Logistic Regression for Diabetes Prediction

In [58]:
```
#import applicable packages
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, roc_auc_score, r
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

Step 1: Describe the Problem

We want to use the features in this kaggle healthcare dataset https://www.kaggle.com/datasets/nanditapore/healthcare-diabetes?resource=download to predict on the "Outcome" column 0/1 for diabetes prediction using Linear Regression. Having a binary classifier makes this a great Logistic Regression test!

Step 2: Explore the Data

In [9]:
```
#load dataset
df = pd.read_csv("Healthcare-Diabetes.csv", encoding = 'latin-1' )
#briefly see stats about the data columns
df.describe()
```

Out[9]:

	Id	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin
count	2768.000000	2768.000000	2768.000000	2768.000000	2768.000000	2768.000000
mean	1384.500000	3.742775	121.102601	69.134393	20.824422	80.127890
std	799.197097	3.323801	32.036508	19.231438	16.059596	112.301933
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	692.750000	1.000000	99.000000	62.000000	0.000000	0.000000
50%	1384.500000	3.000000	117.000000	72.000000	23.000000	37.000000
75%	2076.250000	6.000000	141.000000	80.000000	32.000000	130.000000
max	2768.000000	17.000000	199.000000	122.000000	110.000000	846.000000

In [10]:
```
#sneak peak at the data
df.head()
```

Out[10]:

	Id	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeI
0	1	6	148	72	35	0	33.6	
1	2	1	85	66	29	0	26.6	
2	3	8	183	64	0	0	23.3	
3	4	1	89	66	23	94	28.1	
4	5	0	137	40	35	168	43.1	

In [16]:
```
#see most common occurances especially for our Outcome response var, this suggests
df["Outcome"].mode()
```

Out[16]:
```
0    0
Name: Outcome, dtype: int64
```

Step 3: Scale & Split the data

Now that we have taken a look at our dataset, its time to create our X and y variables as well as scale our data as Logistic Regression is sensitive to feature scale due to is use of regularization. By default LR uses the L2.

L2 (Ridge, default)

Penalizes the sum of squares of coefficients.

Shrinks weights but does not force them to 0.

Keeps all features but with reduced impact.

L1 (Lasso)

Penalizes the sum of absolute values of coefficients.

Can force some coefficients to 0 → performs feature selection.

Elastic Net

Combines L1 + L2 penalties.

Balance controlled by l1_ratio.

In [15]:
```
#extract response column and separate it from our features
X = df.drop(columns = ["Outcome"])
y = df["Outcome"]
#scale the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [22]:
```
#split our data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
                                                    test_size = 0.2,
                                                    random_state = 42,
                                                    stratify = y
                                                     )
```

Step 4: Fit our model!

In [24]:
```
lr = LogisticRegression(max_iter = 1000)
lr.fit(X_train, y_train)
```

Out[24]:
```
▾ LogisticRegression  i ?

▸ Parameters
```

Step 5: Accuracy!

In [38]:
```
y_pred = lr.predict(X_test)
#true labels against predictions
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.7707581227436823
```

In [41]:
```
#Accuracy looks great! Now for the classificaiton report or conf matrix!
print(classification_report(y_test, y_pred))
```

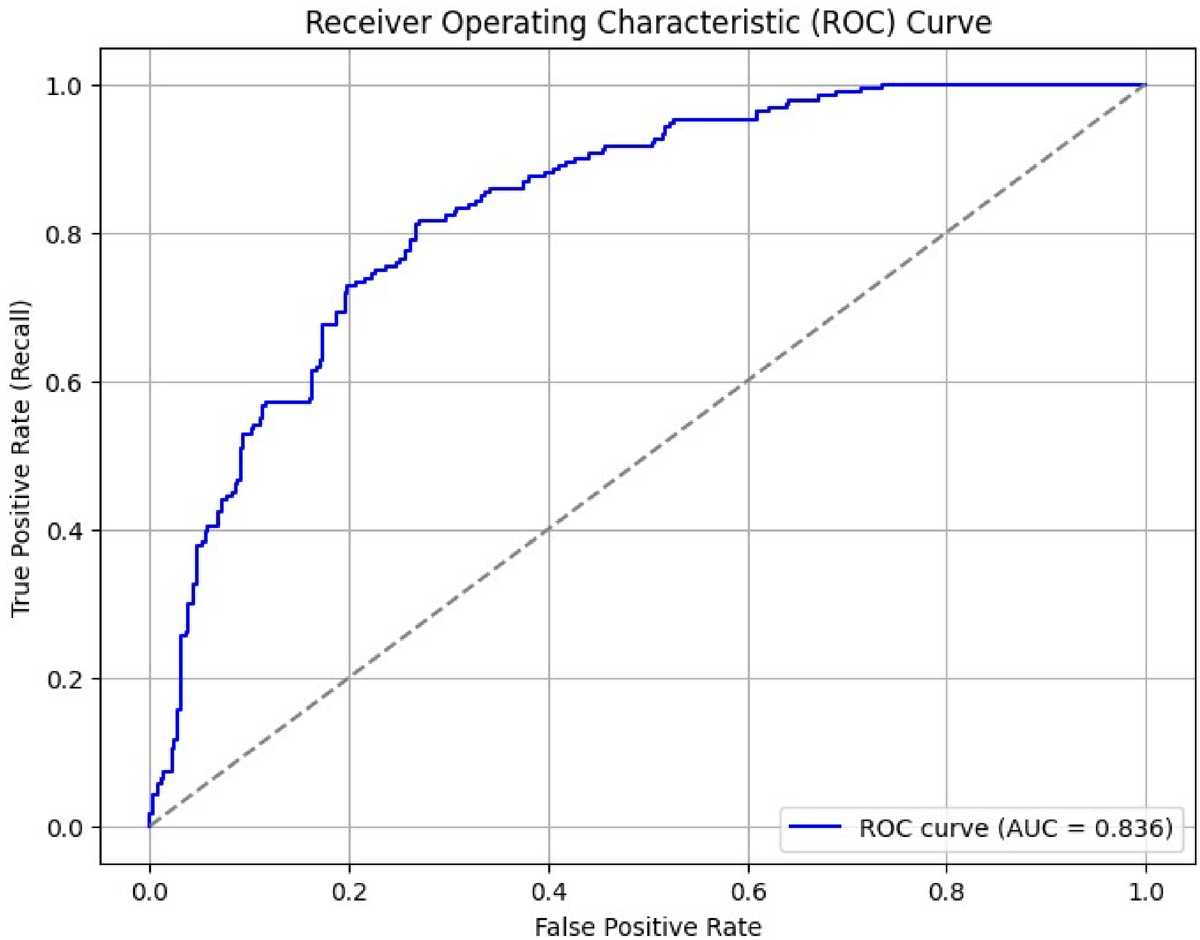
```
              precision    recall  f1-score   support

           0       0.79      0.89      0.84       363
           1       0.72      0.54      0.62       191

    accuracy                           0.77       554
   macro avg       0.76      0.72      0.73       554
weighted avg       0.77      0.77      0.76       554
```

In [52]:
```
#AUC AND ROC
#predict probabilities
y_probs = lr.predict_proba(X_test)[:,1]
#see the roc auc score
roc_auc = roc_auc_score(y_test, y_probs)
print(f"ROC AUC Score: {roc_auc:.3f}")
```

```
ROC AUC Score: 0.836
```

In [59]:
```
#lets visualize it!
# Compute ROC curve data
fpr, tpr, thresholds = roc_curve(y_test, y_probs)
# Plot ROC curve
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'ROC curve (AUC = {roc_auc:.3f})', color='blue')
```

```
plt.plot([0,1], [0,1], linestyle='--', color='grey')  # diagonal line = random gues
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate (Recall)')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Conclusion

After tring Linear Regression on this same dataset, we saw a low R2 and RMSE score. This led us to try Logistic Regression, which performs better on the dataset due to its strength with binary classification as is the case with the response column "Outcome". This makes Logistic Regression a great model for this approach. Other models that work well and could be tested against this dataset would be SVM,