Diabetes-Prediction-using-ml

1 Diabetes Prediction:

The dataset comprises crucial health-related features such as 'Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction', and 'Age'. The main objective was to predict the 'Outcome' label, which signifies the likelihood of diabetes.

1.1 About the Data:

Data Overview: This is a diabetes.csv data

1.2 Import Required Libraries:

[1]:
```
# Ignore warning messages to prevent them from being displayed during code␣
↪execution
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
import numpy as np    # Importing the NumPy library for linear algebra␣
↪operations
import pandas as pd   # Importing the Pandas library for data processing and␣
↪CSV file handling
```

[3]:
```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/diabetes-data-set/diabetes.csv
```

[4]:
```
import seaborn as sns                    # Importing the Seaborn library for␣
↪statistical data visualization
import matplotlib.pyplot as plt          # Importing the Matplotlib library for␣
↪creating plots and visualizations
import plotly.express as px              # Importing the Plotly Express library␣
↪for interactive visualizations
```

1.3 Exploratory Data Analysis:

1.3.1 Load and Prepare Data:

[5]:
```
df=pd.read_csv('/kaggle/input/diabetes-data-set/diabetes.csv')
```

1.3.2 UnderStanding the Variables

[6]:
```
df.head(10)
```

[6]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1
5            5      116             74              0        0  25.6
6            3       78             50             32       88  31.0
7           10      115              0              0        0  35.3
8            2      197             70             45      543  30.5
9            8      125             96              0        0   0.0

   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
5                     0.201   30        0
6                     0.248   26        1
7                     0.134   29        0
8                     0.158   53        1
9                     0.232   54        1
```

[7]:
```
df.tail(10)
```

[7]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
758            1      106             76              0        0  37.5
759            6      190             92              0        0  35.5
760            2       88             58             26       16  28.4
761            9      170             74             31        0  44.0
762            9       89             62              0        0  22.5
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4
```

```
     DiabetesPedigreeFunction  Age  Outcome
758                     0.197   26        0
759                     0.278   66        1
760                     0.766   22        0
761                     0.403   43        1
762                     0.142   33        0
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
```

[8]:
```python
df.sample(5)
```

[8]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
760            2       88             58             26       16  28.4
687            1      107             50             19        0  28.3
355            9      165             88              0        0  30.4
187            1      128             98             41       58  32.0
235            4      171             72              0        0  43.6

     DiabetesPedigreeFunction  Age  Outcome
760                     0.766   22        0
687                     0.181   29        0
355                     0.302   49        1
187                     1.321   33        1
235                     0.479   26        1
```

[9]:
```python
df.describe()
```

[9]:
```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
```

```
75%    36.600000              0.626250   41.000000    1.000000
max    67.100000              2.420000   81.000000    1.000000
```

[10]:
```
df.dtypes
```

[10]:
```
Pregnancies                   int64
Glucose                       int64
BloodPressure                 int64
SkinThickness                 int64
Insulin                       int64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

[11]:
```
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
```

[12]:
```
df.size
```

[12]: 6912

[13]:
```
df.shape
```

[13]: (768, 9)

1.3.3 Data Cleaning:

[14]:
```
df.shape
```

[14]:
```
(768, 9)
```

[15]:
```
df=df.drop_duplicates()
```

[16]:
```
df.shape
```

[16]:
```
(768, 9)
```

Check null Values

[17]:
```
df.isnull().sum()
```

[17]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

There is no Missing Values present in the Data

[18]:
```
df.columns
```

[18]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

Check the number of Zero Values in Dataset

[19]:
```
print("No. of Zero Values in Glucose ", df[df['Glucose']==0].shape[0])
```

```
No. of Zero Values in Glucose  5
```

[20]:
```
print("No. of Zero Values in Blood Pressure ", df[df['BloodPressure']==0].
 ↪shape[0])
```

```
No. of Zero Values in Blood Pressure  35
```

[21]:
```
print("No. of Zero Values in SkinThickness ", df[df['SkinThickness']==0].
 ↪shape[0])
```

```
No. of Zero Values in SkinThickness  227
```

[22]:
```python
print("No. of Zero Values in Insulin ", df[df['Insulin']==0].shape[0])
```

```
No. of Zero Values in Insulin  374
```

[23]:
```python
print("No. of Zero Values in BMI ", df[df['BMI']==0].shape[0])
```

```
No. of Zero Values in BMI  11
```

Replace zeroes with mean of that Columns

[24]:
```python
df['Glucose']=df['Glucose'].replace(0, df['Glucose'].mean())
print('No of zero Values in Glucose ', df[df['Glucose']==0].shape[0])
```

```
No of zero Values in Glucose  0
```

[25]:
```python
df['BloodPressure']=df['BloodPressure'].replace(0, df['BloodPressure'].mean())
df['SkinThickness']=df['SkinThickness'].replace(0, df['SkinThickness'].mean())
df['Insulin']=df['Insulin'].replace(0, df['Insulin'].mean())
df['BMI']=df['BMI'].replace(0, df['BMI'].mean())
```

Validate the Zero Values:

[26]:
```python
df.describe()
```

[26]:

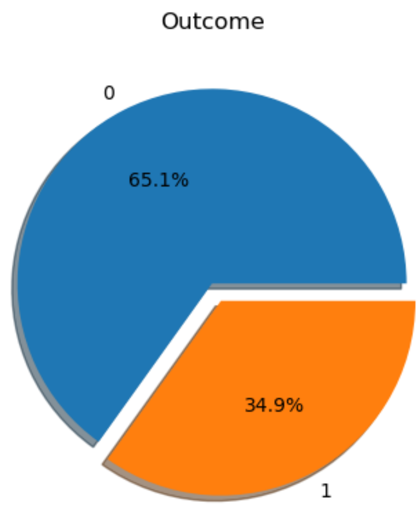
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin
count	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	121.681605	72.254807	26.606479	118.660163
std	3.369578	30.436016	12.115932	9.631241	93.080358
min	0.000000	44.000000	24.000000	7.000000	14.000000
25%	1.000000	99.750000	64.000000	20.536458	79.799479
50%	3.000000	117.000000	72.000000	23.000000	79.799479
75%	6.000000	140.250000	80.000000	32.000000	127.250000
max	17.000000	199.000000	122.000000	99.000000	846.000000

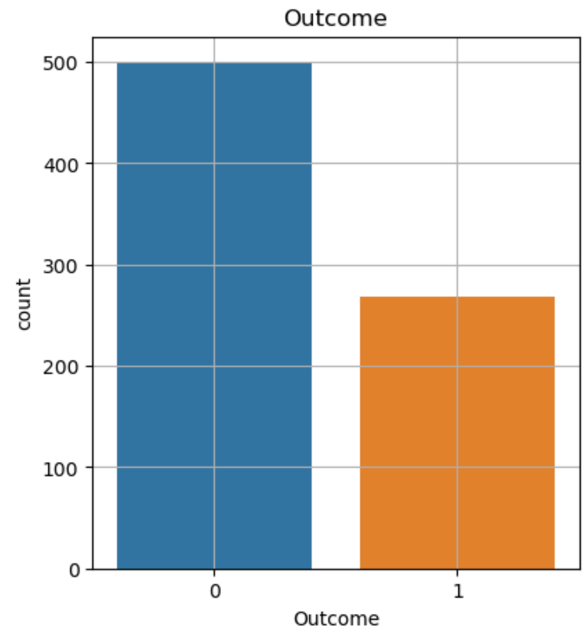
	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000
mean	32.450805	0.471876	33.240885	0.348958
std	6.875374	0.331329	11.760232	0.476951
min	18.200000	0.078000	21.000000	0.000000
25%	27.500000	0.243750	24.000000	0.000000
50%	32.000000	0.372500	29.000000	0.000000
75%	36.600000	0.626250	41.000000	1.000000
max	67.100000	2.420000	81.000000	1.000000

1.4 Data Visualization:

[27]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming 'df' is your DataFrame containing the dataset
# If you haven't imported your dataset yet, import it here

# Create subplots
f, ax = plt.subplots(1, 2, figsize=(10, 5))

# Pie chart for Outcome distribution
df['Outcome'].value_counts().plot.pie(explode=[0, 0.1], autopct='%1.1f%%',␣
↪ax=ax[0], shadow=True)
ax[0].set_title('Outcome')
ax[0].set_ylabel(' ')

# Count plot for Outcome distribution
sns.countplot(x='Outcome', data=df, ax=ax[1])  # Use 'x' instead of 'Outcome'
ax[1].set_title('Outcome')

# Display class distribution
N, P = df['Outcome'].value_counts()
print('Negative (0):', N)
print('Positive (1):', P)

# Adding grid and showing plots
plt.grid()
plt.show()
```

```
Negative (0): 500
Positive (1): 268
```

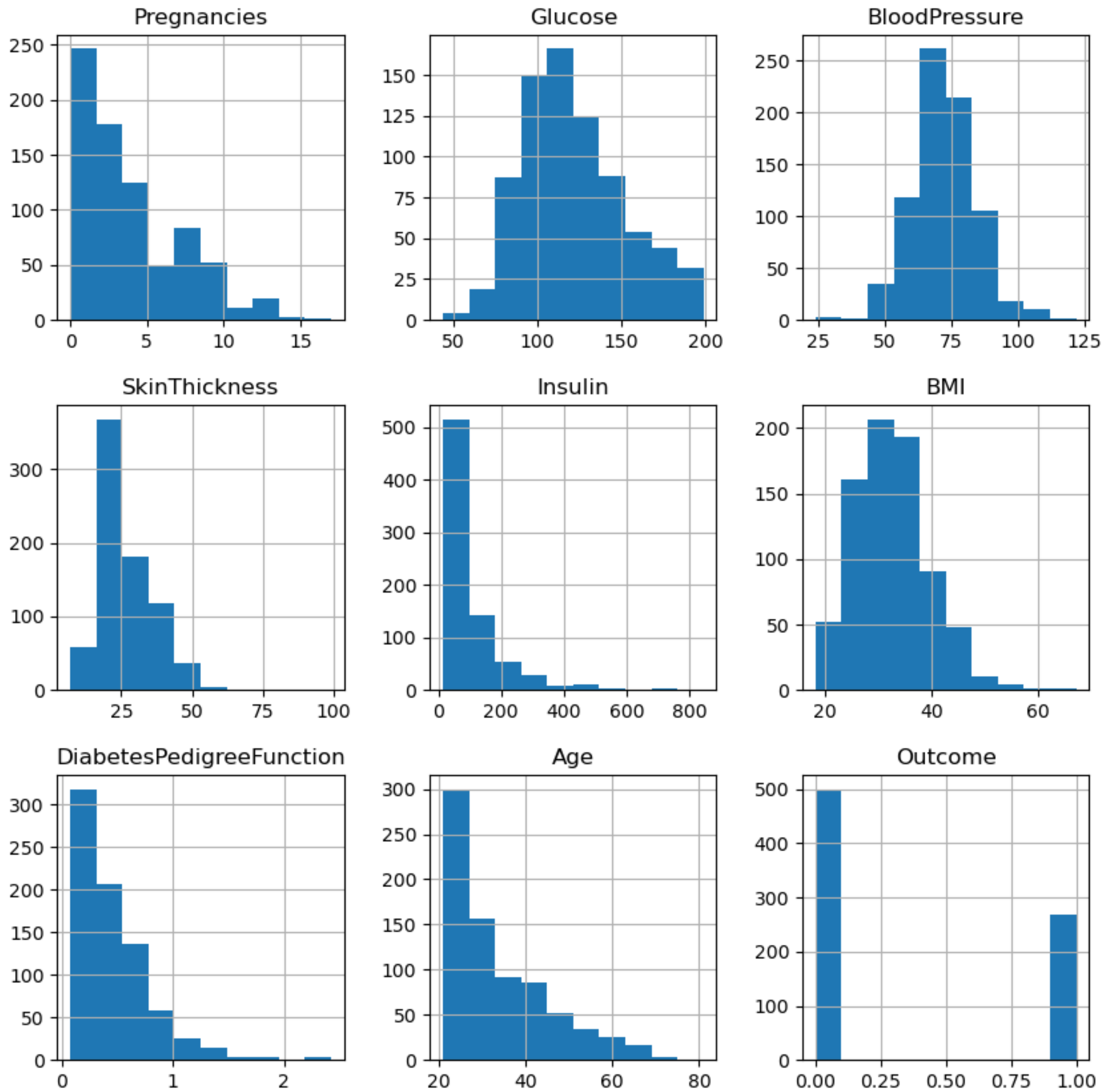




- *1 Represent –> Diabetes Positive*
- *0 Represent –> Daibetes Negative*

1.4.1 Histograms:

[28]:
```
df.hist(bins=10, figsize=(10, 10))
plt.show()
```



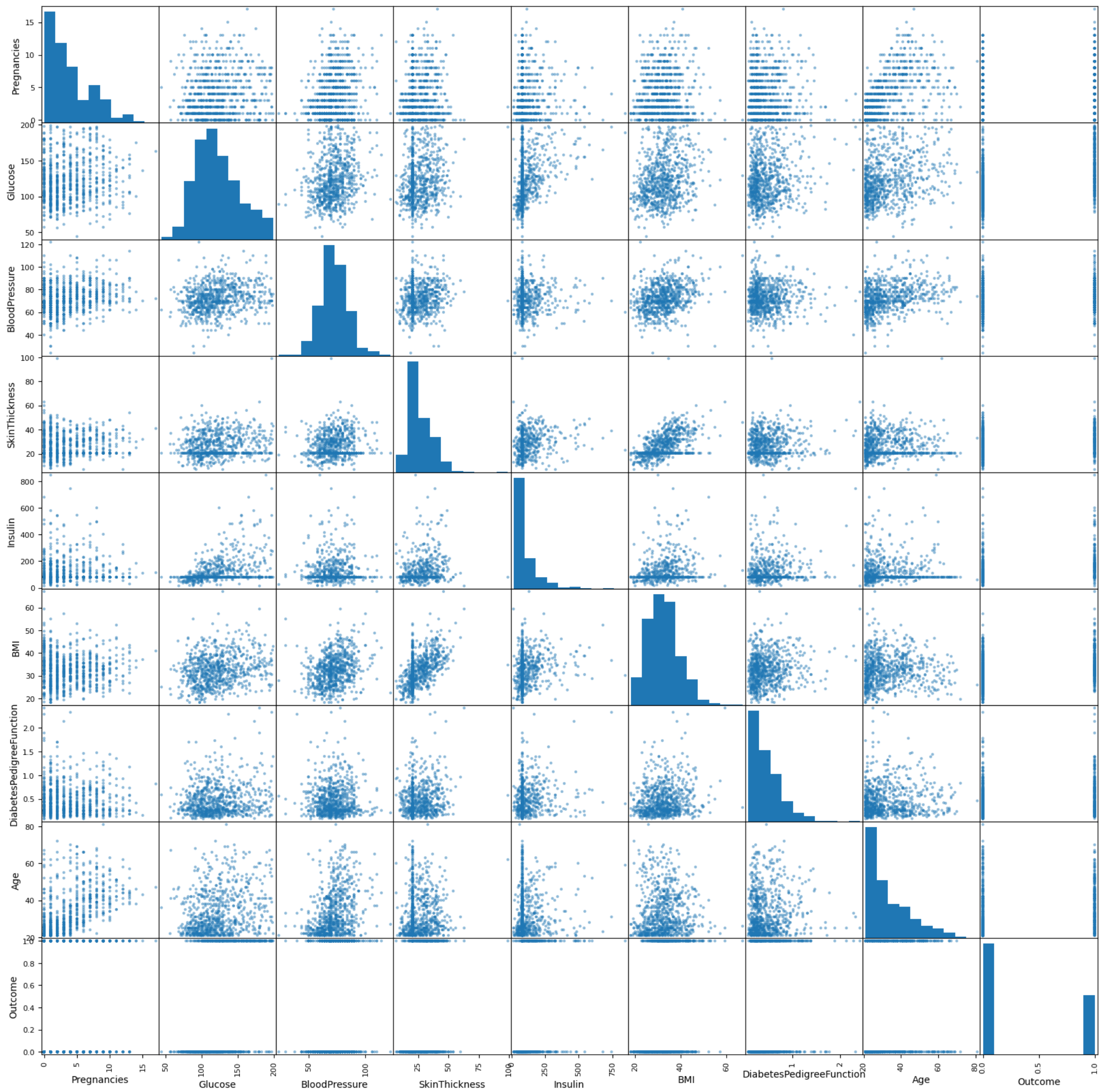
1.4.2 Scatter Plot:

[29]:
```
from pandas.plotting import scatter_matrix
scatter_matrix(df, figsize =(20, 20))
```

[29]:
```
array([[<Axes: xlabel='Pregnancies', ylabel='Pregnancies'>,
        <Axes: xlabel='Glucose', ylabel='Pregnancies'>,
        <Axes: xlabel='BloodPressure', ylabel='Pregnancies'>,
        <Axes: xlabel='SkinThickness', ylabel='Pregnancies'>,
        <Axes: xlabel='Insulin', ylabel='Pregnancies'>,
        <Axes: xlabel='BMI', ylabel='Pregnancies'>,
        <Axes: xlabel='DiabetesPedigreeFunction', ylabel='Pregnancies'>,
        <Axes: xlabel='Age', ylabel='Pregnancies'>,
```

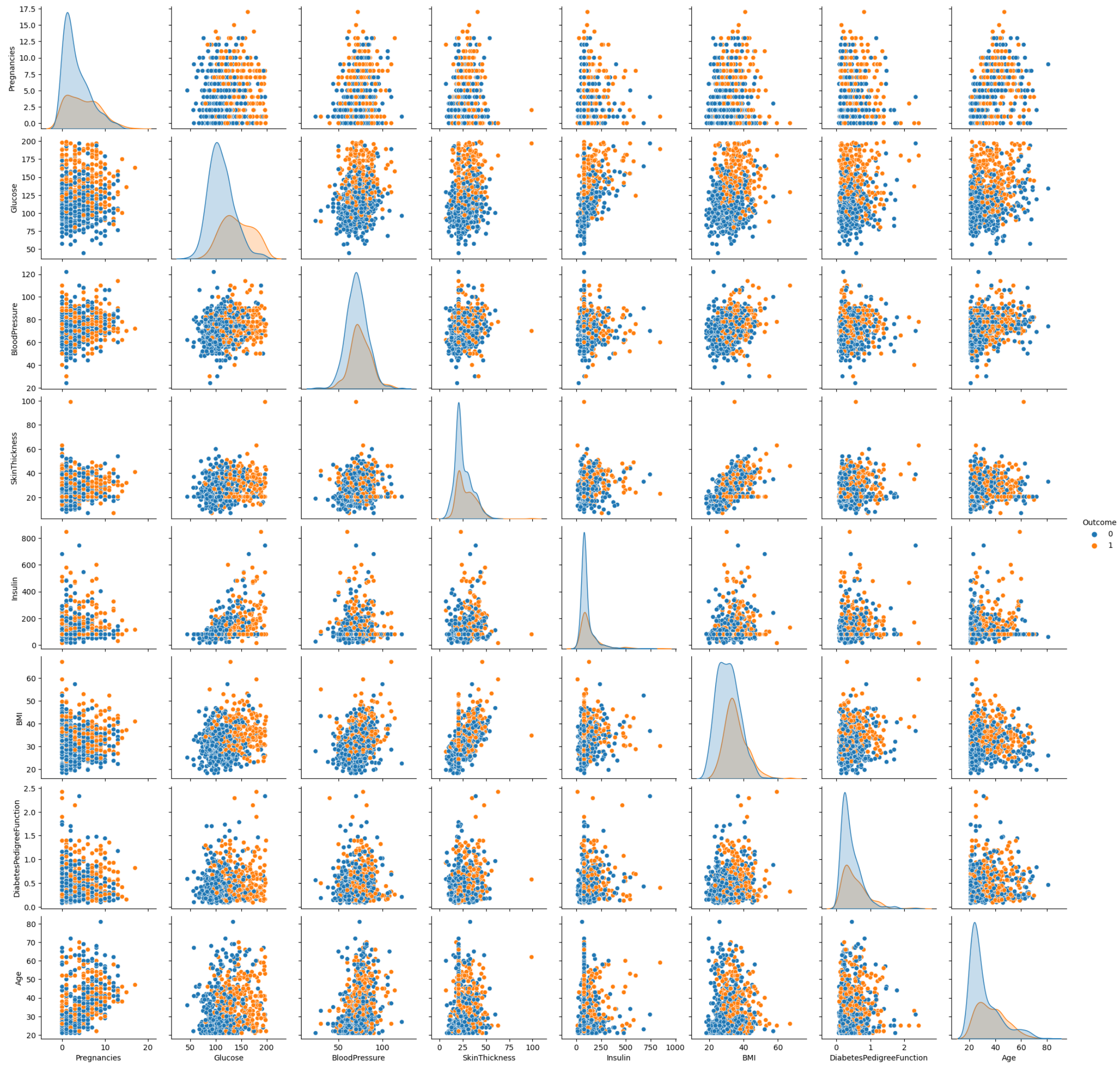
```
 <Axes: xlabel='Outcome', ylabel='Pregnancies'>],
[<Axes: xlabel='Pregnancies', ylabel='Glucose'>,
 <Axes: xlabel='Glucose', ylabel='Glucose'>,
 <Axes: xlabel='BloodPressure', ylabel='Glucose'>,
 <Axes: xlabel='SkinThickness', ylabel='Glucose'>,
 <Axes: xlabel='Insulin', ylabel='Glucose'>,
 <Axes: xlabel='BMI', ylabel='Glucose'>,
 <Axes: xlabel='DiabetesPedigreeFunction', ylabel='Glucose'>,
 <Axes: xlabel='Age', ylabel='Glucose'>,
 <Axes: xlabel='Outcome', ylabel='Glucose'>],
[<Axes: xlabel='Pregnancies', ylabel='BloodPressure'>,
 <Axes: xlabel='Glucose', ylabel='BloodPressure'>,
 <Axes: xlabel='BloodPressure', ylabel='BloodPressure'>,
 <Axes: xlabel='SkinThickness', ylabel='BloodPressure'>,
 <Axes: xlabel='Insulin', ylabel='BloodPressure'>,
 <Axes: xlabel='BMI', ylabel='BloodPressure'>,
 <Axes: xlabel='DiabetesPedigreeFunction', ylabel='BloodPressure'>,
 <Axes: xlabel='Age', ylabel='BloodPressure'>,
 <Axes: xlabel='Outcome', ylabel='BloodPressure'>],
[<Axes: xlabel='Pregnancies', ylabel='SkinThickness'>,
 <Axes: xlabel='Glucose', ylabel='SkinThickness'>,
 <Axes: xlabel='BloodPressure', ylabel='SkinThickness'>,
 <Axes: xlabel='SkinThickness', ylabel='SkinThickness'>,
 <Axes: xlabel='Insulin', ylabel='SkinThickness'>,
 <Axes: xlabel='BMI', ylabel='SkinThickness'>,
 <Axes: xlabel='DiabetesPedigreeFunction', ylabel='SkinThickness'>,
 <Axes: xlabel='Age', ylabel='SkinThickness'>,
 <Axes: xlabel='Outcome', ylabel='SkinThickness'>],
[<Axes: xlabel='Pregnancies', ylabel='Insulin'>,
 <Axes: xlabel='Glucose', ylabel='Insulin'>,
 <Axes: xlabel='BloodPressure', ylabel='Insulin'>,
 <Axes: xlabel='SkinThickness', ylabel='Insulin'>,
 <Axes: xlabel='Insulin', ylabel='Insulin'>,
 <Axes: xlabel='BMI', ylabel='Insulin'>,
 <Axes: xlabel='DiabetesPedigreeFunction', ylabel='Insulin'>,
 <Axes: xlabel='Age', ylabel='Insulin'>,
 <Axes: xlabel='Outcome', ylabel='Insulin'>],
[<Axes: xlabel='Pregnancies', ylabel='BMI'>,
 <Axes: xlabel='Glucose', ylabel='BMI'>,
 <Axes: xlabel='BloodPressure', ylabel='BMI'>,
 <Axes: xlabel='SkinThickness', ylabel='BMI'>,
 <Axes: xlabel='Insulin', ylabel='BMI'>,
 <Axes: xlabel='BMI', ylabel='BMI'>,
 <Axes: xlabel='DiabetesPedigreeFunction', ylabel='BMI'>,
 <Axes: xlabel='Age', ylabel='BMI'>,
 <Axes: xlabel='Outcome', ylabel='BMI'>],
[<Axes: xlabel='Pregnancies', ylabel='DiabetesPedigreeFunction'>,
```

```
        <Axes: xlabel='Glucose', ylabel='DiabetesPedigreeFunction'>,
        <Axes: xlabel='BloodPressure', ylabel='DiabetesPedigreeFunction'>,
        <Axes: xlabel='SkinThickness', ylabel='DiabetesPedigreeFunction'>,
        <Axes: xlabel='Insulin', ylabel='DiabetesPedigreeFunction'>,
        <Axes: xlabel='BMI', ylabel='DiabetesPedigreeFunction'>,
        <Axes: xlabel='DiabetesPedigreeFunction',
ylabel='DiabetesPedigreeFunction'>,
        <Axes: xlabel='Age', ylabel='DiabetesPedigreeFunction'>,
        <Axes: xlabel='Outcome', ylabel='DiabetesPedigreeFunction'>],
       [<Axes: xlabel='Pregnancies', ylabel='Age'>,
        <Axes: xlabel='Glucose', ylabel='Age'>,
        <Axes: xlabel='BloodPressure', ylabel='Age'>,
        <Axes: xlabel='SkinThickness', ylabel='Age'>,
        <Axes: xlabel='Insulin', ylabel='Age'>,
        <Axes: xlabel='BMI', ylabel='Age'>,
        <Axes: xlabel='DiabetesPedigreeFunction', ylabel='Age'>,
        <Axes: xlabel='Age', ylabel='Age'>,
        <Axes: xlabel='Outcome', ylabel='Age'>],
       [<Axes: xlabel='Pregnancies', ylabel='Outcome'>,
        <Axes: xlabel='Glucose', ylabel='Outcome'>,
        <Axes: xlabel='BloodPressure', ylabel='Outcome'>,
        <Axes: xlabel='SkinThickness', ylabel='Outcome'>,
        <Axes: xlabel='Insulin', ylabel='Outcome'>,
        <Axes: xlabel='BMI', ylabel='Outcome'>,
        <Axes: xlabel='DiabetesPedigreeFunction', ylabel='Outcome'>,
        <Axes: xlabel='Age', ylabel='Outcome'>,
        <Axes: xlabel='Outcome', ylabel='Outcome'>]], dtype=object)
```



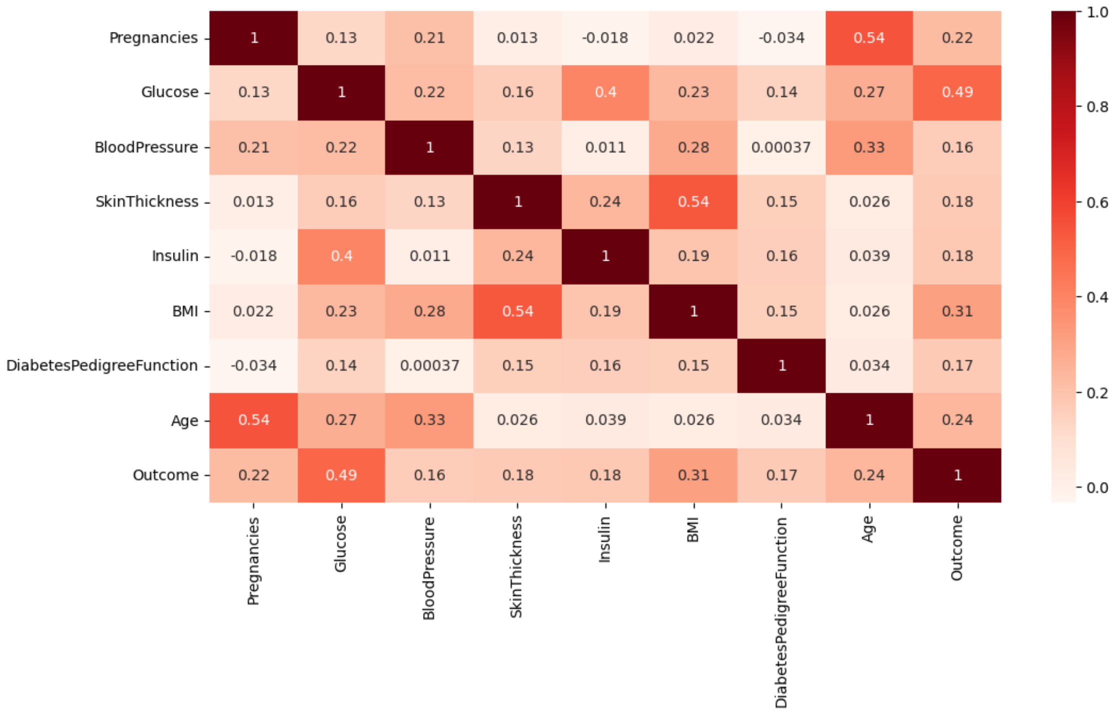
1.4.3 Pair plot:

[30]:
```
sns.pairplot(data=df, hue='Outcome')
plt.show()
```



[31]:
```python
plt.figure(figsize=(12, 6))
sns.heatmap(df.corr(), annot=True, cmap='Reds')
plt.plot()
# Creating a heatmap of the correlation matrix for the columns in the DataFrame␣
↪data
```

[31]: []



[32]:
```
mean = df['Outcome'].mean()
# Calculating the mean value of the 'Outcome' column in the DataFrame data
mean
# Displaying the calculated mean value
```

[32]: 0.3489583333333333

1.5 Split the DataFrame into X and y

[33]:
```
target_name='Outcome'

y=df[target_name]

X= df.drop(target_name, axis=1)
```

[34]:
```
X.head()
```

[34]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness     Insulin   BMI  \
0            6    148.0           72.0      35.000000   79.799479  33.6
1            1     85.0           66.0      29.000000   79.799479  26.6
2            8    183.0           64.0      20.536458   79.799479  23.3
3            1     89.0           66.0      23.000000   94.000000  28.1
4            0    137.0           40.0      35.000000  168.000000  43.1
```

```
   DiabetesPedigreeFunction  Age
0                     0.627   50
1                     0.351   31
2                     0.672   32
3                     0.167   21
4                     2.288   33
```

[35]:
```
y.head()
```

[35]:
```
0    1
1    0
2    1
3    0
4    1
Name: Outcome, dtype: int64
```

1.5.1 Future Scalling

[36]:
```
# Standard Scaler:
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X)
SSX = scaler.transform(X)
```

[37]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(SSX, y, test_size=0.2,␣
 ↪random_state=7)
```

[38]:
```
X_train.shape, y_train.shape
```

[38]:
```
((614, 8), (614,))
```

[39]:
```
X_test.shape, y_test.shape
```

[39]:
```
((154, 8), (154,))
```

2 Classification Algorithms:

2.1 Logistic Regression:

[40]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(solver='liblinear', multi_class='ovr')
lr.fit(X_train, y_train)
```

[40]:
```
LogisticRegression(multi_class='ovr', solver='liblinear')
```

2.2 Descision Tree:

```
[41]: from sklearn.tree import DecisionTreeClassifier
dt=DecisionTreeClassifier()
dt.fit(X_train, y_train)
```

```
[41]: DecisionTreeClassifier()
```

3 Making prediction:

Logistic Regression:

```
[42]: X_test.shape
```

```
[42]: (154, 8)
```

```
[43]: lr_pred=lr.predict(X_test)
```

```
[44]: lr_pred.shape
```

```
[44]: (154,)
```

Decision Tree:

```
[45]: dt_pred=dt.predict(X_test)
```

```
[46]: dt_pred.shape
```

```
[46]: (154,)
```

4 Model Evaluation for Logistic Regression:

Train Score and Test Score

```
[47]: # For Logistic Regression:
from sklearn.metrics import accuracy_score
print("Train Accuracy of Logistic Regression: ", lr.score(X_train, y_train)*100)
print("Accuracy (Test) Score of Logistic Regression: ", lr.score(X_test,␣
 ↪y_test)*100)
print("Accuracy Score of Logistic Regression: ", accuracy_score(y_test,␣
 ↪lr_pred)*100)
```

```
Train Accuracy of Logistic Regression:  77.36156351791531
Accuracy (Test) Score of Logistic Regression:  77.27272727272727
Accuracy Score of Logistic Regression:  77.27272727272727
```

[48]:
```
# For Decesion Tree:
print("Train Accuracy of Decesion Tree: ", dt.score(X_train, y_train)*100)
print("Accuracy (Test) Score of Decesion Tree: ", dt.score(X_test, y_test)*100)
print("Accuracy Score of Decesion Tree: ", accuracy_score(y_test, dt_pred)*100)
```

```
Train Accuracy of Decesion Tree:  100.0
Accuracy (Test) Score of Decesion Tree:  80.51948051948052
Accuracy Score of Decesion Tree:  80.51948051948052
```

5 Confusion Matrix

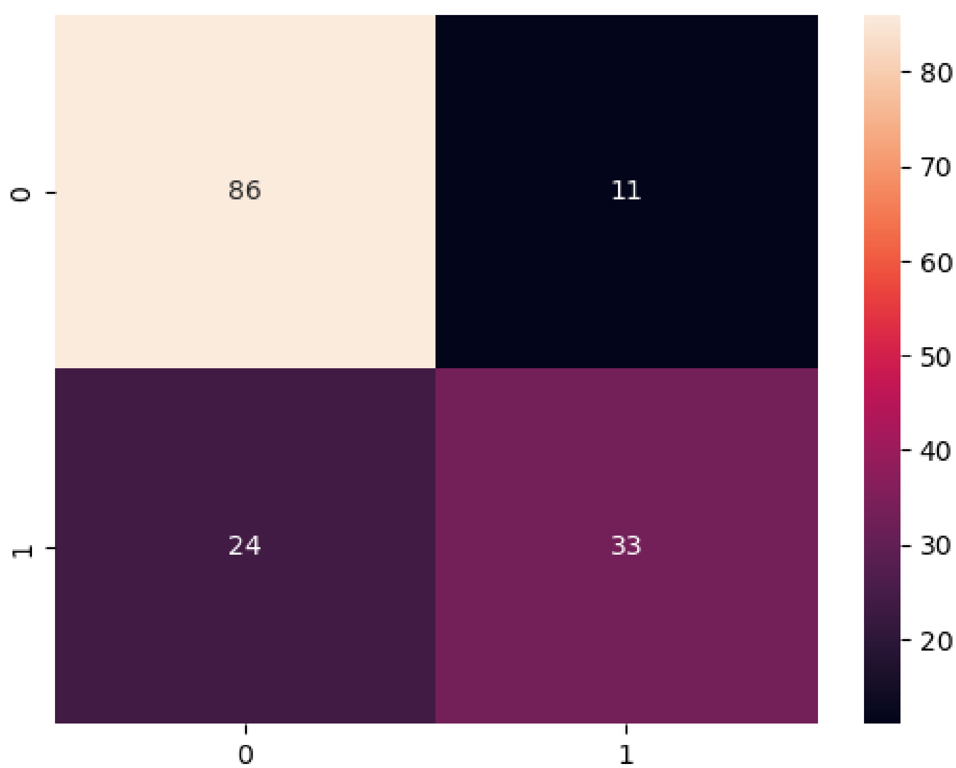
- *Confusion Matrix of "Logistic Regression"*

[49]:
```
from sklearn.metrics import classification_report, confusion_matrix

cm = confusion_matrix(y_test, lr_pred)
cm
```

[49]:
```
array([[86, 11],
       [24, 33]])
```

[50]:
```
sns.heatmap(confusion_matrix(y_test, lr_pred), annot=True, fmt="d")
```

[50]: <Axes: >



```
[51]: TN =cm[0, 0]
      FP =cm[0,1]
      FN = cm[1,0]
      TP  = cm[1,1]
```

```
[52]: TN, FP, FN, TP
```

```
[52]: (86, 11, 24, 33)
```

```
[53]: from sklearn.metrics import classification_report, confusion_matrix
      from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
      cm = confusion_matrix(y_test, lr_pred)

      print('TN - True Negative {}'.format(cm[0,0]))
      print('FP - False Positive {}'.format(cm[0,1]))
      print('FN - False Negative {}'.format(cm[1,0]))
      print('TP - True Positive {}'.format(cm[1,1]))
      print('Accuracy Rate: {}'.format(np.divide(np.sum([cm[0,0], cm[1,1]]), np.
       ↪sum(cm))*100))
      print('Misclassification Rate: {}'.format(np.divide(np.sum([cm[0,1], cm[1,0]]),␣
       ↪np.sum(cm))*100))
```

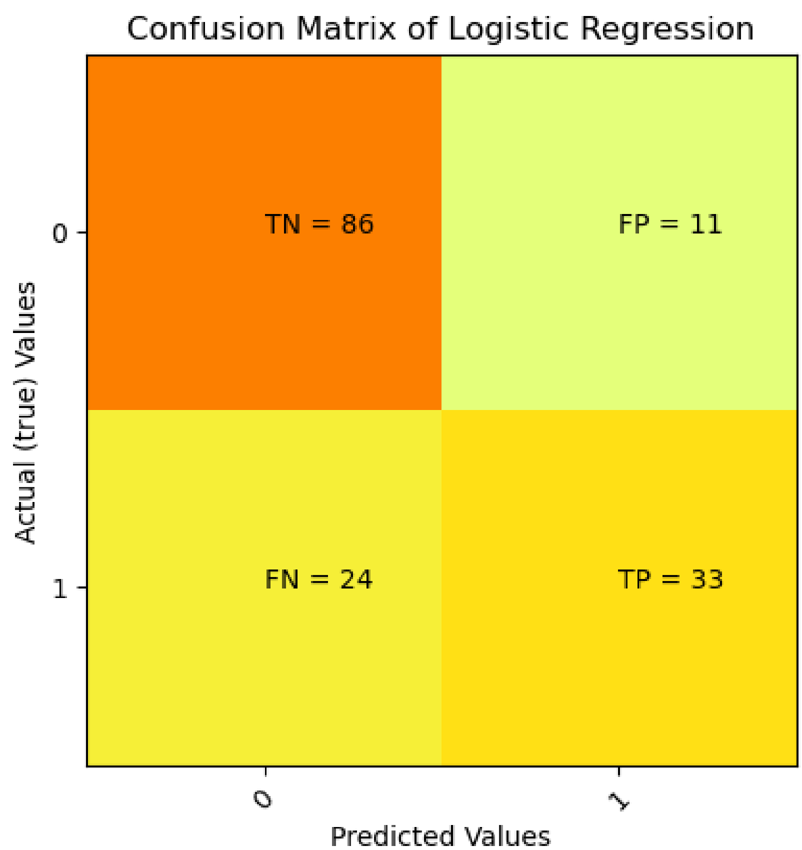
```
TN - True Negative 86
FP - False Positive 11
FN - False Negative 24
TP - True Positive 33
Accuracy Rate: 77.27272727272727
Misclassification Rate: 22.727272727272727
```

```
[54]: 77.27272727272727+22.727272727272727
```

```
[54]: 100.0
```

```
[55]: import matplotlib.pyplot as plt
      import numpy as np

      plt.clf()
      plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Wistia)
      classNames = ['0', '1']
      plt.title('Confusion Matrix of Logistic Regression')
      plt.ylabel('Actual (true) Values')
      plt.xlabel('Predicted Values')
      tick_marks = np.arange(len(classNames))
      plt.xticks(tick_marks, classNames, rotation=45)
      plt.yticks(tick_marks, classNames)
```

```
s = [['TN', 'FP'], ['FN', 'TP']]
for i in range(2):
    for j in range(2):
        plt.text(j, i, str(s[i][j]) + " = " + str(cm[i][j]))

plt.show()
```



[56]:
```
pd.crosstab(y_test, lr_pred, margins=False)
```

[56]:

col_0	0	1
Outcome		
0	86	11
1	24	33

[57]:
```
pd.crosstab(y_test, lr_pred, margins=True)
```

[57]:

col_0	0	1	All
Outcome			
0	86	11	97
1	24	33	57

```
All      110  44  154
```

[58]:
```
pd.crosstab(y_test, lr_pred, rownames=['Actual values'], colnames=['Predicted␣
 ↪values'], margins=True)
```

[58]:
```
Predicted values    0   1  All
Actual values
0                  86  11   97
1                  24  33   57
All               110  44  154
```

5.0.1 Precision:

```
PPV- positive Predictive Value
```

Precision = True Positive/True Positive + False Positive
Precision = TP/TP+FP

[59]:
```
TP, FP
```

[59]:
```
(33, 11)
```

[60]:
```
Precision = TP/(TP+FP)
Precision
```

[60]:
```
0.75
```

[61]:
```
33/(33+11)
```

[61]:
```
0.75
```

[62]:
```
# precision Score:

precision_score = TP/float(TP+FP)*100
print('Precision Score: {0:0.4f}'.format(precision_score))
```

```
Precision Score: 75.0000
```

[63]:
```
from sklearn.metrics import precision_score
print("Precision Score is: ", precision_score(y_test, lr_pred)*100)
print("Micro Average Precision Score is: ", precision_score(y_test, lr_pred,␣
 ↪average='micro')*100)
print("Macro Average Precision Score is: ", precision_score(y_test, lr_pred,␣
 ↪average='macro')*100)
print("Weighted Average Precision Score is: ", precision_score(y_test, lr_pred,␣
 ↪average='weighted')*100)
print("precision Score on Non Weighted score is: ", precision_score(y_test,␣
 ↪lr_pred, average=None)*100)
```

```
Precision Score is:  75.0
Micro Average Precision Score is:  77.27272727272727
Macro Average Precision Score is:  76.5909090909091
Weighted Average Precision Score is:  77.00413223140497
precision Score on Non Weighted score is:  [78.18181818 75.        ]
```

[64]:
```
print('Classification Report of Logistic Regression: \n',␣
↪classification_report(y_test, lr_pred, digits=4))
```

```
Classification Report of Logistic Regression:
               precision    recall  f1-score   support

           0     0.7818    0.8866    0.8309        97
           1     0.7500    0.5789    0.6535        57

    accuracy                         0.7727       154
   macro avg     0.7659    0.7328    0.7422       154
weighted avg     0.7700    0.7727    0.7652       154
```

5.1 Recall

True Positive Rate(TPR)

Recall = True Positive/True Positive + False Negative
Recall = TP/TP+FN

[65]:
```
recall_score = TP/ float(TP+FN)*100
print('recall_score', recall_score)
```

```
recall_score 57.89473684210527
```

[66]:
```
TP, FN
```

[66]: (33, 24)

[67]:
```
33/(33+24)
```

[67]: 0.5789473684210527

[68]:
```
from sklearn.metrics import recall_score
print('Recall or Sensitivity_Score: ', recall_score(y_test, lr_pred)*100)
```

```
Recall or Sensitivity_Score:  57.89473684210527
```

[69]:
```
print("recall Score is: ", recall_score(y_test, lr_pred)*100)
print("Micro Average recall Score is: ", recall_score(y_test, lr_pred,␣
↪average='micro')*100)
```

```
print("Macro Average recall Score is: ", recall_score(y_test, lr_pred,␣
  ↪average='macro')*100)
print("Weighted Average recall Score is: ", recall_score(y_test, lr_pred,␣
  ↪average='weighted')*100)
print("recall Score on Non Weighted score is: ", recall_score(y_test, lr_pred,␣
  ↪average=None)*100)
```

```
recall Score is:  57.89473684210527
Micro Average recall Score is:  77.27272727272727
Macro Average recall Score is:  73.27726532826912
Weighted Average recall Score is:  77.27272727272727
recall Score on Non Weighted score is:  [88.65979381 57.89473684]
```

[70]:
```
print('Classification Report of Logistic Regression: \n',␣
  ↪classification_report(y_test, lr_pred, digits=4))
```

```
Classification Report of Logistic Regression:
               precision    recall  f1-score   support

           0     0.7818    0.8866    0.8309        97
           1     0.7500    0.5789    0.6535        57

    accuracy                         0.7727       154
   macro avg     0.7659    0.7328    0.7422       154
weighted avg     0.7700    0.7727    0.7652       154
```

FPR - False Positve Rate

[71]:
```
FPR = FP / float(FP + TN) * 100
print('False Positive Rate: {:.4f}'.format(FPR))
```

```
False Positive Rate: 11.3402
```

[72]:
```
FP, TN
```

[72]: (11, 86)

[73]:
```
11/(11+86)
```

[73]: 0.1134020618556701

5.2 Specificity:

[74]:
```
specificity = TN /(TN+FP)*100
print('Specificity : {0:0.4f}'.format(specificity))
```

```
Specificity : 88.6598
```

[75]:
```
from sklearn.metrics import f1_score
print('F1_Score of Macro: ', f1_score(y_test, lr_pred)*100)
```

```
F1_Score of Macro:  65.34653465346535
```

[76]:
```
print("Micro Average f1 Score is: ", f1_score(y_test, lr_pred,␣
 ↪average='micro')*100)
print("Macro Average f1 Score is: ", f1_score(y_test, lr_pred,␣
 ↪average='macro')*100)
print("Weighted Average f1 Score is: ", f1_score(y_test, lr_pred,␣
 ↪average='weighted')*100)
print("f1 Score on Non Weighted score is: ", f1_score(y_test, lr_pred,␣
 ↪average=None)*100)
```

```
Micro Average f1 Score is:  77.27272727272727
Macro Average f1 Score is:  74.21916104653944
Weighted Average f1 Score is:  76.52373933045479
f1 Score on Non Weighted score is:  [83.09178744 65.34653465]
```

5.3 Classification Report of Logistic Regression:

[77]:
```
from sklearn.metrics import classification_report
print('Classification Report of Logistic Regression: \n',␣
 ↪classification_report(y_test, lr_pred, digits=4))
```

```
Classification Report of Logistic Regression:
               precision    recall  f1-score   support

           0     0.7818    0.8866    0.8309        97
           1     0.7500    0.5789    0.6535        57

    accuracy                         0.7727       154
   macro avg     0.7659    0.7328    0.7422       154
weighted avg     0.7700    0.7727    0.7652       154
```

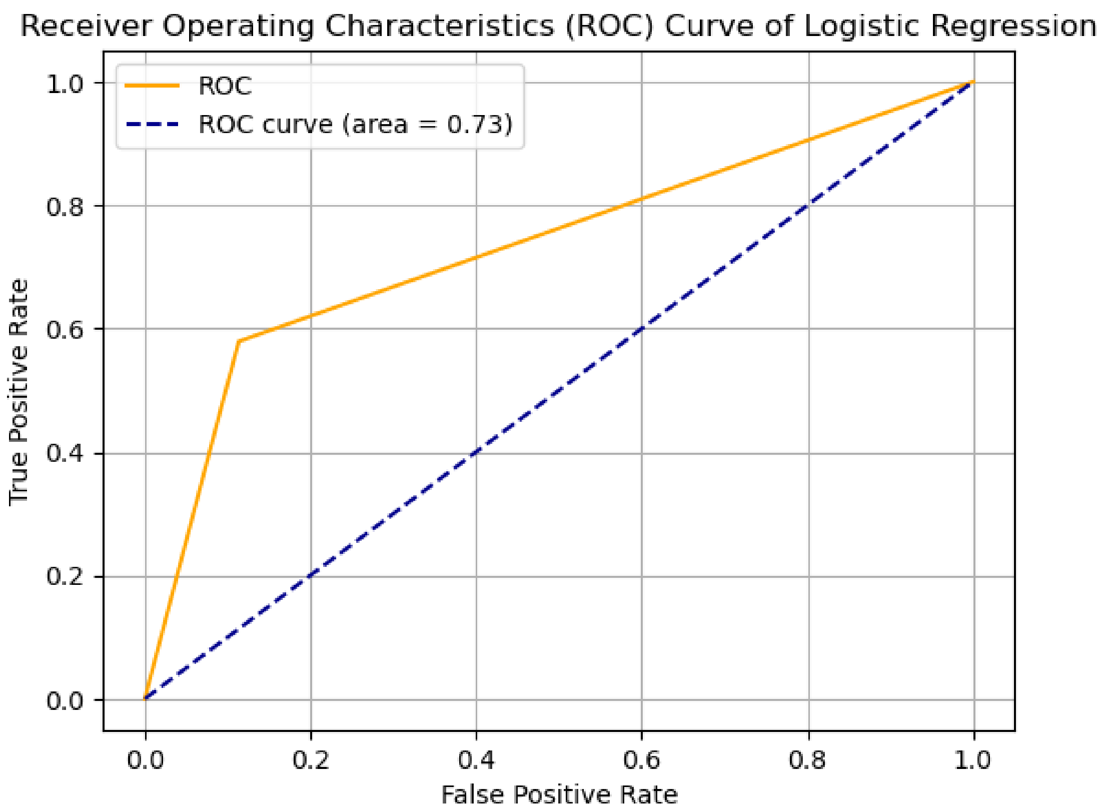
5.4 ROC Curve& ROC AUC

[78]:
```
# Area under Curve:
auc= roc_auc_score(y_test, lr_pred)
print("ROC AUC SCORE of logistic Regression is ", auc)
```

```
ROC AUC SCORE of logistic Regression is  0.7327726532826913
```

[79]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

fpr, tpr, thresholds = roc_curve(y_test, lr_pred)
```

```
plt.plot(fpr, tpr, color='orange', label="ROC")
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve␣
  ↪(area = %0.2f)' % auc(fpr, tpr))
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver Operating Characteristics (ROC) Curve of Logistic␣
  ↪Regression")
plt.legend()
plt.grid()
plt.show()
```



5.5 Confusion Matrix:

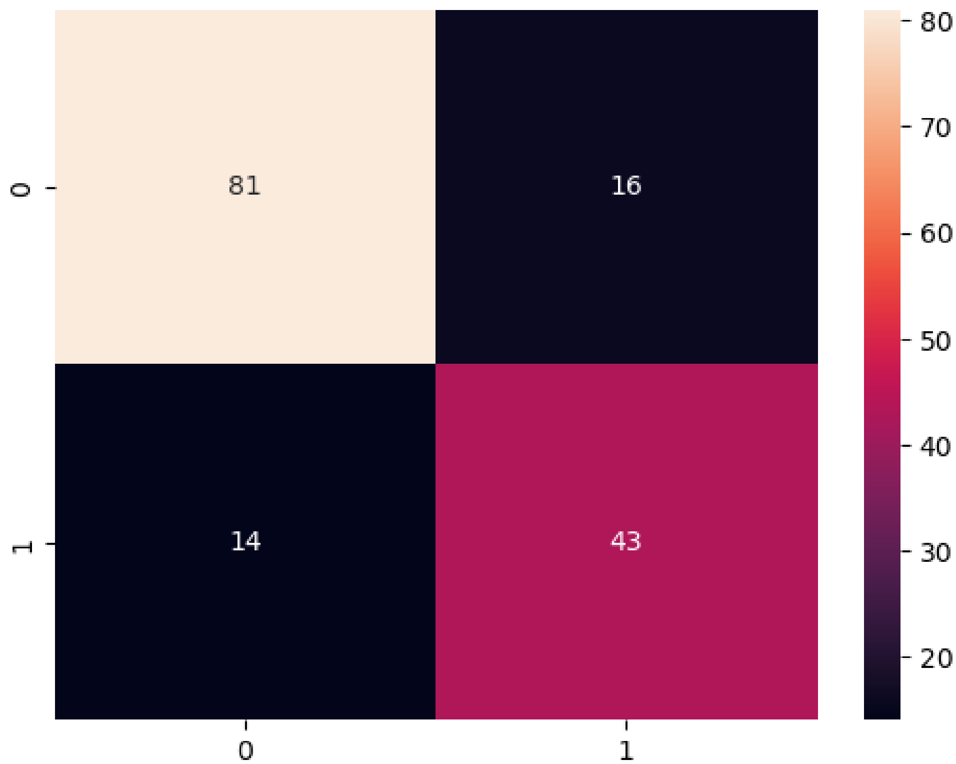
- Confusion matrix of "Decision Tree"

[80]:
```
from sklearn.metrics import classification_report, confusion_matrix

cm = confusion_matrix(y_test, dt_pred)
cm
```

[80]: array([[81, 16],
       [14, 43]])

[81]:
```
sns.heatmap(confusion_matrix(y_test, dt_pred), annot=True, fmt="d")
```

[81]: <Axes: >



[82]:
```
TN =cm[0, 0]
FP =cm[0,1]
FN = cm[1,0]
TP  = cm[1,1]
```

[83]:
```
TN, FP, FN, TP
```

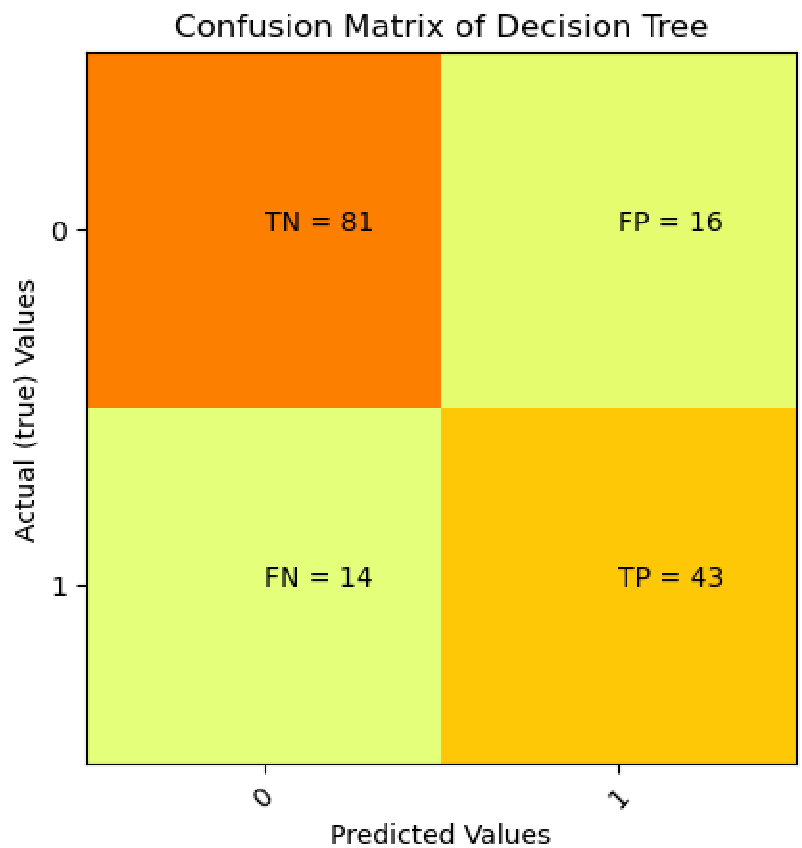
[83]: (81, 16, 14, 43)

[84]:
```
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
cm = confusion_matrix(y_test, dt_pred)

print('TN - True Negative {}'.format(cm[0,0]))
print('FP - False Positive {}'.format(cm[0,1]))
```

```python
print('FN - False Negative {}'.format(cm[1,0]))
print('TP - True Positive {}'.format(cm[1,1]))
print('Accuracy Rate: {}'.format(np.divide(np.sum([cm[0,0], cm[1,1]]), np.
 ↪sum(cm))*100))
print('Misclassification Rate: {}'.format(np.divide(np.sum([cm[0,1], cm[1,0]]),␣
 ↪np.sum(cm))*100))
```

```
TN - True Negative 81
FP - False Positive 16
FN - False Negative 14
TP - True Positive 43
Accuracy Rate: 80.51948051948052
Misclassification Rate: 19.480519480519483
```

[85]:
```python
import matplotlib.pyplot as plt
import numpy as np

plt.clf()
plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Wistia)
classNames = ['0', '1']
plt.title('Confusion Matrix of Decision Tree')
plt.ylabel('Actual (true) Values')
plt.xlabel('Predicted Values')
tick_marks = np.arange(len(classNames))
plt.xticks(tick_marks, classNames, rotation=45)
plt.yticks(tick_marks, classNames)
s = [['TN', 'FP'], ['FN', 'TP']]
for i in range(2):
    for j in range(2):
        plt.text(j, i, str(s[i][j]) + " = " + str(cm[i][j]))

plt.show()
```



5.6 Precision:

[86]:
```
# precision Score:

precision_score = TP/float(TP+FP)*100
print('Precision Score: {0:0.4f}'.format(precision_score))
```

```
Precision Score: 72.8814
```

[87]:
```
from sklearn.metrics import precision_score

print("Precision Score is:", precision_score(y_test, dt_pred) * 100)
print("Micro Average Precision Score is:", precision_score(y_test, dt_pred,␣
  ↪average='micro') * 100)
print("Macro Average Precision Score is:", precision_score(y_test, dt_pred,␣
  ↪average='macro') * 100)
print("Weighted Average Precision Score is:", precision_score(y_test, dt_pred,␣
  ↪average='weighted') * 100)
```

```
print("Precision Score on Non Weighted score is:", precision_score(y_test,␣
↪dt_pred, average=None) * 100)
```

```
Precision Score is: 72.88135593220339
Micro Average Precision Score is: 80.51948051948052
Macro Average Precision Score is: 79.07225691347011
Weighted Average Precision Score is: 80.68028314237056
Precision Score on Non Weighted score is: [85.26315789 72.88135593]
```

5.7 Recall:

[88]:
```
recall_score = TP/ float(TP+FN)*100
print('recall_score', recall_score)
```

```
recall_score 75.43859649122807
```

[89]:
```
from sklearn.metrics import recall_score
print('Recall or Sensitivity_Score: ', recall_score(y_test, dt_pred)*100)
```

```
Recall or Sensitivity_Score:  75.43859649122807
```

[90]:
```
print("recall Score is: ", recall_score(y_test, dt_pred)*100)
print("Micro Average recall Score is: ", recall_score(y_test, dt_pred,␣
↪average='micro')*100)
print("Macro Average recall Score is: ", recall_score(y_test, dt_pred,␣
↪average='macro')*100)
print("Weighted Average recall Score is: ", recall_score(y_test, dt_pred,␣
↪average='weighted')*100)
print("recall Score on Non Weighted score is: ", recall_score(y_test, dt_pred,␣
↪average=None)*100)
```

```
recall Score is:  75.43859649122807
Micro Average recall Score is:  80.51948051948052
Macro Average recall Score is:  79.47187556520167
Weighted Average recall Score is:  80.51948051948052
recall Score on Non Weighted score is:  [83.50515464 75.43859649]
```

5.8 FPR

[91]:
```
FPR = FP / float(FP + TN) * 100
print('False Positive Rate: {:.4f}'.format(FPR))
```

```
False Positive Rate: 16.4948
```

5.9 Specificity:

[92]:
```
specificity = TN /(TN+FP)*100
print('Specificity : {0:0.4f}'.format(specificity))
```

```
Specificity : 83.5052
```

[93]:
```
from sklearn.metrics import f1_score
print('F1_Score of Macro: ', f1_score(y_test, dt_pred)*100)
```

```
F1_Score of Macro:  74.13793103448276
```

[94]:
```
print("Micro Average f1 Score is: ", f1_score(y_test, dt_pred,␣
 ↪average='micro')*100)
print("Macro Average f1 Score is: ", f1_score(y_test, dt_pred,␣
 ↪average='macro')*100)
print("Weighted Average f1 Score is: ", f1_score(y_test, dt_pred,␣
 ↪average='weighted')*100)
print("f1 Score on Non Weighted score is: ", f1_score(y_test, dt_pred,␣
 ↪average=None)*100)
```

```
Micro Average f1 Score is:  80.51948051948051
Macro Average f1 Score is:  79.25646551724138
Weighted Average f1 Score is:  80.58595499328258
f1 Score on Non Weighted score is:  [84.375      74.13793103]
```

5.10 Classification Report of Decision Tree:

[95]:
```
from sklearn.metrics import classification_report
print('Classification Report of Decision Tree: \n',␣
 ↪classification_report(y_test, dt_pred, digits=4))
```

```
Classification Report of Decision Tree:
               precision    recall  f1-score   support

           0     0.8526    0.8351    0.8438        97
           1     0.7288    0.7544    0.7414        57

    accuracy                         0.8052       154
   macro avg     0.7907    0.7947    0.7926       154
weighted avg     0.8068    0.8052    0.8059       154
```

5.11 ROC Curve& ROC AUC

[96]:
```
# Area under Curve:
auc= roc_auc_score(y_test, dt_pred)
print("ROC AUC SCORE of Decision Treeis ", auc)
```

```
ROC AUC SCORE of Decision Treeis  0.7947187556520168
```

[97]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

fpr, tpr, thresholds = roc_curve(y_test, dt_pred)
plt.plot(fpr, tpr, color='orange', label="ROC")
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve␣
↪(area = %0.2f)' % auc(fpr, tpr))
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver Operating Characteristics (ROC) Curve of Decision Tree")
plt.legend()
plt.grid()
plt.show()
```