Github1

February 9, 2024

1 1. Data Wrangling

[3]:
```
import pandas as pd
import numpy as np
```

[4]:
```
df=pd.read_csv('health care diabetes.csv')
```

[5]:
```
df.shape
```

[5]:
```
(768, 9)
```

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

[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

   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
```

[7]:
```
df.columns
```

[7]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

[8]:
```
df.isna().sum()
```

[8]:
```
Pregnancies                 0
Glucose                     0
```

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

[9]:
```
#inference : the dataset contains no null values
```

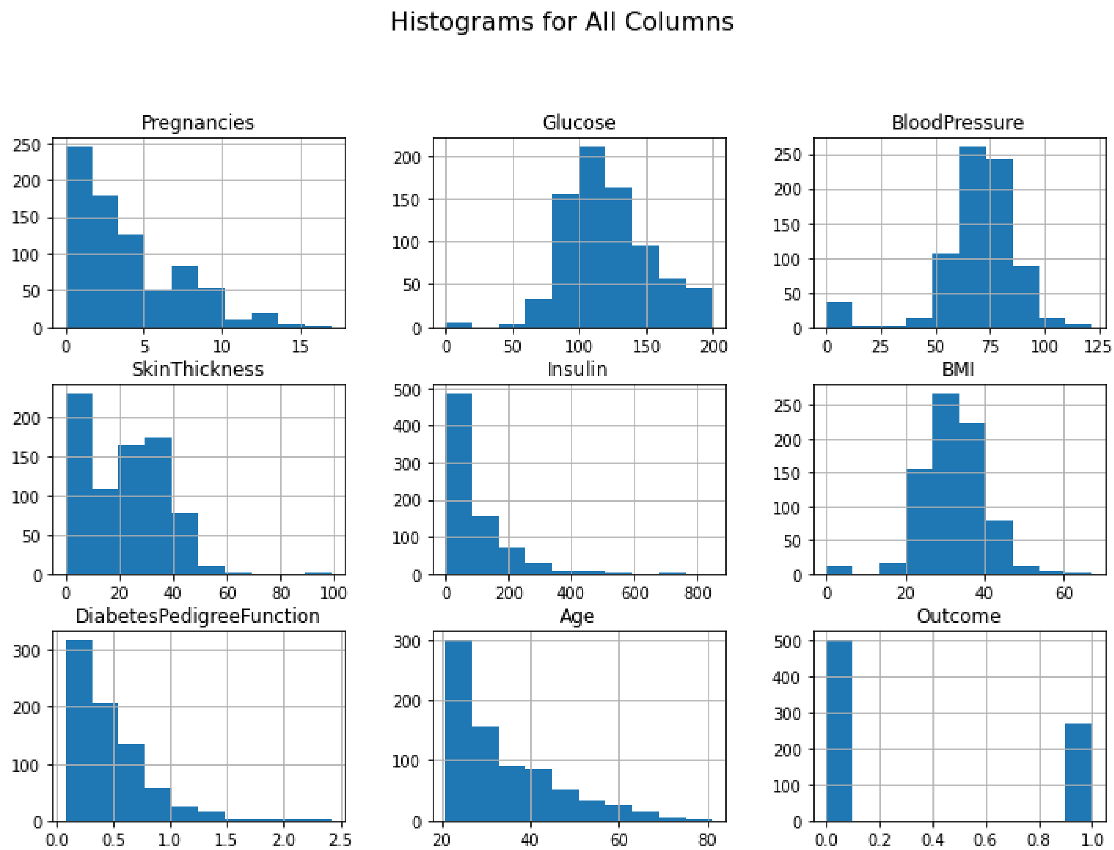
[10]:
```
#check for duplicated values
df.duplicated().sum()
```

[10]: 0

[ ]:
```
#inference : the dataset contains no duplicate entries
```

[11]:
```
import matplotlib.pyplot as plt
```

[12]:
```
df.hist(bins=10, figsize=(12, 8))
plt.suptitle('Histograms for All Columns', x=0.5, y=1.02, fontsize=16)
plt.show()
```



[13]:
```python
zeros_count_per_column = df.eq(0).sum()

print("Number of zeros in each column:")
print(zeros_count_per_column)
```

```
Number of zeros in each column:
Pregnancies                 111
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                     500
dtype: int64
```

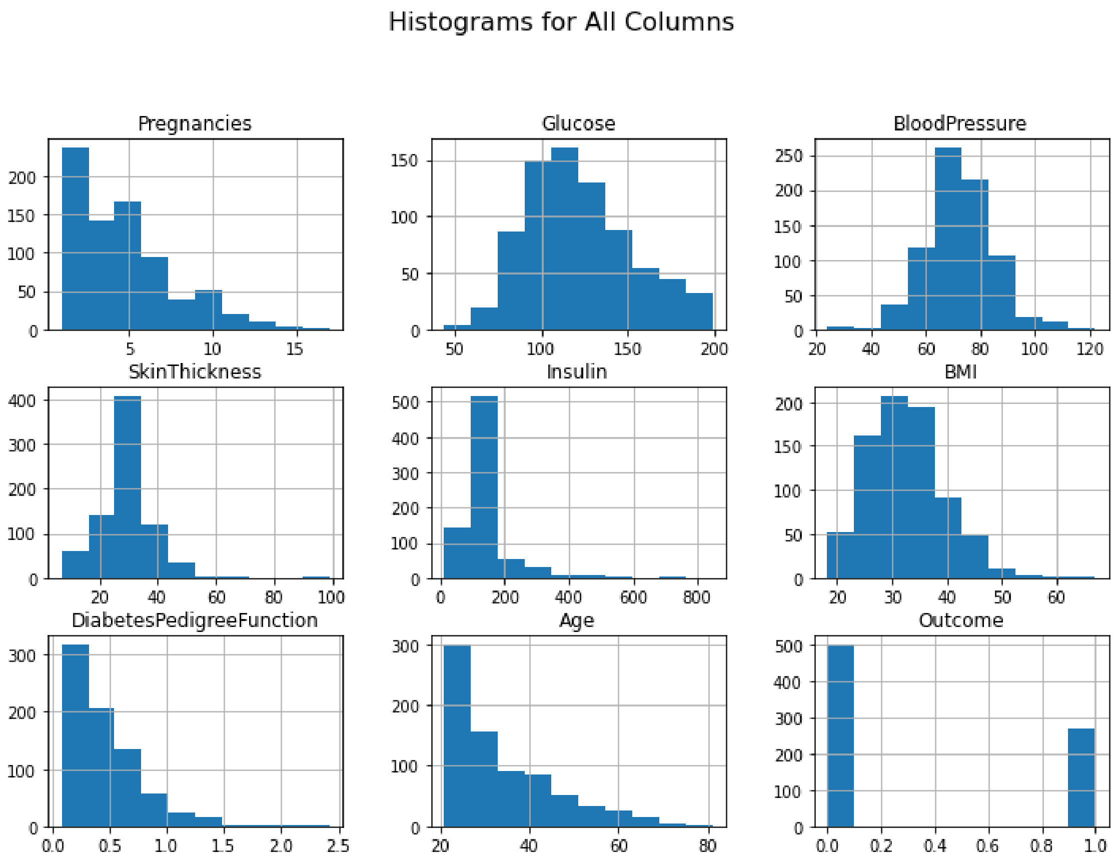
The zero enteries represent null value. Thes zero entries are to be replaced with mean or mode. #### Assumption: As the gender of patients is not given, it is assumed that zero values in Pregnancies represents null value of female patients only.

2 Ques 2(b)

[14]:
```
# Calculate the column-wise mean excluding zeros
column_means = df[df != 0].replace(0, np.nan).mean()

# Replace zeros with the column mean (excluding 'Outcome')
df[df.columns.difference(['Outcome'])] = df[df.columns.difference(['Outcome'])].
↪replace(0, np.nan)
df = df.fillna(column_means)

print(df)
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness     Insulin   BMI  \
0       6.000000    148.0           72.0       35.00000  155.548223  33.6
1       1.000000     85.0           66.0       29.00000  155.548223  26.6
2       8.000000    183.0           64.0       29.15342  155.548223  23.3
3       1.000000     89.0           66.0       23.00000   94.000000  28.1
4       4.494673    137.0           40.0       35.00000  168.000000  43.1
..           …        …             …              …          …    …
763    10.000000    101.0           76.0       48.00000  180.000000  32.9
764     2.000000    122.0           70.0       27.00000  155.548223  36.8
765     5.000000    121.0           72.0       23.00000  112.000000  26.2
766     1.000000    126.0           60.0       29.15342  155.548223  30.1
767     1.000000     93.0           70.0       31.00000  155.548223  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]
```

[15]:
```
df.hist(bins=10, figsize=(12, 8))
plt.suptitle('Histograms for All Columns', x=0.5, y=1.02, fontsize=16)
plt.show()
```



[55]:
```
# We have calculated the mean for each field, by excluding the zero entries and
↪replaced the zero entries with the corresponding mean.
```

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

print("Number of zeros in each column:")
print(zeros_count_per_column)
```

```
Number of zeros in each column:
Pregnancies                   0
Glucose                       0
BloodPressure                 0
SkinThickness                 0
Insulin                       0
BMI                           0
DiabetesPedigreeFunction      0
Age                           0
Outcome                     500
dtype: int64
```

3 2. EDA

[17]:
```
df.dtypes
```

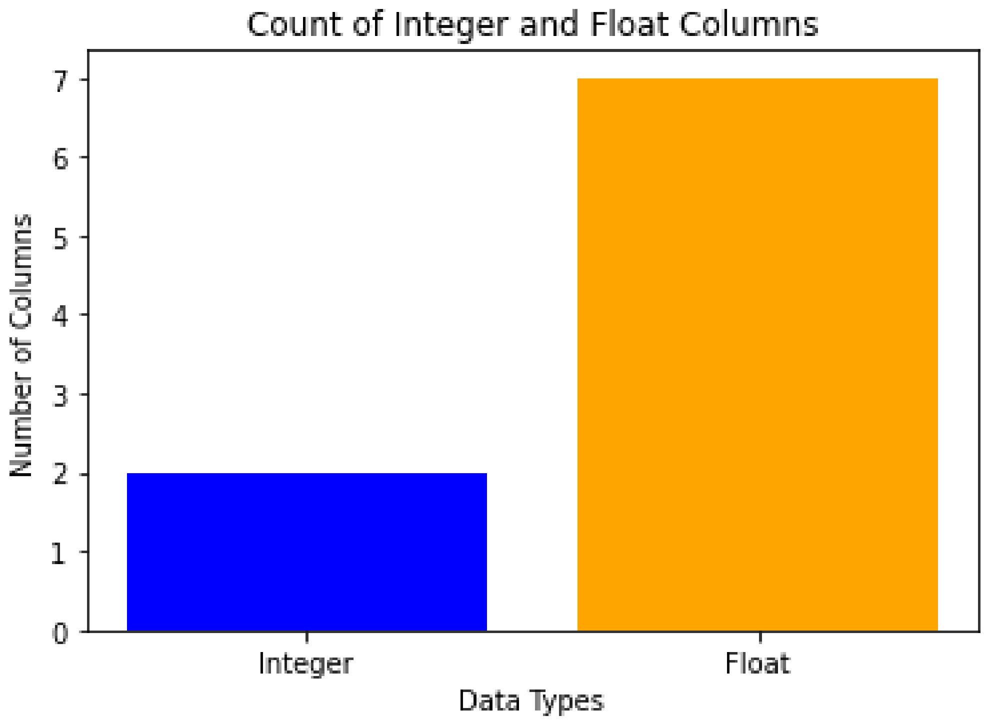
[17]:
```
Pregnancies                 float64
Glucose                     float64
BloodPressure               float64
SkinThickness               float64
Insulin                     float64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

3.1 Univariate Analysis

3.1.1 Creating a count (frequency) plot describing the data types and the count of variables.

[18]:
```
import seaborn as sns
```

[19]:
```
int_columns = df.select_dtypes(include='int').columns
float_columns = df.select_dtypes(include='float').columns

# Count the number of columns in each category
int_count = len(int_columns)
float_count = len(float_columns)

# Plot the count plot
plt.bar(['Integer', 'Float'], [int_count, float_count], color=['blue',␣
 ↪'orange'])
plt.xlabel('Data Types')
plt.ylabel('Number of Columns')
plt.title('Count of Integer and Float Columns')
plt.show()
```



[56]:
```
# inference :  The given data set had 2 integer variables and 7 Float variables.
```

3.1.2 Plotting the count of outcomes by their value.

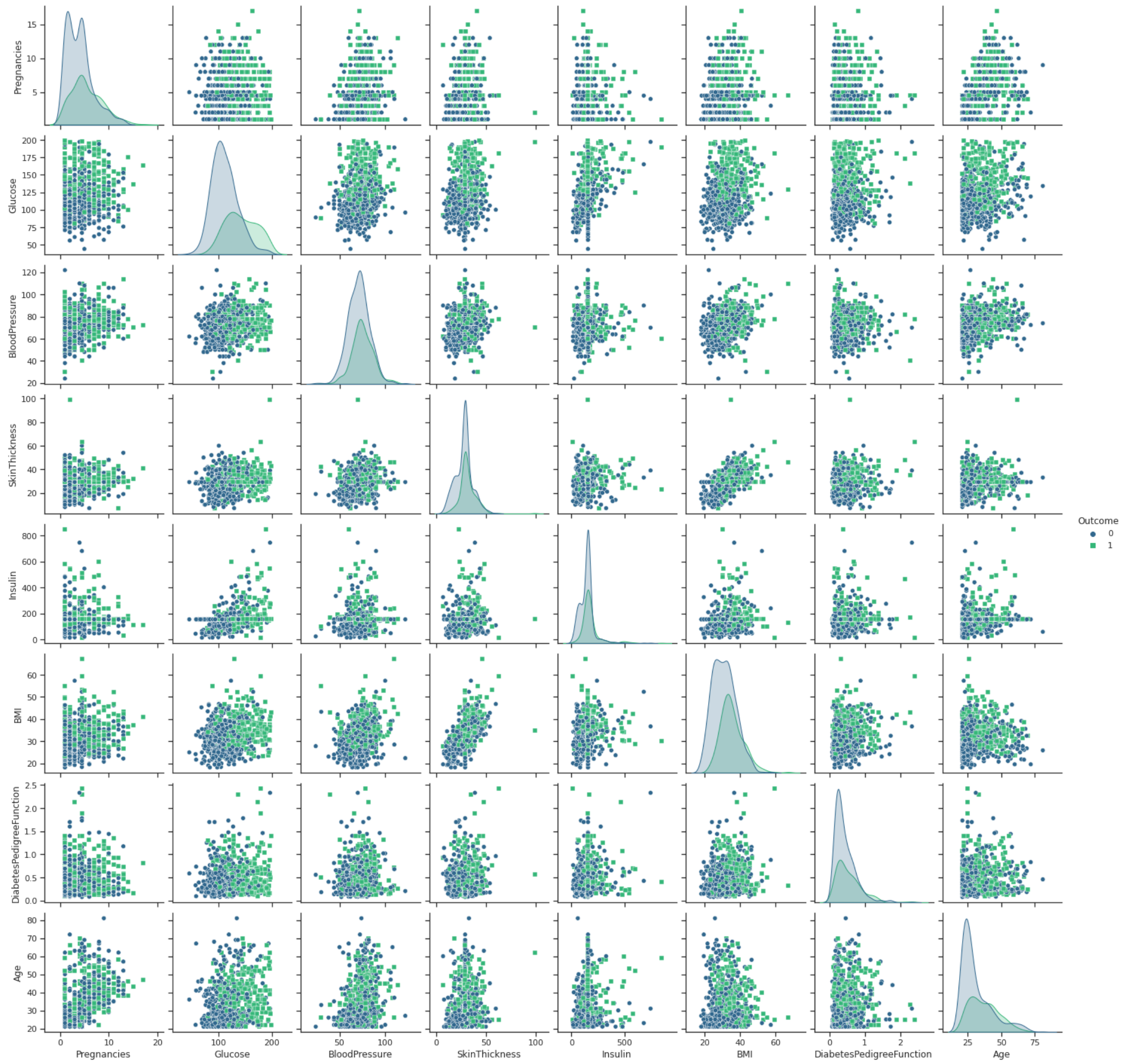
[59]:
```
# Create a count plot for the outcome
sns.set(style="whitegrid")
plt.figure(figsize=(6, 4))
ax = sns.countplot(x="Outcome", data=df,palette='viridis')

# Add count labels on top of the bars
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.
 ↪get_height()),
                ha='center', va='center', xytext=(0, 10), textcoords='offset␣
 ↪points')

# Add plot labels and title
plt.xlabel('Outcome')
plt.ylabel('Count')
plt.title('Count Plot of Outcome')

# Show the plot
plt.show()
```

inference : 268 paitents are positive for Diabetes against 500 negative cases. The outcome field may be a little biased towards negative outcomes.

3.2 Bivariate Analysis

3.2.1 Scatter charts between the pair of variables to understand the relationships.

[21]:
```
sns.set(style="ticks")
sns.pairplot(df, hue='Outcome', markers=["o", "s"], palette='viridis')
plt.show()
```



Inference : From the histogram diagrams we can say that other than Glucose and Blood Pressure and other features have a positive skewness. Also, at a given BMI, higher glucose level is observed for diabetic patient.

3.3 Multivariate Analysis

3.3.1 Correlation analysis, using a heat map.

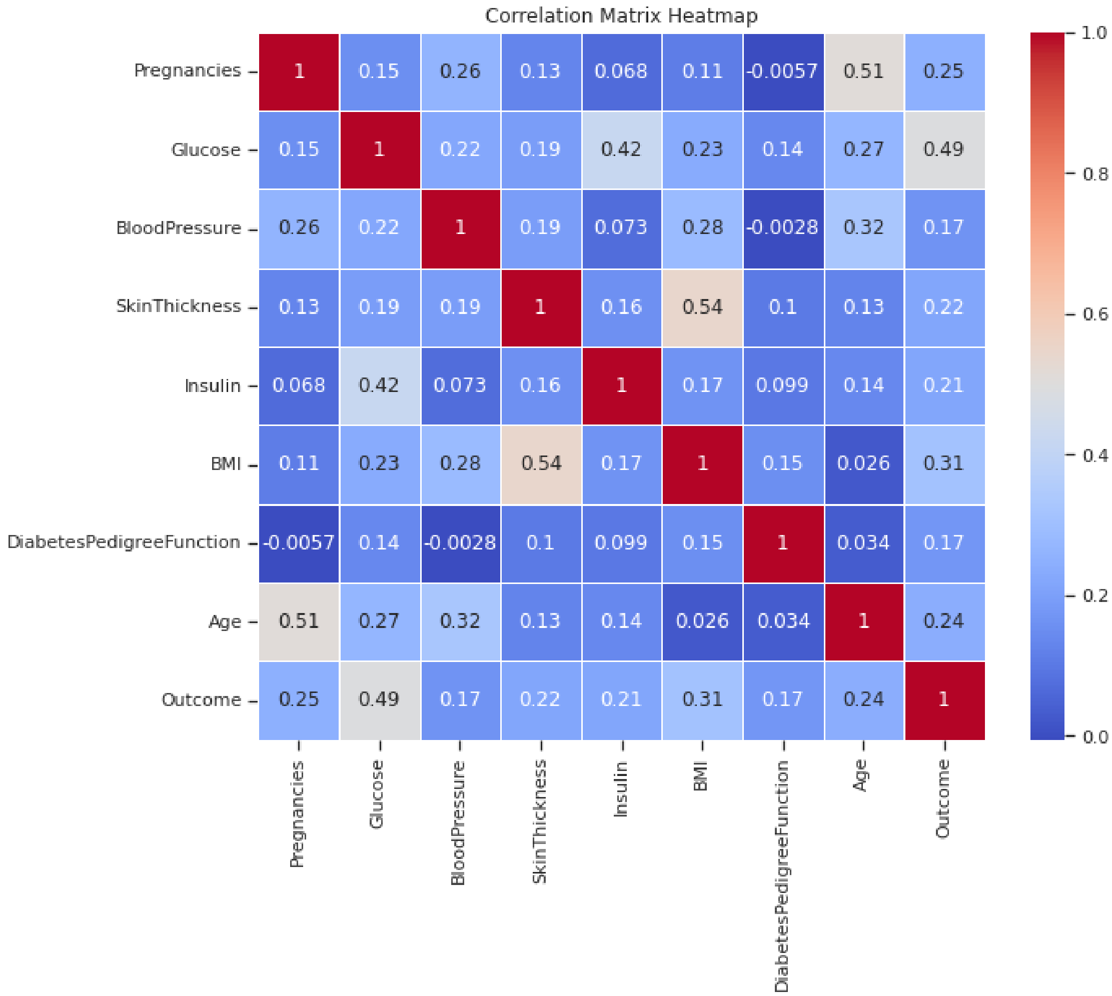
[22]:
```
correlation_matrix = df.corr()

# Display the correlation matrix
print("Correlation Matrix:")
print(correlation_matrix)
```

```
Correlation Matrix:
```

```
                          Pregnancies   Glucose  BloodPressure  SkinThickness  \
Pregnancies                  1.000000  0.154290       0.259117       0.131819
Glucose                      0.154290  1.000000       0.218367       0.192991
BloodPressure                0.259117  0.218367       1.000000       0.192816
SkinThickness                0.131819  0.192991       0.192816       1.000000
Insulin                      0.068077  0.420157       0.072517       0.158139
BMI                          0.110590  0.230941       0.281268       0.542398
DiabetesPedigreeFunction    -0.005658  0.137060      -0.002763       0.100966
Age                          0.511662  0.266534       0.324595       0.127872
Outcome                      0.248263  0.492928       0.166074       0.215299

                           Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies               0.068077  0.110590                 -0.005658
Glucose                   0.420157  0.230941                  0.137060
BloodPressure             0.072517  0.281268                 -0.002763
SkinThickness             0.158139  0.542398                  0.100966
Insulin                   1.000000  0.166586                  0.098634
BMI                       0.166586  1.000000                  0.153400
DiabetesPedigreeFunction  0.098634  0.153400                  1.000000
Age                       0.136734  0.025519                  0.033561
Outcome                   0.214411  0.311924                  0.173844

                               Age   Outcome
Pregnancies               0.511662  0.248263
Glucose                   0.266534  0.492928
BloodPressure             0.324595  0.166074
SkinThickness             0.127872  0.215299
Insulin                   0.136734  0.214411
BMI                       0.025519  0.311924
DiabetesPedigreeFunction  0.033561  0.173844
Age                       1.000000  0.238356
Outcome                   0.238356  1.000000
```

[23]:

```
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



3.3.2 Inference : The heatmap shows that all variables have positive correlation with the target variable. blood pressue is least correlated and glucose is most correlated with target variable followed by BMI.

4 3. Data Modeling

[24]:
```
import sklearn
```

[25]:
```
X=df.drop('Outcome', axis = 1)
Y=df['Outcome']
```

[26]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.
↪25,random_state=32)
```

[27]:
```
X_train.shape
```

[27]: (576, 8)

[28]:
```
X_test.shape
```

[28]: (192, 8)

5 Logistic Regression

[29]:
```
from sklearn.linear_model import LogisticRegression
```

[30]:
```
logmodel = LogisticRegression()
```

[31]:
```
logmodel.fit(X_train,Y_train)
```

```
/usr/local/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:460:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[31]: LogisticRegression()

[32]:
```
predictions = logmodel.predict(X_test)
predictions
```

[32]:
```
array([0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1])
```

[33]:
```
Y_pred=logmodel.predict(X_test)
Y_pred
```

[33]:
```
array([0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1])
```

[34]:
```
test_results=pd.DataFrame(X_test.copy())
test_results['Y_test'] = Y_test
test_results['predictions']=Y_pred
test_results
```

[34]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness     Insulin   BMI  \
642     6.000000    147.0      80.000000       29.15342  155.548223  29.5
695     7.000000    142.0      90.000000       24.00000  480.000000  30.4
453     2.000000    119.0      72.405184       29.15342  155.548223  19.6
565     2.000000     95.0      54.000000       14.00000   88.000000  26.1
99      1.000000    122.0      90.000000       51.00000  220.000000  49.7
..           …        …            …              …           …    …
585     1.000000     93.0      56.000000       11.00000  155.548223  22.5
487     4.494673    173.0      78.000000       32.00000  265.000000  46.5
58      4.494673    146.0      82.000000       29.15342  155.548223  40.5
438     1.000000     97.0      70.000000       15.00000  155.548223  18.2
394     4.000000    158.0      78.000000       29.15342  155.548223  32.9

     DiabetesPedigreeFunction  Age  Y_test  predictions
642                     0.178   50       1            0
695                     0.128   43       1            0
453                     0.832   72       0            0
565                     0.748   22       0            0
99                      0.325   31       1            0
..                        …    …     …          …
585                     0.417   22       0            0
487                     1.159   58       0            1
58                      1.781   44       0            1
438                     0.147   21       0            0
394                     0.803   31       1            1

[192 rows x 10 columns]
```

[35]:
```
from sklearn.metrics import confusion_matrix

confusion = confusion_matrix(Y_test, Y_pred)
```

```
print("Confusion Matrix:")
print(confusion)
```

```
Confusion Matrix:
[[107  16]
 [ 26  43]]
```

[36]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score

accuracy = accuracy_score(Y_test, Y_pred)

precision = precision_score(Y_test, Y_pred)

recall = recall_score(Y_test, Y_pred)

f1 = f1_score(Y_test, Y_pred)

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Accuracy: 0.78125
Precision: 0.7288135593220338
Recall: 0.6231884057971014
F1 Score: 0.671875
```

[37]:
```
results = {'Model': [], 'Accuracy': [], 'Precision': [], 'Recall': [], 'F1␣
↪Score': []}

results['Model'].append("LogisticRegression")
results['Accuracy'].append(accuracy)
results['Precision'].append(precision)
results['Recall'].append(recall)
results['F1 Score'].append(f1)
```

5.0.1 Inference :

1. Approximately 78% of the predictions made by the model are correct.
2. A precision of 0.72 means that, out of all instances predicted as positive, 72% are truly positive.
3. A recall of 0.623 indicates that the model captures 62.3% of all actual positive instances.
4. An F1 score of 0.671 suggests a reasonable balance between precision and recall, taking into account both false positives and false negatives.

6 KNN Model

[38]:
```
from sklearn.neighbors import KNeighborsClassifier

knn_clf=KNeighborsClassifier(n_neighbors=5, metric = 'euclidean')
knn_clf.fit(X_train,Y_train)
```

[38]:
```
KNeighborsClassifier(metric='euclidean')
```

[39]:
```
Y_pred_knn=knn_clf.predict(X_test)
Y_pred_knn
```

[39]:
```
array([1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1,
       0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0,
       0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1])
```

[40]:
```
accuracy_knn = accuracy_score(Y_test, Y_pred_knn)

precision_knn = precision_score(Y_test, Y_pred_knn)

recall_knn = recall_score(Y_test, Y_pred_knn)

f1_knn = f1_score(Y_test, Y_pred_knn)

print("Accuracy:", accuracy_knn)
print("Precision:", precision_knn)
print("Recall:", recall_knn)
print("F1 Score:", f1_knn)
```

```
Accuracy: 0.765625
Precision: 0.6764705882352942
Recall: 0.6666666666666666
F1 Score: 0.6715328467153284
```

[41]:
```
results['Model'].append("KNN")
results['Accuracy'].append(accuracy_knn)
results['Precision'].append(precision_knn)
results['Recall'].append(recall_knn)
results['F1 Score'].append(f1_knn)
```

6.0.1 Inference :

1. the model correctly predicts the class of instances in the dataset approximately 76% of the time.
2. A precision of 0.67 indicates that, out of all instances predicted as positive, around 67% are truly positive.
3. A recall of 0.66 suggests that the model captures about 66% of all actual positive instances.
4. An F1 score of 0.67 reflects a reasonable balance between precision and recall, considering both false positives and false negatives.

7 SVM Algo

[42]:
```
from sklearn.svm import SVC
```

[43]:
```
svm=SVC()
svm.fit(X_train,Y_train)
```

[43]:
```
SVC()
```

[44]:
```
Y_pred_svm=svm.predict(X_test)
Y_pred_svm
```

[44]:
```
array([1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1,
       0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1])
```

[45]:
```
accuracy_svm = accuracy_score(Y_test, Y_pred_svm)

precision_svm = precision_score(Y_test, Y_pred_svm)

recall_svm = recall_score(Y_test, Y_pred_svm)

f1_svm = f1_score(Y_test, Y_pred_svm)

print("Accuracy:", accuracy_svm)
print("Precision:", precision_svm)
print("Recall:", recall_svm)
print("F1 Score:", f1_svm)
```

```
Accuracy: 0.8020833333333334
Precision: 0.7924528301886793
```

```
Recall: 0.6086956521739131
F1 Score: 0.6885245901639344
```

[46]:
```
results['Model'].append("SVM")
results['Accuracy'].append(accuracy_svm)
results['Precision'].append(precision_svm)
results['Recall'].append(recall_svm)
results['F1 Score'].append(f1_svm)
```

7.0.1 Inference

1. An accuracy of approximately 80% indicates that the model correctly predicts the class of instances in the dataset the majority of the time.
2. A precision of 0.79 means that, out of all instances predicted as positive, about 79% are truly positive.
3. A recall of 0.60 indicates that the model captures about 60% of all actual positive instances.
4. An F1 score of 0.68 suggests a reasonable balance between precision and recall, considering both false positives and false negatives.

8 Decision Tree

[47]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

[48]:
```
clf = DecisionTreeClassifier()
clf.fit(X_train, Y_train)
```

[48]:
```
DecisionTreeClassifier()
```

[49]:
```
Y_pred_dt = clf.predict(X_test)
Y_pred_dt
```

[49]:
```
array([0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0,
       0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0,
       0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1,
       0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1])
```

[50]:
```
accuracy_dt = accuracy_score(Y_test, Y_pred_dt)

precision_dt = precision_score(Y_test, Y_pred_dt)
```

```
recall_dt = recall_score(Y_test, Y_pred_dt)

f1_dt = f1_score(Y_test, Y_pred_dt)

print("Accuracy:", accuracy_dt)
print("Precision:", precision_dt)
print("Recall:", recall_dt)
print("F1 Score:", f1_dt)
```

```
Accuracy: 0.7239583333333334
Precision: 0.6025641025641025
Recall: 0.6811594202898551
F1 Score: 0.6394557823129252
```

[51]:
```
results['Model'].append("Decision Tree")
results['Accuracy'].append(accuracy_dt)
results['Precision'].append(precision_dt)
results['Recall'].append(recall_dt)
results['F1 Score'].append(f1_dt)
```

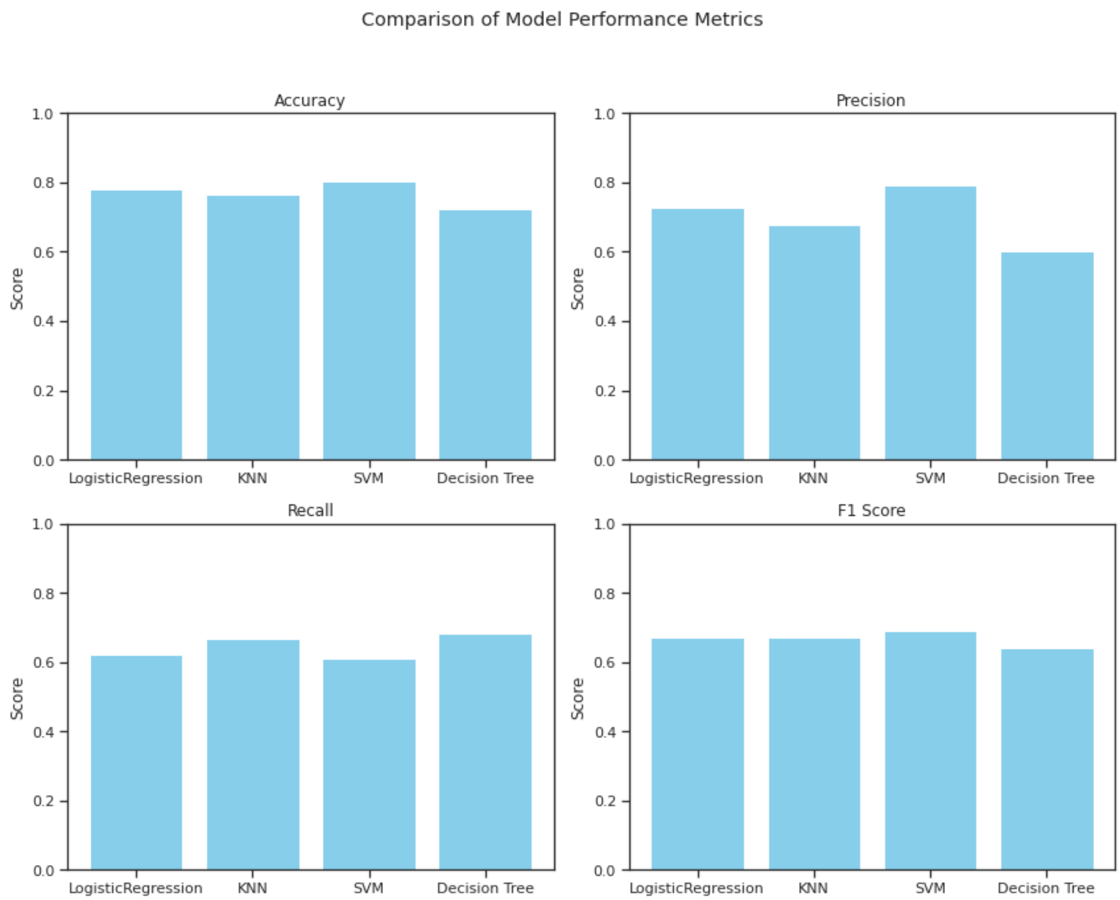
8.0.1 Inference :

1. The model correctly predicts the class of instances in the dataset approximately 72% of the time.
2. A precision of 0.0 indicates that, out of all instances predicted as positive, around 60% are truly positive.
3. A recall of 0.68 suggests that the model captures about 68% of all actual positive instances.
4. An F1 score of 0.63 reflects a reasonable balance between precision and recall, considering both false positives and false negatives.

9 Comparision of Model Performances

[52]:
```
# Visualize results
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))
fig.suptitle('Comparison of Model Performance Metrics')

metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

for i, metric in enumerate(metrics):
    ax = axes[i // 2, i % 2]
    ax.bar(results['Model'], results[metric], color='skyblue')
    ax.set_title(metric)
    ax.set_ylim(0, 1)
    ax.set_ylabel('Score')

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```python
# Display summary table
import pandas as pd

results_df = pd.DataFrame(results)
print(results_df)
```




```
                Model  Accuracy  Precision    Recall  F1 Score
0  LogisticRegression  0.781250   0.728814  0.623188  0.671875
1                 KNN  0.765625   0.676471  0.666667  0.671533
2                 SVM  0.802083   0.792453  0.608696  0.688525
3       Decision Tree  0.723958   0.602564  0.681159  0.639456
```

9.0.1 Inference :

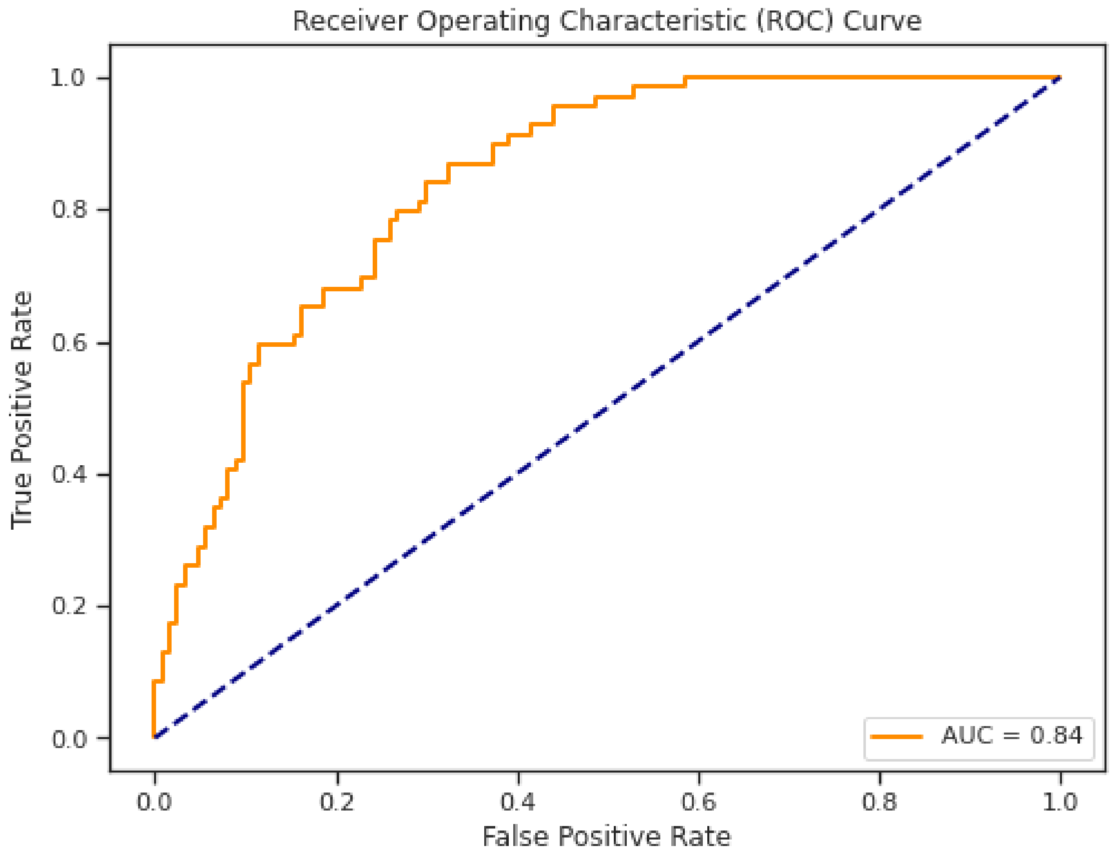
1. The SVM model has the highest accuracy, Precision and F1 Score among the four models.
2. Decision Tree has the best Recall score among the four models.

9.1 Classification report by analyzing sensitivity, specificity, AUC (ROC curve)

[53]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, roc_auc_score, roc_curve,␣
↪confusion_matrix

# Create and train an SVM classifier
svm_model = SVC(probability=True, kernel='linear')
svm_model.fit(X_train, Y_train)

# Make predictions and probability estimates
Y_pred = svm_model.predict(X_test)
Y_pred_proba = svm_model.predict_proba(X_test)[:, 1]

# Generate classification report
print("Classification Report:")
print(classification_report(Y_test, Y_pred))

# Calculate Sensitivity and Specificity
cm = confusion_matrix(Y_test, Y_pred)
sensitivity = cm[1, 1] / (cm[1, 0] + cm[1, 1])  # True Positive Rate or Recall
specificity = cm[0, 0] / (cm[0, 0] + cm[0, 1])

print(f"Sensitivity (True Positive Rate): {sensitivity:.4f}")
print(f"Specificity (True Negative Rate): {specificity:.4f}")

# Calculate ROC-AUC
roc_auc = roc_auc_score(Y_test, Y_pred_proba)
print(f"ROC-AUC: {roc_auc:.4f}")

# Plot ROC curve
fpr, tpr, _ = roc_curve(Y_test, Y_pred_proba)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

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

           0       0.79      0.89      0.84       123
           1       0.74      0.58      0.65        69

    accuracy                           0.78       192
```

```
   macro avg       0.77      0.73      0.74       192
weighted avg       0.77      0.78      0.77       192

Sensitivity (True Positive Rate): 0.5797
Specificity (True Negative Rate): 0.8862
ROC-AUC: 0.8436
```



9.1.1 Inference :

1. The model demonstrates good performance with high specificity (ability to correctly identify negatives) and moderate sensitivity (ability to correctly identify positives).
2. The ROC-AUC value of 0.8436 indicates strong discriminatory power, suggesting effective separation between positive and negative instances.

[ ]: