DS5220 Project: Using Machine Learning Models to Predict the onset of Diabetes

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Exploratory Data Analysis

In [1]:
```
# import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, accuracy_score, f1_score, auc, roc_curve
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from imblearn.over_sampling import SMOTE
```

In [2]:
```
# Data load and preliminary data info
data = pd.read_csv("diabetes.csv")
diabetes_df = data.copy()
diabetes_df.info()
diabetes_df.head(3)
```

```
<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
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Out
0	6	148	72	35	0	33.6	0.627	50	
1	1	85	66	29	0	26.6	0.351	31	
2	8	183	64	0	0	23.3	0.672	32	

Dataset contains 8 numerical independent variables / features and a binary classification dependent variable.

In [3]:
```
# Summary Stats
```

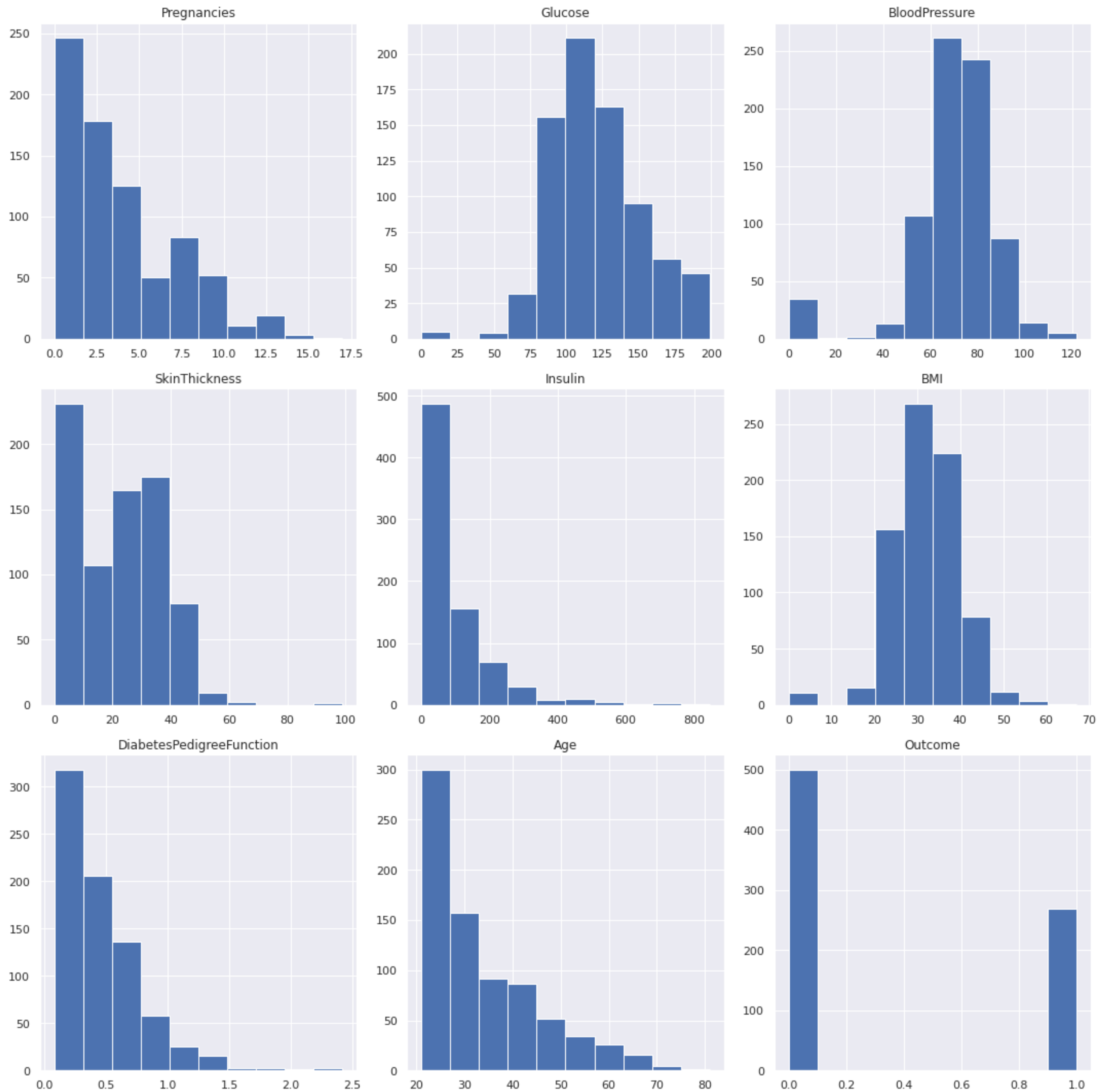
```
diabetes_df.describe()
```

Out[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigree
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	76
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	

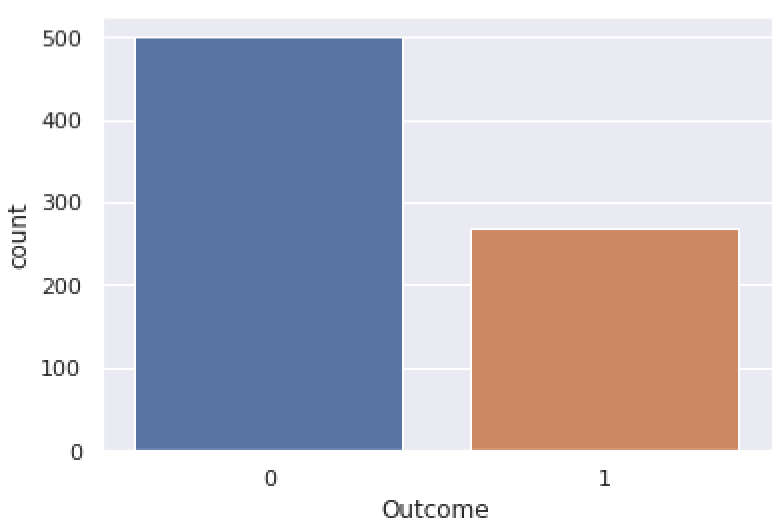
In [ ]:

```
# Histograms of the variables
diabetes_df.hist(figsize=(15,15))
plt.tight_layout()
plt.show()
```



In [ ]:
```
sns.countplot(x=diabetes_df['Outcome'])
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3473869fa0>



In [ ]:
```
# Imbalanced data should be 10:1 ratio but with a small dataset 2:1 ratio is significant
diabetes_df.Outcome.value_counts()
```

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

In [4]:
```
# Correlation table
corr_table = diabetes_df.corr()
corr_table.style.background_gradient(cmap='viridis')
```

Out[4]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Dial
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	

Glucose has the highest correlation to the Outcome followed by BMI, Age and Pregnancies. All features are positively correlated to the Outcome / target feature.

In [5]:
```
features = diabetes_df.columns
features = features.tolist()
features
```

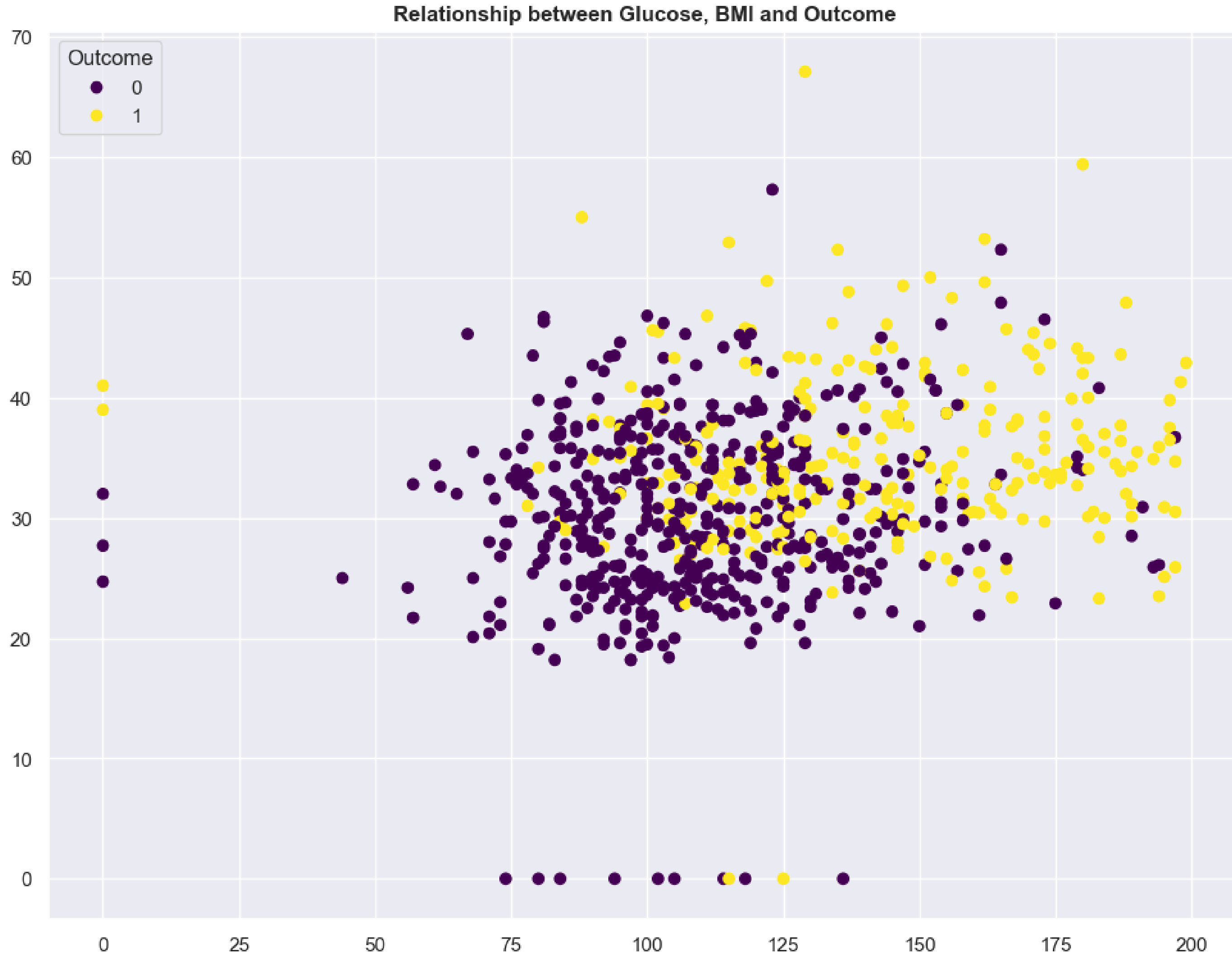
Out[5]:
```
['Pregnancies',
 'Glucose',
 'BloodPressure',
 'SkinThickness',
 'Insulin',
 'BMI',
 'DiabetesPedigreeFunction',
 'Age',
 'Outcome']
```

Dataset contains more observations without diabetes.

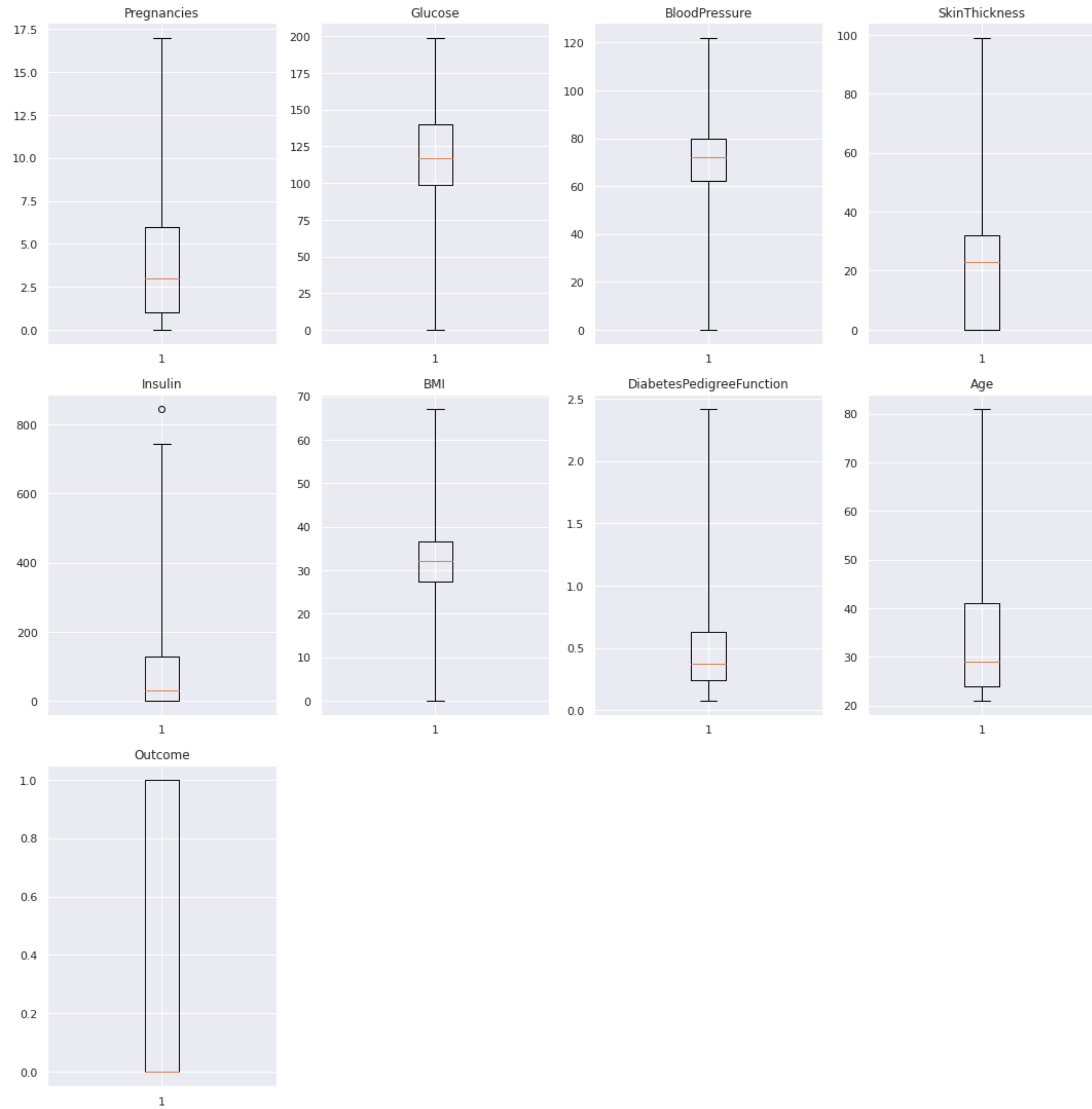
In [6]:
```
sns.pairplot(diabetes_df[features], height = 2.5)
plt.show()
```

- Women that have had high number of pregnancies tend to be diabetic.
- Women with low blood sugar tend to be non-diabetic.
- Women with low blood pressure tend to be non-diabetic.
- No clear relationship between SkinThickness and the Outcome
- Women with high levels of Insulin tend to be diabetic.
- Women with high BMI tend to diabetic.
- No clear relationship between DiabetesPedigreeFunction and the Outcome.
- Older women tend to be diabetic.

In [7]:
```
plt.figure(figsize=(12,9))
scatter = plt.scatter(x=diabetes_df['Glucose'], y=diabetes_df['BMI'], c = diabetes_df['O
plt.legend(*scatter.legend_elements(), loc = "upper left", title = 'Outcome')
plt.title("Relationship between Glucose, BMI and Outcome", weight='bold')
plt.show()
```



In [ ]:
```
# boxplots to visualize the outliers in a dataset
i = 1
plt.figure(figsize=(15,30))
for var in features: #plotting boxplot for each variable
   plt.subplot(round(len(features),0)/3+3,4,i)
   plt.boxplot(diabetes_df[var], whis=5)
   plt.title(var)
   i+=1
plt.tight_layout()
plt.show()
```



No outliers in the dataset

Data Preprocessing

In [8]:
```
# Declare X(independent) and y(dependent) variables
X = diabetes_df.drop('Outcome', axis=1)
y = diabetes_df['Outcome']
X.head()
```

Out[8]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148	72	35	0	33.6	0.627	50
1	1	85	66	29	0	26.6	0.351	31
2	8	183	64	0	0	23.3	0.672	32
3	1	89	66	23	94	28.1	0.167	21
4	0	137	40	35	168	43.1	2.288	33

In [9]:
```python
# Taking care of missing data(Zeros) in columns below :-
# Glucose - 5 observations with 0 reading (0.7% of the observations)
# BloodPressure - 35 observations with 0 reading (5% of the observations)
# SkinThickness - 227 observations with 0 reading (30% of the observations)
# Insulin - 374 observations with 0 reading, (49% of the observations)
# BMI - 11 observations with 0 reading (1.4 % of the observations)
imp_mean = SimpleImputer(missing_values=0, strategy='mean')
imp_mean.fit(X.iloc[:, 1:6])
X.iloc[:, 1:6] = imp_mean.transform(X.iloc[:, 1:6])
X.head()
```

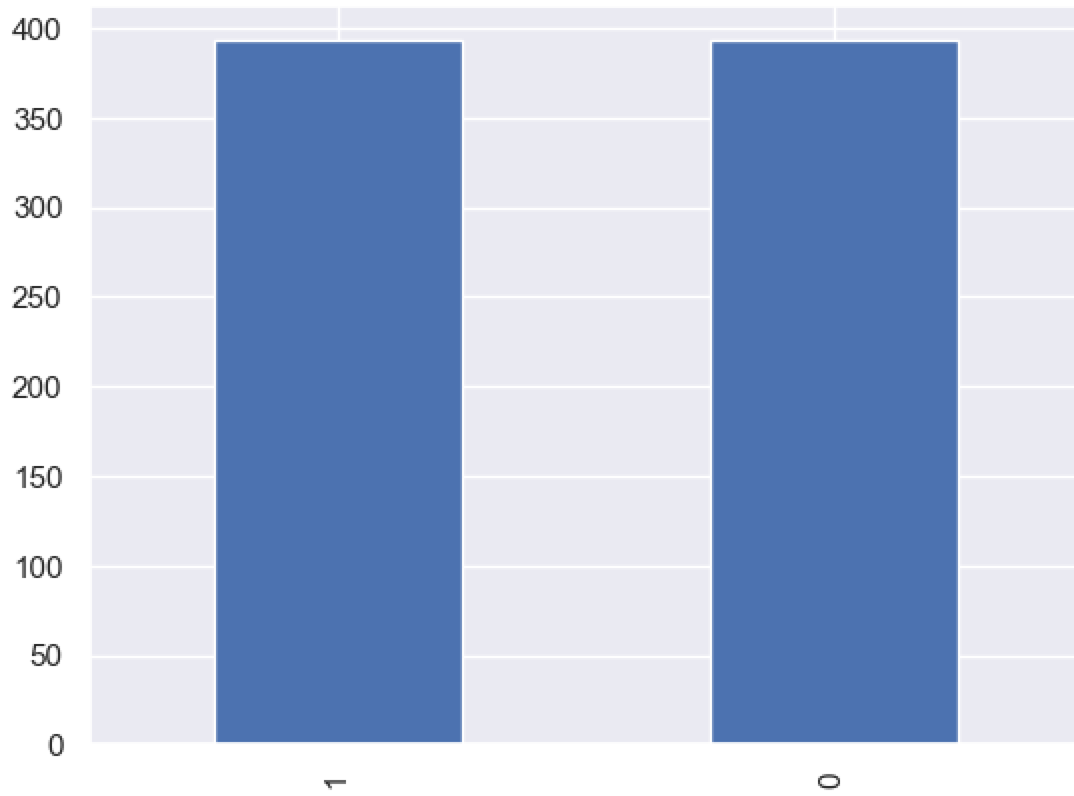
Out[9]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148.0	72.0	35.00000	155.548223	33.6	0.627	50
1	1	85.0	66.0	29.00000	155.548223	26.6	0.351	31
2	8	183.0	64.0	29.15342	155.548223	23.3	0.672	32
3	1	89.0	66.0	23.00000	94.000000	28.1	0.167	21
4	0	137.0	40.0	35.00000	168.000000	43.1	2.288	33

In [10]:
```python
from pandas.core.common import random_state
# Splitting dataset into training and test sets
seed = 0
X_train1, X_test1, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state
#X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote, test_size=0.20, r

# Feature Scaling by Standardization
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train1)
X_test = scaler.transform(X_test1)

# Dealing with imbalance in the dataset
smote = SMOTE(random_state=seed)
X_train, y_train = smote.fit_resample(X_train, y_train)
y_train.value_counts().plot.bar()
```

Out[10]:

```
<AxesSubplot:>
```



Feature Selection

In [ ]:
```
# feature selection using best subset selection using logistic regression

features = X.columns
print(features)

import statsmodels.api as sm
from itertools import combinations
## do logistic regressio for each feature_set selected
def processSubset(feature_set):
    x= X_train[list(feature_set)]
    x = sm.add_constant(x)
    regr = sm.OLS(y_train,x).fit()
    aic = regr.aic
    bic = regr.bic
    RSS_adj = regr.rsquared_adj
    param = regr.params
    print(aic, bic, RSS_adj)
    return {"model":regr, "param": param, "rss_adj":RSS_adj, "aic": aic, "bic": bic, "su

subsets_df = []
subsetsList = []
index = np.arange(1,8)


## get combo of subsets
for i in index:
  subsets_i = combinations(features, i)
  #print(list(subsets_i))
  subset = []
  subsetsList.append(list(subsets_i))
#print(subsetsList[2])

sets_df =  pd.DataFrame();
nums = []
k= np.arange(1,8)
```

```python
def getInfoForK(k):  #k range from 1-3
  subsets = subsetsList[k-1]
  aics = []
  bics = []
  rss_adjs = []
  models = []
  params= []
  for s in subsets:
    num = processSubset(s)
    nums.append(num)
    aics.append(num['aic'])
    bics.append(num['bic'])
    rss_adjs.append(num['rss_adj'])
    models.append(num['model'])
    params.append(num['param'])
  #print(aics)
  #print(bics)
  return{"aics": aics, "bics": bics, "rss_adjs": rss_adjs, "models": models, "subset_val


### save info for size k and then put them into a list
subsets_infos = []
for i in index:
  results = getInfoForK(i);
  subsets_infos.append(results);
print(subsets_infos[2])

subset_df = pd.DataFrame(subsets_infos)
print(subset_df.head())

nums_df = pd.DataFrame(nums)
display(nums_df)
```

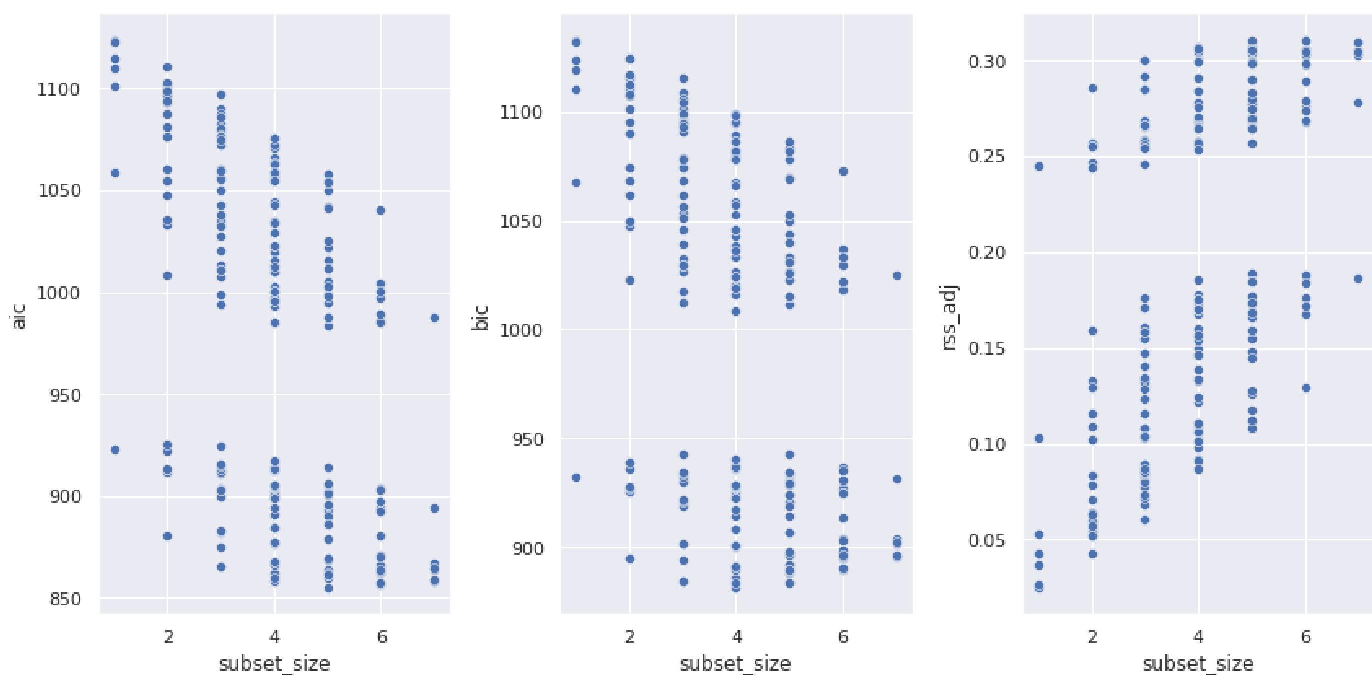
In [ ]:

```python
best = []


best_rssa = nums_df[ nums_df.rss_adj == nums_df.rss_adj.min()]
print("best rss_a",best_rssa['subset'],best_rssa["param"])

for i in np.arange(1,8):
  df1 =  nums_df[ nums_df.subset_size == i]
  best_aic_3 = df1[ df1.rss_adj == df1.rss_adj.min()]
  print("best aic",  best_aic_3['subset'], best_aic_3["param"])
  best.append(best_aic_3)
```

```
best rss_a 2    [BloodPressure]
Name: subset, dtype: object 2    const            -0.010703
BloodPressure    0.0...
Name: param, dtype: object
best aic 2    [BloodPressure]
Name: subset, dtype: object 2    const            -0.010703
BloodPressure    0.0...
Name: param, dtype: object
best aic 9    [Pregnancies, BloodPressure]
Name: subset, dtype: object 9    const            -0.007751
Pregnancies      0.0...
Name: param, dtype: object
best aic 46    [Pregnancies, BloodPressure, Age]
Name: subset, dtype: object 46    const            -0.077221
Pregnancies      0.0...
Name: param, dtype: object
best aic 110    [Pregnancies, BloodPressure, SkinThickness, Age]
Name: subset, dtype: object 110    const            -0.274946
Pregnancies      0.0...
Name: param, dtype: object
```

```
best aic 187    [Pregnancies, BloodPressure, SkinThickness, Di...
Name: subset, dtype: object 187    const                          -0.367978
Pregnanci...
Name: param, dtype: object
best aic 235    [Pregnancies, BloodPressure, SkinThickness, In...
Name: subset, dtype: object 235    const                          -0.438648
Pregnanci...
Name: param, dtype: object
best aic 252    [Pregnancies, BloodPressure, SkinThickness, In...
Name: subset, dtype: object 252    const                          -0.740418
Pregnanci...
Name: param, dtype: object
```

In [ ]:
```
### select best for each k, and plot here

#aics
import matplotlib.pyplot as plt
import seaborn as sns

aics = nums_df["aic"]
bics = nums_df["bic"]
rss_adjs = nums_df["rss_adj"]
size = nums_df["subset_size"]

fig, axes = plt.subplots(1, 3, squeeze=False, figsize=(12, 6))
sns.scatterplot(data=nums_df, x='subset_size', y='aic', ax=axes[0, 0])
sns.scatterplot(data=nums_df, x='subset_size', y='bic', ax=axes[0, 1])
sns.scatterplot(data=nums_df, x='subset_size', y='rss_adj', ax=axes[0, 2])

plt.tight_layout()

### from the graph here, lowest for aic is size 5, lowerst for bic is size 4, lowest fr
```



In [ ]:
```
df1 =  nums_df[ nums_df.subset_size == 5]
best_aic_3 = df1[ df1.rss_adj == df1.rss_adj.min()]
display(best_aic_3)
print( best_aic_3['subset'], best_aic_3["param"])
best.append(best_aic_3)
features5 = ["Pregnancies","BloodPressure","SkinThickness","DiabetesPedigreeFunction","A
new_x_train = X_train1[features5]
new_x_test = X_test1[features5]
display(new_x_train.head())
display(new_x_test)
```

```
## best subset is Pregnancies,BloodPressure,SkinThickness,DiabetesPedigreeFunction,Age
## best parameter DiabetesLedigreeFunction,  pregnancy, SkinThickness, Age, BloodPress
```

	model	param	rss_adj	aic	bic	subse
187	<statsmodels.regression.linear_model.Regressio...	const -0.367978 Pregnanci...	0.108049	1058.047364	1086.049105	

```
187    [Pregnancies, BloodPressure, SkinThickness, Di...
Name: subset, dtype: object 187    const                          -0.367978
Pregnanci...
Name: param, dtype: object
```

	Pregnancies	BloodPressure	SkinThickness	DiabetesPedigreeFunction	Age
603	7	78.000000	29.00000	0.692	54
118	4	60.000000	23.00000	0.443	22
247	0	90.000000	33.00000	0.427	23
157	1	56.000000	21.00000	0.833	23
468	8	72.405184	29.15342	0.183	38

	Pregnancies	BloodPressure	SkinThickness	DiabetesPedigreeFunction	Age
661	1	76.0	43.00000	1.394	22
122	2	74.0	30.00000	0.404	23
113	4	62.0	29.15342	0.391	25
14	5	72.0	19.00000	0.587	51
529	0	65.0	29.15342	0.660	31
...	...	...	...	...	...
476	2	80.0	45.00000	0.711	29
482	4	58.0	22.00000	0.306	28
230	4	86.0	29.15342	0.645	22
527	3	74.0	15.00000	0.107	24
380	1	72.0	30.00000	0.821	24

154 rows × 5 columns

Modeling

In [11]:

```
# Logistic Regression
log_reg = LogisticRegression(random_state=seed)
log_reg.fit(X_train, y_train)
log_reg_y_pred = log_reg.predict(X_test)

log_reg_accuracy_score = accuracy_score(y_test, log_reg_y_pred)
log_reg_roc_auc_score = roc_auc_score(log_reg_y_pred, y_test)
log_reg_confusion_matrix = confusion_matrix(y_test, log_reg_y_pred)
log_reg_precision_score = precision_score(y_test, log_reg_y_pred)
log_reg_recall_score = recall_score(y_test, log_reg_y_pred)
log_reg_f1_score = f1_score(y_test, log_reg_y_pred)
```

```
print("Logistic Regression Model Accuracy Score is: {:.3f}".format(log_reg_accuracy_scor
print("Logistic Regression Model Confusion Matrix: ", log_reg_confusion_matrix)
print("Logistic Regression Model Precision Score: {:.3f}".format(log_reg_precision_score
print("Logistic Regression Model Recall Score: {:.3f}".format(log_reg_recall_score))
print("Logistic Regression Model F1 Score: {:.3f}".format(log_reg_f1_score))
print("Logistic Regression Model ROC AUC Score: {:.3f}".format(log_reg_roc_auc_score))
```

```
Logistic Regression Model Accuracy Score is: 0.747
Logistic Regression Model Confusion Matrix:  [[82 25]
 [14 33]]
Logistic Regression Model Precision Score: 0.569
Logistic Regression Model Recall Score: 0.702
Logistic Regression Model F1 Score: 0.629
Logistic Regression Model ROC AUC Score: 0.712
```

In [ ]:
```
# Logistic Regression Grid Search
grid = {
    'penalty': ['l1', 'l2'],
    'C': np.logspace(-4, 4, 20),
    'solver' : ['liblinear']
}

log_reg1 = LogisticRegression(random_state=seed)
log_reg_cv = GridSearchCV(log_reg1, grid, cv = 10, verbose=True, scoring='accuracy')
log_reg_cv.fit(X_train, y_train)

print("Logistic Regression Grid Search Best parameters:", log_reg_cv.best_params_)
print("Logistic Regression Grid Search Best Training Score: {:.3f}".format(log_reg_cv.be
print("Logistic Regression Grid Search Best Test score: {:.3f}".format(log_reg_cv.score(
```

```
Fitting 10 folds for each of 40 candidates, totalling 400 fits
Logistic Regression Grid Search Best parameters: {'C': 0.03359818286283781, 'penalty':
'l2', 'solver': 'liblinear'}
Logistic Regression Grid Search Best Training Score: 0.749
Logistic Regression Grid Search Best Test score: 0.760
```

In [ ]:
```
# Gradient Boosting Classifier
gb_cls = GradientBoostingClassifier(random_state=seed)
gb_cls.fit(X_train, y_train)
gb_cls_y_pred = gb_cls.predict(X_test)

gb_cls_accuracy_score = accuracy_score(y_test, gb_cls_y_pred)
gb_cls_roc_auc_score = roc_auc_score(gb_cls_y_pred, y_test)
gb_cls_confusion_matrix = confusion_matrix(y_test, gb_cls_y_pred)
gb_cls_precision_score = precision_score(y_test, gb_cls_y_pred)
gb_cls_recall_score = recall_score(y_test, gb_cls_y_pred)
gb_cls_f1_score = f1_score(y_test, gb_cls_y_pred)

print("Gradient Boosting Classifier Model Accuracy Score is: {:.3f} ".format(gb_cls_accu
print("Gradient Boosting Classifier Model Confusion Matrix: ", gb_cls_confusion_matrix)
print("Gradient Boosting Classifier Model Precision Score: {:.3f}".format(gb_cls_precisi
print("Gradient Boosting Classifier Model Recall Score: {:.3f}".format(gb_cls_recall_sco
print("Gradient Boosting Classifier Model F1 Score: {:.3f}".format(gb_cls_f1_score))
print("Gradient Boosting Classifier Model ROC AUC Score: {:.3f} ".format(gb_cls_roc_auc_
```

```
Gradient Boosting Classifier Model Accuracy Score is: 0.779
Gradient Boosting Classifier Model Confusion Matrix:  [[82 25]
 [ 9 38]]
Gradient Boosting Classifier Model Precision Score: 0.603
Gradient Boosting Classifier Model Recall Score: 0.809
Gradient Boosting Classifier Model F1 Score: 0.691
Gradient Boosting Classifier Model ROC AUC Score: 0.752
```

In [ ]:
```
# Gradient Boosting Classifier Grid Search
grid = {
    'learning_rate': np.arange(0.01, 0.05, 0.01),
```

```
    'n_estimators': np.arange(10, 100, 10),
    'max_depth': np.arange(1, 5, 1)

}

gbc = GradientBoostingClassifier(random_state=seed)
gbc_cv = GridSearchCV(gbc, grid, cv = 10, verbose=True, scoring='accuracy')
gbc_cv.fit(X_train, y_train)

print("Gradient Boosting Classifier Grid Search Best parameters:", gbc_cv.best_params_)
print("Gradient Boosting Classifier Grid Search Best Training Score: {:.3f}".format(gbc_
print("Gradient Boosting Classifier Grid Search Best Test score: {:.3f}".format(gbc_cv.s
```

```
Fitting 10 folds for each of 144 candidates, totalling 1440 fits
Gradient Boosting Classifier Grid Search Best parameters: {'learning_rate': 0.04, 'max_d
epth': 4, 'n_estimators': 90}
Gradient Boosting Classifier Grid Search Best Training Score: 0.795
Gradient Boosting Classifier Grid Search Best Test score: 0.773
```

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_validate

# Random Forest with no tuning
rf = RandomForestClassifier(random_state=seed)
rf.fit(X_train, y_train)
rf_y_pred = rf.predict(X_test)

rf_accuracy_score = accuracy_score(y_test, rf_y_pred)
rf_roc_auc_score = roc_auc_score(rf_y_pred, y_test)
rf_confusion_matrix = confusion_matrix(y_test, rf_y_pred)
rf_precision_score = precision_score(y_test, rf_y_pred)
rf_recall_score = recall_score(y_test, rf_y_pred)
rf_f1_score = f1_score(y_test, rf_y_pred)

print("Random Forest Classifier Model Accuracy Score is:{:.3f} ".format(rf_accuracy_scor
print("Random Forest Classifier Model Confusion Matrix: ", rf_confusion_matrix)
print("Random Forest Classifier Model Precision Score: {:.3f}".format(rf_precision_score
print("Random Forest Classifier Model Recall Score: {:.3f}".format(rf_recall_score))
print("Random Forest Classifier Model F1 Score: {:.3f}".format(rf_f1_score))
print("Random Forest Classifier Model ROC AUC Score: {:.3f}".format(rf_roc_auc_score))
```

```
Random Forest Classifier Model Accuracy Score is:0.799
Random Forest Classifier Model Confusion Matrix:  [[89 18]
 [13 34]]
Random Forest Classifier Model Precision Score: 0.654
Random Forest Classifier Model Recall Score: 0.723
Random Forest Classifier Model F1 Score: 0.687
Random Forest Classifier Model ROC AUC Score: 0.763
```

In [ ]:
```
## Random forest Cross Validation
print(X_train.shape)
tree_num = [1,5,10,50,100,150,200,250,300,350,400]
rf =   RandomForestClassifier(max_depth=6, random_state=0, bootstrap = True)
rf.fit(X_train, y_train)
print("Best Test score:", rf.score(X_test, y_test) )


# train using different values of tree(n_estimators)
rf_scores = []
for t in tree_num:
  rf =   RandomForestClassifier( random_state=0, bootstrap = True, n_estimators=t)
  rf.fit(X_train, y_train)
  rf_scores.append(rf.score(X_test, y_test))
  cv_results = cross_validate(rf, X_train, y_train, cv=5)
  print("test-error:", (cv_results['test_score'].mean()), "number ", t)
```

```
# train using different values of tree(with max)
rf_max_features = [1,2,3,4,5,6,7,8]

for f in rf_max_features:
  rf =   RandomForestClassifier( random_state=0, bootstrap = True, max_features = f, n_e
  rf.fit(X_train, y_train)
  rf_scores.append(rf.score(X_test, y_test))
  cv_results = cross_validate(rf, X_train, y_train, cv=5)
  print("test-error:", (cv_results['test_score'].mean()), "number ", t)

## cross - validation to get the best max_depth, cross_validation for max n_samples,
  """
  n_estimators = number of trees in the foreset
  max_features = max number of features considered for splitting a node
  max_depth = max number of levels in each decision tree
  min_samples_split = min number of data points placed in a node before the node is spli
  min_samples_leaf = min number of data points allowed in a leaf node
  bootstrap = method for sampling data points (with or without replacement)
  """

## highest score is 300
```

```
test-error: 0.8040635330162058 number  400
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.8027896476658875 number  400
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7989518664839153 number  400
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7951543981294849 number  400
```

In [ ]:

```
# train using different values of tree(with max)
rf_max_features = [1,2,3,4,5,6,7,8]

for f in rf_max_features:
  rf =   RandomForestClassifier( random_state=0, bootstrap = True, max_features = f, n_e
  rf.fit(X_train, y_train)
  rf_scores.append(rf.score(X_test, y_test))
  cv_results = cross_validate(rf, X_train, y_train, cv=5)
  print("test-error:", (cv_results['test_score'].mean()), "number ", f)

## selected mbest is 3 with test score of 0.816
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.8078851890671611 number  1
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.8027896476658872 number  2
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.8104248972022898 number  3
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.8091590744174798 number  4
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.8040635330162058 number  5
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.8027896476658875 number  6
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7989518664839153 number  7
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7951543981294849 number  8
```

In [ ]:

```
# train using different values of tree(with max)
rf_max_depth = [1,2,3,4,5,6,7,8,9,10]

for f in rf_max_depth:
  rf =   RandomForestClassifier( random_state=0, bootstrap = True, max_depth= f, n_estim
  rf.fit(X_train, y_train)
  rf_scores.append(rf.score(X_test, y_test))
  cv_results = cross_validate(rf, X_train, y_train, cv=5)
  print("test-error:", (cv_results['test_score'].mean()), "number ", f)

  ## max feature of 9 is 0.77
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7149641215834878 number  1
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7404176408933323 number  2
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.760759493670886 number  3
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7747802950898977 number  4
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7824316697573168 number  5
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.790058856728211 number  6
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.793872450213658 number  7
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7976860436991051 number  8
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
```

```
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7989760541804403 number  9
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have
valid feature names, but RandomForestClassifier was fitted with feature names
  warnings.warn(
test-error: 0.7977102313956301 number  10
```

In [12]:
```
## random forest with selected parameters
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
clf = RandomForestClassifier(max_depth=9, random_state=0, max_features =  6,n_estimators
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
test_score = accuracy_score(y_test, y_pred)
print("test_score", test_score)
```

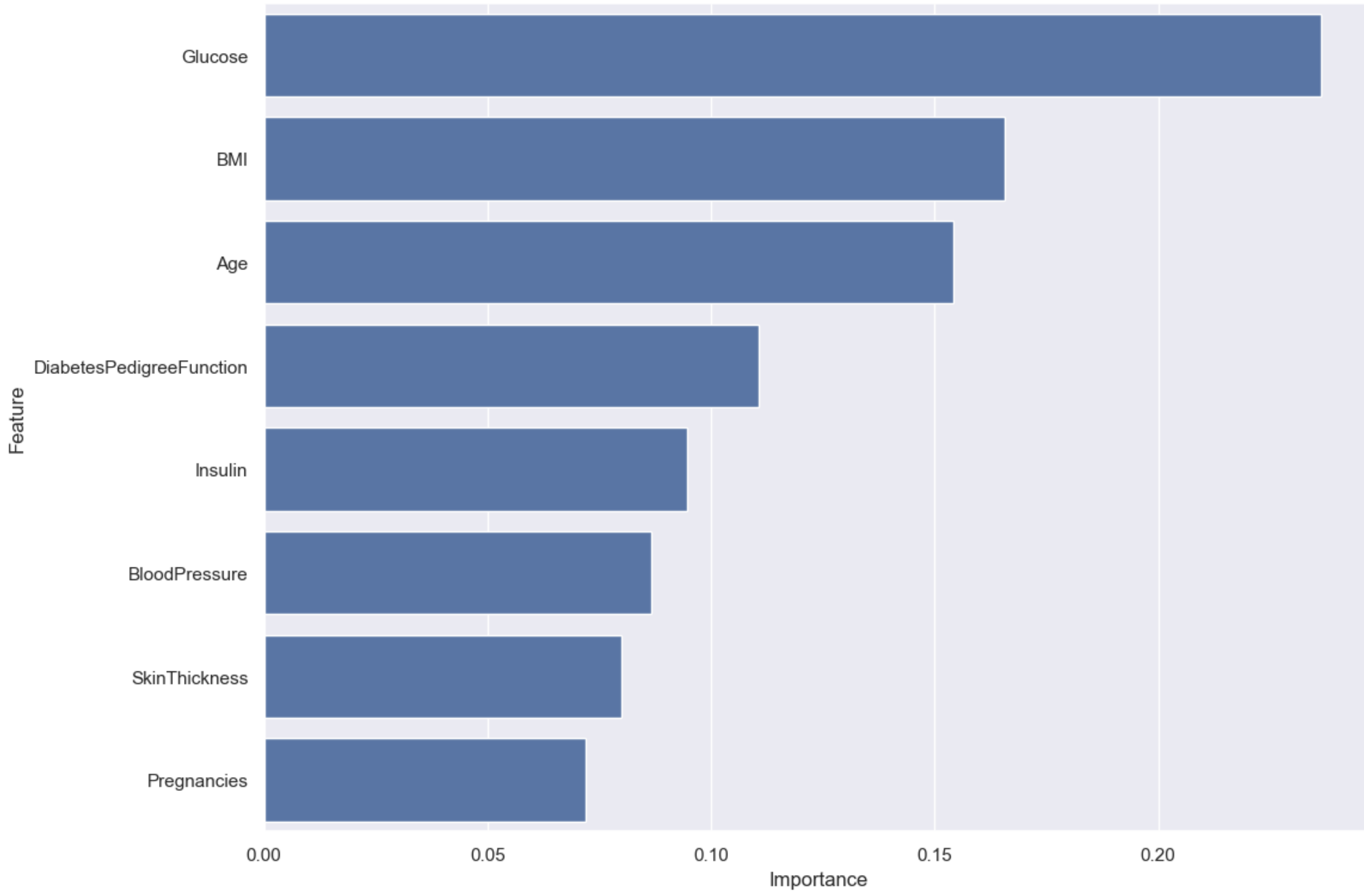
```
test_score 0.7987012987012987
```

In [13]:
```
# Random Forest  with tuned hyperparameters
rf_cls = RandomForestClassifier(n_estimators=300, bootstrap = True, max_features = 'sqrt
rf_cls.fit(X_train, y_train)
rf_cls_y_pred = rf_cls.predict(X_test)

rf_cls_accuracy_score = accuracy_score(y_test, rf_cls_y_pred)
rf_cls_roc_auc_score = roc_auc_score(rf_cls_y_pred, y_test)
rf_cls_confusion_matrix = confusion_matrix(y_test, rf_cls_y_pred)
rf_cls_precision_score = precision_score(y_test, rf_cls_y_pred)
rf_cls_recall_score = recall_score(y_test, rf_cls_y_pred)
rf_cls_f1_score = f1_score(y_test, rf_cls_y_pred)

print("Random Forest Classifier Model Accuracy Score is:{:.3f} ".format(rf_cls_accuracy_
print("Random Forest Classifier Model Confusion Matrix: ", rf_cls_confusion_matrix)
print("Random Forest Classifier Model Precision Score: {:.3f}".format(rf_cls_precision_s
print("Random Forest Classifier Model Recall Score: {:.3f}".format(rf_cls_recall_score))
print("Random Forest Classifier Model F1 Score: {:.3f}".format(rf_cls_f1_score))
print("Random Forest Classifier Model ROC AUC Score: {:.3f}".format(rf_cls_roc_auc_score
```

```
Random Forest Classifier Model Accuracy Score is:0.818
Random Forest Classifier Model Confusion Matrix:  [[90 17]
 [11 36]]
Random Forest Classifier Model Precision Score: 0.679
Random Forest Classifier Model Recall Score: 0.766
Random Forest Classifier Model F1 Score: 0.720
Random Forest Classifier Model ROC AUC Score: 0.785
```

In [14]:
```
# Use the importance() function to determine which variables are most important.
plot_df = pd.DataFrame({'Feature': ['Pregnancies','Glucose','BloodPressure','SkinThickne
plt.figure(figsize=(12,9))
sns.barplot(x='Importance', y='Feature', data=plot_df.sort_values('Importance', ascendin
            color='b')
```

Out[14]:
```
<AxesSubplot:xlabel='Importance', ylabel='Feature'>
```



Glucose
BMI
Age
DiabetesPedigreeFunction
Insulin
BloodPressure
SkinThickness
Pregnancies
Feature
0.00
0.05
0.10
0.15
0.20
Importance


```
In [ ]:
```