Contents

Introduction

In this project we would perform analysis and prediction on Diabetes Data-set. Our main goal would be to extract information from the data and get a high accuracy from our prediction model. First, we will explore the data-set which would in-turn help us with data pre-processing and cleaning. After pre-processing and cleaning we will visualise and analyse the data in order to extract meaningful information. Finally we will design a prediction model with the aim to maximize accuracy.

Import the required libraries

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import missingno as msno
import warnings
warnings.filterwarnings('ignore')
```

Read the Dataset

In [2]:

```
df1 = pd.read_csv("diabetes_data.csv")
```

Data Exploration

In [3]:

```
df1.shape #check the total number of rows and columns
```

Out[3]:

```
(768, 11)
```

In [4]:

```
df1.head() #check the first 5 entries in the dataset
```

Out[4]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28

In [5]:

```
df1.tail() #check the last 5 entries in the dataset
```

Out[5]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunct
763	10	101	76	48	180	32.9	0.
764	2	122	70	27	0	36.8	0.
765	5	121	72	23	112	26.2	0.
766	1	126	60	0	0	30.1	0.
767	1	93	70	31	0	30.4	0.

In [6]:

```
df1.describe()
```

Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabet
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

Data Preprocessing

In [7]:

```
df1.columns
```

Out[7]:

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insuli
n',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome', 'Doctor',
       'Hospital'],
      dtype='object')
```

In our dataset the columns that have '0' are null values, hence for cleaning purpose we are replacing the '0' values in columns with 'NaN'.

Replacing "null" values with "NaN"

In [8]:

```
df1[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']] = df1[['Glucose','BloodPre
```

In [9]:

```
df1.isnull().sum() #checking null values
```

Out[9]:

```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
Doctor                        0
Hospital                    138
dtype: int64
```

The column "Hospital" has "138" null values, column "Glucose" has "5" null values, column "BloodPressure" has "35" null values, column "SkinThickness" has "227" null values, column "Insulin" has "374" null values and column "BMI" has "11" null values and other columns do not have any null values in them.

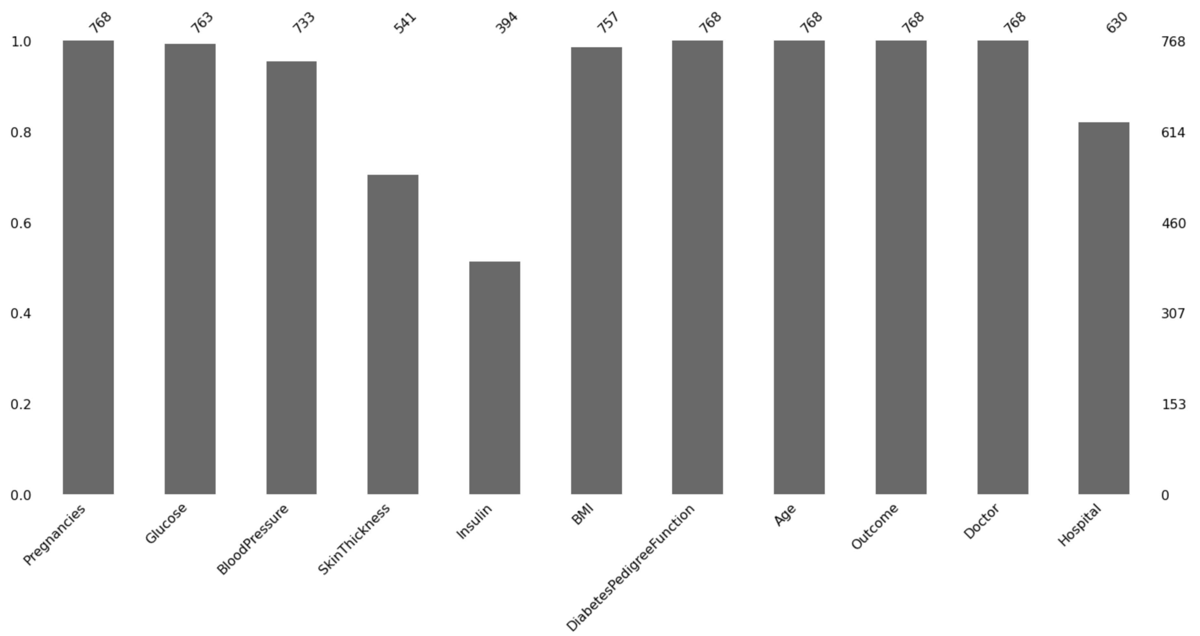
Data Cleaning

In [10]:

```
msno.bar(df1) #graph to dislay number of null values
```

Out[10]:

```
<AxesSubplot:>
```



Droping the unrequired columns from the dataset

In [11]:

```
df1.drop(['Doctor'], axis = 1, inplace = True) #Removing the column doctor as it is not req
```

In [12]:

```
df1.drop(['Hospital'],axis = 1, inplace = True) #Removing 'Hospital' as it is not required
```

In [13]:

```
df1.head()
```

Out[13]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	6	148.0	72.0	35.0	NaN	33.6	0.62
1	1	85.0	66.0	29.0	NaN	26.6	0.35
2	8	183.0	64.0	NaN	NaN	23.3	0.67
3	1	89.0	66.0	23.0	94.0	28.1	0.16
4	0	137.0	40.0	35.0	168.0	43.1	2.28

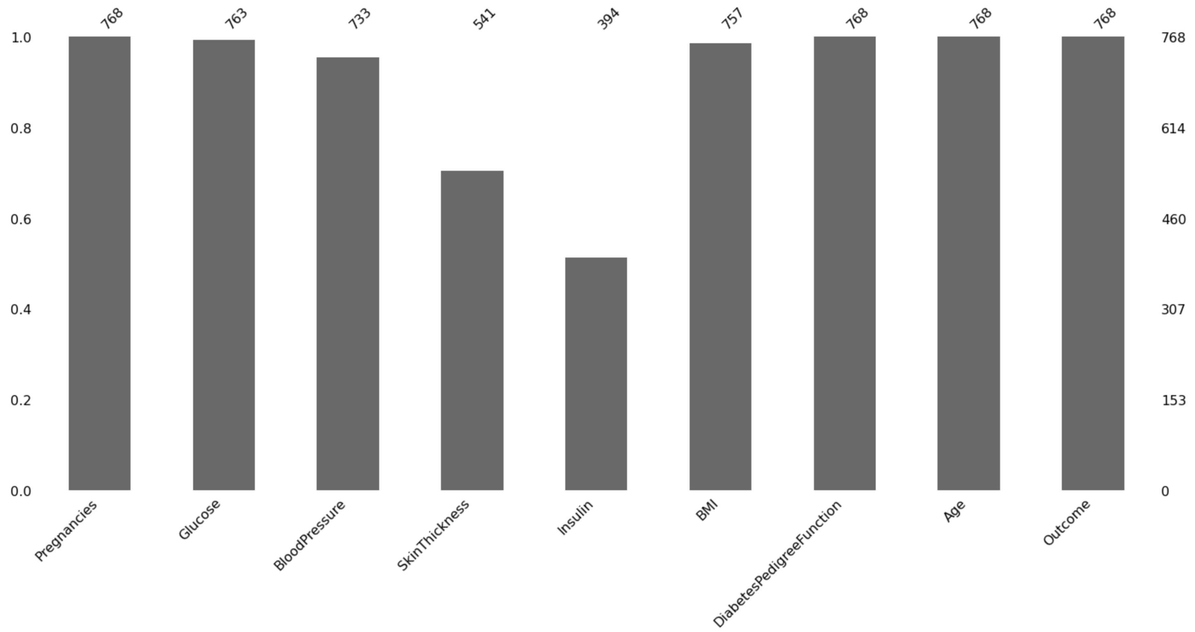
Handling other null values

In [14]:

```
msno.bar(df1) #graph to dislay number of null values after dropping 'Doctor' and 'Hospital'
```

Out[14]:

<AxesSubplot:>



Handling other missing values

We propose to clean the data by replacing the null values with meadian values. We create a funtion to find the meadian values in the given column. We find meadin values according to the "Outcome" values i.e. we handle the null values by finding median for "Outcome" having value "0" and "1" sepratly and replacing them respectively.

In [15]:

```
def outcome_median(column_name): #function to find median
    median = df1[df1[column_name].notnull()]
    median = median[[column_name, 'Outcome']].groupby(['Outcome'])[[column_name]].median().
    return median
```

In [16]:

```
outcome_median('Insulin') #Finding median for column 'Insulin'
```

Out[16]:

	Outcome	Insulin
0	0	102.5
1	1	169.5

In [17]:

```
#Replacing null values with their respective median values
df1.loc[(df1['Outcome'] == 0 )&(df1['Insulin'].isnull()),'Insulin'] = 102.5
df1.loc[(df1['Outcome'] == 1 )&(df1['Insulin'].isnull()),'Insulin'] = 169.5
```

In [18]:

```
outcome_median('Glucose') #Finding median for column 'Glucose'
```

Out[18]:

	Outcome	Glucose
0	0	107.0
1	1	140.0

In [19]:

```
#Replacing null values with their respective median values
df1.loc[(df1['Outcome'] == 0)&(df1['Glucose'].isnull()),'Glucose'] = 107
df1.loc[(df1['Outcome'] == 1)&(df1['Glucose'].isnull()),'Glucose'] = 140
```

In [20]:

```
outcome_median('SkinThickness') #Finding median for column 'SkinThickness'
```

Out[20]:

	Outcome	SkinThickness
0	0	27.0
1	1	32.0

In [21]:

```
#Replacing null values with their respective median values
df1.loc[(df1['Outcome'] == 0)&(df1['SkinThickness'].isnull()),'SkinThickness'] = 27
df1.loc[(df1['Outcome'] == 1)&(df1['SkinThickness'].isnull()),'SkinThickness'] = 32
```

In [22]:

```
outcome_median('BloodPressure') #Finding median for column 'BloodPressure'
```

Out[22]:

	Outcome	BloodPressure
0	0	70.0
1	1	74.5

In [23]:

```
#Replacing null values with their respective median values
df1.loc[(df1['Outcome'] == 0)&(df1['BloodPressure'].isnull()),'BloodPressure'] = 70
df1.loc[(df1['Outcome'] == 1)&(df1['BloodPressure'].isnull()),'BloodPressure'] = 74.5
```

In [24]:

```
outcome_median('BMI') #Finding median for column 'BMI'
```

Out[24]:

	Outcome	BMI
0	0	30.1
1	1	34.3

In [25]:

```
#Replacing null values with their respective median values
df1.loc[(df1['Outcome'] == 0 )&(df1['BMI'].isnull()),'BMI'] = 30.1
df1.loc[(df1['Outcome'] == 1 )&(df1['BMI'].isnull()),'BMI'] = 34.3
```

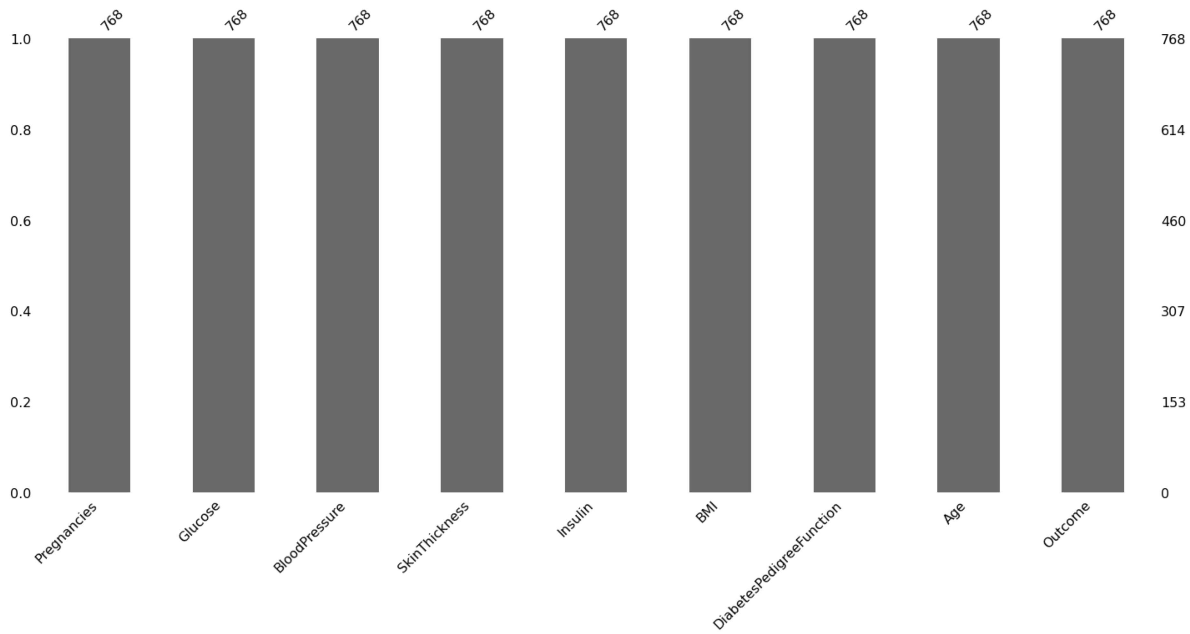
Checking if there is anyother "null" values are in the dataset.

In [26]:

```
msno.bar(df1) #graph to dislay number of null values data cleaning
```

Out[26]:

<AxesSubplot:>



In [27]:

```
df1.head()
```

Out[27]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	6	148.0	72.0	35.0	169.5	33.6	0.62
1	1	85.0	66.0	29.0	102.5	26.6	0.35
2	8	183.0	64.0	32.0	169.5	23.3	0.67
3	1	89.0	66.0	23.0	94.0	28.1	0.16
4	0	137.0	40.0	35.0	168.0	43.1	2.28

From the above graph we can say that now there are no null values in our dataset. Hence, our dataset is clean.

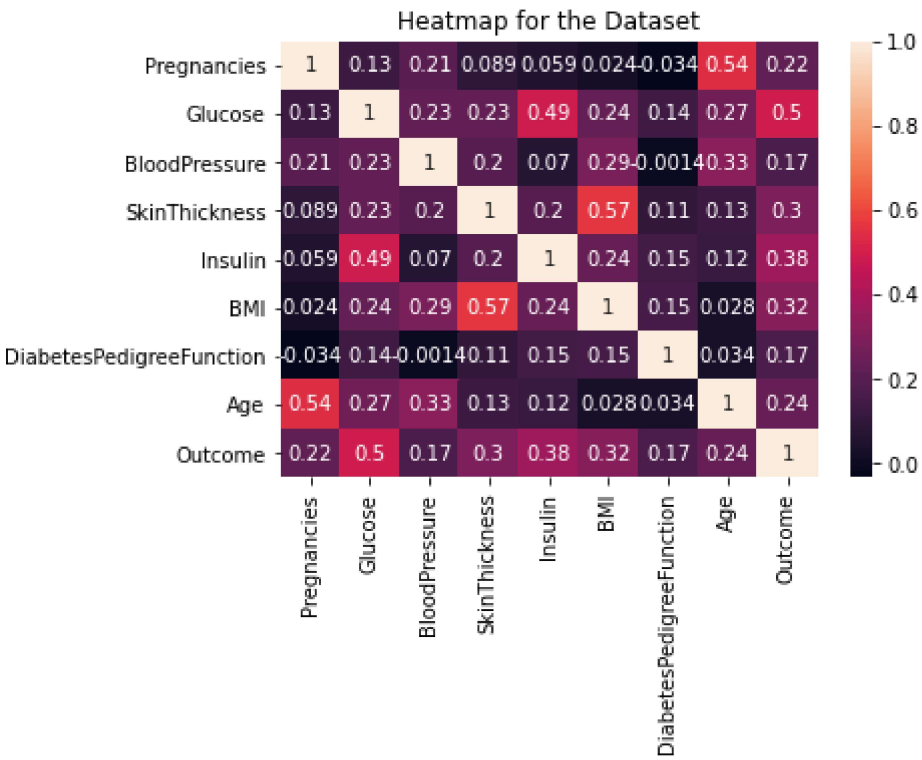
Data Visualisation

In [28]:

```
sns.heatmap(df1.corr(), annot = True)
plt.title('Heatmap for the Dataset')
```

Out[28]:

```
Text(0.5, 1.0, 'Heatmap for the Dataset')
```

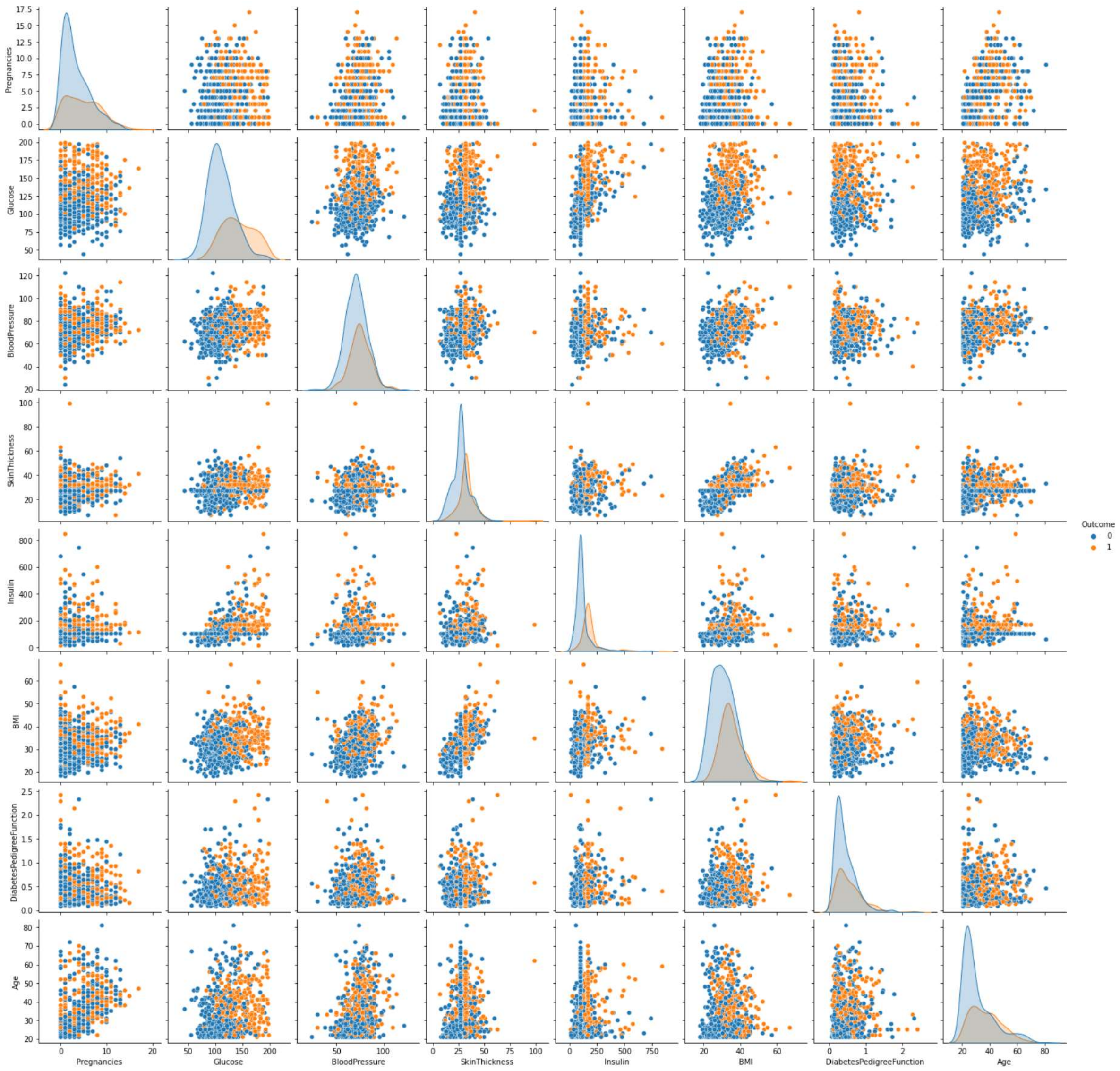


In [29]:

```
sns.pairplot(data = df1, hue = 'Outcome')
```

Out[29]:

```
<seaborn.axisgrid.PairGrid at 0x28b7acf6ac0>
```



Data Analysis

In order to analyze the relationship between different attributes present in the dataset, we plotted a heatmap and pairplot as shown in Data Visualisation. From that we can see that glucose and insulin are highly correlated with diabetes. We can also see that BMI and skin thickness have a high correlation with each other. There is a correlation between age and pregnancies. Insulin and glucose are also strongly correlated with each other.

Machine Learning

For prediction, we will implement different supervised machine learning algorithms. We will try to maximize the accuracy of these models. To further increase the accuracy we will design a hybrid ensemble model in which we will combine three algorithms with the highest accuracy and feed their output as input to another model.

Import the required Libraries

In [30]:

```
import sklearn
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import accuracy_score
```

KNN

Import all required Libraries

In [31]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import neighbors
```

Preparing the data for KNN Model

Spliting the data into training and testing data.

In [32]:

```
X_train,X_test,y_train,y_test=train_test_split(df1.drop('Outcome',axis = 1),df1['Outcome'],
```

In [33]:

```
n = KNeighborsClassifier()
n.fit(X_train,y_train)

y_expect = y_test
y_pred1 = n.predict(X_test)

print(metrics.classification_report(y_expect,y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.90      0.92      0.91       103
           1       0.84      0.80      0.82        51

    accuracy                           0.88       154
   macro avg       0.87      0.86      0.87       154
weighted avg       0.88      0.88      0.88       154
```

In [34]:

```
accuracy_KNN = accuracy_score(y_test, y_pred1)
print(accuracy_KNN*100)
```

```
88.31168831168831
```

In [35]:

```
n = KNeighborsClassifier(n_neighbors = 3)
n.fit(X_train,y_train)

y_expect = y_test
y_pred2 = n.predict(X_test)

print(metrics.classification_report(y_expect,y_pred2))
```

```
              precision    recall  f1-score   support

           0       0.88      0.90      0.89       103
           1       0.79      0.75      0.77        51

    accuracy                           0.85       154
   macro avg       0.83      0.82      0.83       154
weighted avg       0.85      0.85      0.85       154
```

In [36]:

```
accuracy_KNN1 = accuracy_score(y_test, y_pred2)
print(accuracy_KNN1*100)
```

```
85.06493506493507
```

In [37]:

```
n = KNeighborsClassifier(n_neighbors = 6)
n.fit(X_train,y_train)

y_expect = y_test
y_pred3 = n.predict(X_test)

print(metrics.classification_report(y_expect,y_pred3))
```

```
              precision    recall  f1-score   support

           0       0.89      0.93      0.91       103
           1       0.85      0.76      0.80        51

    accuracy                           0.88       154
   macro avg       0.87      0.85      0.86       154
weighted avg       0.88      0.88      0.87       154
```

In [38]:

```
accuracy_KNN3 = accuracy_score(y_test, y_pred3)
print(accuracy_KNN3*100)
```

```
87.66233766233766
```

Conclusion

After implementing the KNN algorithm it was found that the accuracy of model is best at n = 5 (Default) i.e. 88.31 %.

Logistic Regression

Import the required Libraries

In [39]:

```
from sklearn.linear_model import LogisticRegression
```

Preparing data for Logistic Regression Model

In [40]:

```
X_train,X_test,y_train,y_test=train_test_split(df1.drop('Outcome',axis = 1),df1['Outcome'],
```

In [41]:

```
LRModel = LogisticRegression()
LRModel.fit(X_train,y_train)

y_expect = y_test
y_pred4 = LRModel.predict(X_test)

print(metrics.classification_report(y_expect,y_pred4))
```

```
              precision    recall  f1-score   support

           0       0.82      0.86      0.84       103
           1       0.70      0.63      0.66        51

    accuracy                           0.79       154
   macro avg       0.76      0.75      0.75       154
weighted avg       0.78      0.79      0.78       154
```

In [42]:

```
accuracy_LR = accuracy_score(y_test, y_pred4)
print(accuracy_LR*100)
```

```
78.57142857142857
```

Conclusion

After implementing the Logistic Regression algorithm it was found that the accuracy of model 78.57 %.

Decision Tree

Import the required Libraries

In [43]:

```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
```

Preparing data for Decision Tree Model

In [44]:

```
X_train,X_test,y_train,y_test=train_test_split(df1.drop('Outcome',axis = 1),df1['Outcome'],
```

In [45]:

```
clf = tree.DecisionTreeClassifier(random_state=0, max_depth=2)
clf.fit(X_train,y_train)

y_expect = y_test
y_pred5 = clf.predict(X_test)

print(metrics.classification_report(y_expect,y_pred5))
```

```
              precision    recall  f1-score   support

           0       0.89      0.90      0.89       103
           1       0.80      0.76      0.78        51

    accuracy                           0.86       154
   macro avg       0.84      0.83      0.84       154
weighted avg       0.86      0.86      0.86       154
```

In [46]:

```
accuracy_DT = accuracy_score(y_test, y_pred5)
print(accuracy_DT*100)
```

```
85.71428571428571
```

Conclusion

After implementing the Decision Tree algorithm it was found that the accuracy of model is 85.71 %.

Random Forest

Import the required Libraries

In [47]:

```
from sklearn.ensemble import RandomForestClassifier
```

Preparing data for Random Forest Model

In [48]:

```
X_train,X_test,y_train,y_test=train_test_split(df1.drop('Outcome',axis = 1),df1['Outcome'],
```

In [49]:

```
ranfor = RandomForestClassifier(n_estimators = 11, criterion = 'entropy', random_state = 42
ranfor.fit(X_train, y_train)

y_expect = y_test
y_pred6 = ranfor.predict(X_test)

print(metrics.classification_report(y_expect,y_pred6))
```

```
              precision    recall  f1-score   support

           0       0.88      0.88      0.88       103
           1       0.76      0.75      0.75        51

    accuracy                           0.84       154
   macro avg       0.82      0.81      0.82       154
weighted avg       0.84      0.84      0.84       154
```

In [50]:

```
accuracy_ranfor = accuracy_score(y_test, y_pred6)
print(accuracy_ranfor*100)
```

```
83.76623376623377
```

Conclusion

After implementing the Random Forest algorithm it was found that the accuracy of model is 83.76 %.

Naive Bayes

Import the required Libraries

In [51]:

```
from sklearn.naive_bayes import GaussianNB
```

Preparing data for Naive Bayes Model

In [52]:

```
X_train,X_test,y_train,y_test=train_test_split(df1.drop('Outcome',axis = 1),df1['Outcome'],
```

In [53]:

```
nb = GaussianNB()
nb.fit(X_train, y_train)

y_expect = y_test
y_pred7 = nb.predict(X_test)

print(metrics.classification_report(y_expect,y_pred7))
```

```
              precision    recall  f1-score   support

           0       0.83      0.83      0.83       103
           1       0.65      0.67      0.66        51

    accuracy                           0.77       154
   macro avg       0.74      0.75      0.74       154
weighted avg       0.77      0.77      0.77       154
```

In [54]:

```
accuracy_nb = accuracy_score(y_test, y_pred7)
print(accuracy_nb*100)
```

```
77.27272727272727
```

Conclusion

After implementing the Naive Bayes algorithm it was found that the accuracy of model is 77.27 %.

SVM

Import the required Libraries

In [55]:

```
from sklearn import svm
```

Preparing data for SVM Model

In [56]:

```
X_train,X_test,y_train,y_test=train_test_split(df1.drop('Outcome',axis = 1),df1['Outcome'],
```

In [57]:

```
SM = svm.SVC()
SM.fit(X_train, y_train)

y_expect = y_test
y_pred8 = SM.predict(X_test)

print(metrics.classification_report(y_expect,y_pred8))
```

```
              precision    recall  f1-score   support

           0       0.93      0.87      0.90       103
           1       0.77      0.86      0.81        51

    accuracy                           0.87       154
   macro avg       0.85      0.87      0.86       154
weighted avg       0.88      0.87      0.87       154
```

In [58]:

```
accuracy_SVM = accuracy_score(y_test, y_pred8)
print(accuracy_SVM*100)
```

```
87.01298701298701
```

Conclusion

After implementing the Support Vector Machine (SVM) algorithm it was found that the accuracy of model is 87.01 %.

Expected Outcome

In [59]:

```
x = ['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','DiabetesPedig
data = [1,148,126,60,90,30.1,0.349,47]
paitentid_54 = pd.DataFrame([data],columns = x)
paitentid_54.head()
```

Out[59]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	1	148	126	60	90	30.1	0.34

In [60]:

```
predictions_diabetes = n.predict(paitentid_54)
print(predictions_diabetes)
```

[0]

In [62]:

```
x2 = ['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','DiabetesPedi
data2 = [5,144,122,85,136,34,0.9,88]
paitentid_SVM = pd.DataFrame([data2],columns = x2)
paitentid_SVM.head()
```

Out[62]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctior
0	5	144	122	85	136	34	0.9

In [63]:

```
predictions_diabetes2 = SM.predict(paitentid_SVM)
print(predictions_diabetes2)
```

[1]

In [64]:

```
x3 = ['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','DiabetesPedi
data3 = [6,288,72,35,150,33.6,0.627,50]
paitentid_DT = pd.DataFrame([data3],columns = x3)
paitentid_DT.head()
```

Out[64]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctioi
0	6	288	72	35	150	33.6	0.62

In [65]:

```
predictions_diabetes3 = clf.predict(paitentid_DT)
print(predictions_diabetes3)
```

[1]

In [ ]: