Masters Program - DATA SCIENCE & BUSINESS ANALYTICS
Capstone Project: Healthcare

Problem Statement:

- 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 dataset used in this project is originally from NIDDK. 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.

Dataset Description: The datasets consists of several medical predictor variables and one target variable (Outcome). Predictor variables includes the number of pregnancies the patient has had, their BMI, insulin level, age, and more.

Variables - Description

- 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

Week 1:

Data Exploration:

1. Perform descriptive analysis. Understand the variables and their corresponding values. On the columns below, a value of zero does not make sense and thus indicates missing value:
   - `Glucose`
   - `BloodPressure`
   - `SkinThickness`
   - `Insulin`
   - `BMI`
2. Visually explore these variables using histograms. Treat the missing values accordingly.
3. There are integer and float data type variables in this dataset. Create a count (frequency) plot describing the data types and the count of variables.

Week 2:

Data Exploration:

1. Check the balance of the data by plotting the count of outcomes by their value. Describe your findings and plan future course of action.
2. Create scatter charts between the pair of variables to understand the relationships. Describe your findings.
3. Perform correlation analysis. Visually explore it using a heat map.

Week 3:

Data Modeling:

1. Devise strategies for model building. It is important to decide the right validation framework. Express your thought process.
2. Apply an appropriate classification algorithm to build a model. Compare various models with the results from KNN algorithm.

Week 4:

Data Modeling:

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

Data Reporting:

1. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

```
 a. Pie chart to describe the diabetic or non-diabetic population
 b. Scatter charts between relevant variables to analyze the relationships
 c. Histogram or frequency charts to analyze the distribution of the data
 d. Heatmap of correlation analysis among the relevant variables
 e. Create bins of these age values: 20-25, 25-30, 30-35, etc. Analyze different
variables for these age brackets using a bubble chart.
```

>>>>>-->>>>>

Solution:

Week 1:

Data Exploration:

(1) Read Data and Perform descriptive analysis:

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="white", color_codes=True)
sns.set(font_scale=1.2)
```

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

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

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.

In [3]:

```
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)
```

In [4]:

```
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
```

In [5]:

```
df.isnull().sum()
```

Out[5]:

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

In [6]:

```
df.describe()
```

Out[6]:

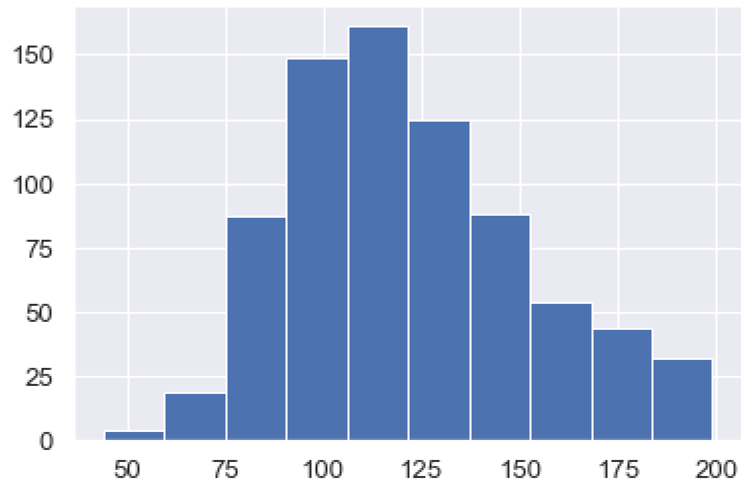
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	
count	768.000000	763.000000	733.000000	541.000000	394.000000	757.000000	768.000000	768

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	
mean	3.845052	121.686763	72.405184	29.153420	155.548223	32.457464	0.471876	33
std	3.369578	30.535641	12.382158	10.476982	118.775855	6.924988	0.331329	1
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.200000	0.078000	2
25%	1.000000	99.000000	64.000000	22.000000	76.250000	27.500000	0.243750	24
50%	3.000000	117.000000	72.000000	29.000000	125.000000	32.300000	0.372500	29
75%	6.000000	141.000000	80.000000	36.000000	190.000000	36.600000	0.626250	4
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	8

(2) Visually explore these variables using histograms and treat the missing values accordingly:

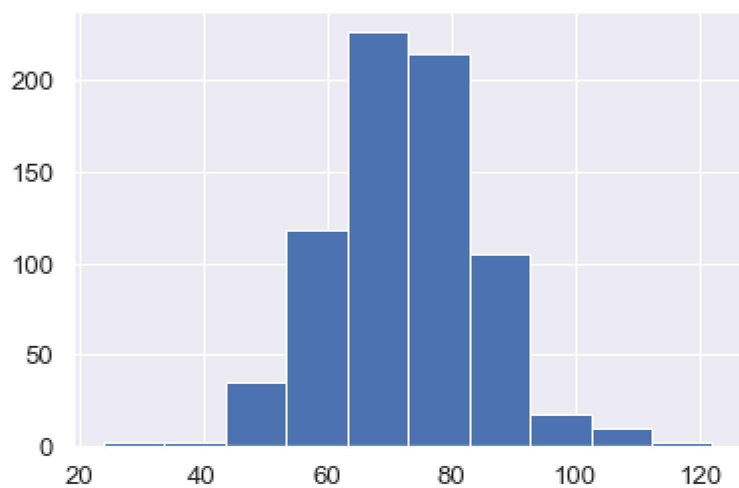
In [7]:

```
df['Glucose'].hist();
```



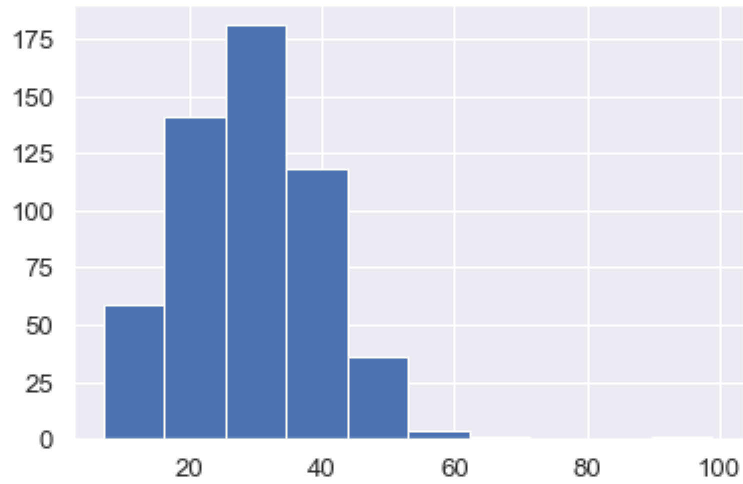
In [8]:

```
df['BloodPressure'].hist();
```

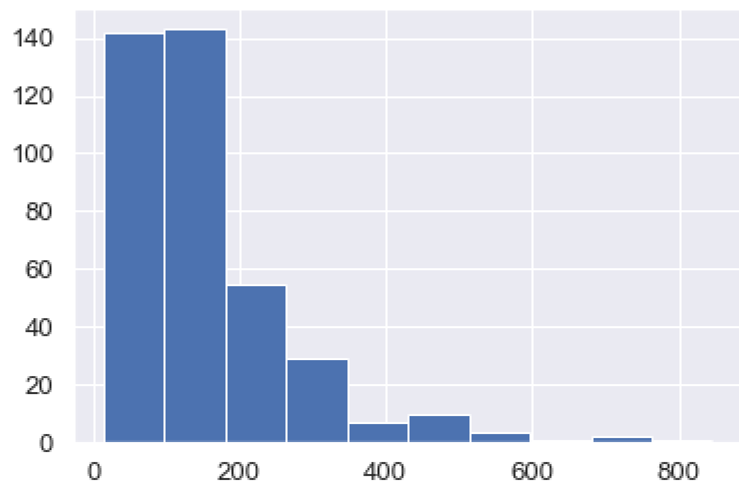


In [9]:

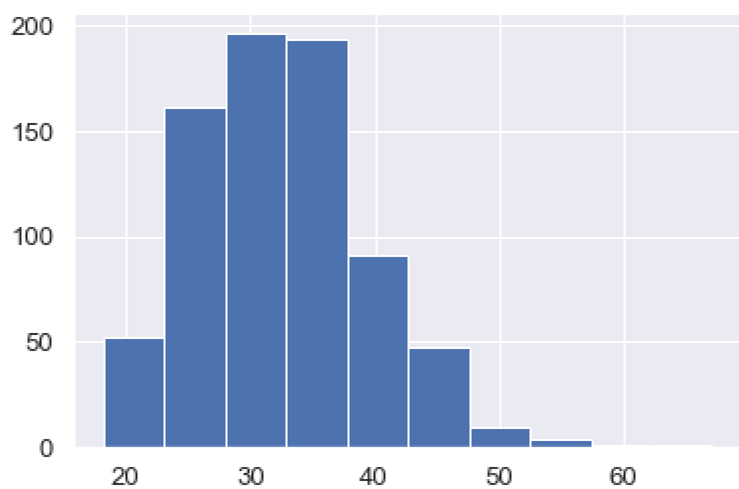
```
df['SkinThickness'].hist();
```



In [10]:
```
df['Insulin'].hist();
```



In [11]:
```
df['BMI'].hist();
```



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.

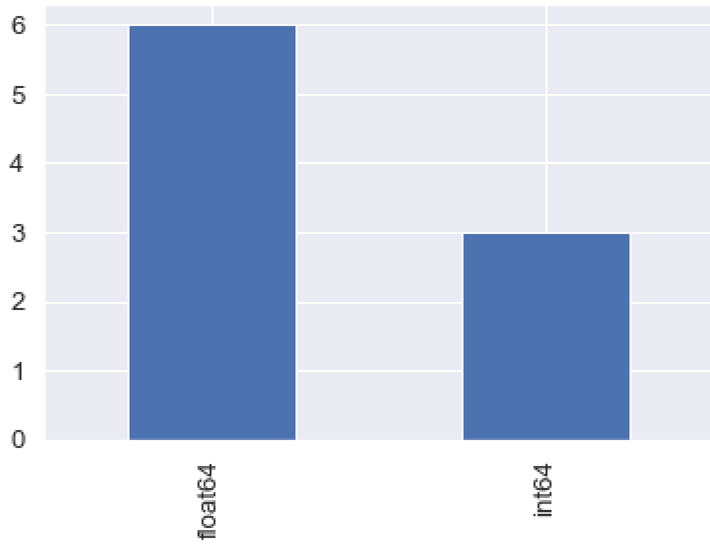
- BMI - replace missing values with mean of values.

In [12]:
```
df['Insulin'] = df['Insulin'].fillna(df['Insulin'].median())
```

In [13]:
```
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) Create a count (frequency) plot describing the data types and the count of variables:

In [14]:
```
df.dtypes.value_counts().plot(kind='bar');
```



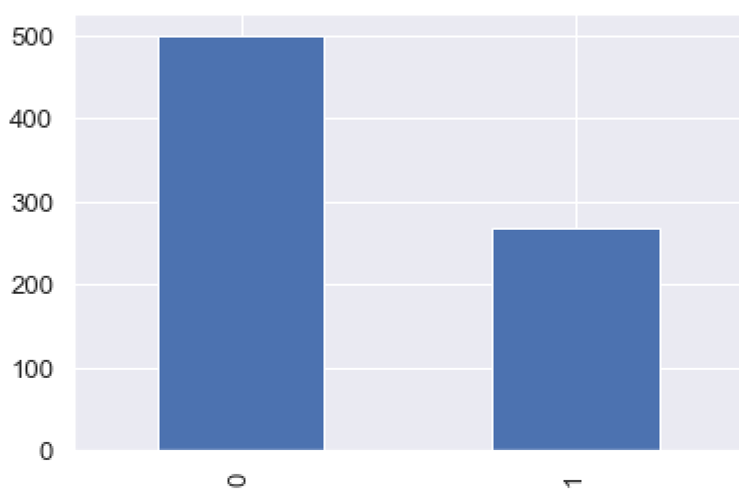
Week 2:

Data Exploration:

(1) 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 [15]:
```
df['Outcome'].value_counts().plot(kind='bar')
df['Outcome'].value_counts()
```

Out[15]:
```
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.

In [16]:
```
df_X = df.drop('Outcome', axis=1)
df_y = df['Outcome']
print(df_X.shape, df_y.shape)
```

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

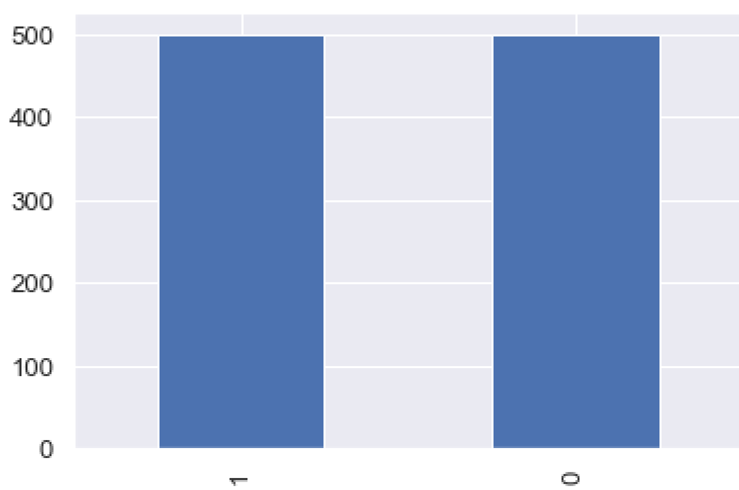
In [17]:
```
from imblearn.over_sampling import SMOTE
```

In [18]:
```
df_X_resampled, df_y_resampled = SMOTE(random_state=108).fit_resample(df_X, df_y)
print(df_X_resampled.shape, df_y_resampled.shape)
```

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

In [19]:
```
df_y_resampled.value_counts().plot(kind='bar')
df_y_resampled.value_counts()
```

Out[19]:
```
1    500
0    500
Name: Outcome, dtype: int64
```



(2) Create scatter charts between the pair of variables to understand the relationships. Describe your findings:

In [20]:
```
df_resampled = pd.concat([df_X_resampled, df_y_resampled], axis=1)
df_resampled
```

Out[20]:

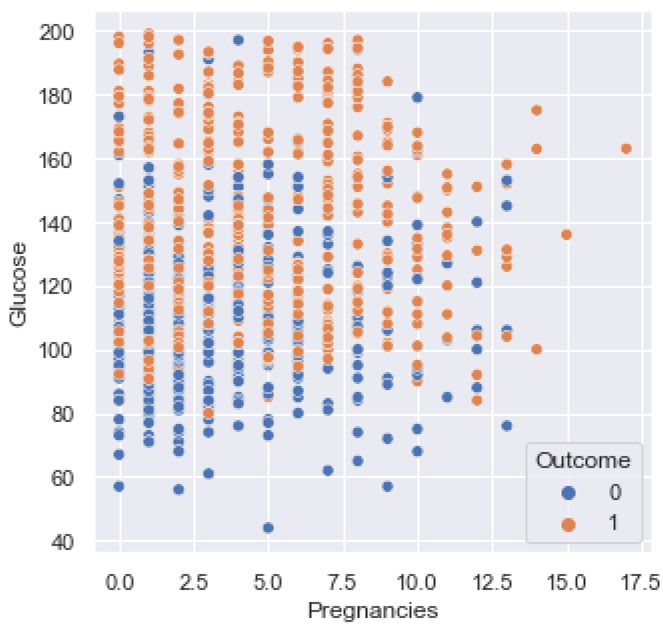
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148.000000	72.000000	35.000000	125.000000	33.600000	0.627000	50
1	1	85.000000	66.000000	29.000000	125.000000	26.600000	0.351000	31
2	8	183.000000	64.000000	29.153420	125.000000	23.300000	0.672000	32
3	1	89.000000	66.000000	23.000000	94.000000	28.100000	0.167000	21
4	0	137.000000	40.000000	35.000000	168.000000	43.100000	2.288000	33

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
...	...	...	...	...	...	...	...	...
995	3	164.686765	74.249021	29.153420	125.000000	42.767110	0.726091	29
996	0	138.913540	69.022720	27.713033	127.283849	39.177649	0.703702	24
997	10	131.497740	66.331574	33.149837	125.000000	45.820819	0.498032	38
998	0	105.571347	83.238205	29.153420	125.000000	27.728596	0.649204	60
999	0	127.727025	108.908879	44.468195	129.545366	65.808840	0.308998	26

1000 rows × 9 columns

In [21]:

```
sns.set(rc={'figure.figsize':(5,5)})
sns.scatterplot(x="Pregnancies", y="Glucose", data=df_resampled, hue="Outcome");
```

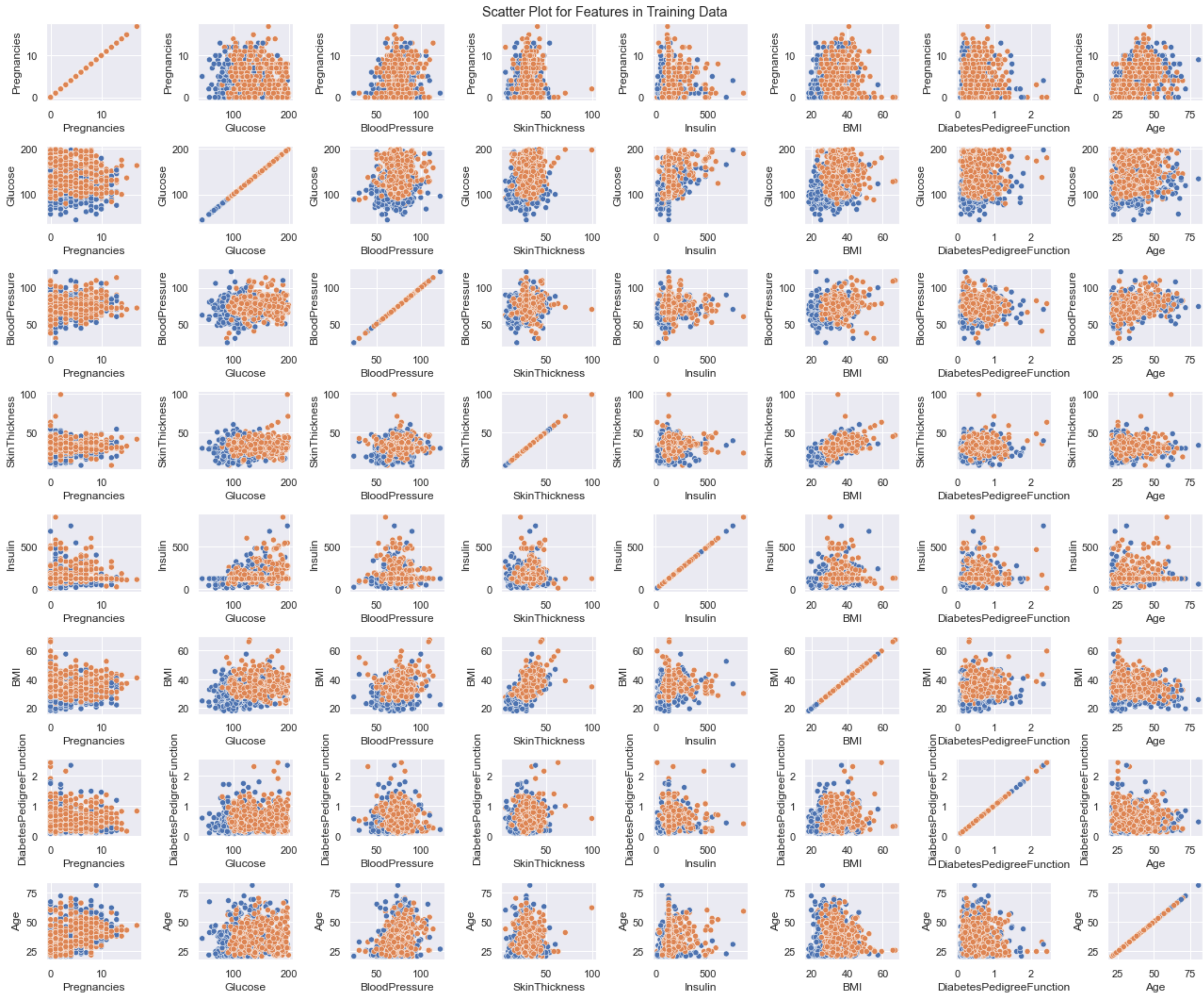


In [22]:

```
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",

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**.

(3) Perform correlation analysis. Visually explore it using a heat map:

In [23]:

```
df_X_resampled.corr()
```

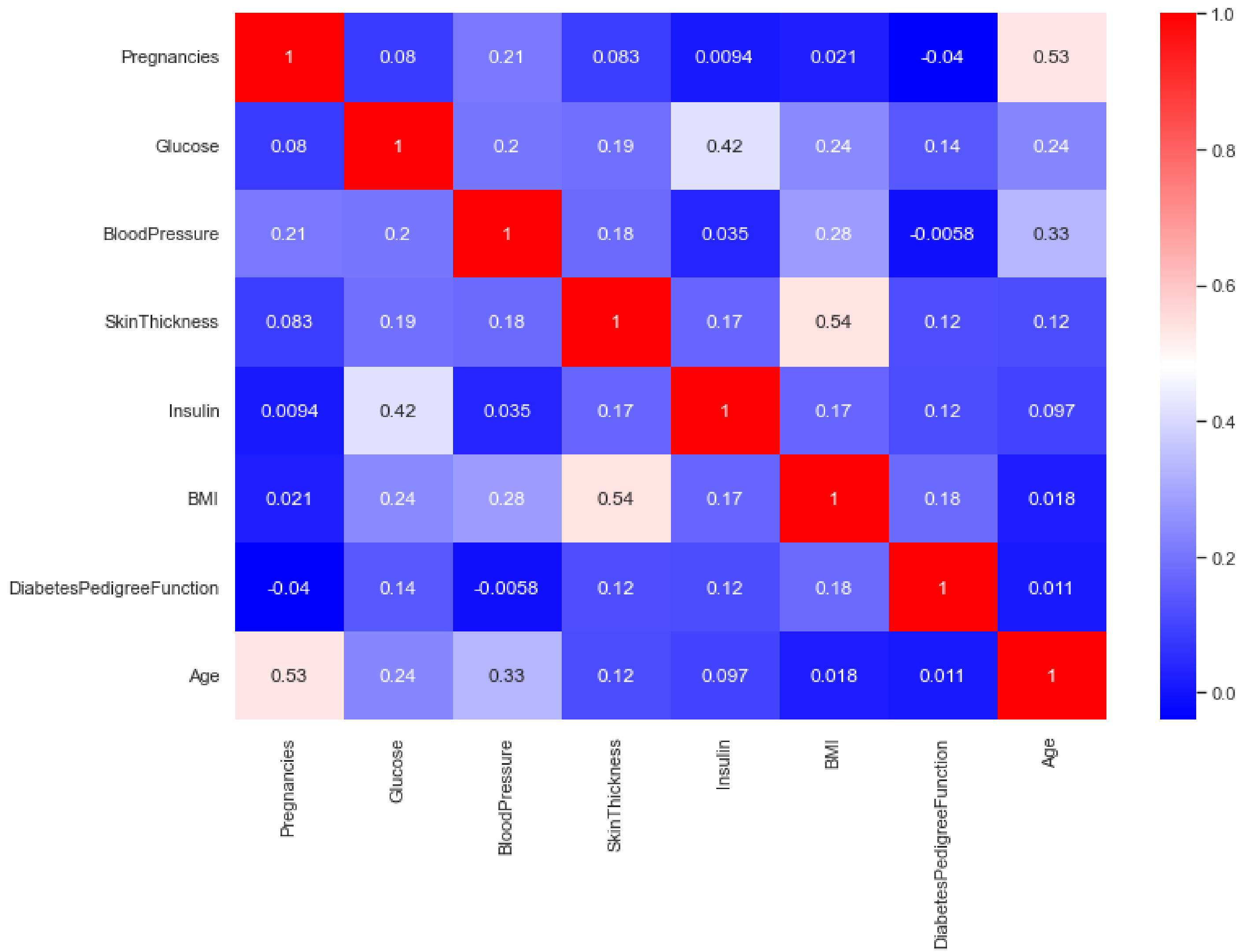
Out[23]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree
Pregnancies	1.000000	0.079953	0.205232	0.082752	0.009365	0.021006	-
Glucose	0.079953	1.000000	0.200717	0.189776	0.418830	0.242501	
BloodPressure	0.205232	0.200717	1.000000	0.176496	0.034861	0.277565	-
SkinThickness	0.082752	0.189776	0.176496	1.000000	0.170719	0.538207	
Insulin	0.009365	0.418830	0.034861	0.170719	1.000000	0.168702	
BMI	0.021006	0.242501	0.277565	0.538207	0.168702	1.000000	
DiabetesPedigreeFunction	-0.040210	0.138945	-0.005850	0.120799	0.115187	0.177915	

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree
Age	0.532660	0.235522	0.332015	0.117644	0.096940	0.017529	

In [24]:

```
plt.figure(figsize=(12,8))
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

Also we can see that no pair of variables have negative correlation.

Week 3:

Data Modeling:

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

Answer: 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):

In [25]:
```
from sklearn.model_selection import train_test_split, KFold, RandomizedSearchCV
from sklearn.metrics import accuracy_score, average_precision_score, f1_score, confusion_r
```

In [26]:
```
X_train, X_test, y_train, y_test = train_test_split(df_X_resampled, df_y_resampled, test_s
```

In [27]:
```
X_train.shape, X_test.shape
```

Out[27]:
```
((850, 8), (150, 8))
```

2. Apply an appropriate classification algorithm to build a model. Compare various models with the results from KNN algorithm.

In [28]:
```
models = []
model_accuracy = []
model_f1 = []
model_auc = []
```

1) Logistic Regression:

In [29]:
```
from sklearn.linear_model import LogisticRegression
lr1 = LogisticRegression(max_iter=300)
```

In [30]:
```
lr1.fit(X_train,y_train)
```

Out[30]:
```
LogisticRegression(max_iter=300)
```

In [31]:
```
lr1.score(X_train,y_train)
```

Out[31]:
```
0.7294117647058823
```

In [32]:
```
lr1.score(X_test, y_test)
```
Out[32]:
```
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.

In [33]:
```
from sklearn.model_selection import GridSearchCV, cross_val_score
```
In [34]:
```
parameters = {'C':np.logspace(-5, 5, 50)}
```
In [35]:
```
gs_lr = GridSearchCV(lr1, param_grid = parameters, cv=5, verbose=0)
gs_lr.fit(df_X_resampled, df_y_resampled)
```
Out[35]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(max_iter=300),
             param_grid={'C': array([1.00000000e-05, 1.59985872e-05, 2.55954792e-05, 4.094
91506e-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])})
```
In [36]:
```
gs_lr.best_params_
```
Out[36]:
```
{'C': 13.257113655901108}
```
In [37]:
```
gs_lr.best_score_
```
Out[37]:
```
0.738
```
In [38]:
```
lr2 = LogisticRegression(C=13.257113655901108, max_iter=300)
```
In [39]:
```
lr2.fit(X_train,y_train)
```
Out[39]:
```
LogisticRegression(C=13.257113655901108, max_iter=300)
```
In [40]:
```
lr2.score(X_train,y_train)
```
Out[40]:
```
0.7305882352941176
```
In [41]:
```
lr2.score(X_test, y_test)
```
Out[41]:
```
0.7733333333333333
```

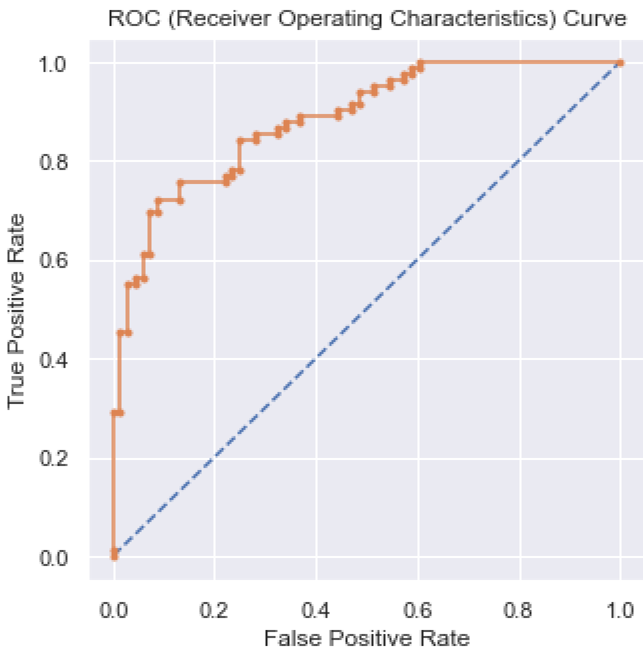
In [42]:

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

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

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: 0.884
```

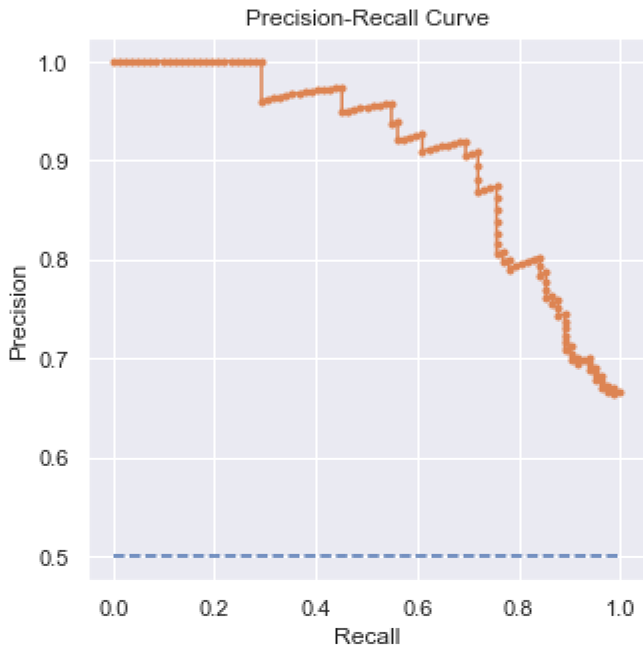


In [43]:

```
# Precision Recall Curve

pred_y_test = lr2.predict(X_test)                                       # predict class valu
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                      # calculate F1 score
auc_lr_pr = auc(recall, precision)                                      # calculate precisio
ap = average_precision_score(y_test, probs)                             # calculate average
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 precisior
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.790 auc_pr=0.908 ap=0.909
```



In [44]:
```
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:

In [45]:
```
from sklearn.tree import DecisionTreeClassifier
dt1 = DecisionTreeClassifier(random_state=0)
```

In [46]:
```
dt1.fit(X_train,y_train)
```

Out[46]:
```
DecisionTreeClassifier(random_state=0)
```

In [47]:
```
dt1.score(X_train,y_train)            # Decision Tree always 100% accuracy over train data
```

Out[47]:
```
1.0
```

In [48]:
```
dt1.score(X_test, y_test)
```

Out[48]:
```
0.7733333333333333
```

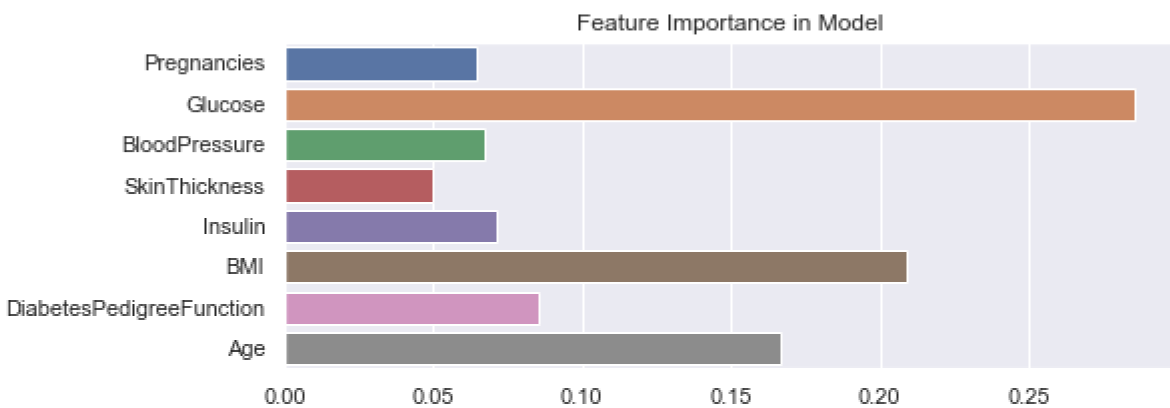
Performance evaluation and optimizing parameters using GridSearchCV:

In [49]:
```
parameters = {
    'max_depth':[1,2,3,4,5,None]
}
```

In [50]:
```
gs_dt = GridSearchCV(dt1, param_grid = parameters, cv=5, verbose=0)
gs_dt.fit(df_X_resampled, df_y_resampled)
```

Out[50]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=0),
             param_grid={'max_depth': [1, 2, 3, 4, 5, None]})
```

In [51]:
```
gs_dt.best_params_
```
Out[51]:
```
{'max_depth': 4}
```
In [52]:
```
gs_dt.best_score_
```
Out[52]:
```
0.76
```
In [53]:
```
dt1.feature_importances_
```
Out[53]:
```
array([0.06452226, 0.28556999, 0.06715314, 0.04979714, 0.07150365,
       0.20905992, 0.08573109, 0.16666279])
```
In [54]:
```
X_train.columns
```
Out[54]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age'],
      dtype='object')
```
In [55]:
```
import seaborn as sns
import matplotlib.pyplot as plt

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


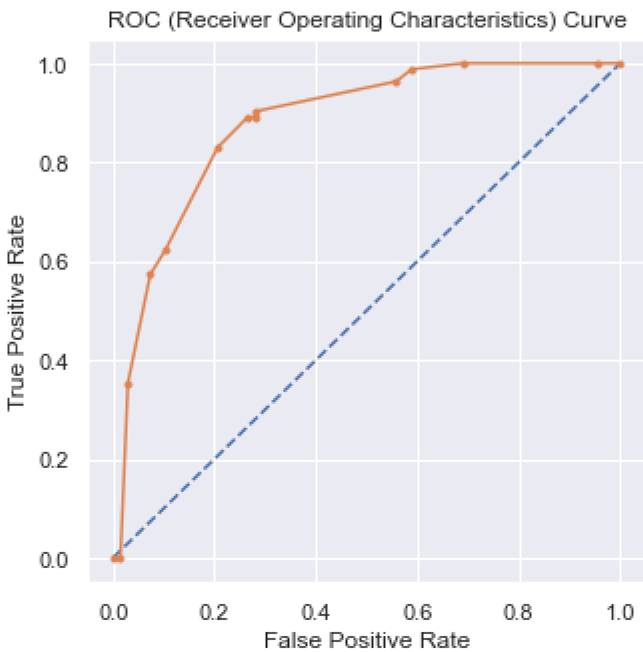
In [56]:
```
dt2 = DecisionTreeClassifier(max_depth=4)
```
In [57]:
```
dt2.fit(X_train,y_train)
```
Out[57]:
```
DecisionTreeClassifier(max_depth=4)
```
In [58]:
```
dt2.score(X_train,y_train)
```
Out[58]:
```
0.8070588235294117
```
In [59]:
```
dt2.score(X_test, y_test)
```
Out[59]:
```
0.82
```
In [60]:

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

probs = dt2.predict_proba(X_test)                    # predict probabilities
probs = probs[:, 1]                                  # keep probabilities for the positive ou

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: 0.879
```

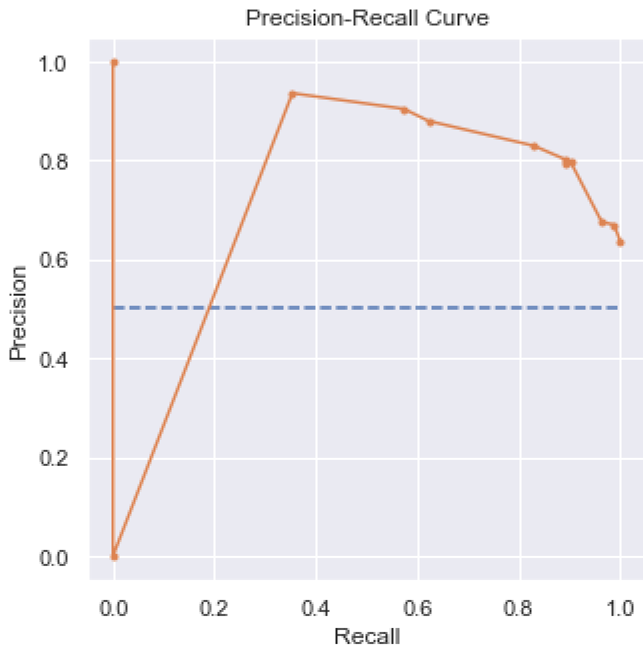


In [61]:

```
# Precision Recall Curve

pred_y_test = dt2.predict(X_test)                                          # predict class valu
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                         # calculate F1 score
auc_dt_pr = auc(recall, precision)                                         # calculate precisio
ap = average_precision_score(y_test, probs)                                # calculate average
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=0.844 auc_pr=0.717 ap=0.868
```



In [62]:

```
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

In [63]:

```
from sklearn.ensemble import RandomForestClassifier
rf1 = RandomForestClassifier()
```

In [64]:

```
rf1 = RandomForestClassifier(random_state=0)
```

In [65]:

```
rf1.fit(X_train, y_train)
```

Out[65]:

```
RandomForestClassifier(random_state=0)
```

In [66]:

```
rf1.score(X_train, y_train)            # Random Forest also 100% accuracy over train data
```

Out[66]:

```
1.0
```

In [67]:

```
rf1.score(X_test, y_test)
```

Out[67]:

```
0.8466666666666667
```

Performance evaluation and optimizing parameters using GridSearchCV:

In [68]:

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

In [69]:

```
gs_dt = GridSearchCV(estimator=rf1, param_grid=parameters, cv=5, verbose=0)
```

```
gs_dt.fit(df_X_resampled, df_y_resampled)
```

Out[69]:
```
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]})
```

In [70]:
```
gs_dt.best_params_
```

Out[70]:
```
{'max_depth': None, 'min_samples_leaf': 1, 'n_estimators': 100}
```

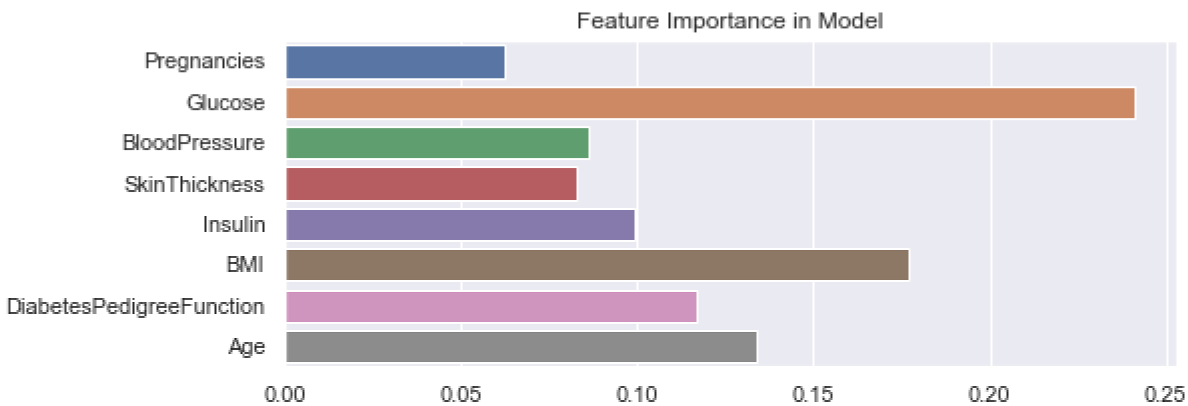
In [71]:
```
gs_dt.best_score_
```

Out[71]:
```
0.813
```

In [72]:
```
rf1.feature_importances_
```

Out[72]:
```
array([0.06264995, 0.24106573, 0.08653626, 0.08301549, 0.09945063,
       0.17678287, 0.11685244, 0.13364664])
```

In [73]:
```
plt.figure(figsize=(8,3))
sns.barplot(y=X_train.columns, x=rf1.feature_importances_);
plt.title("Feature Importance in Model");
```



In [74]:
```
rf2 = RandomForestClassifier(max_depth=None, min_samples_leaf=1, n_estimators=100)
```

In [75]:
```
rf2.fit(X_train,y_train)
```

Out[75]:
```
RandomForestClassifier()
```

In [76]:
```
rf2.score(X_train,y_train)
```

Out[76]:
```
1.0
```

In [77]:
```
rf2.score(X_test, y_test)
```

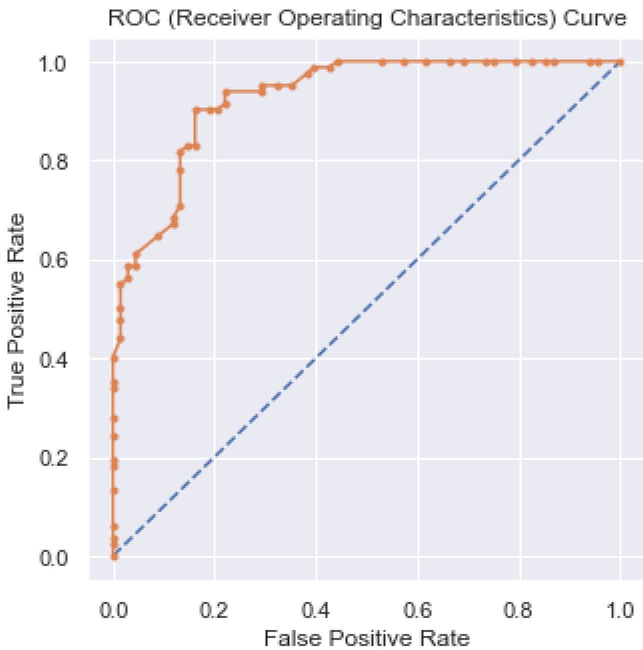
Out[77]:
```
0.86
```

In [78]:
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)
```

```
probs = rf2.predict_proba(X_test)                   # predict probabilities
probs = probs[:, 1]                                 # keep probabilities for the positive ou

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: 0.928
```

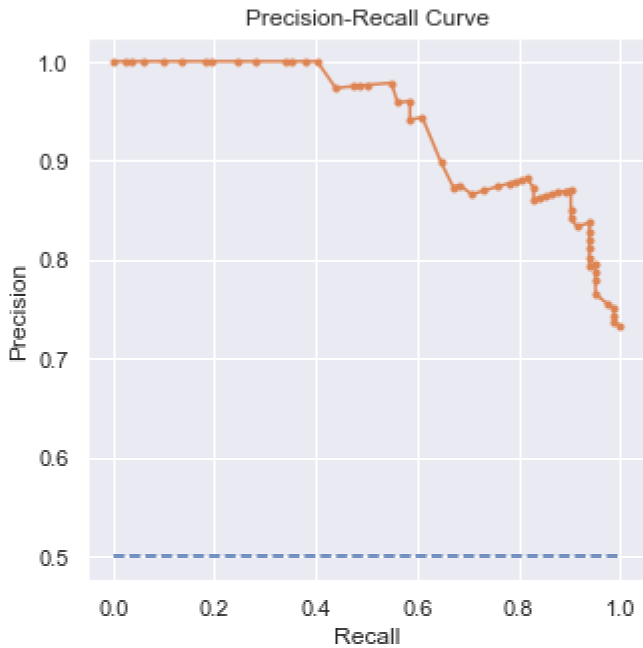


In [79]:

```
# Precision Recall Curve

pred_y_test = rf2.predict(X_test)                                          # predict class valu
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                         # calculate F1 score
auc_rf_pr = auc(recall, precision)                                         # calculate precisio
ap = average_precision_score(y_test, probs)                                # calculate average
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=0.873 auc_pr=0.938 ap=0.936
```



In [80]:
```
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:

In [81]:
```
from sklearn.neighbors import KNeighborsClassifier
knn1 = KNeighborsClassifier(n_neighbors=3)
```

In [82]:
```
knn1.fit(X_train, y_train)
```

Out[82]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [83]:
```
knn1.score(X_train,y_train)
```

Out[83]:
```
0.8835294117647059
```

In [84]:
```
knn1.score(X_test,y_test)
```

Out[84]:
```
0.7866666666666666
```

Performance evaluation and optimizing parameters using GridSearchCV:

In [85]:
```
knn_neighbors = [i for i in range(2,16)]
parameters = {
    'n_neighbors': knn_neighbors
}
```

In [86]:
```
gs_knn = GridSearchCV(estimator=knn1, param_grid=parameters, cv=5, verbose=0)
gs_knn.fit(df_X_resampled, df_y_resampled)
```

Out[86]:
```
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]})
```

In [87]:
```
gs_knn.best_params_
```

Out[87]:
```
{'n_neighbors': 3}
```

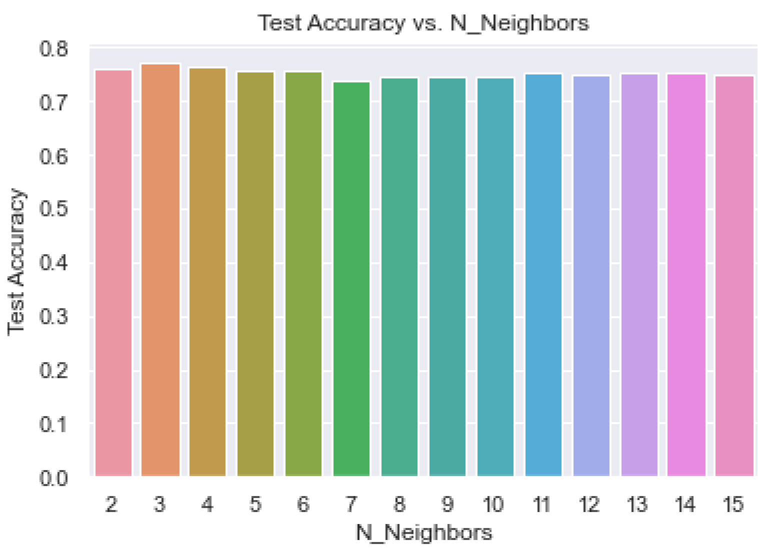
In [88]:
```
gs_knn.best_score_
```

Out[88]:
```
0.771
```

In [89]:
```
# gs_knn.cv_results_
gs_knn.cv_results_['mean_test_score']
```

Out[89]:
```
array([0.76 , 0.771, 0.765, 0.757, 0.757, 0.739, 0.744, 0.746, 0.744,
       0.755, 0.751, 0.755, 0.754, 0.749])
```

In [90]:
```
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");
```



In [91]:
```
knn2 = KNeighborsClassifier(n_neighbors=3)
```

In [92]:
```
knn2.fit(X_train, y_train)
```

Out[92]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [93]:
```
knn2.score(X_train,y_train)
```

Out[93]:
```
0.8835294117647059
```

In [94]:
```
knn2.score(X_test,y_test)
```

Out[94]:
```
0.7866666666666666
```

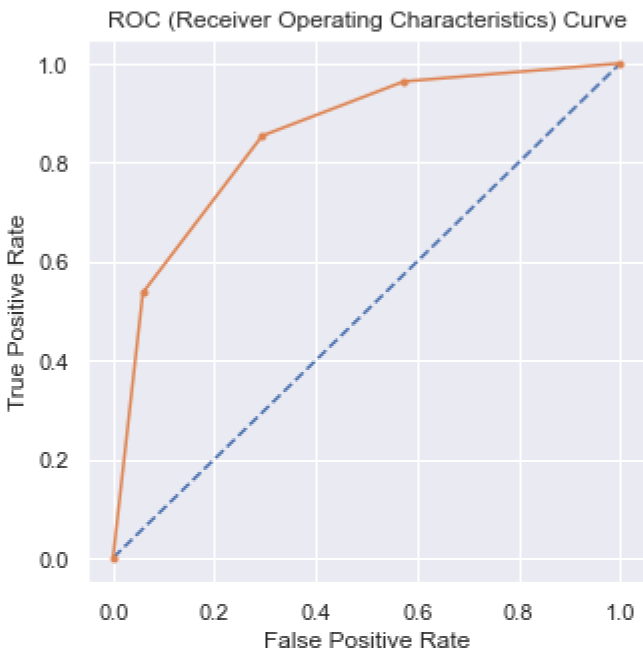
In [95]:

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

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

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: 0.852
```

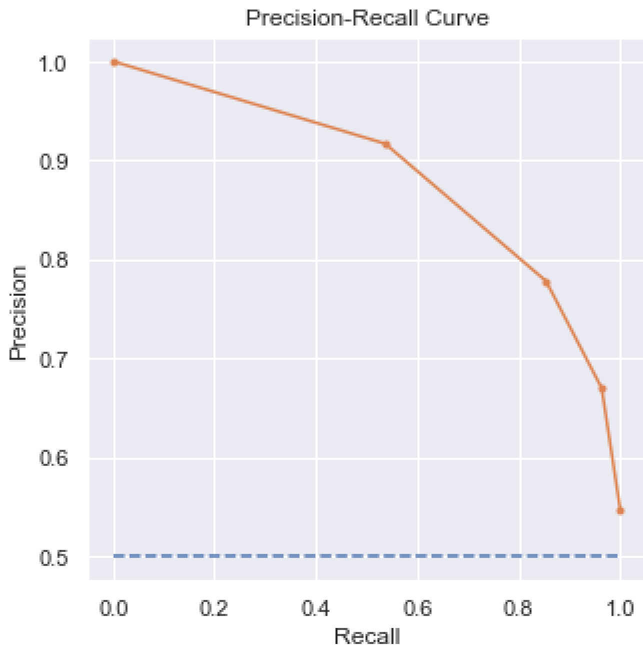


In [96]:

```
# Precision Recall Curve

pred_y_test = knn2.predict(X_test)                                          # predict class va
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                        # calculate F1 score
auc_knn_pr = auc(recall, precision)                                        # calculate precisi
ap = average_precision_score(y_test, probs)                               # calculate average
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=0.814 auc_pr=0.885 ap=0.832
```



In [97]:

```
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:

In [98]:

```
from sklearn.svm import SVC
svm1 = SVC(kernel='rbf')
```

In [99]:

```
svm1.fit(X_train, y_train)
```

Out[99]:

```
SVC()
```

In [100…

```
svm1.score(X_train, y_train)
```

Out[100…

```
0.7282352941176471
```

In [101…

```
svm1.score(X_test, y_test)
```

Out[101…

```
0.78
```

Performance evaluation and optimizing parameters using GridSearchCV:

In [102…

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

In [103…

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

Out[103…

```
GridSearchCV(cv=5, estimator=SVC(),
             param_grid={'C': [1, 5, 10, 15, 20, 25],
```

```
'gamma': [0.001, 0.005, 0.0001, 1e-05]})
```

In [104…

```
gs_svm.best_params_
```

Out[104…

```
{'C': 20, 'gamma': 0.005}
```

In [105…

```
gs_svm.best_score_
```

Out[105…

```
0.8089999999999999
```

In [106…

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

In [107…

```
svm2.fit(X_train, y_train)
```

Out[107…

```
SVC(C=20, gamma=0.005, probability=True)
```

In [108…

```
svm2.score(X_train, y_train)
```

Out[108…

```
0.9941176470588236
```

In [109…

```
svm2.score(X_test, y_test)
```

Out[109…

```
0.8133333333333334
```

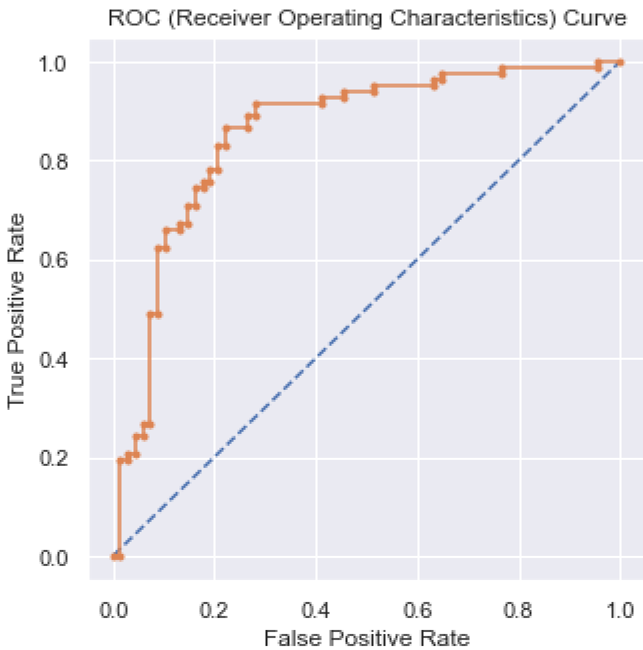
In [110…

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

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

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: 0.857
```

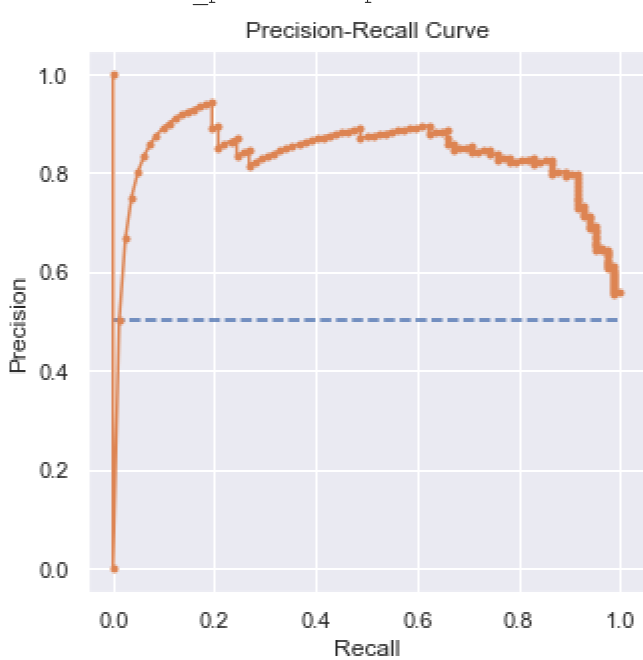


In [111…

```
# Precision Recall Curve

pred_y_test = svm2.predict(X_test)                                     # predict class valu
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                     # calculate F1 score
auc_svm_pr = auc(recall, precision)                                    # calculate precisio
ap = average_precision_score(y_test, probs)                            # calculate average
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 precisior
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve");
```

```
f1=0.829 auc_pr=0.830 ap=0.837
```



In [112…

```
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:

In [113…
```
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
gnb = GaussianNB()
```

In [114…
```
gnb.fit(X_train, y_train)
```

Out[114…
```
GaussianNB()
```

In [115…
```
gnb.score(X_train, y_train)
```

Out[115…
```
0.7294117647058823
```

In [116…
```
gnb.score(X_test, y_test)
```

Out[116…
```
0.8
```

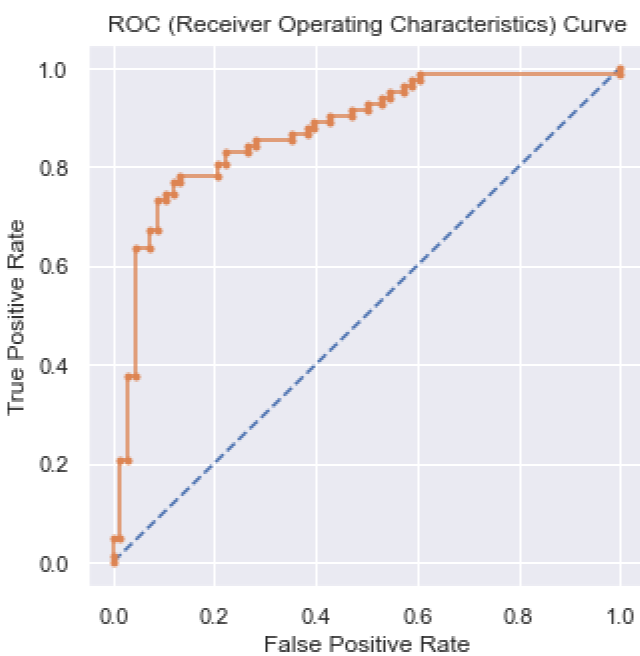
Naive Bayes has almost no hyperparameters to tune, so it usually generalizes well.

In [117…
```
# Preparing ROC Curve (Receiver Operating Characteristics Curve)

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

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");
```

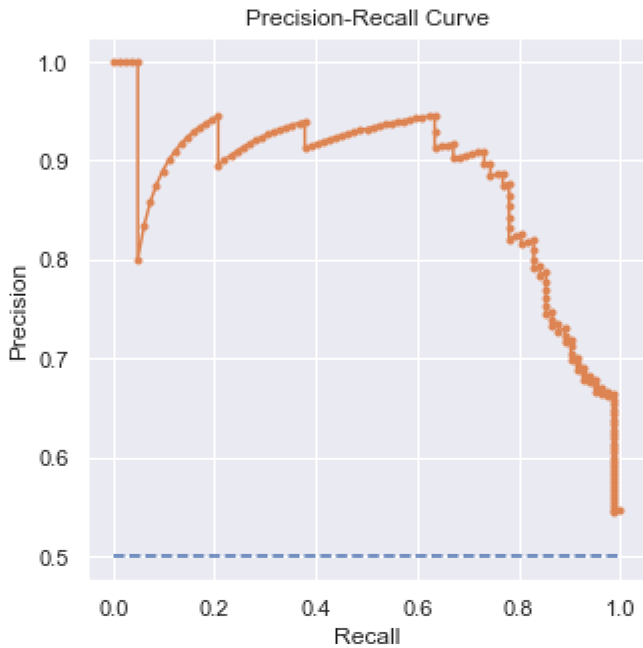
```
AUC: 0.873
```



In [118…
```
# Precision Recall Curve
```

```
pred_y_test = gnb.predict(X_test)                                         # predict class valu
precision, recall, thresholds = precision_recall_curve(y_test, probs)  # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                       # calculate F1 score
auc_gnb_pr = auc(recall, precision)                                       # calculate precisi
ap = average_precision_score(y_test, probs)                              # calculate average
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=0.819 auc_pr=0.879 ap=0.880
```



In [119…

```
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:

In [120…

```
from sklearn.ensemble import AdaBoostClassifier
ada1 = AdaBoostClassifier(n_estimators=100)
```

In [121…

```
ada1.fit(X_train,y_train)
```

Out[121…

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

In [122…

```
ada1.score(X_train,y_train)
```

Out[122…

```
0.8564705882352941
```

In [123…

```
ada1.score(X_test, y_test)
```

Out[123…

```
0.7666666666666667
```

Performance evaluation and optimizing parameters using cross_val_score:

In [124…
```
parameters = {'n_estimators': [100,200,300,400,500,700,1000]}
```

In [125…
```
gs_ada = GridSearchCV(ada1, param_grid = parameters, cv=5, verbose=0)
gs_ada.fit(df_X_resampled, df_y_resampled)
```

Out[125…
```
GridSearchCV(cv=5, estimator=AdaBoostClassifier(n_estimators=100),
             param_grid={'n_estimators': [100, 200, 300, 400, 500, 700, 1000]})
```

In [126…
```
gs_ada.best_params_
```

Out[126…
```
{'n_estimators': 500}
```

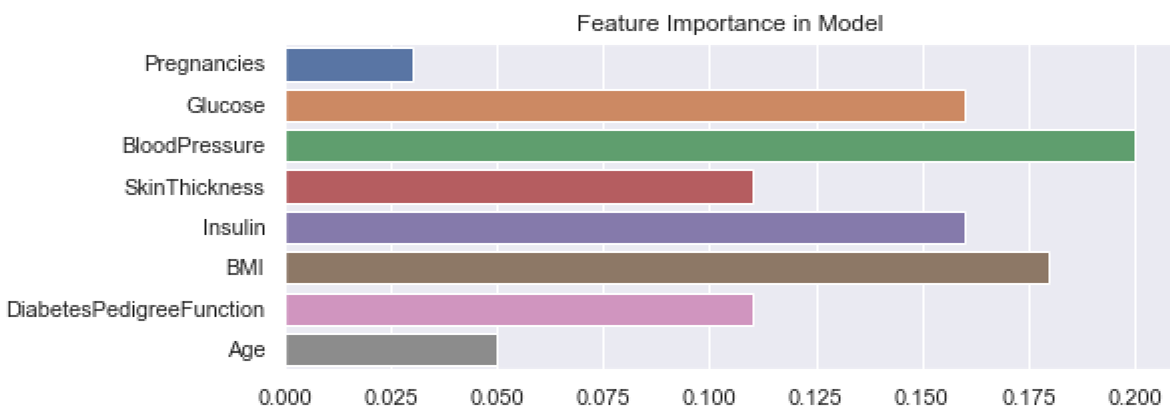
In [127…
```
gs_ada.best_score_
```

Out[127…
```
0.785
```

In [128…
```
ada1.feature_importances_
```

Out[128…
```
array([0.03, 0.16, 0.2 , 0.11, 0.16, 0.18, 0.11, 0.05])
```

In [129…
```
plt.figure(figsize=(8,3))
sns.barplot(y=X_train.columns, x=ada1.feature_importances_)
plt.title("Feature Importance in Model");
```



In [130…
```
ada2 = AdaBoostClassifier(n_estimators=500)
```

In [131…
```
ada2.fit(X_train,y_train)
```

Out[131…
```
AdaBoostClassifier(n_estimators=500)
```

In [132…
```
ada2.score(X_train,y_train)
```

Out[132…
```
0.9247058823529412
```

In [133…
```
ada2.score(X_test, y_test)
```

Out[133…
```
0.7733333333333333
```

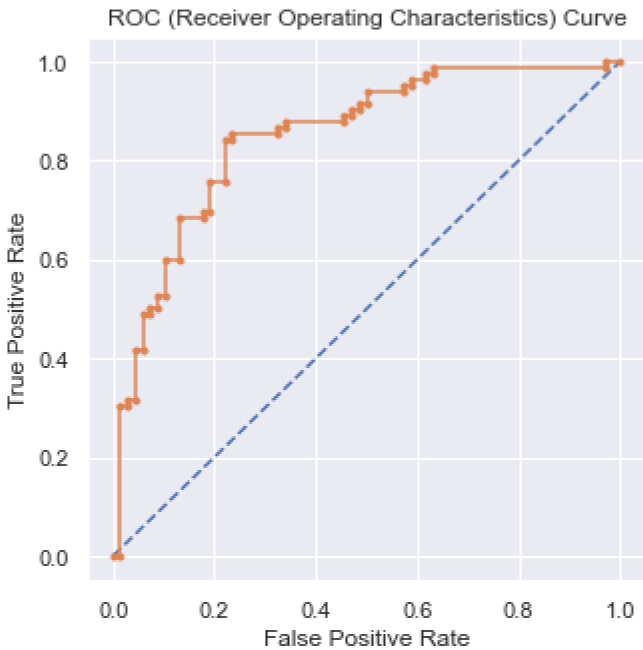
In [134…

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

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

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: 0.850
```

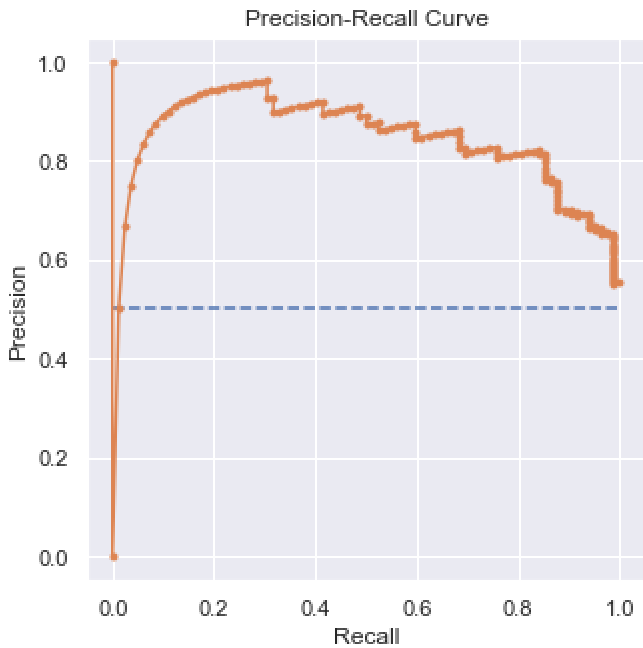


In [135…

```
# Precision Recall Curve

pred_y_test = ada2.predict(X_test)                                         # predict class valu
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                         # calculate F1 score
auc_ada_pr = auc(recall, precision)                                        # calculate precisio
ap = average_precision_score(y_test, probs)                                # calculate average
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=0.785 auc_pr=0.838 ap=0.845
```



In [136…

```
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):

In [137…

```
from xgboost import XGBClassifier
xgb1 = XGBClassifier(use_label_encoder=False, objective = 'binary:logistic', nthread=4, se
```

In [138…

```
xgb1.fit(X_train, y_train)
```

```
[01:58:23] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learn
er.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objecti
ve 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
```

Out[138…

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=4, nthread=4,
              num_parallel_tree=1, predictor='auto', random_state=10,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=10,
              subsample=1, tree_method='exact', use_label_encoder=False,
              validate_parameters=1, ...)
```

In [139…

```
xgb1.score(X_train, y_train)
```

Out[139…

```
1.0
```

In [140…

```
xgb1.score(X_test, y_test)
```

Out[140…

```
0.8266666666666667
```

Performance evaluation and optimizing parameters using GridSearchCV:

In [141…

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

In [142…

```
gs_xgb = GridSearchCV(xgb1, param_grid = parameters, scoring = 'roc_auc', n_jobs = 10, cv=
gs_xgb.fit(df_X_resampled, df_y_resampled)
```

```
[02:00:05] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learn
er.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objecti
ve 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
```

Out[142…

```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode=1,
                                     colsample_bytree=1,
                                     enable_categorical=False, gamma=0,
                                     gpu_id=-1, importance_type=None,
                                     interaction_constraints='',
                                     learning_rate=0.300000012,
                                     max_delta_step=0, max_depth=6,
                                     min_child_weight=1, missing=nan,
                                     monotone_constraints='()',
                                     n_estimators=100, n_jobs=4, nthread=4,
                                     num_parallel_tree=1, predictor='auto',
                                     random_state=10, reg_alpha=0, reg_lambda=1,
                                     scale_pos_weight=1, seed=10, subsample=1,
                                     tree_method='exact',
                                     use_label_encoder=False,
                                     validate_parameters=1, ...),
             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')
```

In [143…

```
gs_xgb.best_params_
```

Out[143…

```
{'learning_rate': 0.05, 'max_depth': 7, 'n_estimators': 180}
```

In [144…

```
gs_xgb.best_score_
```

Out[144…

```
0.88522
```

In [145…

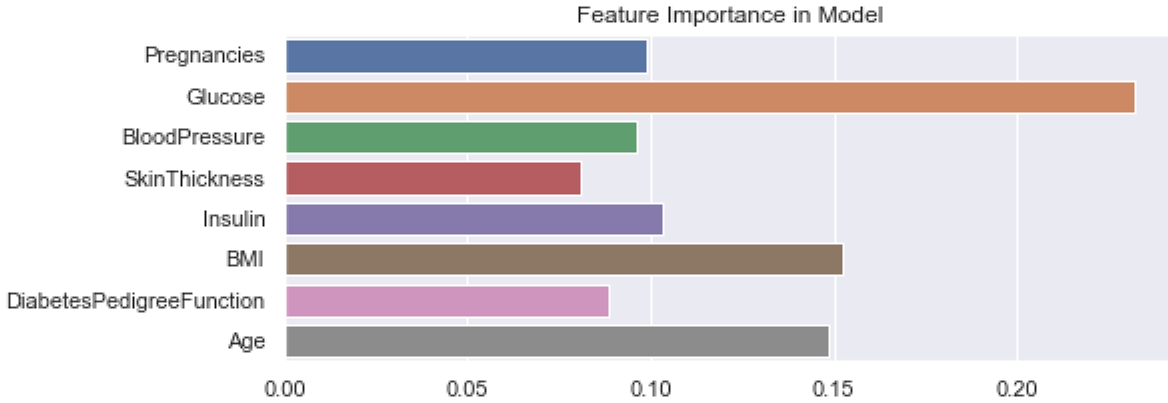
```
xgb1.feature_importances_
```

Out[145…

```
array([0.09883171, 0.23199296, 0.09590795, 0.08073226, 0.10332598,
       0.15247224, 0.08829137, 0.14844562], dtype=float32)
```

In [146…

```
plt.figure(figsize=(8,3))
sns.barplot(y=X_train.columns, x=xgb1.feature_importances_)
plt.title("Feature Importance in Model");
```



In [147…

```
xgb2 = XGBClassifier(use_label_encoder=False, objective = 'binary:logistic',
                     nthread=4, seed=10, learning_rate= 0.05, max_depth= 7, n_estimators= 1
```

In [148…

```
xgb2.fit(X_train,y_train)
```

```
[02:00:06] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learn
er.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objecti
ve 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
```

Out[148…

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.05, max_delta_step=0,
              max_depth=7, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=180, n_jobs=4, nthread=4,
              num_parallel_tree=1, predictor='auto', random_state=10,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=10,
              subsample=1, tree_method='exact', use_label_encoder=False,
              validate_parameters=1, ...)
```

In [149…

```
xgb2.score(X_train,y_train)
```

Out[149…

```
0.9976470588235294
```

In [150…

```
xgb2.score(X_test, y_test)
```

Out[150…

```
0.8066666666666666
```

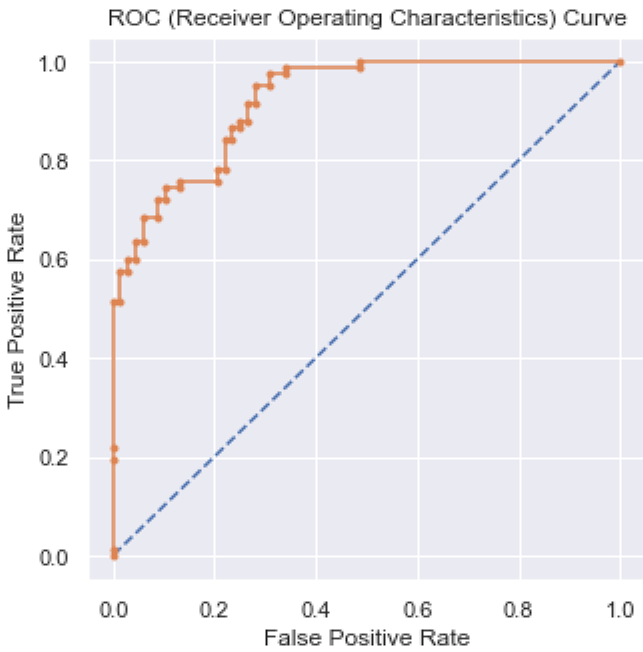
In [151…

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

probs = xgb2.predict_proba(X_test)                # predict probabilities
probs = probs[:, 1]                              # keep probabilities for the positive ou

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: 0.922
```

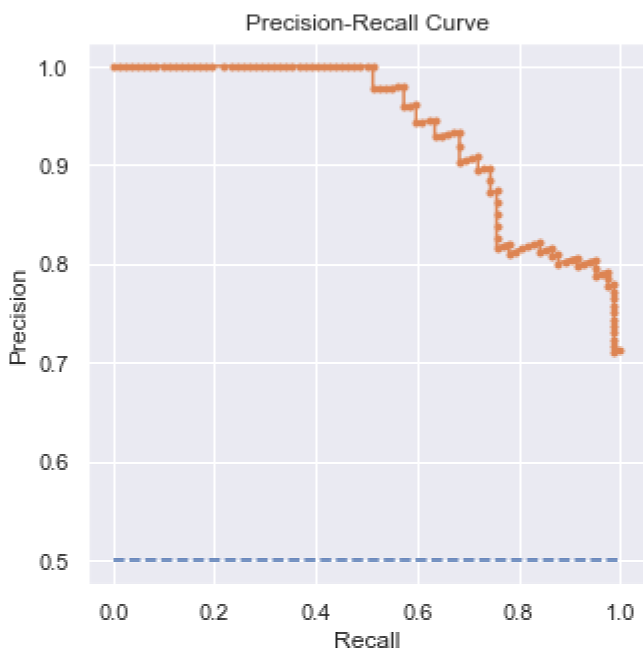


In [152…

```
# Precision Recall Curve

pred_y_test = xgb2.predict(X_test)                                        # predict class va
precision, recall, thresholds = precision_recall_curve(y_test, probs) # calculate precisio
f1 = f1_score(y_test, pred_y_test)                                      # calculate F1 score
auc_xgb_pr = auc(recall, precision)                                      # calculate precisi
ap = average_precision_score(y_test, probs)                             # calculate average
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=0.824 auc_pr=0.936 ap=0.937
```

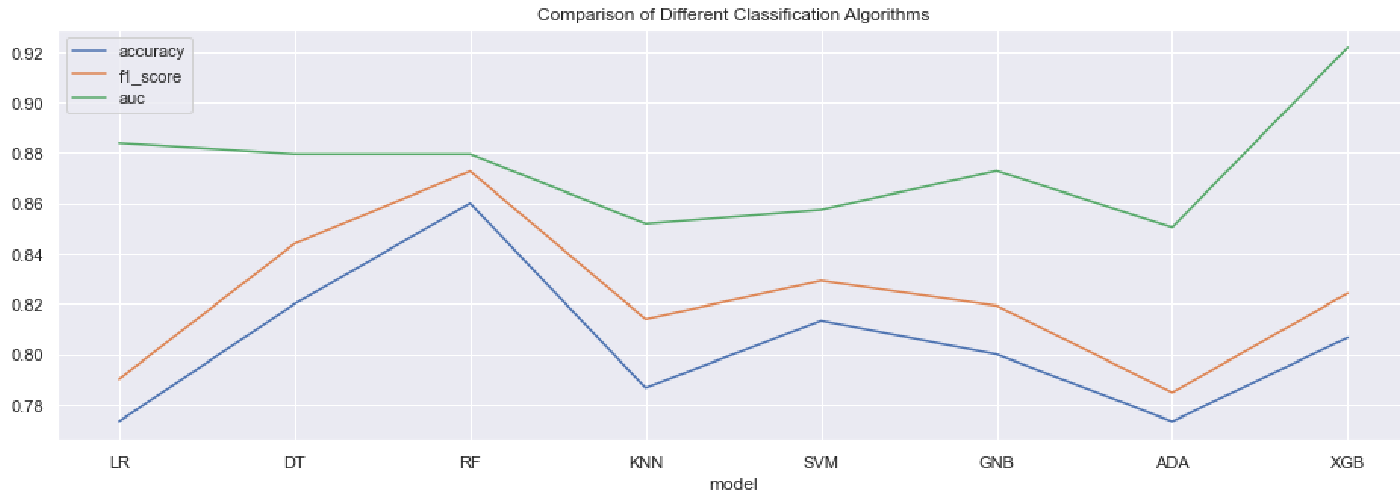


In [153…

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

In [154…
```
model_summary = pd.DataFrame(zip(models,model_accuracy,model_f1,model_auc), columns = ['mc
model_summary = model_summary.set_index('model')
```

In [155…
```
model_summary.plot(figsize=(16,5))
plt.title("Comparison of Different Classification Algorithms");
```



In [156…
```
model_summary
```

Out[156…

model	accuracy	f1_score	auc
LR	0.773333	0.790123	0.883967
DT	0.820000	0.843931	0.879484
RF	0.860000	0.872727	0.879484
KNN	0.786667	0.813953	0.851865
SVM	0.813333	0.829268	0.857425
GNB	0.800000	0.819277	0.872848
ADA	0.773333	0.784810	0.850430
XGB	0.806667	0.824242	0.921808

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

FINAL CLASSIFIER:

In [157…
```
final_model = rf2
```

Week 4:

Data Modeling:

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

In [158…

```
cr = classification_report(y_test, final_model.predict(X_test))
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.84        68
           1       0.87      0.88      0.87        82

    accuracy                           0.86       150
   macro avg       0.86      0.86      0.86       150
weighted avg       0.86      0.86      0.86       150
```

In [159…

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

```
Confusion Matrix:
 [[57 11]
 [10 72]]
```

In [160…

```
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)
```

In [161…

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

```
Accuracy: 0.860
Precision: 0.867
Sensitivity: 0.878
Specificity: 0.838
AUC: 0.928
```

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.

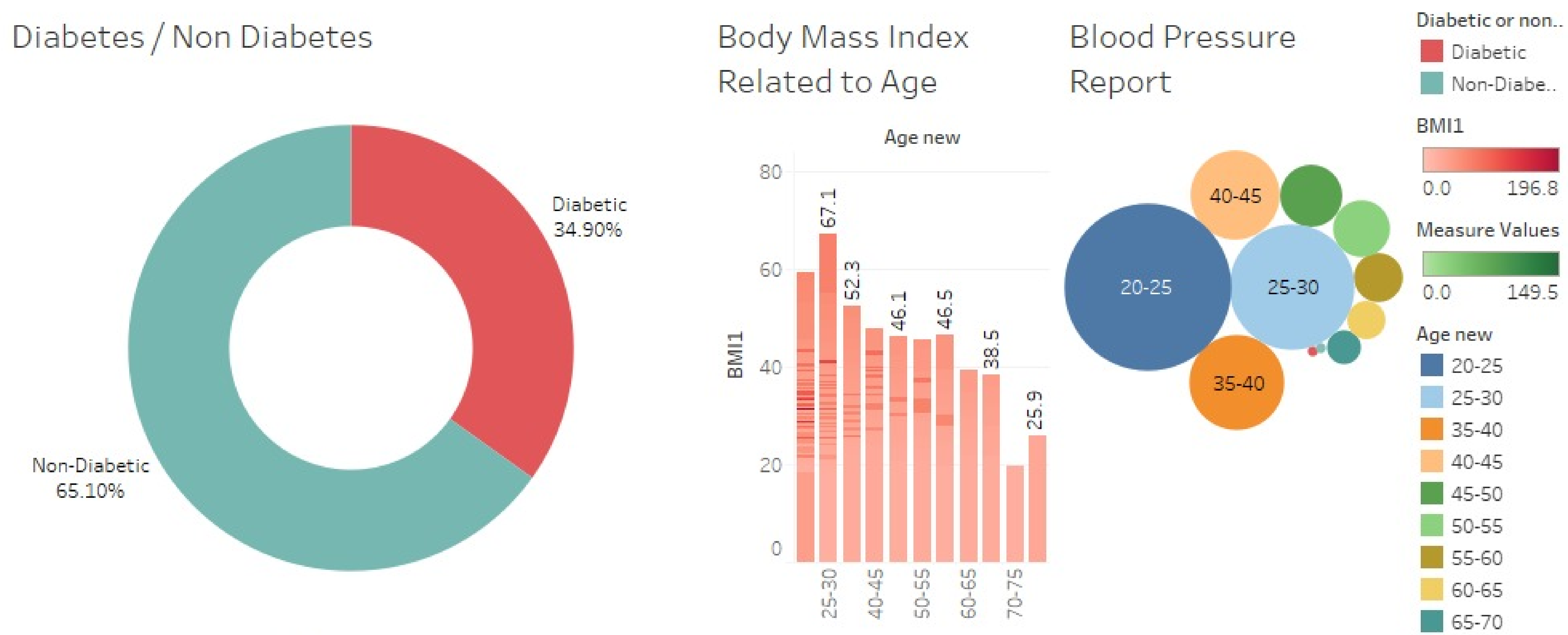
The threshold is set based on business problem. There are some cases where Sensitivity is important and need to be near to 1. There are business cases where Specificity is important and need to be near to 1. We need to understand the business problem and decide the importance of Sensitivity and Specificity.

Data Reporting:

2. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

a. Pie chart to describe the diabetic or non-diabetic population
b. Scatter charts between relevant variables to analyze the relationships
c. Histogram or frequency charts to analyze the distribution of the data
d. Heatmap of correlation analysis among the relevant variables
e. Create bins of these age values: 20-25, 25-30, 30-35, etc. Analyze different variables for these age brackets using a bubble chart.

DASHBOARD SCREENSHOT BELOW FROM TABLEAU, CREATED FOR DATA REPORTING TASK.



Heat Map with Diff Variables

Age new

	20-25	25-30	35-40	40-45	45-50	50-55	55-60	60-65	65-70	70-75	80-85
Avg. BMI1	30.4	33.0	33.1	35.3	32.9	31.8	30.2	29.9	27.5	19.6	25.9
Avg. Blood Pressure	63.8	68.0	72.3	73.3	77.9	81.9	77.5	76.0	80.7	0.0	74.0
Avg. Glucose1	110.7	120.3	127.5	125.1	124.5	143.2	138.3	136.4	139.0	119.0	134.0
Avg. Insulin1	84.3	84.3	61.3	56.7	67.6	109.9	149.5	26.4	0.0	0.0	60.0

Donut Pie chart | Body Mass to age | Blood Pressure Report | Heat Map with Diff Variables | **Dashboard 1**