CP-2

February 3, 2024

0.1 HealthCare Capstone Project

Importing Required libraries

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Importing Required Dataset

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

Getting shape of the dataset

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

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

Getting info about datatype

[5]:
```
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
```

Checking top and bottom records

[6]:
```
df.head(2)
```

[6]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
```

[7]:
```
df.tail(2)
```

[7]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
766                     0.349   47        1
767                     0.315   23        0
```

Checking null values in dataset

[7]:
```
df.isna().sum()
```

[7]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

No null values in dataset

Values = 0 in feature columns (except pregnancies) means that value is missing and should be treated as null values

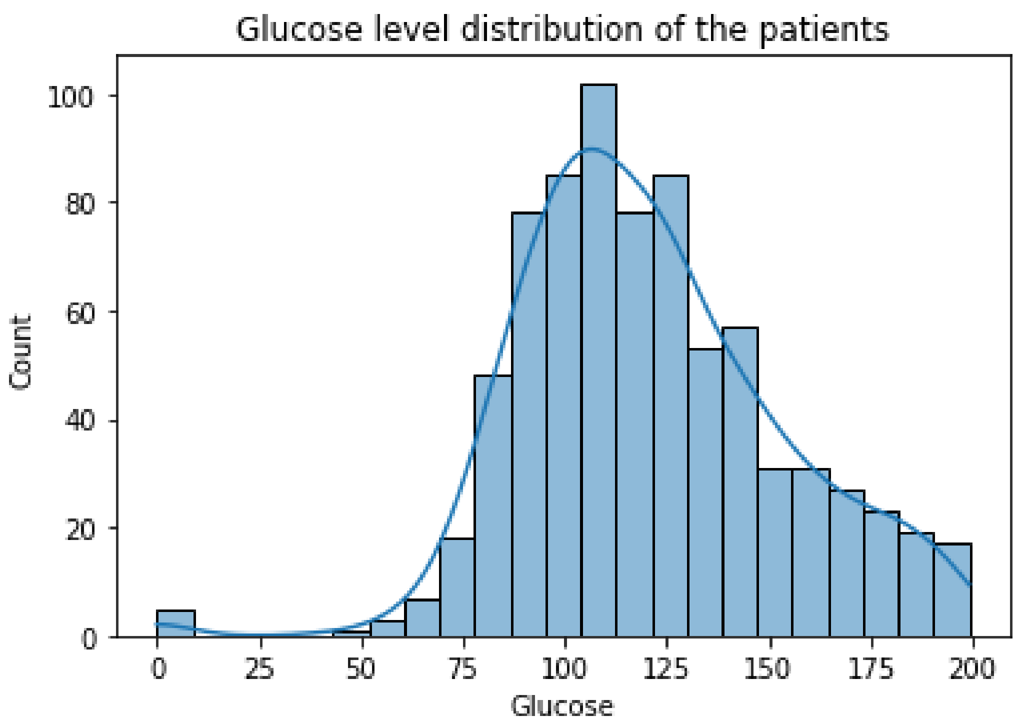
0.1.1 Checking '0' values in various columns wth Visualization

[8]:
```
(df.Glucose==0).sum()
```

[8]: 5

5 values are 0 in Glucose column

[9]:
```
#Glucose
sns.histplot(data=df.Glucose,kde=True)
plt.title('Glucose level distribution of the patients')
plt.show()
plt.savefig('Glucose.png')
```




```
<Figure size 432x288 with 0 Axes>
```

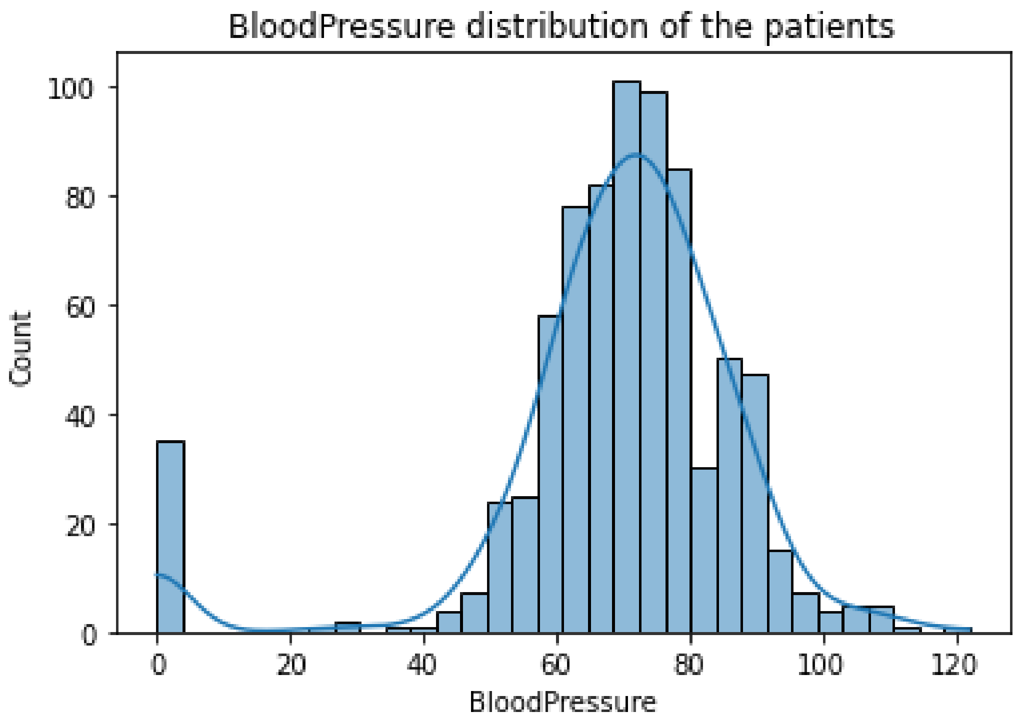
Checking '0' values in BloodPressure columns

[10]:
```
(df.BloodPressure==0).sum()
```

[10]: 35

35 values are 0 in BloodPressure column

[11]:
```python
#BloodPressure
sns.histplot(data=df.BloodPressure,kde=True)
plt.title('BloodPressure distribution of the patients')
plt.show()
plt.savefig('BloodPressure.png')
```




```
<Figure size 432x288 with 0 Axes>
```

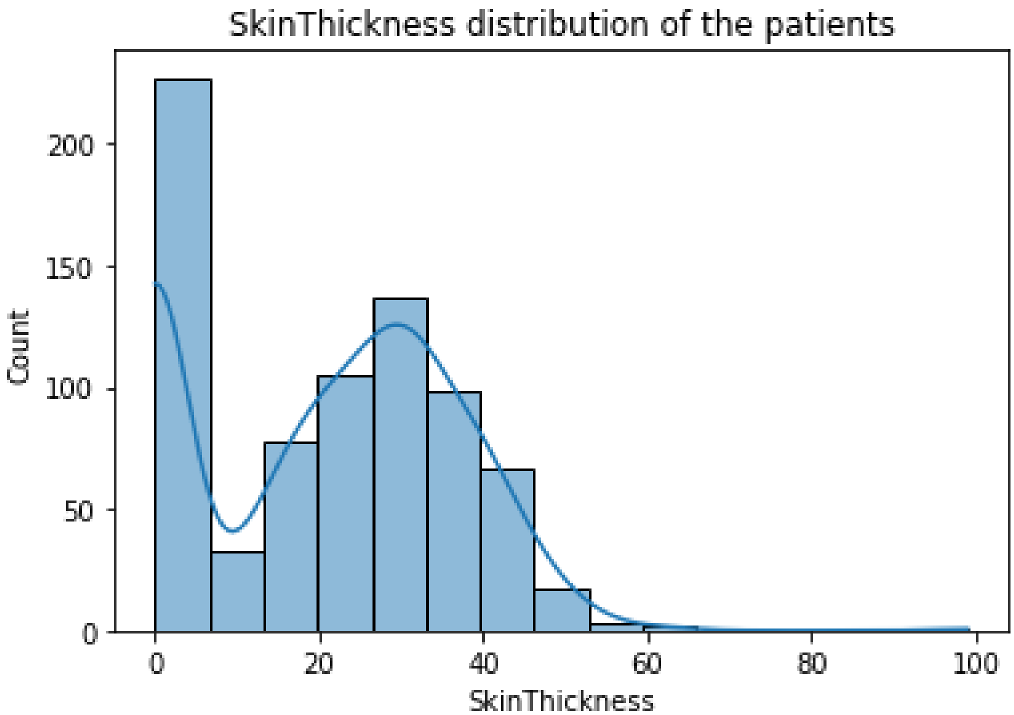
Checking '0' values in SkinThickness column

[12]:
```python
(df.SkinThickness==0).sum()
```

[12]: 227

227 values are 0 in SkinThickness column

[13]:
```python
#SkinThickness
sns.histplot(data=df.SkinThickness,kde=True)
plt.title('SkinThickness distribution of the patients')
plt.show()
plt.savefig('SkinThickness.png')
```




```
<Figure size 432x288 with 0 Axes>
```

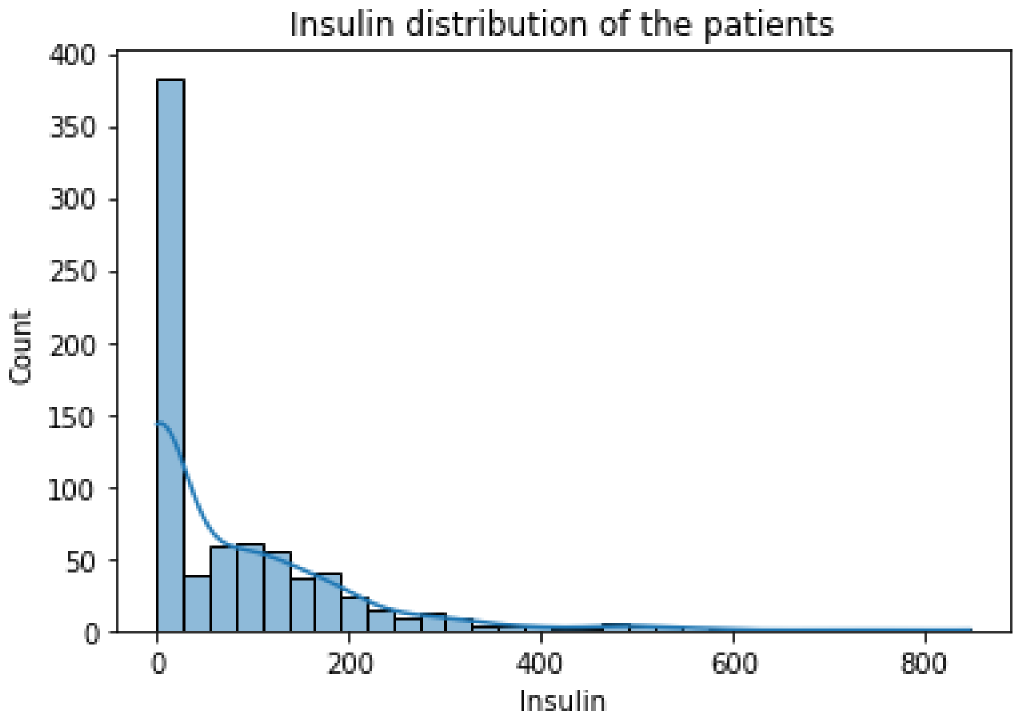
Checking '0' values in Insulin column

[14]:
```
(df.Insulin==0).sum()
```

[14]:
```
374
```

374 values are 0 in Insulin column

[15]:
```
#Insulin
sns.histplot(data=df.Insulin,kde=True)
plt.title('Insulin distribution of the patients')
plt.show()
plt.savefig('Insulin.png')
```




```
<Figure size 432x288 with 0 Axes>
```

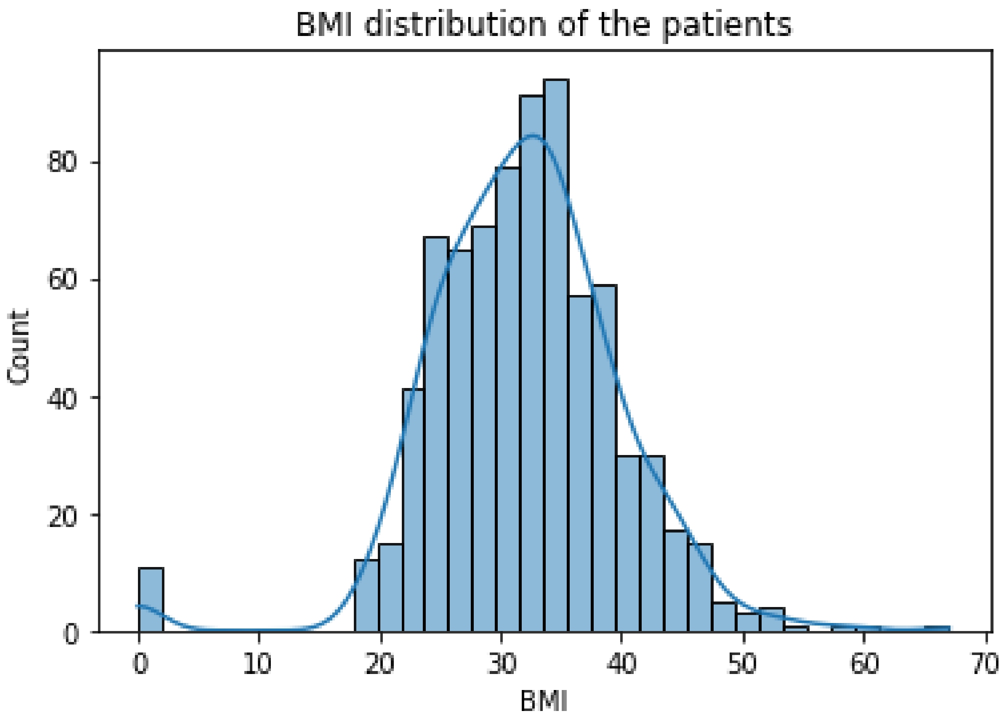
Checking '0' values in Insulin column

[16]:
```
(df.BMI==0).sum()
```

[16]:
```
11
```

11 values are 0 in Insulin column

[17]:
```
#BMI
sns.histplot(data=df.BMI,kde=True)
plt.title('BMI distribution of the patients')
plt.show()
plt.savefig('BMI.png')
```

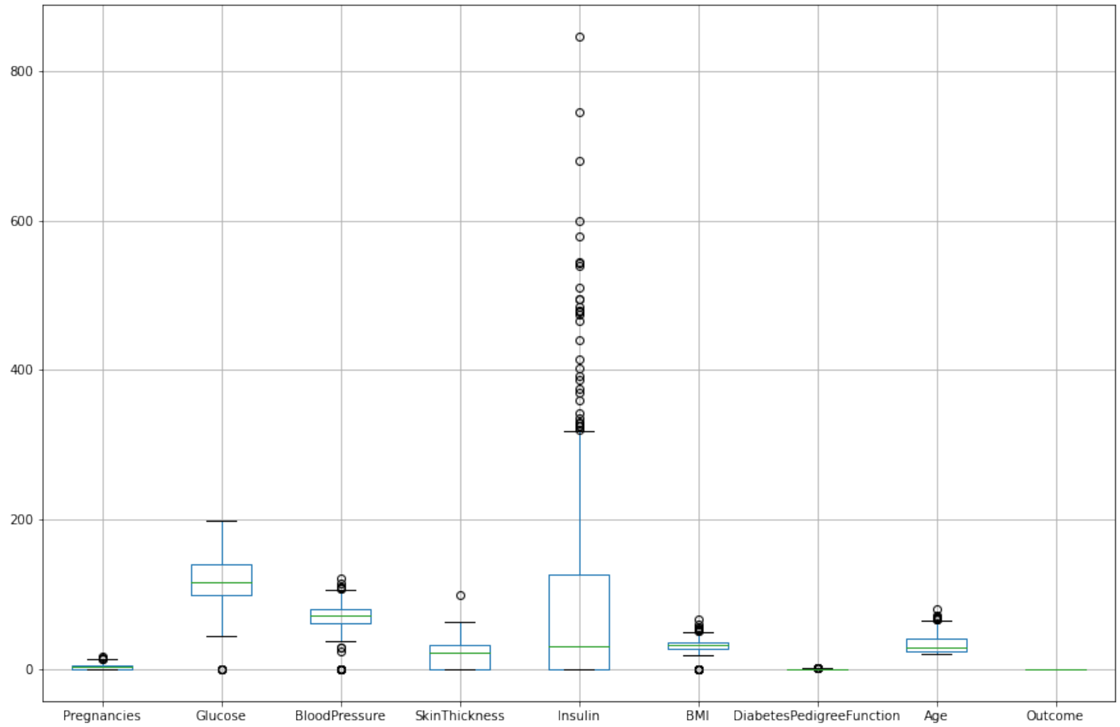


<Figure size 432x288 with 0 Axes>

0.1.2 Checking outliers present in dataset

[18]:
```
df.boxplot(figsize=(15,10))
```

[18]: <AxesSubplot: >



Insulin having huge outlier present as '0' which is missing values

0.1.3 Treating missing values

Importing simple imputer to replace 0 with the median of column

[19]:
```
from sklearn.impute import SimpleImputer
impute=SimpleImputer(missing_values=0,strategy='median') #0 is treated as the␣
↪missing value
```

Creating new dataframe with imputed values

[20]:
```
imputed=pd.DataFrame(impute.
↪fit_transform(df[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']]),columns=('Gl
imputed
```

[20]:

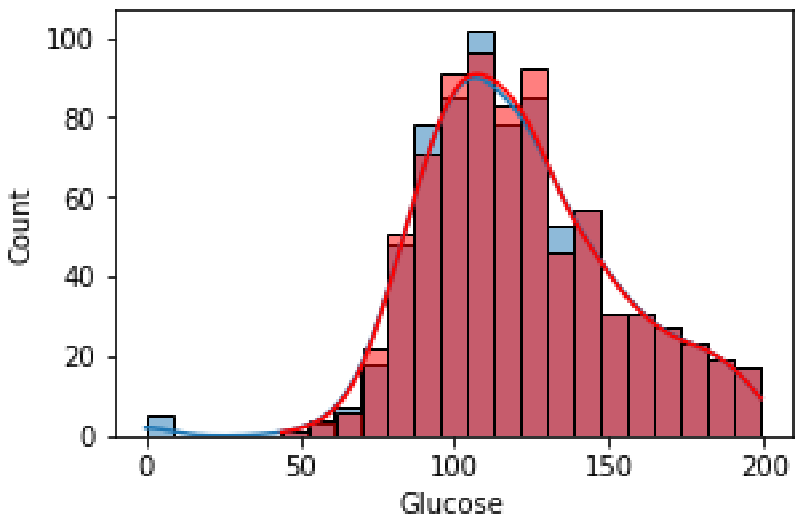
	Glucose	BloodPressure	SkinThickness	Insulin	BMI
0	148.0	72.0	35.0	125.0	33.6
1	85.0	66.0	29.0	125.0	26.6
2	183.0	64.0	29.0	125.0	23.3
3	89.0	66.0	23.0	94.0	28.1
4	137.0	40.0	35.0	168.0	43.1
..	…	…	…	…	…
763	101.0	76.0	48.0	180.0	32.9
764	122.0	70.0	27.0	125.0	36.8

```
765    121.0            72.0            23.0   112.0  26.2
766    126.0            60.0            29.0   125.0  30.1
767     93.0            70.0            31.0   125.0  30.4

[768 rows x 5 columns]
```

comparing imputed and original data with histplot

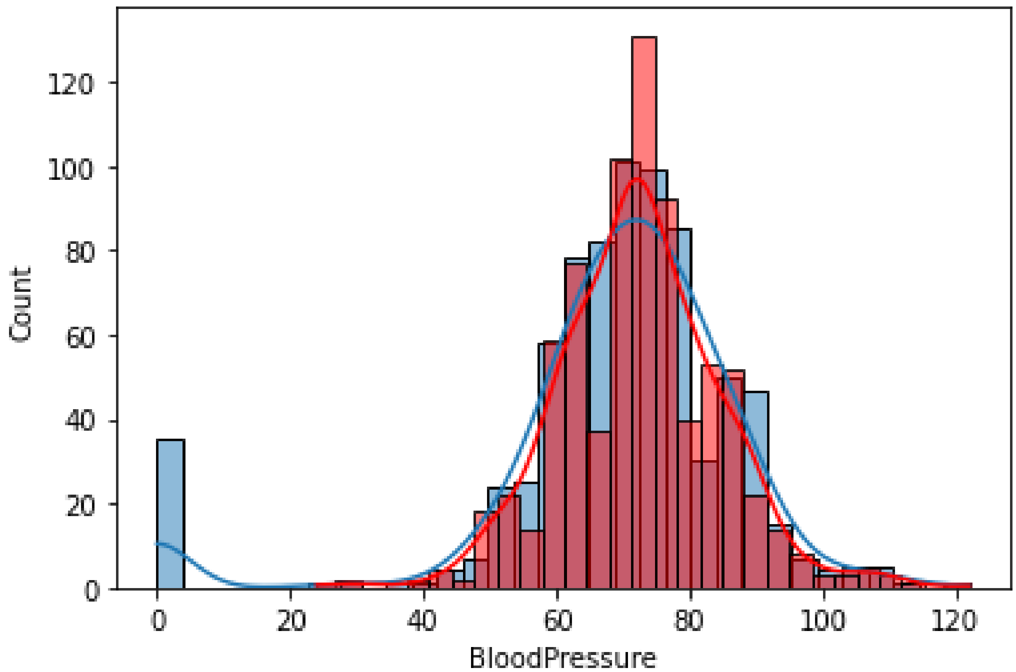
[21]:
```
plt.figure(figsize=(10,10))
plt.subplot(321)
sns.histplot(data=df.Glucose,kde=True)
plt.subplot(321)
sns.histplot(data=imputed.Glucose,color='r',kde=True)
```

[21]: <AxesSubplot: xlabel='Glucose', ylabel='Count'>



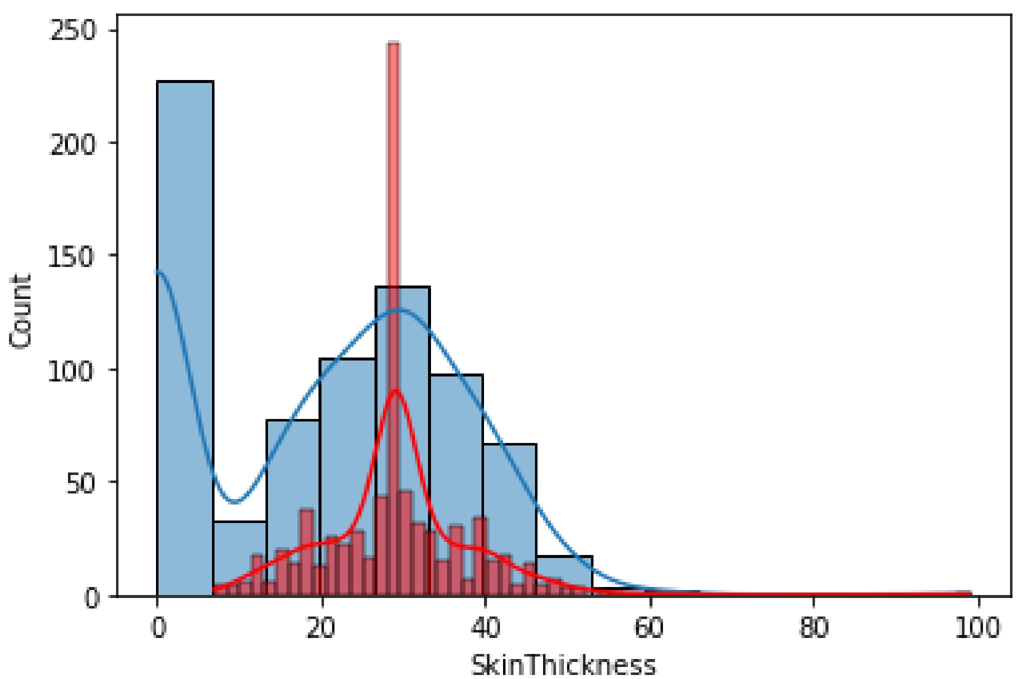
[22]:
```
sns.histplot(data=df.BloodPressure,kde=True)
sns.histplot(data=imputed.BloodPressure,color='r',kde=True)
```

[22]: <AxesSubplot: xlabel='BloodPressure', ylabel='Count'>



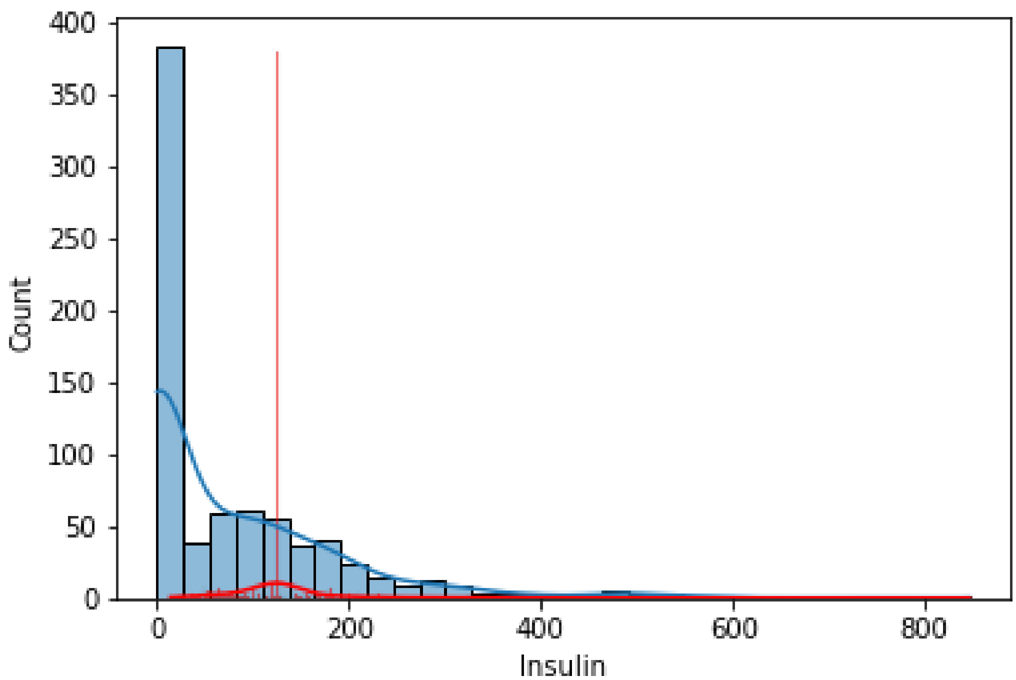
[23]:
```
sns.histplot(data=df.SkinThickness,kde=True)
sns.histplot(data=imputed.SkinThickness,color='r',kde=True)
```

[23]: <AxesSubplot: xlabel='SkinThickness', ylabel='Count'>



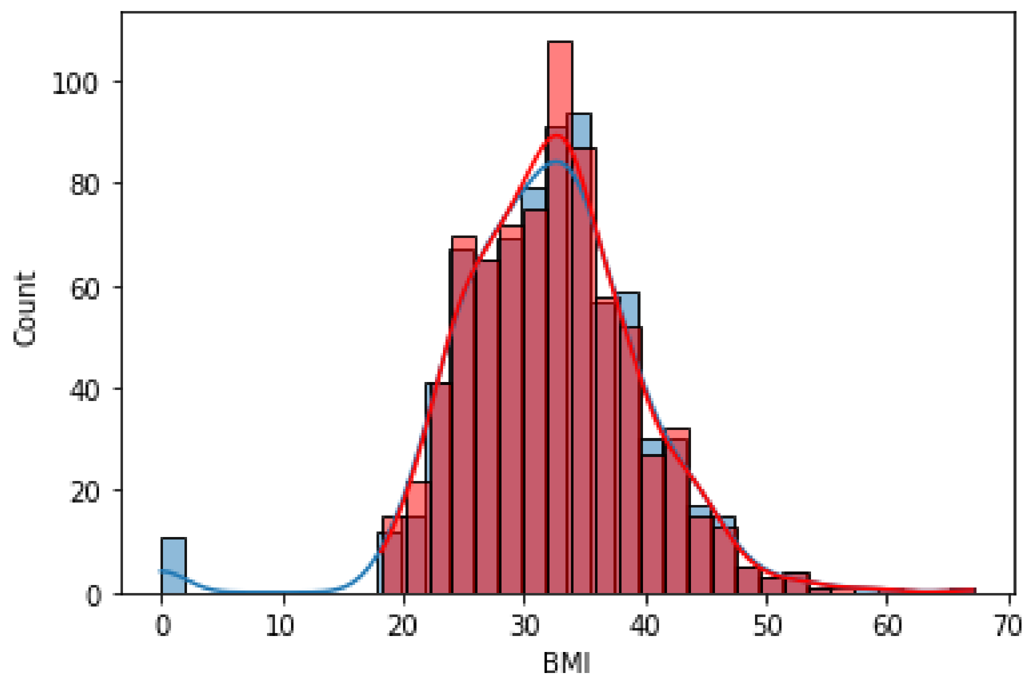
[24]:
```
sns.histplot(data=df.Insulin,kde=True)
sns.histplot(data=imputed.Insulin,color='r',kde=True)
```

[24]: <AxesSubplot: xlabel='Insulin', ylabel='Count'>



[25]:
```
sns.histplot(data=df.BMI,kde=True)
sns.histplot(data=imputed.BMI,color='r',kde=True)
```

[25]: <AxesSubplot: xlabel='BMI', ylabel='Count'>



[26]:
```
df.Glucose=imputed.Glucose
df.BloodPressure=imputed.BloodPressure
df.SkinThickness=imputed.SkinThickness
df.Insulin=imputed.Insulin
df.BMI=imputed.BMI
```

[27]:
```
df
```

[27]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6    148.0           72.0           35.0    125.0  33.6
1              1     85.0           66.0           29.0    125.0  26.6
2              8    183.0           64.0           29.0    125.0  23.3
3              1     89.0           66.0           23.0     94.0  28.1
4              0    137.0           40.0           35.0    168.0  43.1
..           …        …             …              …       …     …
763           10    101.0           76.0           48.0    180.0  32.9
764            2    122.0           70.0           27.0    125.0  36.8
765            5    121.0           72.0           23.0    112.0  26.2
766            1    126.0           60.0           29.0    125.0  30.1
767            1     93.0           70.0           31.0    125.0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
```

```
3                        0.167   21         0
4                        2.288   33         1
..                         …   …       …
763                      0.171   63         0
764                      0.340   27         0
765                      0.245   30         0
766                      0.349   47         1
767                      0.315   23         0

[768 rows x 9 columns]
```

[28]:
```
df[df[['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin','BMI']]==0].
 ↪count()
```

[28]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

Now, no null values are present

Checking for any duplicate values in data

[29]:
```
df[df.duplicated()]
```

[29]:
```
Empty DataFrame
Columns: [Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI,
DiabetesPedigreeFunction, Age, Outcome]
Index: []
```

[30]:
```
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    float64
 2   BloodPressure             768 non-null    float64
 3   SkinThickness             768 non-null    float64
 4   Insulin                   768 non-null    float64
```

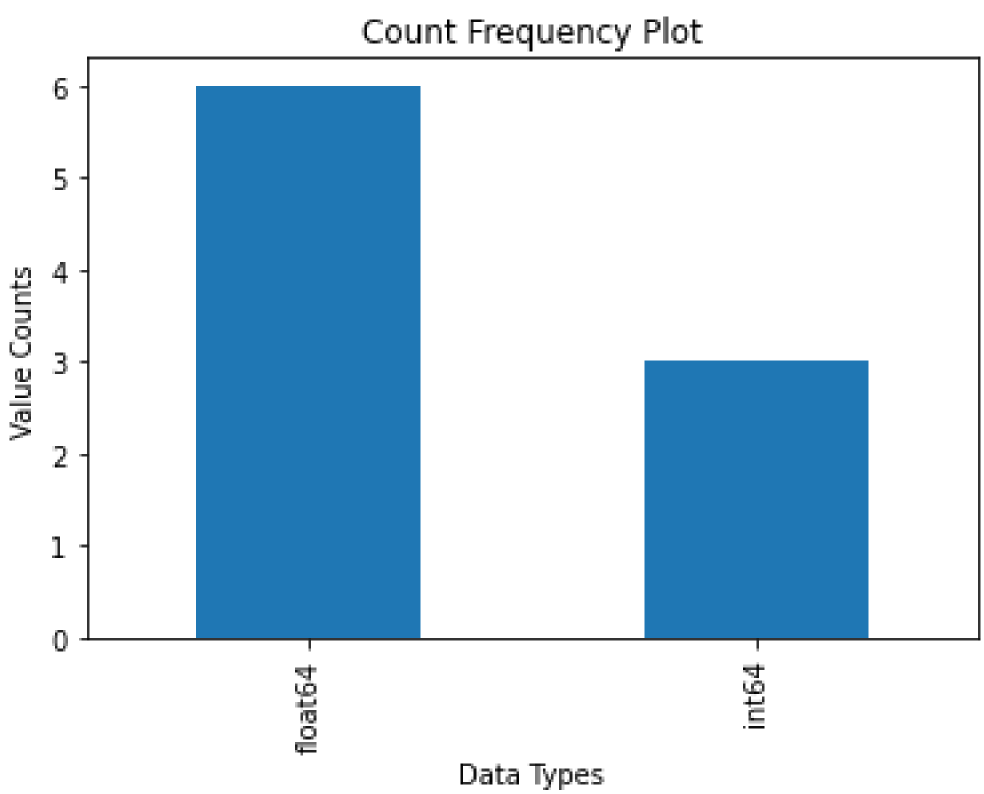
```
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(6), int64(3)
memory usage: 54.1 KB
```

Ploting count frequency plot for describing the data types and the count of variables

[31]:
```python
df.dtypes.value_counts()
```

[31]:
```
float64    6
int64      3
dtype: int64
```

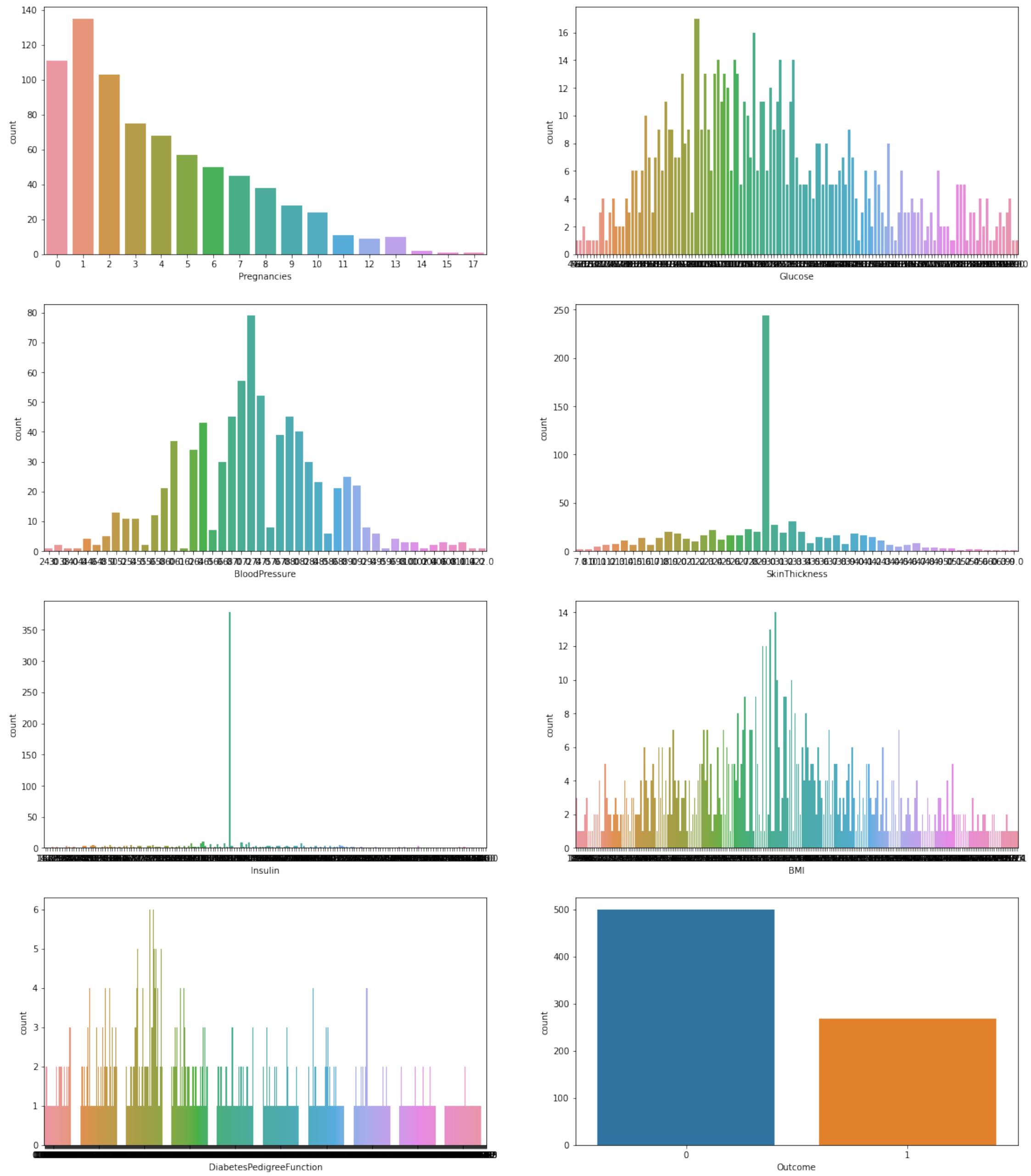
[32]:
```python
df1=df.dtypes.value_counts()
df1.plot.bar()
plt.title('Count Frequency Plot')
plt.xlabel('Data Types')
plt.ylabel('Value Counts')
plt.show()
```



Plotting countplot to show count of variables

[33]:
```
plt.figure(figsize=(20,24))
plt.subplot(421)
sns.countplot(x=df.Pregnancies)
plt.subplot(422)
sns.countplot(x=df.Glucose)
plt.subplot(423)
sns.countplot(x=df.BloodPressure)
plt.subplot(424)
sns.countplot(x=df.SkinThickness)
plt.subplot(425)
sns.countplot(x=df.Insulin)
plt.subplot(426)
sns.countplot(x=df.BMI)
plt.subplot(427)
sns.countplot(x=df.DiabetesPedigreeFunction)
plt.subplot(428)
sns.countplot(x=df.Outcome)
```

[33]:
```
<AxesSubplot: xlabel='Outcome', ylabel='count'>
```



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

[34]:
```
df['Outcome'].value_counts()
```

[34]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

[35]:
```
df['Outcome'].value_counts(normalize=True)
```

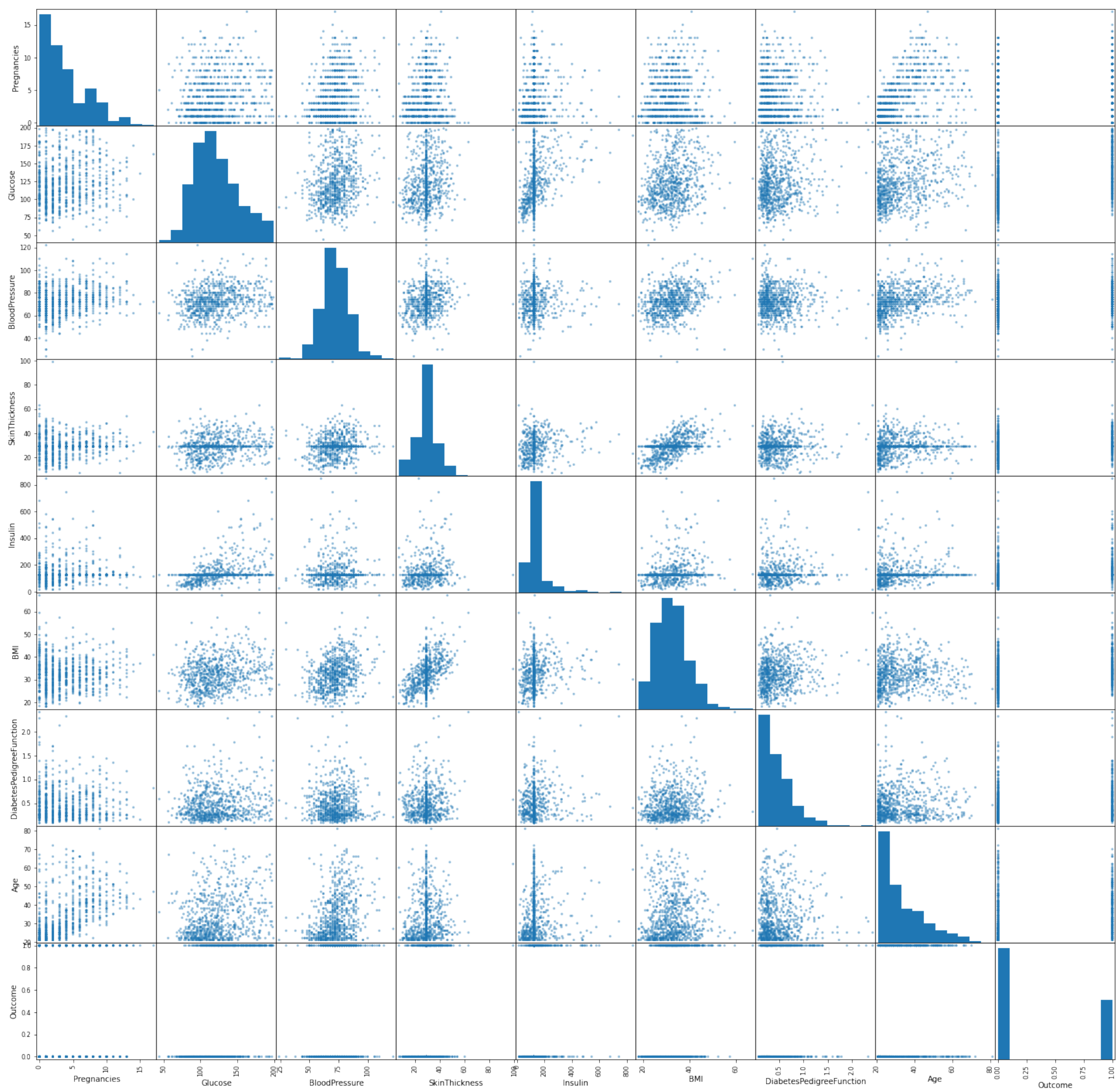
[35]:
```
0    0.651042
1    0.348958
Name: Outcome, dtype: float64
```

there are 500 negative or 0 and 268 positive or 1 instances hence we can say that the given dataset it imbalanced

In order to balance the data, we will add weights to each class.

0.1.4 Ploting scatter charts between the pair of variables to understand the relationships

[36]:
```
from pandas.plotting import scatter_matrix
scatter = scatter_matrix(df,figsize=(25, 25))
```



[37]:
```
sns.pairplot(df, hue = 'Outcome')
```

[37]: <seaborn.axisgrid.PairGrid at 0x7fb3e2256bf0>

0.1.5 Ploting heatmap for performing correlation analysis

Here, Value 1 represent the max correlation between variables Value 0 represent the no correlation between variables

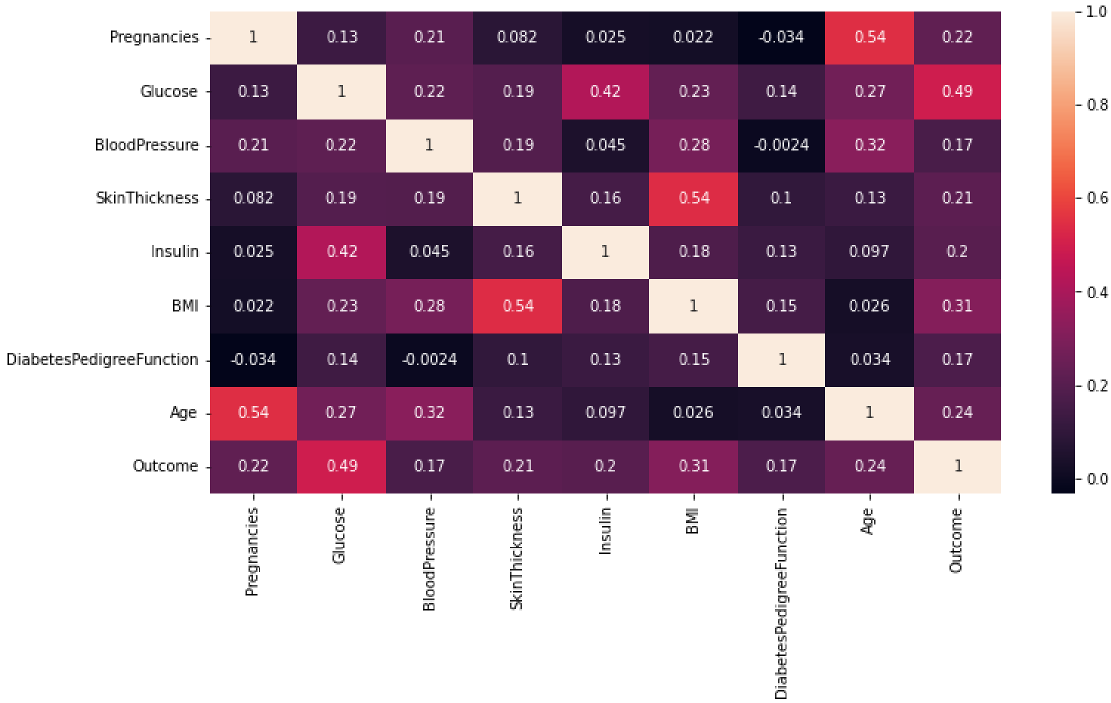
[38]:
```
df.corr()
```

[38]:

```
                          Pregnancies   Glucose  BloodPressure  SkinThickness  \
Pregnancies                  1.000000  0.128213       0.208615       0.081770
Glucose                      0.128213  1.000000       0.218937       0.192615
BloodPressure                0.208615  0.218937       1.000000       0.191892
SkinThickness                0.081770  0.192615       0.191892       1.000000
Insulin                      0.025047  0.419451       0.045363       0.155610
BMI                          0.021559  0.231049       0.281257       0.543205
DiabetesPedigreeFunction    -0.033523  0.137327      -0.002378       0.102188
Age                          0.544341  0.266909       0.324915       0.126107
Outcome                      0.221898  0.492782       0.165723       0.214873

                           Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies               0.025047  0.021559                 -0.033523
Glucose                   0.419451  0.231049                  0.137327
BloodPressure             0.045363  0.281257                 -0.002378
SkinThickness             0.155610  0.543205                  0.102188
Insulin                   1.000000  0.180241                  0.126503
BMI                       0.180241  1.000000                  0.153438
DiabetesPedigreeFunction  0.126503  0.153438                  1.000000
Age                       0.097101  0.025597                  0.033561
Outcome                   0.203790  0.312038                  0.173844

                               Age   Outcome
Pregnancies               0.544341  0.221898
Glucose                   0.266909  0.492782
BloodPressure             0.324915  0.165723
SkinThickness             0.126107  0.214873
Insulin                   0.097101  0.203790
BMI                       0.025597  0.312038
DiabetesPedigreeFunction  0.033561  0.173844
Age                       1.000000  0.238356
Outcome                   0.238356  1.000000
```

[39]:

```
plt.figure(figsize = (12, 6))
heatmap = sns.heatmap(df.corr(), annot=True)
```



0.2 Data Modeling

Splitting the data into feature and Target variable

[71]:
```
x = df.iloc[: , :-1]
y = df.iloc[: , -1:]
x,y
```

[71]:
```
(     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
 0              6    148.0           72.0           35.0    125.0  33.6
 1              1     85.0           66.0           29.0    125.0  26.6
 2              8    183.0           64.0           29.0    125.0  23.3
 3              1     89.0           66.0           23.0     94.0  28.1
 4              0    137.0           40.0           35.0    168.0  43.1
 ..           …        …            …            …       …     …
 763           10    101.0           76.0           48.0    180.0  32.9
 764            2    122.0           70.0           27.0    125.0  36.8
 765            5    121.0           72.0           23.0    112.0  26.2
 766            1    126.0           60.0           29.0    125.0  30.1
 767            1     93.0           70.0           31.0    125.0  30.4

      DiabetesPedigreeFunction  Age
 0                       0.627   50
 1                       0.351   31
 2                       0.672   32
```

```
3                        0.167   21
4                        2.288   33
..                         …   …
763                      0.171   63
764                      0.340   27
765                      0.245   30
766                      0.349   47
767                      0.315   23

[768 rows x 8 columns],
     Outcome
0          1
1          0
2          1
3          0
4          1
..       …
763        0
764        0
765        0
766        1
767        0

[768 rows x 1 columns])
```

Performing Train Test split

[72]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=10,test_size=0.
↪2)
x_train,x_test,y_train,y_test
```

[72]:
```
(     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
 120            0    162.0           76.0           56.0    100.0  53.2
 172            2     87.0           72.0           23.0    125.0  28.9
 307            0    137.0           68.0           14.0    148.0  24.8
 7             10    115.0           72.0           29.0    125.0  35.3
 448            0    104.0           64.0           37.0     64.0  33.6
 ..           …      …            …            …      …   …
 369            1    133.0          102.0           28.0    140.0  32.8
 320            4    129.0           60.0           12.0    231.0  27.5
 527            3    116.0           74.0           15.0    105.0  26.3
 125            1     88.0           30.0           42.0     99.0  55.0
 265            5     96.0           74.0           18.0     67.0  33.6

      DiabetesPedigreeFunction  Age
 120                     0.759   25
```

```
172                        0.773   25
307                        0.143   21
7                          0.134   29
448                        0.510   22
..                           …   …
369                        0.234   45
320                        0.527   31
527                        0.107   24
125                        0.496   26
265                        0.997   43

[614 rows x 8 columns],
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
568            4    154.0           72.0           29.0    126.0  31.3
620            2    112.0           86.0           42.0    160.0  38.4
456            1    135.0           54.0           29.0    125.0  26.7
197            3    107.0           62.0           13.0     48.0  22.9
714            3    102.0           74.0           29.0    125.0  29.5
..           …       …             …              …       …    …
264            4    123.0           62.0           29.0    125.0  32.0
706           10    115.0           72.0           29.0    125.0  32.3
194            8     85.0           55.0           20.0    125.0  24.4
179            5    130.0           82.0           29.0    125.0  39.1
514            3     99.0           54.0           19.0     86.0  25.6

     DiabetesPedigreeFunction  Age
568                        0.338   37
620                        0.246   28
456                        0.687   62
197                        0.678   23
714                        0.121   32
..                           …   …
264                        0.226   35
706                        0.261   30
194                        0.136   42
179                        0.956   37
514                        0.154   24

[154 rows x 8 columns],
     Outcome
120        1
172        0
307        0
7          0
448        1
..       …
369        1
```

```
320        0
527        0
125        1
265        0

[614 rows x 1 columns],
     Outcome
568        0
620        0
456        0
197        1
714        0
..       …
264        1
706        1
194        0
179        1
514        0

[154 rows x 1 columns])
```

0.2.1 Logistic Regression Model

[73]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix,classification_report
lr_model=LogisticRegression()
lr_model.fit(x_train,y_train)
```

[73]:
```
LogisticRegression()
```

[74]:
```python
print('Accuracy on Train Data = ',lr_model.score(x_train,y_train))
print('Accuracy on Test Data = ',lr_model.score(x_test,y_test))
print('Confusion matrix :\n ',confusion_matrix(y,lr_model.predict(x)))
print('Classification report : \n',classification_report(y,lr_model.predict(x)))
```

```
Accuracy on Train Data =  0.7833876221498371
Accuracy on Test Data =  0.7272727272727273
Confusion matrix :
  [[445  55]
 [120 148]]
Classification report :
               precision    recall  f1-score   support

           0       0.79      0.89      0.84       500
           1       0.73      0.55      0.63       268

    accuracy                           0.77       768
```

```
   macro avg       0.76      0.72      0.73       768
weighted avg       0.77      0.77      0.76       768
```

0.2.2 Logistic Regression Model (With Added weights => 'Balanced')

[75]:
```
lrw_model=LogisticRegression(class_weight='balanced')
lrw_model.fit(x_train,y_train)
print('Accuracy on Train Data = ',lrw_model.score(x_train,y_train))
print('Accuracy on Test Data = ',lrw_model.score(x_test,y_test))
print('Confusion matrix : \n',confusion_matrix(y,lrw_model.predict(x)))
print('Classification report : \n',classification_report(y,lrw_model.
 ↪predict(x)))
```

```
Accuracy on Train Data =  0.747557003257329
Accuracy on Test Data =  0.7207792207792207
Confusion matrix :
 [[377 123]
 [ 75 193]]
Classification report :
               precision    recall  f1-score   support

           0       0.83      0.75      0.79       500
           1       0.61      0.72      0.66       268

    accuracy                           0.74       768
   macro avg       0.72      0.74      0.73       768
weighted avg       0.76      0.74      0.75       768
```

0.2.3 Logistic Regression Model (With Manual weights)

[76]:
```
# for class 0, weigth = 1
# for class 1, weight = occurances of class 0 / occurances of class 1 = 500/267␣
 ↪= 1.872
lrwm_model=LogisticRegression(class_weight={0:1,1:1.872})
lrwm_model.fit(x_train,y_train)
print('Accuracy on Train Data = ',lrwm_model.score(x_train,y_train))
print('Accuracy on Test Data = ',lrwm_model.score(x_test,y_test))
print('Confusion matrix : \n',confusion_matrix(y,lrwm_model.predict(x)))
print('Classification report : \n',classification_report(y,lrwm_model.
 ↪predict(x)))
```

```
Accuracy on Train Data =  0.747557003257329
Accuracy on Test Data =  0.7467532467532467
Confusion matrix :
 [[381 119]
 [ 75 193]]
```

```
Classification report :
               precision    recall  f1-score   support

           0       0.84      0.76      0.80       500
           1       0.62      0.72      0.67       268

    accuracy                           0.75       768
   macro avg       0.73      0.74      0.73       768
weighted avg       0.76      0.75      0.75       768
```

0.2.4 Decision Tree Model

[77]:
```python
from sklearn.tree import DecisionTreeClassifier
dt_model=DecisionTreeClassifier()
dt_model.fit(x_train,y_train)
```

[77]:
```
DecisionTreeClassifier()
```

[78]:
```python
print('Accuracy on Train Data = ',dt_model.score(x_train,y_train))
print('Accuracy on Test Data = ',dt_model.score(x_test,y_test))
print('Confusion matrix : \n',confusion_matrix(y,dt_model.predict(x)))
print('Classification report : \n',classification_report(y,dt_model.predict(x)))
```

```
Accuracy on Train Data =  1.0
Accuracy on Test Data =  0.7402597402597403
Confusion matrix :
 [[483  17]
 [ 23 245]]
Classification report :
               precision    recall  f1-score   support

           0       0.95      0.97      0.96       500
           1       0.94      0.91      0.92       268

    accuracy                           0.95       768
   macro avg       0.94      0.94      0.94       768
weighted avg       0.95      0.95      0.95       768
```

0.2.5 Random Forest Model

[79]:
```python
from sklearn.ensemble import RandomForestClassifier
rf_model=RandomForestClassifier()
rf_model.fit(x_train,y_train)
```

[79]:
```
RandomForestClassifier()
```

[80]:
```
print('Accuracy on Train Data = ',rf_model.score(x_train,y_train))
print('Accuracy on Test Data = ',rf_model.score(x_test,y_test))
print('Confusion matrix : \n',confusion_matrix(y,rf_model.predict(x)))
print('Classification report : \n',classification_report(y,rf_model.predict(x)))
```

```
Accuracy on Train Data =  1.0
Accuracy on Test Data =  0.7077922077922078
Confusion matrix :
 [[484  16]
 [ 29 239]]
Classification report :
               precision    recall  f1-score   support

           0       0.94      0.97      0.96       500
           1       0.94      0.89      0.91       268

    accuracy                           0.94       768
   macro avg       0.94      0.93      0.93       768
weighted avg       0.94      0.94      0.94       768
```

0.2.6 SVC Model

[83]:
```
from sklearn.svm import SVC
svc_model=SVC(probability=True)
svc_model.fit(x_train,y_train)
```

[83]:
```
SVC(probability=True)
```

[84]:
```
print('Accuracy on Train Data = ',svc_model.score(x_train,y_train))
print('Accuracy on Test Data = ',svc_model.score(x_test,y_test))
print('Confusion matrix : \n',confusion_matrix(y,svc_model.predict(x)))
print('Classification report : \n',classification_report(y,svc_model.
 ↪predict(x)))
```

```
Accuracy on Train Data =  0.7785016286644951
Accuracy on Test Data =  0.6948051948051948
Confusion matrix :
 [[457  43]
 [140 128]]
Classification report :
               precision    recall  f1-score   support

           0       0.77      0.91      0.83       500
           1       0.75      0.48      0.58       268

    accuracy                           0.76       768
   macro avg       0.76      0.70      0.71       768
```

```
weighted avg       0.76      0.76      0.75       768
```

0.2.7 KNN Model

[85]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model=KNeighborsClassifier()
knn_model.fit(x_train,y_train)
```

[85]:
```
KNeighborsClassifier()
```

[86]:
```
print('Accuracy on Train Data = ',knn_model.score(x_train,y_train))
print('Accuracy on Test Data = ',knn_model.score(x_test,y_test))
print('Confusion matrix : \n',confusion_matrix(y,knn_model.predict(x)))
print('Classification report : \n',classification_report(y,knn_model.
 ↪predict(x)))
```

```
Accuracy on Train Data =  0.8127035830618893
Accuracy on Test Data =  0.6883116883116883
Confusion matrix :
 [[433  67]
 [ 96 172]]
Classification report :
               precision    recall  f1-score   support

           0       0.82      0.87      0.84       500
           1       0.72      0.64      0.68       268

    accuracy                           0.79       768
   macro avg       0.77      0.75      0.76       768
weighted avg       0.78      0.79      0.78       768
```

0.2.8 AUC and ROC Curve fo various Model

[87]:
```
from sklearn.metrics import roc_auc_score,roc_curve
# getting prediction probalities for different models
lr_probs=lr_model.predict_proba(x)
lrw_probs=lrw_model.predict_proba(x)
lrwm_probs=lrwm_model.predict_proba(x)
dt_probs=dt_model.predict_proba(x)
rf_probs=rf_model.predict_proba(x)
svc_probs=svc_model.predict_proba(x)
knn_probs=knn_model.predict_proba(x)
# We need pred probs only for outcome = 1
lr_probs=lr_probs[:,1]
lrw_probs=lrw_probs[:,1]
lrwm_probs=lrwm_probs[:,1]
```

```python
dt_probs=dt_probs[:,1]
rf_probs=rf_probs[:,1]
svc_probs=svc_probs[:,1]
knn_probs=knn_probs[:,1]
```

[88]:
```python
# getting AUC score
auc_lr=roc_auc_score(y,lr_probs)
auc_lrw=roc_auc_score(y,lrw_probs)
auc_lrwm=roc_auc_score(y,lrwm_probs)
auc_dt=roc_auc_score(y,dt_probs)
auc_rf=roc_auc_score(y,rf_probs)
auc_svc=roc_auc_score(y,svc_probs)
auc_knn=roc_auc_score(y,knn_probs)
print('\n AUC for different models : \n')
print('Logistic regression model without weight AUC : ',auc_lr)
print('Logistic Regression model with Balanced weight AUC : ',auc_lrw)
print('Logistic Regression model with manual weight AUC : ',auc_lrwm)
print('Decision Tree model AUC : ',auc_dt)
print('Random Forest model AUC : ',auc_rf)
print('SVC model AUC : ',auc_svc)
print('KNN model AUC : ',auc_knn)
```

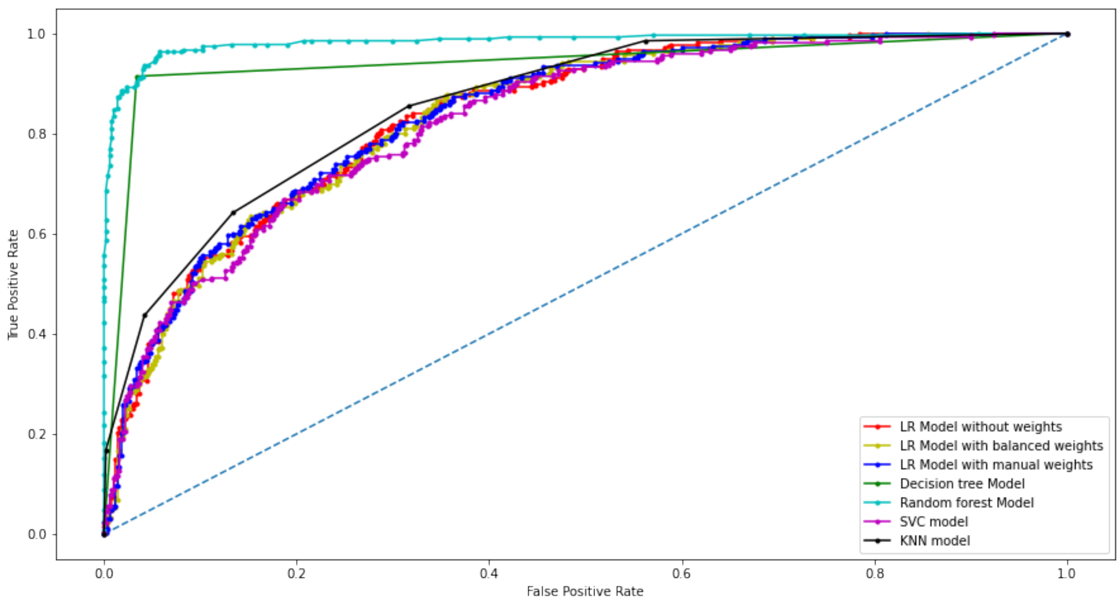
```
 AUC for different models :

Logistic regression model without weight AUC :  0.8374477611940299
Logistic Regression model with Balanced weight AUC :  0.8353358208955224
Logistic Regression model with manual weight AUC :  0.8385820895522388
Decision Tree model AUC :  0.940089552238806
Random Forest model AUC :  0.9838768656716419
SVC model AUC :  0.8259701492537312
KNN model AUC :  0.8590186567164179
```

[89]:
```python
# calculating values for ROC curve
lr_fpr, lr_tpr, lr_thresholds = roc_curve(y, lr_probs)
lrw_fpr, lrw_tpr, lrw_thresholds = roc_curve(y, lrw_probs)
lrwm_fpr, lrwm_tpr, lrwm_thresholds = roc_curve(y, lrwm_probs)
dt_fpr, dt_tpr, dt_thresholds = roc_curve(y, dt_probs)
rf_fpr, rf_tpr, rf_thresholds = roc_curve(y, rf_probs)
svc_fpr, svc_tpr, svc_thresholds = roc_curve(y, svc_probs)
knn_fpr, knn_tpr, knn_thresholds = roc_curve(y, knn_probs)
```

[90]:
```python
# plotting for random predictor model
print('\nROC curves for various models \n')
plt.figure(figsize=(15,8))
plt.plot([0, 1], [0, 1], linestyle='--')
# plotting ROC curve for various models
```

```
plt.plot(lr_fpr, lr_tpr, marker='.',c='r',label='LR Model without weights')
plt.plot(lrw_fpr, lrw_tpr, marker='.',c='y',label='LR Model with balanced␣
 ↪weights')
plt.plot(lrwm_fpr, lrwm_tpr, marker='.',c='b',label='LR Model with manual␣
 ↪weights')
plt.plot(dt_fpr, dt_tpr, marker='.',c='g',label='Decision tree Model')
plt.plot(rf_fpr, rf_tpr, marker='.',c='c',label='Random forest Model')
plt.plot(svc_fpr, svc_tpr, marker='.',c='m',label='SVC model')
plt.plot(knn_fpr, knn_tpr, marker='.',c='k',label='KNN model')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc='lower right')
plt.show()
```

```
ROC curves for various models
```



0.2.9 Calculating Sensitivity and Specificity for various models

[91]:
```
def get_confusion_matrix_values(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred)
    return(cm[0][0], cm[0][1], cm[1][0], cm[1][1])

lr_TP, lr_FP, lr_FN, lr_TN = get_confusion_matrix_values(y, lr_model.predict(x))
lrw_TP, lrw_FP, lrw_FN, lrw_TN = get_confusion_matrix_values(y, lrw_model.
 ↪predict(x))
```

```
lrwm_TP, lrwm_FP, lrwm_FN, lrwm_TN = get_confusion_matrix_values(y, lrwm_model.
↪predict(x))
dt_TP, dt_FP, dt_FN, dt_TN = get_confusion_matrix_values(y, dt_model.predict(x))
rf_TP, rf_FP, rf_FN, rf_TN = get_confusion_matrix_values(y, rf_model.predict(x))
svc_TP, svc_FP, svc_FN, svc_TN = get_confusion_matrix_values(y, svc_model.
↪predict(x))
knn_TP, knn_FP, knn_FN, knn_TN = get_confusion_matrix_values(y, knn_model.
↪predict(x))
```

[92]:
```
print('SENSITIVITY: \n')
print('Sensitivity of Logistic Regression model : ',(lr_TP/(lr_TP+lr_FN)))
print('Sensitivity of Logistic Regression model with balanced weight :␣
↪',(lrw_TP/(lrw_TP+lrw_FN)))
print('Sensitivity of Logistic regression model with manual weight : ',(lrwm_TP/
↪(lrwm_TP+lrwm_FN)))
print('Sensitivity of Decision Tree model : ',(dt_TP/(dt_TP+dt_FN)))
print('Sensitivity of Random forest model : ',(rf_TP/(rf_TP+rf_FN)))
print('Sensitivity of SVC model : ',(svc_TP/(svc_TP+svc_FN)))
print('Sensitivity of KNN model : ',(knn_TP/(knn_TP+knn_FN)))
```

```
SENSITIVITY:

Sensitivity of Logistic Regression model :  0.7876106194690266
Sensitivity of Logistic Regression model with balanced weight :
0.834070796460177
Sensitivity of Logistic regression model with manual weight :
0.8355263157894737
Sensitivity of Decision Tree model :  0.9545454545454546
Sensitivity of Random forest model :  0.9434697855750487
Sensitivity of SVC model :  0.7654941373534339
Sensitivity of KNN model :  0.8185255198487713
```

[93]:
```
print('\nSPECIFICITY: \n')
print('Specificity of Logistic Regression model : ',(lr_TN/(lr_TN+lr_FP)))
print('Specificity of Logistic Regression model with balanced weight :␣
↪',(lrw_TN/(lrw_TN+lrw_FP)))
print('Specificity of Logistic regression model with manual weight : ',(lrwm_TN/
↪(lrwm_TN+lrwm_FP)))
print('Specificity of Decision Tree model : ',(dt_TN/(dt_TN+dt_FP)))
print('Specificity of Random forest model : ',(rf_TN/(rf_TN+rf_FP)))
print('Specificity of SVC model : ',(svc_TN/(svc_TN+svc_FP)))
print('Specificity of KNN model : ',(knn_TN/(knn_TN+knn_FP)))
```

```
SPECIFICITY:

Specificity of Logistic Regression model :  0.729064039408867
```

```
Specificity of Logistic Regression model with balanced weight :
0.6107594936708861
Specificity of Logistic regression model with manual weight :
0.6185897435897436
Specificity of Decision Tree model :  0.9351145038167938
Specificity of Random forest model :  0.9372549019607843
Specificity of SVC model :  0.7485380116959064
Specificity of KNN model :  0.7196652719665272
```

0.2.10 Various models are analysed and compared using different criterias and below are the findings

0.2.11 Based on accuracy of models on test data:

Decision Tree model has highest accuracy of almost 74%. KNN model has an accuracy of 69% and so does Logistic Regression model.

0.2.12 Based on ROC curve and AUC:

Random Forest model shows best results followed by Decision Tree model, KNN model is far behind.

0.2.13 Based on Sensitivity and Specificity:¶

Decision Tree model has best sensitivity rate (95.45%) closely followed by Random forest (94.34%) while KNN model has a rate of 82.78%.

Specificity of Random Forest model is highest (93.72%) followed by Decision Tree model (93.51%). KNN model falls behind these two with a rate of 71.96%.

In this case we are building a model for disease detection and that's why we need to strictly minimize the number of False Negative hence we need maximum sensitivity in our model and based on this criteria we can choose Decision Tree model. The Random Forest model is performing Slightly better than any other model in all aspects except sensitivity, though it is very close to the top. Random Forest model can also be considered as it has almost equal sensitivity as Decision Tree model and far better specificity hence can reduce cost by reducing number of false positives

[ ]:

```
```