature Importance in Model")
```

[355]:
```
Text(0.5, 1.0, 'Feature Importance in Model')
```



[356]:
```
xgb2 = XGBClassifier(use_label_encoder=False, objective = 'binary:logistic',
                     nthread=4, seed=10, learning_rate= 0.1, max_depth= 7,␣
 ↪n_estimators= 140)
```

```
C:\Users\91940\anaconda\lib\site-packages\xgboost\sklearn.py:1421: UserWarning:
`use_label_encoder` is deprecated in 1.7.0.
  warnings.warn("`use_label_encoder` is deprecated in 1.7.0.")
```

[357]:
```
xgb2.fit(X_train,y_train)
```

[357]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.1, max_bin=256,
              max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
              max_depth=7, max_leaves=0, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=140, n_jobs=4, nthread=4,
              num_parallel_tree=1, predictor='auto', …)
```

[358]:
```
xgb2.score(X_train,y_train)
```

[358]: 1.0

[359]:
```
xgb2.score(X_test, y_test)
```

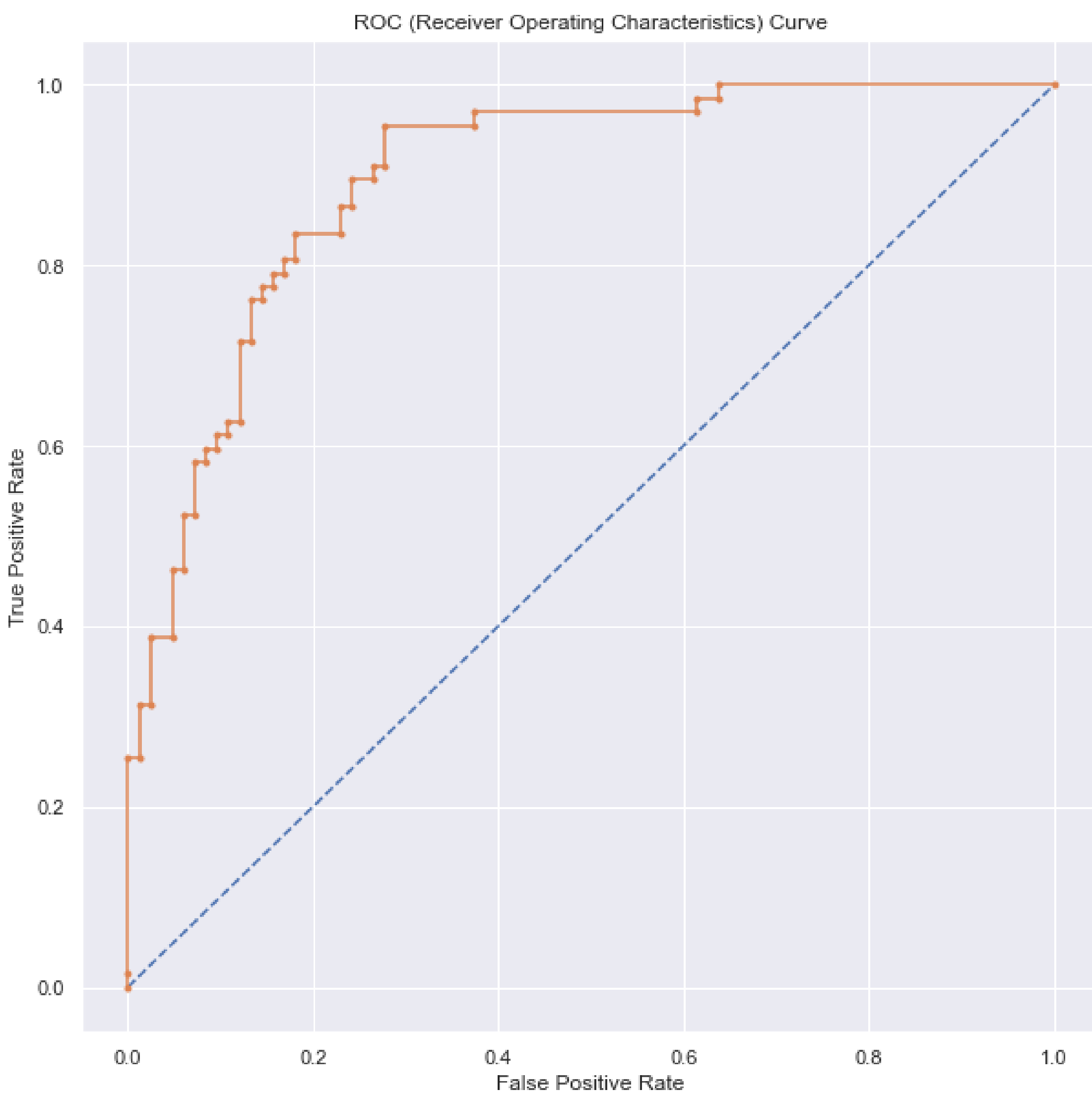
[359]: 0.8066666666666666

[360]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = xgb2.predict_proba(X_test)                # predict probabilities
```

```
probs = probs[:, 1]                                   # keep probabilities for the␣
 ↪positive outcome only

auc_xgb = roc_auc_score(y_test, probs)                 # calculate AUC
print('AUC: %.3f' %auc_xgb)
fpr, tpr, thresholds = roc_curve(y_test, probs)       # calculate roc curve
plt.plot([0, 1], [0, 1], linestyle='--')              # plot no skill
plt.plot(fpr, tpr, marker='.')                        # plot the roc curve for the␣
 ↪model
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC (Receiver Operating Characteristics) Curve")
```

```
AUC: 0.898
```

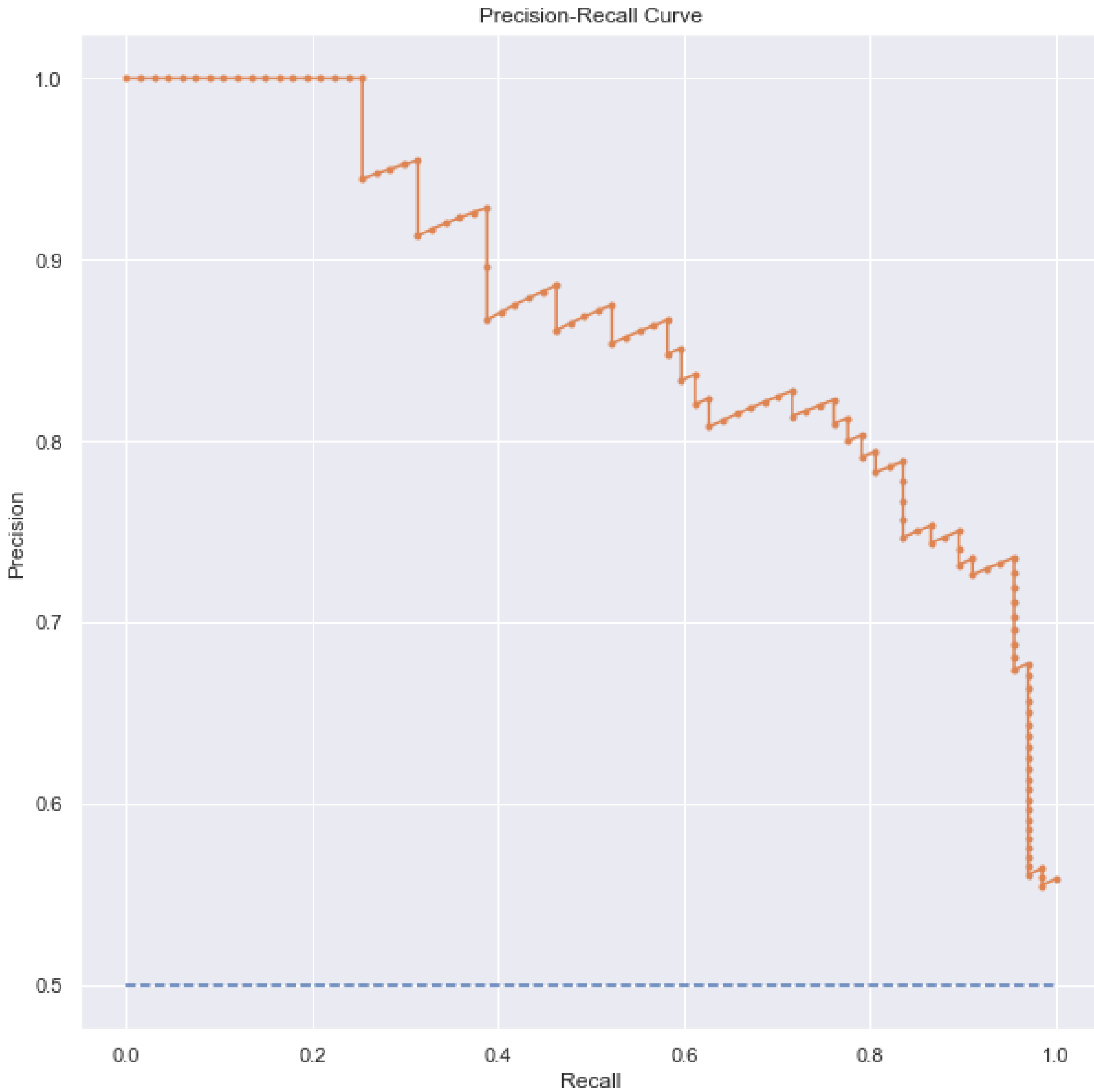
[360]:
```
Text(0.5, 1.0, 'ROC (Receiver Operating Characteristics) Curve')
```



[361]:
```
# Precision Recall Curve

pred_y_test = xgb2.predict(X_test)                                          #␣
↪predict class values
precision, recall, thresholds = precision_recall_curve(y_test, probs) #␣
↪calculate precision-recall curve
f1 = f1_score(y_test, pred_y_test)                                    #␣
↪calculate F1 score
auc_xgb_pr = auc(recall, precision)                                    #␣
↪calculate precision-recall AUC
ap = average_precision_score(y_test, probs)                            #␣
↪calculate average precision score
print('f1=%.3f auc_pr=%.3f ap=%.3f' % (f1, auc_xgb_pr, ap))
plt.plot([0, 1], [0.5, 0.5], linestyle='--')                          # plot no␣
↪skill
plt.plot(recall, precision, marker='.')                               # plot␣
↪the precision-recall curve for the model
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
```

```
f1=0.800 auc_pr=0.870 ap=0.871
```

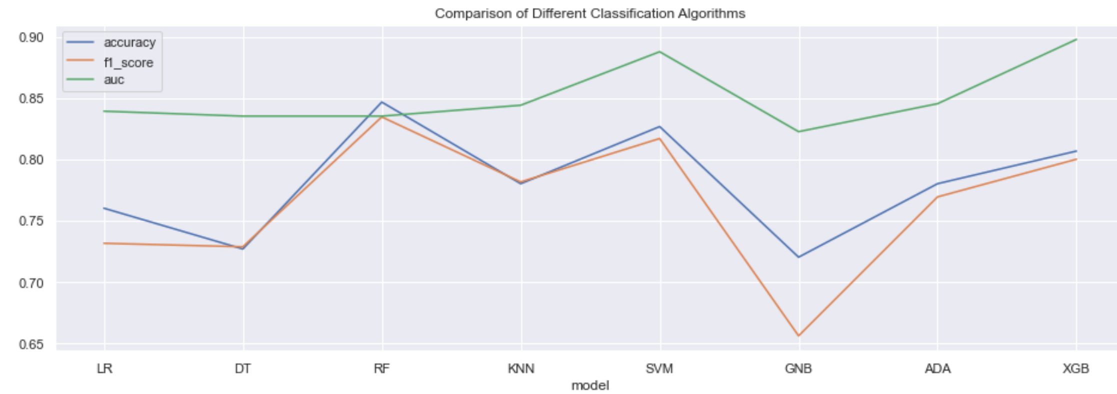
[361]:
```
Text(0.5, 1.0, 'Precision-Recall Curve')
```



[362]:
```
models.append('XGB')
model_accuracy.append(accuracy_score(y_test, pred_y_test))
model_f1.append(f1)
model_auc.append(auc_xgb)
```

[363]:
```
model_summary = pd.DataFrame(zip(models,model_accuracy,model_f1,model_auc),␣
 ↪columns = ['model','accuracy','f1_score','auc'])
model_summary = model_summary.set_index('model')
```

[364]:
```
model_summary.plot(figsize=(16,5))
plt.title("Comparison of Different Classification Algorithms")
```



[365]:
```
model_summary
```

[365]:

model	accuracy	f1_score	auc
LR	0.760000	0.731343	0.839238
DT	0.726667	0.728477	0.835192
RF	0.846667	0.834532	0.835192
KNN	0.780000	0.781457	0.844093
SVM	0.826667	0.816901	0.887790
GNB	0.720000	0.655738	0.822514
ADA	0.780000	0.769231	0.845352
XGB	0.806667	0.800000	0.897860

Among all models, RandomForest has given best accuracy and f1_score. Therefore we will build final model using RandomForest.

FINAL CLASSIFIER:

[367]:
```
final_model = rf2
```

DATA MODELLING

(1) Creating a classification report by analyzing sensitivity, specificity, AUC (ROC curve), etc. Please be descriptive to explain what values of these parameter you have used:

[369]:
```
cr = classification_report(y_test, final_model.predict(X_test))
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.88      0.83      0.86        83
           1       0.81      0.87      0.83        67

    accuracy                           0.85       150
   macro avg       0.85      0.85      0.85       150
```

```
weighted avg       0.85      0.85      0.85       150
```

[370]:
```python
confusion = confusion_matrix(y_test, final_model.predict(X_test))
print("Confusion Matrix:\n", confusion)
```

```
Confusion Matrix:
 [[69 14]
 [ 9 58]]
```

[373]:
```python
TP = confusion[1,1] # true positive
TN = confusion[0,0] # true negatives
FP = confusion[0,1] # false positives
FN = confusion[1,0] # false negatives

Accuracy = (TP+TN)/(TP+TN+FP+FN)
Precision = TP/(TP+FP)
Sensitivity = TP/(TP+FN)                    # also called recall
Specificity = TN/(TN+FP)
```

[374]:
```python
print("Accuracy: %.3f"%Accuracy)
print("Precision: %.3f"%Precision)
print("Sensitivity: %.3f"%Sensitivity)
print("Specificity: %.3f"%Specificity)
print("AUC: %.3f"%auc_rf)
```

```
Accuracy: 0.847
Precision: 0.806
Sensitivity: 0.866
Specificity: 0.831
AUC: 0.936
```

Sensitivity and Specificity: By changing the threshold, target classification will be changed hence the sensitivity and specificity will also be changed. Which one of these two we should maximize? What should be ideal threshold?

Ideally we want to maximize both Sensitivity & Specificity. But this is not possible always. There is always a trade-off. Sometimes we want to be 100% sure on Predicted negatives, sometimes we want to be 100% sure on Predicted positives. Sometimes we simply don't want to compromise on sensitivity sometimes we don't want to compromise on specificity.

The threshold is set based on business problem. There are some cases where Sensitivity is important and need to be near to 1. There are business cases where Specificity is important and need to be near to 1. We need to understand the business problem and decide the importance of Sensitivity and Specificity.

[375]:
```python
writer = pd.ExcelWriter('C:\\Users\\91940\\Documents\\Capston Proj␣
 ↪Healthcare\\final_healtcare.xlsx', engine='xlsxwriter')
```

```python
df_resampled.to_excel(writer, sheet_name='master_data', index=False)
writer.save()
```

[ ]:

```python

```