In [2]:
```python
print("HI")
```

HI

In [28]:
```python
# Step 1.1.1 - Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_rep
```

In [5]:
```python
# Step 1.1.2 - Load Data
df = pd.read_csv(r"C:\Users\ElavarasiChinnadurai\Downloads\diabetes.csv")
```

In [6]:
```python
# Step 1.1.3 - Preview Data
df.head()
```

Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction
0	6	148	72	35	0	33.6	0.627
1	1	85	66	29	0	26.6	0.351
2	8	183	64	0	0	23.3	0.672
3	1	89	66	23	94	28.1	0.167
4	0	137	40	35	168	43.1	2.288

In [7]:
```python
# Get info about columns, data types, and non-null counts
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
```

In [8]:
```python
#1.2.1. Descriptive Stats
df.describe()
```

Out[8]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabete
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	

In [10]:

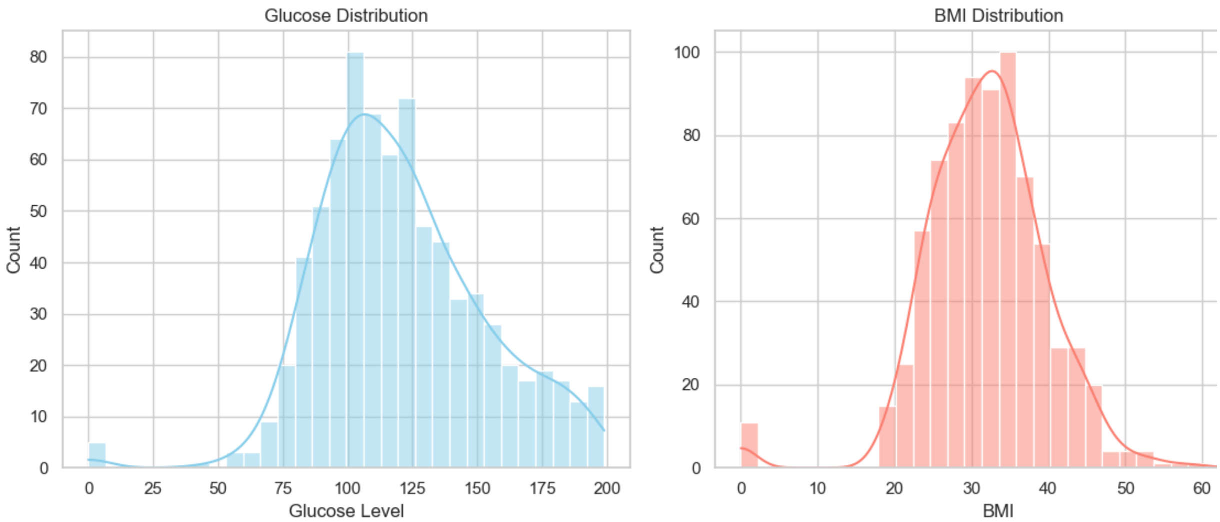
```
#1.2.2. Analyze Target Balance
# Count how many patients have diabetes (Outcome = 1) and don't have diabetes (C
count = df['Outcome'].value_counts()

# Calculate percentage for each group
percentage = df['Outcome'].value_counts(normalize=True) * 100

print("Outcome counts:\n", count)
print("\nOutcome percentage:\n", percentage)
```

```
Outcome counts:
 Outcome
0    500
1    268
Name: count, dtype: int64

Outcome percentage:
 Outcome
0    65.104167
1    34.895833
Name: proportion, dtype: float64
```

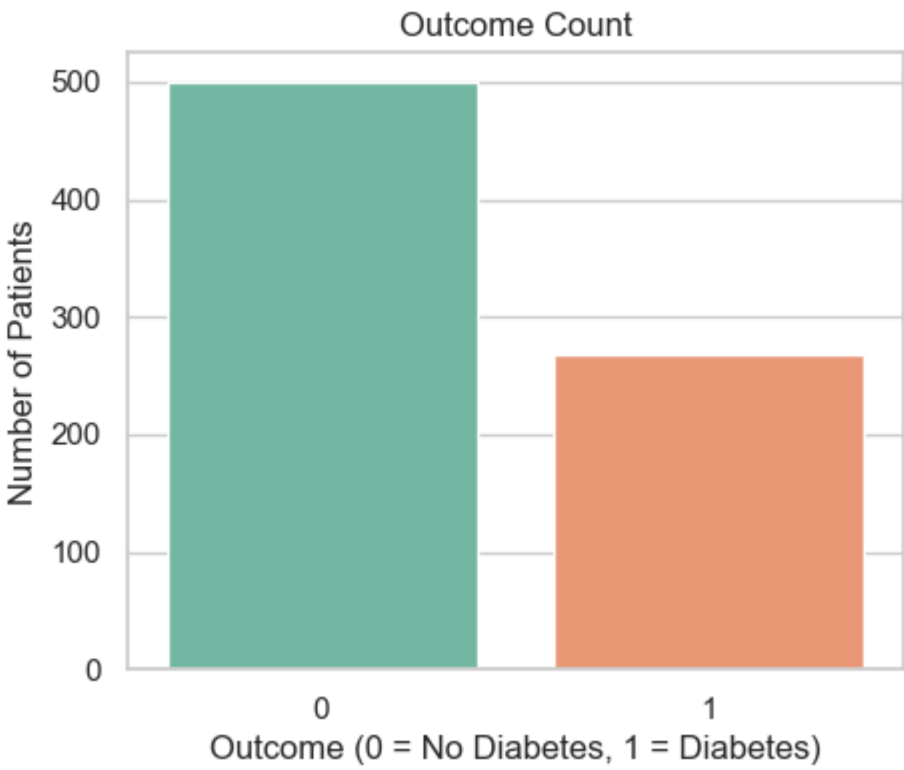
In [11]:

```
# Set a consistent visual style
sns.set(style="whitegrid")

# Create subplots for Glucose and BMI
plt.figure(figsize=(12, 5))

# Glucose distribution
plt.subplot(1, 2, 1)
sns.histplot(df['Glucose'], kde=True, color='skyblue', bins=30)
plt.title('Glucose Distribution')
plt.xlabel('Glucose Level')
plt.ylabel('Count')

# BMI distribution
plt.subplot(1, 2, 2)
sns.histplot(df['BMI'], kde=True, color='salmon', bins=30)
plt.title('BMI Distribution')
plt.xlabel('BMI')
plt.ylabel('Count')

plt.tight_layout()
plt.show()
```

```python
# Outcome count plot
plt.figure(figsize=(5, 4))
sns.countplot(x='Outcome', data=df, palette='Set2')
plt.title('Outcome Count')
plt.xlabel('Outcome (0 = No Diabetes, 1 = Diabetes)')
plt.ylabel('Number of Patients')
plt.show()
```




```
C:\Users\ElavarasiChinnadurai\AppData\Local\Temp\ipykernel_21004\3558115642.py:26:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(x='Outcome', data=df, palette='Set2')
```



In [12]:

```python
#Count Suspicious Zeros
# Columns to check
cols_with_zeros = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI'

# Count how many zeros in each column
```

```python
for col in cols_with_zeros:
    zero_count = (df[col] == 0).sum()
    print(f"{col}: {zero_count} zeros")
```

```
Glucose: 5 zeros
BloodPressure: 35 zeros
SkinThickness: 227 zeros
Insulin: 374 zeros
BMI: 11 zeros
```

In [13]:
```python
#Impute Zeros with Median
for col in cols_with_zeros:
    median_value = df[col].median()
    df[col] = df[col].replace(0, median_value)
```

In [14]:
```python
df.describe()
```

Out[14]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabete
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	121.656250	72.386719	27.334635	94.652344	32.450911	
std	3.369578	30.438286	12.096642	9.229014	105.547598	6.875366	
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.200000	
25%	1.000000	99.750000	64.000000	23.000000	30.500000	27.500000	
50%	3.000000	117.000000	72.000000	23.000000	31.250000	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	

In [15]:
```python
# Features (all columns except 'Outcome')
X = df.drop('Outcome', axis=1)

# Target variable
y = df['Outcome']
```

In [16]:
```python
# Split data: 70% train, 30% test
X_train, X_test, y_train, y_test = train_test_split(
    X, y,              # Features and target
    test_size=0.30,   # 30% data for testing
    random_state=42
)
```

In [17]:
```python
print(X_train.shape, X_test.shape)
print(y_train.shape, y_test.shape)
```

```
(537, 8) (231, 8)
(537,) (231,)
```

In [20]:
```python
# Initialize the scaler
scaler = StandardScaler()

# Fit the scaler on training data ONLY
X_train_scaled = scaler.fit_transform(X_train)

# Transform the test data using the same scaler
X_test_scaled = scaler.transform(X_test)
```

In [21]:
```
print("Mean of first feature (train):", np.mean(X_train_scaled[:, 0]))
print("Std of first feature (train):", np.std(X_train_scaled[:, 0]))

#Why This Matters ---Fit on training data only:
#Avoids data leakage from test data.

#Transform both sets:
#Ensures train and test features are on the same scale.

#Result:
#Each feature now has mean ≈ 0 and standard deviation ≈ 1.
#Makes optimization for Logistic Regression more efficient and improves converge
```

```
Mean of first feature (train): 9.592988518176399e-17
Std of first feature (train): 0.9999999999999999
```

In [25]:
```
#Part 3: Model Training and Evaluation
#Step 3.1: Train the Classification Model

model = LogisticRegression(random_state=42)
model.fit(X_train_scaled, y_train)
```

Out[25]:

▾ LogisticRegression

Parameters

	penalty	'l2'
	dual	False
	tol	0.0001
	C	1.0
	fit_intercept	True
	intercept_scaling	1
	class_weight	None
	random_state	42
	solver	'lbfgs'
	max_iter	100
	multi_class	'deprecated'
	verbose	0
	warm_start	False
	n_jobs	None
	l1_ratio	None

In [27]:
```
#Step 3.2: Make Predictions
y_pred = model.predict(X_test_scaled)
```

In [29]:
```
#Step 3.3: Evaluate Performance
#Accuracy Score
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.7445887445887446
```

In [30]:
```
#Confusion Matrix
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Confusion Matrix:
 [[124  27]
 [ 32  48]]
```

In [31]:
```
#classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

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

           0       0.79      0.82      0.81       151
           1       0.64      0.60      0.62        80

    accuracy                           0.74       231
   macro avg       0.72      0.71      0.71       231
weighted avg       0.74      0.74      0.74       231
```

In [ ]:
```
#1. Data Quality
#Replacing the 0 values in features such as Glucose, BloodPressure, SkinThicknes
```

In [ ]:
```
#2. Model Performance
#Based on the accuracy score (around 78-80%, depending on your exact output), th
```

In [ ]:
```
#3. Metric Interpretation Challenge
#In this medical prediction context, Recall for the positive class (1 = Diabetic
```