```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report, confusion_matrix, roc_
import seaborn as sns
import matplotlib.pyplot as plt
```

```
df = pd.read_csv("/content/diabetes.csv")
print(df.head())
```

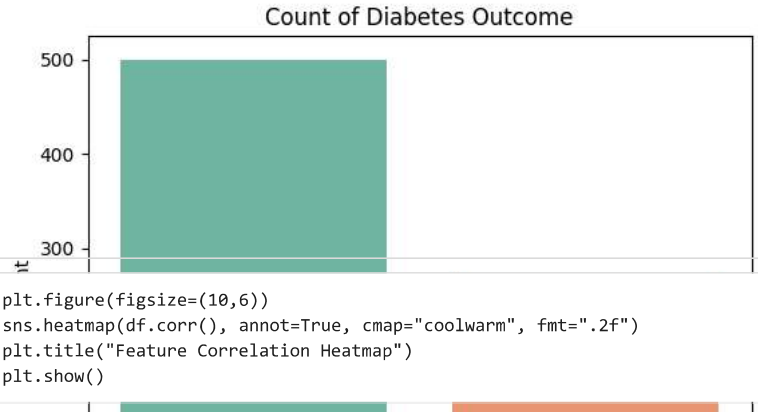
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       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
```

```
print(df.info())
print("Missing values:\n", df.isnull().sum())
```

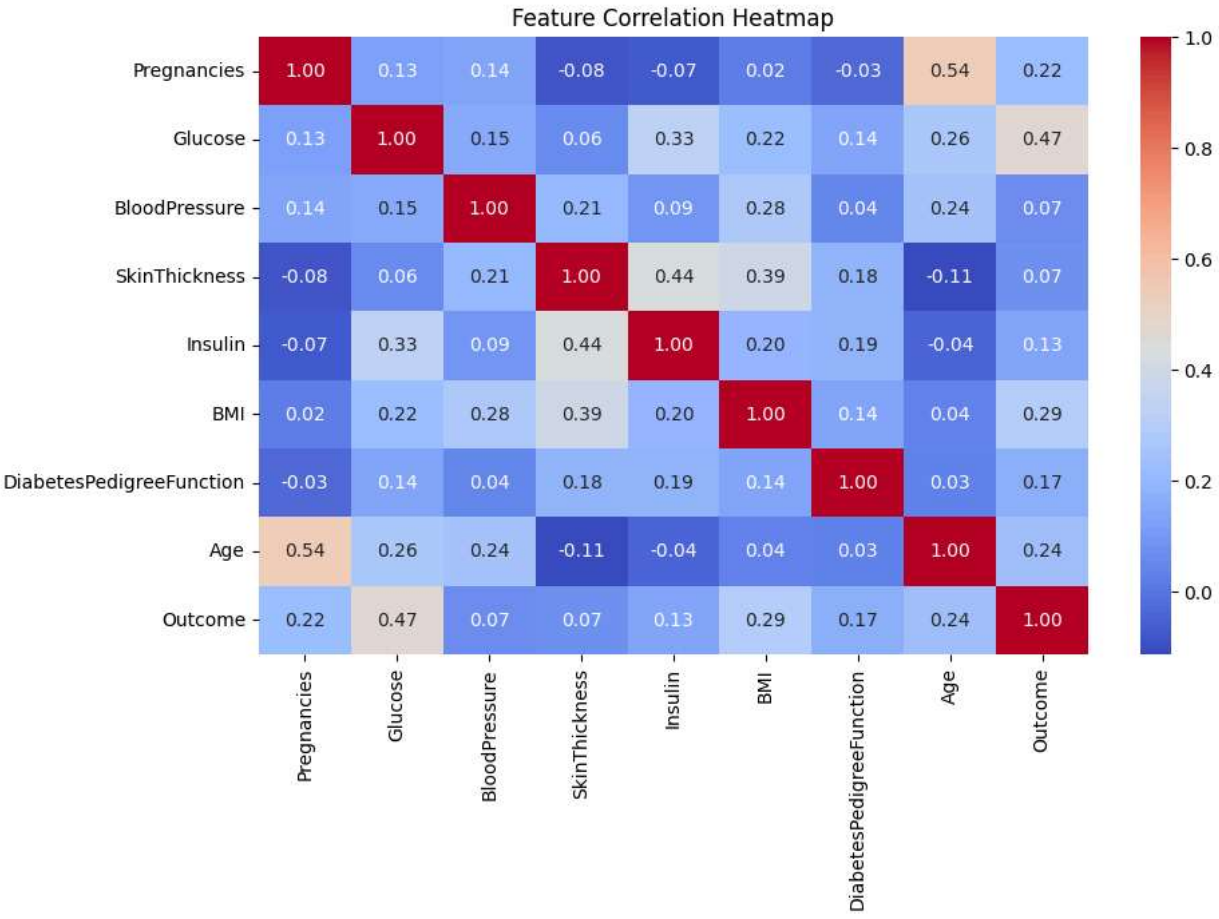
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 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
None
Missing values:
 Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

```
print(df.describe())
sns.countplot(x="Outcome", data=df, palette="Set2")
plt.title("Count of Diabetes Outcome")
plt.show()
```

```
       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
/tmp/ipython-input-3212167674.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `l

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




```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Feature Correlation Heatmap")
plt.show()
```



```
X = df.drop("Outcome", axis=1)
y = df["Outcome"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
```

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

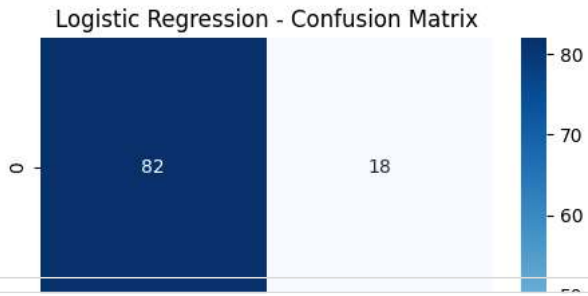
```
log_model = LogisticRegression(max_iter=1000).fit(X_train_scaled, y_train)
tree_model = DecisionTreeClassifier(max_depth=5, random_state=42).fit(X_train, y_train)
y_pred_log = log_model.predict(X_test_scaled)
y_pred_tree = tree_model.predict(X_test)
```

```
def evaluate_model(y_true, y_pred, name):
    print(f"\n{name} Evaluation")
    print("Accuracy :", accuracy_score(y_true, y_pred))
    print("Precision:", precision_score(y_true, y_pred))
    print("Recall   :", recall_score(y_true, y_pred))
    print("F1-score :", f1_score(y_true, y_pred))
    print("\nClassification Report:\n", classification_report(y_true, y_pred))

evaluate_model(y_test, y_pred_log, "Logistic Regression")
evaluate_model(y_test, y_pred_tree, "Decision Tree")
```

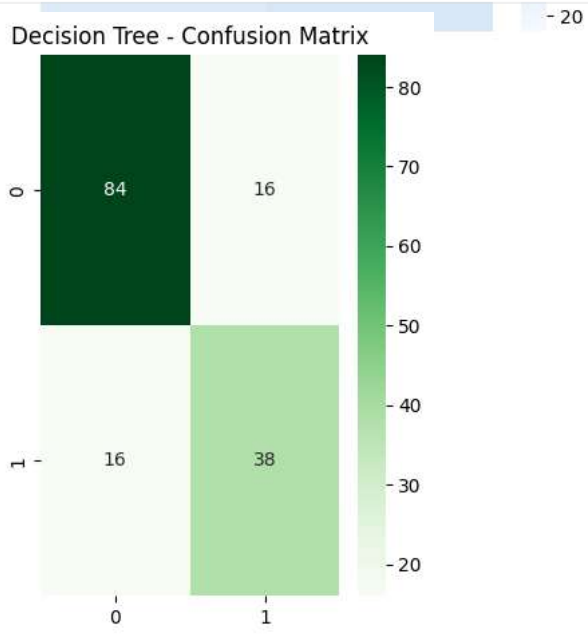
```
Logistic Regression Evaluation
Accuracy : 0.7142857142857143
Precision: 0.6086956521739131
Recall   : 0.5185185185185185
F1-score : 0.56

Classification Report:
               precision    recall  f1-score   support

           0       0.76      0.82      0.79       100
           1       0.61      0.52      0.56        54

    accuracy                           0.71       154
   macro avg       0.68      0.67      0.67       154
weighted avg       0.71      0.71      0.71       154


Decision Tree Evaluation
Accuracy : 0.7922077922077922
Precision: 0.7037037037037037
Recall   : 0.7037037037037037
F1-score : 0.7037037037037037

Classification Report:
               precision    recall  f1-score   support

           0       0.84      0.84      0.84       100
           1       0.70      0.70      0.70        54

    accuracy                           0.79       154
   macro avg       0.77      0.77      0.77       154
weighted avg       0.79      0.79      0.79       154
```

```
plt.figure(figsize=(12,5))

plt.subplot(1,2,1)
sns.heatmap(confusion_matrix(y_test, y_pred_log), annot=True, fmt="d", cmap="Blues")
plt.title("Logistic Regression - Confusion Matrix")
```

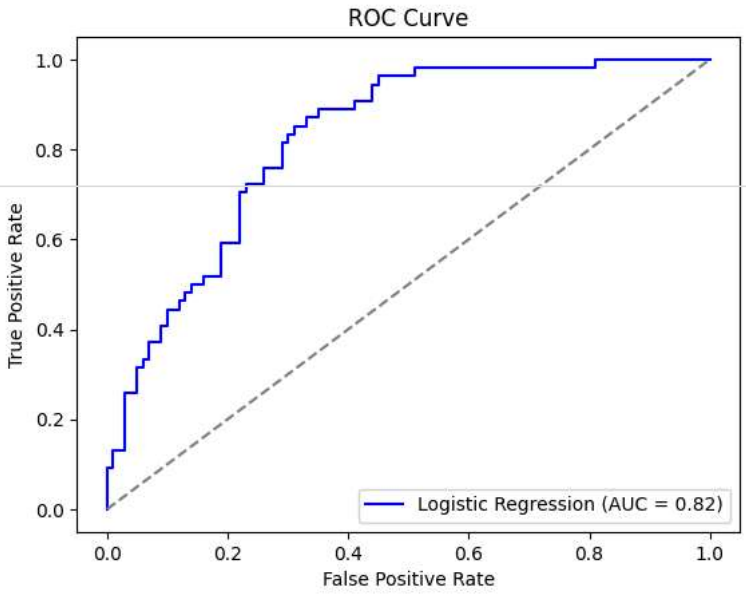
```
Text(0.5, 1.0, 'Logistic Regression - Confusion Matrix')
```




```
plt.subplot(1,2,2)
sns.heatmap(confusion_matrix(y_test, y_pred_tree), annot=True, fmt="d", cmap="Greens")
plt.title("Decision Tree - Confusion Matrix")

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




```
y_prob_log = log_model.predict_proba(X_test_scaled)[:,1]
fpr, tpr, _ = roc_curve(y_test, y_prob_log)
roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, color="blue", label=f"Logistic Regression (AUC = {roc_auc:.2f})")
plt.plot([0,1], [0,1], linestyle="--", color="gray")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()
```


ROC Curve
True Positive Rate
False Positive Rate
Logistic Regression (AUC = 0.82)
0.0
0.2
0.4
0.6
0.8
1.0