In [ ]:
```
import pandas as pd
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.metrics import accuracy_score,classification_report,confusion_matri
import matplotlib.pyplot as plt
```

In [ ]:
```
X,y=load_iris(return_X_y=True)
print(X)
print(y)
```

```
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
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 [4.6 3.4 1.4 0.3]
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 [4.8 3.4 1.9 0.2]
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 [4.9 3.1 1.5 0.2]
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 [5.  3.5 1.6 0.6]
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 [6.4 3.2 4.5 1.5]
 [6.9 3.1 4.9 1.5]
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 [6.5 2.8 4.6 1.5]
 [5.7 2.8 4.5 1.3]
 [6.3 3.3 4.7 1.6]
 [4.9 2.4 3.3 1. ]
 [6.6 2.9 4.6 1.3]
 [5.2 2.7 3.9 1.4]
```

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 [5.  2.  3.5 1. ]
 [5.9 3.  4.2 1.5]
 [6.  2.2 4.  1. ]
 [6.1 2.9 4.7 1.4]
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 [7.1 3.  5.9 2.1]
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 [4.9 2.5 4.5 1.7]
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 [7.7 2.6 6.9 2.3]
 [6.  2.2 5.  1.5]
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 [6.  3.  4.8 1.8]
 [6.9 3.1 5.4 2.1]
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 [5.8 2.7 5.1 1.9]
 [6.8 3.2 5.9 2.3]
 [6.7 3.3 5.7 2.5]
 [6.7 3.  5.2 2.3]
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 2 2]
```

In [ ]:

```
x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=33
```

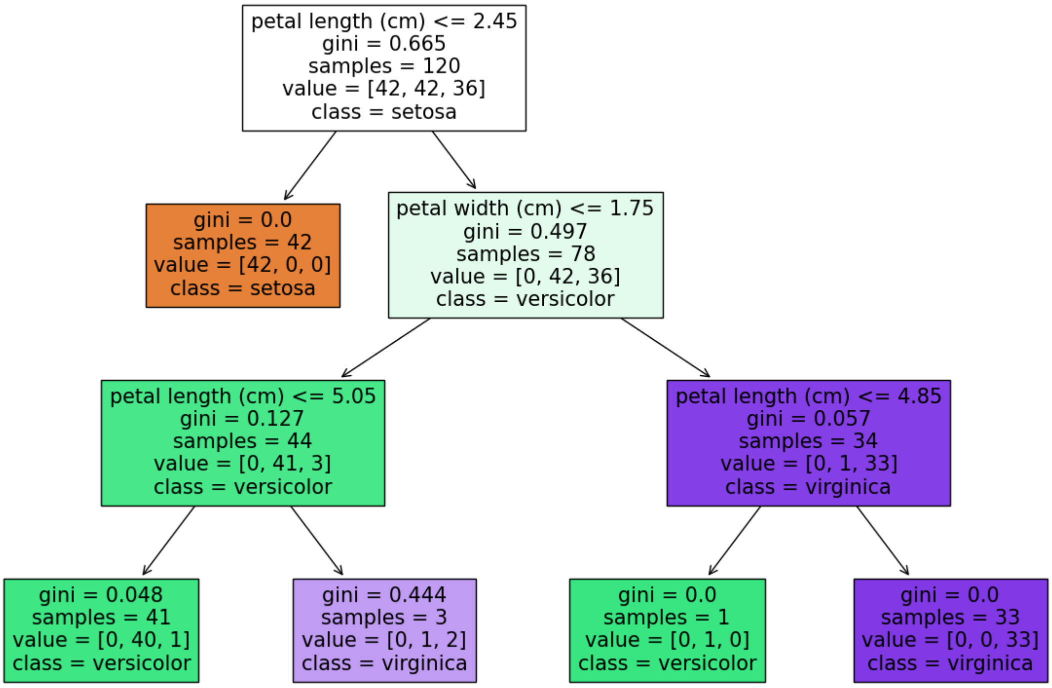
In [ ]:

```
cl=DecisionTreeClassifier()
cl.fit(x_train,y_train)
print("Accuracy",cl.score(x_test,y_test))
y_pred=cl.predict(x_test)
print(confusion_matrix(y_test,y_pred))
```

```
Accuracy 0.8666666666666667
[[ 8  0  0]
 [ 0  8  0]
 [ 0  4 10]]
```

In [ ]:

```
iris=load_iris()
fig = plt.figure(figsize=(15,10))
_ = plot_tree(cl,
                   feature_names=iris.feature_names,
                   class_names=iris.target_names,
                   filled=True)
```

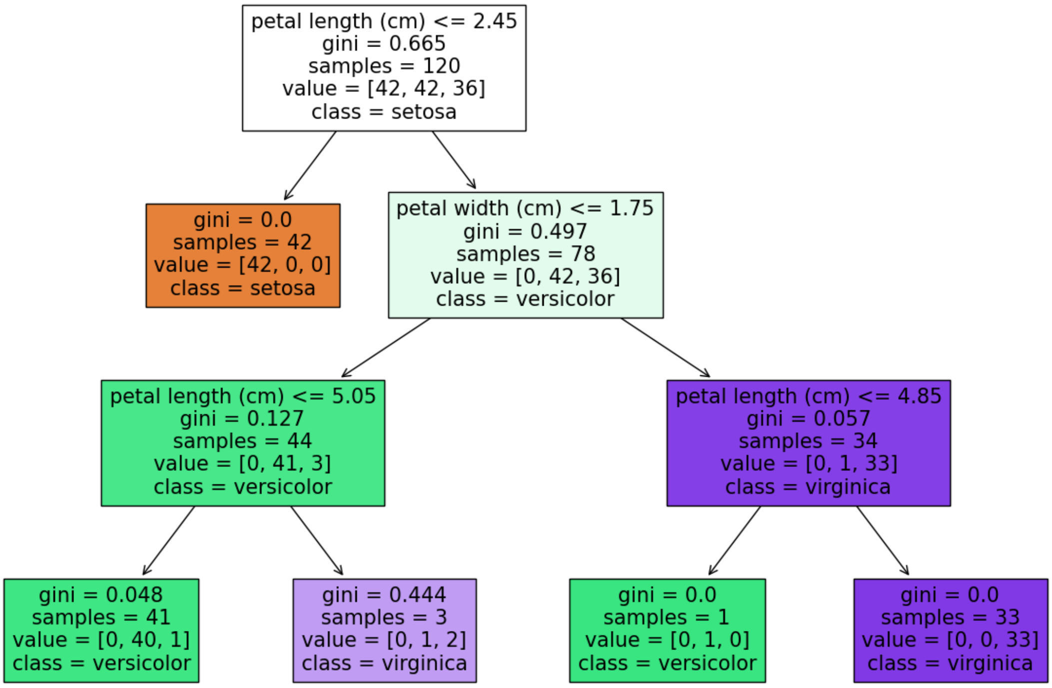


Pre-Pruning

In [ ]:
```
cl_pre=DecisionTreeClassifier(max_depth=3,max_leaf_nodes=6)
cl_pre.fit(x_train,y_train)
print("Accuracy",cl_pre.score(x_test,y_test))
y_pred=cl_pre.predict(x_test)
print(confusion_matrix(y_test,y_pred))
```

```
Accuracy 0.9
[[ 8  0  0]
 [ 0  8  0]
 [ 0  3 11]]
```

In [ ]:
```
iris=load_iris()
fig = plt.figure(figsize=(15,10))
_ = plot_tree(cl_pre,
                   feature_names=iris.feature_names,
                   class_names=iris.target_names,
                   filled=True)
```



Post Pruning

In [ ]:
```
path=cl.cost_complexity_pruning_path(x_train,y_train)
ccp_alphas,impurities=path.ccp_alphas,path.impurities
print("ccp alpha wil give list of values :\n",ccp_alphas)
print("************************************************************")
print("Impurities in Decision Tree :\n",impurities)
```

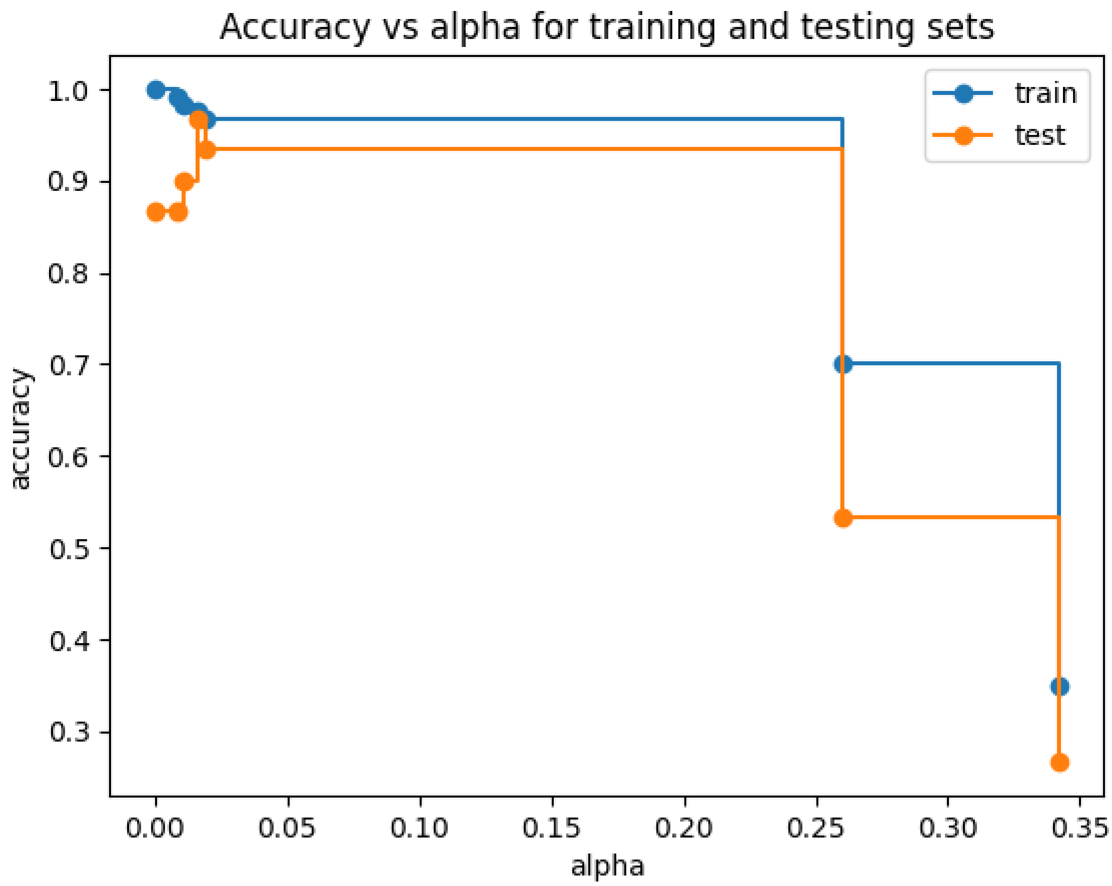
```
ccp alpha wil give list of values :
 [0.         0.00813008 0.01111111 0.01617647 0.01921964 0.26030954
 0.34192308]
************************************************************
Impurities in Decision Tree :
 [0.         0.01626016 0.02737127 0.04354774 0.06276738 0.32307692
 0.665     ]
```

In [ ]:
```
clfs=[]
for ccp_alpha in ccp_alphas:
    clf=DecisionTreeClassifier(random_state=23,ccp_alpha=ccp_alpha)
    clf.fit(x_train,y_train)
    clfs.append(clf)
print("Last node in Decision Tree is {} and ccp_alpha for last node is {}".forma
```

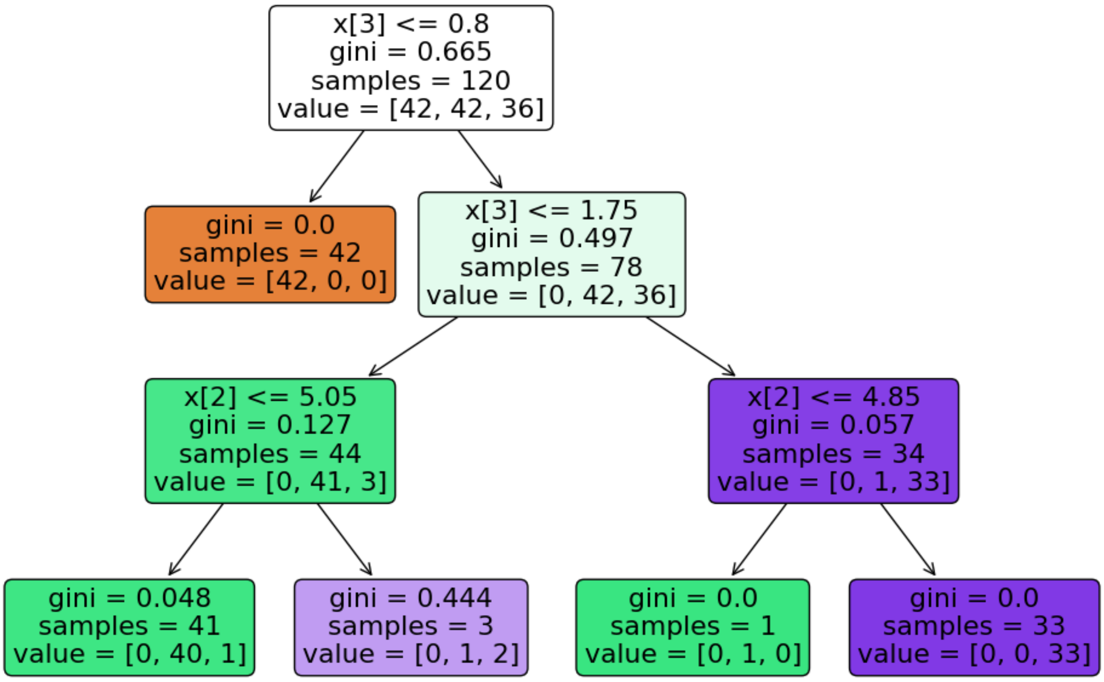
```
Last node in Decision Tree is DecisionTreeClassifier(ccp_alpha=0.34192307692307
71, random_state=23) and ccp_alpha for last node is 0.3419230769230771
```

In [ ]:
```
train_scores = [clf.score(x_train, y_train) for clf in clfs]
test_scores = [clf.score(x_test, y_test) for clf in clfs]
fig, ax = plt.subplots()
ax.set_xlabel("alpha")
ax.set_ylabel("accuracy")
ax.set_title("Accuracy vs alpha for training and testing sets")
ax.plot(ccp_alphas, train_scores, marker='o', label="train",drawstyle="steps-pos
ax.plot(ccp_alphas, test_scores, marker='o', label="test",drawstyle="steps-post"
```

```
ax.legend()
plt.show()
```



In [ ]:
```
from sklearn import tree
clf=DecisionTreeClassifier(random_state=0,ccp_alpha=0.015)
clf.fit(x_train,y_train)
plt.figure(figsize=(12,8))
tree.plot_tree(clf,rounded=True,filled=True)
plt.show()
```


x[3] <= 0.8
gini = 0.665
samples = 120
value = [42, 42, 36]
gini = 0.0
samples = 42
value = [42, 0, 0]
x[3] <= 1.75
gini = 0.497
samples = 78
value = [0, 42, 36]
x[2] <= 5.05
gini = 0.127
samples = 44
value = [0, 41, 3]
x[2] <= 4.85
gini = 0.057
samples = 34
value = [0, 1, 33]
gini = 0.048
samples = 41
value = [0, 40, 1]
gini = 0.444
samples = 3
value = [0, 1, 2]
gini = 0.0
samples = 1
value = [0, 1, 0]
gini = 0.0
samples = 33
value = [0, 0, 33]

In [ ]:
```
import numpy as np
from collections import Counter
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

In [ ]:
```
class Node:
    '''
    Helper class which implements a single tree node.
    '''
    def __init__(self, feature=None, threshold=None, data_left=None, data_right=
        self.feature = feature
        self.threshold = threshold
        self.data_left = data_left
        self.data_right = data_right
        self.gain = gain
        self.value = value

class DecisionTree:
    '''
    Class which implements a decision tree classifier algorithm.
    '''
    def __init__(self, min_samples_split=2, max_depth=5):
        self.min_samples_split = min_samples_split
        self.max_depth = max_depth
        self.root = None

    @staticmethod
    def _entropy(s):
        '''
        Helper function, calculates entropy from an array of integer values.

        :param s: list
        :return: float, entropy value
        '''
        # Convert to integers to avoid runtime errors
        counts = np.bincount(np.array(s, dtype=np.int64))
        # Probabilities of each class label
        percentages = counts / len(s)

        # Caclulate entropy
        entropy = 0
        for pct in percentages:
            if pct > 0:
                entropy += pct * np.log2(pct)
        return -entropy

    def _information_gain(self, parent, left_child, right_child):
        '''
        Helper function, calculates information gain from a parent and two child

        :param parent: list, the parent node
        :param left_child: list, left child of a parent
        :param right_child: list, right child of a parent
        :return: float, information gain
        '''
        num_left = len(left_child) / len(parent)
        num_right = len(right_child) / len(parent)
```

```
        # One-liner which implements the previously discussed formula
        return self._entropy(parent) - (num_left * self._entropy(left_child) + r

    def _best_split(self, X, y):
        '''
        Helper function, calculates the best split for given features and target

        :param X: np.array, features
        :param y: np.array or list, target
        :return: dict
        '''
        best_split = {}
        best_info_gain = -1
        n_rows, n_cols = X.shape

        # For every dataset feature
        for f_idx in range(n_cols):
            X_curr = X[:, f_idx]
            # For every unique value of that feature
            for threshold in np.unique(X_curr):
                # Construct a dataset and split it to the left and right parts
                # Left part includes records lower or equal to the threshold
                # Right part includes records higher than the threshold
                df = np.concatenate((X, y.reshape(1, -1).T), axis=1)
                df_left = np.array([row for row in df if row[f_idx] <= threshold
                df_right = np.array([row for row in df if row[f_idx] > threshold

                # Do the calculation only if there's data in both subsets
                if len(df_left) > 0 and len(df_right) > 0:
                    # Obtain the value of the target variable for subsets
                    y = df[:, -1]
                    y_left = df_left[:, -1]
                    y_right = df_right[:, -1]

                    # Caclulate the information gain and save the split paramete
                    # if the current split if better then the previous best
                    gain = self._information_gain(y, y_left, y_right)
                    if gain > best_info_gain:
                        best_split = {
                            'feature_index': f_idx,
                            'threshold': threshold,
                            'df_left': df_left,
                            'df_right': df_right,
                            'gain': gain
                        }
                        best_info_gain = gain
        return best_split

    def _build(self, X, y, depth=0):
        '''
        Helper recursive function, used to build a decision tree from the input

        :param X: np.array, features
        :param y: np.array or list, target
        :param depth: current depth of a tree, used as a stopping criteria
        :return: Node
        '''
        n_rows, n_cols = X.shape
```

```
        # Check to see if a node should be leaf node
        if n_rows >= self.min_samples_split and depth <= self.max_depth:
            # Get the best split
            best = self._best_split(X, y)
            # If the split isn't pure
            if best['gain'] > 0:
                # Build a tree on the left
                left = self._build(
                    X=best['df_left'][:, :-1],
                    y=best['df_left'][:, -1],
                    depth=depth + 1
                )
                right = self._build(
                    X=best['df_right'][:, :-1],
                    y=best['df_right'][:, -1],
                    depth=depth + 1
                )
                return Node(
                    feature=best['feature_index'],
                    threshold=best['threshold'],
                    data_left=left,
                    data_right=right,
                    gain=best['gain']
                )
        # Leaf node - value is the most common target value
        return Node(
            value=Counter(y).most_common(1)[0][0]
        )

    def fit(self, X, y):
        '''
        Function used to train a decision tree classifier model.

        :param X: np.array, features
        :param y: np.array or list, target
        :return: None
        '''
        # Call a recursive function to build the tree
        self.root = self._build(X, y)

    def _predict(self, x, tree):
        '''
        Helper recursive function, used to predict a single instance (tree trave

        :param x: single observation
        :param tree: built tree
        :return: float, predicted class
        '''
        # Leaf node
        if tree.value != None:
            return tree.value
        feature_value = x[tree.feature]

        # Go to the left
        if feature_value <= tree.threshold:
            return self._predict(x=x, tree=tree.data_left)

        # Go to the right
        if feature_value > tree.threshold:
            return self._predict(x=x, tree=tree.data_right)
```

```
    def predict(self, X):
        '''
        Function used to classify new instances.

        :param X: np.array, features
        :return: np.array, predicted classes
        '''
        # Call the _predict() function for every observation
        return [self._predict(x, self.root) for x in X]
```

In [ ]:

```
iris = load_iris()

X = iris['data']
y = iris['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
model=DecisionTree()
model.fit(X_train,y_train)
y_pred=model.predict(X_test)

print("Test Results:",y_test)
print("Predicted Results: ",y_pred)
# print(np.concatenate((np.array(y_test).reshape(len(y_test),1),np.array(y_pred)

print("Confusion Matrix\n",confusion_matrix(y_test,y_pred))
```

```
Test Results: [1 0 2 1 1 0 1 2 1 1 2 0 0 0 0 1 2 1 1 2 0 2 0 2 2 2 2 2 0 0]
Predicted Results:  [1.0, 0.0, 2.0, 1.0, 1.0, 0.0, 1.0, 2.0, 1.0, 1.0, 2.0, 0.
0, 0.0, 0.0, 0.0, 1.0, 2.0, 1.0, 1.0, 2.0, 0.0, 2.0, 0.0, 2.0, 2.0, 2.0, 2.0,
2.0, 0.0, 0.0]
Confusion Matrix
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```