Data-set Import

```
import pandas as pd

df = pd.read_csv('https://raw.githubusercontent.com/supunsathsara/NIBM-ML-data-sets/main/output-cleaned.csv')
df
```

	gpa	Introduction to Computer Science	Mathematics for Computing	Programming Fundamentals	Fundamentals of Electronics	result
0	3.69	4.3	3.3	4.0	4.0	PASS
1	1.30	2.7	1.7	0.0	0.0	FAIL
2	0.00	0.0	0.0	0.0	0.0	FAIL
3	2.70	4.0	4.0	3.0	4.0	FAIL
4	2.98	3.7	2.7	4.0	3.3	FAIL
5	3.04	4.0	4.0	2.7	4.0	FAIL
6	3.25	4.0	4.0	3.3	4.0	FAIL
7	0.00	0.0	0.0	0.0	0.0	FAIL
8	2.03	3.0	3.3	0.0	3.7	FAIL
9	3.53	4.0	4.3	3.0	3.7	PASS
10	2.46	3.3	2.7	1.7	3.3	FAIL
11	2.48	3.7	1.7	3.3	1.3	FAIL
12	2.89	4.0	4.3	3.0	3.7	FAIL
13	4.00	4.3	4.3	4.3	4.0	PASS
14	3.31	4.0	4.3	3.7	3.7	PASS
15	2.32	3.7	2.7	1.0	3.0	FAIL
16	1.64	2.0	2.3	2.0	1.0	FAIL
17	2.94	3.7	4.0	2.7	3.3	FAIL
18	1.85	4.0	3.0	1.7	3.0	FAIL
19	3.08	3.3	3.3	2.0	4.0	FAIL
20	2.21	2.7	2.7	1.7	2.0	FAIL
21	0.00	0.0	0.0	0.0	0.0	FAIL

22	3.12	4.0	4.0	2.3	4.0	FAIL
23	3.04	2.7	3.7	3.7	2.0	FAIL
24	2.26	3.7	2.0	2.7	3.7	FAIL
25	1.88	2.0	2.7	1.3	2.7	FAIL
26	2.56	4.0	3.7	1.7	3.0	FAIL
27	2.36	1.0	2.3	1.7	1.7	FAIL
28	2.48	4.0	3.7	3.3	3.0	FAIL
29	2.03	3.3	2.3	2.7	3.0	FAIL
30	0.96	3.7	2.3	1.7	0.0	FAIL
31	1.38	4.0	1.7	1.3	0.0	FAIL
32	3.56	4.3	4.3	4.0	3.3	PASS
33	2.69	3.3	3.3	3.0	3.0	FAIL
34	0.00	0.0	0.0	0.0	0.0	FAIL
35	2.51	4.0	2.7	2.7	3.0	FAIL
36	3.47	4.0	3.7	3.7	4.0	PASS
37	2.86	3.3	3.7	2.3	3.7	FAIL
38	2.23	2.7	3.0	2.0	2.0	FAIL
39	3.71	4.0	4.0	4.3	4.0	PASS
40	3.30	4.0	3.3	4.3	4.0	PASS
41	0.00	0.0	0.0	0.0	0.0	FAIL
42	1.62	4.3	4.0	3.3	2.3	FAIL

Pass/Fail Predict Model

Extracting Target and Features

In this section, we prepare our dataset for machine learning by defining our target variable (y) and feature variables (x).

```
y = df["result"]
x = df.drop(columns=['gpa', 'result'])
y
```

```
0     PASS
1     FAIL
2     FAIL
3     FAIL
4     FAIL
5     FAIL
6     FAIL
7     FAIL
8     FAIL
9     PASS
10    FAIL
11    FAIL
12    FAIL
13    PASS
14    PASS
15    FAIL
16    FAIL
17    FAIL
18    FAIL
19    FAIL
20    FAIL
21    FAIL
22    FAIL
23    FAIL
24    FAIL
25    FAIL
```

```
26    FAIL
27    FAIL
28    FAIL
29    FAIL
30    FAIL
31    FAIL
32    PASS
33    FAIL
34    FAIL
35    FAIL
36    PASS
37    FAIL
38    FAIL
39    PASS
40    PASS
41    FAIL
42    FAIL
Name: result, dtype: object
```

Training the Decision Tree

we train our Decision Tree classifier. Harnessing the power of the sklearn library, we split our dataset into a training set (80%) and a testing set (20%). With the wisdom of randomness (random_state=42)

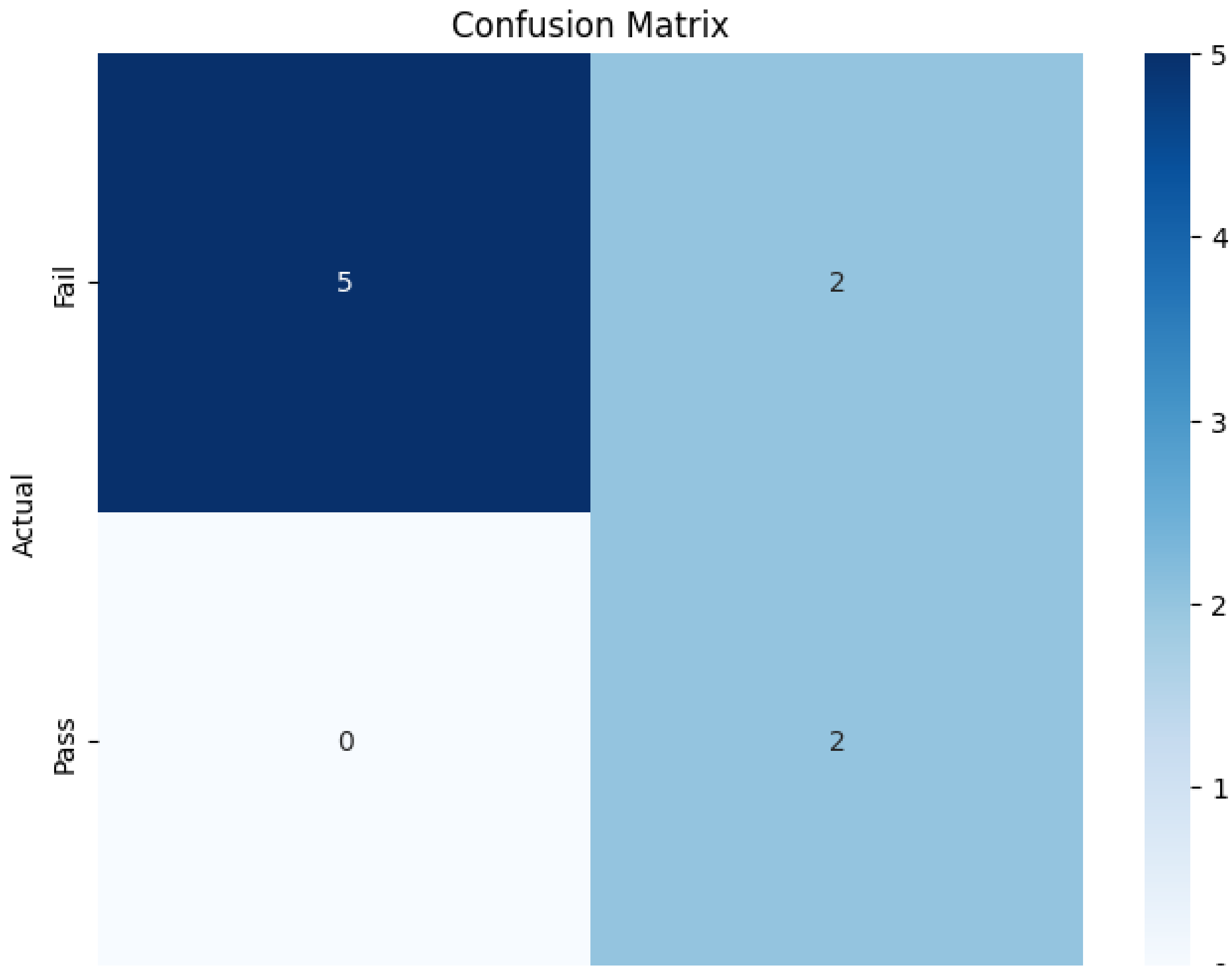
```
# Import necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Split the data into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

# Initialize the DecisionTreeClassifier
clf = DecisionTreeClassifier(random_state=42)

# Train the classifier on the training data
clf.fit(X_train, y_train)

# Make predictions on the test data
y_pred = clf.predict(X_test)

# Calculate the accuracy score
accuracy = accuracy_score(y_test, y_pred)

print("Accuracy:", accuracy)
```

```
Accuracy: 0.7777777777777778
```

Model Evaluation

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Calculate and print the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Generate and print the classification report
class_report = classification_report(y_test, y_pred)
print("Classification Report:\n", class_report)

# Generate and print the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", conf_matrix)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='g', cmap='Blues', xticklabels=['Fail', 'Pass'], yticklabels=['Fail', 'Pass'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Accuracy: 0.7777777777777778
Classification Report:
              precision    recall  f1-score   support

        FAIL       1.00      0.71      0.83         7
        PASS       0.50      1.00      0.67         2

    accuracy                           0.78         9
   macro avg       0.75      0.86      0.75         9
weighted avg       0.89      0.78      0.80         9

Confusion Matrix:
 [[5 2]
 [0 2]]
```



Predicting using the model

```
# Load the input data into a DataFrame with feature names
feature_names = ['Introduction to Computer Science', 'Mathematics for Computing', 'Programming Fundamentals', 'Fundamental
input_data = pd.DataFrame({
    'Introduction to Computer Science': [4],
    'Mathematics for Computing': [3],
    'Programming Fundamentals': [4],
    'Fundamentals of Electronics': [2]
}, columns=feature_names)

predictions = clf.predict(input_data)
predictions
```

```
array(['FAIL'], dtype=object)
```

Summery

Accuracy: 0.78

> Our model correctly predicted the outcome 78% of the time. Think of it as hitting the target almost 8 out of 10 times. Classification Report:

Precision (for PASS): 50%

> When our model predicts a PASS, it's correct 50% of the time. This is like saying it's a bit cautious but still gets it right sometimes.

Recall (for PASS): 100%

> Explanation: Out of all the actual PASS outcomes, our model captured every single one. It's like not letting any PASS slip away.

F1-score (for PASS): 67%

> Combining precision and recall, this score indicates overall performance. Think of it as a balanced measure, striving for precision and not missing out on PASS outcomes.

Weighted Average F1-score: 80%

> Taking into account both PASS and FAIL, the model shows an overall balanced performance with an 80% score. It's like maintaining a good balance in accuracy across different outcomes.

In simpler terms, our model is pretty good at catching PASS instances but may need a bit more confidence in its predictions. Overall, it's doing well with an 80% balanced performance.

GPA Predict Model

Extracting Target and Features

In this section, we prepare our dataset for machine learning by defining our target variable (y) and feature variables (x).

```
yr = df['gpa']
Xr = df.drop(columns=['gpa', 'result'])
```

Training the Model

Splitting data into train and test sets

```
from sklearn.model_selection import train_test_split

Xr_train, Xr_test, yr_train, yr_test = train_test_split(Xr, yr, test_size=0.2, random_state=42)
```

Training the model using Linear Regression

```
from sklearn.linear_model import LinearRegression

# Initialize the Linear Regression model
regressor = LinearRegression()

# Train the model
regressor.fit(Xr_train, yr_train)

# Make predictions
predictions = regressor.predict(Xr_test)
```

Evaluate the Model

```
# Import necessary libraries
from sklearn.metrics import mean_squared_error, r2_score, explained_variance_score
import matplotlib.pyplot as plt

# Calculate and print RMSE
mse = mean_squared_error(yr_test, predictions)
rmse = mse ** 0.5
print("Root Mean Squared Error:", rmse)

# Calculate and print R-squared (R2) score
r2 = r2_score(yr_test, predictions)
print("R-squared (R2) Score:", r2)

# Calculate and print Explained Variance Score
explained_variance = explained_variance_score(yr_test, predictions)
print("Explained Variance Score:", explained_variance)

print()
print()
# Plot predicted vs actual values with a line representing perfect alignment
plt.figure(figsize=(8, 6))
plt.scatter(yr_test, predictions, alpha=0.7, label='Predicted vs Actual GPA')
plt.plot([min(yr_test), max(yr_test)], [min(yr_test), max(yr_test)], color='red', linestyle='--', linewidth=2, label='Perf
```