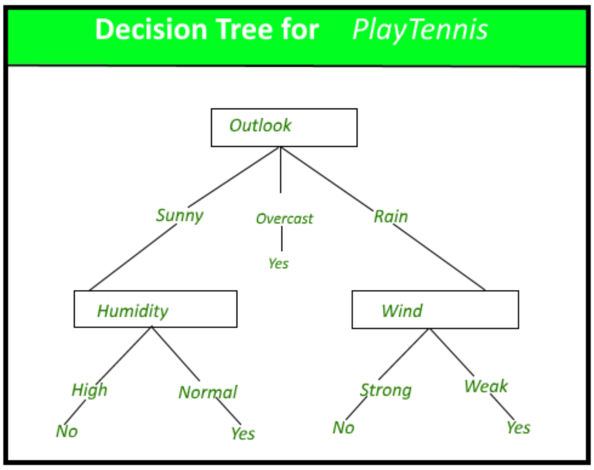
Experiment No. 3
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

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

Objective: Able to perform various feature engineering tasks, apply Decision Tree Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score.

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, Married-spouse-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, Outlying-US(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.

CODE & OUTPUT:

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

csv_path = 'adult_dataset.csv'
df = pd.read_csv(csv_path)

print(df.head())

   age workclass  fnlwgt     education  education.num marital.status  \
0   90         ?   77053       HS-grad              9        Widowed
1   82   Private  132870       HS-grad              9        Widowed
2   66         ?  186061  Some-college             10        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated

          occupation   relationship   race     sex  capital.gain  \
0                  ?  Not-in-family  White  Female             0
1    Exec-managerial  Not-in-family  White  Female             0
2                  ?      Unmarried  Black  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0

   capital.loss  hours.per.week native.country income
0          4356              40  United-States  <=50K
1          4356              18  United-States  <=50K
2          4356              40  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K

print ("Rows     : \n" ,df.shape[0])
print ("Columns  : \n" ,df.shape[1])
print ("\nFeatures : \n" ,df.columns.tolist())
```

```
print ("\nMissing values : \n", df.isnull().sum().values.sum())
print ("\nUnique values : \n", df.nunique())
```

```
Rows     :
 32561
Columns  :
 15

Features :
 ['age', 'workclass', 'fnlwgt', 'education', 'education.num', 'marital.sta
tus', 'occupation', 'relationship', 'race', 'sex', 'capital.gain', 'capita
l.loss', 'hours.per.week', 'native.country', 'income']

Missing values :
 0

Unique values :
 age                  73
workclass             9
fnlwgt            21648
education            16
education.num        16
marital.status        7
occupation           15
relationship          6
race                  5
sex                   2
capital.gain        119
capital.loss         92
hours.per.week       94
native.country       42
income                2
dtype: int64
```

```
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
```

```
print(df.describe())
```

```
                age        fnlwgt  education.num  capital.gain  capital.lo
ss  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000  32561.0000
00
mean      38.581647  1.897784e+05      10.080679   1077.648844     87.3038
30
std       13.640433  1.055500e+05       2.572720   7385.292085    402.9602
19
min       17.000000  1.228500e+04       1.000000      0.000000      0.0000
00
25%       28.000000  1.178270e+05       9.000000      0.000000      0.0000
00
50%       37.000000  1.783560e+05      10.000000      0.000000      0.0000
00
75%       48.000000  2.370510e+05      12.000000      0.000000      0.0000
00
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.0000
00

       hours.per.week
count    32561.000000
mean        40.437456
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

```
df_missing_workclass = (df['workclass']=='?').sum()
df_missing_workclass
```

```
1836
```

```
df_missing = (df=='?').sum()
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     583
income               0
dtype: int64
```

```
percent_missing = (df=='?').sum() * 100/len(df)
percent_missing
```

```
age               0.000000
workclass         5.638647
fnlwgt            0.000000
education         0.000000
education.num     0.000000
marital.status    0.000000
occupation        5.660146
relationship      0.000000
race              0.000000
sex               0.000000
capital.gain      0.000000
capital.loss      0.000000
hours.per.week    0.000000
native.country    1.790486
income            0.000000
dtype: float64
```

```
df.apply(lambda x: x !='?',axis=1).sum()
```

```
age               32561
workclass         30725
fnlwgt            32561
education         32561
education.num     32561
marital.status    32561
occupation        30718
relationship      32561
race              32561
sex               32561
capital.gain      32561
capital.loss      32561
hours.per.week    32561
native.country    31978
income            32561
dtype: int64
```

```
df_categorical = df.select_dtypes(include=['object'])

# checking whether any other column contains '?' value
df_categorical.apply(lambda x: x=='?',axis=1).sum()
```

```
workclass         1836
education            0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
native.country     583
income               0
dtype: int64
```

```
df = df[df['native.country'] != '?']
df = df[df['occupation'] !='?']

print(df)
```

```
       age workclass  fnlwgt     education  education.num      marital.sta
tus  \
0       90         ?   77053       HS-grad              9             Wido
wed
1       82   Private  132870       HS-grad              9             Wido
wed
2       66         ?  186061  Some-college             10             Wido
wed
3       54   Private  140359       7th-8th              4            Divor
ced
4       41   Private  264663  Some-college             10           Separa
ted
...    ...       ...     ...           ...            ...
...
32556   22   Private  310152  Some-college             10        Never-marr
ied
32557   27   Private  257302    Assoc-acdm             12   Married-civ-spo
use
32558   40   Private  154374       HS-grad              9   Married-civ-spo
use
32559   58   Private  151910       HS-grad              9             Wido
wed
32560   22   Private  201490       HS-grad              9        Never-marr
ied

              occupation   relationship   race     sex  capital.gain  \
0                      ?  Not-in-family  White  Female             0
1        Exec-managerial  Not-in-family  White  Female             0
2                      ?      Unmarried  Black  Female             0
3      Machine-op-inspct      Unmarried  White  Female             0
```

```
4        Prof-specialty      Own-child  White  Female             0
...                 ...            ...    ...     ...           ...
32556    Protective-serv  Not-in-family  White    Male             0
32557       Tech-support           Wife  White  Female             0
32558  Machine-op-inspct        Husband  White    Male             0
32559       Adm-clerical      Unmarried  White  Female             0
32560       Adm-clerical      Own-child  White    Male             0

       capital.loss  hours.per.week native.country income
0              4356              40  United-States  <=50K
1              4356              18  United-States  <=50K
2              4356              40  United-States  <=50K
3              3900              40  United-States  <=50K
4              3900              40  United-States  <=50K
...             ...             ...            ...    ...
32556             0              40  United-States  <=50K
32557             0              38  United-States  <=50K
32558             0              40  United-States   >50K
32559             0              40  United-States  <=50K
32560             0              20  United-States  <=50K

[32561 rows x 15 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 30162 entries, 1 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             30162 non-null  int64
 1   workclass       30162 non-null  object
 2   fnlwgt          30162 non-null  int64
 3   education       30162 non-null  object
 4   education.num   30162 non-null  int64
 5   marital.status  30162 non-null  object
 6   occupation      30162 non-null  object
 7   relationship    30162 non-null  object
 8   race            30162 non-null  object
 9   sex             30162 non-null  object
 10  capital.gain    30162 non-null  int64
 11  capital.loss    30162 non-null  int64
 12  hours.per.week  30162 non-null  int64
 13  native.country  30162 non-null  object
 14  income          30162 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
from sklearn import preprocessing

# encode categorical variables using label Encoder
```

```
# select all categorical variables
df_categorical = df.select_dtypes(include=['object'])
print(df_categorical.head())
```

```
  workclass     education marital.status         occupation   relationship  \
0         ?       HS-grad        Widowed                  ?  Not-in-family

1   Private       HS-grad        Widowed    Exec-managerial  Not-in-family

2         ?  Some-college        Widowed                  ?      Unmarried

3   Private       7th-8th       Divorced  Machine-op-inspct      Unmarried

4   Private  Some-college      Separated     Prof-specialty      Own-child


    race     sex native.country income
0  White  Female  United-States  <=50K
1  White  Female  United-States  <=50K
2  Black  Female  United-States  <=50K
3  White  Female  United-States  <=50K
4  White  Female  United-States  <=50K
```

```
#appy label encoding
le = preprocessing.LabelEncoder()
df_categorical = df_categorical.apply(le.fit_transform)
print(df_categorical.head())
```

```
   workclass  education  marital.status  occupation  relationship  race  s
ex  \
0          0         11               6           0             1     4
 0
1          4         11               6           4             1     4
 0
2          0         15               6           0             4     2
 0
3          4          5               0           7             4     4
 0
4          4         15               5          10             3     4
 0

   native.country  income
0              39       0
1              39       0
2              39       0
3              39       0
4              39       0
```

```
df = df.drop(df_categorical.columns,axis=1)
print(df)
```

```
       age  fnlwgt  education.num  capital.gain  capital.loss  hours.per.w
eek
0       90   77053              9             0          4356             
 40
1       82  132870              9             0          4356             
 18
2       66  186061             10             0          4356             
 40
3       54  140359              4             0          3900             
 40
4       41  264663             10             0          3900             
 40
...    ...     ...            ...           ...           ...             
...
32556   22  310152             10             0             0             
 40
32557   27  257302             12             0             0             
 38
32558   40  154374              9             0             0             
 40
32559   58  151910              9             0             0             
 40
32560   22  201490              9             0             0             
 20

[32561 rows x 6 columns]
```

```
df = pd.concat([df,df_categorical],axis=1)
print(df.head())
```

```
   age  fnlwgt  education.num  capital.gain  capital.loss  hours.per.week
 \
0   90   77053              9             0          4356              40

1   82  132870              9             0          4356              18

2   66  186061             10             0          4356              40

3   54  140359              4             0          3900              40

4   41  264663             10             0          3900              40


   workclass  education  marital.status  occupation  relationship  race  s
ex  \
0          0         11               6           0             1     4  
 0
1          4         11               6           4             1     4  
 0
2          0         15               6           0             4     2  
 0
```

```
3             4           5                0           7            4      4
 0
4             4          15                5          10            3      4
 0

   native.country  income
0              39       0
1              39       0
2              39       0
3              39       0
4              39       0
```

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

print(df)
```

```
       age  fnlwgt  education.num  capital.gain  capital.loss  hours.per.w
eek  \
0       90   77053              9             0          4356
 40
1       82  132870              9             0          4356
 18
2       66  186061             10             0          4356
 40
3       54  140359              4             0          3900
 40
4       41  264663             10             0          3900
 40
...    ...     ...            ...           ...           ...
...
32556   22  310152             10             0             0
 40
32557   27  257302             12             0             0
 38
32558   40  154374              9             0             0
 40
32559   58  151910              9             0             0
 40
32560   22  201490              9             0             0
 20

       workclass  education  marital.status  occupation  relationship  rac
e  \
0              0         11               6           0             1
4
1              4         11               6           4             1
4
2              0         15               6           0             4
2
3              4          5               0           7             4
4
```

```
4               4        15                5         10            3
4
...            ...       ...              ...        ...          ...    ..
.
32556           4        15                4         11            1
4
32557           4         7                2         13            5
4
32558           4        11                2          7            0
4
32559           4        11                6          1            4
4
32560           4        11                4          1            3
4

       sex  native.country  income
0        0              39       0
1        0              39       0
2        0              39       0
3        0              39       0
4        0              39       0
...    ...             ...     ...
32556    1              39       0
32557    0              39       0
32558    1              39       1
32559    0              39       0
32560    1              39       0

[32561 rows x 15 columns]
```

```
from sklearn.model_selection import train_test_split

# independent features to X
X = df.drop('income',axis=1)

# dependent variable to Y
Y = df['income']

print(X.head())
```

```
   age  fnlwgt  education.num  capital.gain  capital.loss  hours.per.week
 \
1   82  132870              9             0          4356              18

3   54  140359              4             0          3900              40

4   41  264663             10             0          3900              40

5   34  216864              9             0          3770              45

6   38  150601              6             0          3770              40
```

```
   workclass  education  marital.status  occupation  relationship  race  s
ex  \
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

   native.country
1              38
3              38
4              38
5              38
6              38
```

```
Y.head()
```

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

```
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.30,random
_state=99)
```

```
print(X_train.head())
```

```
       age  fnlwgt  education.num  capital.gain  capital.loss  hours.per.w
eek  \
24351   42  289636              9             0             0
 46
15626   37   52465              9             0             0
 40
4347    38  125933             14             0             0
 40
23972   44  183829             13             0             0
 38
26843   35  198841             11             0             0
 35

       workclass  education  marital.status  occupation  relationship  rac
```

```
e  \
24351           2         11                 2          13              0
4
15626           1         11                 4           7              1
4
4347            0         12                 2           9              0
4
23972           5          9                 4           0              1
4
26843           2          8                 0          12              3
4

       sex  native.country
24351    1              38
15626    1              38
4347     1              19
23972    0              38
26843    1              38
```

```
Y_train.head()
```

```
24351    0
15626    0
4347     1
23972    0
26843    0
Name: income, dtype: category
Categories (2, int64): [0, 1]
```

```
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("Y_train shape:", Y_train.shape)
print("Y_test shape:", Y_test.shape)
```

```
X_train shape: (21113, 14)
X_test shape: (9049, 14)
Y_train shape: (21113,)
Y_test shape: (9049,)
```

```
from sklearn.tree import DecisionTreeClassifier
dec_tree = DecisionTreeClassifier(max_depth=5, random_state=42)
```

```
dec_tree.fit(X_train, Y_train)
```

```
DecisionTreeClassifier(max_depth=5, random_state=42)
```

```
Y_pred_dec_tree = dec_tree.predict(X_test)
Y_pred_dec_tree
```

```
array([0, 0, 0, ..., 0, 0, 0])
```

```
from sklearn.metrics import accuracy_score
```

```
from sklearn.metrics import f1_score

print('Decision Tree Classifier:')
print('Accuracy score:', round(accuracy_score(Y_test, Y_pred_dec_tree) * 1
00, 2))
print('F1 score:', round(f1_score(Y_test, Y_pred_dec_tree) * 100, 2))
```

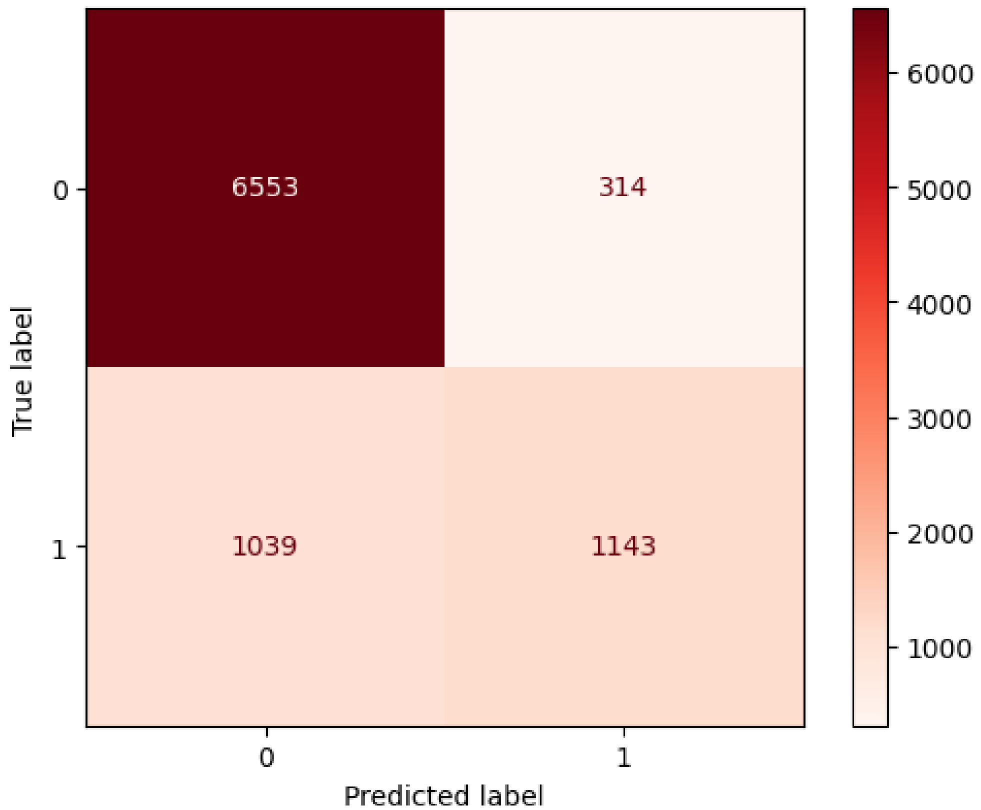
```
Decision Tree Classifier:
Accuracy score: 85.05
F1 score: 62.82
```

```
from sklearn.metrics import ConfusionMatrixDisplay, confusion_matrix
cm = confusion_matrix(Y_test, Y_pred_dec_tree)
cm
```

```
array([[6553,  314],
       [1039, 1143]])
```

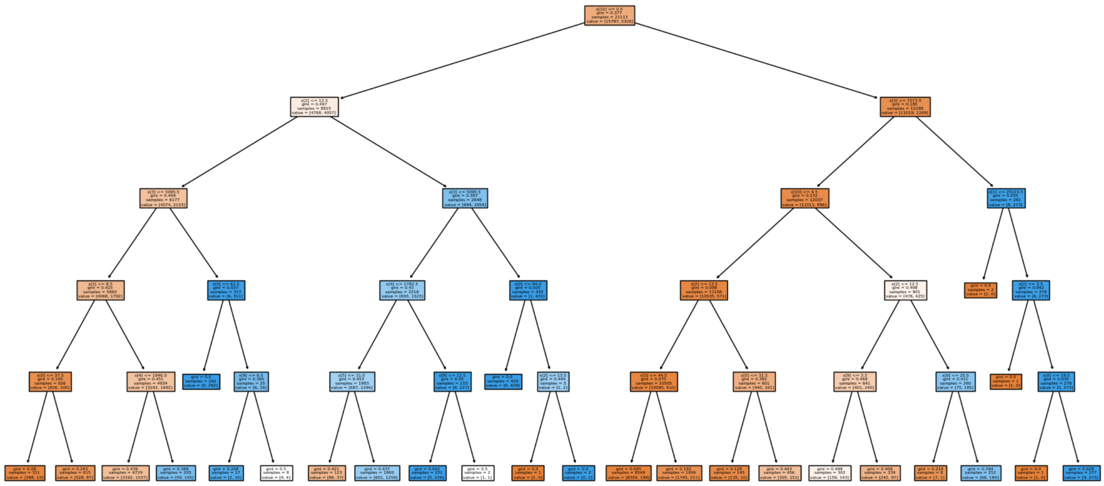
```
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap='Reds')
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7e8aea
c056c0>
```




```
from sklearn import tree
import matplotlib.pyplot as plt
```

```
# Assuming 'clf' is your trained decision tree classifier
plt.figure(figsize=(20,10))
tree.plot_tree(dec_tree, filled=True)
plt.show()
```



```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid to search
param_grid = {
    'max_depth': [3, 5, 10, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy'],
    'max_features': [None, 'sqrt', 'log2']
}

# Create the GridSearchCV object
grid_search = GridSearchCV(estimator=DecisionTreeClassifier(random_state=4
2),
                           param_grid=param_grid,
                           scoring='accuracy',  # You can change this to '
f1' if you prefer
                           cv=5,  # 5-fold cross-validation
                           verbose=1,
                           n_jobs=-1)

# Fit the model using GridSearchCV
grid_search.fit(X_train, Y_train)
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits

GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=42), n_jo
bs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
```

```
                    'max_depth': [3, 5, 10, None],
                    'max_features': [None, 'sqrt', 'log2'],
                    'min_samples_leaf': [1, 2, 4],
                    'min_samples_split': [2, 5, 10]},
          scoring='accuracy', verbose=1)
```

```
print(f"Best Parameters: {grid_search.best_params_}")
print(f"Best Score: {grid_search.best_score_}")
```

```
Best Parameters: {'criterion': 'gini', 'max_depth': 10, 'max_features': No
ne, 'min_samples_leaf': 4, 'min_samples_split': 10}
Best Score: 0.848339847441651
```

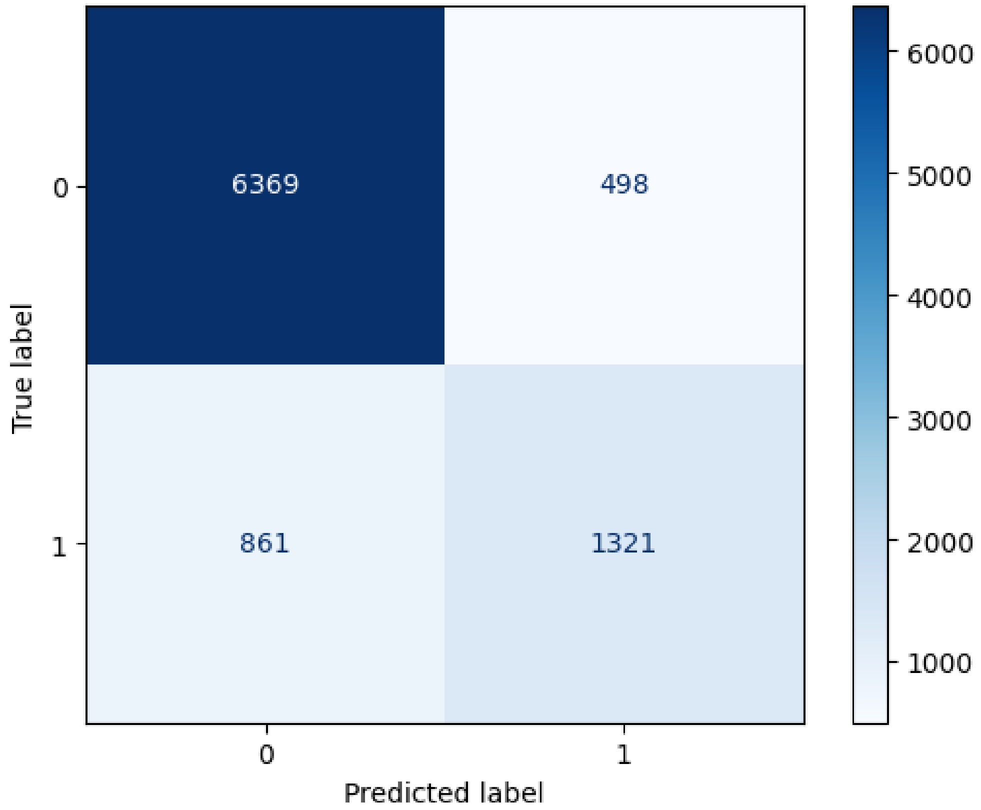
```
best_dec_tree = grid_search.best_estimator_
Y_pred_best_dec_tree = best_dec_tree.predict(X_test)
```

```
print('Tuned Decision Tree Classifier:')
print('Accuracy score:', round(accuracy_score(Y_test, Y_pred_best_dec_tree
) * 100, 2))
print('F1 score:', round(f1_score(Y_test, Y_pred_best_dec_tree) * 100, 2))
```

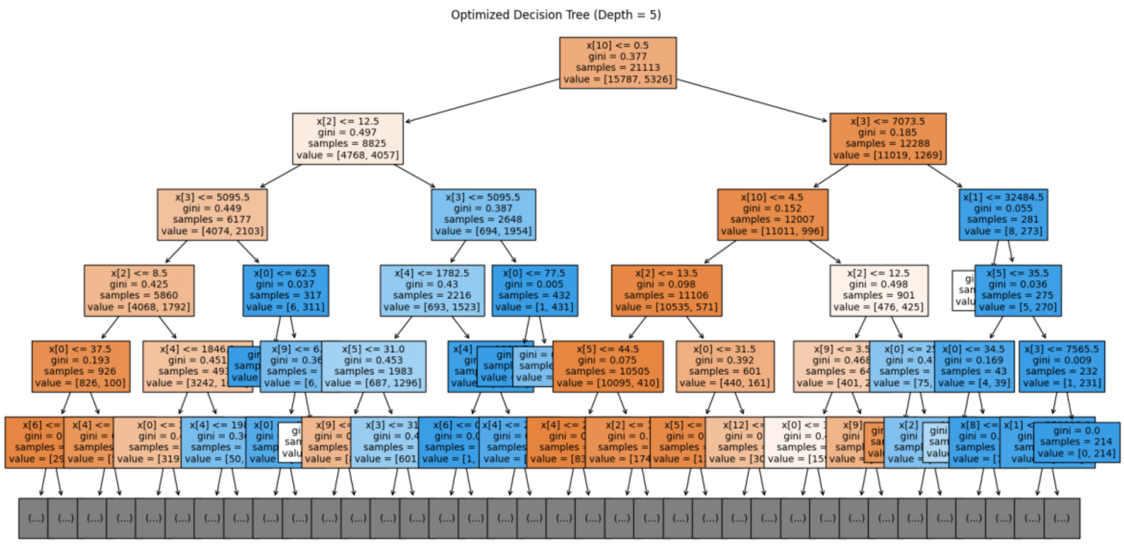
```
Tuned Decision Tree Classifier:
Accuracy score: 84.98
F1 score: 66.03
```

```
cm_best = confusion_matrix(Y_test, Y_pred_best_dec_tree)
disp_best = ConfusionMatrixDisplay(confusion_matrix=cm_best)
disp_best.plot(cmap='Blues')
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7e8ae9
fbd4e0>
```




```python
plt.figure(figsize=(20,10))
tree.plot_tree(best_dec_tree, max_depth=5, filled=True, fontsize=10)
plt.title('Optimized Decision Tree (Depth = 5)')
plt.show()
```



Before Hyperparameter Tuning

> Add blockquote

```
from sklearn.metrics import precision_score, recall_score, accuracy_score,
 f1_score, confusion_matrix

precision_before = precision_score(Y_test, Y_pred_dec_tree)
recall_before = recall_score(Y_test, Y_pred_dec_tree)
accuracy_before = accuracy_score(Y_test, Y_pred_dec_tree)
f1_before = f1_score(Y_test, Y_pred_dec_tree)
confusion_matrix_before = confusion_matrix(Y_test, Y_pred_dec_tree)

print("Before Tuning")
print(f"Accuracy: {accuracy_before:.2f}")
print(f"F1 Score: {f1_before:.2f}")
print(f"Precision: {precision_before:.2f}")
print(f"Recall: {recall_before:.2f}")
print(f"Confusion Matrix: \n{confusion_matrix_before}")
```

```
Before Tuning
Accuracy: 0.85
F1 Score: 0.63
Precision: 0.78
Recall: 0.52
Confusion Matrix:
[[6553  314]
 [1039 1143]]
```

After Hyperparameter Tuning

```
precision_after = precision_score(Y_test, Y_pred_best_dec_tree)
recall_after = recall_score(Y_test, Y_pred_best_dec_tree)
accuracy_after = accuracy_score(Y_test, Y_pred_best_dec_tree)
f1_after = f1_score(Y_test, Y_pred_best_dec_tree)
confusion_matrix_after = confusion_matrix(Y_test, Y_pred_best_dec_tree)

print("After Tuning")
print(f"Accuracy: {accuracy_after:.2f}")
print(f"F1 Score: {f1_after:.2f}")
print(f"Precision: {precision_after:.2f}")
print(f"Recall: {recall_after:.2f}")
print(f"Confusion Matrix: \n{confusion_matrix_after}")
```

```
After Tuning
Accuracy: 0.85
F1 Score: 0.66
Precision: 0.73
Recall: 0.61
Confusion Matrix:
[[6369  498]
 [ 861 1321]]
```

Conclusion:

After hyperparameter tuning, the Decision Tree model showed improved accuracy and balance in predicting income levels. The adjustments made the model better at correctly identifying both high and low-income classes, resulting in more reliable and precise predictions. This indicates that tuning the model's parameters made it more effective overall.