ML LAB 07 - LOGISTIC REGRESSION

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Importing Libraries

In [40]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

In [41]:
```
df = pd.read_csv('Student-Pass-Fail-Data.csv')
df.head()
```

Out[41]:

	Self_Study_Daily	Tution_Monthly	Pass_Or_Fail
0	7	27	1
1	2	43	0
2	7	26	1
3	8	29	1
4	3	42	0

In [42]:
```
df.describe()
```

Out[42]:

	Self_Study_Daily	Tution_Monthly	Pass_Or_Fail
count	1000.000000	1000.000000	1000.000000
mean	5.744000	31.230000	0.499000
std	2.121076	5.976355	0.500249
min	0.000000	20.000000	0.000000
25%	4.000000	26.000000	0.000000
50%	6.000000	30.000000	0.000000
75%	7.000000	36.000000	1.000000
max	10.000000	50.000000	1.000000

In [43]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Self_Study_Daily  1000 non-null   int64
 1   Tution_Monthly    1000 non-null   int64
 2   Pass_Or_Fail      1000 non-null   int64
dtypes: int64(3)
memory usage: 23.6 KB
```

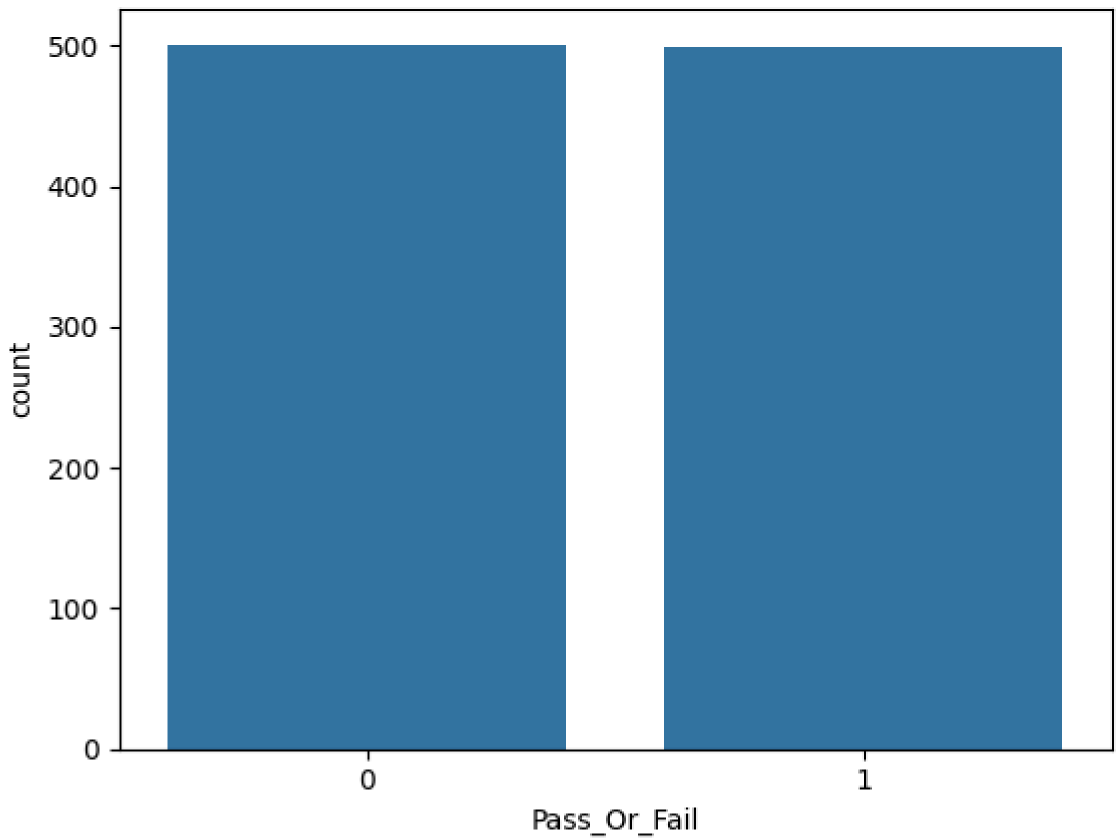
Data Visualization

In [44]:

```
sns.countplot(x='Pass_Or_Fail', data=df)
```

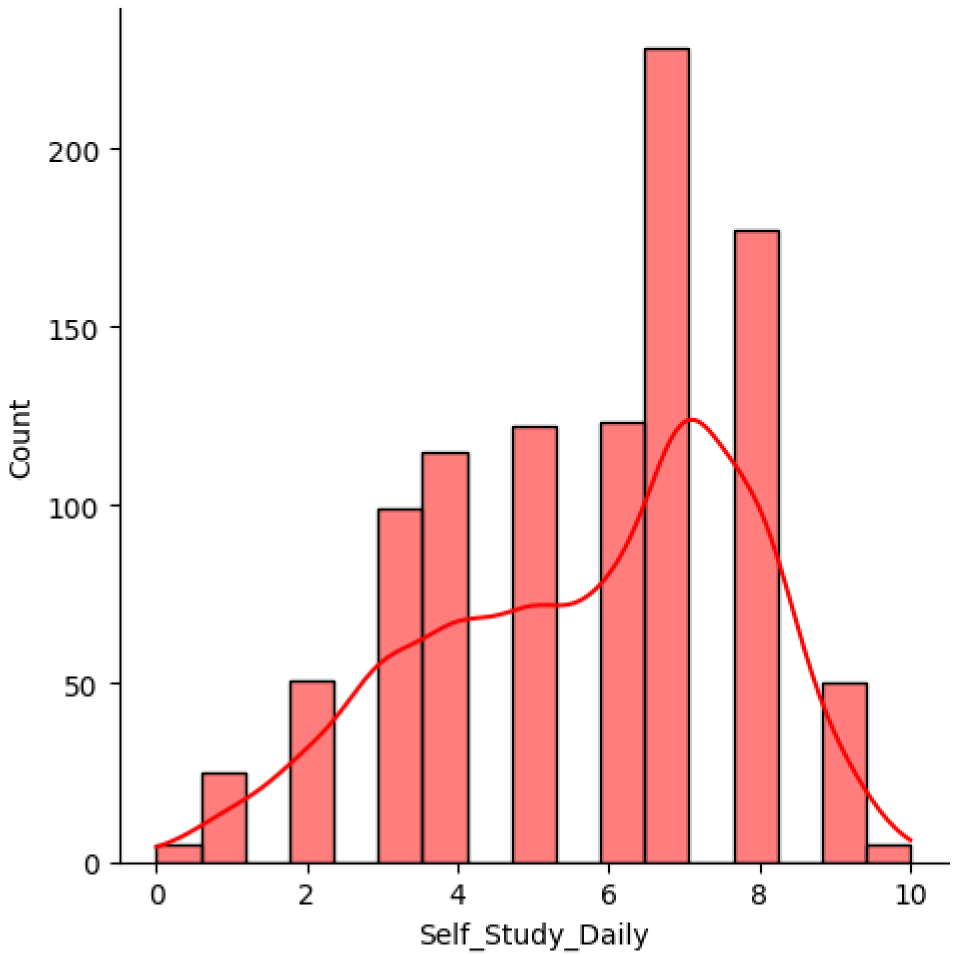
Out[44]:

```
<Axes: xlabel='Pass_Or_Fail', ylabel='count'>
```



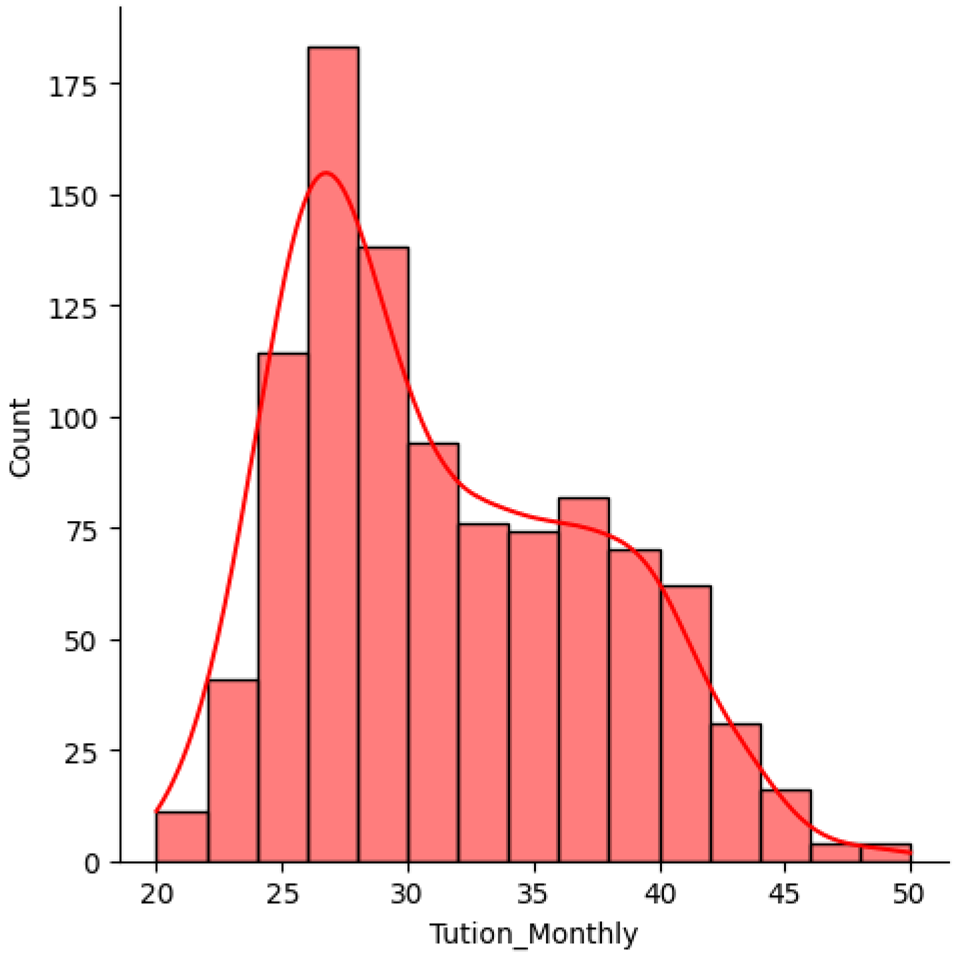
In [45]:
```
sns.displot(x='Self_Study_Daily', data=df, color='red', kde=True)
```

Out[45]: <seaborn.axisgrid.FacetGrid at 0x1a8a79bef60>



In [46]:
```
sns.displot(x='Tution_Monthly', data=df, color='red', kde=True)
```

Out[46]: <seaborn.axisgrid.FacetGrid at 0x1a8a79cda90>



Splitting the data into independent(X) and dependent(y) variables

In [47]:
```
X = df.iloc[:,[0,1]]
X.head()
```

Out[47]:

	Self_Study_Daily	Tution_Monthly
0	7	27
1	2	43
2	7	26
3	8	29
4	3	42

In [48]:
```
y = df.iloc[:, 2]
y.head()
```

Out[48]:
```
0    1
1    0
2    1
3    1
4    0
Name: Pass_Or_Fail, dtype: int64
```

Feature scaling

In [49]:
```
sc = StandardScaler()
X = sc.fit_transform(X)
X
```

Out[49]:
```
array([[ 0.59244861, -0.70814346],
       [-1.76602516,  1.97041337],
       [ 0.59244861, -0.87555326],
       ...,
       [-1.29433041,  1.30077416],
       [ 0.59244861, -1.04296307],
       [-0.3509409 ,  0.96595456]])
```

Splitting the dataset into train and test sets

In [50]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(700, 2)
(300, 2)
(700,)
(300,)
```

Fitting the logistic regression model and predicting test results

In [51]:
```
classifier = LogisticRegression()
classifier.fit(X_train, y_train)
```

Out[51]:
```
▾ LogisticRegression
LogisticRegression()
```

In [52]:
```
y_pred = classifier.predict(X_test)
```

In [53]:
```
result = pd.DataFrame({'Actual' : y_test, 'Predicted' : y_pred})
result
```

Out[53]:

	Actual	Predicted
507	0	1
818	1	1
452	0	0
368	1	1
242	1	1
...	...	...
459	0	0
415	1	1
61	1	1
347	0	0
349	0	0

300 rows × 2 columns

Coefficient and Intercept

In [54]:
```
classifier.coef_
```

Out[54]:
```
array([[ 3.82639026, -3.54178377]])
```

In [55]:
```
classifier.intercept_
```

Out[55]:
```
array([-2.68767548])
```

Evaluating the model

In [56]:
```
print(classifier.predict_proba(X))
```

```
[[1.10331924e-01 8.89668076e-01]
 [9.99999926e-01 7.36490110e-08]
 [6.41467981e-02 9.35853202e-01]
 ...
 [9.99995202e-01 4.79779388e-06]
 [3.65016338e-02 9.63498366e-01]
 [9.99419891e-01 5.80108870e-04]]
```

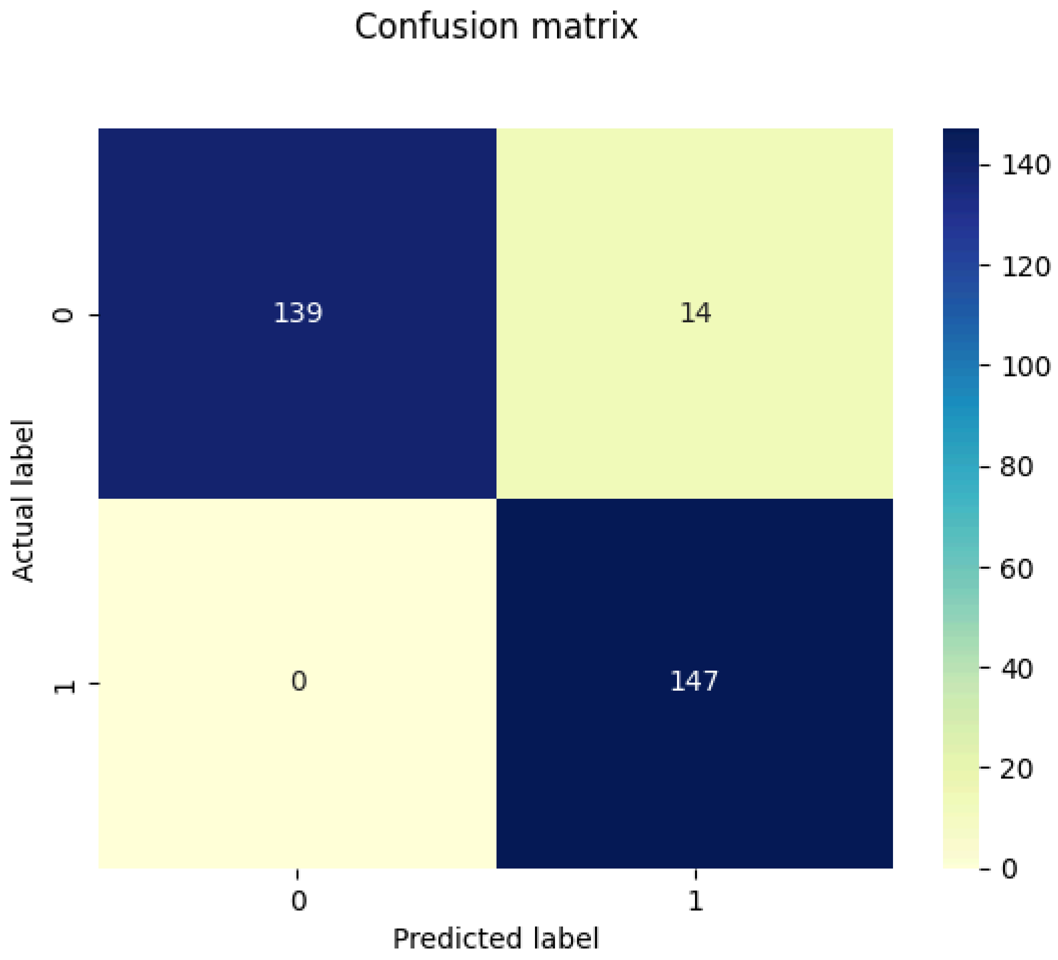
In [57]:
```
cf_matrix = confusion_matrix(y_test, y_pred)
cf_matrix
```

Out[57]:
```
array([[139,  14],
       [  0, 147]], dtype=int64)
```

In [58]:
```
sns.heatmap(pd.DataFrame(cf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
```

```
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[58]: Text(0.5, 23.52222222222222, 'Predicted label')



In [59]:
```
accuracy_score(y_test,y_pred)
```

Out[59]: 0.9533333333333334

Classification Report

In [60]:
```
target_names = ['Fail', 'Pass']
print(classification_report(y_test, y_pred,target_names=target_names))
```

```
              precision    recall  f1-score   support

        Fail       1.00      0.91      0.95       153
        Pass       0.91      1.00      0.95       147

    accuracy                           0.95       300
   macro avg       0.96      0.95      0.95       300
weighted avg       0.96      0.95      0.95       300
```

Model Interpretation

Why logistic regression?

- Here we have a large dataset of where the predictor variables and the log-odds of the response variable are in linear relationship.
- Dependant variable is a binary datatype and independant variables have very little or no multicollinearity.

Model Observation:

- Coefficient i.e, the Slope of the line is [3.82639026, -3.54178377], which means the change of "Self_Study_Daily" for a unit, X increases and the change of "Tution_Monthly" for a unit, X decreases.
- The intercept represents the value of the dependent variable when all independent variables are zero. For logistic regression model here, the intercept of -2.68767548 would represent the estimated pass percentage for students with zero years of experience will result in fail.
- From the classification report we can see that the precision and recall for class "Fail" is 1.00 and 0.91 respectively meaning that the 100% of the predictions made by the model is correct and 91% of the relevant data points were correctly identified. Similary for class "Pass" precision is 91% and recall is 100%. Means the preprocessed dataset is well trained and processed such that it yeilds about 95% precise outcome.
- And as for the accuracy of the model it is 0.95 i.e., 95% of outcomes were predicted correct.