Import the libraries

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Read the dataset

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

Out[3]:

	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
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

In [4]:
```
df.shape
```

Out[4]:
```
(768, 9)
```

Data Preprocessing

1) Handling Null

In [5]:
```
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
```

2) Handling Duplicates

In [6]:
```
df.duplicated().sum()
```

Out[6]:
```
0
```

In [7]:
```
df.drop_duplicates(inplace=True)
df.duplicated().sum()
```

Out[7]:
```
0
```

3) Check data types

In [8]:
```
df.dtypes
```

Out[8]:
```
Pregnancies                   int64
Glucose                       int64
BloodPressure                 int64
SkinThickness                 int64
Insulin                       int64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

In [9]:
```
for i in df.columns:
    print(f'{i} - {df[i].nunique()}')
```

```
Pregnancies - 17
Glucose - 136
BloodPressure - 47
SkinThickness - 51
Insulin - 186
BMI - 248
DiabetesPedigreeFunction - 517
Age - 52
Outcome - 2
```

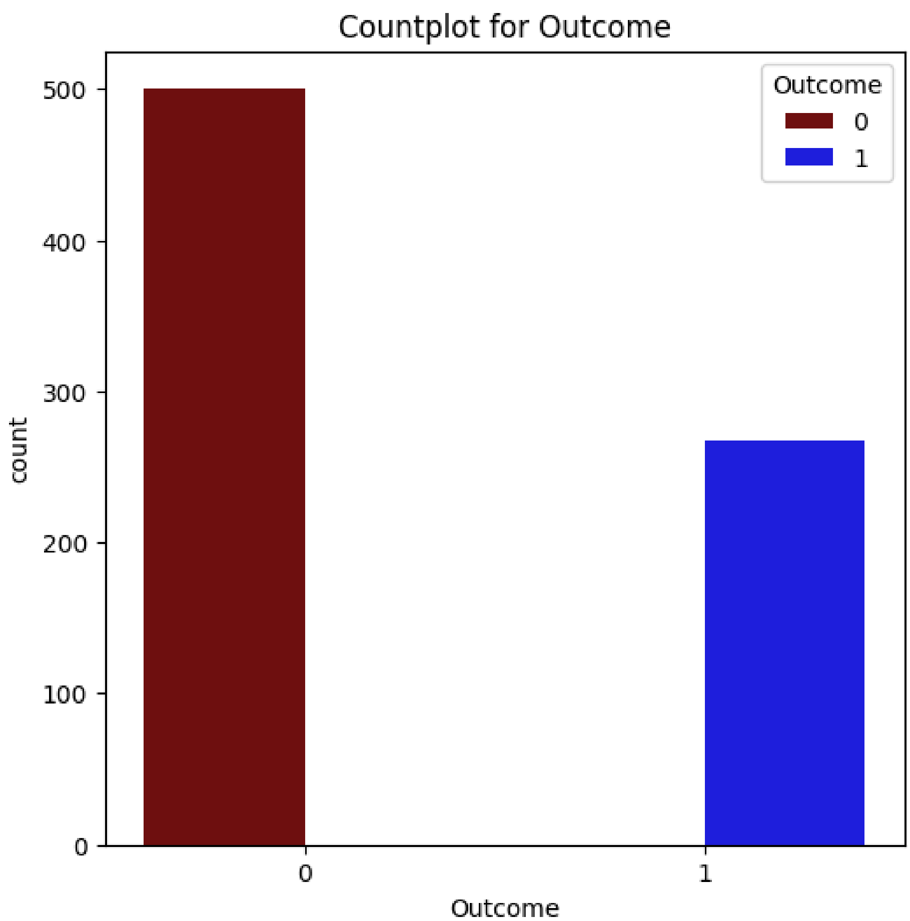
In [10]:
```
cat_cols = ['Outcome']
cont_cols = ['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','Diabetes
```

In [ ]:
```

```

Bivariate Analysis

Countplot

In [14]:
```
plt.figure(figsize=(20,20))
for i in range(0,len(cat_cols)):
    plt.subplot(3,3,i+1)
    sns.countplot(x=df[cat_cols[i]],hue= df['Outcome'],palette=['maroon','blue'])

    plt.title(f'Countplot for {cat_cols[i]}')
plt.show()
```

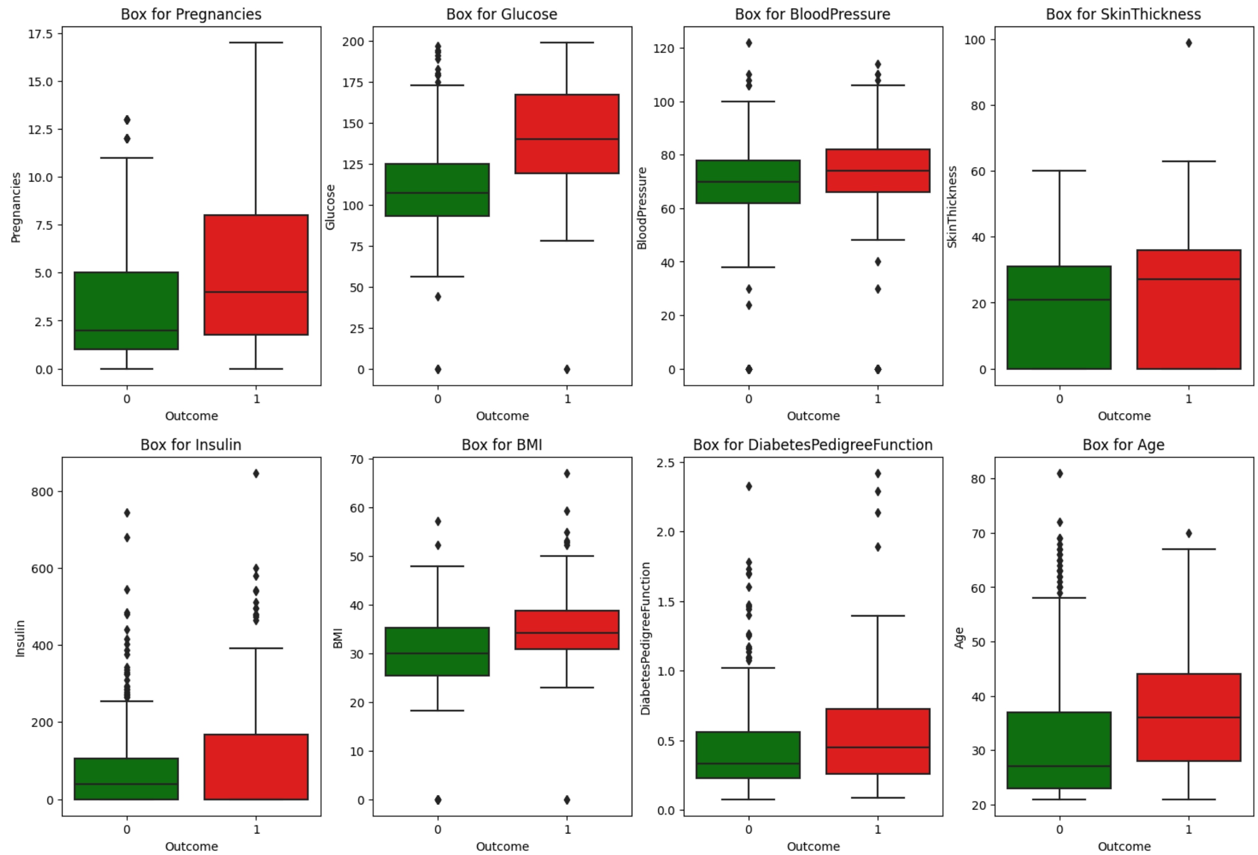


Boxplot - cont vs target

In [15]:
```
print(cont_cols)
```

```
['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedig
reeFunction', 'Age']
```

In [23]:
```
plt.figure(figsize=(18,12))
for i in range(0,len(cont_cols)):
    plt.subplot(2,4,i+1)
    sns.boxplot(y=df[cont_cols[i]],x=df['Outcome'],palette=['green','red'])
    plt.title(f'Box for {cont_cols[i]}')
plt.show()
```



Inferences:

1. Some people dont have diabetes but their insulin levels are extremely high as observed by outliers.
2. Diebetes Pedigree Function also is very imbalanced and scattered for non diabetic women.
3. Typically beyond 55 diabetes is common among women but some outliers do lie in non diabetic zone.
4. Women with less than 5 pregnancies, predominently ones with only 2 preganancies are less likely to get diabetes and as number of pregnancies increases the chances of diabetes increases.
5. As skin tickness increases that is as fat increases the likeliness of diabetes increases.
6. Women with high BMI are highly likely to get diabetes.

In [19]:
```
df.columns
```

Out[19]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

In [24]:
```
r1 = df.groupby('Outcome')[['Age','Glucose','Insulin','BMI']].agg(['min','max','mean'])
r1
```

Out[24]:

	Age			Glucose			Insulin			BMI		
	min	max	mean	min	max	mean	min	max	mean	min	max	mean
Outcome												
0	21	81	31.190000	0	197	109.980000	0	744	68.792000	0.0	57.3	30.304200
1	21	70	37.067164	0	199	141.257463	0	846	100.335821	0.0	67.1	35.142537

In [25]:
```
cont_cols
```

Out[25]:
```
['Pregnancies',
 'Glucose',
 'BloodPressure',
 'SkinThickness',
 'Insulin',
 'BMI',
 'DiabetesPedigreeFunction',
 'Age']
```

In [27]:
```
r2 = df.groupby('Outcome').agg({'Age':['mean','median'],
                               'DiabetesPedigreeFunction':['min','max'],
                               'Pregnancies':['min','max','mean']})
r2
```

Out[27]:

	Age		DiabetesPedigreeFunction		Pregnancies		
	mean	median	min	max	min	max	mean
Outcome							
0	31.190000	27.0	0.078	2.329	0	13	3.298000
1	37.067164	36.0	0.088	2.420	0	17	4.865672

Find Age_bins based mean cholestrol for each target. use Pivot_table

In [28]:
```
df['Age'].describe()  #where have we found age bins based mean????
```

Out[28]:
```
count    768.000000
mean      33.240885
std       11.760232
min       21.000000
25%       24.000000
50%       29.000000
75%       41.000000
max       81.000000
Name: Age, dtype: float64
```

In [29]:
```
# Binning
df['Age_bins']  = pd.cut(df['Age'],bins=list(range(25,85,5)))
df['Age_bins'].value_counts()
```

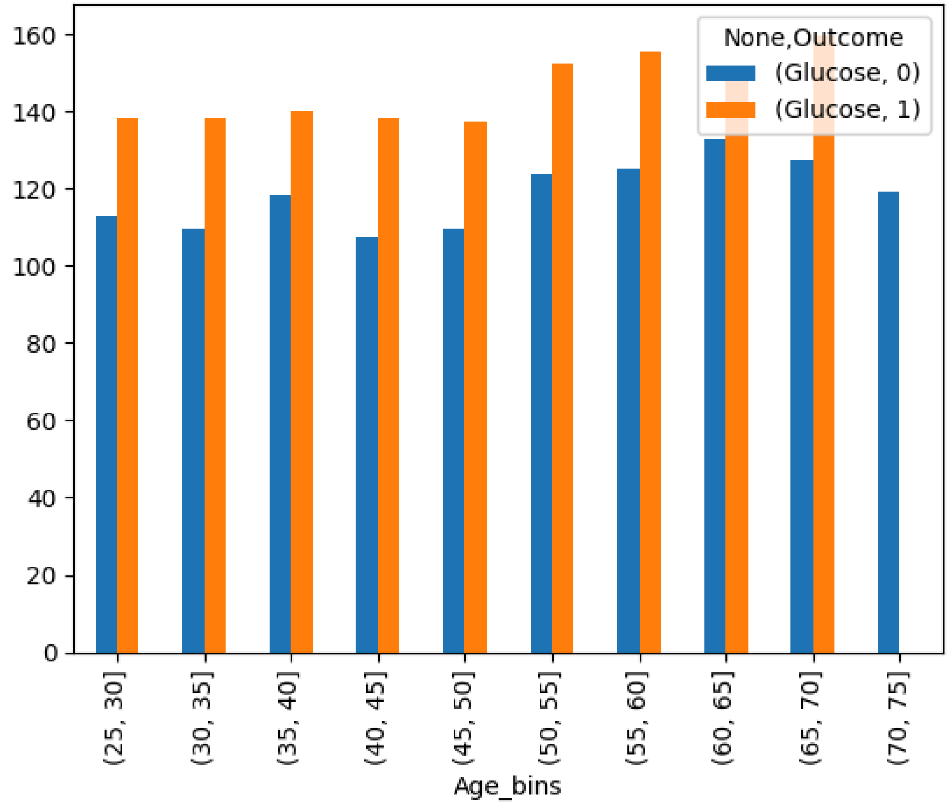
Out[29]:
```
(25, 30]    150
(30, 35]     81
(35, 40]     76
(40, 45]     76
(45, 50]     37
(50, 55]     31
(55, 60]     23
(60, 65]     14
(65, 70]     11
(70, 75]      1
(75, 80]      0
Name: Age_bins, dtype: int64
```

In [30]:
```
pt1 = pd.pivot_table(data=df,columns=['Outcome'],index=['Age_bins'],values=['Glucose'])
pt1  # default agg used is mean
```

Out[30]:

	Glucose	
Outcome	**0**	**1**
Age_bins		
(25, 30]	112.704762	138.111111
(30, 35]	109.725000	138.243902
(35, 40]	118.463415	139.885714
(40, 45]	107.187500	138.045455
(45, 50]	109.529412	137.300000
(50, 55]	123.800000	152.476190
(55, 60]	125.153846	155.500000
(60, 65]	132.909091	149.333333
(65, 70]	127.142857	159.750000
(70, 75]	119.000000	NaN

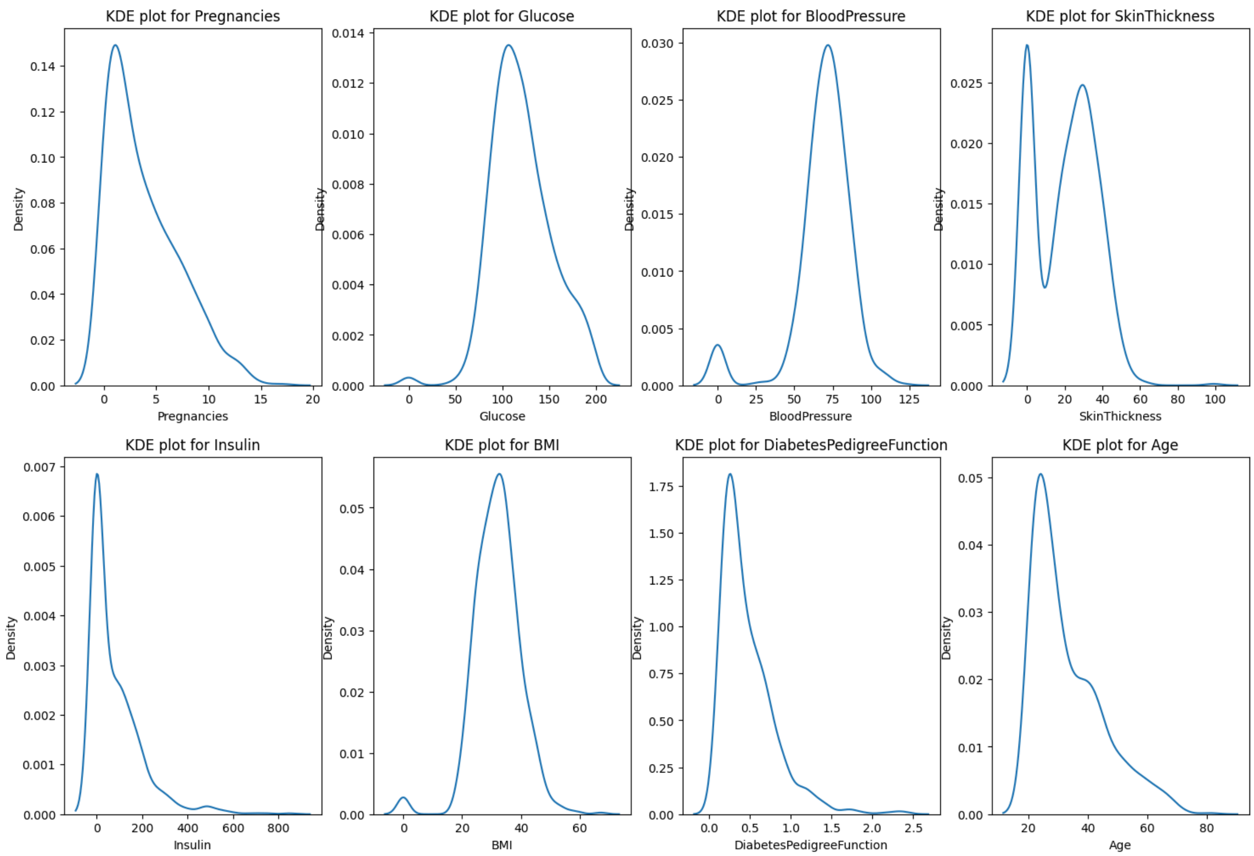
In [31]:
```
pt1.plot(kind='bar')
plt.show()
```



Inferences:

1. After age of 50 a tremendous hike in glucose is evidshowing ent among both diabetic and non diabetic patients indicating buiding of insulin resistense. .

In [33]:
```
plt.figure(figsize=(18,12))
for i in range(0,len(cont_cols)):
    plt.subplot(2,4,i+1)
    sns.kdeplot(x=df[cont_cols[i]])
    plt.title(f'KDE plot for {cont_cols[i]}')
plt.show()
```



Correlation

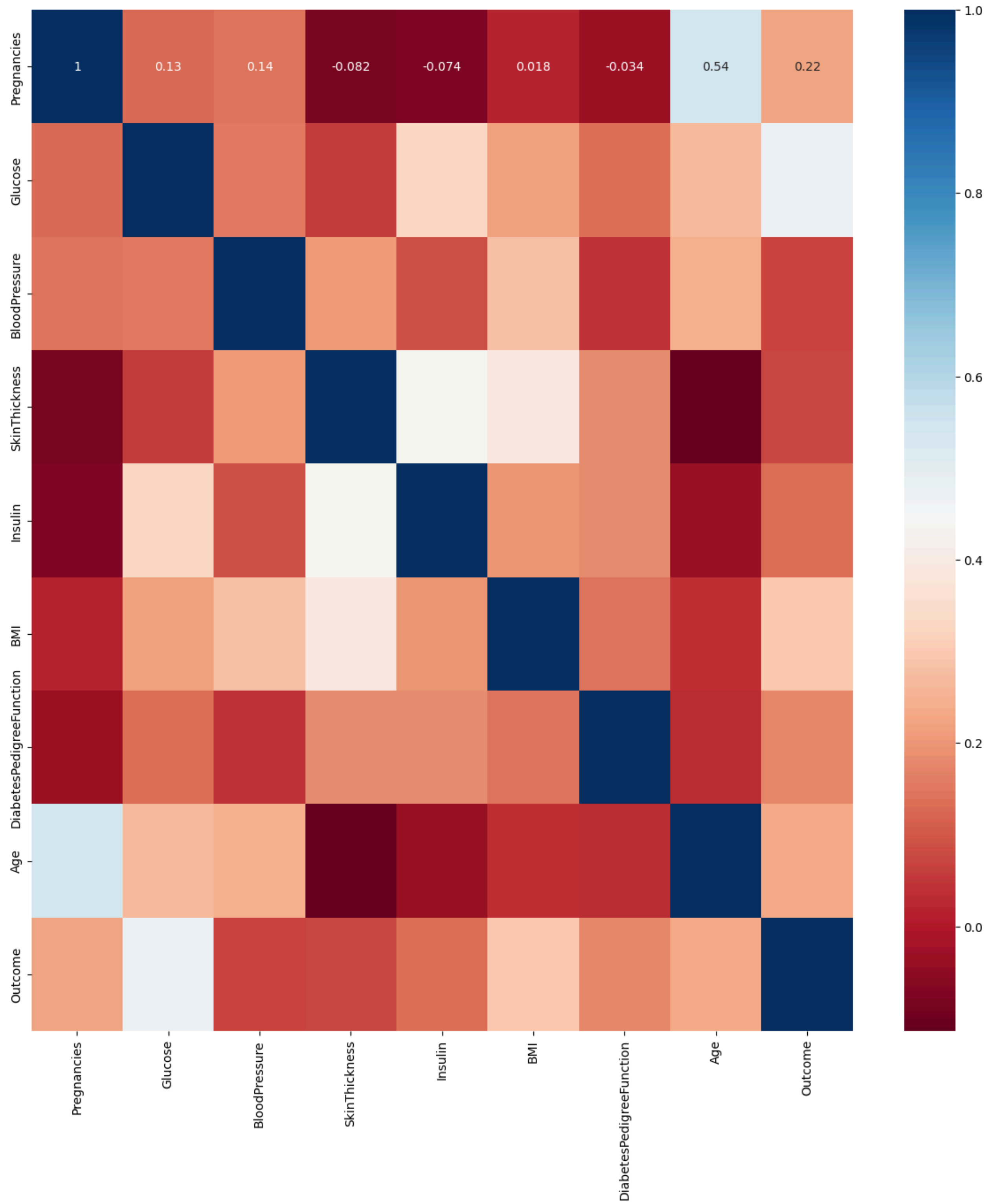
In [34]:
```
df[cont_cols].head()
```

Out[34]:

	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 [35]:
```
corr = df.corr()

plt.figure(figsize=(15,15))
sns.heatmap(corr,annot=True,cmap='RdBu')
plt.show()
```

```
C:\Users\win 8.1\AppData\Local\Temp\ipykernel_19692\3849691348.py:1: FutureWarning: The defau
lt value of numeric_only in DataFrame.corr is deprecated. In a future version, it will defaul
t to False. Select only valid columns or specify the value of numeric_only to silence this wa
rning.
  corr = df.corr()
```



Inference

Highly correlated features are not present

Outlier Treatment

In [36]:
```
a = df[cont_cols].describe(percentiles=[0.01,0.02,0.05,0.95,0.97,0.98,0.988]).T
a = a.iloc[:,3:]
a
```

Out[36]:

	min	1%	2%	5%	50%	95%	97%	98%	98.8'
Pregnancies	0.000	0.00000	0.00000	0.00000	3.0000	10.00000	11.00000	12.00000	13.00000
Glucose	0.000	57.00000	69.02000	79.00000	117.0000	181.00000	187.99000	192.32000	195.00000
BloodPressure	0.000	0.00000	0.00000	38.70000	72.0000	90.00000	94.99000	99.32000	105.59200
SkinThickness	0.000	0.00000	0.00000	0.00000	23.0000	44.00000	46.00000	48.00000	50.00000
Insulin	0.000	0.00000	0.00000	0.00000	30.5000	293.00000	369.90000	470.94000	495.00000
BMI	0.000	0.00000	19.16800	21.80000	32.0000	44.39500	46.10000	47.52600	49.67960
DiabetesPedigreeFunction	0.078	0.09468	0.11902	0.14035	0.3725	1.13285	1.25793	1.39066	1.57470
Age	21.000	21.00000	21.00000	21.00000	29.0000	58.00000	62.00000	64.66000	66.00000

In [37]:
```
def outlier_treatment(x):
    x = x.clip(upper=x.quantile(0.99))
    x = x.clip(lower=x.quantile(0.01))
    return x
```

In [38]:
```
df1 = df.copy()
```

In [39]:
```
df[cont_cols] = df[cont_cols].apply(outlier_treatment)
```

In [40]:
```
a = df[cont_cols].describe(percentiles=[0.01,0.02,0.05,0.95,0.97,0.98,0.99]).T
a = a.iloc[:,3:]
a
```

Out[40]:

	min	1%	2%	5%	50%	95%	97%	98%	
Pregnancies	0.00000	0.000000	0.00000	0.00000	3.0000	10.00000	11.00000	12.00000	13.0(
Glucose	57.00000	57.000000	69.02000	79.00000	117.0000	181.00000	187.99000	192.32000	196.0(
BloodPressure	0.00000	0.000000	0.00000	38.70000	72.0000	90.00000	94.99000	99.32000	106.0(
SkinThickness	0.00000	0.000000	0.00000	0.00000	23.0000	44.00000	46.00000	48.00000	51.1(
Insulin	0.00000	0.000000	0.00000	0.00000	30.5000	293.00000	369.90000	470.94000	513.2(
BMI	0.00000	0.000000	19.16800	21.80000	32.0000	44.39500	46.10000	47.52600	50.2(
DiabetesPedigreeFunction	0.09468	0.095564	0.11902	0.14035	0.3725	1.13285	1.25793	1.39066	1.6(
Age	21.00000	21.000000	21.00000	21.00000	29.0000	58.00000	62.00000	64.66000	67.0(

Select x and y

In [41]:
```
df.columns
```

Out[41]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome', 'Age_bins'],
      dtype='object')
```

In [42]:
```
x = df.drop(['Outcome', 'Age_bins'],axis=1)
y = df['Outcome']
print(x.shape)
print(y.shape)
```

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

Split data into train and test

In [43]:
```
from sklearn.model_selection import train_test_split
```

In [44]:
```
x_train,x_test,y_train,y_test  = train_test_split(x,y,test_size=0.3,random_state=42)
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(537, 8)
(231, 8)
(537,)
(231,)
```

Function to evalaute model

In [45]:
```
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
from sklearn.metrics import precision_score,recall_score
```

In [46]:
```
def eval_model(ytest,ypred):
    cm = confusion_matrix(ytest,ypred)
    cr = classification_report(ytest,ypred)
    print('Confusion Matrix\n',cm)
    print('Classification Report\n',cr)

def gen_res(model,xtrain,xtest,ytrain,ytest,ypred,model_name):
    eval_model(ytest,ypred)
    train_acc = model.score(xtrain,ytrain)  # Train Acc
    test_acc = model.score(xtest,ytest)     # Test Acc
    pre1 = precision_score(ytest,ypred)  # pre score = 1
    rec1 = recall_score(ytest,ypred)     # rec score = 1
    res = pd.DataFrame({'Train Acc':train_acc,'Test Acc':test_acc,
                       'Pre1':pre1,'Rec1':rec1},index=[model_name])
    return res
```

Train the model

In [47]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
```

Model-1 : DT1

In [48]:
```
dt1 = DecisionTreeClassifier(criterion='gini',random_state=25)
dt1.fit(x_train,y_train)
```

Out[48]:
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=25)
```

In [49]:
```
ypred_dt1 = dt1.predict(x_test)
dt1_res = gen_res(dt1,x_train,x_test,y_train,y_test,ypred_dt1,'DT1(gini)')
dt1_res
```

```
Confusion Matrix
 [[109  42]
 [ 29  51]]
Classification Report
               precision    recall  f1-score   support

           0       0.79      0.72      0.75       151
           1       0.55      0.64      0.59        80

    accuracy                           0.69       231
   macro avg       0.67      0.68      0.67       231
weighted avg       0.71      0.69      0.70       231
```

Out[49]:

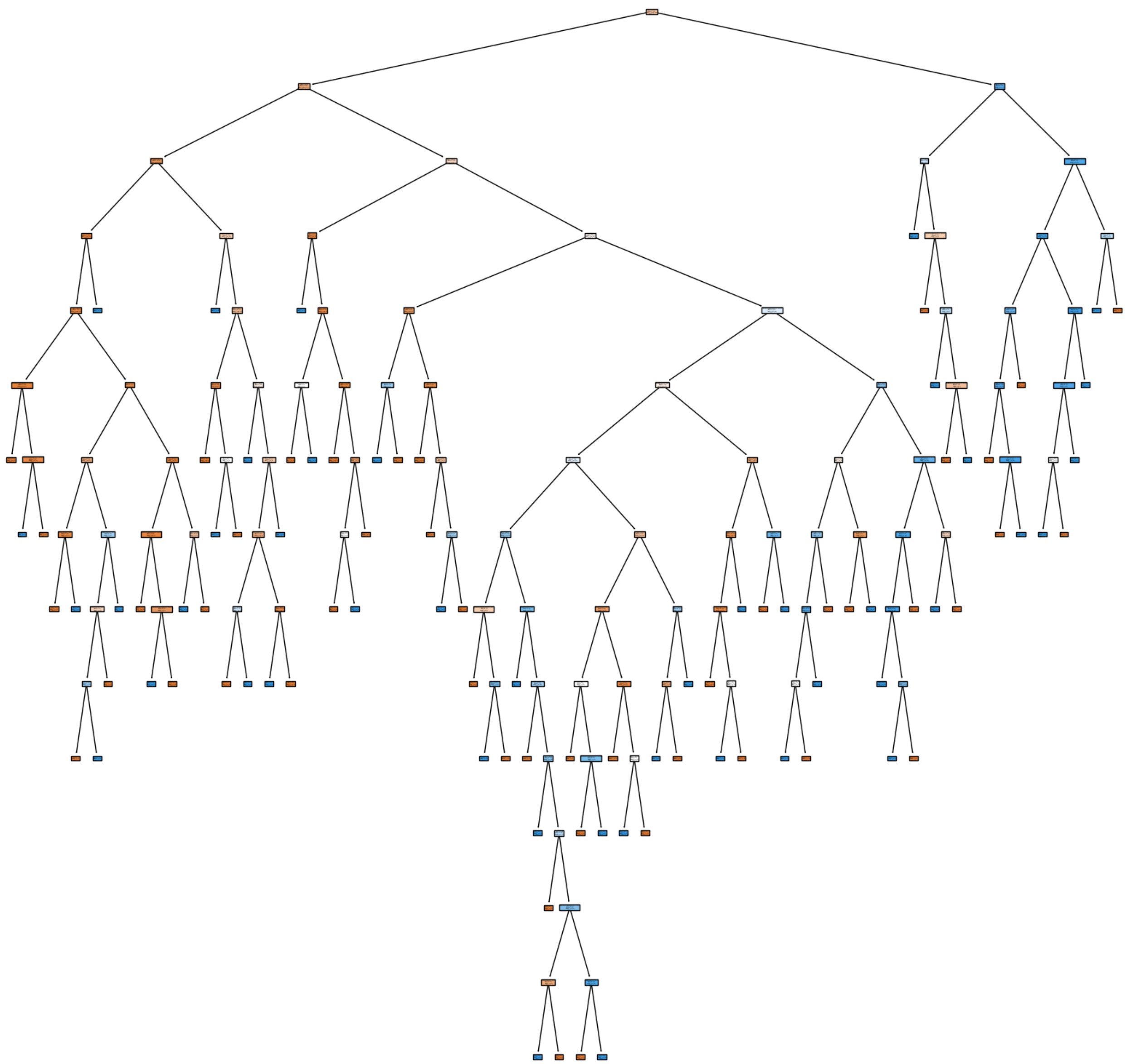
	Train Acc	Test Acc	Pre1	Rec1
DT1(gini)	1.0	0.692641	0.548387	0.6375

Inference

Overfitting exists

In [50]:
```
from sklearn.tree import plot_tree
```

In [51]:
```
cn = ['0','1']
plt.figure(figsize=(20,20))
plot_tree(dt1,feature_names=x_train.columns,class_names=cn,filled=True)
plt.show()
```



Model-2 : DT2

In [52]:
```
dt2 = DecisionTreeClassifier(criterion='gini',max_depth=6,min_samples_split=10,random_state=25
dt2.fit(x_train,y_train)
```

Out[52]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=6, min_samples_split=10, random_state=25)
```

In [53]:
```
ypred_dt2 = dt2.predict(x_test)
dt2_res =  gen_res(dt2,x_train,x_test,y_train,y_test,ypred_dt2,'DT2(gini,md=6,mss=10)')
dt2_res
```

```
Confusion Matrix
 [[110  41]
 [ 29  51]]
Classification Report
               precision    recall  f1-score   support

           0       0.79      0.73      0.76       151
           1       0.55      0.64      0.59        80

    accuracy                           0.70       231
   macro avg       0.67      0.68      0.68       231
weighted avg       0.71      0.70      0.70       231
```

Out[53]:

	Train Acc	Test Acc	Pre1	Rec1
DT2(gini,md=6,mss=15)	0.837989	0.69697	0.554348	0.6375

Model-3 : DT3

In [54]:
```
dt3 = DecisionTreeClassifier(criterion='entropy',max_depth=10,
                             min_samples_split=20,random_state=25)
dt3.fit(x_train,y_train)
```

Out[54]:
```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=10, min_samples_split=20,
                       random_state=25)
```

In [81]:
```
ypred_dt3 = dt3.predict(x_test)
dt3_res =  gen_res(dt3,x_train,x_test,y_train,y_test,ypred_dt2,'DT3(gini,md=10,mss=20)')
dt3_res
```

```
Confusion Matrix
 [[110  41]
 [ 29  51]]
Classification Report
               precision    recall  f1-score   support

           0       0.79      0.73      0.76       151
           1       0.55      0.64      0.59        80

    accuracy                           0.70       231
   macro avg       0.67      0.68      0.68       231
weighted avg       0.71      0.70      0.70       231
```

Out[81]:

	Train Acc	Test Acc	Pre1	Rec1
DT3(gini,md=10,mss=20)	0.86406	0.718615	0.554348	0.6375

Inference

By changing the hyperparameters(criterion,max_depth,min_samples_split), the performace of the model changes. So we need to tune the hyperparameters

HyperParameter Tuning

1. GridSearchCV
   a) It consumes a lot of time. Time inefficient.
   b) It works on all combination of hyperparameters and then it returns the best set of hyperparemeters that generated the best results on different splits.
2. RandomizedSearchCV
   a) It consumes a comparatively less time. Time efficient.
   b) It works on all random subset of hyperparameters and then it returns the best set of hyperparemeters that generated the best results.

In [56]:
```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

In [61]:
```
hparams = {'criterion':['gini','entropy'],
          'max_depth':[8,9,10,11],
          'min_samples_split':[15,20,22,25]}

# 2 * 4 * 4 = 32
```

GridSearchCV

In [62]:
```
dt_model = DecisionTreeClassifier(random_state=0)

gs1 = GridSearchCV(dt_model,param_grid=hparams,scoring='accuracy',cv=5)
gs1.fit(x_train,y_train)
```

Out[62]:
```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

In [63]:
```
print(gs1.best_params_)
print(gs1.best_estimator_)
print(gs1.best_score_)
```

```
{'criterion': 'gini', 'max_depth': 10, 'min_samples_split': 22}
DecisionTreeClassifier(max_depth=10, min_samples_split=22, random_state=0)
0.7466424368293527
```

Analysis of Grid SearchCV Results

In [64]:
```
gs1_res = pd.DataFrame(gs1.cv_results_)
gs1_res.head(2)
```

Out[64]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_criterion	param_max_depth	param_min_sam
0	0.008980	0.003364	0.002066	0.001386	gini	8	
1	0.006252	0.006362	0.001799	0.000979	gini	8	

In [65]:
```
print(gs1_res.shape)
print(gs1_res.columns)
```

```
(32, 16)
Index(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time',
       'param_criterion', 'param_max_depth', 'param_min_samples_split',
       'params', 'split0_test_score', 'split1_test_score', 'split2_test_score',
       'split3_test_score', 'split4_test_score', 'mean_test_score',
       'std_test_score', 'rank_test_score'],
      dtype='object')
```

In [66]:
```
gs1_res = gs1_res[['param_criterion', 'param_max_depth', 'param_min_samples_split','params',
                  'mean_test_score','rank_test_score']]
gs1_res.head()
```

Out[66]:

	param_criterion	param_max_depth	param_min_samples_split	params	mean_test_score	rank_test_score
0	gini	8	15	{'criterion': 'gini', 'max_depth': 8, 'min_sam...	0.731810	27
1	gini	8	20	{'criterion': 'gini', 'max_depth': 8, 'min_sam...	0.741035	19
2	gini	8	22	{'criterion': 'gini', 'max_depth': 8, 'min_sam...	0.742904	13
3	gini	8	25	{'criterion': 'gini', 'max_depth': 8, 'min_sam...	0.741018	20
4	gini	9	15	{'criterion': 'gini', 'max_depth': 9, 'min_sam...	0.735549	25

In [67]:
```
gs1_res.sort_values('rank_test_score').head()  # asc order or rank
```

Out[67]:

	param_criterion	param_max_depth	param_min_samples_split	params	mean_test_score	rank_test_score
10	gini	10	22	{'criterion': 'gini', 'max_depth': 10, 'min_sa...	0.746642	1
14	gini	11	22	{'criterion': 'gini', 'max_depth': 11, 'min_sa...	0.746642	1
25	entropy	10	20	{'criterion': 'entropy', 'max_depth': 10, 'min...	0.744877	3
26	entropy	10	22	{'criterion': 'entropy', 'max_depth': 10, 'min...	0.744843	4
5	gini	9	20	{'criterion': 'gini', 'max_depth': 9, 'min_sam...	0.744773	5

In [68]:
```
print(gs1.best_params_)
# {'criterion': 'entropy', 'max_depth': 5, 'min_samples_split': 10}
# {'criterion': 'entropy', 'max_depth': 5, 'min_samples_split': 12}
```

```
{'criterion': 'gini', 'max_depth': 10, 'min_samples_split': 22}
```

Model 4 : DT4 (based on GridSearchCV Results)

In [69]:
```
dt4 = DecisionTreeClassifier(**gs1.best_params_)
dt4.fit(x_train,y_train)
```

Out[69]:

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=10, min_samples_split=22)
```

In [80]:
```
ypred_dt4 = dt4.predict(x_test)
dt4_res = gen_res(dt4,x_train,x_test,y_train,y_test,ypred_dt4,'DT4_GS1(gini,md=10,mss=22)')
dt4_res
```

```
Confusion Matrix
 [[112  39]
 [ 29  51]]
Classification Report
               precision    recall  f1-score   support

           0       0.79      0.74      0.77       151
           1       0.57      0.64      0.60        80

    accuracy                           0.71       231
   macro avg       0.68      0.69      0.68       231
weighted avg       0.72      0.71      0.71       231
```

Out[80]:

	Train Acc	Test Acc	Pre1	Rec1
DT4_GS1(gini,md=10,mss=22)	0.886406	0.705628	0.566667	0.6375

Randomized SearchCV

In [71]:
```
dt_model1 = DecisionTreeClassifier(random_state=0)
rs1 = RandomizedSearchCV(dt_model1,param_distributions=hparams,scoring='accuracy',cv=5,
                        n_iter=20)
# n_iter = number of random cobintaion to select best hparams from
rs1.fit(x_train,y_train)
```

Out[71]:
```
RandomizedSearchCV
estimator: DecisionTreeClassifier
    DecisionTreeClassifier
```

In [72]:
```
print(rs1.best_params_)
print(rs1.best_estimator_)
print(rs1.best_score_)
```

```
{'min_samples_split': 22, 'max_depth': 11, 'criterion': 'gini'}
DecisionTreeClassifier(max_depth=11, min_samples_split=22, random_state=0)
0.7466424368293527
```

In [73]:
```
rs1_res = pd.DataFrame(rs1.cv_results_)
print(rs1_res.shape)
```

```
(20, 16)
```

Logestic Regression Reg

In [74]:
```
lr1 = LogisticRegression(max_iter=1000)
lr1.fit(x_train,y_train)
```

Out[74]:
```
LogisticRegression
LogisticRegression(max_iter=1000)
```

In [82]:
```
ypred_lr1 = lr1.predict(x_test)
lr1_res = gen_res(lr1,x_train,x_test,y_train,y_test,ypred_lr1,'LogReg(at threshold=0.5)')
```

```
Confusion Matrix
 [[120  31]
 [ 30  50]]
Classification Report
               precision    recall  f1-score   support

           0       0.80      0.79      0.80       151
           1       0.62      0.62      0.62        80

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

In [83]:
```
model_res = pd.concat([dt1_res,dt2_res,dt3_res,dt4_res,lr1_res])
model_res
```

Out[83]:

	Train Acc	Test Acc	Pre1	Rec1
DT1(gini)	1.000000	0.692641	0.548387	0.6375
DT2(gini,md=6,mss=15)	0.837989	0.696970	0.554348	0.6375
DT3(gini,md=10,mss=20)	0.864060	0.718615	0.554348	0.6375
DT4_GS1(gini,md=10,mss=22)	0.886406	0.705628	0.566667	0.6375
LogReg(at threshold=0.5)	0.787709	0.735931	0.617284	0.6250

In [84]:
```
print(ypred_lr1[:7])
```

```
[0 0 0 0 1 0 0]
```

In [85]:
```
from collections import Counter
```

In [86]:
```
print(Counter(y_test))
print(Counter(ypred_lr1))
```

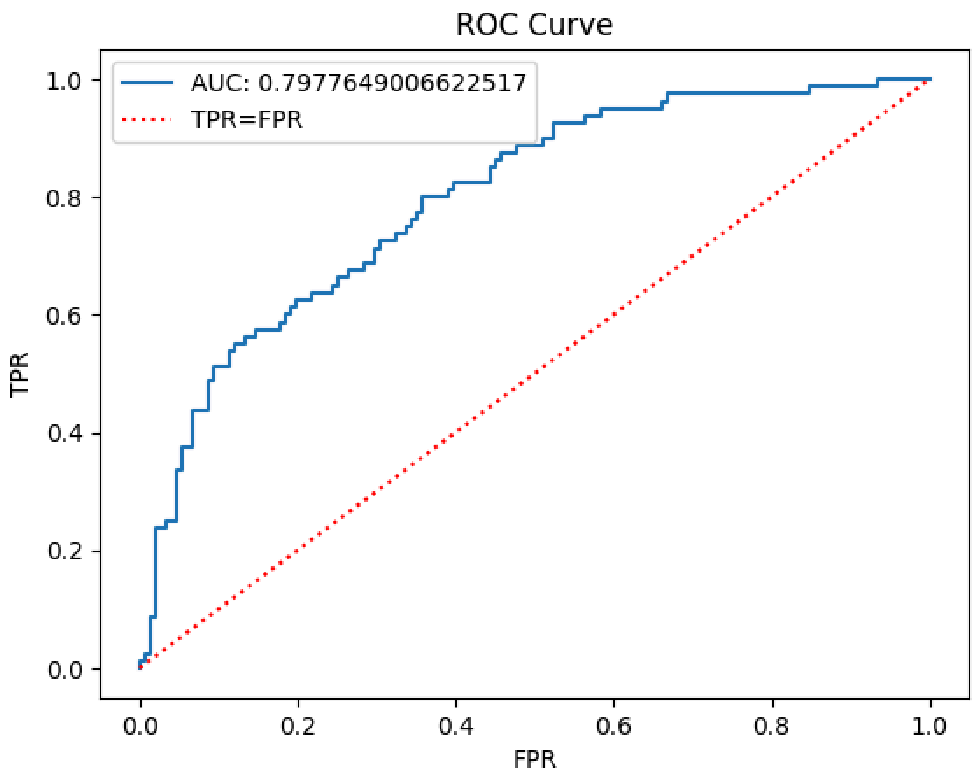
```
Counter({0: 151, 1: 80})
Counter({0: 150, 1: 81})
```

In [87]:
```
ypred_prob = lr1.predict_proba(x_test)
ypred_prob[:7]
```

Out[87]:
```
array([[0.74523542, 0.25476458],
       [0.81380271, 0.18619729],
       [0.88413607, 0.11586393],
       [0.86307712, 0.13692288],
       [0.49279184, 0.50720816],
       [0.5558228 , 0.4441772 ],
       [0.98851245, 0.01148755]])
```

In [88]:
```
from sklearn.metrics import roc_auc_score,roc_curve
```

In [89]:
```
fpr,tpr,thresh = roc_curve(y_test,ypred_prob[:,1])   # ROC curve
auc_score = roc_auc_score(y_test,ypred_prob[:,1])    # AUC_score
plt.plot(fpr,tpr,label='AUC: '+str(auc_score))
plt.plot([0,1],[0,1],color='red',linestyle='dotted',label='TPR=FPR')
plt.title('ROC Curve')
plt.xlabel('FPR')  # FP/(TN+FP)
plt.ylabel('TPR')  # TP/(TP+FN)
plt.legend()
plt.show()
```



In [90]:
```
print(len(thresh))
print(thresh)
```

```
89
[1.96881391 0.96881391 0.96860686 0.96442536 0.92093407 0.89650448
 0.89521527 0.83173868 0.8198793  0.81546155 0.81396697 0.78440072
 0.78145972 0.76525833 0.76388141 0.72376563 0.68892655 0.67136937
 0.66719663 0.6660234  0.64440928 0.63431059 0.62927243 0.62902754
 0.61536005 0.61059385 0.59724658 0.59216721 0.54410438 0.53764129
 0.527425   0.52456184 0.52375435 0.52252841 0.51963301 0.51110323
 0.47964227 0.46888283 0.42501636 0.42238628 0.42093033 0.39773673
 0.39467686 0.39086841 0.35888336 0.35451767 0.35039655 0.34352689
 0.33735942 0.33309661 0.31605668 0.31472408 0.30590853 0.30138273
 0.29893604 0.29102869 0.28996122 0.27168004 0.27059411 0.26196212
 0.25523813 0.25478572 0.25476458 0.25456667 0.23306517 0.22732781
 0.22625731 0.22153925 0.21731029 0.21672908 0.20473432 0.19965939
 0.17719553 0.17149037 0.15782293 0.15510836 0.13419347 0.13240101
 0.11586393 0.1141886  0.10277541 0.09819638 0.09502948 0.09275297
 0.05551583 0.05544609 0.02807519 0.02627662 0.0025315 ]
```

Best Threshhold

In [91]:
```
best_thresh1 = thresh[np.argmax(abs(tpr-fpr))]
print(best_thresh1)
```

```
0.26196212250220663
```

Generate Predictions at best threhsold

In [92]:
```
ypred_lr2 = np.where(ypred_prob[:,1]>best_thresh1,1,0)
print(ypred_lr2)
```

```
[0 0 0 0 1 1 0 1 1 1 0 1 1 0 0 1 0 0 1 1 0 0 1 0 1 1 0 0 1 0 1 1 1 1 1 1 1
 0 1 1 0 1 1 1 0 1 1 0 1 1 0 1 1 0 0 0 1 0 1 1 1 1 0 0 0 1 0 1 0 1 1 0 0 0
 0 1 0 0 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 1 1 1 1 0 1 0 1 0 1 1 1 0 0 1 0 1 0
 1 0 1 0 1 1 0 0 1 0 0 0 0 1 1 0 1 1 1 1 1 0 1 1 0 0 1 1 0 0 0 0 1 0 0 0 0
 1 1 0 1 1 0 0 1 1 1 1 0 1 1 0 0 0 1 0 1 1 1 1 0 1 1 1 0 1 0 0 1 1 1 1 1 1
 0 0 0 1 1 0 0 1 0 0 0 0 0 0 1 0 0 1 0 1 0 0 0 1 1 1 0 0 0 1 0 1 0 1 1 1 0
 0 0 0 1 1 0 1 0 0]
```

In [98]:
```
acc_lr2 = accuracy_score(y_test,ypred_lr2)
pre_lr2 = precision_score(y_test,ypred_lr2)  # pre_score for 1
rec_lr2 = recall_score(y_test,ypred_lr2)     # rec_score for 1

lr2_res = pd.DataFrame({'Pre1':pre_lr2,'Rec1':rec_lr2,'Test Acc':acc_lr2},
                       index=[f'LogReg(th={round(best_thresh1,3)})'])
lr2_res
```

Out[98]:

	Pre1	Rec1	Test Acc
LogReg(th=0.262)	0.538462	0.7875	0.692641

In [94]:
```
# Recall has increased
```

In [99]:
```
res = pd.concat([model_res,lr2_res])
res
```

Out[99]:

	Train Acc	Test Acc	Pre1	Rec1
DT1(gini)	1.000000	0.692641	0.548387	0.6375
DT2(gini,md=6,mss=15)	0.837989	0.696970	0.554348	0.6375
DT3(gini,md=10,mss=20)	0.864060	0.718615	0.554348	0.6375
DT4_GS1(gini,md=10,mss=22)	0.886406	0.705628	0.566667	0.6375
LogReg(at threshold=0.5)	0.787709	0.735931	0.617284	0.6250
LogReg(th=0.262)	NaN	0.692641	0.538462	0.7875

In [ ]:
```
# In diabetes detection our main focus shoud be in elimination false negatives so we can go wi
# the two logistc Regression results depending on the need to baalnce precion and recall.
```

Saving the Model

In [100]:
```
import pickle
```

In [101]:
```
pickle.dump(lr1,open('Diabetes.pkl','wb'))  # write binary
```

In [102]:
```
model = pickle.load(open('Diabetes.pkl','rb'))
```

In [ ]: