PROJECT-2: ANALYSIS REPORT OF DIABETES PATIENTS

Objective:

The main objective of this project is to diagnostically predict whether a patient has diabetes or not.

Note: The dataset used for this analysis is sourced from the National Institute of Diabetes and Digestive and Kidney Diseases.

About the dataset:

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases.

- **1. Pregnancies:** This variable represents the number of times the patient has been pregnant.
- **2. Glucose:** It is the plasma glucose concentration measured in milligrams per deciliter (mg/dL) of blood. This is a key indicator for diabetes diagnosis.
- **3. Blood Pressure:** This variable represents the diastolic blood pressure (mm Hg) of the patient.
- **4. Skin Thickness:** It indicates the skin thickness (mm) at the triceps area. Skin thickness can sometimes be relevant in diabetes diagnosis.
- **5. Insulin:** This variable represents the serum insulin level (mu U/ml). Insulin is a hormone that regulates blood sugar levels, and its measurement can be important in diabetes diagnosis.
- **6. BMI (Body Mass Index):** BMI is calculated from the weight and height of the patient. It's a measure of body fat and is often used to assess whether a person is underweight, normal weight, overweight, or obese.
- **7. Diabetes Pedigree Function:** This function is used to represent the diabetes pedigree function, which provides information about diabetes mellitus history in relatives and genetic influence.
- **8. Age:** This variable represents the age of the patient in years.
- **9. Outcome:** This is the target variable, and it indicates whether the patient has diabetes or not. It is binary, with values 0 and 1, where:
 - 0 typically indicates that the patient does not have diabetes.
 - 1 typically indicates that the patient has diabetes.

Steps:

Step-1: load the dataset and import necessary libraries

```
#importing libraries and loading csv file
import pandas as pd
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, classification_report, confusion_matrix
data = pd.read_csv("diabetes.csv")
```

Step-2: Data Exploration

```
: #Get the summary statistics
  print(data.describe())
         Pregnancies
                                   BloodPressure SkinThickness
                                                                     Insulin
                          Glucose
          768.000000
                      768.000000
                                                      768.000000 768.000000
  count
                                      768.000000
            3.845052
                      120.894531
                                       69.105469
                                                       20.536458
                                                                   79.799479
  mean
            3.369578
                       31.972618
                                       19.355807
                                                       15.952218
                                                                  115.244002
  std
  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%
                      140.250000
                                                       32.000000
            6.000000
                                       80.000000
                                                                  127.250000
  max
           17.000000
                      199.000000
                                      122.000000
                                                       99.000000
                                                                  846.000000
                BMI
                     DiabetesPedigreeFunction
                                                                Outcome
                                                        Age
         768.000000
                                    768.000000
                                                768.000000
                                                             768.000000
  count
          31.992578
                                      0.471876
                                                 33.240885
                                                               0.348958
  mean
  std
           7.884160
                                      0.331329
                                                  11.760232
                                                               0.476951
           0.000000
                                      0.078000
                                                  21.000000
                                                               0.000000
  min
  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
          67.100000
                                                 81.000000
  max
                                      2.420000
                                                               1.000000
```

Step-3: Data Pre-processing

```
#data preprocessing
#check for the missing values
print(data.isnull().sum())
data = data.dropna()
```

Pregnancies 0 Glucose 0 BloodPressure 0 SkinThickness Insulin 0 BMI 0 DiabetesPedigreeFunction 0 Age 0 Outcome 0 dtype: int64

#Hence, there are no missing values in the data

```
#checking for duplicate data
print(data[data.duplicated()])
```

Empty DataFrame

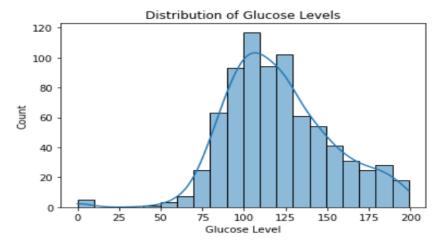
Columns: [Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction,

Age, Outcome]
Index: []

#There are no duplicates in the data

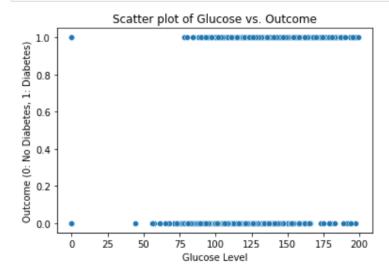
Step-4: Data Visualization

```
#Create histograms for numeric variables
sns.histplot(data['Glucose'], bins=20, kde=True)
plt.xlabel('Glucose Level')
plt.ylabel('Count')
plt.title('Distribution of Glucose Levels')
plt.show()
```

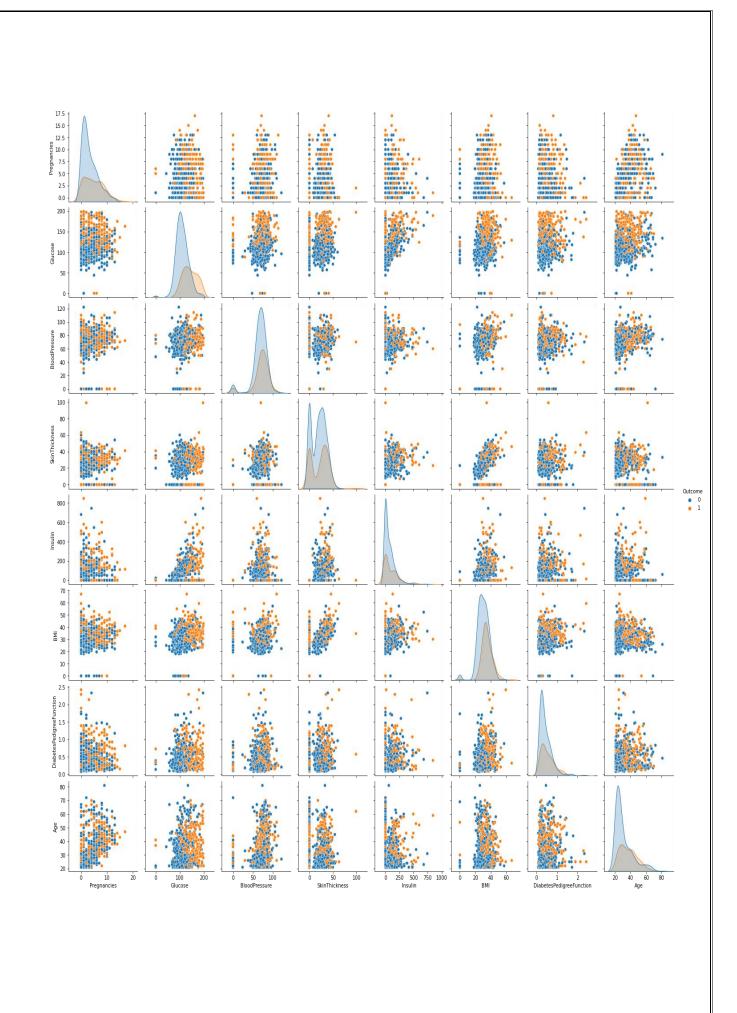


Step-5: Feature analysis

```
In [81]: # Scatter plot between Glucose and Outcome
sns.scatterplot(x='Glucose', y='Outcome', data=data)
plt.xlabel('Glucose Level')
plt.ylabel('Outcome (0: No Diabetes, 1: Diabetes)')
plt.title('Scatter plot of Glucose vs. Outcome')
plt.show()
```



```
#creating visualization to understand the data better
sns.pairplot(data, hue= "Outcome")
plt.show()
```



```
#Correlation matrix
correlation matrix = data.corr()
sns.heatmap(correlation_matrix, annot=True)
plt.show()
                                                                                  -1.0
              Pregnancies - 1
                                 0.13 0.14 0.082-0.0740.018-0.034 0.54 0.22
                                       0.15 0.057 0.33 0.22 0.14 0.26 0.47
                  Glucose - 0.13
                                                                                   - 0.8
                                            0.21 0.089 0.28 0.041 0.24 0.065
            BloodPressure - 0.14 0.15
                                                                                  - 0.6
                                                  0.44 0.39 0.18 -0.11 0.075
            SkinThickness -0.0820.057 0.21
                   Insulin -0.074 0.33 0.089 0.44
                                                        0.2
                                                  1
                                                            0.19 -0.042 0.13
                                                                                   - 0.4
                      BMI -0.018 0.22 0.28 0.39 0.2
                                                         1
                                                             0.14 0.036 0.29
 DiabetesPedigreeFunction -0.034 0.14 0.041 0.18 0.19 0.14
                                                                  0.034 0.17
                                                                                  - 0.2
                      Age - 0.54 0.26 0.24 -0.11 -0.042 0.036 0.034
                                                                                    0.0
                 Outcome - 0.22 0.47 0.065 0.075 0.13 0.29 0.17
                                                                    Age
                                  Glucose
                                             SkinThickness
                                                              Diabetes Pedigree Function
                                                                         Outcome
```

Step-6: Model building and evaluation

```
#splitting the data into features(x) and target (y)
x = data.drop("Outcome", axis=1)
y= data["Outcome"]
#importing the libraries
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, classification report, confusion matrix
#splitting into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
#feature scaling
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
# training machine learning model using logistic regression
model= LogisticRegression()
model.fit(x_train, y_train)
LogisticRegression()
```

#evaluate the model-accuracy, precision, recall and F1 Score

```
#make predictions in the test set
y_pred= model.predict(x_test)
```

```
#evaluate the model
accuracy= accuracy_score(y_test, y_pred)
```

```
#classification report
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0 1	0.81 0.65	0.80 0.67	0.81 0.66	99 55
accuracy macro avg weighted avg	0.73 0.76	0.74 0.75	0.75 0.73 0.75	154 154 154

```
#calculating the performance metrics
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)

#report model performance
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

Accuracy: 0.75 Precision: 0.65 Recall: 0.67 F1-score: 0.66

Conclusion:

- It has a decent level of precision, indicating that when it predicts positive cases (diabetes), it's correct about 65% of the time.
- The recall value indicates that the model is reasonably effective at identifying actual positive cases, capturing about 67% of them.
- The F1-score of 0.66 suggests that the model provides a balanced performance in terms of precision and recall.
- Out of a total of 768 patients, 268 have been diagnosed with diabetes.
- A higher number of pregnancies is associated with a decreased likelihood of diabetes.
- Patients with above-average blood pressure tend to have a lower likelihood of diabetes.
- An increase in blood pressure, BMI, and skin thickness is correlated with an increased likelihood of developing diabetes.
- Rising levels of glucose and insulin are linked to an increased risk of diabetes.