NIDDK (National Institute of Diabetes and Digestive and Kidney Diseases) research creates knowledge about and treatments for the most chronic, costly, and consequential diseases.

The objective is to predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset.

Build a model to accurately predict whether the patients in the dataset have diabetes or not.

In [162]:

```
#import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [163]:

```
df = pd.read_csv('health care diabetes.csv')
```

In [164]:

```
df.head()
```

Out[164]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctioı
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28

```
Pregnancies    - Number of times pregnant

Glucose        - Plasma glucose concentration in an oral glucose tolerance test

BloodPressure  - Diastolic blood pressure (mm Hg)

SkinThickness  - Triceps skinfold thickness (mm)

Insulin        - Two hour serum insulin

BMI            - Body Mass Index

DiabetesPedigreeFunction    - Diabetes pedigree function

Age            - Age in years
```

```
Outcome        - Class variable (either 0 or 1). 268 of 768 values are 1, and the others
are 0
```

In [165]:

```
df.shape
```

Out[165]:

```
(768, 9)
```

In [166]:

```
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                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

Processing Missing Values

In [167]:

```
#column-wise missing values
round((df.isnull().sum()/df.shape[0])*100,2)
```

Out[167]:

```
Pregnancies                 0.0
Glucose                     0.0
BloodPressure               0.0
SkinThickness               0.0
Insulin                     0.0
BMI                         0.0
DiabetesPedigreeFunction    0.0
Age                         0.0
Outcome                     0.0
dtype: float64
```

#No missing values available

zero does not make sense and thus indicates missing value for columns Glucose/BloodPressure/SkinThickness/Insulin/BMI

In [168]:

```
missing_value_columns = ["Glucose","BloodPressure","SkinThickness","Insulin","BMI"]
```

In [169]:

```
#Missing values in Glucose
df["Glucose"].value_counts()[0]
```

Out[169]:

```
5
```

In [170]:

```
#Missing values in BloodPressure
df["BloodPressure"].value_counts()[0]
```

Out[170]:

```
35
```

In [171]:

```
#Missing values in SkinThickness
df["SkinThickness"].value_counts()[0]
```

Out[171]:

```
227
```

In [172]:

```
#Missing values in Insulin
df["Insulin"].value_counts()[0]
```

Out[172]:

```
374
```

In [173]:

```
#Missing values in BMI
df["BMI"].value_counts()[0]
```

Out[173]:

```
11
```

In [174]:

```
df.describe()
```

Out[174]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabet
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

In [175]:

```
mean_df_glucose = df.groupby('Outcome')['Glucose'].mean()
mean_df_glucose
```

Out[175]:

```
Outcome
0    109.980000
1    141.257463
Name: Glucose, dtype: float64
```

In [176]:

```
missing_value_col_updated = ["Glucose","BloodPressure","SkinThickness","Insulin","BMI"]
```

In [177]:

```
mean_nonDiabestes = df.loc[df["Outcome"]==0].mean()
mean_nonDiabestes
```

Out[177]:

```
Pregnancies                   3.298000
Glucose                     109.980000
BloodPressure                68.184000
SkinThickness                19.664000
Insulin                      68.792000
BMI                          30.304200
DiabetesPedigreeFunction      0.429734
Age                          31.190000
Outcome                       0.000000
dtype: float64
```

In [178]:

```
nonDiabetic_Glucose_Mean = round(mean_nonDiabestes["Glucose"],0)
nonDiabetic_Glucose_Mean
```

Out[178]:

```
110.0
```

In [114]:

```
mean_diabestes = df.loc[df["Outcome"]==1].mean()
mean_diabestes
```

Out[114]:

```
Pregnancies                   4.865672
Glucose                     141.257463
BloodPressure                70.824627
SkinThickness                22.164179
Insulin                     100.335821
BMI                          35.142537
DiabetesPedigreeFunction      0.550500
Age                          37.067164
Outcome                       1.000000
dtype: float64
```

In [179]:

```
diabetic_Glucose_Mean = round(mean_diabestes["Glucose"],0)
diabetic_Glucose_Mean
```

Out[179]:

```
141.0
```

In [180]:

```
df.head()
```

Out[180]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28

In [181]:

```
etMissingValues(missing_value_columns) :
or column in missing_value_columns:
   df[column] = np.where((df[column] == 0) & (df['Outcome'] == 0), round(df.loc[df['Outcome'
   df[column] = np.where((df[column] == 0) & (df['Outcome'] == 1), round(df.loc[df['Outcome'
```

In [182]:

```
missing_value_col_updated = ["Glucose","BloodPressure","SkinThickness","Insulin"]
```

In [183]:

```
setMissingValues(missing_value_col_updated)
```

In [184]:

```
df["BMI"] = np.where((df["BMI"] == 0) & (df['Outcome'] == 0), round(df.loc[df['Outcome']==0
df["BMI"] = np.where((df["BMI"] == 0) & (df['Outcome'] == 1), round(df.loc[df['Outcome']==1
```

In [185]:

```
df.describe()
```

Out[185]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabet
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	121.691406	72.266927	26.677083	118.971354	32.435286	
std	3.369578	30.460693	12.117110	9.601847	93.535785	6.881492	
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.200000	
25%	1.000000	99.750000	64.000000	20.000000	69.000000	27.500000	
50%	3.000000	117.000000	72.000000	23.000000	100.000000	32.050000	
75%	6.000000	141.000000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

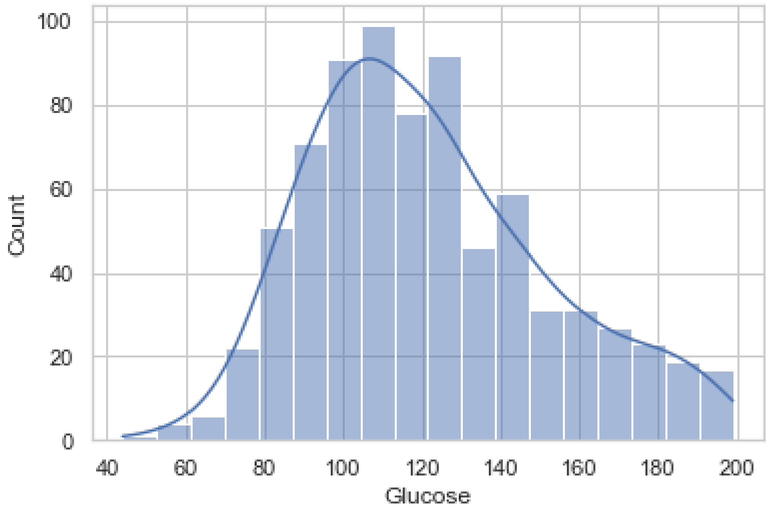
Visually explore these variables using histogram

In [186]:

```
sns.set(style='whitegrid')
sns.histplot(data = df, x= "Glucose", kde=True)
```

Out[186]:

```
<AxesSubplot:xlabel='Glucose', ylabel='Count'>
```

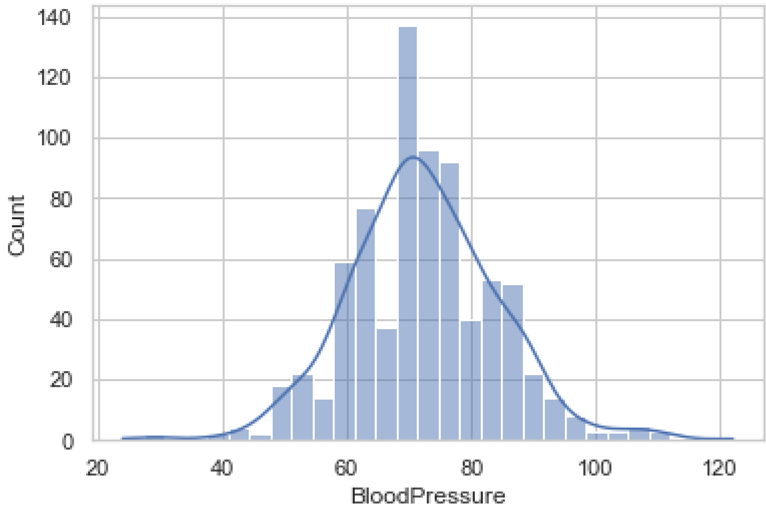


In [133]:

```
sns.histplot(data = df, x= "BloodPressure", kde=True)
```

Out[133]:

```
<AxesSubplot:xlabel='BloodPressure', ylabel='Count'>
```

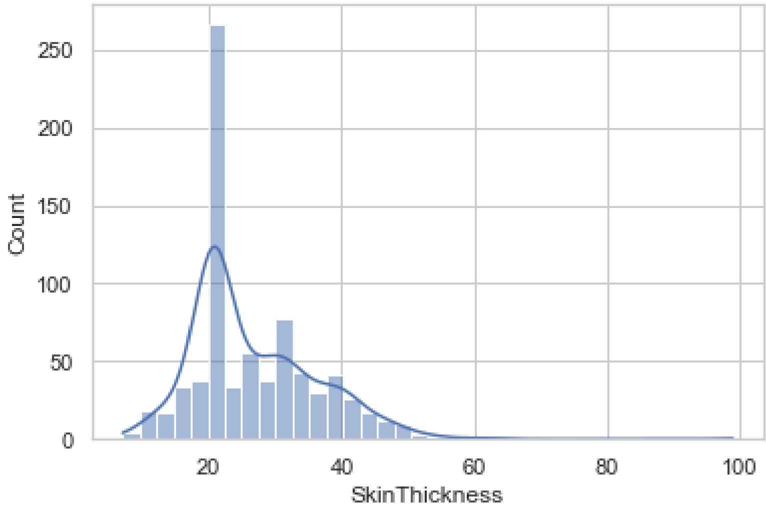


In [187]:

```
sns.histplot(data = df, x= "SkinThickness", kde=True)
```

Out[187]:

```
<AxesSubplot:xlabel='SkinThickness', ylabel='Count'>
```

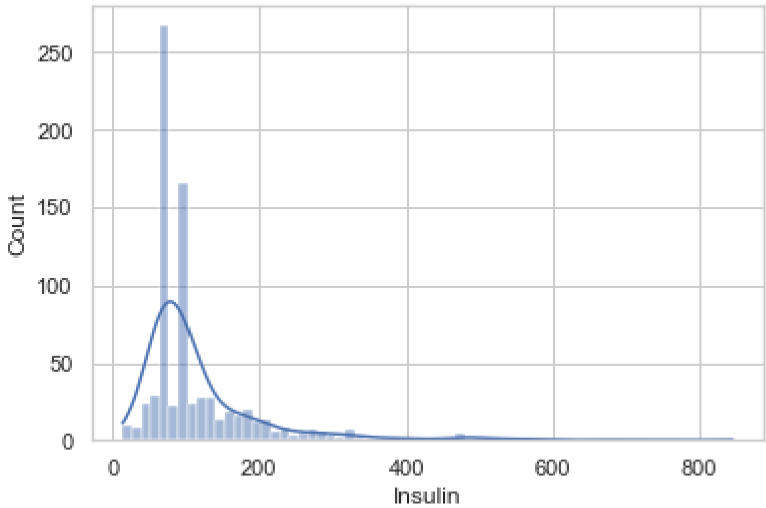


In [188]:

```
sns.histplot(data = df, x= "Insulin", kde=True)
```

Out[188]:

```
<AxesSubplot:xlabel='Insulin', ylabel='Count'>
```

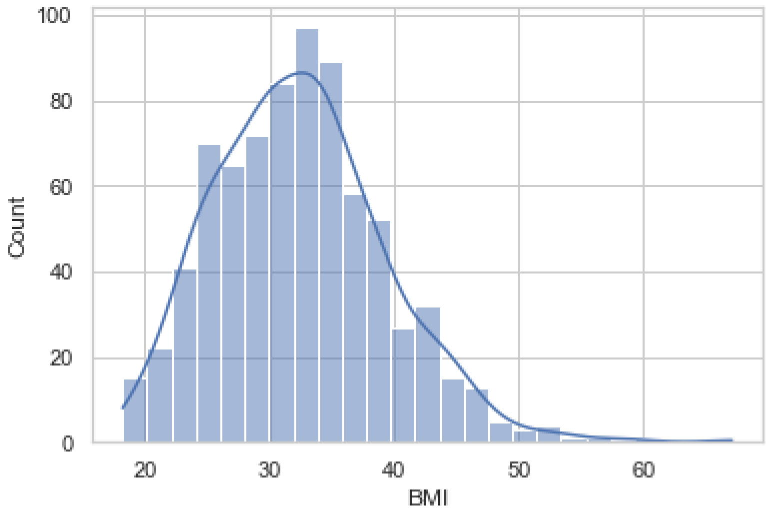


In [189]:

```
sns.histplot(data = df, x= "BMI", kde=True)
```

Out[189]:

```
<AxesSubplot:xlabel='BMI', ylabel='Count'>
```



Skewness is almost normal except few outlier observed which we can consider later

count (frequency) plot describing the data types and the count of variables

In [190]:

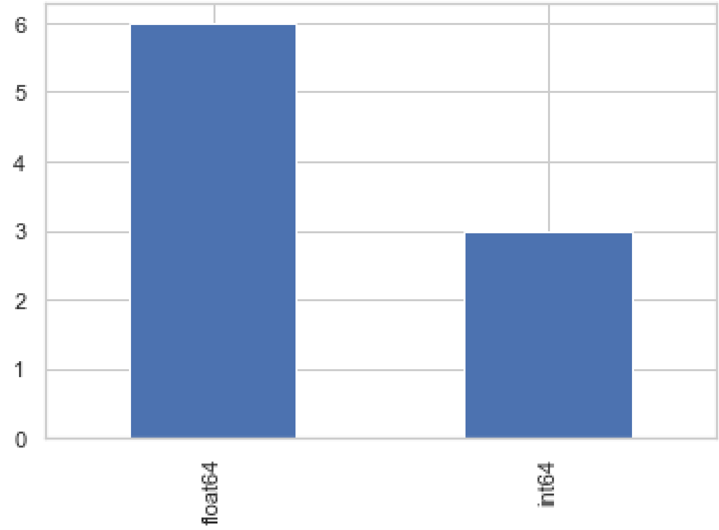
```
## Removing outliers
def remove_outliers(df1):
    IQR = df1.quantile(0.75) - df1.quantile(0.25)
    ub = df1.quantile(0.75) + 1.5*IQR
    lb = df1.quantile(0.25) - 1.5*IQR

    new_vals = []
    for val in df1.values:
        if val<lb:
            new_vals.append(lb)
        elif val>ub:
            new_vals.append(ub)
        else: new_vals.append(val)

    return new_vals
```

In [191]:

```
df['Glucose'] = remove_outliers(df['Glucose'])
df['BloodPressure'] = remove_outliers(df['BloodPressure'])
df['SkinThickness'] = remove_outliers(df['SkinThickness'])
df['Insulin'] = remove_outliers(df['Insulin'])
df['BMI'] = remove_outliers(df['BMI'])
df['DiabetesPedigreeFunction'] = remove_outliers(df['DiabetesPedigreeFunction'])
df['Age'] = remove_outliers(df['Age'])
```

In [192]:

```
df.dtypes.value_counts().plot(kind='bar');
```



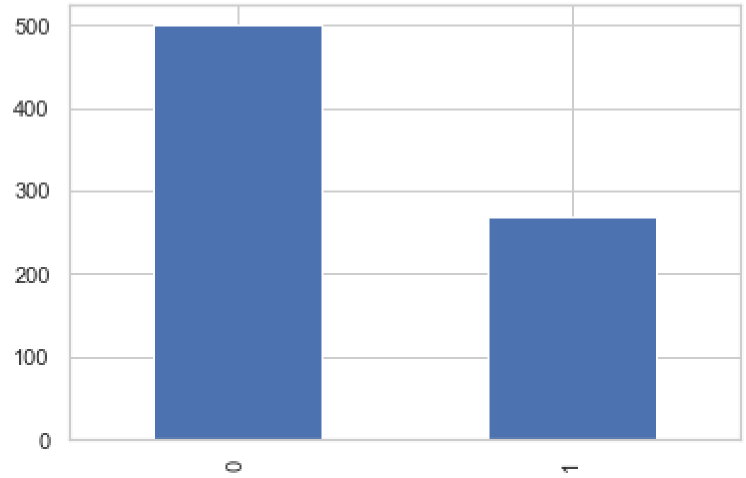
Check the balance of the data by plotting the count of outcomes by their value. Describe your findings and plan future course of action

In [193]:

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

Out[193]:

```
0    500
1    268
Name: Outcome, dtype: int64
```



As the Outcome is skewed required SMOTE for class 1

In [194]:

```
X = df.drop(['Outcome'],axis=1)
y = df['Outcome']
```

In [195]:

```
X.shape
```

Out[195]:

```
(768, 8)
```

In [196]:

```
y.shape
```

Out[196]:

```
(768,)
```

In [144]:

```
# installing imblearn to implement smote and random oversampling
!pip install imblearn
```

```
Collecting imblearn
  Downloading imblearn-0.0-py2.py3-none-any.whl (1.9 kB)
Collecting imbalanced-learn
  Downloading imbalanced_learn-0.9.1-py3-none-any.whl (199 kB)
     ------------------------------------ 199.3/199.3 kB 549.7 kB/s eta 0:0
0:00
Requirement already satisfied: scikit-learn>=1.1.0 in c:\software_install_de
tails\anaconda3\envs\tensorflow_keras\lib\site-packages (from imbalanced-lea
rn->imblearn) (1.1.1)
Requirement already satisfied: numpy>=1.17.3 in c:\software_install_details
\anaconda3\envs\tensorflow_keras\lib\site-packages (from imbalanced-learn->i
mblearn) (1.22.3)
Requirement already satisfied: joblib>=1.0.0 in c:\software_install_details
\anaconda3\envs\tensorflow_keras\lib\site-packages (from imbalanced-learn->i
mblearn) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\software_install_d
etails\anaconda3\envs\tensorflow_keras\lib\site-packages (from imbalanced-le
arn->imblearn) (2.2.0)
Requirement already satisfied: scipy>=1.3.2 in c:\software_install_details\a
naconda3\envs\tensorflow_keras\lib\site-packages (from imbalanced-learn->imb
learn) (1.7.3)
Installing collected packages: imbalanced-learn, imblearn
Successfully installed imbalanced-learn-0.9.1 imblearn-0.0
```

In [197]:

```
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=100)
print("No. of rows before smote implementation: ",X.shape[0])
X_res, y_res = sm.fit_resample(X, y)
print("No. of rows after smote implementation: ",X_res.shape[0])
```

```
No. of rows before smote implementation:  768
No. of rows after smote implementation:  1000
```

In [198]:

```
from collections import Counter
print("Class distribution before Smote: ",Counter(y))
print("Class distribution after Smote: ",Counter(y_res))
```

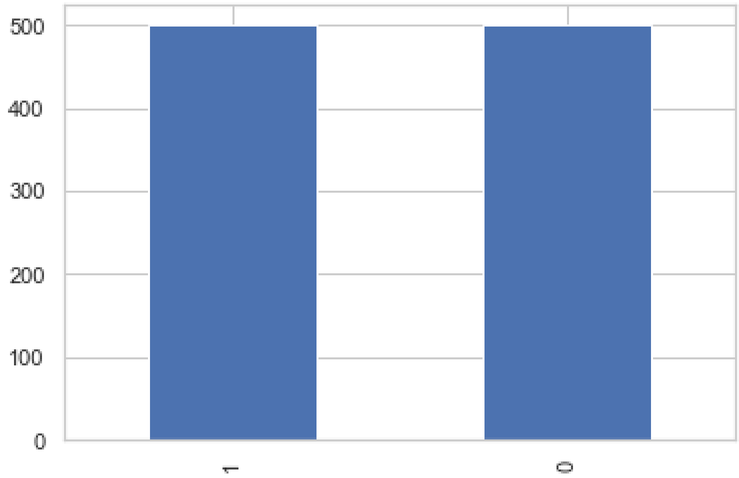
```
Class distribution before Smote:  Counter({0: 500, 1: 268})
Class distribution after Smote:  Counter({1: 500, 0: 500})
```

In [199]:

```
y_res.value_counts().plot(kind='bar')
y_res.value_counts()
```

Out[199]:

```
1    500
0    500
Name: Outcome, dtype: int64
```



Scatter charts between the pair of variables to understand the relationships.

In [200]:

```
df.columns
```

Out[200]:

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insuli
n',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

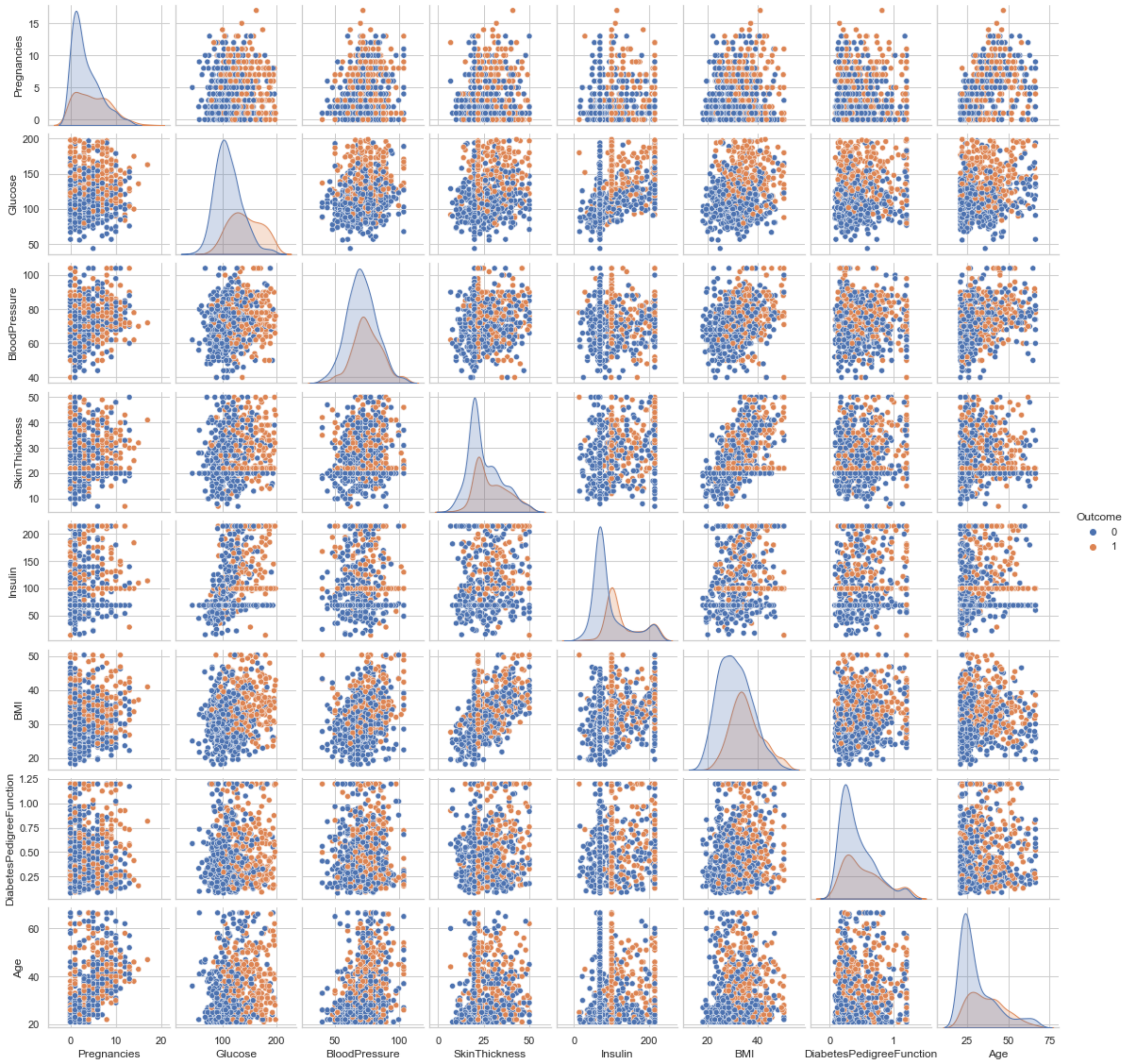
In [201]:

```
sns.set(style='whitegrid')
cols = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'Diab
sns.pairplot(df, hue="Outcome", size=2)
```

```
C:\Software_Install_Details\Anaconda3\envs\TENSORFLOW_KERAS\lib\site-package
s\seaborn\axisgrid.py:2076: UserWarning: The `size` parameter has been renam
ed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

Out[201]:

<seaborn.axisgrid.PairGrid at 0x2a69f1a6670>



In [202]:

```
df_res = pd.concat([X_res, y_res], axis=1)
df_res
```

Out[202]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	
0	6	148	72.000000	35.000000	100.000	33.600000	0.627000	5
1	1	85	66.000000	29.000000	69.000	26.600000	0.351000	3
2	8	183	64.000000	22.000000	100.000	23.300000	0.672000	3
3	1	89	66.000000	23.000000	94.000	28.100000	0.167000	2
4	0	137	40.000000	35.000000	168.000	43.100000	1.200000	3
...	...	...	...	...	...	...	...	
995	1	194	67.339649	39.147229	214.625	30.393586	0.221848	5
996	1	123	67.577838	20.605540	100.000	28.792743	0.245522	3
997	4	146	84.512270	22.000000	100.000	35.104316	0.528838	6

In [203]:

```
sns.pairplot(df_res, hue="Outcome", size=2)
```

Glucose has direct relationship with Outcome. None of the feature cannot distinguish the Outcome

Perform correlation analysis. Visually explore it using a heat map

In [204]:

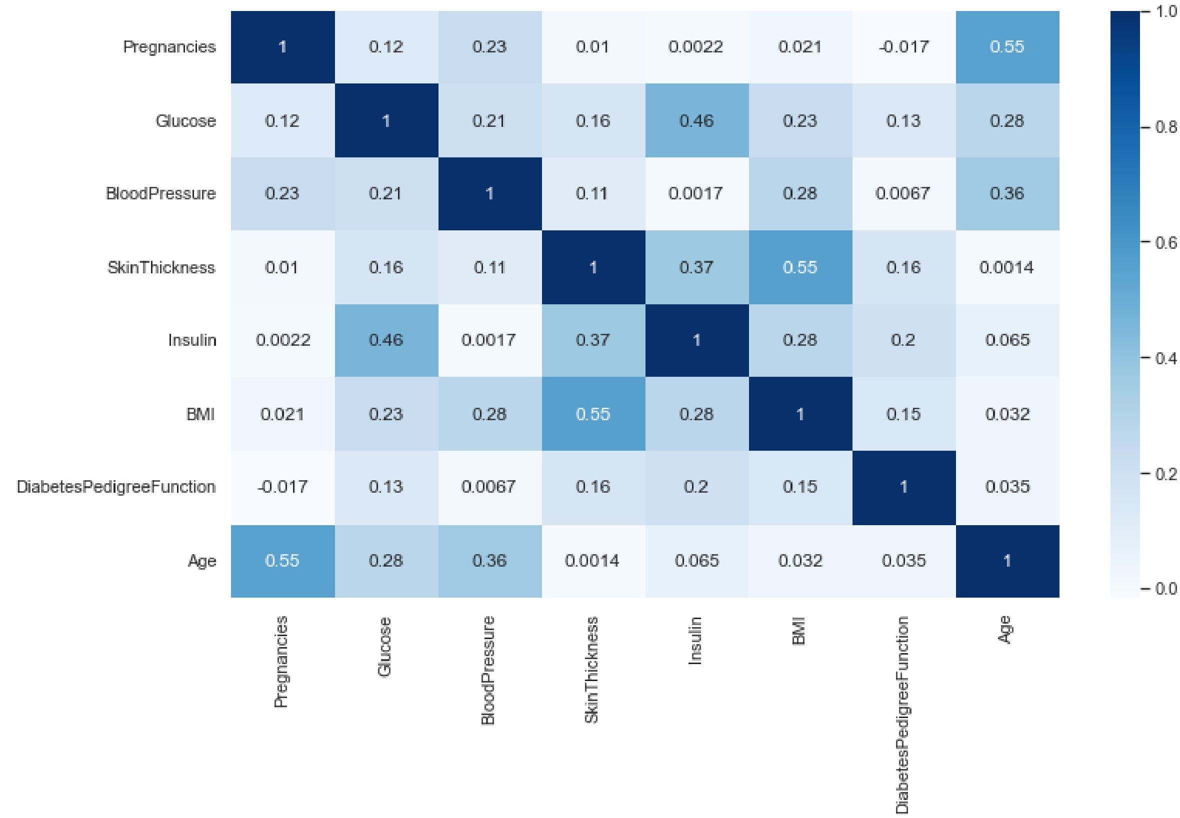
```
X_res.corr()
```

Out[204]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	
Pregnancies	1.000000	0.116768	0.230917	0.010173	0.002220	0.02
Glucose	0.116768	1.000000	0.207077	0.157186	0.458336	0.22
BloodPressure	0.230917	0.207077	1.000000	0.106406	0.001746	0.27
SkinThickness	0.010173	0.157186	0.106406	1.000000	0.368001	0.55
Insulin	0.002220	0.458336	0.001746	0.368001	1.000000	0.27
BMI	0.021314	0.229038	0.277786	0.552147	0.276885	1.00
DiabetesPedigreeFunction	-0.016627	0.128014	0.006742	0.157079	0.195965	0.14
Age	0.549501	0.280322	0.360853	0.001379	0.064783	0.03

In [205]:

```
plt.figure(figsize=(12,7))
sns.heatmap(X_res.corr(), cmap='Blues', annot=True);
```



There is significant relationship between two pairs - Pregnancies-Age and SkinThickness-BMI

Data Modeling:

Devise strategies for model building. It is important to decide the right validation framework. Express your thought process.

Apply an appropriate classification algorithm to build a model.

Compare various models with the results from KNN algorithm.

Create a classification report by analyzing sensitivity, specificity, AUC (ROC curve), etc.

For this classication problem we will check all the classification machine learning algorithm to get better performance and result

Logistic Regression

Decision Tree

RandomForest Classifier

K-Nearest Neighbour (KNN)

Support Vector Machine (SVM)

Naive Bayes Classifier

Ensemble Learning - Adaptive Boosting

Ensemble Learning - Gradient Boosting (XGBClassifier)

Scaling

In [207]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X_res,y_res,train_size=0.75,random_state=1
```

In [208]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test  = scaler.transform(X_test)
```

In [209]:

```
X_train.shape, X_test.shape
```

Out[209]:

```
((750, 8), (250, 8))
```

In [333]:

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

Logistic Regression

In [334]:

```
#Hyperparameter tuning
from sklearn.linear_model import LogisticRegression
parameters = {
    'penalty' : ['l1','l2','elasticnet'],
    'solver' : ['newton-cg','liblinear','lbfgs'] ,
    'C':np.logspace(-5, 5, 50)
}
```

In [335]:

```
from sklearn.model_selection import GridSearchCV
logreg = LogisticRegression()
clf = GridSearchCV(logreg,
             param_grid=parameters,
             scoring = "accuracy",
             cv=5)
```

In [336]:

```
import warnings
warnings.filterwarnings('ignore')
clf.fit(X_train,y_train)
```

Out[336]:

```
▸ GridSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

In [337]:

```
clf.best_params_
```

Out[337]:

```
{'C': 0.04714866363457394, 'penalty': 'l2', 'solver': 'liblinear'}
```

In [338]:

```
clf.best_score_
```

Out[338]:

```
0.7586666666666668
```

Model Building

In [339]:

```
logreg = LogisticRegression(penalty='l2',solver = 'liblinear')
logreg.fit(X_train,y_train)
```

Out[339]:

```
▾          LogisticRegression
LogisticRegression(solver='liblinear')
```

In [340]:

```
logreg.score(X_test,y_test)
```

Out[340]:

```
0.78
```

In [341]:

```
y_pred = logreg.predict(X_test)
```

In [342]:

```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.79      0.77      0.78       128
           1       0.77      0.79      0.78       122

    accuracy                           0.78       250
   macro avg       0.78      0.78      0.78       250
weighted avg       0.78      0.78      0.78       250
```

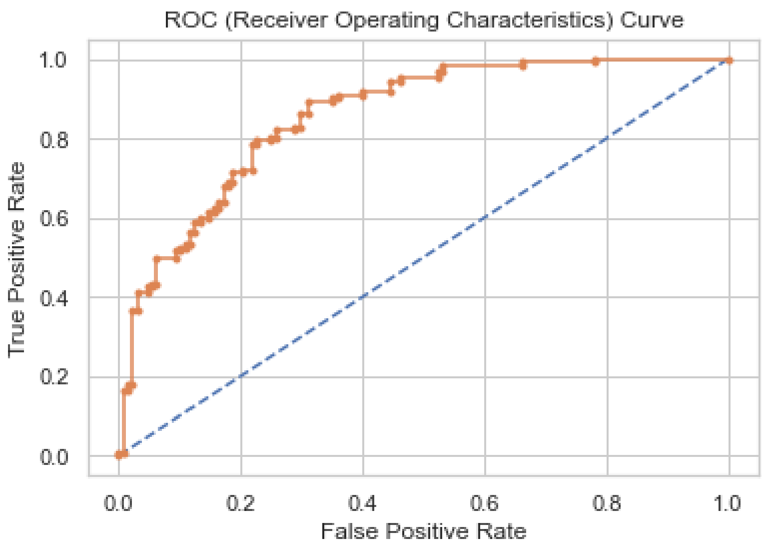
In [343]:

```
sification_report, auc, roc_curve, roc_auc_score,precision_recall_curve,average_precision_sc
```

In [344]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = logreg.predict_proba(X_test)             # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the positive outc
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");
```

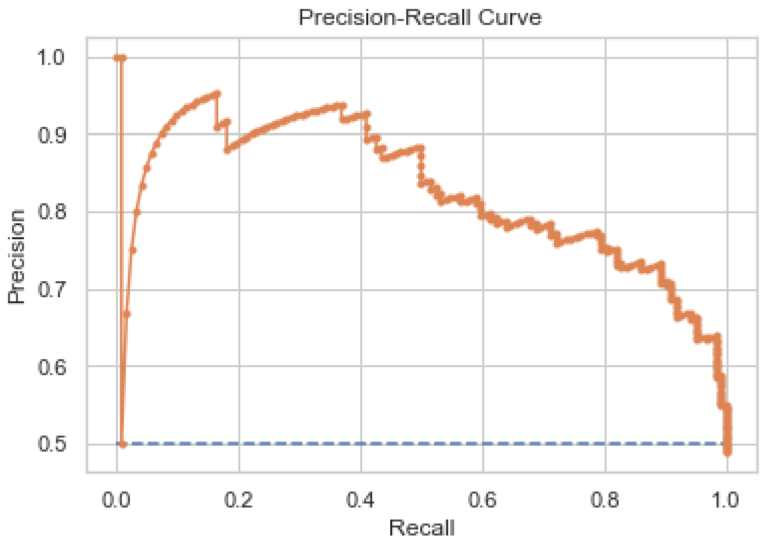
```
AUC: 0.857
```



In [345]:

```
# Precision Recall Curve

precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_pred)                                       # calculate F1 score
auc_lr_pr = auc(recall, precision)                                      # calculate precision
ap = average_precision_score(y_test, probs)                             # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.777 auc_pr=0.824 ap=0.827
```



In [346]:

```
models.append('LR')
model_accuracy.append(accuracy_score(y_test, y_pred))
model_f1.append(f1)
model_auc.append(auc_lr)
```

DecisionTree

In [347]:

```
#Performing hypermarameter tunning using RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import RandomizedSearchCV
tree = DecisionTreeClassifier()
param_grid = {
              "criterion": ["gini", "entropy"],
              "max_depth": [3,4,5],
              "max_features":[3,5,7],
              "min_samples_leaf": [2,3,5,7]
}

randomized_cv = RandomizedSearchCV(estimator = tree,
                   param_distributions = param_grid,
                   cv=5)
randomized_cv.fit(X_train,y_train)
```

Out[347]:

```
▸ RandomizedSearchCV
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

In [348]:

```
randomized_cv.best_params_
```

Out[348]:

```
{'min_samples_leaf': 3, 'max_features': 7, 'max_depth': 5, 'criterion': 'gin
i'}
```

In [349]:

```
#creating model with Decision tree algorithm
dt = DecisionTreeClassifier(criterion = 'gini',
                               max_depth= 4,
                               max_features= 5,
                               min_samples_leaf = 5)

dt.fit(X_train,y_train)
```

Out[349]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=4, max_features=5, min_samples_leaf=5)
```

In [350]:

```
#Checking accuracy on train and test
y_test_pred = dt.predict(X_test)
y_train_pred = dt.predict(X_train)

print("Train Accuracy is: ", metrics.accuracy_score(y_train,y_train_pred))
print("Test Accuracy is: ", metrics.accuracy_score(y_test,y_test_pred))
```

```
Train Accuracy is:  0.876
Test Accuracy is:  0.88
```

In [351]:

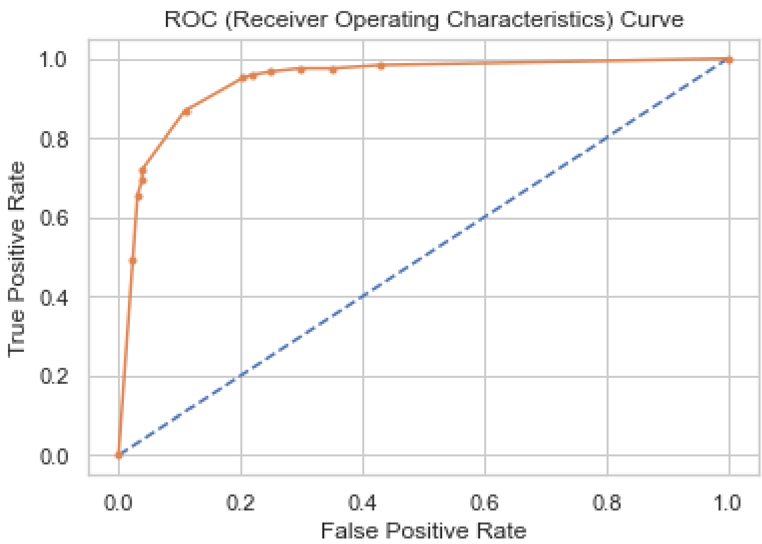
```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.89      0.88       128
           1       0.88      0.87      0.88       122

    accuracy                           0.88       250
   macro avg       0.88      0.88      0.88       250
weighted avg       0.88      0.88      0.88       250
```

In [352]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = dt.predict_proba(X_test)                # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the positive outc

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");
```

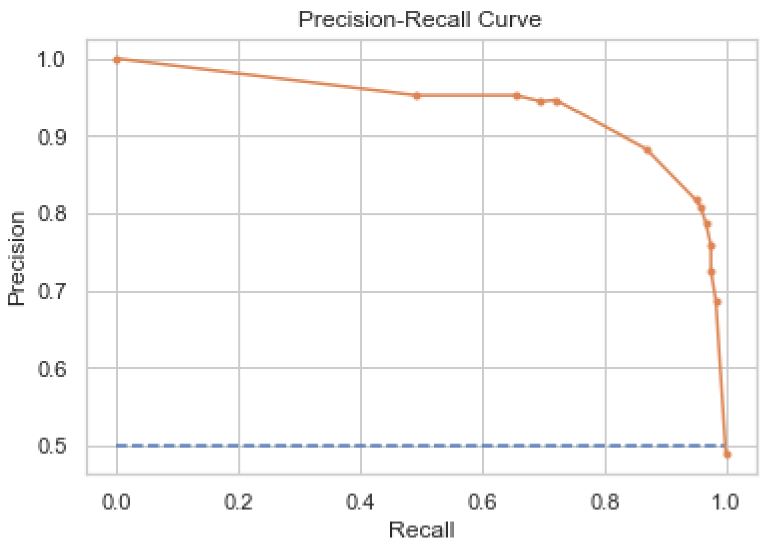
```
AUC: 0.943
```



In [353]:

```
# Precision Recall Curve

precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_test_pred)                                    # calculate F1 score
auc_dt_pr = auc(recall, precision)                                    # calculate precision
ap = average_precision_score(y_test, probs)                           # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.876 auc_pr=0.938 ap=0.917
```



In [354]:

```
models.append('DT')
model_accuracy.append(accuracy_score(y_test, y_test_pred))
model_f1.append(f1)
model_auc.append(auc_dt)
```

RandomForest Classifier

In [355]:

```
#Performing hypermarameter tunning using RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
parameters = {
    'n_estimators': [50,100,150],
    'max_depth': [None,1,3,5,7],
    'min_samples_leaf': [1,3,5]
}

gs_rf = GridSearchCV(estimator=rf, param_grid=parameters, cv=5, verbose=0)
gs_rf.fit(X_train,y_train)
```

Out[355]:

```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [357]:

```
gs_rf.best_params_
```

Out[357]:

```
{'max_depth': None, 'min_samples_leaf': 1, 'n_estimators': 50}
```

In [358]:

```
gs_rf.best_score_
```

Out[358]:

```
0.9120000000000001
```

In [359]:

```
#creating model with RandomForest algorithm
rf = RandomForestClassifier(max_depth=None, min_samples_leaf=5, n_estimators=100)

rf.fit(X_train,y_train)
```

Out[359]:

```
▾ RandomForestClassifier
RandomForestClassifier(min_samples_leaf=5)
```

In [360]:

```
#Checking accuracy on train and test
y_test_pred = rf.predict(X_test)
y_train_pred = rf.predict(X_train)

print("Train Accuracy is: ", metrics.accuracy_score(y_train,y_train_pred))
print("Test Accuracy is: ", metrics.accuracy_score(y_test,y_test_pred))
```

```
Train Accuracy is:  0.9466666666666667
Test Accuracy is:  0.904
```

In [361]:

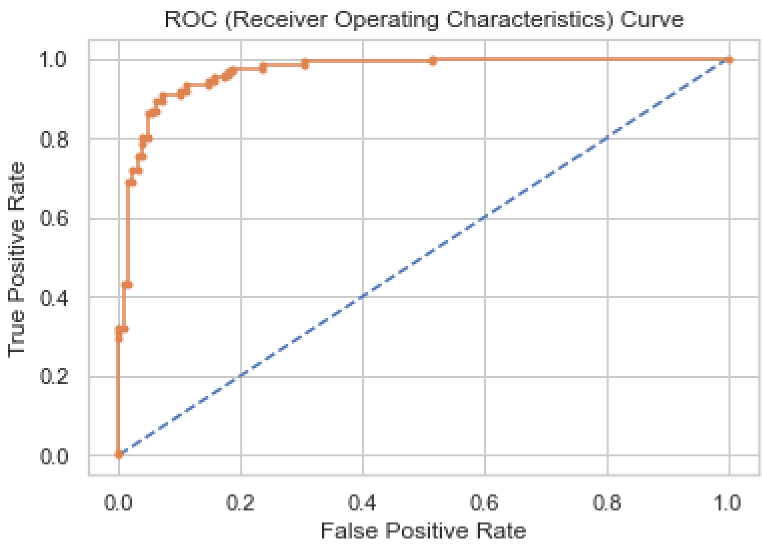
```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.93      0.88      0.90       128
           1       0.88      0.93      0.90       122

    accuracy                           0.90       250
   macro avg       0.91      0.90      0.90       250
weighted avg       0.91      0.90      0.90       250
```

In [362]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = rf.predict_proba(X_test)                 # predict probabilities
probs = probs[:, 1]                               # keep probabilities for the positive outc

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");
```

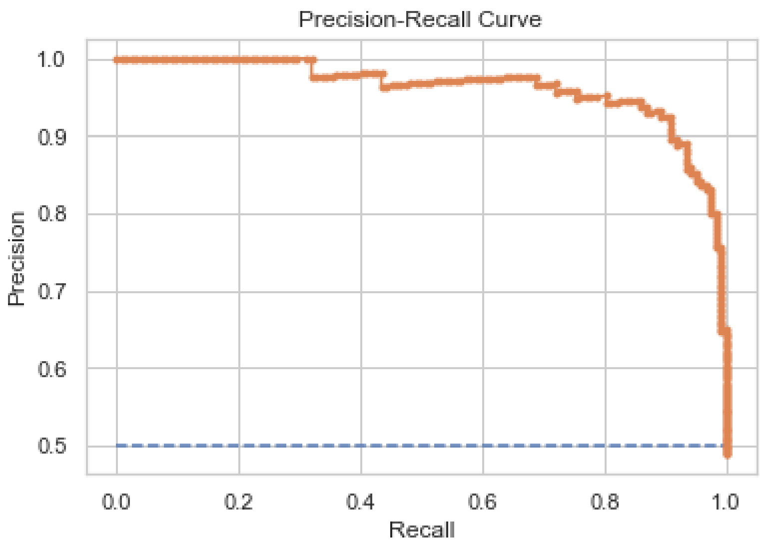
AUC: 0.967



In [363]:

```
# Precision Recall Curve

precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_test_pred)                                    # calculate F1 score
auc_rf_pr = auc(recall, precision)                                    # calculate precision
ap = average_precision_score(y_test, probs)                           # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.905 auc_pr=0.963 ap=0.963
```



In [364]:

```
models.append('RF')
model_accuracy.append(accuracy_score(y_test, y_test_pred))
model_f1.append(f1)
model_auc.append(auc_rf)
```

K-Nearest Neighbour (KNN) Classification

In [365]:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn_neighbors = [i for i in range(2,16)]
parameters = {
    'n_neighbors': knn_neighbors
}
gs_knn = GridSearchCV(estimator=knn, param_grid=parameters, cv=5, verbose=0)
gs_knn.fit(X_train,y_train)
```

Out[365]:

```
▸ GridSearchCV
▸ estimator: KNeighborsClassifier
    ▸ KNeighborsClassifier
```

In [366]:

```
gs_knn.best_params_, gs_knn.best_score_
```

Out[366]:

```
({'n_neighbors': 8}, 0.8346666666666668)
```

In [367]:

```
knn = KNeighborsClassifier(n_neighbors=8)
knn.fit(X_train,y_train)
```

Out[367]:

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=8)
```

In [368]:

```
#Checking accuracy on train and test
y_test_pred = knn.predict(X_test)
y_train_pred = knn.predict(X_train)

print("Train Accuracy is: ", metrics.accuracy_score(y_train,y_train_pred))
print("Test Accuracy is: ", metrics.accuracy_score(y_test,y_test_pred))
```

```
Train Accuracy is:  0.8746666666666667
Test Accuracy is:  0.816
```

#slightly overfitting

In [369]:

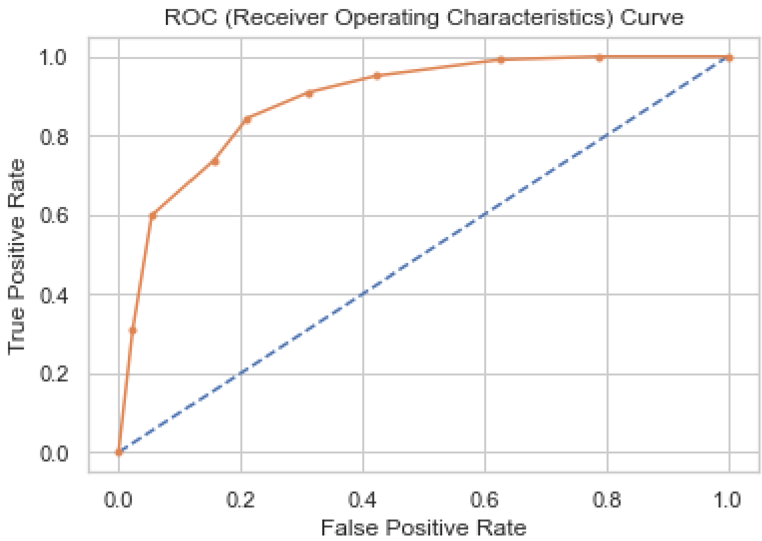
```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.79      0.81       128
           1       0.79      0.84      0.82       122

    accuracy                           0.82       250
   macro avg       0.82      0.82      0.82       250
weighted avg       0.82      0.82      0.82       250
```

In [370]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = knn.predict_proba(X_test)               # predict probabilities
probs = probs[:, 1]                             # keep probabilities for the positive outc

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");
```

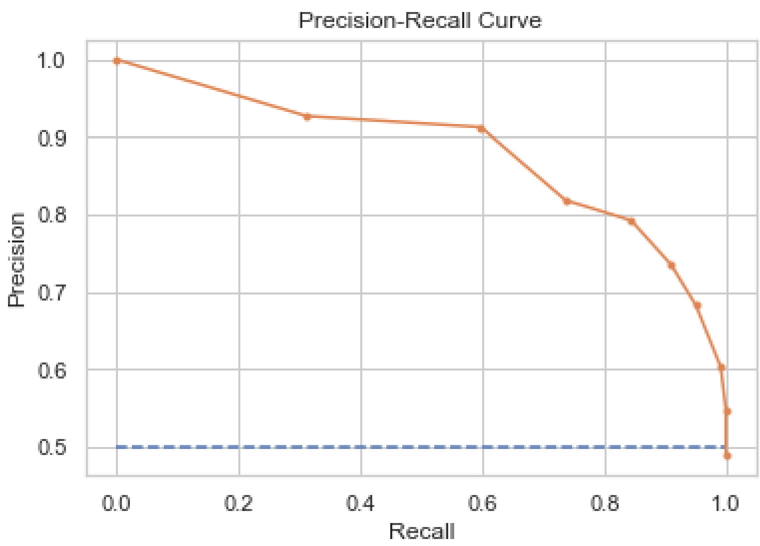
```
AUC: 0.891
```



In [371]:

```
# Precision Recall Curve

precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_test_pred)                                   # calculate F1 score
auc_knn_pr = auc(recall, precision)                                   # calculate precisio
ap = average_precision_score(y_test, probs)                          # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.817 auc_pr=0.880 ap=0.854
```



In [372]:

```
models.append('KNN')
model_accuracy.append(accuracy_score(y_test, y_test_pred))
model_f1.append(f1)
model_auc.append(auc_knn)
```

Support Vector Machine (SVM)

In [373]:

```
from sklearn.svm import SVC
svm = SVC()
parameters = {
    'C':[1, 5, 10, 15, 20, 25],
    'gamma':[0.001, 0.005, 0.0001, 0.00001]
}
gs_svm = GridSearchCV(estimator=svm, param_grid=parameters, cv=5, verbose=0)
gs_svm.fit(X_train,y_train)
```

Out[373]:

```
▸ GridSearchCV
▸ estimator: SVC
    ▸ SVC
```

In [374]:

```
gs_svm.best_params_, gs_svm.best_score_
```

Out[374]:

```
({'C': 10, 'gamma': 0.005}, 0.7493333333333334)
```

In [375]:

```
svm = SVC(kernel='rbf', C=10, gamma=0.005, probability=True)
svm.fit(X_train, y_train)
```

Out[375]:

```
▾ SVC
SVC(C=10, gamma=0.005, probability=True)
```

In [376]:

```
#Checking accuracy on train and test
y_test_pred = svm.predict(X_test)
y_train_pred = svm.predict(X_train)

print("Train Accuracy is: ", metrics.accuracy_score(y_train,y_train_pred))
print("Test Accuracy is: ", metrics.accuracy_score(y_test,y_test_pred))
```

```
Train Accuracy is:  0.752
Test Accuracy is:  0.76
```

In [377]:

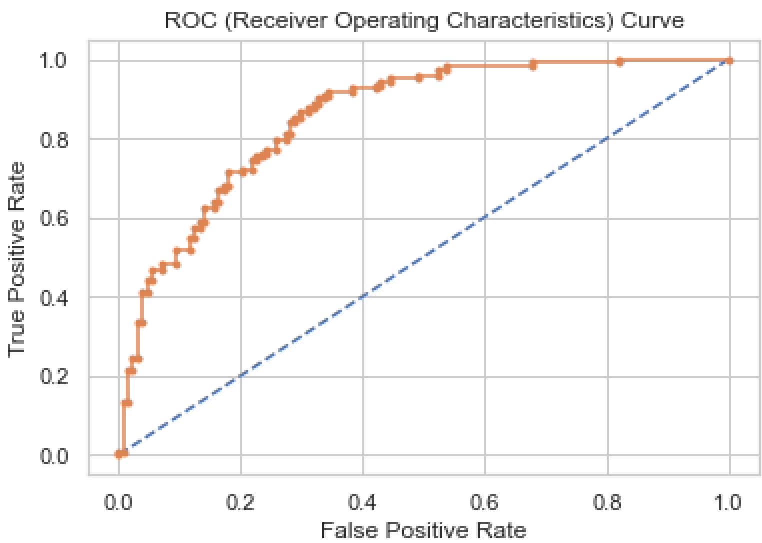
```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.77      0.77      0.77       128
           1       0.75      0.75      0.75       122

    accuracy                           0.76       250
   macro avg       0.76      0.76      0.76       250
weighted avg       0.76      0.76      0.76       250
```

In [378]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = svm.predict_proba(X_test)                  # predict probabilities
probs = probs[:, 1]                                # keep probabilities for the positive outc

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");
```

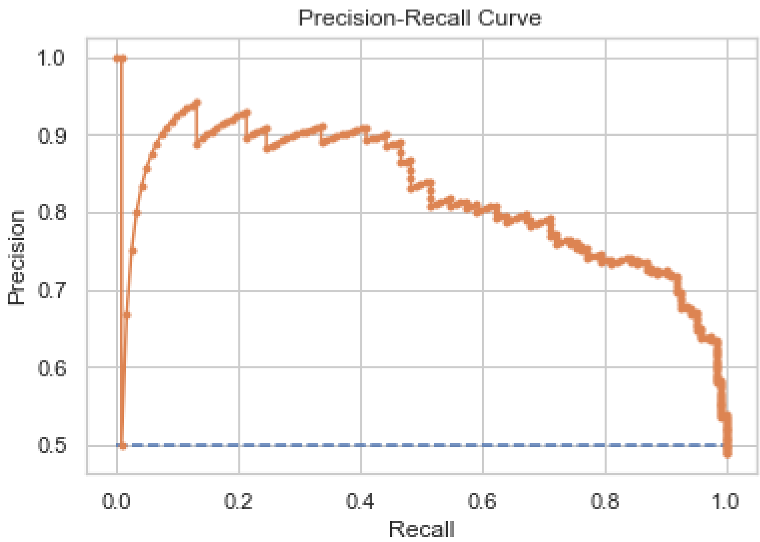
```
AUC: 0.856
```



In [379]:

```
# Precision Recall Curve

precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_test_pred)                                    # calculate F1 score
auc_svm_pr = auc(recall, precision)                                    # calculate precisio
ap = average_precision_score(y_test, probs)                           # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.754 auc_pr=0.820 ap=0.822
```



In [380]:

```
models.append('SVM')
model_accuracy.append(accuracy_score(y_test, y_test_pred))
model_f1.append(f1)
model_auc.append(auc_svm)
```

Naive Bayes

In [285]:

```
pip install scikit-optimize
```

```
Collecting scikit-optimizeNote: you may need to restart the kernel to use up
dated packages.

  Downloading scikit_optimize-0.9.0-py2.py3-none-any.whl (100 kB)
     ------------------------------------ 100.3/100.3 kB 720.2 kB/s eta 0:0
0:00
Requirement already satisfied: scipy>=0.19.1 in c:\software_install_details
\anaconda3\envs\tensorflow_keras\lib\site-packages (from scikit-optimize)
(1.7.3)
Requirement already satisfied: joblib>=0.11 in c:\software_install_details\a
naconda3\envs\tensorflow_keras\lib\site-packages (from scikit-optimize) (1.
1.0)
Collecting pyaml>=16.9
  Downloading pyaml-21.10.1-py2.py3-none-any.whl (24 kB)
Requirement already satisfied: numpy>=1.13.3 in c:\software_install_details
\anaconda3\envs\tensorflow_keras\lib\site-packages (from scikit-optimize)
(1.22.3)
Requirement already satisfied: scikit-learn>=0.20.0 in c:\software_install_d
etails\anaconda3\envs\tensorflow_keras\lib\site-packages (from scikit-optimi
ze) (1.1.1)
Requirement already satisfied: PyYAML in c:\software_install_details\anacond
a3\envs\tensorflow_keras\lib\site-packages (from pyaml>=16.9->scikit-optimiz
e) (6.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\software_install_d
etails\anaconda3\envs\tensorflow_keras\lib\site-packages (from scikit-learn>
=0.20.0->scikit-optimize) (2.2.0)
Installing collected packages: pyaml, scikit-optimize
Successfully installed pyaml-21.10.1 scikit-optimize-0.9.0
```

In [381]:

```
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
gnb = GaussianNB()
gnb.fit(X_train, y_train)
```

Out[381]:

```
▾ GaussianNB
GaussianNB()
```

In [382]:

```
#Checking accuracy on train and test
y_test_pred = gnb.predict(X_test)
y_train_pred = gnb.predict(X_train)

print("Train Accuracy is: ", metrics.accuracy_score(y_train,y_train_pred))
print("Test Accuracy is: ", metrics.accuracy_score(y_test,y_test_pred))
```

```
Train Accuracy is:  0.764
Test Accuracy is:  0.78
```

In [383]:

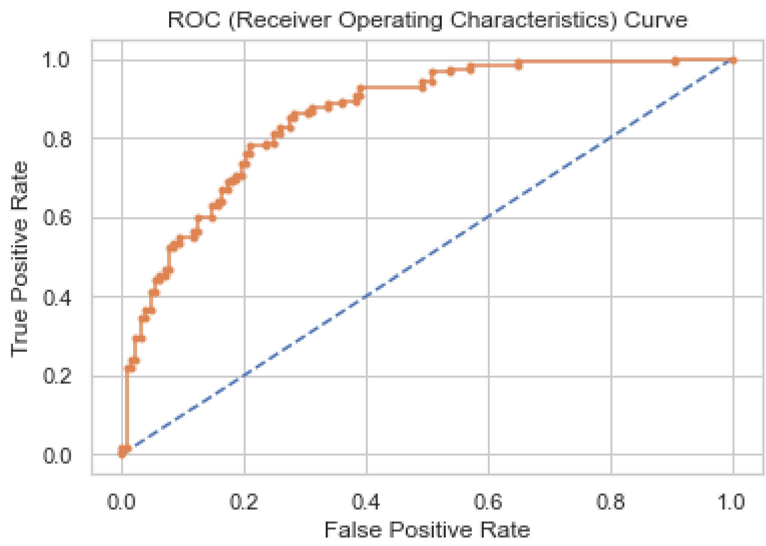
```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.79      0.79       128
           1       0.78      0.77      0.77       122

    accuracy                           0.78       250
   macro avg       0.78      0.78      0.78       250
weighted avg       0.78      0.78      0.78       250
```

In [384]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

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

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");
```

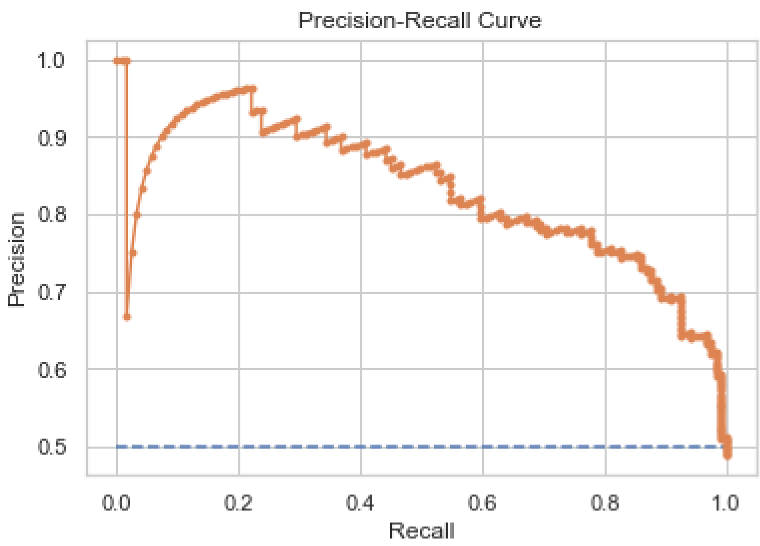
```
AUC: 0.857
```



In [385]:

```
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_test_pred)                                    # calculate F1 score
auc_gnb_pr = auc(recall, precision)                                    # calculate precisio
ap = average_precision_score(y_test, probs)                           # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.774 auc_pr=0.829 ap=0.832
```



In [386]:

```
models.append('NB')
model_accuracy.append(accuracy_score(y_test, y_test_pred))
model_f1.append(f1)
model_auc.append(auc_gnb)
```

Ensemble Learning - Ada Boosting

In [387]:

```
from sklearn.ensemble import AdaBoostClassifier
ada = AdaBoostClassifier()
parameters = {'n_estimators': [100,200,300,400,500,700,1000]}
gs_ada = GridSearchCV(ada, param_grid = parameters, cv=5, verbose=0)
gs_ada.fit(X_train, y_train)
```

Out[387]:

```
▸          GridSearchCV
▸ estimator: AdaBoostClassifier
     ▸ AdaBoostClassifier
```

In [388]:

```
gs_ada.best_params_,gs_ada.best_score_
```

Out[388]:

```
({'n_estimators': 100}, 0.8893333333333333)
```

In [389]:

```
ada = AdaBoostClassifier(n_estimators=100)
ada.fit(X_train, y_train)
```

Out[389]:

```
▾          AdaBoostClassifier
AdaBoostClassifier(n_estimators=100)
```

In [390]:

```
#Checking accuracy on train and test
y_test_pred = ada.predict(X_test)
y_train_pred = ada.predict(X_train)

print("Train Accuracy is: ", metrics.accuracy_score(y_train,y_train_pred))
print("Test Accuracy is: ", metrics.accuracy_score(y_test,y_test_pred))
```

```
Train Accuracy is:  0.9586666666666667
Test Accuracy is:  0.888
```

#overfitting

In [391]:

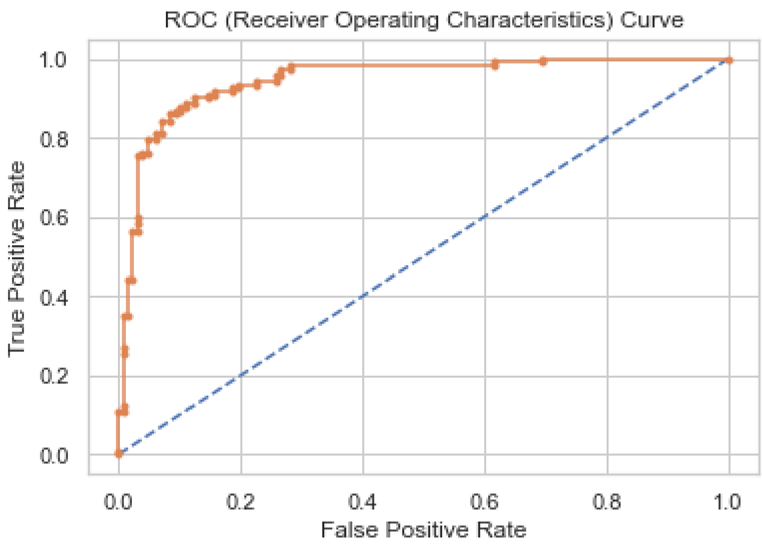
```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.88      0.89       128
           1       0.87      0.90      0.89       122

    accuracy                           0.89       250
   macro avg       0.89      0.89      0.89       250
weighted avg       0.89      0.89      0.89       250
```

In [392]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = ada.predict_proba(X_test)                # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the positive outc

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");
```

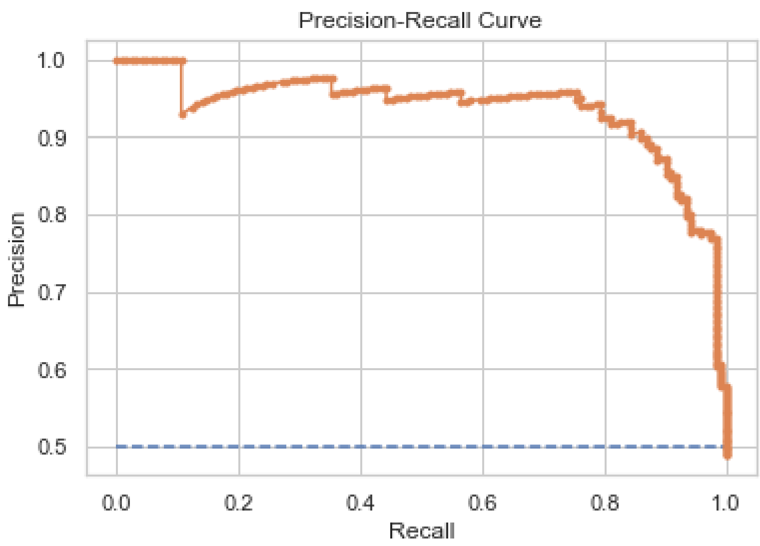
```
AUC: 0.948
```



In [393]:

```
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_test_pred)                                    # calculate F1 score
auc_ada_pr = auc(recall, precision)                                    # calculate precisio
ap = average_precision_score(y_test, probs)                           # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.887 auc_pr=0.937 ap=0.937
```



In [394]:

```
models.append('ADA')
model_accuracy.append(accuracy_score(y_test, y_test_pred))
model_f1.append(f1)
model_auc.append(auc_ada)
```

Ensemble Learning - Gradient Boosting

In [316]:

```
pip install XGBoost
```

```
Collecting XGBoost
  Downloading xgboost-1.6.2-py3-none-win_amd64.whl (125.4 MB)
     ---------------------------------------- 125.4/125.4 MB 2.1 MB/s eta 0:0
0:00
Requirement already satisfied: numpy in c:\software_install_details\anaconda
3\envs\tensorflow_keras\lib\site-packages (from XGBoost) (1.22.3)
Requirement already satisfied: scipy in c:\software_install_details\anaconda
3\envs\tensorflow_keras\lib\site-packages (from XGBoost) (1.7.3)
Installing collected packages: XGBoost
Successfully installed XGBoost-1.6.2
Note: you may need to restart the kernel to use updated packages.
```

In [395]:

```
from xgboost import XGBClassifier
xgb = XGBClassifier(use_label_encoder=False, objective = 'binary:logistic', nthread=4, seed
parameters = {
    'max_depth': range (2, 10, 1),
    'n_estimators': range(60, 220, 40),
    'learning_rate': [0.1, 0.01, 0.05]
}
gs_xgb = GridSearchCV(xgb, param_grid = parameters, scoring = 'roc_auc', n_jobs = 10, cv=5,
gs_xgb.fit(X_train, y_train)
```

Out[395]:

```
▸ GridSearchCV
▸ estimator: XGBClassifier
  ▸ XGBClassifier
```

In [396]:

```
gs_xgb.best_params_,gs_xgb.best_score_
```

Out[396]:

```
({'learning_rate': 0.05, 'max_depth': 6, 'n_estimators': 180},
 0.9705565544491861)
```

In [397]:

```
xgb = XGBClassifier(use_label_encoder=False, objective = 'binary:logistic',
                    nthread=4, seed=10, learning_rate= 0.05, max_depth= 6, n_estimators= 18
xgb.fit(X_train,y_train)
```

Out[397]:

XGBClassifier

```
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, gamma=0, gpu_id=-1, grow_policy='depthwi
se',
              importance_type=None, interaction_constraints='',
              learning_rate=0.05, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_wei
ght=1,
```

In [398]:

```
#Checking accuracy on train and test
y_test_pred = xgb.predict(X_test)
y_train_pred = xgb.predict(X_train)

print("Train Accuracy is: ", metrics.accuracy_score(y_train,y_train_pred))
print("Test Accuracy is: ", metrics.accuracy_score(y_test,y_test_pred))
```

```
Train Accuracy is:  1.0
Test Accuracy is:  0.916
```

In [399]:

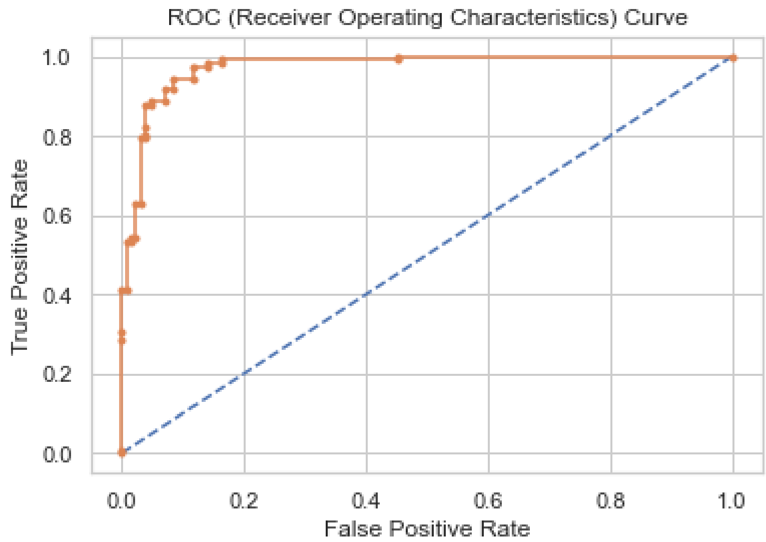
```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.89      0.92       128
           1       0.89      0.94      0.92       122

    accuracy                           0.92       250
   macro avg       0.92      0.92      0.92       250
weighted avg       0.92      0.92      0.92       250
```

In [400]:

```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

probs = xgb.predict_proba(X_test)                # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the positive outc

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");
```

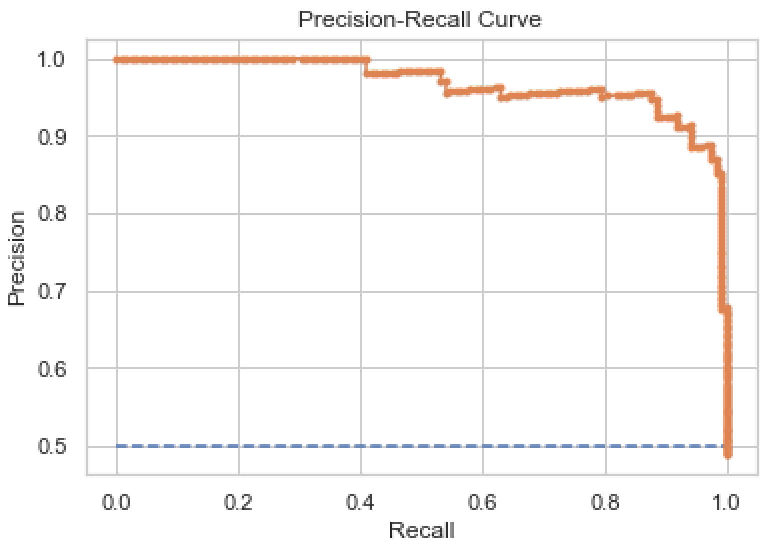
```
AUC: 0.974
```



In [402]:

```
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precision
f1 = f1_score(y_test, y_test_pred)                                    # calculate F1 score
auc_xgb_pr = auc(recall, precision)                                    # calculate precisio
ap = average_precision_score(y_test, probs)                           # calculate average p
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-
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.916 auc_pr=0.969 ap=0.969
```



In [411]:

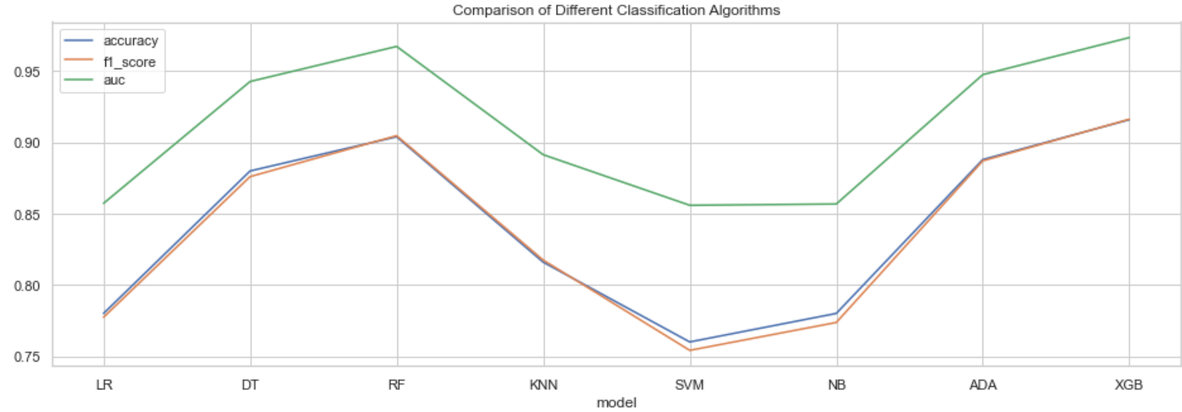
```
models.append('XGB')
model_accuracy.append(accuracy_score(y_test, y_test_pred))
model_f1.append(f1)
model_auc.append(auc_xgb)
```

In [412]:

```
model_summary = pd.DataFrame(zip(models,model_accuracy,model_f1,model_auc), columns = ['mod
model_summary = model_summary.set_index('model')
```

In [413]:

```
model_summary.plot(figsize=(16,5))
plt.title("Comparison of Different Classification Algorithms");
```



In [414]:

```
model_summary
```

Out[414]:

	accuracy	f1_score	auc
model			
LR	0.780	0.777328	0.857262
DT	0.880	0.876033	0.942783
RF	0.904	0.904762	0.967405
KNN	0.816	0.817460	0.891425
SVM	0.760	0.754098	0.855917
NB	0.780	0.773663	0.856814
ADA	0.888	0.887097	0.947618
XGB	0.916	0.916335	0.973617

Both RandomForest and XGBoost has given good accuracy and f1_score. But if we check the train and test accuracy RF does not seems to be overfitted. Therefore we will opt RandomForest. (Decision Tree also given very good result with robust train and test accuracy)

In [415]:

```
#Final Model Report
selected_model = rf
```

In [416]:

```
#Classification Report
print(classification_report(y_test, selected_model.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.93      0.88      0.90       128
           1       0.88      0.93      0.90       122

    accuracy                           0.90       250
   macro avg       0.91      0.90      0.90       250
weighted avg       0.91      0.90      0.90       250
```

In [417]:

```
#Confusion Matrix
confusion = confusion_matrix(y_test, selected_model.predict(X_test))
print("Confusion Matrix:\n", confusion)
```

```
Confusion Matrix:
 [[112  16]
 [  8 114]]
```

In [418]:

```
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)

print("Accuracy: %.4f"%Accuracy)
print("Precision: %.4f"%Precision)
print("Sensitivity: %.4f"%Sensitivity)
print("Specificity: %.4f"%Specificity)
print("AUC: %.4f"%auc_rf)
```

```
Accuracy: 0.9040
Precision: 0.8769
Sensitivity: 0.9344
Specificity: 0.8750
AUC: 0.9674
```

In [ ]: