Practical 6

Implementation of Logistic regression

```
#import pandas
import pandas as pd
#col_names = ['pregnant', 'glucose', 'bp', 'skin', 'insulin',
#'bmi', 'pedigree', 'age', 'label']
# load dataset
pima = pd.read_csv("diabetes.csv")
```

```
pima.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigre
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	

```
#split dataset in features and target variable
feature_cols = ['Pregnancies', 'Insulin', 'BMI', 'Age','Glucose',
                'BloodPressure','DiabetesPedigreeFunction']
X = pima[feature_cols] # Features
y = pima.Outcome # Target variable
```

```
# split X and y into training and testing sets
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=0)
```

Model Development and Prediction

First, import the Logistic Regression module and create a Logistic Regression classifier object using LogisticRegression() function.

Then, fit your model on the train set using fit() and perform prediction on the test set using predict().

```
# import the class
from sklearn.linear_model import LogisticRegression
```

```
# instantiate the model (using the default parameters)
logreg = LogisticRegression()
```

```
# fit the model with data
logreg.fit(X_train,y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: Conver
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(
```

```
▾ LogisticRegression
LogisticRegression()
```

```
# predict the model
y_pred=logreg.predict(X_test)
```

Model Evaluation using Confusion Matrix

A confusion matrix is a table that is used to evaluate the performance of a classification model. You can also visualize the performance of an algorithm.

The fundamental of a confusion matrix is the number of correct and incorrect predictions are summed up class-wise.

```
# import the metrics class
from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix
```

```
array([[117,  13],
       [ 24,  38]])
```

Here, you can see the confusion matrix in the form of the array object. The dimension of this matrix is 2*2 because this model is binary classification.

You have two classes 0 and 1. Diagonal values represent accurate predictions, while non-diagonal elements are inaccurate predictions.

In the output, 117 and 38 are actual predictions, and 24 and 13 are incorrect predictions.

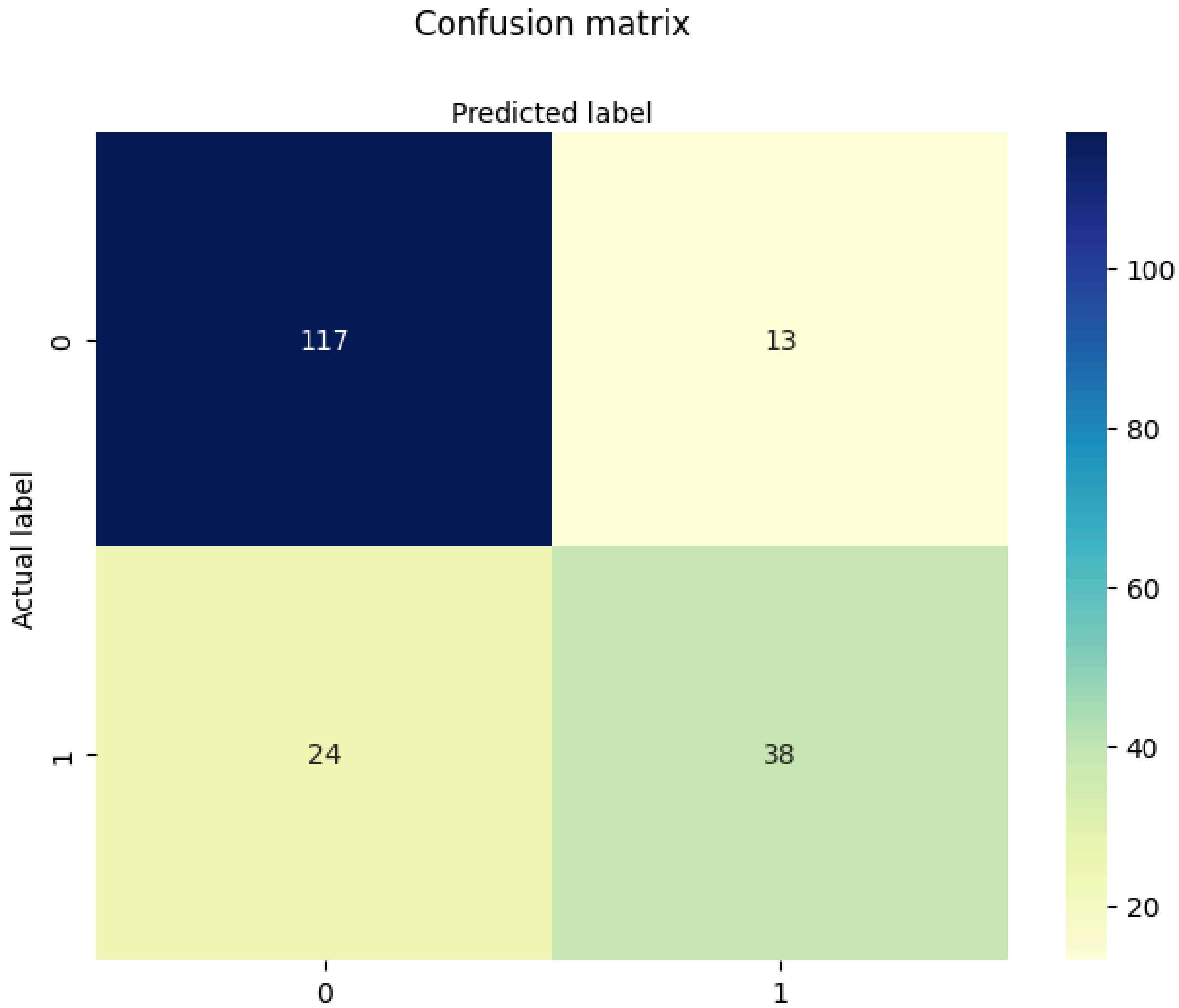
Visualizing Confusion Matrix using Heatmap

Let's visualize the results of the model in the form of a confusion matrix using matplotlib and seaborn.

```
# import required modules
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline


class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
Text(0.5, 427.9555555555555, 'Predicted label')
```



Confusion Matrix Evaluation Metrics

Let's evaluate the model using model evaluation metrics such as accuracy, precision, and recall.

```
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))
```

```
Accuracy: 0.8072916666666666
Precision: 0.7450980392156863
Recall: 0.6129032258064516
```

Well, you got a classification rate of 80%, considered as good accuracy.

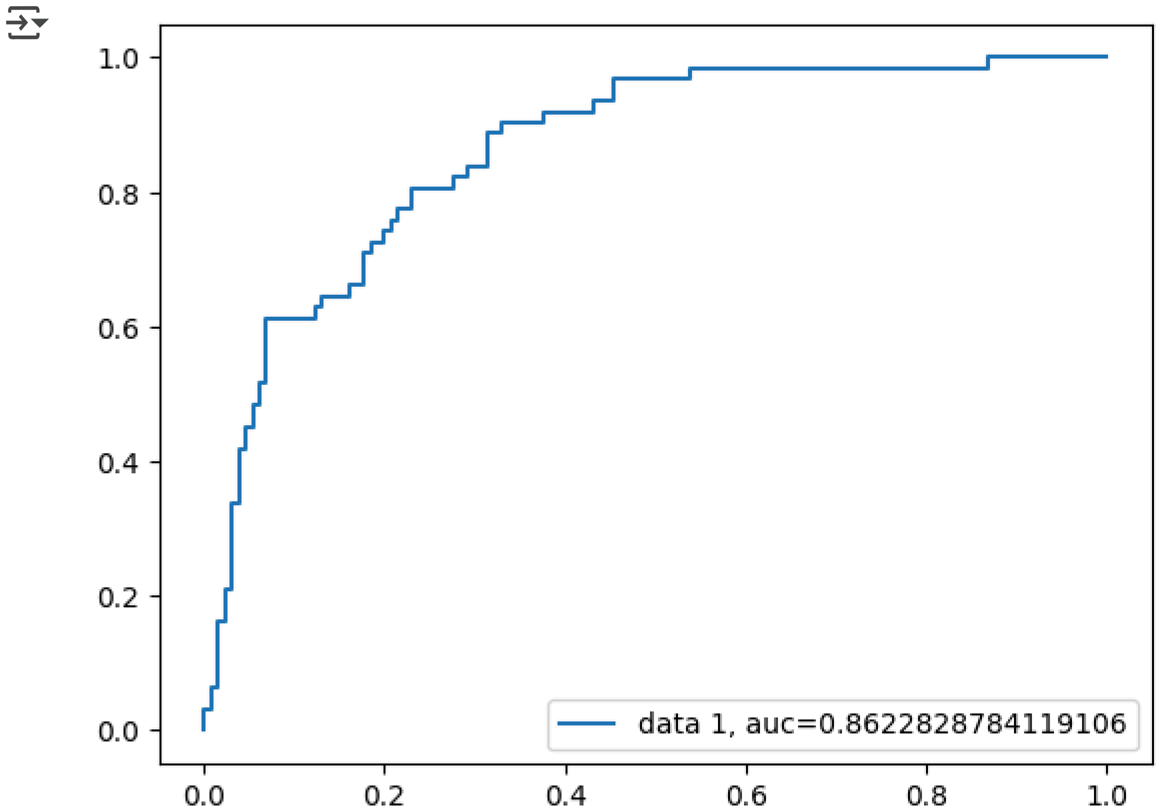
Precision: Precision is about being precise, i.e., how accurate your model is. In other words, you can say, when a model makes a prediction, how often it is correct. In your prediction case, when your Logistic Regression model predicted patients are going to suffer from diabetes, that patients have 74% of the time.

Recall: If there are patients who have diabetes in the test set and your Logistic Regression model can identify it 61% of the time.

ROC Curve

Receiver Operating Characteristic(ROC) curve is a plot of the true positive rate against the false positive rate. It shows the tradeoff between sensitivity and specificity.

```
y_pred_proba = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



AUC score for the case is 0.86. AUC score 1 represents perfect classifier, and 0.5 represents a worthless classifier.