# In [2]: # Importing the Dependencies import numpy as np import pandas as pd import matplotlib.pyplot as plt #Data Collection data=pd.read\_csv("E:\Data Science\Irisdataset.csv") data

#### Out[2]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 5 columns

### In [3]: # Data processing data.head()

#### Out[3]:

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

```
In [5]: data.describe()
```

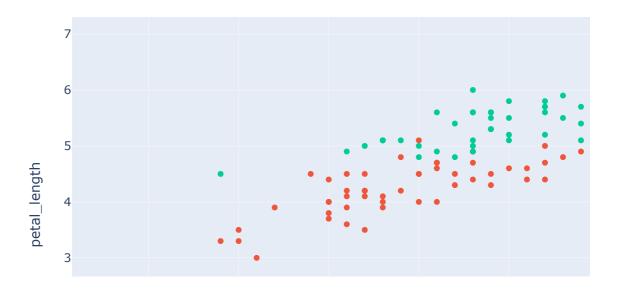
#### Out[5]:

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

```
In [ ]: data.isnull().sum()
```

```
In [ ]: import seaborn as sns
sns.countplot(data['species'])
```

```
In [16]: # Distributions of Data
import plotly.express as px
fig=px.scatter(data,x="sepal_length",y="petal_length",color="species")
fig.show()
```



```
In [6]: # Training the data by using different models
        from sklearn.model_selection import train_test_split
        X=data.drop('species',axis=1)
        Y=data['species']
        print(X)
        print(Y)
        X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.2,random_state=42
             sepal_length sepal_width petal_length petal_width
        0
                      5.1
                                   3.5
                                                 1.4
                                                              0.2
                      4.9
        1
                                   3.0
                                                 1.4
                                                              0.2
        2
                      4.7
                                   3.2
                                                 1.3
                                                              0.2
        3
                      4.6
                                                 1.5
                                                              0.2
                                   3.1
                      5.0
        4
                                   3.6
                                                 1.4
                                                              0.2
                      . . .
                                   . . .
                                                 . . .
                                                              . . .
        . .
                                                 5.2
                                                              2.3
        145
                      6.7
                                   3.0
        146
                      6.3
                                   2.5
                                                 5.0
                                                              1.9
                                  3.0
                                                              2.0
        147
                      6.5
                                                5.2
        148
                      6.2
                                  3.4
                                                5.4
                                                              2.3
                                                 5.1
                                                              1.8
        149
                      5.9
                                   3.0
        [150 rows x 4 columns]
                  Iris-setosa
        1
                  Iris-setosa
        2
                  Iris-setosa
        3
                  Iris-setosa
        4
                  Iris-setosa
                    . . .
        145
               Iris-virginica
        146
               Iris-virginica
        147
               Iris-virginica
        148
               Iris-virginica
        149
               Iris-virginica
```

#### In [18]: data.tail()

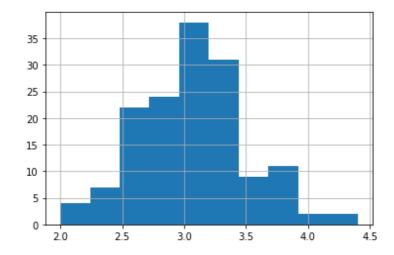
#### Out[18]:

	sepal_length	sepal_width	petal_length	petal_width	species
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

Name: species, Length: 150, dtype: object

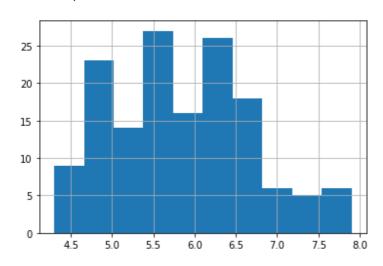
```
In [19]: data['sepal_width'].hist()
```

Out[19]: <AxesSubplot:>



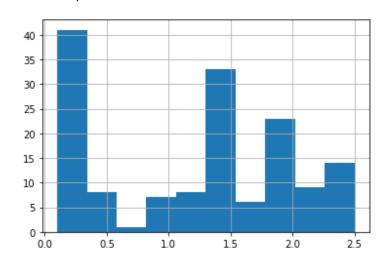
```
In [9]: data['sepal_length'].hist()
```

Out[9]: <AxesSubplot:>



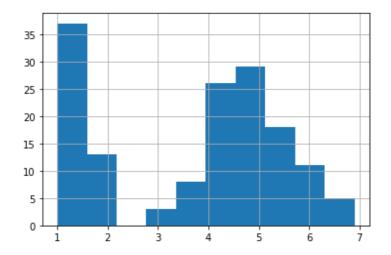
In [10]: data['petal\_width'].hist()

Out[10]: <AxesSubplot:>



```
In [11]: data['petal_length'].hist()
```

#### Out[11]: <AxesSubplot:>



### In [12]: # Corelation Matrix data.corr()

#### Out[12]:

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.109369	0.871754	0.817954
sepal_width	-0.109369	1.000000	-0.420516	-0.356544
petal_length	0.871754	-0.420516	1.000000	0.962757
petal_width	0.817954	-0.356544	0.962757	1.000000

## In [13]: #DecisionTreeClassifier from sklearn.model\_selection import train\_test\_split X=data.drop('species',axis=1) Y=data['species'] X\_train,X\_test,Y\_train,Y\_test=train\_test\_split(X,Y,test\_size=0.2,random\_state=42)

### In [14]: from sklearn.tree import DecisionTreeClassifier f1=DecisionTreeClassifier() f1.fit(X\_train,Y\_train) l1=f1.score(X\_test,Y\_test)\*100 print("Accuracy of Iris Flower Classifer using DecisionTreeClassifier is",l1)

Accuracy of Iris Flower Classifer using DecisionTreeClassifier is 100.0

## In [15]: #KNeighborsClassifier from sklearn.neighbors import KNeighborsClassifier f11=KNeighborsClassifier() f11.fit(X\_train,Y\_train) l11=f11.score(X\_test,Y\_test)\*100 print("Accuracy of Iris Flower Classifer using KNeighborsClassifier is",l11)

Accuracy of Iris Flower Classifer using KNeighborsClassifier is 100.0

```
In [21]: # Classification Algorithm
    from sklearn.neighbors import KNeighborsClassifier
    knn=KNeighborsClassifier(n_neighbors=1)
    knn.fit(X_train,Y_train)
    x=np.array([[4.6,3.1,1.5,0.2]])
    predict=knn.predict(x)
    print("Prediction:{}".format(predict))
```

Prediction:['Iris-setosa']

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning:

 $\boldsymbol{X}$  does not have valid feature names, but KNeighborsClassifier was fitted with  $\boldsymbol{f}$  eature names

In [ ]:	