Department of Computer Science and Engineering (Data Science)

Subject: Machine Learning – I (DJ19DSC402)

AY: 2022-23

Experiment 2 - 3

(Decision Tree)

Aim: Implement Decision Tree on the given Datasets to build a classifier and Regressor. Apply appropriate pruning method to overcome overfitting.

Lab Assignments to complete in this session:

Use the given dataset and perform the following tasks:
Dataset 1: PlayTennis.csv
Dataset 2: Iris.csv
Dataset 3: Breastcancer.csv
Dataset 4: car prediction.csv

Implement decision tree on IRIS dataset

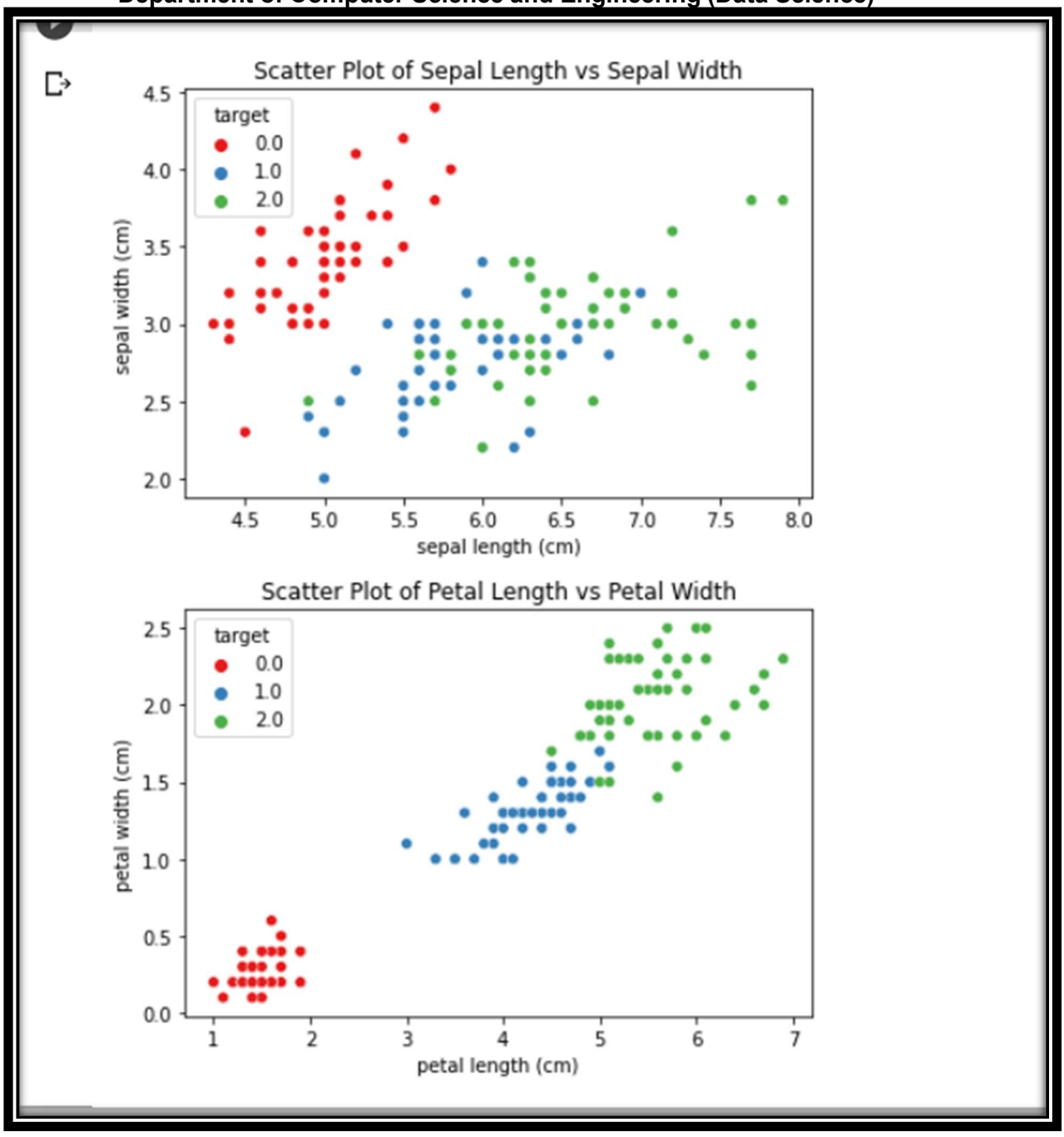
CODE:

```
[15] #libraries
     import random
     import pandas as pd
     import numpy as np
     import seaborn as sns
     import matplotlib.pyplot as plt
```

```
[45] #importing file
     iris = pd.read_csv('/content/Iris.csv')
     iris.head()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

```
data = pd.DataFrame(data= np.c_[iris['data'], iris['target']], columns= iris['feature_names'] + ['target'])

sns.scatterplot(data=data, x='sepal length (cm)', y='sepal width (cm)', hue='target', palette='Set1')
plt.title('Scatter Plot of Sepal Length vs Sepal Width')
plt.show()

sns.scatterplot(data=data, x='petal length (cm)', y='petal width (cm)', hue='target', palette='Set1')
plt.title('Scatter Plot of Petal Length vs Petal Width')
plt.show()
```


Scatter Plot of Sepal Length vs Sepal Width
target
0.0
1.0
2.0
sepal width (cm)
sepal length (cm)
Scatter Plot of Petal Length vs Petal Width
target
0.0
1.0
2.0
petal width (cm)
petal length (cm)

```
#splitting into train and test data
data = np.hstack([iris.data, iris.target.reshape(-1, 1)])
random.shuffle(data)
split_idx = int(0.8 * len(data))    #for 80:20 ratio
train_data = data[:split_idx]

X_train, y_train = train_data[:, :-1], train_data[:, -1]
X_test, y_test = test_data[:, :-1], test_data[:, -1]

print("Data size:",len(data))
print("Training set size:", len(train_data))
print("Testing set size:", len(test_data))
```

```
Data size: 150
Training set size: 120
Testing set size: 30
```

```
[34] def fit(X, y, max_depth=float('inf')):
         tree = _grow_tree(X, y, max_depth=max_depth)
         return tree
```

```
[35] def predict(tree, X):
         y_pred = np.zeros(len(X))
         for i, inputs in enumerate(X):
             y_pred[i] = _predict(tree, inputs)
         return y_pred
```

```
def _predict(node, inputs):
    if node['leaf']:
        return node['value']
    else:
        if inputs[node['feature']] < node['threshold']:
            return _predict(node['left'], inputs)
        else:
            return _predict(node['right'], inputs)
```

+ Code + Text

```python
#tree
def _grow_tree(X, y, depth=0, max_depth=float('inf')):
    num_samples, num_features = X.shape
    num_labels = len(set(y))

    if depth >= max_depth or num_labels == 1 or num_samples < 2:
        return {'leaf': True, 'value': _most_common_label(y)}

    best_feature, best_threshold = _best_split(X, y)

    left_indices = X[:, best_feature] < best_threshold
    right_indices = X[:, best_feature] >= best_threshold
    left = _grow_tree(X[left_indices], y[left_indices], depth + 1, max_depth=max_depth)
    right = _grow_tree(X[right_indices], y[right_indices], depth + 1, max_depth=max_depth)

    return {'leaf': False, 'feature': best_feature, 'threshold': best_threshold, 'left': left, 'right': right}
```

0s

```python
def _best_split(X, y):
    bestgini = float('inf')
    best_feature, best_threshold = None, None

    for feature in range(X.shape[1]):
        thresholds = sorted(set(X[:, feature]))

        for threshold in thresholds:
            left_indices = X[:, feature] < threshold
            left_labels = y[left_indices]
            right_labels = y[~left_indices]

            if len(left_labels) == 0 or len(right_labels) == 0:
                continue

            gini = (len(left_labels) / len(y)) * gini(left_labels) \
                + (len(right_labels) / len(y)) * gini(right_labels)

            if gini < bestgini:
                bestgini = gini
                best_feature = feature
                best_threshold = threshold

    return best_feature, best_threshold
```

```
[ ]  def gini(y):
         counts = {label: 0 for label in set(y)}

         for label in y:
             counts[label] += 1

         impurity = 1
         for label in counts:
             prob = counts[label] / len(y)
             impurity -= prob ** 2

         return impurity
```

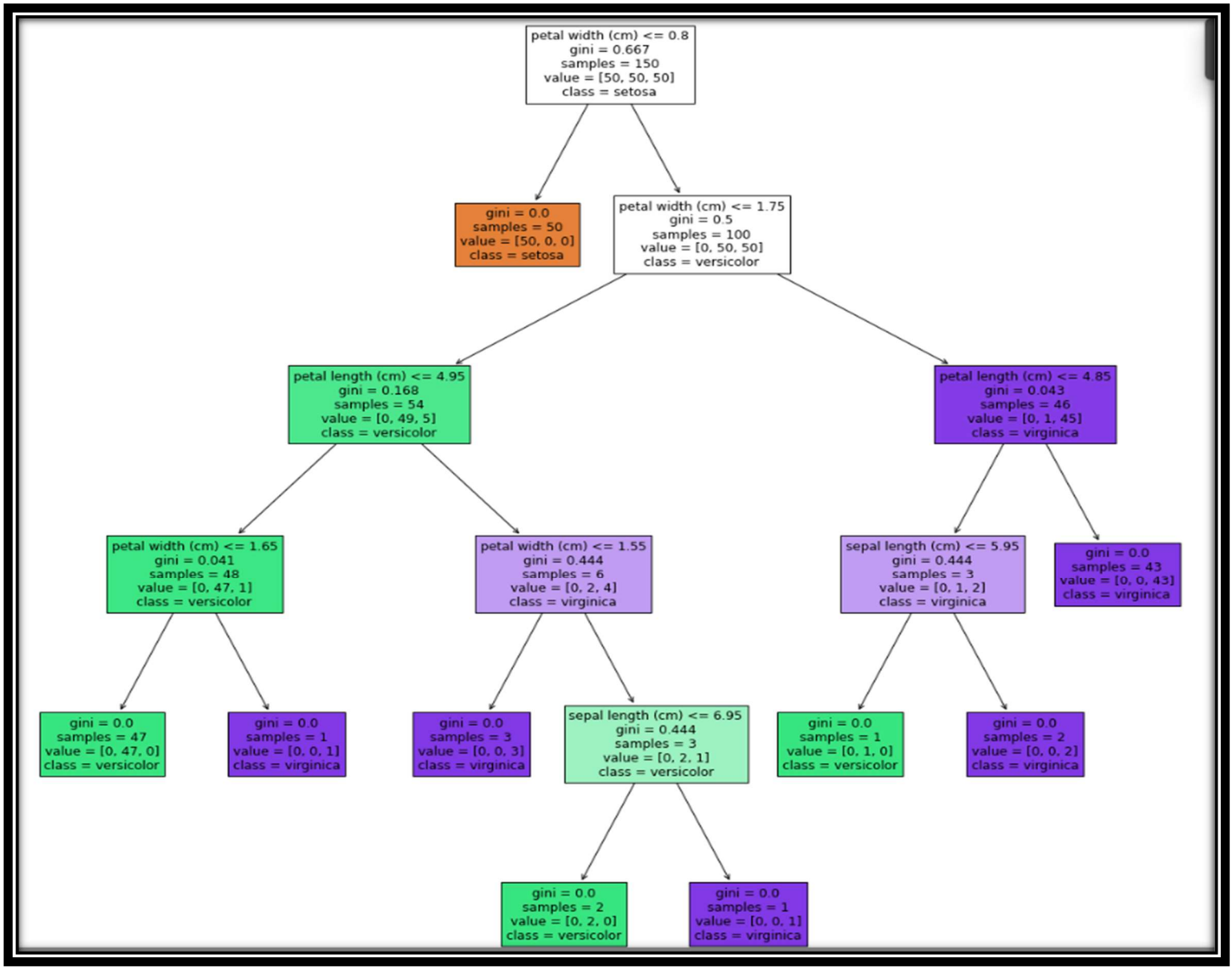
```
[ ]  def _most_common_label(y):
         counts = {label: 0 for label in set(y)}

         for label in y:
             counts[label] += 1

         return max(counts, key=counts.get)
```

```
#implementation
tree = fit(X_train, y_train, max_depth=3)
y_pred = predict(tree, X_test)
accuracy = sum(y_pred == y_test) / len(y_test)
print('The gini index is:',_gini(iris.target))
print(f"Accuracy: {accuracy:.3f}")
```

```
The gini index is: 0.6666666666666665
Accuracy: 0.700
```

Taken from net

```
#printing decision tree
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier, plot_tree
import matplotlib.pyplot as plt

iris = load_iris()

clf = DecisionTreeClassifier()

clf.fit(iris.data, iris.target)

plt.figure(figsize=(20,20))
plot_tree(clf, filled=True, feature_names=iris.feature_names, class_names=iris.target_names)
plt.show()
```



```
#Q2
from sklearn.metrics import confusion_matrix

tree = DecisionTreeClassifier(max_depth=3, random_state=42)
tree.fit(X_train, y_train)

y_pred = tree.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)
```

```
Accuracy: 0.77
Confusion Matrix:
[[ 9  0  0]
 [ 0 12  0]
 [ 0  7  2]]
```

BREAST CANCER DATASET

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

```
[140] breast=pd.read_csv("/content/Breast_cancer_data.csv")
      breast.head()
```

	mean_radius	mean_texture	mean_perimeter	mean_area	mean_smoothness	diagnosis
0	17.99	10.38	122.80	1001.0	0.11840	0
1	20.57	17.77	132.90	1326.0	0.08474	0
2	19.69	21.25	130.00	1203.0	0.10960	0
3	11.42	20.38	77.58	386.1	0.14250	0
4	20.29	14.34	135.10	1297.0	0.10030	0

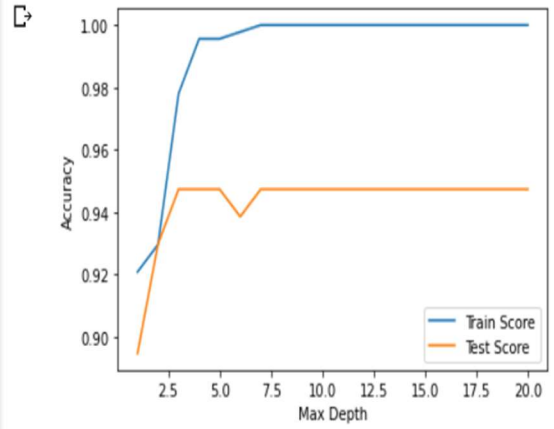
Splitting the dataset

```
X = breast.iloc[:, :-1]
y = breast.iloc[:, -1]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

```
tree = DecisionTreeClassifier(max_depth=3, random_state=42)
tree.fit(X_train, y_train)

# Predict on the testing set
y_pred = tree.predict(X_test)

# Calculate the accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
```

```
Accuracy: 0.77
```

```
#Q3
max_depths = range(1, 21)
train_scores = []
test_scores = []

for max_depth in max_depths:
    tree = DecisionTreeClassifier(max_depth=max_depth, random_state=42)
    tree.fit(X_train, y_train)
    train_score = tree.score(X_train, y_train)
    test_score = tree.score(X_test, y_test)
    train_scores.append(train_score)
    test_scores.append(test_score)

# Plot the training and testing scores
plt.plot(max_depths, train_scores, label="Train Score")
plt.plot(max_depths, test_scores, label="Test Score")
plt.xlabel("Max Depth")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



here the graph tells that If the training score keeps increasing while the testing score starts to plateau and then decrease, it indicates that the model is overfitting on the training data and performing poorly on the testing data

CAR PREDICTOR DATASET

car

```
car=pd.read_csv("/content/carprediction.csv")
car.head()
```

	Make	Model	Year	Engine Fuel Type	Engine HP	Engine Cylinders	Transmission Type	Driven_Wheels	Number of Doors	Market Category	Vehicle Size	Vehicle Style	highway MPG	city mpg	Po
0	BMW	1 Series M	2011	premium unleaded (required)	335.0	6.0	MANUAL	rear wheel drive	2.0	Factory Tuner,Luxury,High-Performance	Compact	Coupe	26	19	
1	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Convertible	28	19	
2	BMW	1 Series	2011	premium unleaded (required)	300.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,High-Performance	Compact	Coupe	28	20	
3	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury,Performance	Compact	Coupe	28	18	
4	BMW	1 Series	2011	premium unleaded (required)	230.0	6.0	MANUAL	rear wheel drive	2.0	Luxury	Compact	Convertible	28	18	

Applying datapreprocessing

```
[276] car.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11914 entries, 0 to 11913
Columns: 1080 entries, Year to Vehicle Style_Wagon
dtypes: float64(3), int64(5), uint8(1072)
memory usage: 12.9 MB
```

```
car.dtypes
```

```
Make                 object
Model                object
Year                  int64
Engine Fuel Type     object
Engine HP           float64
Engine Cylinders    float64
Transmission Type    object
Driven_Wheels        object
Number of Doors     float64
Market Category      object
Vehicle Size         object
Vehicle Style        object
highway MPG           int64
city mpg              int64
Popularity            int64
MSRP                  int64
dtype: object
```

```
[269] car.isnull().sum()
```

```
Make                    0
Model                   0
Year                    0
Engine Fuel Type        3
Engine HP              69
Engine Cylinders       30
Transmission Type       0
Driven_Wheels           0
Number of Doors         6
Market Category      3742
Vehicle Size            0
Vehicle Style           0
highway MPG             0
city mpg                0
Popularity              0
MSRP                    0
dtype: int64
```

```
#replacing null values by mean whereever possible
mean_height = car['Engine HP'].mean()
car['Engine HP'].fillna(mean_height, inplace=True)
```

```
[271] car.isnull().sum()
```

```
Make                    0
Model                   0
Year                    0
Engine Fuel Type        3
Engine HP               0
Engine Cylinders       30
Transmission Type       0
Driven_Wheels           0
Number of Doors         6
Market Category      3742
Vehicle Size            0
Vehicle Style           0
highway MPG             0
city mpg                0
Popularity              0
MSRP                    0
dtype: int64
```

```
[273] car=car.dropna()
```

```
car.isnull().sum()
```

```
Make                 0
Model                0
Year                 0
Engine Fuel Type     0
Engine HP            0
Engine Cylinders     0
Transmission Type    0
Driven_Wheels        0
Number of Doors      0
Market Category      0
Vehicle Size         0
Vehicle Style        0
highway MPG          0
city mpg             0
Popularity           0
MSRP                 0
dtype: int64
```

```
from sklearn.metrics import mean_squared_error, r2_score

# Load the breast cancer dataset
data = load_breast_cancer()
X = data.data
y = data.target

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a decision tree regressor
regressor = DecisionTreeRegressor(random_state=42)

# Train the model on the training data
regressor.fit(X_train, y_train)

# Predict the target values on the test set
y_pred = regressor.predict(X_test)

# Evaluate the performance of the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("Mean squared error: {:.2f}".format(mse))
print("R2 score: {:.2f}".format(r2))
```

```
Mean squared error: 0.05
R2 score: 0.78
```

IRIS

```
from sklearn.datasets import load_iris
import pandas as pd
import numpy as np
```

```
[4] iris = load_iris()
    X = pd.DataFrame(iris.data, columns=iris.feature_names)
    y = pd.Categorical.from_codes(iris.target, iris.target_names)
```

```
X.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

```
[6] print(y)
```

```
['setosa', 'setosa', 'setosa', 'setosa', 'setosa', ..., 'virginica', 'virginica', 'virginica', 'virginica', 'virginica']
Length: 150
Categories (3, object): ['setosa', 'versicolor', 'virginica']
```

```
[7] from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
```

```
[8] #defining decision tree
    from sklearn.tree import DecisionTreeClassifier
    clf = DecisionTreeClassifier()
    clf.fit(X_train, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

```
y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)
```

```
[16] from sklearn.metrics import accuracy_score, confusion_matrix
     print("Train score: ", accuracy_score(y_train_pred, y_train))
```

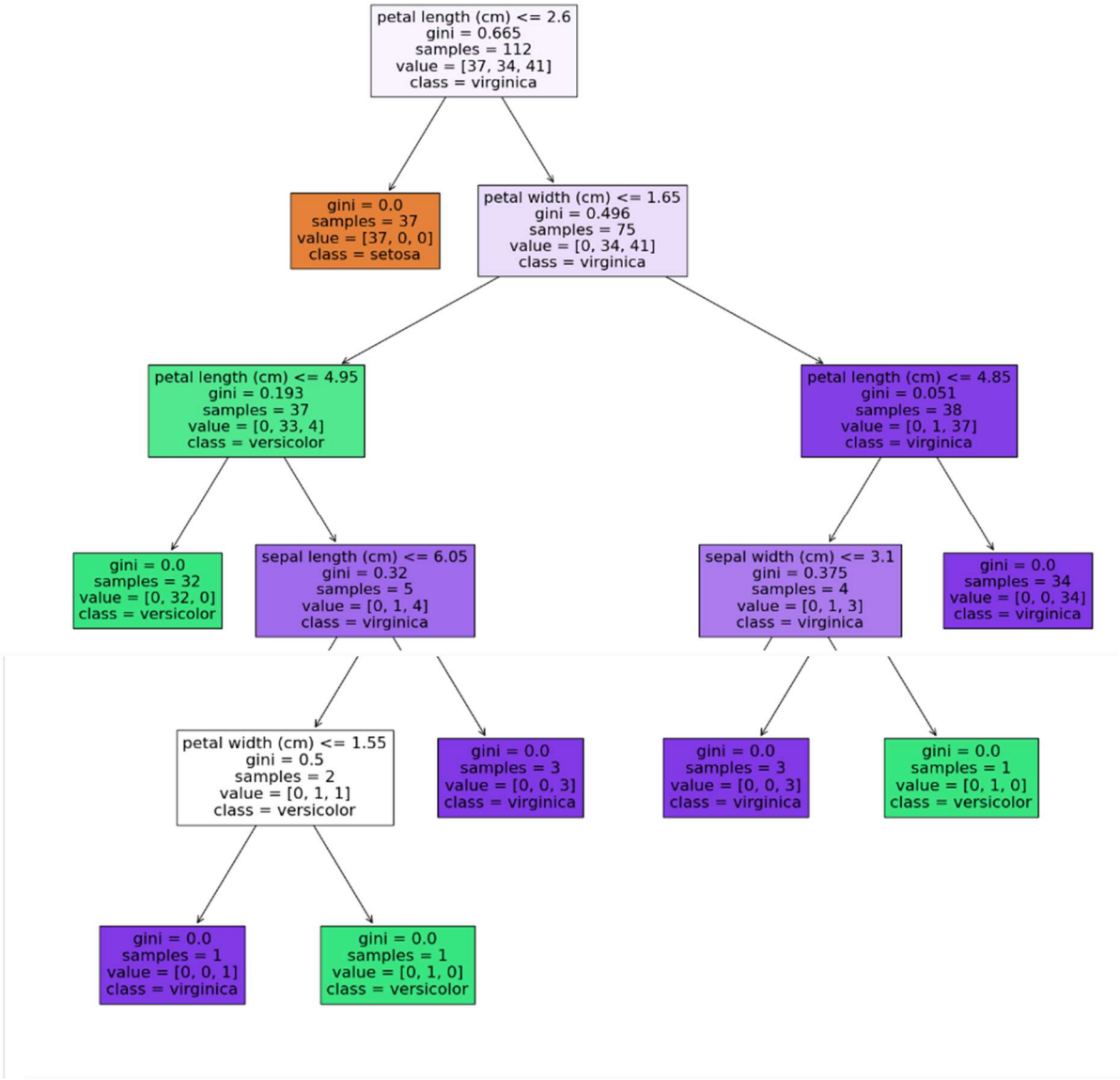
```
Train score:  1.0
```

```
#accuracy
from sklearn import metrics
print("Accuracy: ", metrics.accuracy_score(y_test, y_test_pred))
```

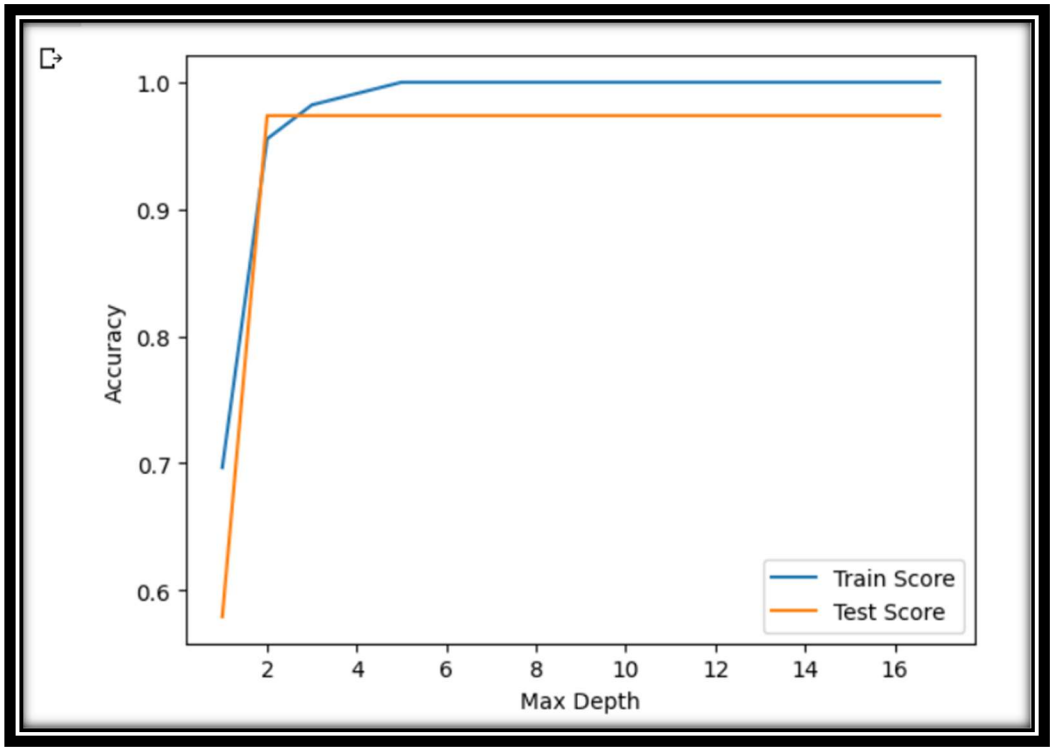
```
Accuracy:  0.9736842105263158
```

```
[18] import matplotlib.pyplot as plt
from sklearn.tree import plot_tree
plt.figure(figsize=(20, 20))
plot_tree(clf, filled=True, feature_names = iris.feature_names, class_names = iris.target_names)
plt.show()
```

[18]



```python
#comparing train and test score
max_depths = range(1, 18)
train_scores = []
test_scores = []

for max_depth in max_depths:
    tree = DecisionTreeClassifier(max_depth=max_depth, random_state=42)
    tree.fit(X_train, y_train)
    train_score = tree.score(X_train, y_train)
    test_score = tree.score(X_test, y_test)
    train_scores.append(train_score)
    test_scores.append(test_score)

plt.plot(max_depths, train_scores, label="Train Score")
plt.plot(max_depths, test_scores, label="Test Score")
plt.xlabel("Max Depth")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



Breast dataset

```
[ ] from sklearn.datasets import load_breast_cancer
```

```
breast_cancer = load_breast_cancer()
X = pd.DataFrame(breast_cancer.data, columns=breast_cancer.feature_names)
y = pd.Categorical.from_codes(breast_cancer.target, breast_cancer.target_names)
```

```
X.head()
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst radius	worst texture	w perim
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	25.38	17.33	18
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	24.99	23.41	15
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	23.57	25.53	15
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	...	14.91	26.50	9
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	...	22.54	16.67	15

5 rows × 30 columns

```
[ ] from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
```

```
[ ] y_train_pred = clf.predict(X_train)
    y_test_pred = clf.predict(X_test)
```

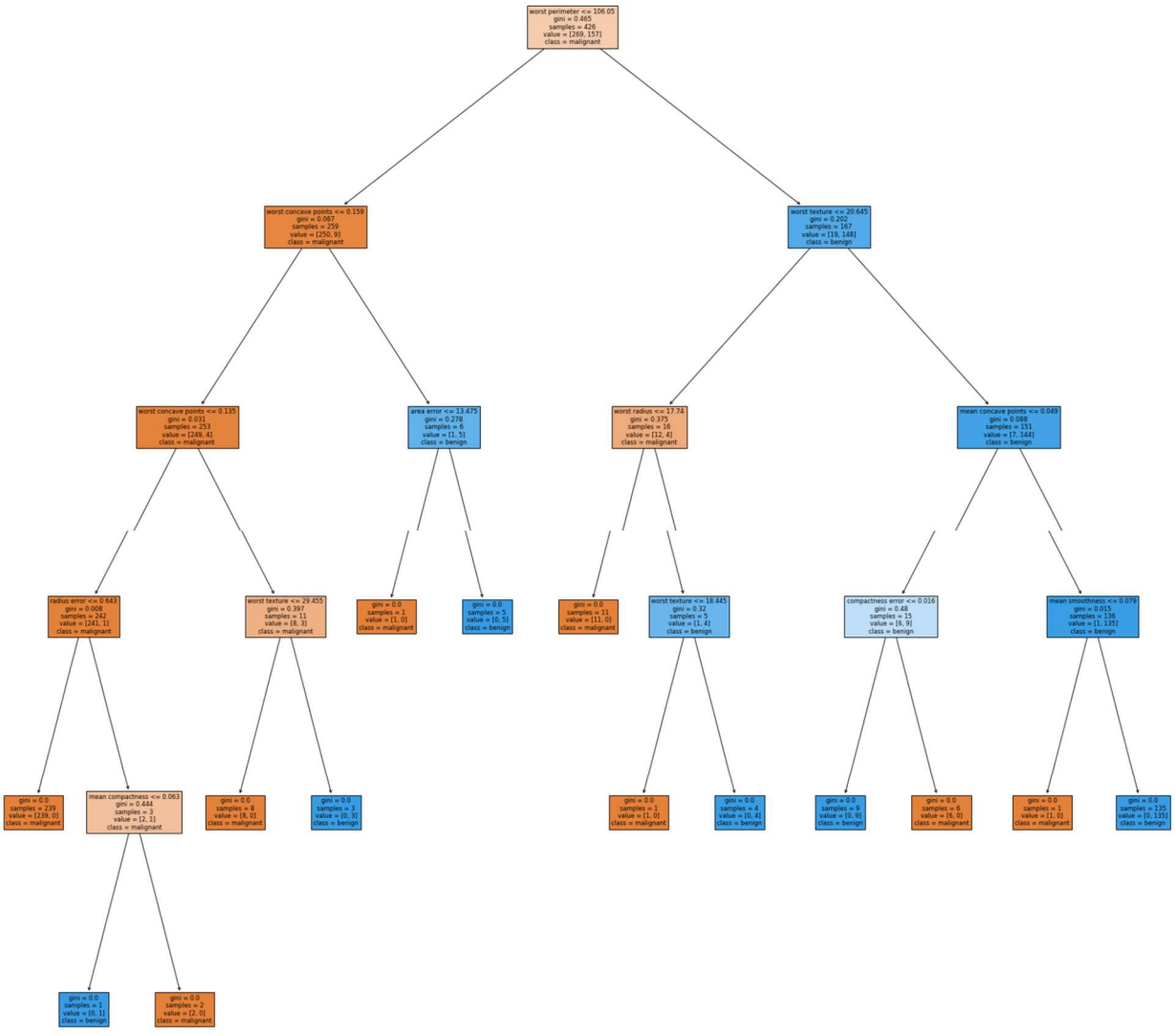
```
[ ] from sklearn.tree import DecisionTreeClassifier
    clf = DecisionTreeClassifier(max_depth=30)
    clf.fit(X_train, y_train)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=30)
```

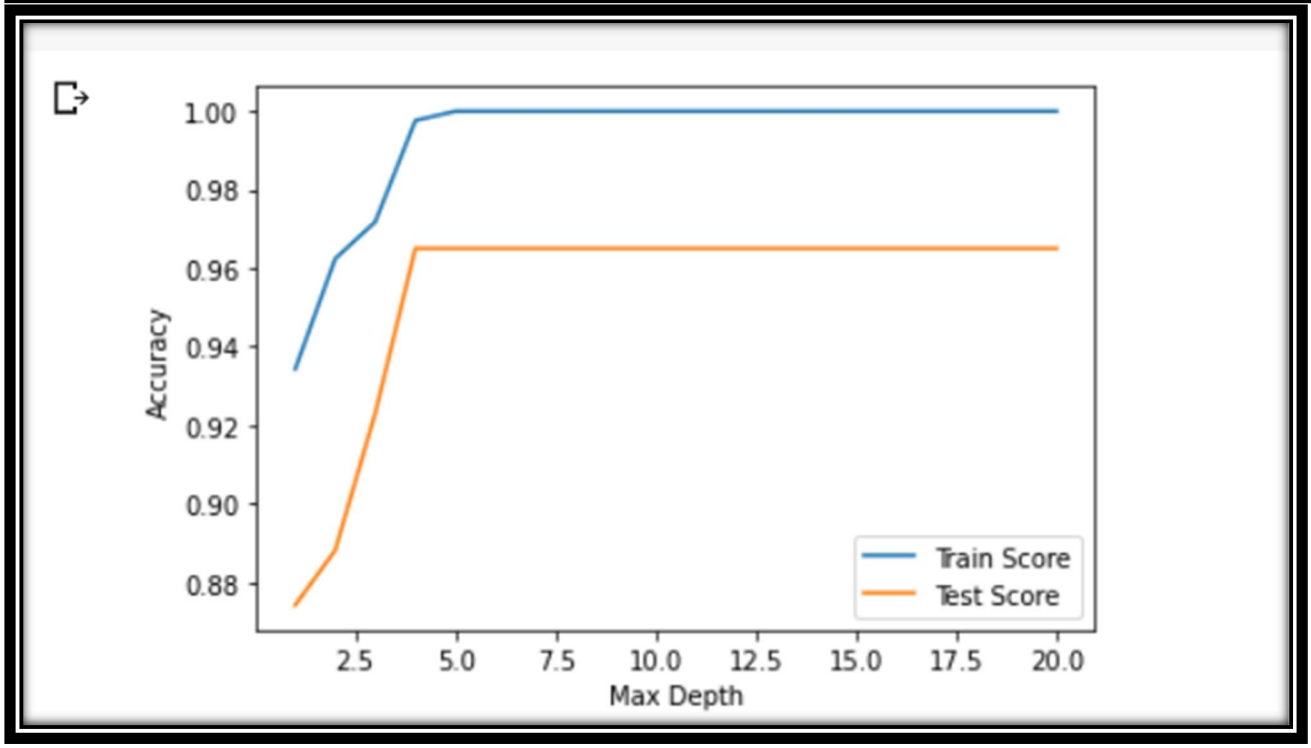
```
[ ] from sklearn.metrics import accuracy_score, confusion_matrix
    print("Train score: ", accuracy_score(y_train_pred, y_train))

    Train score:  1.0

    from sklearn import metrics
    print("Accuracy: ", metrics.accuracy_score(y_test, y_test_pred))

    Accuracy:  0.9300699300699301
```

+ Code + Text

```
[ ] import matplotlib.pyplot as plt
    from sklearn.tree import plot_tree
    plt.figure(figsize=(30, 30))
    plot_tree(clf, filled=True, feature_names = breast_cancer.feature_names, class_names = breast_cancer.target_names)
    plt.show()
```



```
[ ]  max_depths = range(1, 21)
     train_scores = []
     test_scores = []

     for max_depth in max_depths:
         tree = DecisionTreeClassifier(max_depth=max_depth, random_state=42)
         tree.fit(X_train, y_train)
         train_score = tree.score(X_train, y_train)
         test_score = tree.score(X_test, y_test)
         train_scores.append(train_score)
         test_scores.append(test_score)

     plt.plot(max_depths, train_scores, label="Train Score")
     plt.plot(max_depths, test_scores, label="Test Score")
     plt.xlabel("Max Depth")
     plt.ylabel("Accuracy")
     plt.legend()
     plt.show()
```



CAR PREDICT DATASET

```
[ ] df = pd.read_csv("/content/carprediction.csv")
    df.dropna(axis = 0, how ='any', inplace=True)
    X = df.drop(['Make', 'Model', 'Engine Fuel Type', 'Transmission Type', 'Driven_Wheels', 'Market Category', 'Vehicle Size', 'Vehicle Style', 'MSRP'], axis=
    y = df[['MSRP']]
```

```
X.head()
```

	Year	Engine HP	Engine Cylinders	Number of Doors	highway MPG	city mpg	Popularity
0	2011	335.0	6.0	2.0	26	19	3916
1	2011	300.0	6.0	2.0	28	19	3916
2	2011	300.0	6.0	2.0	28	20	3916
3	2011	230.0	6.0	2.0	28	18	3916
4	2011	230.0	6.0	2.0	28	18	3916

```
[ ] from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
```

```
[ ] from sklearn.tree import DecisionTreeRegressor
    tree = DecisionTreeRegressor()
    tree.fit(X_train,y_train)
```

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

```
[ ] prediction = tree.predict(X_test)
```

```
[ ] tree.predict(([[2016, 300, 8, 4, 25 ,30, 3500]]))
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/base.py:420: UserWarning: X does not have valid feature names, but DecisionTreeRegressor was fitted with feature na
  warnings.warn(
array([59475.])
```

```
[ ] tree.predict(X[:5])
```

```
array([46135., 40650., 36350., 31975., 31975.])
```

```
tree.score(X_test, prediction)
```

```
1.0
```

```
train_acc = []
test_acc = []

depth_list = range(1,3)

for d in depth_list:
    temp_tree = DecisionTreeRegressor(max_depth=d, random_state=1)
    temp_tree.fit(X_train, y_train)
    train_acc.append(temp_tree.score(X_train, y_train))
    test_acc.append(temp_tree.score(X_test, y_test))

plt.figure(figsize=([9, 6]))
plt.plot(depth_list, train_acc, label='Training Accuracy')
plt.plot(depth_list, test_acc, label='Validation Accuracy')
plt.xlabel('Maximum Depth')
plt.ylabel('Accuracy')
plt.xticks(depth_list)
plt.legend()
plt.show()
```