Task 6- Exploratory Data Analysis - Prediction using Decision tree algorithm

Exploratory Data Analysis - Prediction using Decision tree algorithm

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Importing the required Libraries

In [1]:

```
%matplotlib inline

import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

from sklearn import tree
```

In [2]:

```
#Importing the dataset
df=pd.read_csv('Iris.csv')
df
```

Out[2]:

	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
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [4]:

```
df.head()
```

Out[4]:

	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

In [5]:

```
df.tail()
```

Out[5]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

In [6]:

```
df.describe()
```

Out[6]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

Checking out the null Values in the dataset

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

Training the Model

In [30]:

```
features = ['SepalLengthCm','SepalWidthCm','PetalLengthCm','PetalWidthCm']

# Create features matrix
x = df.loc[:, features].values
```

In [31]:

```
y=df.Species
x_train,x_test,y_train,y_test=train_test_split(x, y, random_state=0)
```

In [32]:

```
clf = DecisionTreeClassifier(max_depth = 2,
                             random_state = 0)
```

In [33]:

```
clf.fit(x_train, y_train)
```

Out[33]:

```
DecisionTreeClassifier(max_depth=2, random_state=0)
```

In [34]:

```
best_clf = clf
```

In [35]:

```
clf.predict(x_test[0:1])
```

Out[35]:

```
array(['Iris-virginica'], dtype=object)
```

In [36]:

```
from sklearn import metrics
import seaborn as sns
```

In [37]:

```
score = clf.score(x_test, y_test)
print(score)
```

```
0.8947368421052632
```

In [38]:

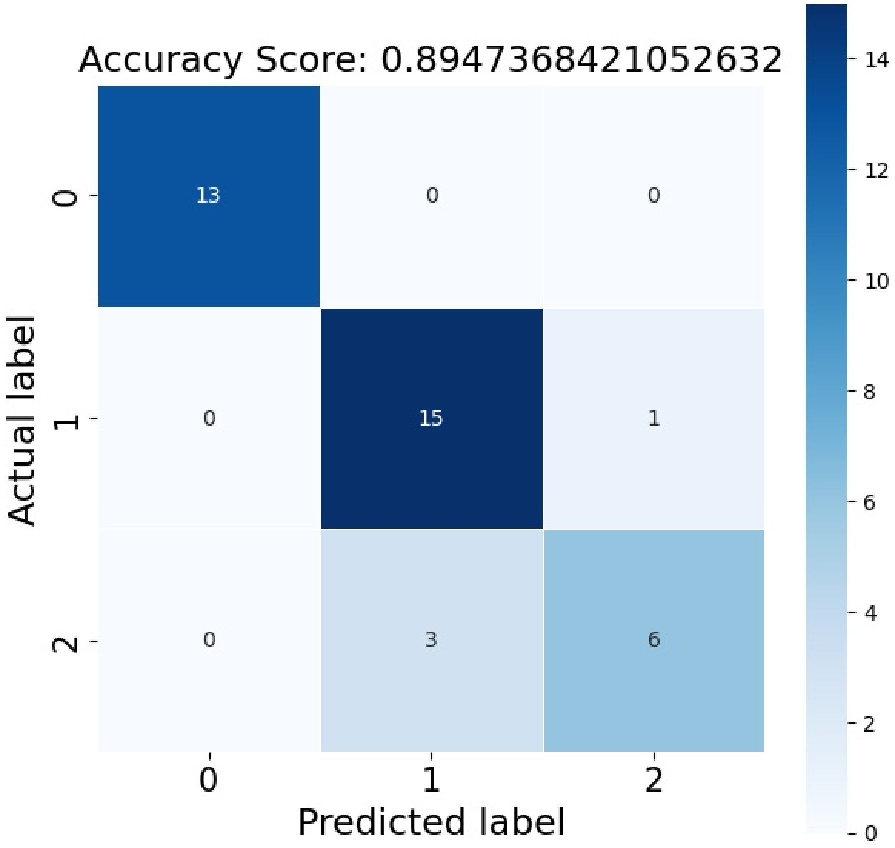
```
print(metrics.classification_report(y_test,clf.predict(x_test)))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        13
Iris-versicolor       0.83      0.94      0.88        16
 Iris-virginica       0.86      0.67      0.75         9

       accuracy                           0.89        38
      macro avg       0.90      0.87      0.88        38
   weighted avg       0.90      0.89      0.89        38
```

Visualing the data

In [39]:

```
cm = metrics.confusion_matrix(y_test, clf.predict(x_test))

plt.figure(figsize=(7,7))
sns.heatmap(cm, annot=True,
            fmt=".0f",
            linewidths=.5,
            square = True,
            cmap = 'Blues');
plt.ylabel('Actual label', fontsize = 17);
plt.xlabel('Predicted label', fontsize = 17);
plt.title('Accuracy Score: {}'.format(score), size = 17);
plt.tick_params(labelsize= 15)
```

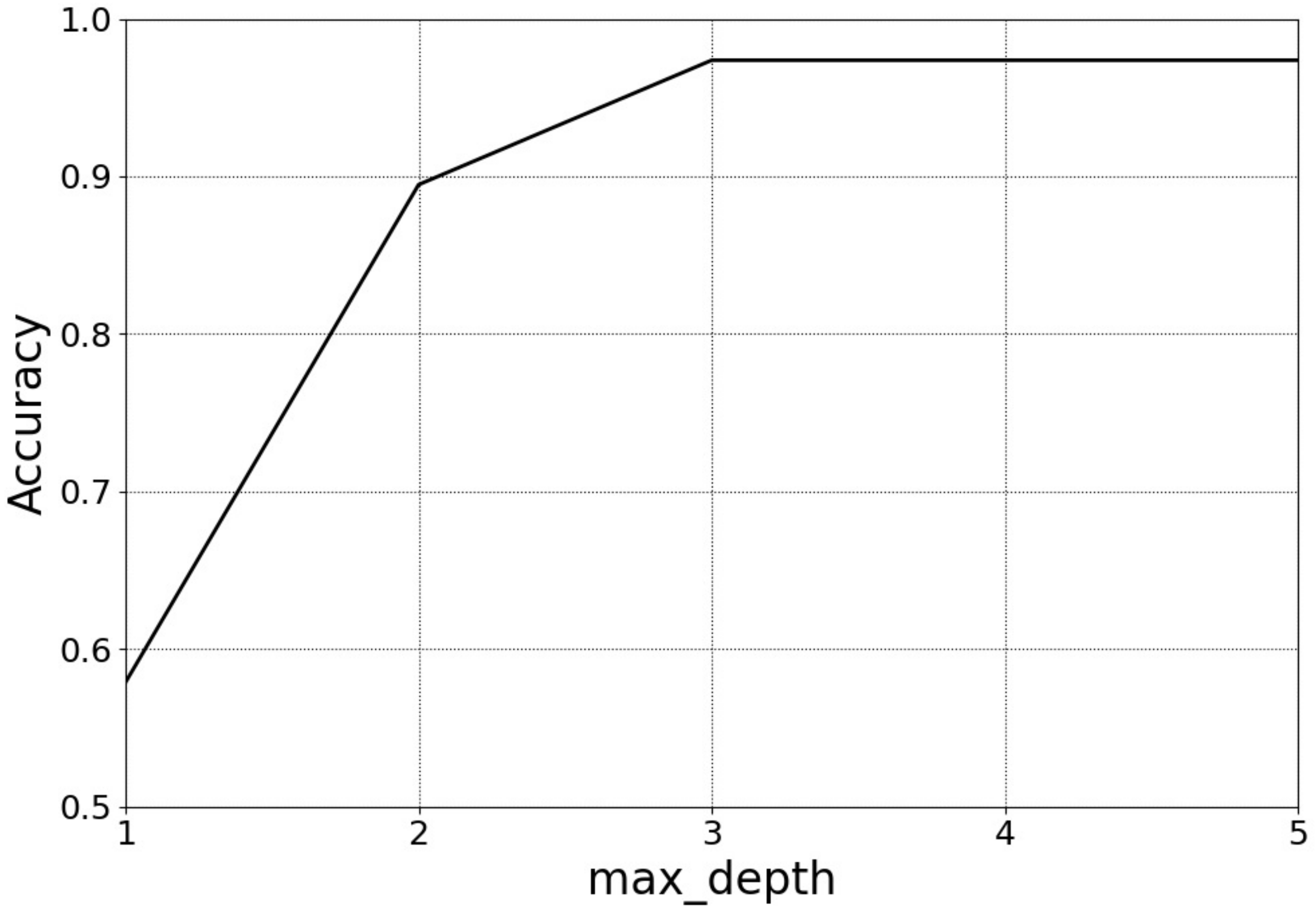


In [40]:

```
# List of values to try for max_depth:
max_depth_range = list(range(1, 6))

# List to store the average RMSE for each value of max_depth:
accuracy = []

for depth in max_depth_range:

    clf = DecisionTreeClassifier(max_depth = depth,
                                 random_state = 0)
    clf.fit(x_train, y_train)

    score = clf.score(x_test, y_test)
    accuracy.append(score)
```

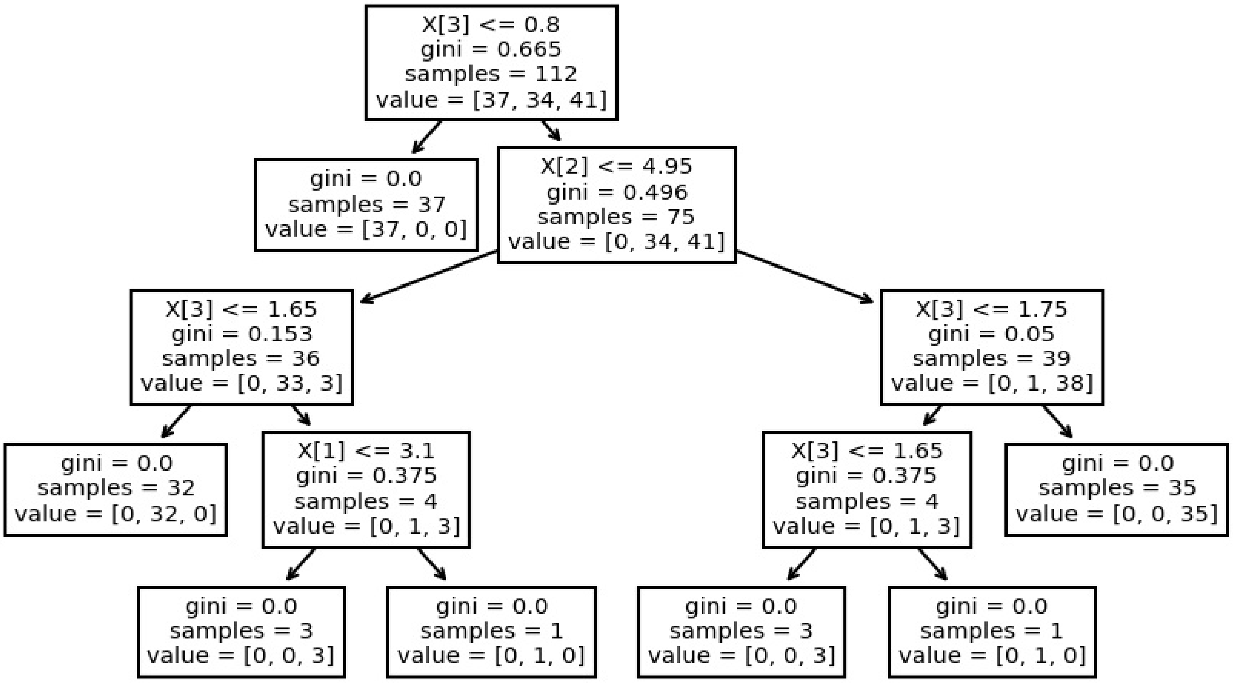
In [41]:

```
#ploting accuracy score depth wise
fig, ax = plt.subplots(nrows = 1, ncols = 1, figsize = (10,7));

ax.plot(max_depth_range,
        accuracy,
        lw=2,
        color='k')

ax.set_xlim([1, 5])
ax.set_ylim([.50, 1.00])
ax.grid(True,
        axis = 'both',
        zorder = 0,
        linestyle = ':',
        color = 'k')


ax.tick_params(labelsize = 18)
ax.set_xticks([1,2,3,4,5])
ax.set_xlabel('max_depth', fontsize = 24)
ax.set_ylabel('Accuracy', fontsize = 24)
fig.tight_layout()
#fig.savefig('images/max_depth_vs_accuracy.png', dpi = 300)
```



In [42]:

```
fig, axes = plt.subplots(nrows = 1, ncols = 1, figsize = (7,4), dpi = 150)

tree.plot_tree(clf);
```

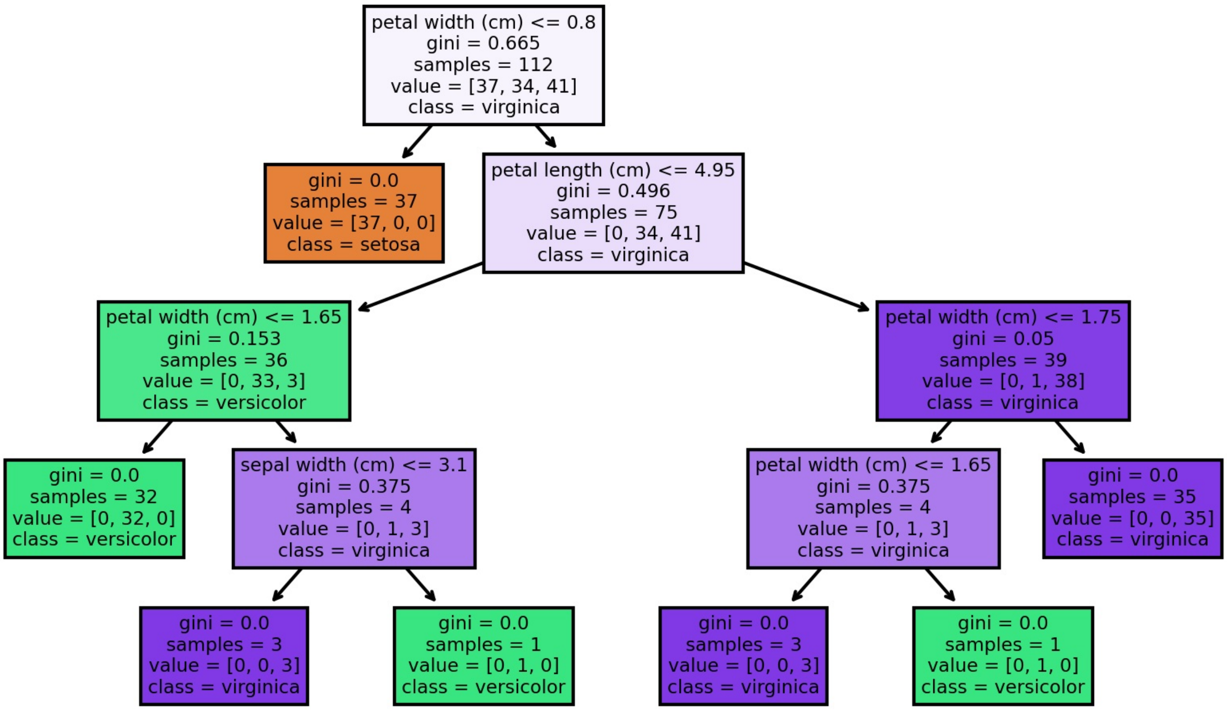


In [43]:

```
# Putting the feature names and class names into variables
```

In [43]:
```
# Putting the feature names and class names into variables
fn = ['sepal length (cm)','sepal width (cm)','petal length (cm)','petal width (cm)']
cn = ['setosa', 'versicolor', 'virginica']
```

In [44]:
```
fig, axes = plt.subplots(nrows = 1, ncols = 1, figsize = (7,4), dpi = 300)

tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
#fig.savefig('images/plottreefncn.png')
```



Conclusion :

- After Importing, Fit our dataset in our model, accuracy is 89.47%.
- We can clearly see model performance by confusion matrix and classification report.
- By ploting accuracy score depth wise graph, optimal depth for model is 3.

In [ ]:

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