Decision Tree

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
from sklearn.datasets import load_iris
```

In [3]:
```
iris = load_iris()
```

In [4]:
```
iris
```

Out[4]:
```
{'data': array([[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],
        [5.4, 3.9, 1.7, 0.4],
        [4.6, 3.4, 1.4, 0.3],
        [5. , 3.4, 1.5, 0.2],
        [4.4, 2.9, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.1],
        [5.4, 3.7, 1.5, 0.2],
        [4.8, 3.4, 1.6, 0.2],
        [4.8, 3. , 1.4, 0.1],
        [4.3, 3. , 1.1, 0.1],
        [5.8, 4. , 1.2, 0.2],
        [5.7, 4.4, 1.5, 0.4],
        [5.4, 3.9, 1.3, 0.4],
        [5.1, 3.5, 1.4, 0.3],
        [5.7, 3.8, 1.7, 0.3],
        [5.1, 3.8, 1.5, 0.3],
        [5.4, 3.4, 1.7, 0.2],
        [5.1, 3.7, 1.5, 0.4],
        [4.6, 3.6, 1. , 0.2],
        [5.1, 3.3, 1.7, 0.5],
        [4.8, 3.4, 1.9, 0.2],
        [5. , 3. , 1.6, 0.2],
        [5. , 3.4, 1.6, 0.4],
        [5.2, 3.5, 1.5, 0.2],
        [5.2, 3.4, 1.4, 0.2],
        [4.7, 3.2, 1.6, 0.2],
        [4.8, 3.1, 1.6, 0.2],
        [5.4, 3.4, 1.5, 0.4],
        [5.2, 4.1, 1.5, 0.1],
        [5.5, 4.2, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.2],
        [5. , 3.2, 1.2, 0.2],
        [5.5, 3.5, 1.3, 0.2],
        [4.9, 3.6, 1.4, 0.1],
        [4.4, 3. , 1.3, 0.2],
        [5.1, 3.4, 1.5, 0.2],
        [5. , 3.5, 1.3, 0.3],
        [4.5, 2.3, 1.3, 0.3],
        [4.4, 3.2, 1.3, 0.2],
        [5. , 3.5, 1.6, 0.6],
        [5.1, 3.8, 1.9, 0.4],
        [4.8, 3. , 1.4, 0.3],
        [5.1, 3.8, 1.6, 0.2],
        [4.6, 3.2, 1.4, 0.2],
        [5.3, 3.7, 1.5, 0.2],
        [5. , 3.3, 1.4, 0.2],
        [7. , 3.2, 4.7, 1.4],
        [6.4, 3.2, 4.5, 1.5],
        [6.9, 3.1, 4.9, 1.5],
        [5.5, 2.3, 4. , 1.3],
        [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],
        [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],
        [5.6, 2.9, 3.6, 1.3],
        [6.7, 3.1, 4.4, 1.4],
        [5.6, 3. , 4.5, 1.5],
        [5.8, 2.7, 4.1, 1. ],
        [6.2, 2.2, 4.5, 1.5],
        [5.6, 2.5, 3.9, 1.1],
        [5.9, 3.2, 4.8, 1.8],
        [6.1, 2.8, 4. , 1.3],
```

```
        [6.3, 2.5, 4.9, 1.5],
        [6.1, 2.8, 4.7, 1.2],
        [6.4, 2.9, 4.3, 1.3],
        [6.6, 3. , 4.4, 1.4],
        [6.8, 2.8, 4.8, 1.4],
        [6.7, 3. , 5. , 1.7],
        [6. , 2.9, 4.5, 1.5],
        [5.7, 2.6, 3.5, 1. ],
        [5.5, 2.4, 3.8, 1.1],
        [5.5, 2.4, 3.7, 1. ],
        [5.8, 2.7, 3.9, 1.2],
        [6. , 2.7, 5.1, 1.6],
        [5.4, 3. , 4.5, 1.5],
        [6. , 3.4, 4.5, 1.6],
        [6.7, 3.1, 4.7, 1.5],
        [6.3, 2.3, 4.4, 1.3],
        [5.6, 3. , 4.1, 1.3],
        [5.5, 2.5, 4. , 1.3],
        [5.5, 2.6, 4.4, 1.2],
        [6.1, 3. , 4.6, 1.4],
        [5.8, 2.6, 4. , 1.2],
        [5. , 2.3, 3.3, 1. ],
        [5.6, 2.7, 4.2, 1.3],
        [5.7, 3. , 4.2, 1.2],
        [5.7, 2.9, 4.2, 1.3],
        [6.2, 2.9, 4.3, 1.3],
        [5.1, 2.5, 3. , 1.1],
        [5.7, 2.8, 4.1, 1.3],
        [6.3, 3.3, 6. , 2.5],
        [5.8, 2.7, 5.1, 1.9],
        [7.1, 3. , 5.9, 2.1],
        [6.3, 2.9, 5.6, 1.8],
        [6.5, 3. , 5.8, 2.2],
        [7.6, 3. , 6.6, 2.1],
        [4.9, 2.5, 4.5, 1.7],
        [7.3, 2.9, 6.3, 1.8],
        [6.7, 2.5, 5.8, 1.8],
        [7.2, 3.6, 6.1, 2.5],
        [6.5, 3.2, 5.1, 2. ],
        [6.4, 2.7, 5.3, 1.9],
        [6.8, 3. , 5.5, 2.1],
        [5.7, 2.5, 5. , 2. ],
        [5.8, 2.8, 5.1, 2.4],
        [6.4, 3.2, 5.3, 2.3],
        [6.5, 3. , 5.5, 1.8],
        [7.7, 3.8, 6.7, 2.2],
        [7.7, 2.6, 6.9, 2.3],
        [6. , 2.2, 5. , 1.5],
        [6.9, 3.2, 5.7, 2.3],
        [5.6, 2.8, 4.9, 2. ],
        [7.7, 2.8, 6.7, 2. ],
        [6.3, 2.7, 4.9, 1.8],
        [6.7, 3.3, 5.7, 2.1],
        [7.2, 3.2, 6. , 1.8],
        [6.2, 2.8, 4.8, 1.8],
        [6.1, 3. , 4.9, 1.8],
        [6.4, 2.8, 5.6, 2.1],
        [7.2, 3. , 5.8, 1.6],
        [7.4, 2.8, 6.1, 1.9],
        [7.9, 3.8, 6.4, 2. ],
        [6.4, 2.8, 5.6, 2.2],
        [6.3, 2.8, 5.1, 1.5],
        [6.1, 2.6, 5.6, 1.4],
        [7.7, 3. , 6.1, 2.3],
        [6.3, 3.4, 5.6, 2.4],
        [6.4, 3.1, 5.5, 1.8],
        [6. , 3. , 4.8, 1.8],
        [6.9, 3.1, 5.4, 2.1],
        [6.7, 3.1, 5.6, 2.4],
        [6.9, 3.1, 5.1, 2.3],
        [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],
        [6.3, 2.5, 5. , 1.9],
        [6.5, 3. , 5.2, 2. ],
        [6.2, 3.4, 5.4, 2.3],
        [5.9, 3. , 5.1, 1.8]]),
 'target': array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2]),
 'frame': None,
 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
 'DESCR': '.. _iris_dataset:\n\nIris plants dataset\n--------------------\n\n**Data Set Characteristics:**\n\n
:Number of Instances: 150 (50 in each of three classes)\n    :Number of Attributes: 4 numeric, predictive attri
```

```
butes and the class\n    :Attribute Information:\n        - sepal length in cm\n        - sepal width in cm\n
- petal length in cm\n        - petal width in cm\n        - class:\n                - Iris-Setosa\n
- Iris-Versicolour\n                - Iris-Virginica\n                \n    :Summary Statistics:\n\n    =======
======= ==== ==== ======= ===== ====================\n                    Min  Max   Mean    SD   Class Correla
tion\n    ============== ==== ==== ======= ===== ====================\n    sepal length:   4.3  7.9   5.84   0.
83    0.7826\n    sepal width:    2.0  4.4   3.05   0.43   -0.4194\n    petal length:   1.0  6.9   3.76   1.76
0.9490  (high!)\n    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)\n    ============== ==== ==== ==
===== ===== ====================\n\n    :Missing Attribute Values: None\n    :Class Distribution: 33.3% for eac
h of 3 classes.\n    :Creator: R.A. Fisher\n    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n    :D
ate: July, 1988\n\nThe famous Iris database, first used by Sir R.A. Fisher. The dataset is taken\nfrom Fisher\'
s paper. Note that it\'s the same as in R, but not as in the UCI\nMachine Learning Repository, which has two wr
ong data points.\n\nThis is perhaps the best known database to be found in the\npattern recognition literature.
Fisher\'s paper is a classic in the field and\nis referenced frequently to this day.  (See Duda & Hart, for exa
mple.)  The\ndata set contains 3 classes of 50 instances each, where each class refers to a\ntype of iris plant
.  One class is linearly separable from the other 2; the\nlatter are NOT linearly separable from each other.\n\
n.. topic:: References\n\n   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"\n     Annu
al Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to\n     Mathematical Statistics" (John Wiley,
NY, 1950).\n   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.\n     (Q327.D83) Jo
hn Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborho
od: A New System\n     Structure and Classification Rule for Recognition in Partially Exposed\n     Environment
s".  IEEE Transactions on Pattern Analysis and Machine\n     Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gat
es, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions\n     on Information Theory, May 1972,
431-433.\n   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II\n     conceptual clusteri
ng system finds 3 classes in the data.\n   - Many, many more ...',
 'feature_names': ['sepal length (cm)',
  'sepal width (cm)',
  'petal length (cm)',
  'petal width (cm)'],
 'filename': 'iris.csv',
 'data_module': 'sklearn.datasets.data'}
```

In [5]:
```
iris.target
```

Out[5]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [6]:
```
import seaborn as sns
df = sns.load_dataset('iris')
```

In [7]:
```
df.head()
```

Out[7]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In [8]:
```
X = df.iloc[:,:-1]
y = iris.target
```

In [9]:
```
X, y
```

Out[9]:
```
(     sepal_length  sepal_width  petal_length  petal_width
 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
 ..            ...          ...           ...          ...
 145           6.7          3.0           5.2          2.3
 146           6.3          2.5           5.0          1.9
 147           6.5          3.0           5.2          2.0
 148           6.2          3.4           5.4          2.3
 149           5.9          3.0           5.1          1.8

 [150 rows x 4 columns],
 array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2]))
```

In [10]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size = 0.33, random_state = 42)
```

In [11]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [12]:
```
# Postprunning
```

In [13]:
```
tree_model = DecisionTreeClassifier()
```

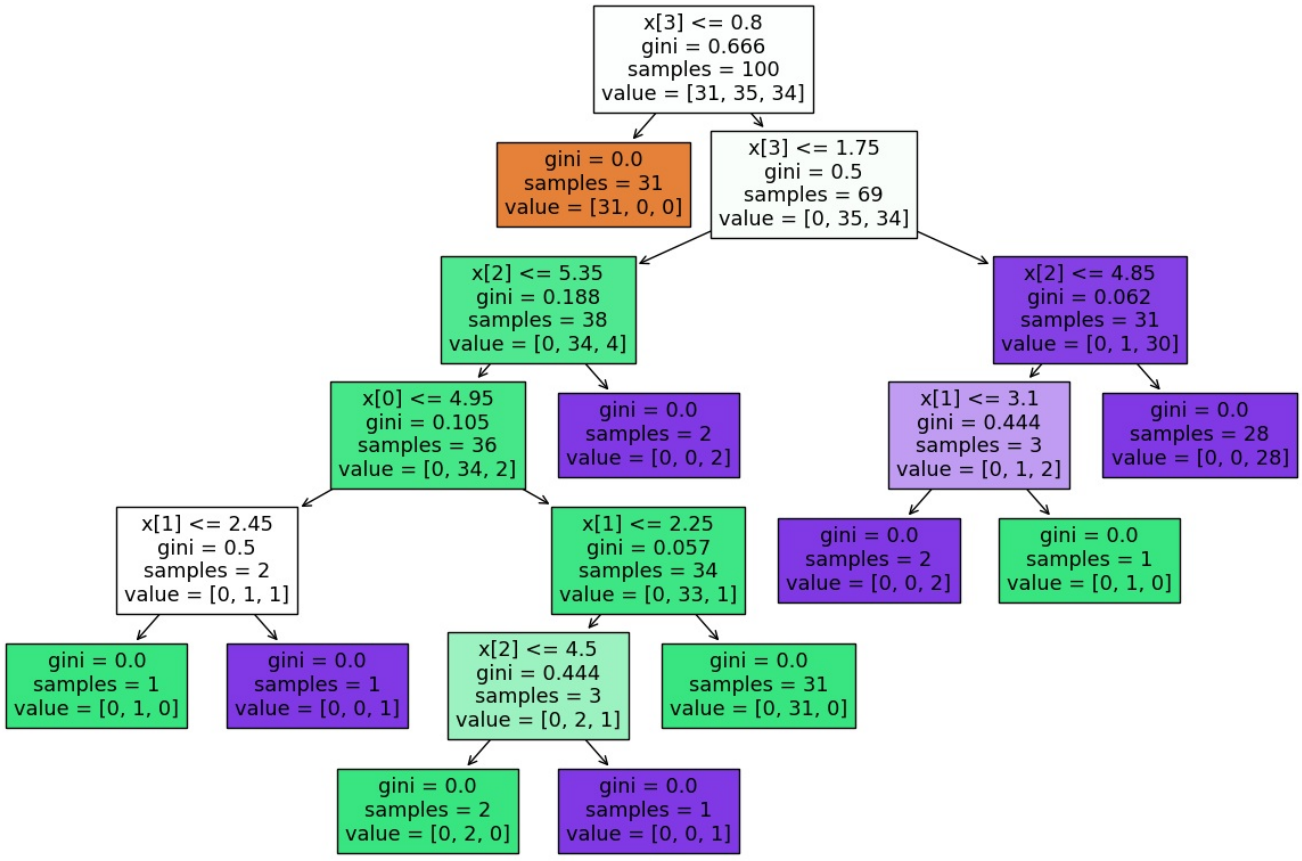
In [14]:
```
tree_model.fit(X_train, y_train)
```

Out[14]:
```
DecisionTreeClassifier
DecisionTreeClassifier()
```

In [15]:
```
from sklearn import tree
```

In [16]:
```
plt.figure(figsize = (15,10))
tree.plot_tree(tree_model, filled = True)
```

Out[16]:
```
[Text(0.5416666666666666, 0.9285714285714286, 'x[3] <= 0.8\ngini = 0.666\nsamples = 100\nvalue = [31, 35, 34]')
,
 Text(0.4583333333333333, 0.7857142857142857, 'gini = 0.0\nsamples = 31\nvalue = [31, 0, 0]'),
 Text(0.625, 0.7857142857142857, 'x[3] <= 1.75\ngini = 0.5\nsamples = 69\nvalue = [0, 35, 34]'),
 Text(0.4166666666666667, 0.6428571428571429, 'x[2] <= 5.35\ngini = 0.188\nsamples = 38\nvalue = [0, 34, 4]'),
 Text(0.3333333333333333, 0.5, 'x[0] <= 4.95\ngini = 0.105\nsamples = 36\nvalue = [0, 34, 2]'),
 Text(0.16666666666666666, 0.35714285714285715, 'x[1] <= 2.45\ngini = 0.5\nsamples = 2\nvalue = [0, 1, 1]'),
 Text(0.08333333333333333, 0.21428571428571427, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]'),
 Text(0.25, 0.21428571428571427, 'gini = 0.0\nsamples = 1\nvalue = [0, 0, 1]'),
 Text(0.5, 0.35714285714285715, 'x[1] <= 2.25\ngini = 0.057\nsamples = 34\nvalue = [0, 33, 1]'),
 Text(0.4166666666666667, 0.21428571428571427, 'x[2] <= 4.5\ngini = 0.444\nsamples = 3\nvalue = [0, 2, 1]'),
 Text(0.3333333333333333, 0.07142857142857142, 'gini = 0.0\nsamples = 2\nvalue = [0, 2, 0]'),
 Text(0.5, 0.07142857142857142, 'gini = 0.0\nsamples = 1\nvalue = [0, 0, 1]'),
 Text(0.5833333333333334, 0.21428571428571427, 'gini = 0.0\nsamples = 31\nvalue = [0, 31, 0]'),
 Text(0.5, 0.5, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 2]'),
 Text(0.8333333333333334, 0.6428571428571429, 'x[2] <= 4.85\ngini = 0.062\nsamples = 31\nvalue = [0, 1, 30]'),
 Text(0.75, 0.5, 'x[1] <= 3.1\ngini = 0.444\nsamples = 3\nvalue = [0, 1, 2]'),
 Text(0.6666666666666666, 0.35714285714285715, 'gini = 0.0\nsamples = 2\nvalue = [0, 0, 2]'),
 Text(0.8333333333333334, 0.35714285714285715, 'gini = 0.0\nsamples = 1\nvalue = [0, 1, 0]'),
 Text(0.9166666666666666, 0.5, 'gini = 0.0\nsamples = 28\nvalue = [0, 0, 28]')]
```



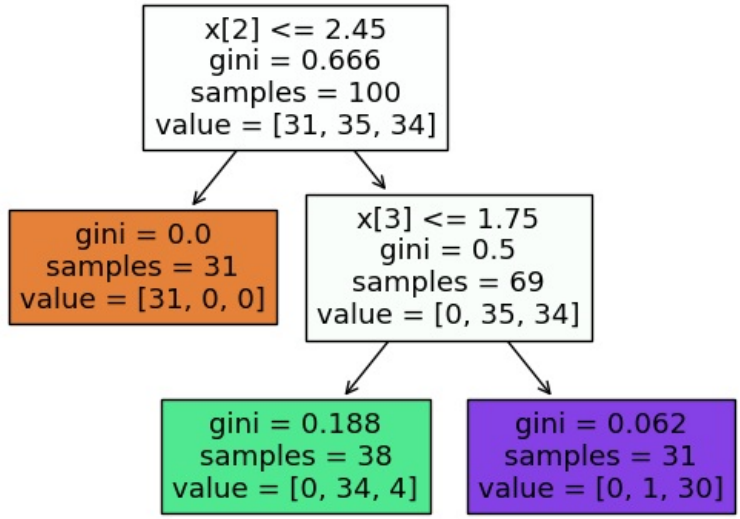
In [17]:
```
# Performing Post Prunning
new_tree_model = DecisionTreeClassifier(max_depth = 2)
```

In [18]:
```
new_tree_model.fit(X_train, y_train)
```

Out[18]:
```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=2)
```

In [19]:
```
tree.plot_tree(new_tree_model, filled = True)
```

Out[19]:
```
[Text(0.4, 0.8333333333333334, 'x[2] <= 2.45\ngini = 0.666\nsamples = 100\nvalue = [31, 35, 34]'),
 Text(0.2, 0.5, 'gini = 0.0\nsamples = 31\nvalue = [31, 0, 0]'),
 Text(0.6, 0.5, 'x[3] <= 1.75\ngini = 0.5\nsamples = 69\nvalue = [0, 35, 34]'),
 Text(0.4, 0.16666666666666666, 'gini = 0.188\nsamples = 38\nvalue = [0, 34, 4]'),
 Text(0.8, 0.16666666666666666, 'gini = 0.062\nsamples = 31\nvalue = [0, 1, 30]')]
```



In [20]:
```
y_pred = new_tree_model.predict(X_test)
```

In [21]:
```
y_pred
```

Out[21]:
```
array([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, 0, 0, 1, 0, 0, 2, 1, 0, 0, 0, 2, 1, 1, 0,
       0, 1, 1, 2, 1, 2])
```

In [22]:
```
from sklearn.metrics import accuracy_score, classification_report
```

In [23]:
```
score = accuracy_score(y_pred, y_test)
print(score)
```

```
0.98
```

In [24]:
```
print(classification_report(y_pred, y_test) )
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      0.94      0.97        16
           2       0.94      1.00      0.97        15

    accuracy                           0.98        50
   macro avg       0.98      0.98      0.98        50
weighted avg       0.98      0.98      0.98        50
```

In [25]:
```
# Preprunning
parameter = {
    'criterion': ['gini','entropy','log_loss'],
    'splitter': ['best','random'],
    'max_depth':[1,2,3,4,5],
    'max_features':['auto','sqrt','log2']
}
```

In [26]:
```
from sklearn.model_selection import GridSearchCV
```

In [27]:
```
treemodel = DecisionTreeClassifier(max_depth = 2)
cv = GridSearchCV(treemodel, param_grid = parameter, cv = 5, scoring = 'accuracy')
```

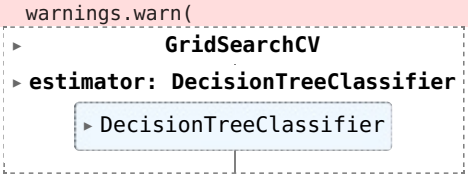
In [28]:
```
cv.fit(X_train, y_train)
```

```
C:\Users\Garima\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py:425: FitFailedWarning:
150 fits failed out of a total of 450.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
150 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\Garima\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py", line 732, in _fit_
and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\Garima\anaconda3\lib\site-packages\sklearn\base.py", line 1144, in wrapper
    estimator._validate_params()
  File "C:\Users\Garima\anaconda3\lib\site-packages\sklearn\base.py", line 637, in _validate_params
    validate_parameter_constraints(
  File "C:\Users\Garima\anaconda3\lib\site-packages\sklearn\utils\_param_validation.py", line 95, in validate_p
arameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of DecisionTreeClassifier m
ust be an int in the range [1, inf), a float in the range (0.0, 1.0], a str among {'log2', 'sqrt'} or None. Got
'auto' instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\Garima\anaconda3\lib\site-packages\sklearn\model_selection\_search.py:976: UserWarning: One or more of
the test scores are non-finite: [ nan  nan 0.66 0.58 0.63 0.56  nan  nan 0.92 0.73 0.93 0.7   nan  nan
 0.87 0.85 0.87 0.9   nan  nan 0.95 0.85 0.9  0.84  nan  nan 0.91 0.93
 0.9  0.89  nan  nan 0.66 0.53 0.63 0.58  nan  nan 0.88 0.73 0.88 0.75
  nan  nan 0.95 0.85 0.89 0.89  nan  nan 0.91 0.89 0.91 0.88  nan  nan
 0.91 0.88 0.94 0.87  nan  nan 0.63 0.56 0.66 0.54  nan  nan 0.88 0.75
 0.88 0.77  nan  nan 0.91 0.87 0.94 0.83  nan  nan 0.9  0.83 0.9  0.9
  nan  nan 0.89 0.9  0.91 0.86]
  warnings.warn(
```

Out[28]:



In [29]:
```
cv.best_params_
```

Out[29]:
```
{'criterion': 'gini',
 'max_depth': 4,
 'max_features': 'sqrt',
 'splitter': 'best'}
```

In [31]:
```
y_pred = cv.predict(X_test)
```

In [33]:
```
from sklearn.metrics import accuracy_score, classification_report
```

In [35]:
```
score = accuracy_score(y_test, y_pred)
```

In [36]:
```
score
```

Out[36]:
```
0.98
```

In [37]:
```
print(classification_report(y_pred,y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       0.93      1.00      0.97        14
           2       1.00      0.94      0.97        17

    accuracy                           0.98        50
   macro avg       0.98      0.98      0.98        50
weighted avg       0.98      0.98      0.98        50
```

In [ ]:
```

```