ELG 5255: Applied Machine Learning Assignment 4

BY: Group 5

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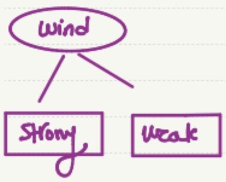
①

Notes

Numerical Question ...



$$\text{Gini}(\text{strong}) = 1 - \left(\frac{2}{7}\right)^2 - \left(\frac{5}{7}\right)^2 = \frac{20}{49}$$

$$\text{Gini}(\text{weak}) = 1 - \left(\frac{2}{3}\right)^2 - \left(\frac{1}{3}\right)^2 = \frac{4}{9}$$

$$\text{Gini}(\text{wind}) = \frac{7}{10} * \frac{20}{49} + \frac{3}{10} * \frac{4}{9} = \underline{\underline{0.42}}$$

②

Notes

	High	Normal
Yes	5	3
No	1	1

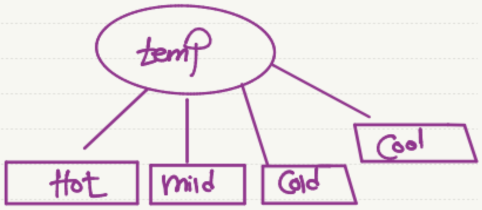
$$\text{Gini}(\text{High}) = 1 - \left(\frac{5}{6}\right)^2 - \left(\frac{1}{6}\right)^2 = \frac{5}{18}$$

$$\text{Gini}(\text{Normal}) = 1 - \left(\frac{3}{4}\right)^2 - \left(\frac{1}{4}\right)^2 = \frac{3}{8}$$

$$\text{Gini}(\text{Humidity}) = \frac{6}{10} * \frac{5}{18} + \frac{4}{10} * \frac{3}{8} = 0.3167$$

③

Notes



	Hot	mild	Cold	Cool
Yes	1	2	1	0
No	3	2	0	1

$$\text{Gini}(\text{Hot}) = 1 - \left(\frac{1}{4}\right)^2 - \left(\frac{3}{4}\right)^2 = \frac{3}{8}$$

$$\text{Gini}(\text{mild}) = 1 - \left(\frac{2}{4}\right)^2 - \left(\frac{2}{4}\right)^2 = \frac{1}{2}$$

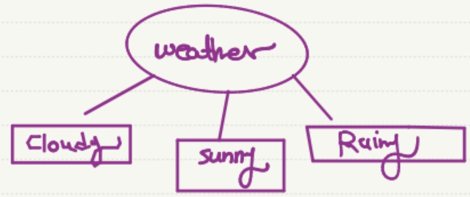
$$\text{Gini}(\text{Cold}) = 1 - \left(\frac{1}{1}\right)^2 = 0$$

$$\text{Gini}(\text{Cool}) = 1 - \left(\frac{1}{1}\right)^2 = 0$$

④

Notes

$$\text{Gini}(\text{temp}) = \frac{3}{8} * \frac{4}{10} + \frac{1}{2} * \frac{4}{10} = 0.35$$



$$\text{Gini}(\text{Cloudy}) = 1 - \left(\frac{2}{3}\right)^2 - \left(\frac{1}{3}\right)^2 = \frac{4}{9}$$

$$\text{Gini}(\text{sunny}) = 1 - \left(\frac{4}{4}\right)^2 = 0$$

$$\text{Gini}(\text{Rainy}) = 1 - \left(\frac{2}{3}\right)^2 - \left(\frac{1}{3}\right)^2 = \frac{4}{9}$$

$$\text{Gini}(\text{weather}) = \frac{3}{10} * \frac{4}{9} + \frac{3}{10} * \frac{4}{9}$$

$= 0.266$

weather is winner

Notes

Children → weather

Cloudy	Hot	High	Strong	No
Cloudy	Mild	Normal	Strong	yes
Cloudy	Mild	high	weak	Yes
Rainy	Cold	Normal	Strong	Yes
Rainy	Cool	Normal	Strong	No
Rainy	Hot	Normal	weak	Yes

Notes

⑥

$\text{Gini (Cool)} = 1-\left(\frac{1}{1}\right)^2 = 0$

$\text{Gini (Cold)} = 1-\left(\frac{1}{1}\right)^2 = 0$

$\text{Gini (Mild)} = 1-\left(\frac{2}{2}\right)^2 = 0$

$\text{Gini (Hot)} = 1-\left(\frac{1}{2}\right)^2-\left(\frac{1}{2}\right)^2 = \frac{1}{2}$

$\text{Gini (Temp)} = \frac{2}{6} * \frac{1}{2} = \frac{1}{6}$

	Hot	Mild	Cool	Cold
yes	1	2	0	1
No	1	0	1	0

Notes

⑦

	High	Normal
Yes	1	3
No	1	1

$\text{Gini (High)} = 1-\left(\frac{1}{2}\right)^2-\left(\frac{1}{2}\right)^2 = \frac{1}{2}$

$\text{Gini (Normal)} = 1-\left(\frac{3}{4}\right)^2-\left(\frac{1}{4}\right)^2 = 0.375$

$\text{Gini (Humidity)} = \frac{1}{2} * \frac{2}{6} + \frac{3}{8} * \frac{4}{6}$

$= 0.4167$

Notes

	Strong	weak
yes	2	2
No	2	0

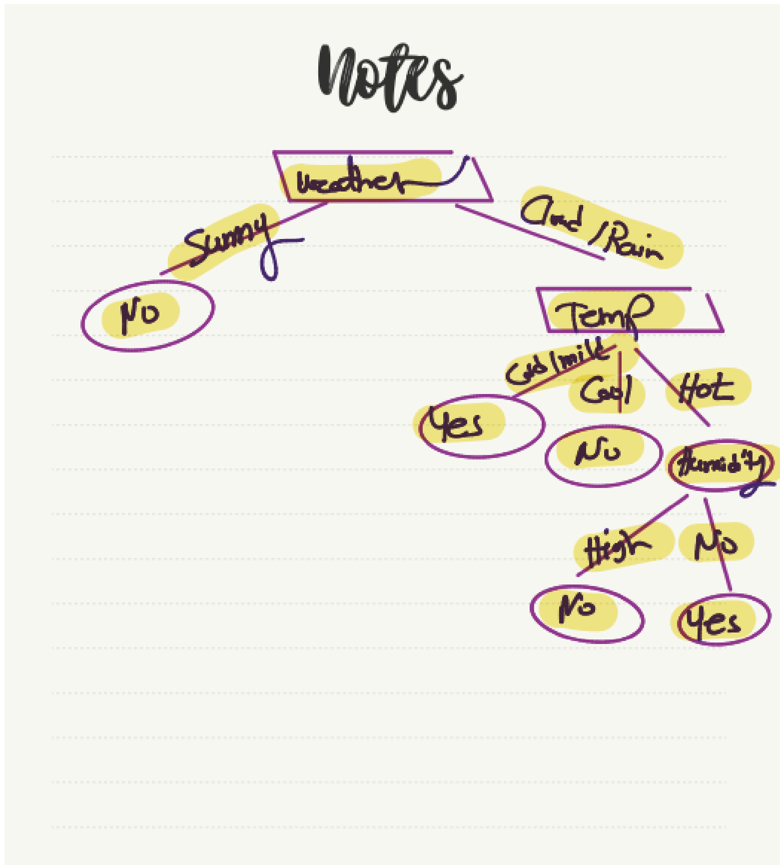
$\text{Gini (weak)} = 1-\left(\frac{2}{2}\right)^2 = 0$

$\text{Gini (strong)} = 1-\left(\frac{2}{4}\right)^2-\left(\frac{2}{4}\right)^2 = \boxed{\frac{1}{2}}$

$\text{Gini (wind)} = \frac{1}{2} * \frac{4}{6} = \frac{1}{3}$

Gini (Temp) → winner 0.167

Cold & Cool & mild → are leaf


Notes
Weather
Sunny
Cloud / Rain
No
Temp
Cold/mild
Cool
Hot
Yes
No
Humidity
High
No
No
Yes

(b)

$$\text{Entropy}(t) = \sum_j P\left(\frac{j}{t}\right) * \log P\left(\frac{j}{t}\right)$$

$$\text{Gain}_{split} = \text{Entropy}(P) - \left[- \sum_{i=1}^{k} \frac{n_i}{n} * \text{Entropy}(i) \right]$$

$$\text{Entropy}(\text{Hiking}) = -\frac{4}{10}\log_2\frac{4}{10} - \frac{6}{10}\log_2\frac{6}{10} \approx 0.971$$

$$\text{Gain}(\text{weather}) = 0.971 - \frac{3}{10}\left[-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right] - \frac{4}{10}\left[-\frac{4}{4}\log\frac{4}{4}\right] - \frac{3}{10}\left[-\frac{2}{3}\log\frac{2}{3} - \frac{1}{3}\log\frac{1}{3}\right]$$

$$= 0.421$$

Notes

$$\text{Gain}(\text{temperature}) = 0.971 - \frac{4}{10}\left[-\frac{3}{10}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4}\right] - \frac{4}{10}\left[-\frac{2}{4}\log_2\frac{2}{4} - \frac{2}{4}\log_2\frac{2}{4}\right] - \frac{1}{10}\left[-\frac{1}{10}\log_2\frac{1}{10}\right] - \frac{1}{10}\left[-\frac{1}{10}\log_2\frac{1}{10}\right]$$

$$= 0.247$$

$$\text{Gain}(\text{Humidity}) = 0.971 - \frac{6}{10}\left[-\frac{5}{6}\log_2\frac{5}{6} - \frac{1}{6}\log_2\frac{1}{6}\right] - \frac{4}{10}\left[-\frac{3}{4}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4}\right]$$

$$\simeq 0.257$$

Notes

$$\text{Gain}(\text{wind}) = 0.971 - \frac{7}{10}\left[-\frac{5}{7}\log_2\frac{5}{7} - \frac{2}{7}\log_2\frac{2}{7}\right] - \frac{3}{10}\left[-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}\right]$$

$$\simeq 0.092$$

∴ Highest Gain ----→ Gain (weather)

So, we will divide based on it.

∴ Root Node for decision Tree

Notes

$$\text{Entropy}(\text{Hiking}) = -\frac{2}{6}\log_2\frac{2}{6} - \frac{4}{6}\log_2\frac{4}{6} \simeq 0.918$$

$$\text{Gain}(\text{Temperature}) = 0.918 - \frac{2}{6}\left[-\frac{1}{2}\log_2\frac{1}{2} - \frac{1}{2}\log_2\frac{1}{2}\right] - \frac{1}{6}\left[-\frac{1}{1}\log\frac{1}{1}\right] - \frac{2}{6}\left[-\frac{2}{2}\log\frac{2}{2}\right] - \frac{1}{6}\left[-\frac{1}{1}\log_2\frac{1}{1}\right] \simeq 0.585$$

Notes

Gain (Humidity) =

$$0.918 - \frac{2}{6}\left[-\frac{1}{2}\log\frac{1}{2} - \frac{1}{2}\log_2\frac{1}{2}\right] - \frac{4}{6}\left[-\frac{3}{4}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4}\right]$$

$$\simeq 0.043$$

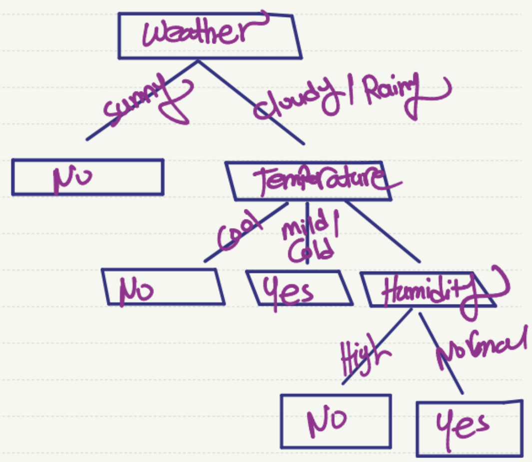
Gain (wind) =

$$0.918 - \frac{4}{6}\left[-\frac{2}{4}\log_2\frac{2}{4} - \frac{2}{4}\log_2\frac{2}{4}\right] - \frac{2}{6}\left[-\frac{2}{2}\log_2\frac{2}{2}\right] \simeq 0.251$$

Notes

Highest Gain ----> Gain (Temperature)

So, we will divide based on it.



Advantages and disadvantages of the Gini Index.

Advantage	Disadvantage
Efficient in terms of computation.	May not perform well with imbalanced class distribution.
Handles continuous variables well	Ignores the magnitude of information gain.
Robust to outliers	

Advantages and disadvantages of the Information Gain.

Advantage	Disadvantage
Considers the magnitude of information gain	Susceptible to overfitting
Effective with the imbalanced class distribution.	Computationally more expensive
Can handle both continuous and categorical variables	

Part 2: Programming

✓ Importing important libraries

```python
import pandas as pd
import numpy as np
from sklearn.exceptions import UndefinedMetricWarning
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
import plotly.express as px

from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.feature_selection import RFECV
from sklearn.pipeline import Pipeline
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.metrics import accuracy_score, f1_score
from sklearn.preprocessing import MinMaxScaler
from yellowbrick.text import TSNEVisualizer
from sklearn.manifold import TSNE
from sklearn.utils.multiclass import unique_labels
from sklearn.feature_selection import SelectKBest, f_classif, VarianceThreshold, mutual_info_classif,r_regression
from sklearn.feature_selection import f_regression
from sklearn.tree import DecisionTreeClassifier, plot_tree

import warnings
warnings.filterwarnings("ignore", category=UndefinedMetricWarning)
warnings.simplefilter(action='ignore', category=FutureWarning)
```

✓ Reading data and preprocessing

```python
[4] KDD_data=pd.read_csv("https://raw.githubusercontent.com/ahmedbadawy11/Machine-Learning-tasks/Assignment4/Assignment4/KDD.csv")
```

Drop null values

```python
KDD_data = KDD_data.dropna()
```

Show the first five rows

```python
[68]
KDD_data.head()
```

	duration	src_bytes	dst_bytes	land	wrong_fragment	urgent	hot	num_failed_logins	logged_in	num_compromised	...	dst_host_srv_count	dst_host_same_srv_rate	dst_host_diff_srv_rate	dst_host_same_src_port_rate	dst_host_srv_diff
0	0	181	5450	0	0	0	0	0	1	0	...	9	1.0	0.0	0.11	
1	0	239	486	0	0	0	0	0	1	0	...	19	1.0	0.0	0.05	
2	0	235	1337	0	0	0	0	0	1	0	...	29	1.0	0.0	0.03	
3	0	219	1337	0	0	0	0	0	1	0	...	39	1.0	0.0	0.03	
4	0	217	2032	0	0	0	0	0	1	0	...	49	1.0	0.0	0.02	

5 rows × 39 columns

✓ Normalize the input feature variables using MinMaxScaler

```python
[69] x = KDD_data.drop("target", axis=1)
     y = KDD_data["target"]
```

Normalize X using MinMaxScaler from sklearn library

```python
[70] scaler = MinMaxScaler()
     normalized_x = scaler.fit_transform(x)
     normalized_x = pd.DataFrame(normalized_x, columns=x.columns)
```

- ✓ **Compute filter-based feature selection algorithm on the dataset by reducing the number of feature variables to 10 (9 input feature variables + 1 target variable)**

```
selector = SelectKBest(score_func=f_classif, k=9)
X_new = selector.fit_transform(normalized_x, y)
selected_features = normalized_x.columns[selector.get_support()]
my_data = pd.concat([normalized_x[selected_features], y], axis=1)
```

- ✓ **Evaluate the performance of the Decision Tree classifier for each subset and generate a classification report**

```
def evaluate_subset(X, y, test_size):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, random_state=42)

    dt = DecisionTreeClassifier()
    dt.fit(X_train, y_train)
    y_pred = dt.predict(X_test)
    report = classification_report(y_test, y_pred)
    print("Classification report:")
    print(report)
    print("--------------------------")
    return X_train, X_test, y_train, y_test
```

- ✓ **Split my data with 70% train & 30% test data and print the classification report**

```
X_train1, X_test1, y_train1, y_test1 = evaluate_subset(x,y,0.30)
```

```
Classification report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     29192
           1       1.00      0.99      0.99    119015

    accuracy                           0.99    148207
   macro avg       0.98      0.99      0.99    148207
weighted avg       0.99      0.99      0.99    148207

--------------------------
```

- ✓ **Split my data with 60% train & 40% test data and print the classification report**

```
] X_train2, X_test2, y_train2, y_test2 =evaluate_subset(x,y,0.40)
```

```
Classification report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     38977
           1       1.00      0.99      0.99    158632

    accuracy                           0.99    197609
   macro avg       0.98      0.99      0.99    197609
weighted avg       0.99      0.99      0.99    197609

--------------------------
```

```
X_train3, X_test3, y_train3, y_test3 =evaluate_subset(x,y,0.50)
```

```
Classification report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     48650
           1       1.00      0.99      0.99    198361

    accuracy                           0.99    247011
   macro avg       0.98      0.99      0.99    247011
weighted avg       0.99      0.99      0.99    247011
```

- ✓ **Visualize the best split of the Decision tree by considering Entropy as a measure of node impurity.**

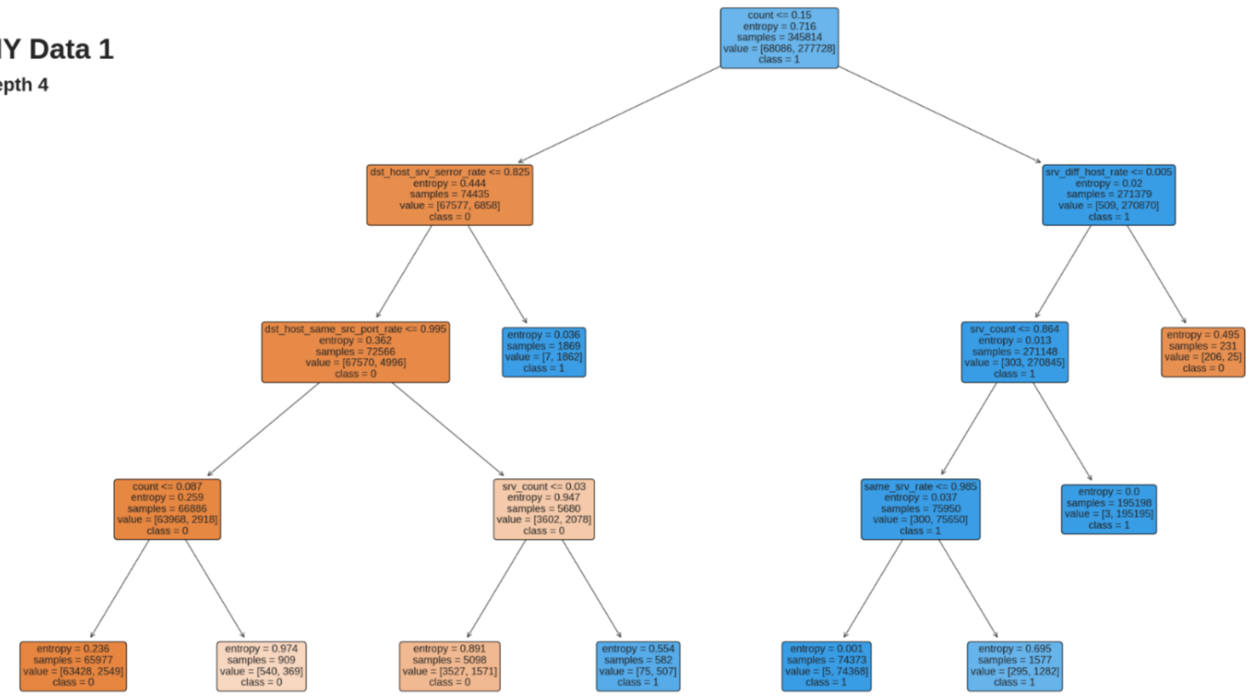
```
header_names = my_data.columns.tolist()
def visualize_decision_tree(max_depth, x_train, y_train,x_test,y_test,index):
    dt = DecisionTreeClassifier(criterion='entropy', max_depth=max_depth,max_leaf_nodes=int((2**max_depth)*0.5 +1), random_state=42)
    dt.fit(x_train, y_train)
    y_pred_entropy = dt.predict(x_test)

    fn = header_names[:-1]
    cn = y.unique().astype(str)
    fig = plt.figure(figsize=(10, 6), dpi=300)
    tree.plot_tree(dt, feature_names=fn, class_names=cn, filled=True, rounded=True)

    plt.text(0.0, 0.9, f"MY Data {index}", horizontalalignment='left', verticalalignment='top', transform=plt.gca().transAxes, fontsize=12, fontweight='bold')
    plt.text(0.0, 0.85, f"Depth {max_depth}", horizontalalignment='left', verticalalignment='top', transform=plt.gca().transAxes, fontsize=8, fontweight='bold')

    plt.show()

    accuracy = accuracy_score(y_test, y_pred_entropy)
    print("Accuracy:", accuracy * 100)
    return y_pred_entropy
```

- ✓ **Compute and compare the classification performance of the tuned Decision Tree for each test size my data1: 30% test data, my data2: 40% test data, my data3: 50% test data and display the accuracy scores, classification report, and confusion matrix respectively**

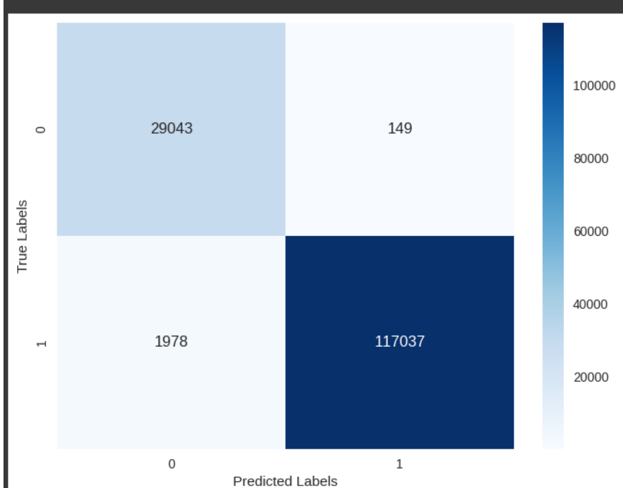
```
max_depths = [4, 6, 8]
x_trains = [X_train1, X_train2, X_train3]
y_trains = [y_train1, y_train2, y_train3]
x_tests = [X_test1, X_test2, X_test3]
y_tests = [y_test1, y_test2, y_test3]
for i in range(3):
    for depth in max_depths:
        y_pred = visualize_decision_tree(depth, x_trains[i], y_trains[i],x_tests[i],y_tests[i],i+1)
        report = classification_report(y_tests[i], y_pred)
        print("Classification Report:")
        print("--------------------------\n")
        print(report)
        cm = confusion_matrix(y_tests[i], y_pred)
        print("\n")
        plt.figure(figsize=(8, 6))
        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
        plt.xlabel("Predicted Labels")
        plt.ylabel("True Labels")
        plt.show()
        print("\n")
```

MY Data 1

Depth 4

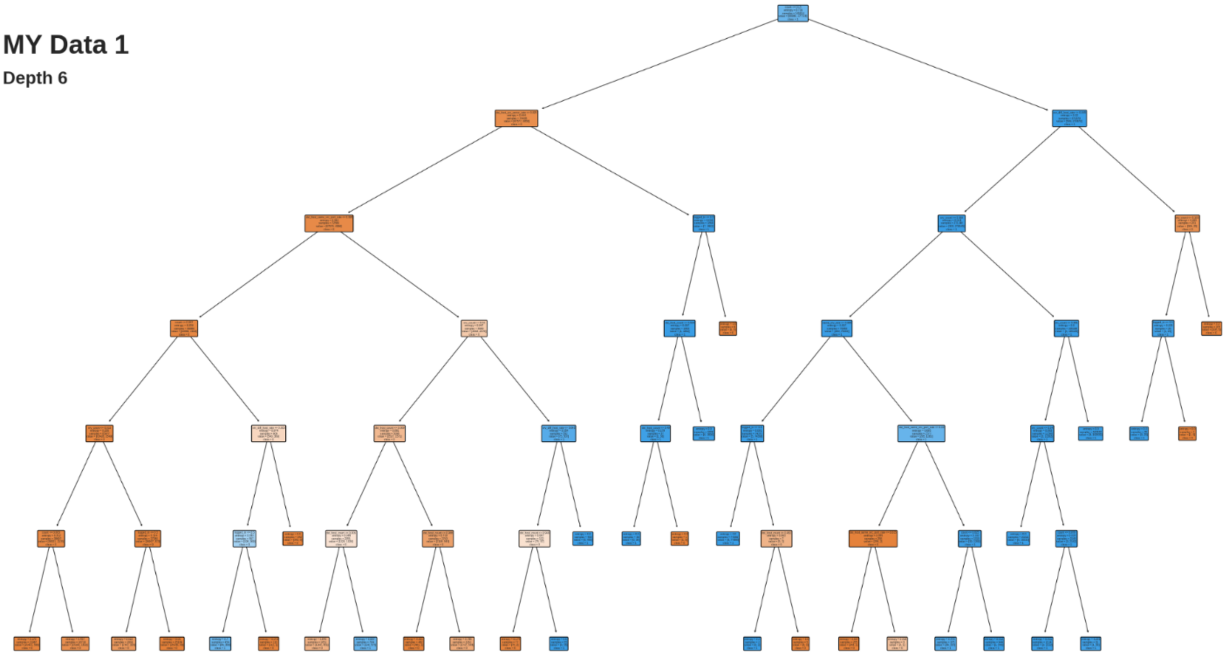



```
Accuracy: 98.56484511527796
Classification Report:
--------------------------

              precision    recall  f1-score   support

           0       0.94      0.99      0.96     29192
           1       1.00      0.98      0.99    119015

    accuracy                           0.99    148207
   macro avg       0.97      0.99      0.98    148207
weighted avg       0.99      0.99      0.99    148207
```

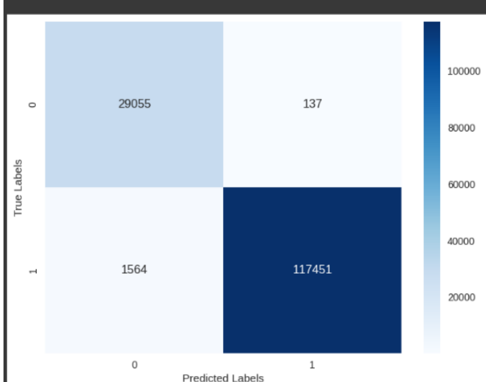


MY Data 1

Depth 6

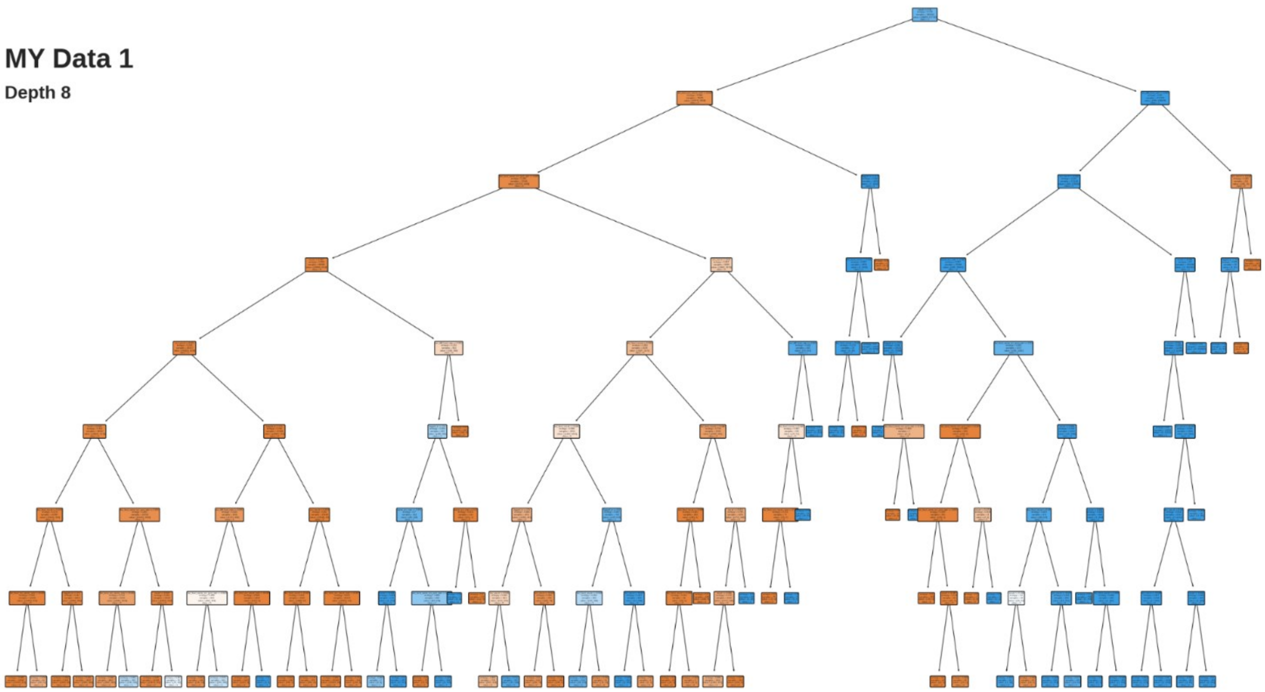


```
Accuracy: 98.8522809314
Classification Report:
---------------------------

              precision    recall  f1-score   support

           0       0.95      1.00      0.97     29192
           1       1.00      0.99      0.99    119015

    accuracy                           0.99    148207
   macro avg       0.97      0.99      0.98    148207
weighted avg       0.99      0.99      0.99    148207
```

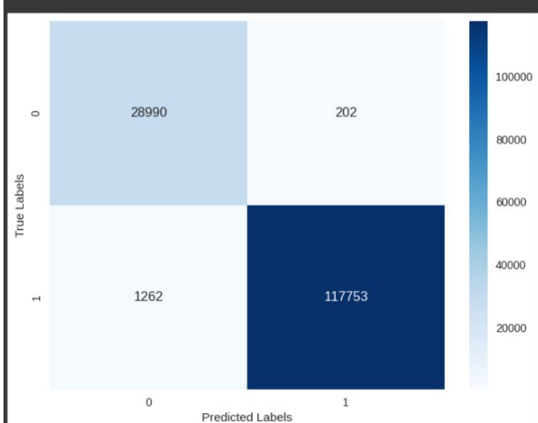


MY Data 1

Depth 8

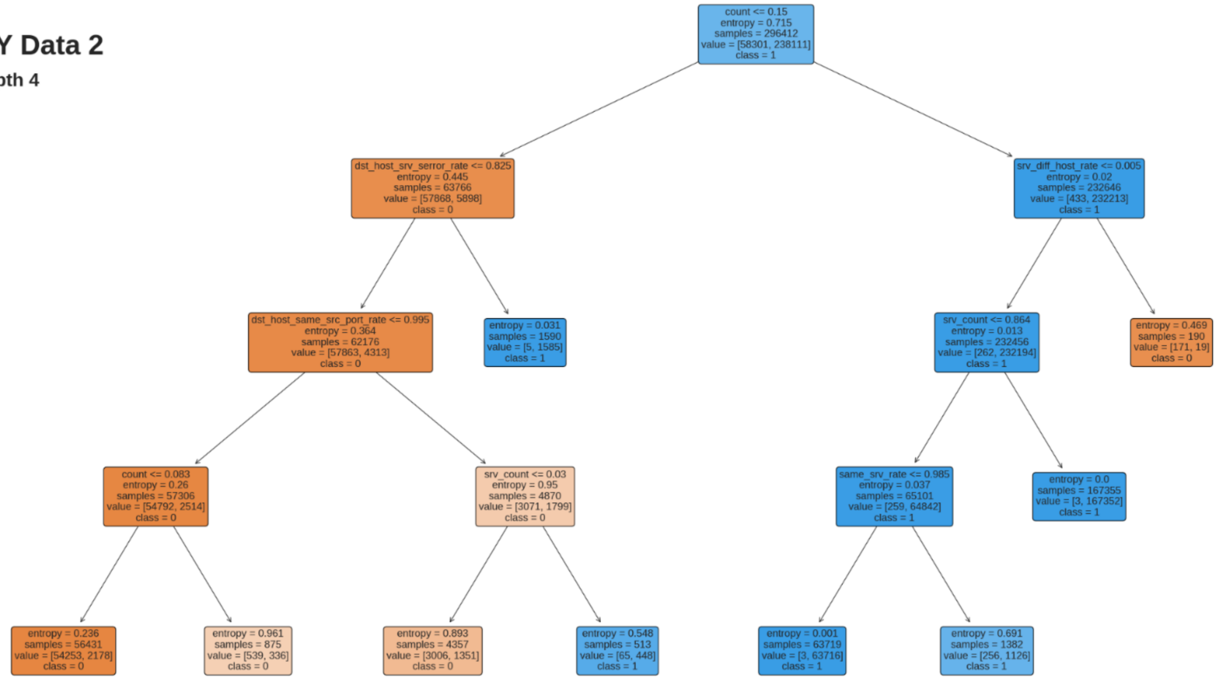


```
Accuracy: 99.01219240656648
Classification Report:
--------------------------

              precision    recall  f1-score   support

           0       0.96      0.99      0.98     29192
           1       1.00      0.99      0.99    119015

    accuracy                           0.99    148207
   macro avg       0.98      0.99      0.98    148207
weighted avg       0.99      0.99      0.99    148207
```

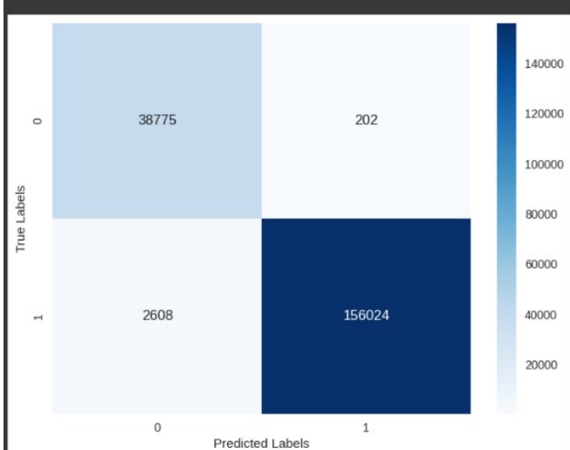


MY Data 2

Depth 4

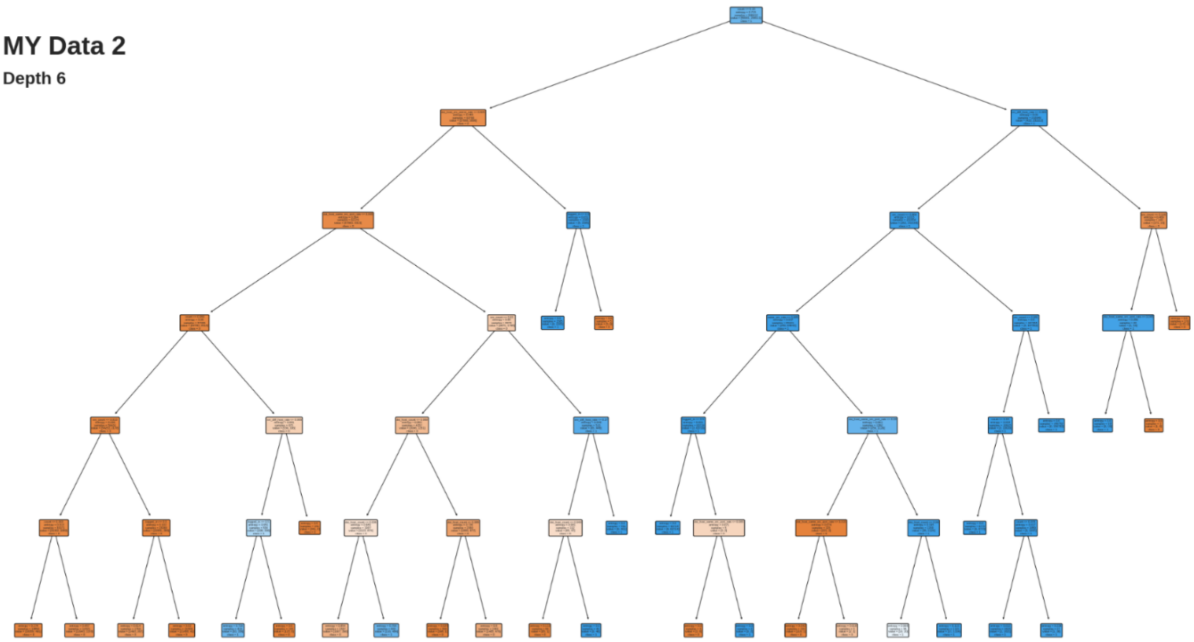



```
Accuracy: 98.577999989879
Classification Report:
--------------------------

              precision    recall  f1-score   support

           0       0.94      0.99      0.97     38977
           1       1.00      0.98      0.99    158632

    accuracy                           0.99    197609
   macro avg       0.97      0.99      0.98    197609
weighted avg       0.99      0.99      0.99    197609
```

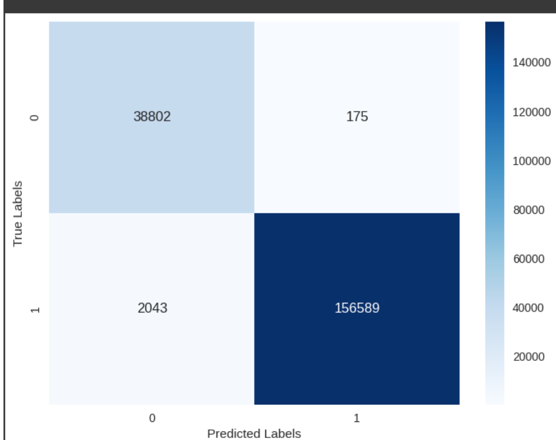


MY Data 2

Depth 6

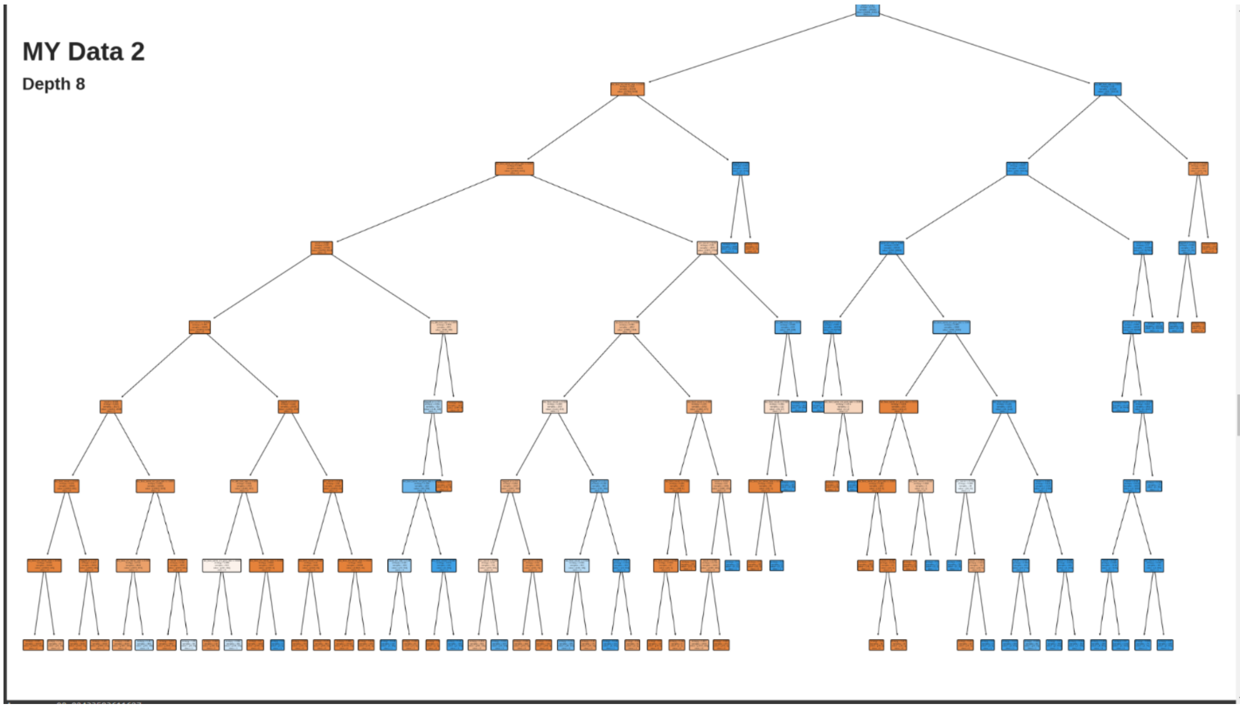


```
Accuracy: 98.87758148667318
Classification Report:
--------------------------

              precision    recall  f1-score   support

           0       0.95      1.00      0.97     38977
           1       1.00      0.99      0.99    158632

    accuracy                           0.99    197609
   macro avg       0.97      0.99      0.98    197609
weighted avg       0.99      0.99      0.99    197609
```

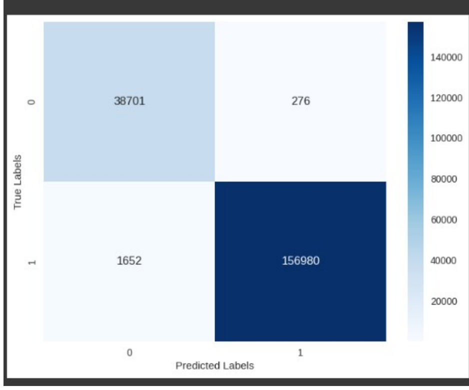


MY Data 2

Depth 8

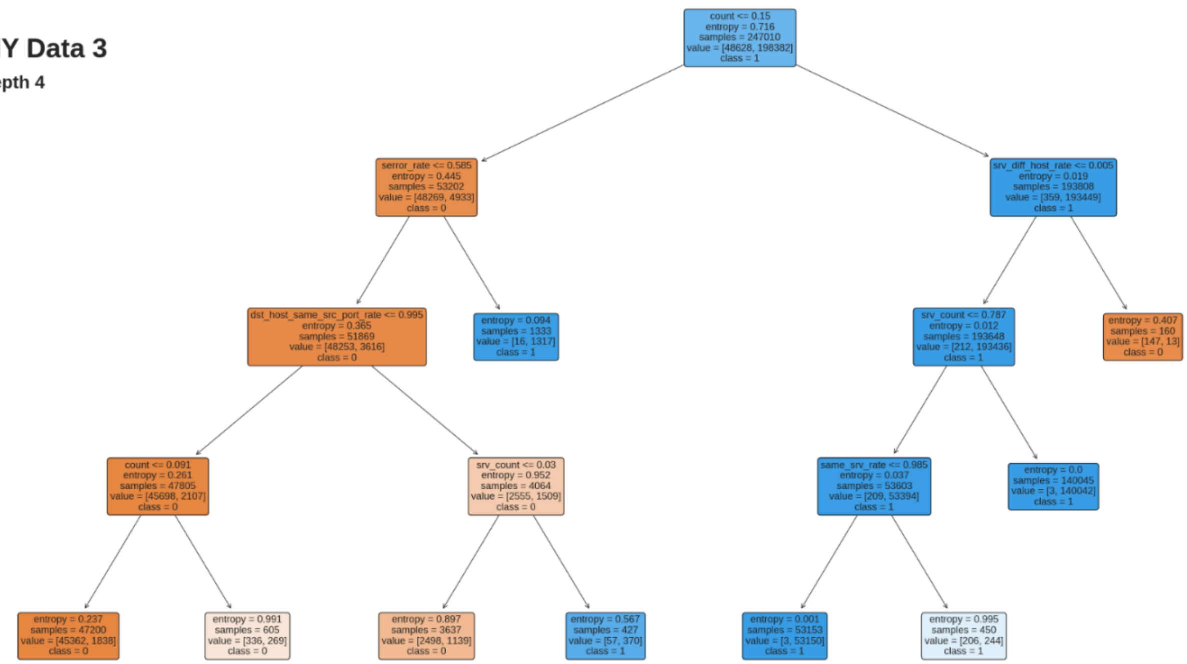


```
Accuracy: 99.02433593611627
Classification Report:
--------------------------

              precision    recall  f1-score   support

           0       0.96      0.99      0.98     38977
           1       1.00      0.99      0.99    158632

    accuracy                           0.99    197609
   macro avg       0.98      0.99      0.98    197609
weighted avg       0.99      0.99      0.99    197609
```

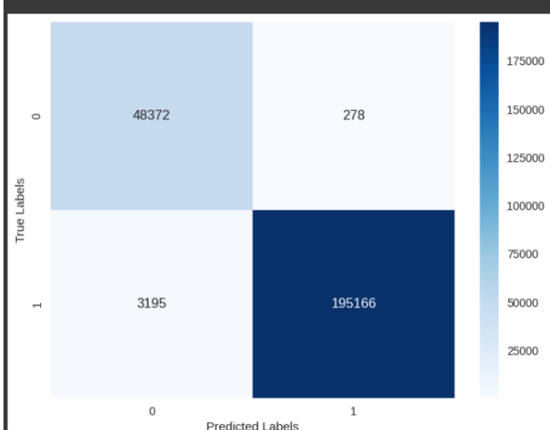


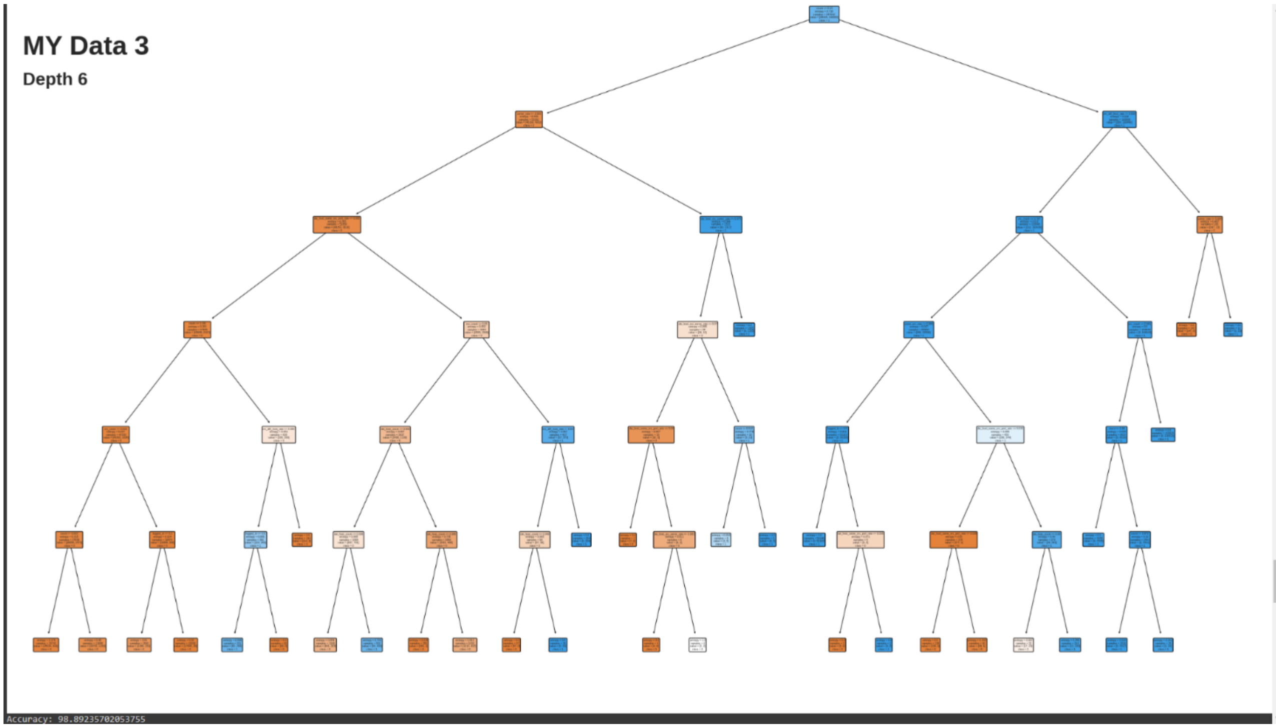
MY Data 3

Depth 4

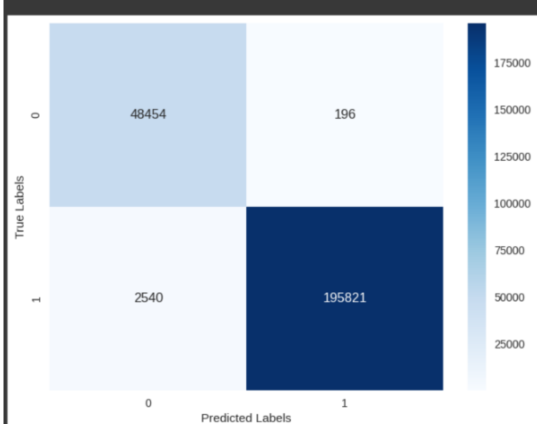



```
Accuracy: 98.59398974134756
Classification Report:
--------------------------

              precision    recall  f1-score   support

           0       0.94      0.99      0.97     48650
           1       1.00      0.98      0.99    198361

    accuracy                           0.99    247011
   macro avg       0.97      0.99      0.98    247011
weighted avg       0.99      0.99      0.99    247011
```



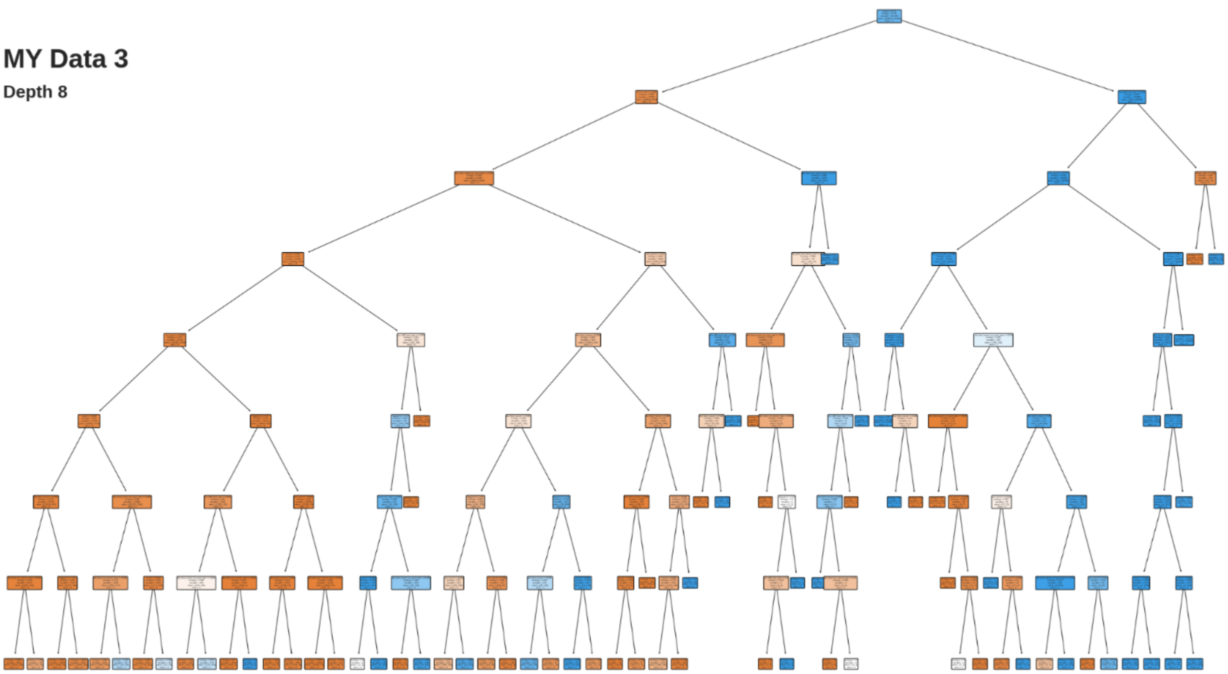



```
Accuracy: 98.89235702053755
Classification Report:
--------------------------

              precision    recall  f1-score   support

           0       0.95      1.00      0.97     48650
           1       1.00      0.99      0.99    198361

    accuracy                           0.99    247011
   macro avg       0.97      0.99      0.98    247011
weighted avg       0.99      0.99      0.99    247011
```

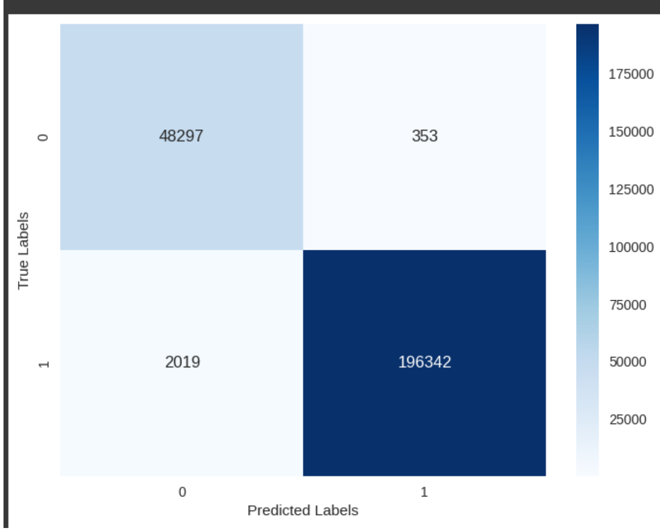


MY Data 3

Depth 8



```
Accuracy: 99.03971887891633
Classification Report:
-------------------------

              precision    recall  f1-score   support

           0       0.96      0.99      0.98     48650
           1       1.00      0.99      0.99    198361

    accuracy                           0.99    247011
   macro avg       0.98      0.99      0.99    247011
weighted avg       0.99      0.99      0.99    247011
```



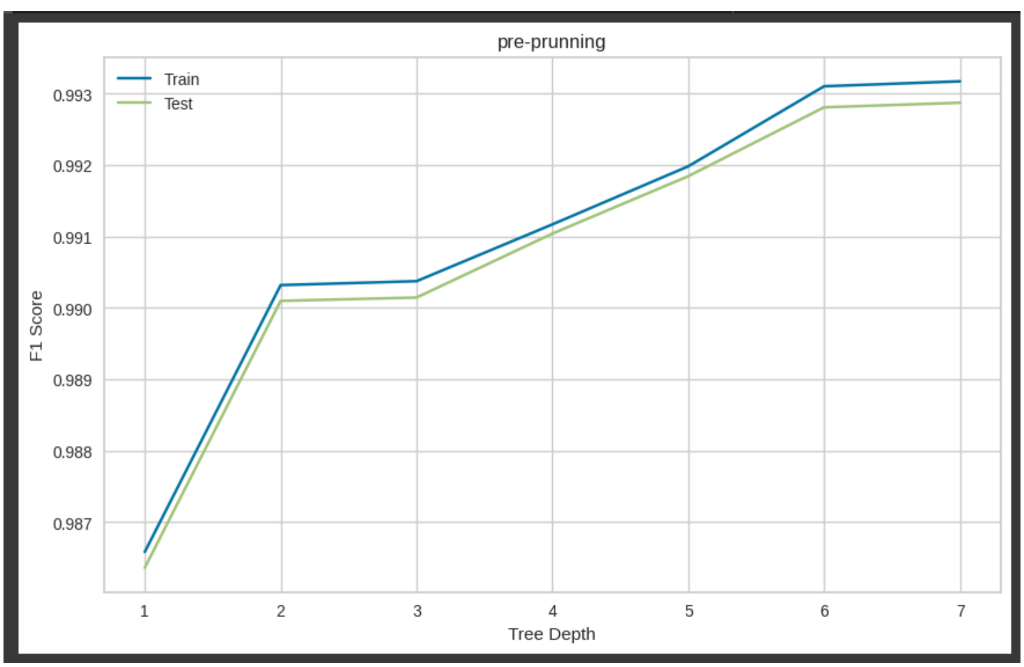
Calculate the F1 score for the training and testing data before applying mitigation strategies

```
clf = DecisionTreeClassifier(criterion='entropy' ,random_state=42)
clf.fit(X_train1, y_train1)
train_pred_before = clf.predict(X_train1)
test_pred_before = clf.predict(X_test1)

train_f1_before = f1_score(y_train1, train_pred_before)
test_f1_before = f1_score(y_test1, test_pred_before)

print (train_f1_before)
print (test_f1_before)
```

```
0.9955735177429821
0.9940742552751781
```

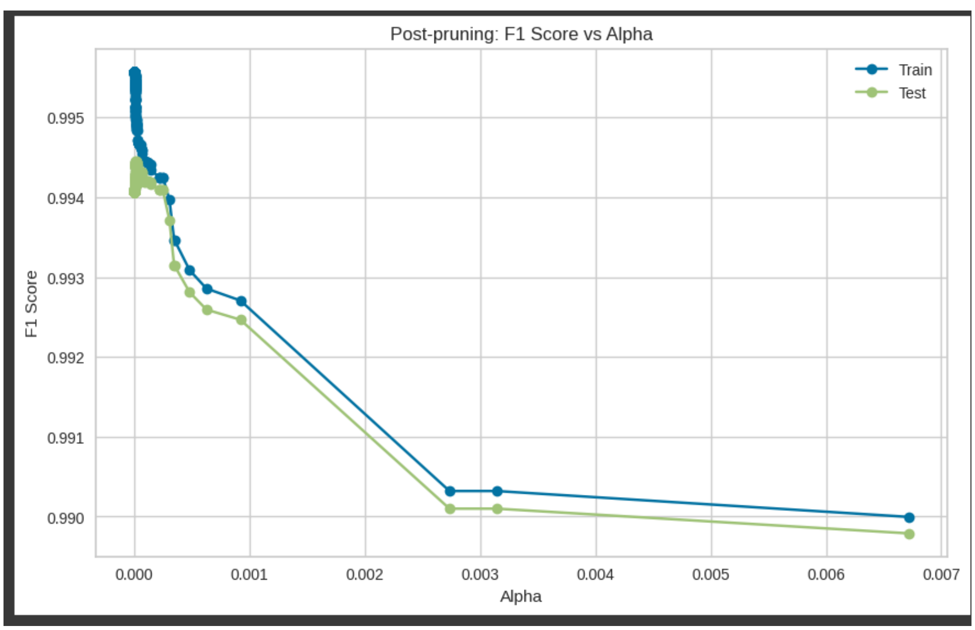
✓ **Apply pre-pruning to mitigate overfitting by adjusting the depth parameter in the range of 1 to 8 and display the F1 scores for the training and testing data**

```
depth = range(1, 8)
train_scores_pre = []
test_scores_pre = []

for dep in depth:
     # Create a decision tree classifier with pre-pruning
     clf = DecisionTreeClassifier(criterion='entropy',max_depth=dep, random_state=42)
    # Fit the classifier on the training data
     clf.fit(X_train1, y_train1)
     train_pred = clf.predict(X_train1)
     test_pred = clf.predict(X_test1)

    # Compute F1 scores
     train_f1 = f1_score(y_train1, train_pred)
     test_f1 = f1_score(y_test1, test_pred)
    # Append the scores to the lists
     train_scores_pre.append(train_f1)
     test_scores_pre.append(test_f1)


# Plot the accuracy scores
plt.figure(figsize=(10, 6))
plt.plot(depth, train_scores_pre, label='Train')
plt.plot(depth, test_scores_pre, label='Test')
plt.xlabel('Tree Depth')
plt.ylabel('F1 Score')
plt.title('pre-prunning')
plt.legend()
plt.show()
```



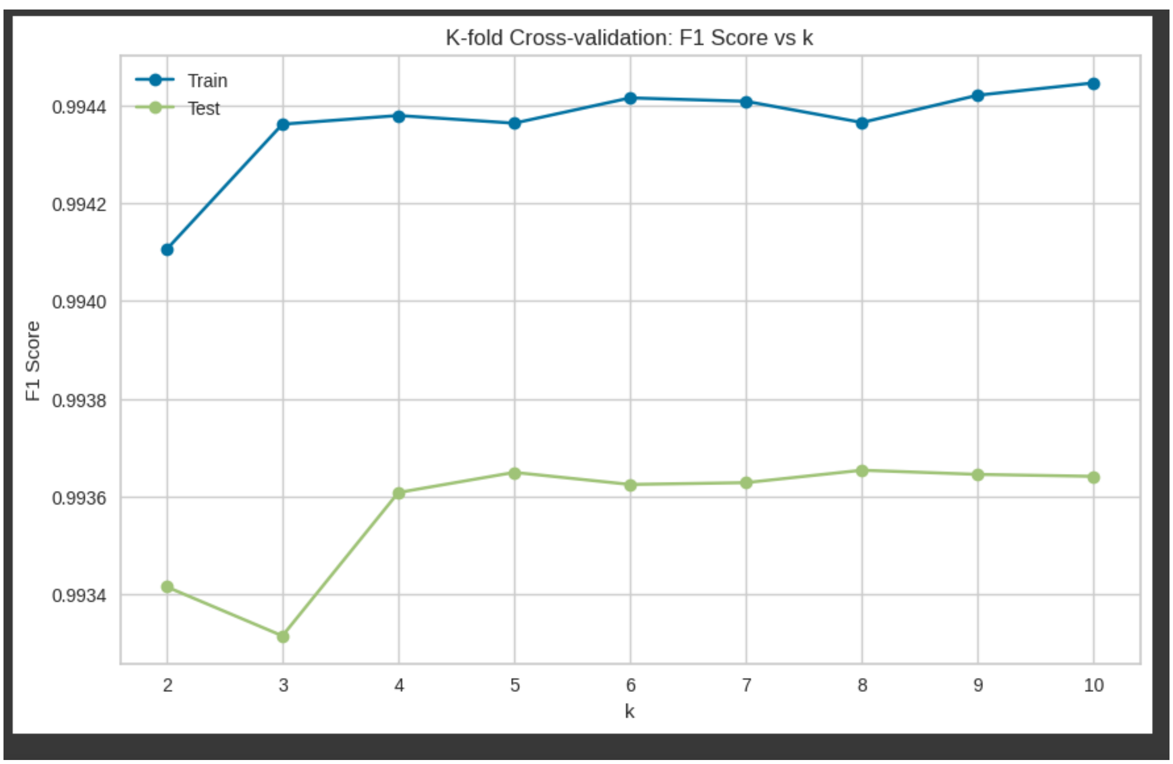
✓ **Apply post-pruning to mitigate overfitting and display the F1 scores for the training and testing data**

```python
clf = DecisionTreeClassifier(random_state=42)

# Fit the classifier on the training data
clf.fit(X_train1, y_train1)

# Apply cost complexity pruning
path = clf.cost_complexity_pruning_path(X_train1, y_train1)
ccp_alphas = path.ccp_alphas[:-1]  # Exclude the maximum alpha

train_scores_post = []
test_scores_post = []
clfs = []

for ccp_alpha in ccp_alphas:
    clf = DecisionTreeClassifier(criterion='entropy',ccp_alpha=ccp_alpha, random_state=42)
    clf.fit(X_train1, y_train1)
    clfs.append(clf)
    train_pred = clf.predict(X_train1)
    test_pred = clf.predict(X_test1)

    # Compute F1 scores
    train_f1 = f1_score(y_train1, train_pred)
    test_f1 = f1_score(y_test1, test_pred)
    # Append the scores to the lists
    train_scores_post.append(train_f1)
    test_scores_post.append(test_f1)

# Plot the test and train accuracy
plt.figure(figsize=(10, 6))
plt.plot(ccp_alphas, train_scores_post, marker='o', label='Train')
plt.plot(ccp_alphas, test_scores_post, marker='o', label='Test')
plt.xlabel("Alpha")
plt.ylabel("F1 Score")
plt.title("Post-pruning: F1 Score vs Alpha")
plt.legend()
plt.show()
```



✓ **Apply k-fold cross-validation to mitigate overfitting and display the F1 scores for the training and testing data**

```
clf = DecisionTreeClassifier(random_state=42)
k_values = range(2, 11)
mean_train_scores = []
mean_test_scores = []

for k in k_values:
    train_scores = cross_val_score(clf, X_train1, y_train1, cv=k, scoring='f1')
    test_scores = cross_val_score(clf, X_test1, y_test1, cv=k, scoring='f1')
    mean_train_scores.append(np.mean(train_scores))
    mean_test_scores.append(np.mean(test_scores))

plt.figure(figsize=(10, 6))
plt.plot(k_values, mean_train_scores, marker='o', label='Train')
plt.plot(k_values, mean_test_scores, marker='o', label='Test')
plt.xlabel("k")
plt.ylabel("F1 Score")
plt.title("K-fold Cross-validation: F1 Score vs k")
plt.legend()
plt.show()
```



- ✓ **Display the F1 scores for the training and testing data, showing improvement**

```
f1_scores_before = [train_f1_before, test_f1_before]
f1_scores_after_pre = [np.mean(train_scores_pre), np.mean(test_scores_pre)]
f1_scores_after_post = [np.mean(train_scores_post), np.mean(test_scores_post)]
mcvf = [np.mean(mean_train_scores), np.mean(mean_test_scores)]

labels = ['Train Data', 'Test Data']

x = range(len(labels))
width = 0.20

fig, ax = plt.subplots(figsize=(10, 6))

ax.bar(x, f1_scores_before, width, label='Before Mitigating')
ax.bar([val + width for val in x], f1_scores_after_pre, width, label='F1 Score - Pre-Pruning')
ax.bar([val + width * 2 for val in x], f1_scores_after_post, width, label='F1 Score - Post-Pruning')
ax.bar([val + width * 3 for val in x], mcvf, width, label='Mean F1 Score (Cross-Validation)')

ax.set_ylim(0.97, 1)


ax.set_ylabel('F1 Score')
ax.set_xlabel('Data')
ax.set_title('F1 Score Before and After Mitigating')
ax.set_xticks([val + width for val in x])
ax.set_xticklabels(labels)

ax.legend(bbox_to_anchor=(1.02, 1), loc='upper left')

plt.tight_layout()
plt.show()
```