Project Name:

Healthcare

Project by: Syed Sabeel

DESCRIPTION

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

1. Business Problem:

Diabetes is a chronic (long-lasting) health condition that affects how our body turns food into energy. Having diabetes means your body either does not make enough insulin or cannot use the insulin it makes as well as it should. When there is not enough insulin or cells stop responding to insulin, too much blood sugar stays in your bloodstream. Over time, that can cause serious health problems, such as heart disease, vision loss and kidney disease.Hence this is known as silent killer out of all diseases.There is no such medicine which can completely cure, so it is adviced to take precaution to maintain normal glucose level in the body rather facing the consequences later in life.

Early knowing of factors leading to diabetes play a vital role in predicting the disease. Based on certain diagnostic measurements included in the dataset and also by building a model to accurately predict the patients diabetes will help patients to take necessary precaution before suffering any further effect on health.

2. Import the necessary libraries:

In [1]:
```
import pandas as pd # pandas is a python package to manipulate data, data operation, d
import numpy as np # numpy is a math library to perform numerical operation using pre-
import matplotlib.pyplot as plt #matplotlib is a library for graphic or data visualiza
import seaborn as sns #Seaborn is a library for making statistical graphics in Python
import warnings # to hide the warning message if any
warnings.filterwarnings('ignore')
```

In [2]:
```
# Scikit-learn is a machine learning library for the Python programming language. It f
from sklearn.impute import KNNImputer # used here to impute/replace zero value in the
from sklearn.model_selection import train_test_split # split the dataset for training
from sklearn.preprocessing import StandardScaler # standardize by distributing values
from imblearn.over_sampling import SMOTE # for imbalance dataset
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import confusion_matrix,accuracy_score, classification_report ,re
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import KFold, cross_val_score
```

3. Load the dataset and identify the dependent and independent variables

Dependent Variable/Label - Outcome of the dataset is the predicted value Independent Variable/feature - all columns other than Outcome column having integer and float datatypes.

In [3]:
```
df= pd.read_csv('health care diabetes.csv')
```

In [4]:
```
df.head()
```

Out[4]:

	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

4. EDA(Exploratory Data Analysis)

In [5]:

```
# Checking missing value/Nan in the dataset
df.isna().sum()
```

Out[5]:

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [6]:

```
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
```

In [7]:

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

In [8]:

```
X.columns
```

Out[8]:

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

In [9]:

```
int_col = [col for col in X.columns if X[col].dtype == 'int']
int_col
```

Out[9]: ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'Age']

In [10]:
```
df
```

Out[10]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Ag
0	6	148	72	35	0	33.6	0.627	5
1	1	85	66	29	0	26.6	0.351	3
2	8	183	64	0	0	23.3	0.672	3
3	1	89	66	23	94	28.1	0.167	2
4	0	137	40	35	168	43.1	2.288	3
...	...	...	...	...	...	...	...	
763	10	101	76	48	180	32.9	0.171	6
764	2	122	70	27	0	36.8	0.340	2
765	5	121	72	23	112	26.2	0.245	3
766	1	126	60	0	0	30.1	0.349	4
767	1	93	70	31	0	30.4	0.315	2

768 rows × 9 columns

In [11]:
```
# There are many zeros in the dataset which cannot add any value in prediction.
#These zero value needs to be replaced with value and can be done using mean, median e
# By treating zero values using knn imputation we can impute zero with calculated valu
# Replace zero values with the values of the nearest neighbours that fills in all zerc

knn= KNNImputer(missing_values=0, n_neighbors=5) # n_neighbors value is chosen by runr
```

In [12]:
```
knn.fit(X)
```

Out[12]: KNNImputer(missing_values=0)

In [13]:
```
df = pd.DataFrame(knn.transform(X),columns=X.columns)
```

In [14]:
```
df[int_col]= df[int_col].apply(np.int64)
```

In [15]:
```
df.head()
```

Out[15]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148	72	35	169	33.6	0.627	50
1	1	85	66	29	58	26.6	0.351	31
2	8	183	64	25	164	23.3	0.672	32
3	1	89	66	23	94	28.1	0.167	21
4	5	137	40	35	168	43.1	2.288	33

In [16]:
```
df['Outcome'] = y
```

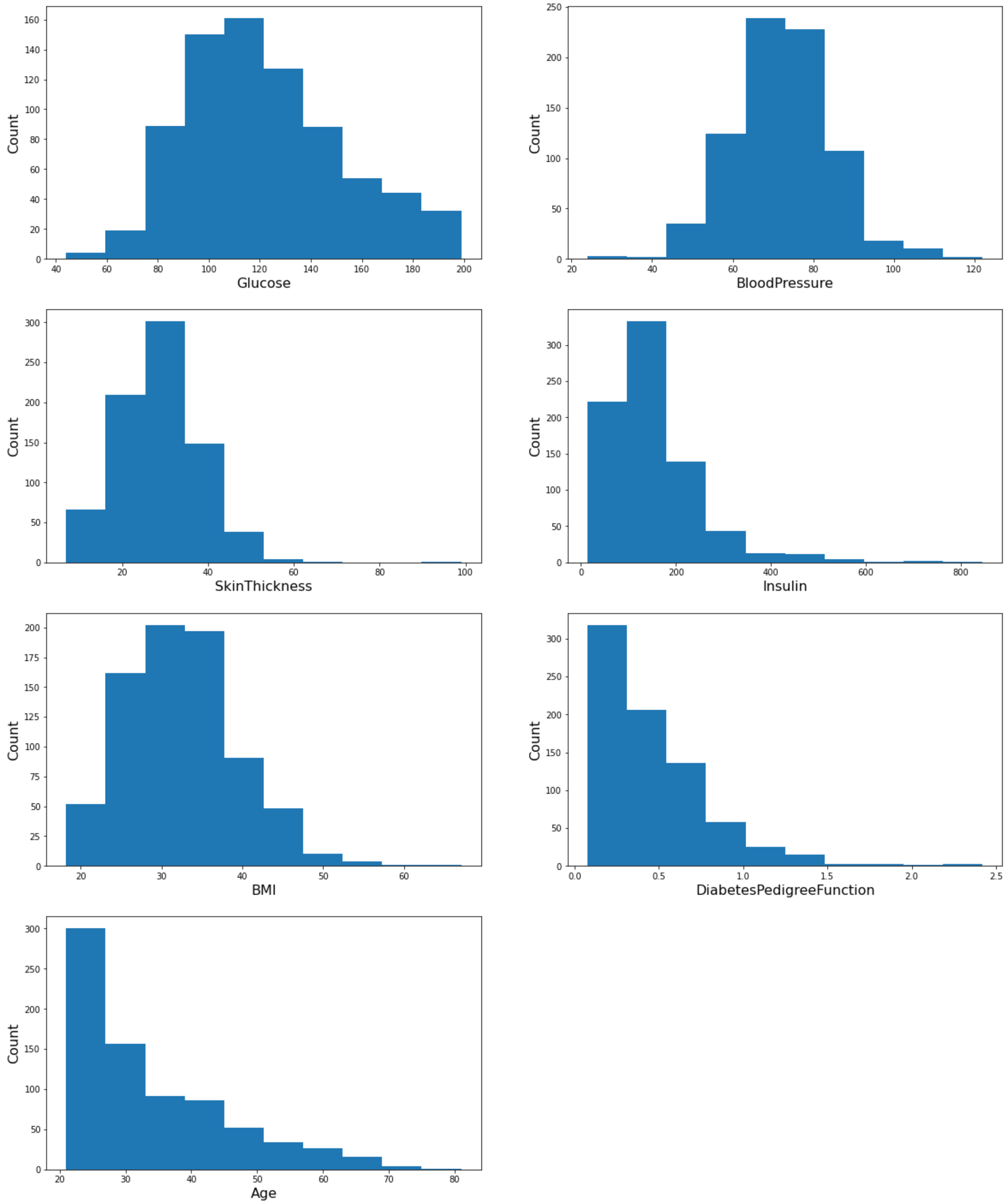
In [17]:
```
df.head()
```

Out[17]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148	72	35	169	33.6	0.627	50
1	1	85	66	29	58	26.6	0.351	31
2	8	183	64	25	164	23.3	0.672	32
3	1	89	66	23	94	28.1	0.167	21
4	5	137	40	35	168	43.1	2.288	33

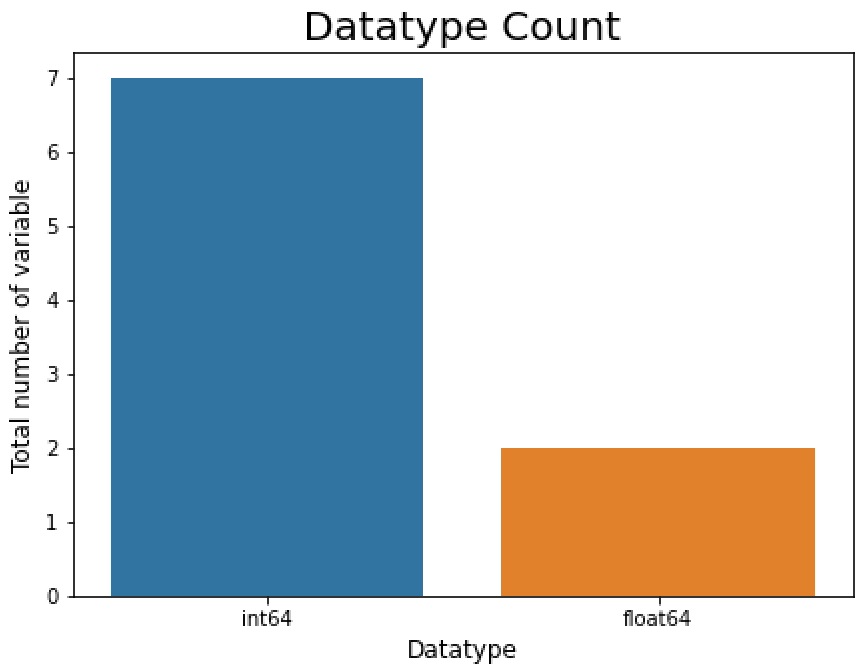
In [18]:
```
X=df.drop('Outcome',axis=1)
y=df['Outcome']
```

In [19]:
```
# By plotting histogram we can divide the entire range of values into a series of inte
plt.figure(figsize=(20,25))
for i in range(1,8):
    axi=plt.subplot(4,2,i)
    plt.hist(X[X.columns[i]],bins=10)
    xlabel = X.columns[i]
    plt.xlabel(xlabel,fontsize='16')
    plt.ylabel('Count',fontsize='16')
```



In [20]:

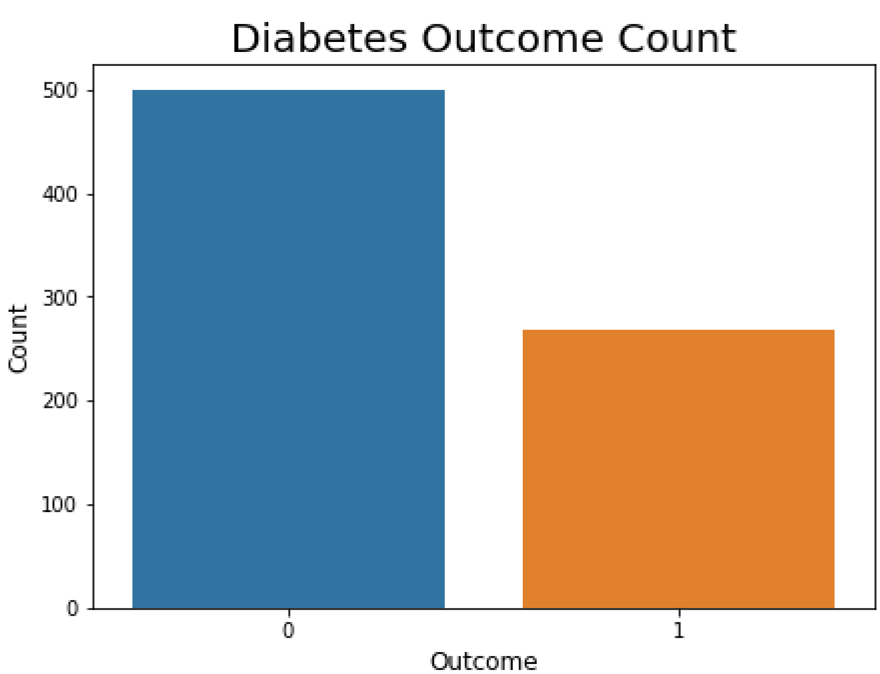
```
# Count (frequency) plot describing the data types and the count of variables.
plt.figure(figsize=(7,5))
sns.countplot(x=df.dtypes, data=df)
plt.xlabel('Datatype',fontsize='12')
plt.ylabel('Total number of variable',fontsize='12')
plt.title('Datatype Count', fontsize='20')
plt.show()
```



In [21]:
```
y.value_counts()
```

Out[21]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

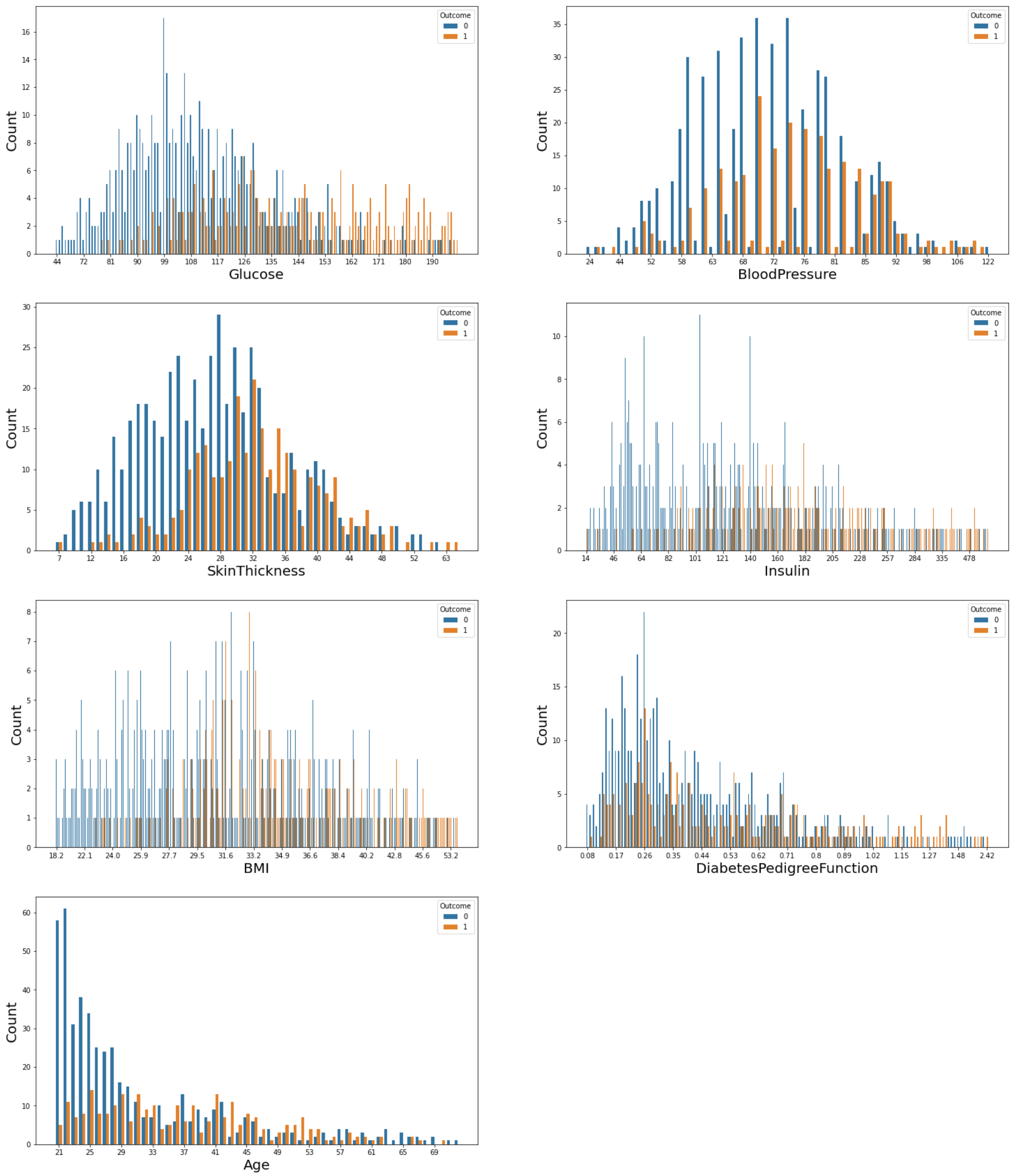
In [22]:
```
#Count Plot of outcome/Label
plt.figure(figsize=(7,5))
sns.countplot(x=y, data=df)
plt.xlabel('Outcome',fontsize='12')
plt.ylabel('Count',fontsize='12')
plt.title('Diabetes Outcome Count', fontsize='20')
plt.show()
```



By plotting the count of outcomes by their value, we can see there are 500 non diabetes and 268 diabetes. There are more non diabetes patients and this imbalance data can be balanced.

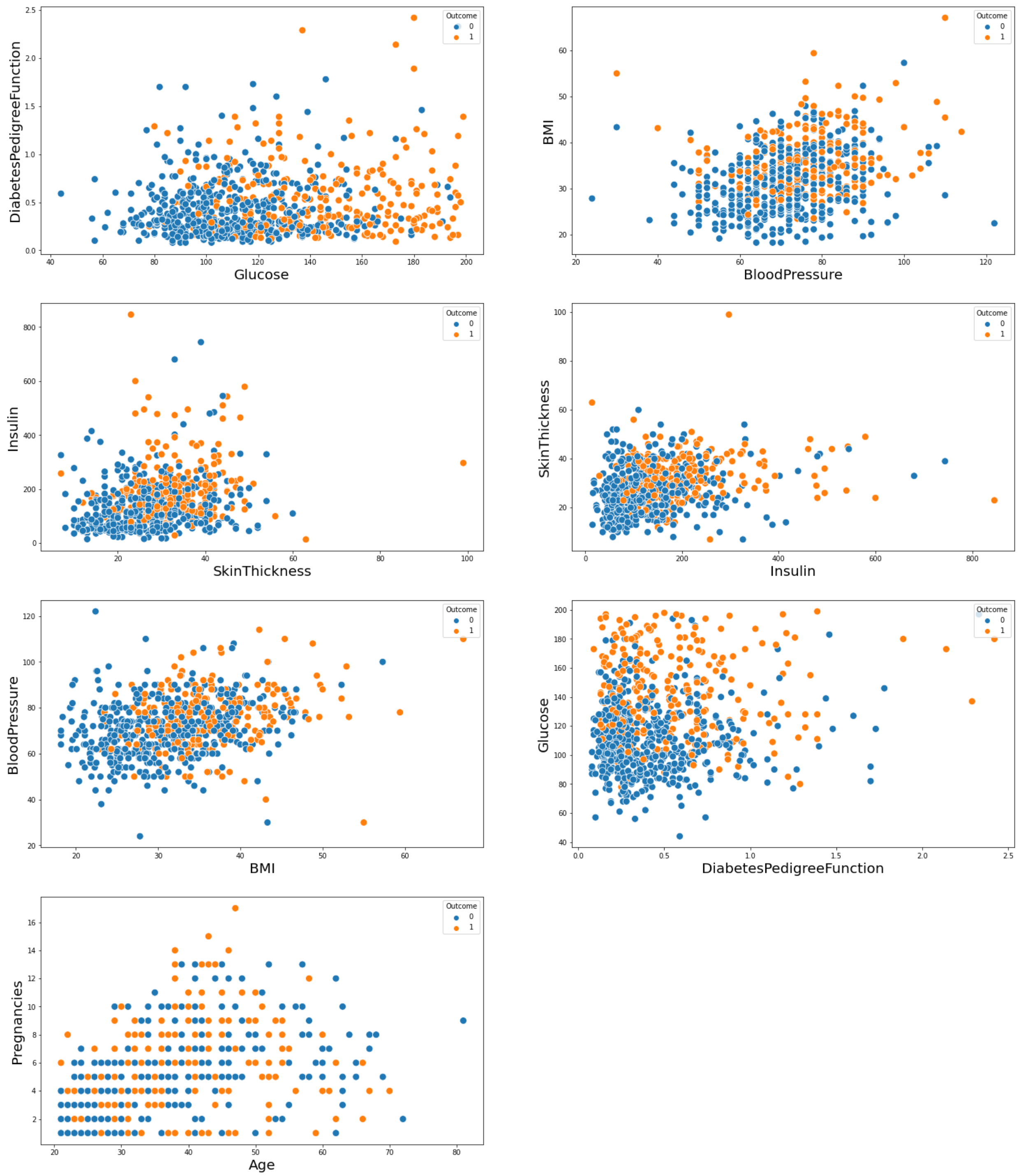
Training dataset is balanced by oversampling using SMOTE method.

In [23]:
```
#Countplot of all independent variable with outcomes colored for overall visualizatio
plt.figure(figsize=(25,30))
for i in range(1,8):
    axi=plt.subplot(4,2,i)
    sns.countplot(x=round(X[X.columns[i]],2),hue=y,data=df,ax=axi)
    plt.locator_params(axis='x', nbins=15)
    xlabel = X.columns[i]
    plt.xlabel(xlabel, fontsize='20')
    plt.ylabel('Count',fontsize='20')
    plt.legend(title='Outcome',loc='upper right')
```



In [24]:
```
#Scatter plot between variables for analysis by selecting random variable.
colors = {0:'blue', 1:'orange'}
```

```
y_ls= y.values.tolist()
color_ls = [colors[i] for i in y_ls ]
plt.figure(figsize=(25,30))
for i in range(1,8):
    axi=plt.subplot(4,2,i)
    sns.scatterplot(x=round(X[X.columns[i]],2),y=round(X[X.columns[7-i]],2),hue=y,data
    xlabel = X.columns[i]
    ylabel = X.columns[7-i]
    plt.xlabel(xlabel, fontsize='20')
    plt.ylabel(ylabel,fontsize='20')
    plt.legend(title='Outcome',loc='upper right')
```



Above Scatter plot analysis:

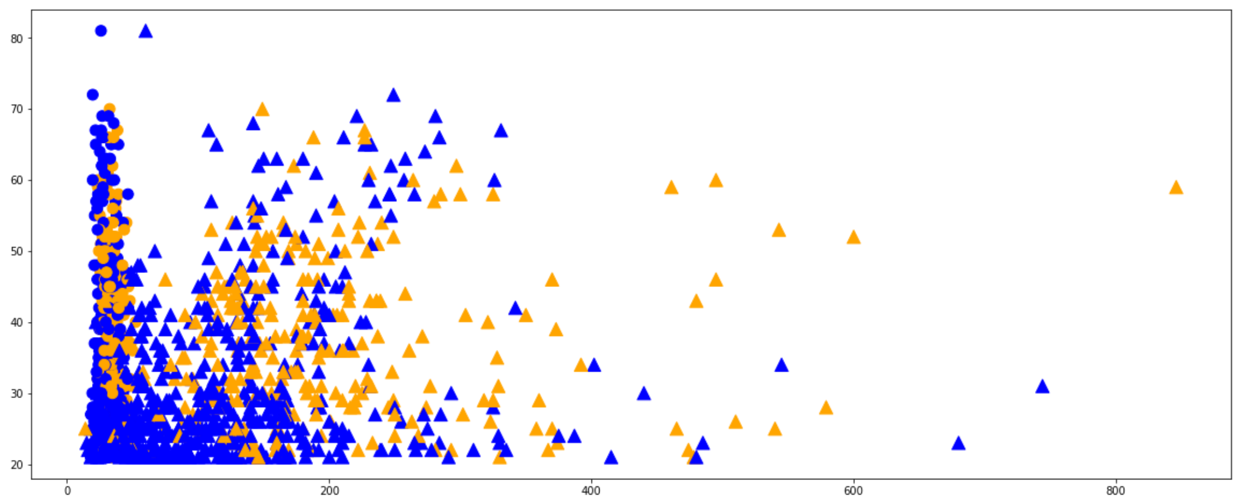
plot 1 : High Glucose level with low diabetes pedigree function are more prone to diabetes. More non diabetes patients with low glucose.

plot 2 : More diabetes found with High Blood pressure and high BMI

plot 7: Age does not matter for diabetes in case of pregnancies and can occur at any age during pregnancy

Below Plot : With respect to BMI and Insulin level age is not the factor for diabetes. Maintaining good BMI and Insulin level can keep diabetes away.

In [25]:
```
plt.figure(figsize=(20,8))
plt.scatter(x=df['BMI'],y= df['Age'], c=color_ls,s=100)
plt.scatter(x=df['Insulin'],y= df['Age'], c=color_ls, marker='^',s=150)
plt.show()
```



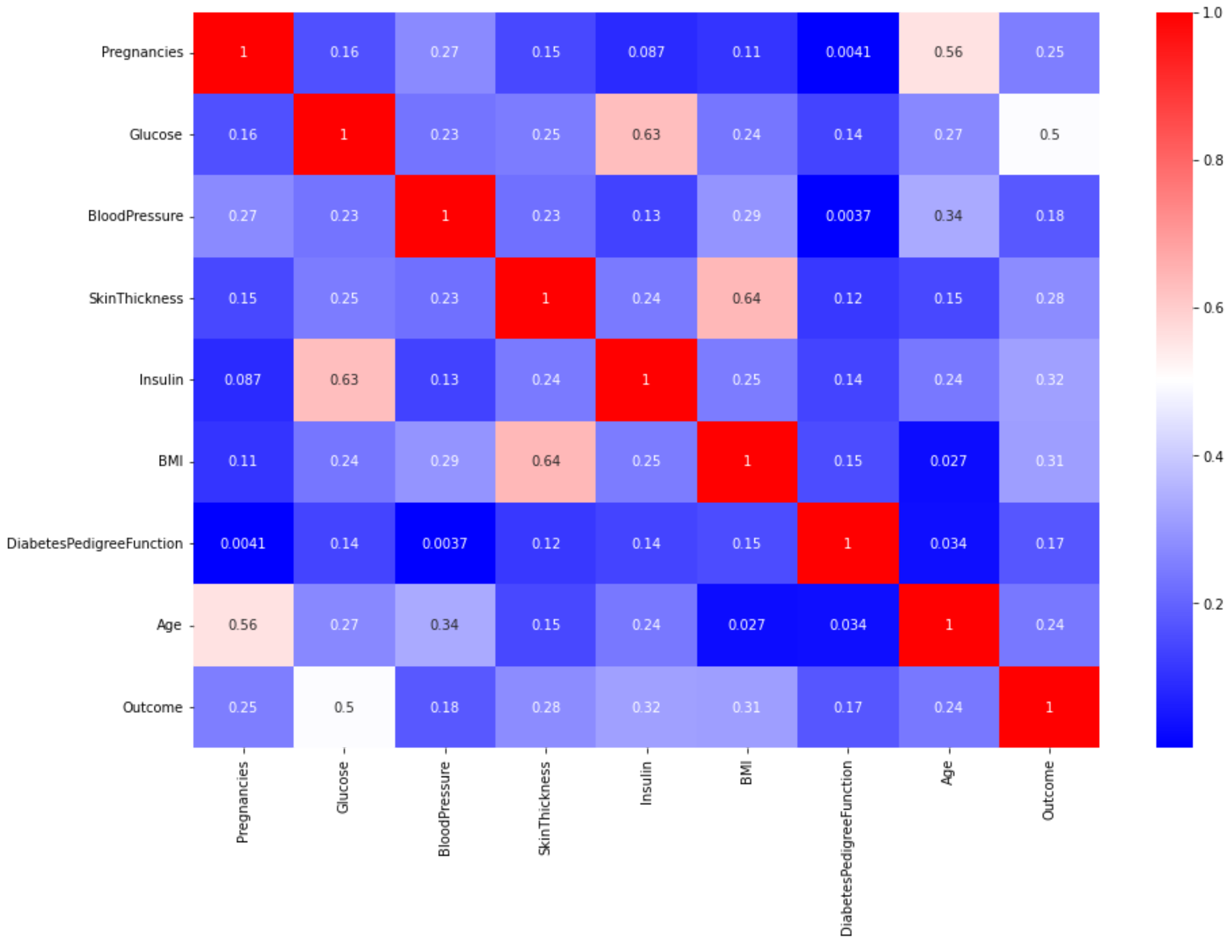
In [26]:
```
# Analysis using Corelation
df.corr()
```

Out[26]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	D
Pregnancies	1.000000	0.160064	0.274583	0.147417	0.087091	0.105805	
Glucose	0.160064	1.000000	0.231918	0.246727	0.627695	0.236708	
BloodPressure	0.274583	0.231918	1.000000	0.225316	0.134606	0.292661	
SkinThickness	0.147417	0.246727	0.225316	1.000000	0.244180	0.641102	
Insulin	0.087091	0.627695	0.134606	0.244180	1.000000	0.248560	
BMI	0.105805	0.236708	0.292661	0.641102	0.248560	1.000000	
DiabetesPedigreeFunction	0.004083	0.139273	0.003695	0.116022	0.137714	0.153602	
Age	0.558149	0.270197	0.335528	0.145173	0.238188	0.027380	
Outcome	0.250365	0.495830	0.175720	0.277750	0.317367	0.313878	

In [27]:
```
# Correlation of variable using Heat map from Seaborn library
plt.figure(figsize=(15,10))
```

```
sns.heatmap(df.corr(),cmap='bwr',annot= True)
plt.show()
```



Correlation value lies betweeen -1 & +1, where as 1 means strong positive correlation, -1 means negative correlation and 0 means there is no correlation. Glucose & Insulin, BMI & Skin thickness are on positive relation, with increase in either one other increase. There are no negative correlation which will have indirect impact on outcome.

In [28]:
```
#Splitting entire dataset to train and test,by training model on training set we can p
X_train,x_test,y_train,y_test= train_test_split(X,y,test_size=0.3, random_state=42)
```

In [29]:
```
# Standardization to be on same scale range
X_sc= StandardScaler()
X_train_sc = X_sc.fit_transform(X_train)
x_test_sc = X_sc.transform(x_test)
```

In [30]:
```
print(X_train_sc.shape)
print(x_test_sc.shape)
print(y_train.shape)
print(y_test.shape)
print(y_train.value_counts())
```

```
(537, 8)
(231, 8)
(537,)
(231,)
0    349
1    188
Name: Outcome, dtype: int64
```

In [31]:
```
# Balancing data using SMOTE method
smote= SMOTE(sampling_strategy='minority',random_state=42)
X_sm,y_sm = smote.fit_resample(X_train_sc,y_train)
```

In [32]:
```
print(X_sm.shape)
print(y_sm.shape)
```

```
(698, 8)
(698,)
```

In [33]:
```
y_sm.value_counts()
```

Out[33]:
```
1    349
0    349
Name: Outcome, dtype: int64
```

Model Selection & Evaluation

Since the outcome of this dataset is classification i.e diabetes or non- diabetes, Classification model of machine learning shall be considered.

1. Decision Tree Classifier
2. Random Forest Classifier
3. AdaBoost Classifier
4. Gradient Boosting Classifier
5. KNN Classifier

Model evaluation for classification type is done by using confusion matrix, accuracy score.

In [34]:
```
# 1. Decision Tree Classifier:

DC = DecisionTreeClassifier(random_state=42)
DC.fit(X_sm,y_sm)
print(confusion_matrix(y_true= y_test, y_pred = DC.predict(x_test_sc)))
print('Accuracy Score is', accuracy_score(y_true= y_test, y_pred = DC.predict(x_test_s
print(classification_report(y_true= y_test, y_pred = DC.predict(x_test_sc)))
```

```
[[114  37]
 [ 31  49]]
Accuracy Score is 70.56277056277057
              precision    recall  f1-score   support

           0       0.79      0.75      0.77       151
           1       0.57      0.61      0.59        80

    accuracy                           0.71       231
   macro avg       0.68      0.68      0.68       231
weighted avg       0.71      0.71      0.71       231
```

In [35]:
```
DC_train = DecisionTreeClassifier(random_state=42)
DC_train.fit(X_train_sc,y_train)
print(confusion_matrix(y_true= y_test, y_pred = DC_train.predict(x_test_sc)))
print('Accuracy Score is', accuracy_score(y_true= y_test, y_pred = DC_train.predict(x_
print(classification_report(y_true= y_test, y_pred = DC_train.predict(x_test_sc)))
```

```
[[111  40]
 [ 36  44]]
Accuracy Score is 67.09956709956711
              precision    recall  f1-score   support

           0       0.76      0.74      0.74       151
           1       0.52      0.55      0.54        80

    accuracy                           0.67       231
   macro avg       0.64      0.64      0.64       231
weighted avg       0.68      0.67      0.67       231
```

In [36]:
```
# 2. Random Forest Classifier
rf = RandomForestClassifier(n_jobs=-1, random_state=42)
rf.fit(X_sm,y_sm)
print(confusion_matrix(y_true= y_test, y_pred = rf.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = rf.predict(x_test_sc
print(classification_report(y_true= y_test, y_pred = rf.predict(x_test_sc)))
print('Sensitivity/True Positive rate', recall_score(y_true= y_test, y_pred = rf.predi
print('Specificity/True Negative rate', recall_score(y_true= y_test, y_pred = rf.predi
print('roc_auc_score',roc_auc_score(y_true= y_test,y_score=rf.predict(x_test_sc)))
roc_curve(y_true= y_test,y_score=rf.predict(x_test_sc))
```

```
[[117  34]
 [ 20  60]]
Accuracy Score is 76.62337662337663
              precision    recall  f1-score   support

           0       0.85      0.77      0.81       151
           1       0.64      0.75      0.69        80

    accuracy                           0.77       231
   macro avg       0.75      0.76      0.75       231
weighted avg       0.78      0.77      0.77       231

Sensitivity/True Positive rate 0.7748344370860927
Specificity/True Negative rate 0.75
roc_auc_score 0.7624172185430463
```

Out[36]:
```
(array([0.        , 0.22516556, 1.        ]),
 array([0.  , 0.75, 1.  ]),
 array([2, 1, 0]))
```

In [37]:
```
rf_train = RandomForestClassifier(n_jobs=-1, random_state=42)
rf_train.fit(X_train_sc,y_train)
print(confusion_matrix(y_true= y_test, y_pred = rf_train.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = rf_train.predict(x_t
print(classification_report(y_true= y_test, y_pred = rf_train.predict(x_test_sc)))
```

```
[[119  32]
 [ 29  51]]
Accuracy Score is 73.59307359307358
              precision    recall  f1-score   support

           0       0.80      0.79      0.80       151
           1       0.61      0.64      0.63        80

    accuracy                           0.74       231
   macro avg       0.71      0.71      0.71       231
weighted avg       0.74      0.74      0.74       231
```

In [38]:

```
# 3. Ada Boost Classifier
ab = AdaBoostClassifier(random_state=42)
ab.fit(X_sm,y_sm)
print(confusion_matrix(y_true= y_test, y_pred = ab.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = ab.predict(x_test_sc
print(classification_report(y_true= y_test, y_pred = ab.predict(x_test_sc)))
```

```
[[114  37]
 [ 22  58]]
Accuracy Score is 74.45887445887446
              precision    recall  f1-score   support

           0       0.84      0.75      0.79       151
           1       0.61      0.72      0.66        80

    accuracy                           0.74       231
   macro avg       0.72      0.74      0.73       231
weighted avg       0.76      0.74      0.75       231
```

In [39]:

```
ab_train = AdaBoostClassifier(random_state=42)
ab_train.fit(X_train_sc,y_train)
print(confusion_matrix(y_true= y_test, y_pred = ab_train.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = ab_train.predict(x_t
print(classification_report(y_true= y_test, y_pred = ab_train.predict(x_test_sc)))
```

```
[[119  32]
 [ 26  54]]
Accuracy Score is 74.89177489177489
              precision    recall  f1-score   support

           0       0.82      0.79      0.80       151
           1       0.63      0.68      0.65        80

    accuracy                           0.75       231
   macro avg       0.72      0.73      0.73       231
weighted avg       0.75      0.75      0.75       231
```

In [40]:

```
# 4.Gradient Boosting Classifier
gb= GradientBoostingClassifier(random_state=42)
gb.fit(X_sm,y_sm)
print(confusion_matrix(y_true= y_test, y_pred = gb.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = gb.predict(x_test_sc
print(classification_report(y_true= y_test, y_pred = gb.predict(x_test_sc)))
```

```
[[110  41]
 [ 24  56]]
Accuracy Score is 71.86147186147186
              precision    recall  f1-score   support

           0       0.82      0.73      0.77       151
           1       0.58      0.70      0.63        80

    accuracy                           0.72       231
   macro avg       0.70      0.71      0.70       231
weighted avg       0.74      0.72      0.72       231
```

In [41]:
```
gb_train= GradientBoostingClassifier(random_state=42)
gb_train.fit(X_train_sc,y_train)
print(confusion_matrix(y_true= y_test, y_pred = gb_train.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = gb_train.predict(x_t
print(classification_report(y_true= y_test, y_pred = gb_train.predict(x_test_sc)))
```

```
[[120  31]
 [ 28  52]]
Accuracy Score is 74.45887445887446
              precision    recall  f1-score   support

           0       0.81      0.79      0.80       151
           1       0.63      0.65      0.64        80

    accuracy                           0.74       231
   macro avg       0.72      0.72      0.72       231
weighted avg       0.75      0.74      0.75       231
```

In [42]:
```
# 5. KNN Classifier
knn = KNeighborsClassifier(n_neighbors=7,weights='uniform',algorithm='auto',leaf_size=
                          metric='minkowski',metric_params=None,n_jobs=None)
knn.fit(X_sm,y_sm)
print(confusion_matrix(y_true= y_test, y_pred = knn.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = knn.predict(x_test_s
print(classification_report(y_true= y_test, y_pred = knn.predict(x_test_sc)))
print('Sensitivity/True Positive rate', recall_score(y_true= y_test, y_pred = knn.pred
print('Specificity/True Negative rate', recall_score(y_true= y_test, y_pred = knn.pred
print('roc_auc_score',roc_auc_score(y_true= y_test,y_score=knn.predict(x_test_sc)))
roc_curve(y_true= y_test,y_score=knn.predict(x_test_sc))
```

```
[[95 56]
 [13 67]]
Accuracy Score is 70.12987012987013
              precision    recall  f1-score   support

           0       0.88      0.63      0.73       151
           1       0.54      0.84      0.66        80

    accuracy                           0.70       231
   macro avg       0.71      0.73      0.70       231
weighted avg       0.76      0.70      0.71       231

Sensitivity/True Positive rate 0.6291390728476821
Specificity/True Negative rate 0.8375
roc_auc_score 0.7333195364238411
```

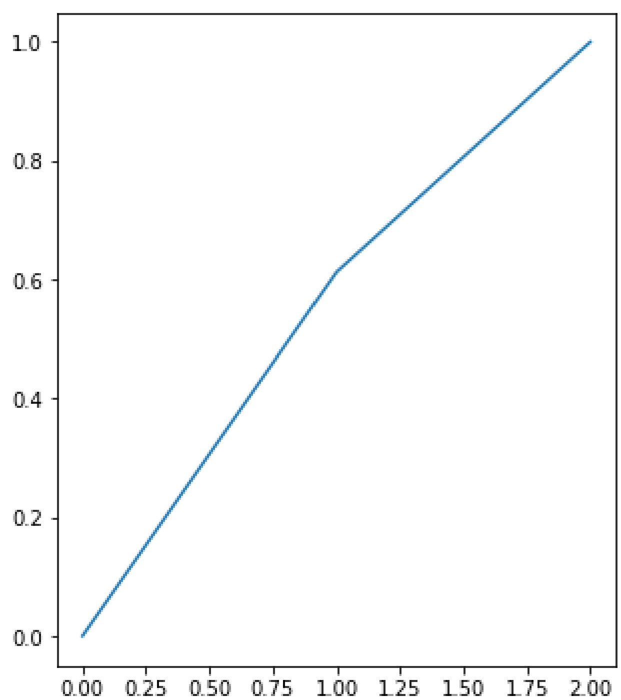
Out[42]:
```
(array([0.        , 0.37086093, 1.        ]),
 array([0.    , 0.8375, 1.    ]),
 array([2, 1, 0]))
```

In [43]:
```
knn_train = KNeighborsClassifier(n_neighbors=13,weights='uniform',algorithm='auto',lea
                          metric='minkowski',metric_params=None,n_jobs=None)
knn_train.fit(X_train_sc,y_train)
print(confusion_matrix(y_true= y_test, y_pred = knn_train.predict(x_test_sc)))
print('Accuracy Score is',accuracy_score(y_true= y_test, y_pred = knn_train.predict(x_
print(classification_report(y_true= y_test, y_pred = knn_train.predict(x_test_sc)))
print('Sensitivity/True Positive rate', recall_score(y_true= y_test, y_pred = knn_trai
print('Specificity/True Negative rate', recall_score(y_true= y_test, y_pred = knn_trai
print('roc_auc_score',roc_auc_score(y_true= y_test,y_score=knn_train.predict(x_test_sc
roc_curve(y_true= y_test,y_score=knn_train.predict(x_test_sc))
```

```
[[119  32]
 [ 31  49]]
Accuracy Score is 72.72727272727273
              precision    recall  f1-score   support

           0       0.79      0.79      0.79       151
           1       0.60      0.61      0.61        80

    accuracy                           0.73       231
   macro avg       0.70      0.70      0.70       231
weighted avg       0.73      0.73      0.73       231

Sensitivity/True Positive rate 0.7880794701986755
Specificity/True Negative rate 0.6125
roc_auc_score 0.7002897350993378
```

Out[43]:
```
(array([0.        , 0.21192053, 1.        ]),
 array([0.    , 0.6125, 1.    ]),
 array([2, 1, 0]))
```

In [44]:
```
plt.figure(figsize=(5,6))
plt.plot(roc_curve(y_true= y_test,y_score=knn_train.predict(x_test_sc))[1])
plt.show()
```



In [45]:
```
kfold_model = KFold(n_splits=10)
kf_model = KNeighborsClassifier(n_neighbors=7)
results = cross_val_score(kf_model, X_sm, y_sm, cv=kfold_model)
```

In [46]:
```
results.mean()*100
```

Out[46]:
```
79.13250517598344
```

After running many model classifier, Random Forest classifier results in better accuracy with 76%. After imputing with Knn and also balancing the data , recall value 0.77,0.75 is found for True positiver rate/ True negative rate. Both sensitivity and specificty for the prediction of diabetes / non diabetes has good value. This classifier is more prefered than other classifier.

Modeling using Deep learning tensorflow using keras

In [47]:
```
import tensorflow as tf
```

In [48]:
```
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Dense(12, input_dim=8, activation ='relu'))
model.add(tf.keras.layers.Dense(8, activation = 'relu'))
model.add(tf.keras.layers.Dense(1, activation = 'sigmoid'))
```

In [49]:
```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics='accuracy')
```

In [50]:
```
model.fit(X_train_sc,y_train,epochs=60, batch_size=10)
```

```
Epoch 1/60
54/54 [==============================] - 5s 2ms/step - loss: 0.7244 - accuracy: 0.424
6
Epoch 2/60
54/54 [==============================] - 0s 2ms/step - loss: 0.6422 - accuracy: 0.653
6
Epoch 3/60
54/54 [==============================] - 0s 1ms/step - loss: 0.5876 - accuracy: 0.716
9
Epoch 4/60
54/54 [==============================] - 0s 2ms/step - loss: 0.5451 - accuracy: 0.739
3
Epoch 5/60
54/54 [==============================] - 0s 1ms/step - loss: 0.5146 - accuracy: 0.754
2
Epoch 6/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4923 - accuracy: 0.767
2
Epoch 7/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4775 - accuracy: 0.778
4
Epoch 8/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4671 - accuracy: 0.772
8
Epoch 9/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4589 - accuracy: 0.772
8
Epoch 10/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4517 - accuracy: 0.780
3
Epoch 11/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4469 - accuracy: 0.784
0
Epoch 12/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4431 - accuracy: 0.787
7
Epoch 13/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4401 - accuracy: 0.787
7
Epoch 14/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4364 - accuracy: 0.785
8
Epoch 15/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4342 - accuracy: 0.785
8
Epoch 16/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4332 - accuracy: 0.789
6
Epoch 17/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4298 - accuracy: 0.784
0
Epoch 18/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4269 - accuracy: 0.785
8
Epoch 19/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4256 - accuracy: 0.785
8
Epoch 20/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4237 - accuracy: 0.784
0
```

```
Epoch 21/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4225 - accuracy: 0.785
8
Epoch 22/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4207 - accuracy: 0.789
6
Epoch 23/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4191 - accuracy: 0.789
6
Epoch 24/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4178 - accuracy: 0.785
8
Epoch 25/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4172 - accuracy: 0.789
6
Epoch 26/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4154 - accuracy: 0.787
7
Epoch 27/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4151 - accuracy: 0.785
8
Epoch 28/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4127 - accuracy: 0.785
8
Epoch 29/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4112 - accuracy: 0.787
7
Epoch 30/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4099 - accuracy: 0.789
6
Epoch 31/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4093 - accuracy: 0.793
3
Epoch 32/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4078 - accuracy: 0.789
6
Epoch 33/60
54/54 [==============================] - 0s 2ms/step - loss: 0.4076 - accuracy: 0.795
2
Epoch 34/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4064 - accuracy: 0.785
8
Epoch 35/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4054 - accuracy: 0.795
2
Epoch 36/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4049 - accuracy: 0.795
2
Epoch 37/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4044 - accuracy: 0.795
2
Epoch 38/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4031 - accuracy: 0.791
4
Epoch 39/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4018 - accuracy: 0.791
4
Epoch 40/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4014 - accuracy: 0.798
9
```

```
Epoch 41/60
54/54 [==============================] - 0s 1ms/step - loss: 0.4011 - accuracy: 0.798
9
Epoch 42/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3995 - accuracy: 0.797
0
Epoch 43/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3994 - accuracy: 0.798
9
Epoch 44/60
54/54 [==============================] - 0s 2ms/step - loss: 0.3980 - accuracy: 0.804
5
Epoch 45/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3969 - accuracy: 0.800
7
Epoch 46/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3964 - accuracy: 0.800
7
Epoch 47/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3952 - accuracy: 0.800
7
Epoch 48/60
54/54 [==============================] - 0s 2ms/step - loss: 0.3951 - accuracy: 0.804
5
Epoch 49/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3951 - accuracy: 0.797
0
Epoch 50/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3936 - accuracy: 0.800
7
Epoch 51/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3926 - accuracy: 0.810
1
Epoch 52/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3918 - accuracy: 0.810
1
Epoch 53/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3907 - accuracy: 0.810
1
Epoch 54/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3902 - accuracy: 0.808
2
Epoch 55/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3896 - accuracy: 0.811
9
Epoch 56/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3883 - accuracy: 0.813
8
Epoch 57/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3876 - accuracy: 0.811
9
Epoch 58/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3875 - accuracy: 0.808
2
Epoch 59/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3854 - accuracy: 0.811
9
Epoch 60/60
54/54 [==============================] - 0s 1ms/step - loss: 0.3854 - accuracy: 0.811
9
```

Out[50]: <keras.callbacks.History at 0x7f5610289490>

In [51]:
```
loss,accuracy = model.evaluate(X_train_sc,y_train)
print('Accuracy : %.2f' %(accuracy*100))
```

```
17/17 [==============================] - 0s 1ms/step - loss: 0.3818 - accuracy: 0.813
8
Accuracy : 81.38
```

In [ ]:
```
#df.to_csv('Health care Tableau.csv')
```