In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [5]:
```
from sklearn.datasets import load_iris
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix,accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score
```

In [6]:
```
iris_data=load_iris()
iris_data.keys()
```

Out[6]:
```
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_name
s', 'filename', 'data_module'])
```

In [7]:
```
print(iris_data['DESCR'])
```

```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica

    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to
a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

.. topic:: References

   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
     Mathematical Statistics" (John Wiley, NY, 1950).
   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysi
s.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
```

```
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactio
ns
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...
```

In [8]:
```
df=pd.DataFrame(iris_data.data,columns=iris_data.feature_names)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   sepal length (cm)  150 non-null    float64
 1   sepal width (cm)   150 non-null    float64
 2   petal length (cm)  150 non-null    float64
 3   petal width (cm)   150 non-null    float64
dtypes: float64(4)
memory usage: 4.8 KB
```

In [9]:
```
df.head()
```

Out[9]:

	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

In [10]:
```
df['target']=iris_data.target
df.head()
```

Out[10]:

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

In [11]:
```
df[df.target==1].head()
```

Out[11]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
50	7.0	3.2	4.7	1.4	1
51	6.4	3.2	4.5	1.5	1
52	6.9	3.1	4.9	1.5	1
53	5.5	2.3	4.0	1.3	1
54	6.5	2.8	4.6	1.5	1

In [12]:
```
df[df.target==2].head()
```

Out[12]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
100	6.3	3.3	6.0	2.5	2
101	5.8	2.7	5.1	1.9	2
102	7.1	3.0	5.9	2.1	2
103	6.3	2.9	5.6	1.8	2
104	6.5	3.0	5.8	2.2	2

In [13]:
```
iris_data['target_names']
```

Out[13]:
```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

In [15]:
```
df['flower_name']=df.target.apply(lambda x:iris_data.target_names[x])
df.head()
```

Out[15]:

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

In [16]:
```
df [45:55]
```

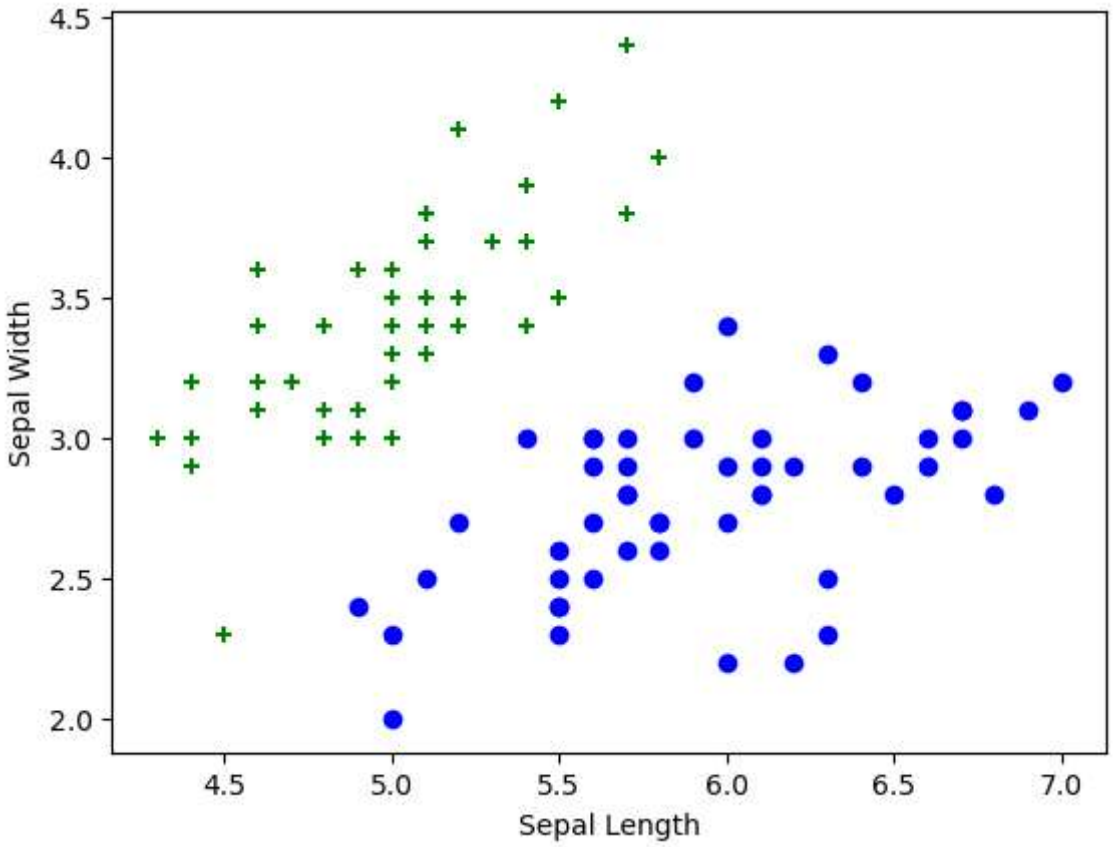
Out[16]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	flower_name
45	4.8	3.0	1.4	0.3	0	setosa
46	5.1	3.8	1.6	0.2	0	setosa
47	4.6	3.2	1.4	0.2	0	setosa
48	5.3	3.7	1.5	0.2	0	setosa
49	5.0	3.3	1.4	0.2	0	setosa
50	7.0	3.2	4.7	1.4	1	versicolor
51	6.4	3.2	4.5	1.5	1	versicolor
52	6.9	3.1	4.9	1.5	1	versicolor
53	5.5	2.3	4.0	1.3	1	versicolor
54	6.5	2.8	4.6	1.5	1	versicolor

In [18]:
```
df0=df[:50]
df1=df[50:100]
df2=df[100:]
```

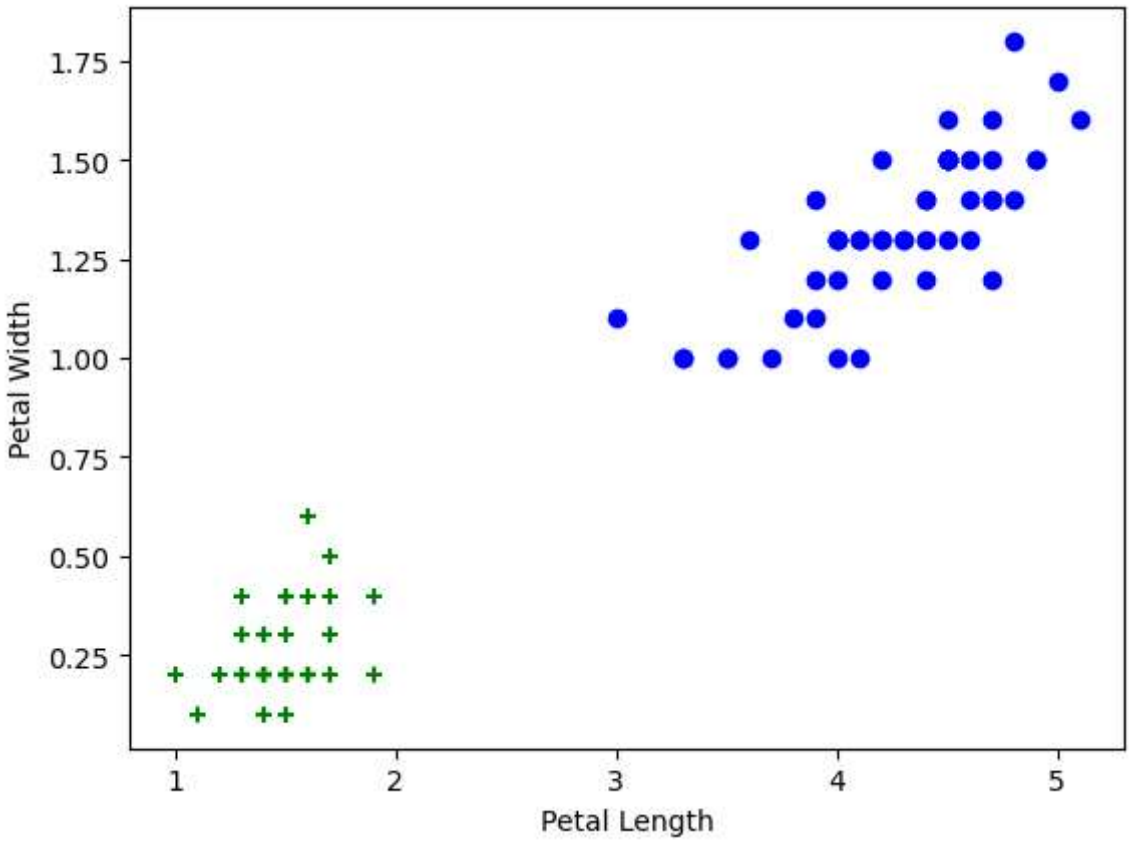
In [27]:
```
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.scatter(df0['sepal length (cm)'], df0['sepal width (cm)'],color='green',ma
plt.scatter(df1['sepal length (cm)'], df1['sepal width (cm)'],color='blue',mar
```

Out[27]:
```
<matplotlib.collections.PathCollection at 0x18ed9d632b0>
```



In [28]:
```
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.scatter(df0['petal length (cm)'], df0['petal width (cm)'],color='green',ma
plt.scatter(df1['petal length (cm)'], df1['petal width (cm)'],color='blue',mar
```

Out[28]:
```
<matplotlib.collections.PathCollection at 0x18ed72487f0>
```



In [29]:
```
df.head()
```

Out[29]:

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

In [30]:
```
x=df.drop(['target','flower_name'],axis='columns')
y=df.target
```

In [31]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state
```

In [32]:
```
len(x_train)
```

Out[32]:
```
105
```

In [33]:
```
len(x_test)
```

Out[33]:
```
45
```

In [36]:
```
knn= KNeighborsClassifier(n_neighbors=3)
knn.fit(x_train,y_train)
```

Out[36]:
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

In [38]:
```
#acuracy
acuracy=accuracy_score(y_test,y_pred)
accuracy
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[38], line 2
      1 #acuracy
----> 2 acuracy=accuracy_score(y_test,y_pred)
      3 accuracy

NameError: name 'y_pred' is not defined
```

In [40]:
```
knn.score(x_test,y_test)
```

Out[40]:
```
0.9777777777777777
```

In [41]:
```
knn.predict([[5.2,3.1,1.5,0.3]])
```

```
C:\Users\DELL\anaconda3\lib\site-packages\sklearn\base.py:420: UserWarning: X
does not have valid feature names, but KNeighborsClassifier was fitted with f
eature names
  warnings.warn(
```

Out[41]:
```
array([0])
```

In [43]:
```
y_pred=knn.predict(x_test)
cm=confusion_matrix(y_test,y_pred)
cm
```

Out[43]:
```
array([[14,  0,  0],
       [ 0, 18,  0],
       [ 0,  1, 12]], dtype=int64)
```

In [45]:
```
#acuracy
accuracy=accuracy_score(y_test,y_pred)
accuracy
```

Out[45]:
```
0.9777777777777777
```

In [47]:
```
cm1=pd.DataFrame(data=cm,index=[0,1,2],columns=['setosa','versicolor','virgini
cm1
```

Out[47]:

	setosa	versicolor	virginica
0	14	0	0
1	0	18	0
2	0	1	12

In [49]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.95      1.00      0.97        18
           2       1.00      0.92      0.96        13

    accuracy                           0.98        45
   macro avg       0.98      0.97      0.98        45
weighted avg       0.98      0.98      0.98        45
```

In [ ]:
```

```