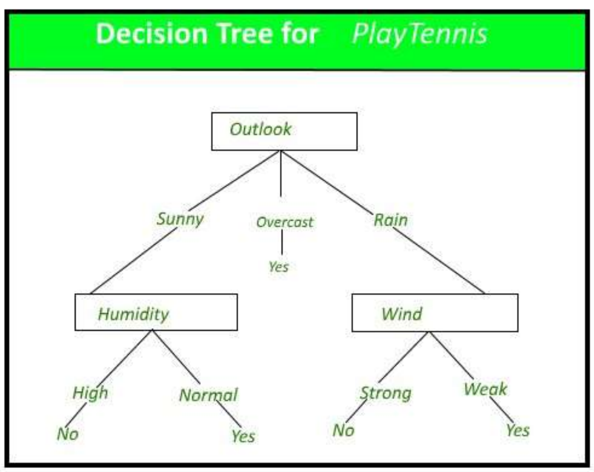
Experiment No. 3
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

Aim: Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model.

Objective: To perform various feature engineering tasks, apply Decision Tree Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score. Improve the performance by performing different data engineering and feature engineering tasks.

Theory:

Decision Tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.



Dataset:

Predict whether income exceeds $50K/yr based on census data. Also known as "Adult" dataset.

Attribute Information:

Listing of attributes:

>50K, <=50K.
age: continuous.

workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked. fnlwgt: continuous.

education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool. education-num: continuous.

marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Marriedspouse-absent, Married-AF-spouse.

occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.

relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.

race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black. sex:

Female, Male.

capital-gain: continuous. capital-loss:

continuous. hours-per-week: continuous.

native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, OutlyingUS(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines,
Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

Conclusion:

1. **Dealing with Categorical Attributes during Data Pre-processing:**

In the code, categorical attributes are handled as follows:

Label Encoding: Categorical attributes are transformed into numerical format using label encoding. The LabelEncoder from Scikit-Learn is applied to convert categorical values into unique integers.

Dropping Missing Values: Rows containing missing values in categorical columns ('workclass', 'occupation', 'native.country') are dropped from the dataset to maintain data quality.

2. **Hyper parameter Tuning:**

Hyperparameter tuning is minimal in the code. The Decision Tree classifier is created with a max_depth of 5. However, there's no comprehensive hyperparameter tuning process, such as grid search or random search, to optimize the model's performance. Tuning hyperparameters like max_depth, min_samples_split, and min_samples_leaf could potentially improve the model's accuracy.

3. **Accuracy, Confusion Matrix, Precision, Recall, and F1-Score**:

Accuracy: Measures overall correctness of predictions.

Confusion Matrix: Summarizes true positives, true negatives, false positives, and false negatives.

Precision: Measures accurate positive classifications.

Recall (Sensitivity): Measures identifying relevant instances.

F1-Score: Balances precision and recall, especially useful for imbalanced classes.

```
confusion matrix
 [[ 764  735]
 [ 214 4315]]
              precision    recall  f1-score   support

           0       0.78      0.51      0.62      1499
           1       0.85      0.95      0.90      4529

    accuracy                           0.84      6028
   macro avg       0.82      0.73      0.76      6028
weighted avg       0.84      0.84      0.83      6028
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df = pd.read_csv("adult.csv")
df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relatio
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-
2	66	?	186061	Some-college	10	Widowed	?	Unm
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unm
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Ow

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64 
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64 
 11  capital.loss    32561 non-null  int64 
 12  hours.per.week  32561 non-null  int64 
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
df.describe()
```

```
df.describe()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.w
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.00
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40.43
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12.34
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.00
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40.00
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.00
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.00
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.00

```
# Info for categorical features
df.describe(include=['O'])
```

	workclass	education	marital.status	occupation	relationship	race	sex	na
count	32561	32561	32561	32561	32561	32561	32561	
unique	9	16	7	15	6	5	2	
top	Private	HS-grad	Married-civ-spouse	Prof-specialty	Husband	White	Male	
freq	22696	10501	14976	4140	13193	27816	21790	

```
duplicated_rows = df.duplicated()
any_duplicates = duplicated_rows.any()

print("Duplicated Rows:")
df[duplicated_rows]
```

Duplicated Rows:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	rel
8453	25	Private	308144	Bachelors	13	Never-married	Craft-repair	N
8645	90	Private	52386	Some-college	10	Never-married	Other-service	N
12202	21	Private	250051	Some-college	10	Never-married	Prof-specialty	
14346	20	Private	107658	Some-college	10	Never-married	Tech-support	N
15603	25	Private	195994	1st-4th	2	Never-married	Priv-house-serv	N
17344	21	Private	243368	Preschool	1	Never-married	Farming-fishing	N
19067	46	Private	173243	HS-grad	9	Married-civ-spouse	Craft-repair	
20388	30	Private	144593	HS-grad	9	Never-married	Other-service	N
20507	19	Private	97261	HS-grad	9	Never-married	Farming-fishing	N
22783	19	Private	138153	Some-college	10	Never-married	Adm-clerical	
22934	19	Private	146679	Some-college	10	Never-married	Exec-managerial	
23276	49	Private	31267	7th-8th	4	Married-civ-spouse	Craft-repair	
23660	25	Private	195994	1st-4th	2	Never-married	Priv-house-serv	N
23720	44	Private	367749	Bachelors	13	Never-married	Prof-specialty	N
23827	49	Self-emp-not-inc	43479	Some-college	10	Married-civ-spouse	Craft-repair	
26738	23	Private	240137	5th-6th	3	Never-married	Handlers-cleaners	N
27133	28	Private	274679	Masters	14	Never-married	Prof-specialty	N
28796	27	Private	255582	HS-grad	9	Never-married	Machine-op-inspct	N
29051	42	Private	204235	Some-college	10	Married-civ-spouse	Prof-specialty	

29334	39	Private	30916	HS-grad	9	Married-civ-spouse	Craft-repair

```
df = df.drop_duplicates()
```

```
# Correction of target value using a map
income_map = {'<=50K': 1, '>50K': 0}
df['income'] = df['income'].map(income_map)
```

```
<ipython-input-47-00c8c2884cd1>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  df['income'] = df['income'].map(income_map)
```

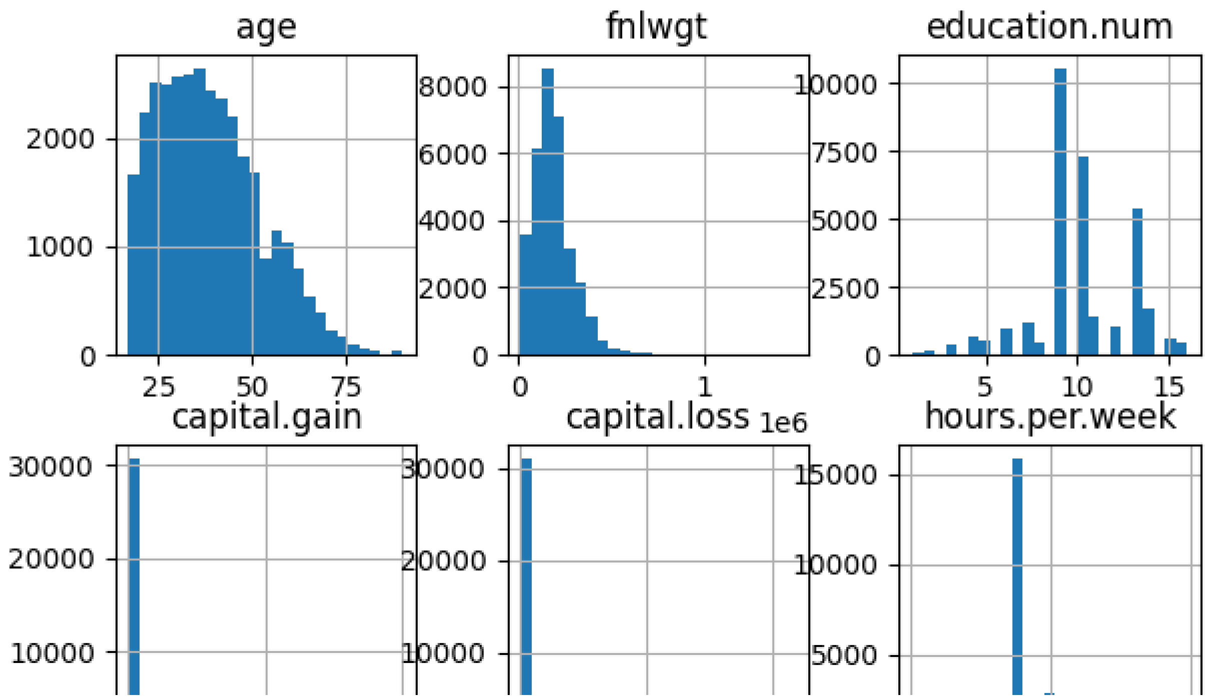
```
df['income'] = df['income'].astype('int')
```

```
<ipython-input-48-c88e10f6120e>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  df['income'] = df['income'].astype('int')
```

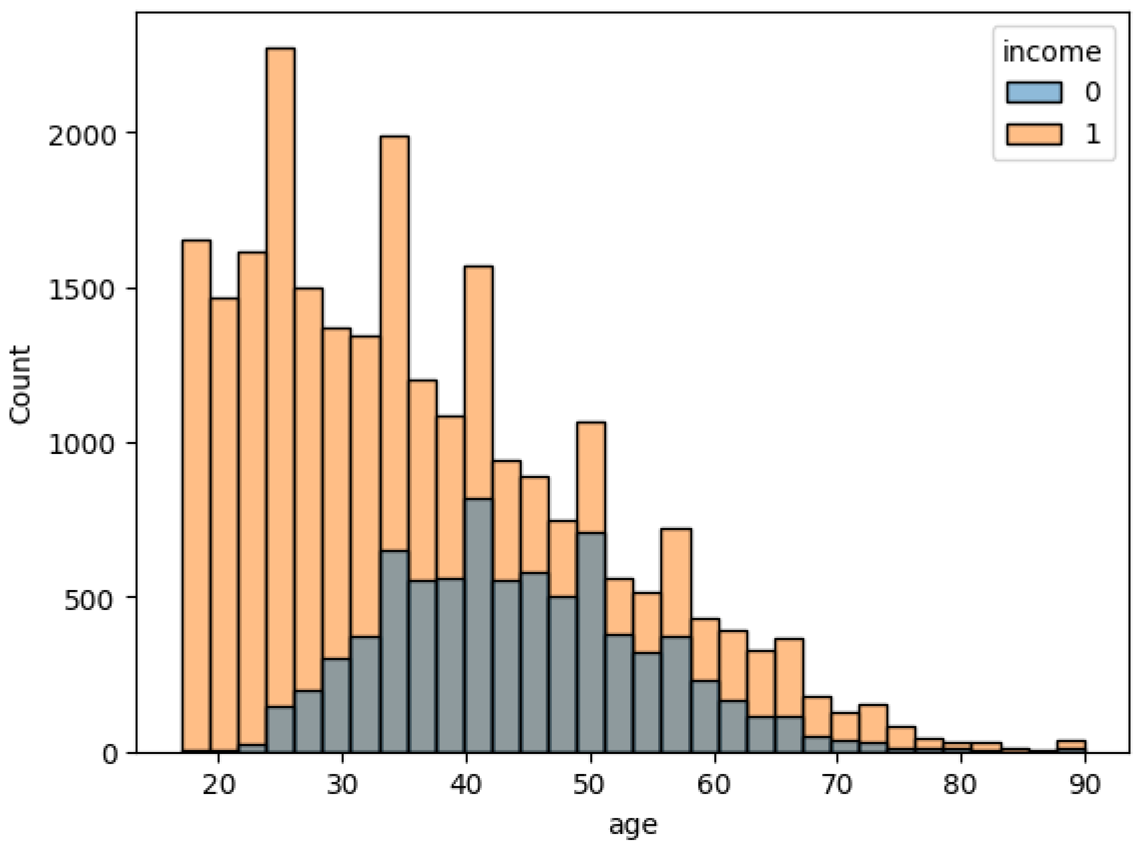
```
categorical = [col for col in df.columns if df[col].dtype == 'object' ]
numerical = [col for col in df.columns if df[col].dtype != 'object' ]
```

```
df[numerical].hist(bins=25, figsize=(7, 7))
plt.show()
```




```
sns.histplot(df, x='age', hue='income', bins=32)
```

<Axes: xlabel='age', ylabel='Count'>



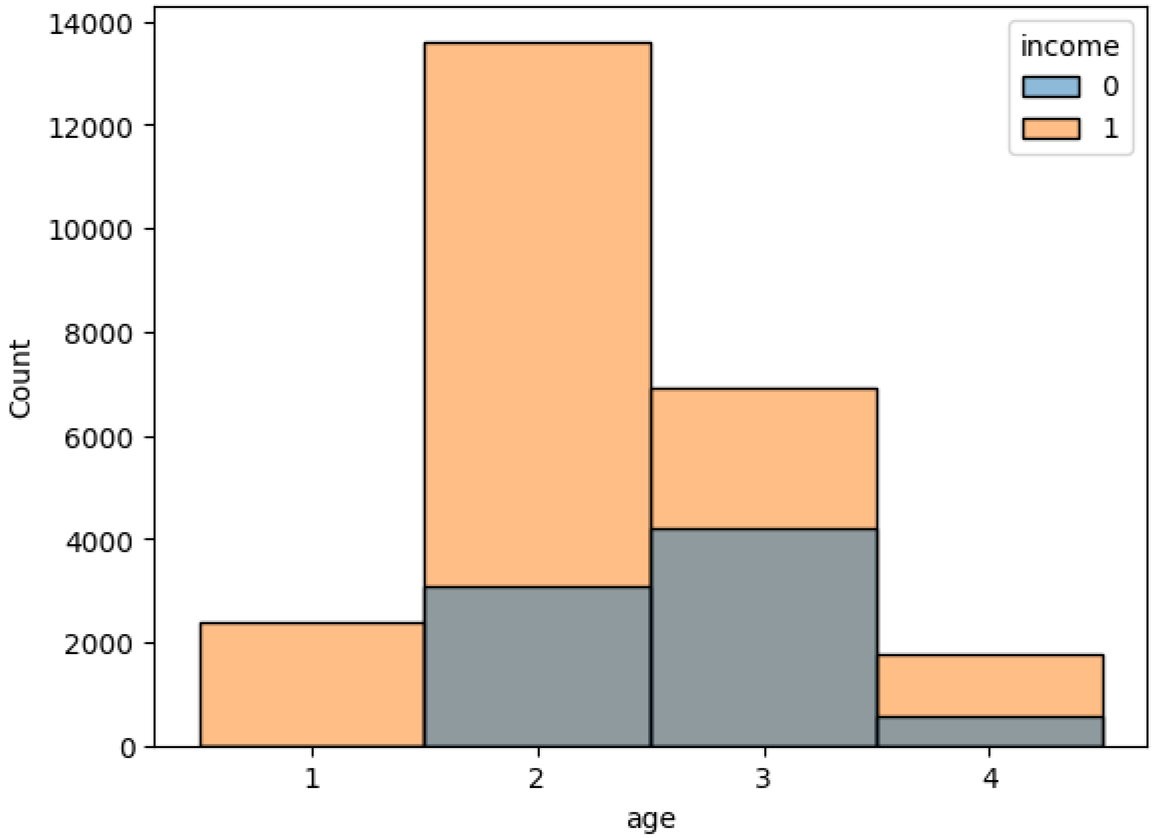

```
#describe ages in classes
def age_group(df):
    age_bins = [0, 20, 40, 60, float('inf')]
    age_labels = ['1', '2', '3', '4']
    df_age_range = df.copy()
```

```
    df_age_range['age'] = pd.cut(df_age_range['age'], bins=age_bins, labels=age_lab
    return df_age_range

df = age_group(df).copy()


sns.histplot(df, x='age', hue='income', bins= 32)
```

```
<Axes: xlabel='age', ylabel='Count'>
```



Missing Values

```
df_missing = (df=='?').sum()
print(df_missing)
```

```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
```

```
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     582
income               0
dtype: int64
```

```
#droping row having missing values from dataset
df = df[df['workclass'] !='?']
df = df[df['occupation'] !='?']
df = df[df['native.country'] !='?']
df.head()
```

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relatio
1	4	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-
3	3	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unm
4	3	Private	264663	Some-college	10	Separated	Prof-specialty	Ow
5	2	Private	216864	HS-grad	9	Divorced	Other-service	Unm
6	2	Private	150601	10th	6	Separated	Adm-clerical	Unm

```
df_missing = (df=='?').sum()
print(df_missing)
```

```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

Data Preparation

```
from sklearn import preprocessing
df_categorical = df.select_dtypes(include=['object'])
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native
1	Private	HS-grad	Widowed	Exec-managerial	Not-in-family	White	Female	Unit
3	Private	7th-8th	Divorced	Machine-op-inspct	Unmarried	White	Female	Unit
4	Private	Some-college	Separated	Prof-specialty	Own-child	White	Female	Unit
5	Private	HS-grad	Divorced	Other-service	Unmarried	White	Female	Unit
6	Private	10th	Separated	Adm-clerical	Unmarried	White	Male	Unit

```
le = preprocessing.LabelEncoder()
df_categorical = df_categorical.apply(le.fit_transform)
df_categorical.head()
```

	workclass	education	marital.status	occupation	relationship	race	sex	native.cou
1	2	11	6	3	1	4	0	
3	2	5	0	6	4	4	0	
4	2	15	5	9	3	4	0	
5	2	11	0	7	4	4	0	
6	2	0	5	0	4	4	1	

```
df = df.drop(df_categorical.columns, axis=1)
df = pd.concat([df,df_categorical],axis=1)
df['income']=df['income'].astype('category')
df.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	income	workc
1	4	132870	9	0	4356	18	1	
3	3	140359	4	0	3900	40	1	
4	3	264663	10	0	3900	40	1	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30139 entries, 1 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype   
---  ------          --------------  -----   
 0   age             30139 non-null  category
 1   fnlwgt          30139 non-null  int64   
 2   education.num   30139 non-null  int64   
 3   capital.gain    30139 non-null  int64   
 4   capital.loss    30139 non-null  int64   
 5   hours.per.week  30139 non-null  int64   
 6   income          30139 non-null  category
 7   workclass       30139 non-null  int64   
 8   education       30139 non-null  int64   
 9   marital.status  30139 non-null  int64   
 10  occupation      30139 non-null  int64   
 11  relationship    30139 non-null  int64   
 12  race            30139 non-null  int64   
 13  sex             30139 non-null  int64   
 14  native.country  30139 non-null  int64   
dtypes: category(2), int64(13)
memory usage: 3.3 MB
```

Splitting dataset

```
from sklearn.model_selection import train_test_split
```

```
X = df.drop('income',axis=1)
X = X.drop('sex',axis=1)
y=df['income']
X.head()
```

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week	workclass	ed
1	4	132870	9	0	4356	18	2	

```
y.head()
```

```
1    1
3    1
4    1
5    1
6    1
Name: income, dtype: category
Categories (2, int64): [0, 1]
```

```
X_train , X_test , y_train , y_test = train_test_split(X,y,test_size=0.20)
```

Applying Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
dt_default = DecisionTreeClassifier(max_depth=5)
dt_default.fit(X_train,y_train)
```

```
▾       DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5)
```

```
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
```

```
y_pred_default=dt_default.predict(X_test)
print("confusion matrix\n",confusion_matrix(y_test,y_pred_default))
print(classification_report(y_test,y_pred_default))
```

```
confusion matrix
 [[ 764  735]
 [ 214 4315]]
              precision    recall  f1-score   support

           0       0.78      0.51      0.62      1499
           1       0.85      0.95      0.90      4529

    accuracy                           0.84      6028
   macro avg       0.82      0.73      0.76      6028
weighted avg       0.84      0.84      0.83      6028
```

```
print("accuracy score", accuracy_score(y_test, y_pred_default))
```

```
accuracy score 0.8425680159256802
```

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