Iris Flower Prediction

```
# Importing essential libraries

# for numerical operations
import numpy as np
import pandas as pd
# for Vizualisation
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing and Understanding Dataset

```
# loading dataset
iris=pd.read_csv('/content/drive/MyDrive/Datasets/CodSoft/IRIS.xls')
iris
```

	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

```
# print no. of rows and columns(order)
iris.shape
```

```
(150, 5)
```

```
# print total no. of elements(size)
iris.size
```

```
750
```

```
# printing first five rows
iris.head()
```

	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

```
# printing last five rows
iris.tail()
```

	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

```
# print column labels
iris.columns
```

```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',
       'species'],
      dtype='object')
```

```
# print datatype of each column
iris.dtypes
```

```
sepal_length    float64
sepal_width     float64
petal_length    float64
petal_width     float64
species          object
dtype: object
```

```
# count of unique values in Species
count=iris['species'].value_counts()
count
```

```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: species, dtype: int64
```

```
# print information about dataframe
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

```
# print statistical summary of dataframe
iris.describe()
```

	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

```
# checking for missing values
iris.isna().sum()
```

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

```
# separating input and output
x=iris.iloc[:,:-1].values
y=iris.iloc[:,-1].values
print("Dimensions \nX :",x.ndim,"\nY :",y.ndim)
```

```
Dimensions
X : 2
Y : 1
```

```
x
```

```
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, 0.1],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.1, 1.5, 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. ],
```

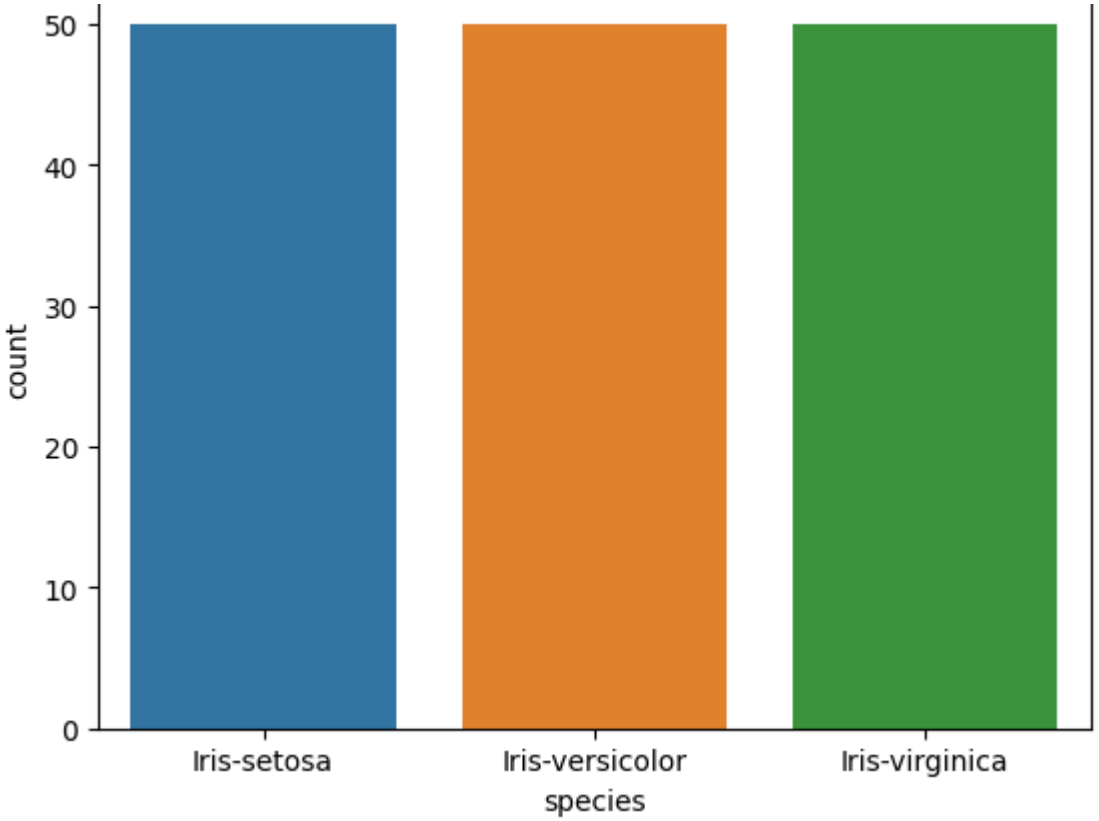
```
y
```

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

Data Visualization

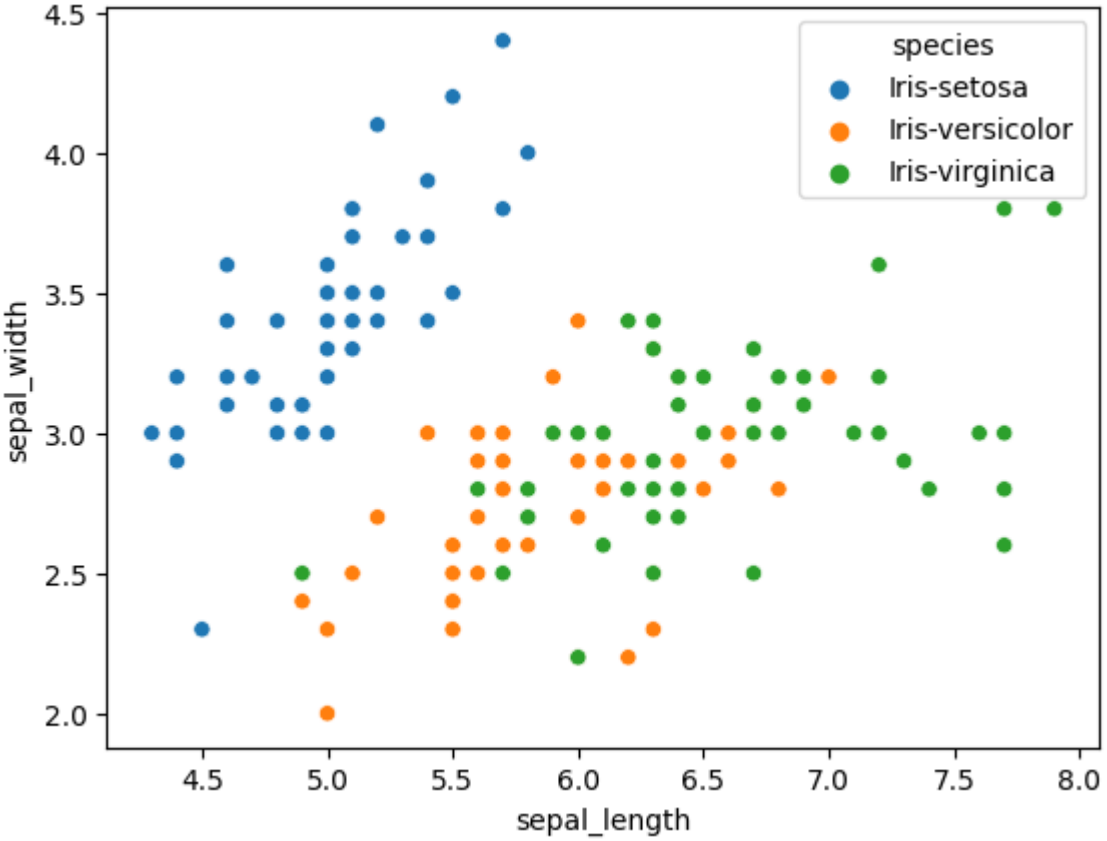
```
#countplot
sns.countplot(data=iris,x='species')
```

```
<Axes: xlabel='species', ylabel='count'>
```



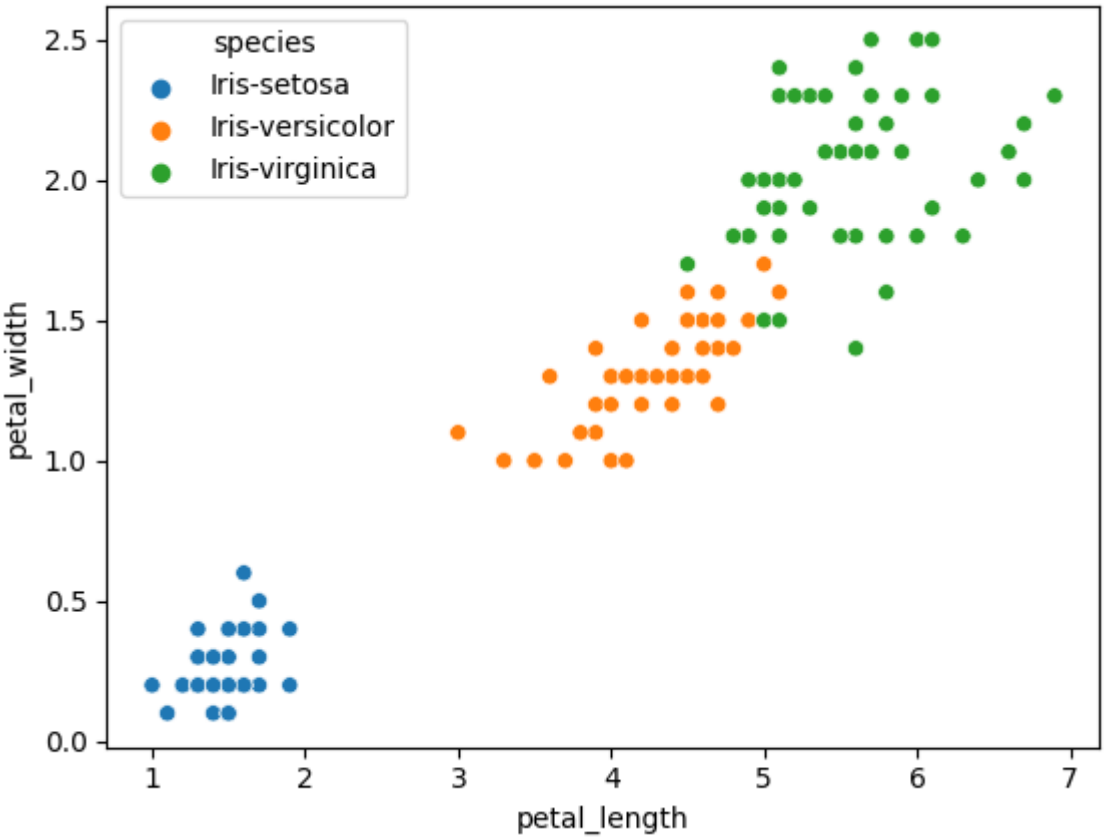

```
# scatterplot
sns.scatterplot(data=iris,x='sepal_length',y='sepal_width',hue='species')
```

```
<Axes: xlabel='sepal_length', ylabel='sepal_width'>
```



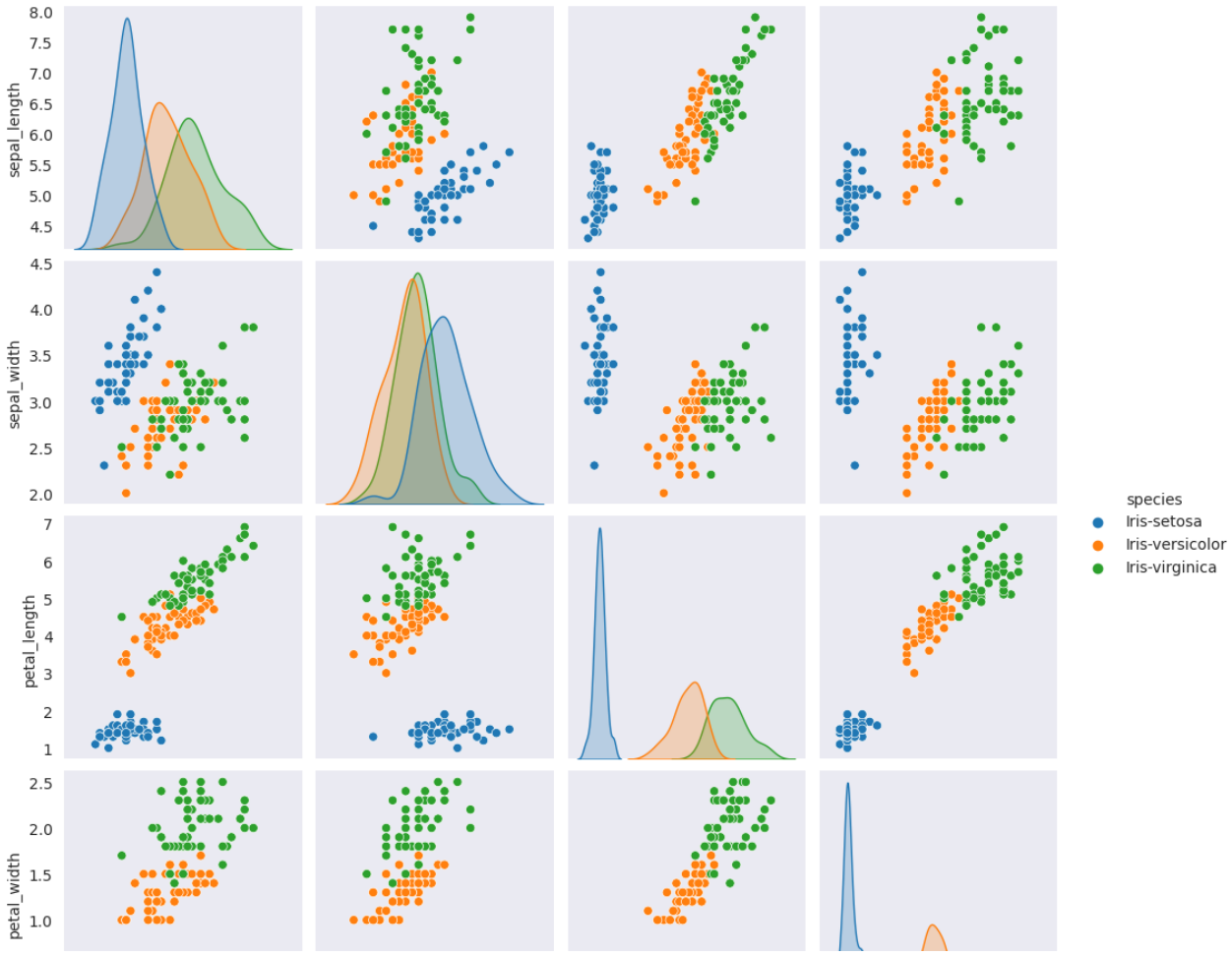

```
sns.scatterplot(data=iris,x='petal_length',y='petal_width',hue='species')
```

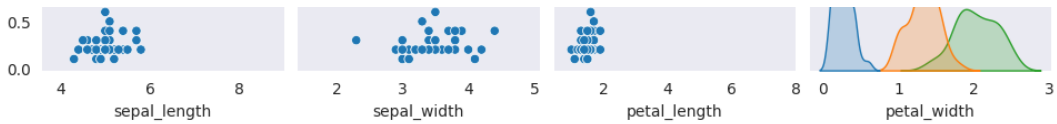
```
<Axes: xlabel='petal_length', ylabel='petal_width'>
```




```
# pairplot
sns.set_style('dark')
sns.pairplot(data=iris,hue='species')
```

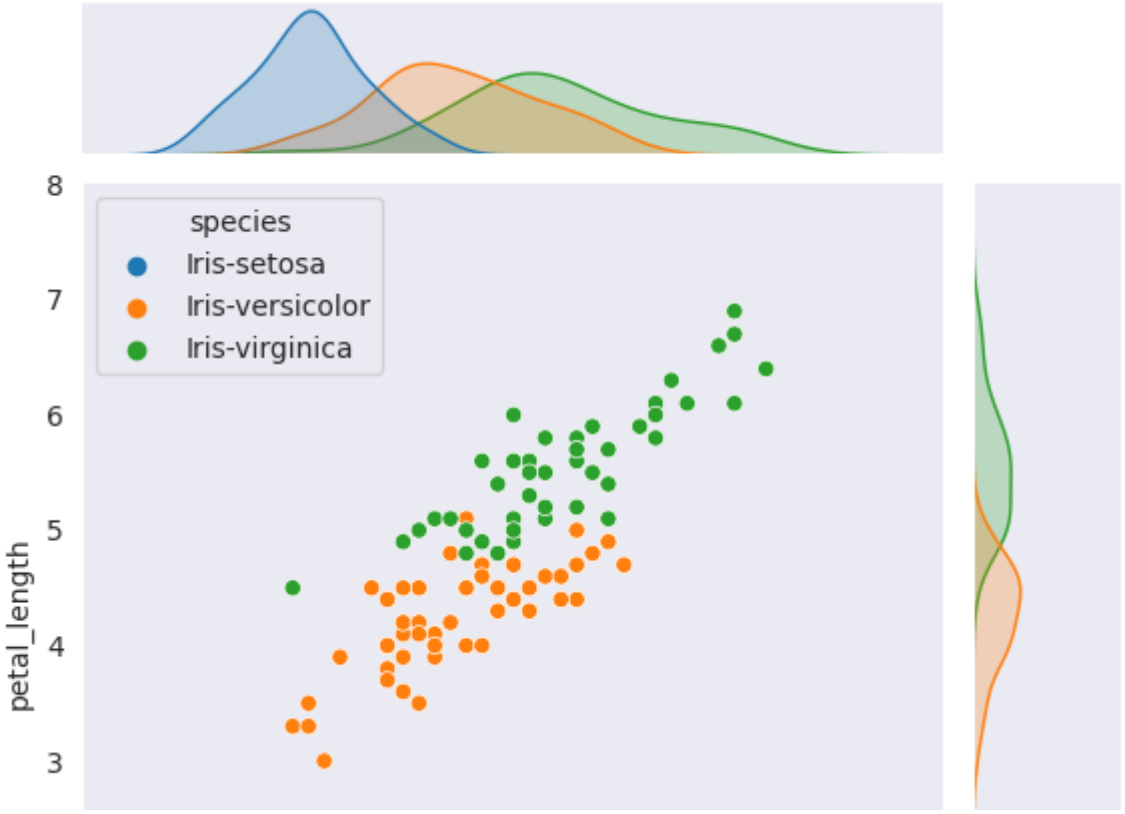
```
<seaborn.axisgrid.PairGrid at 0x7cab99527790>
```

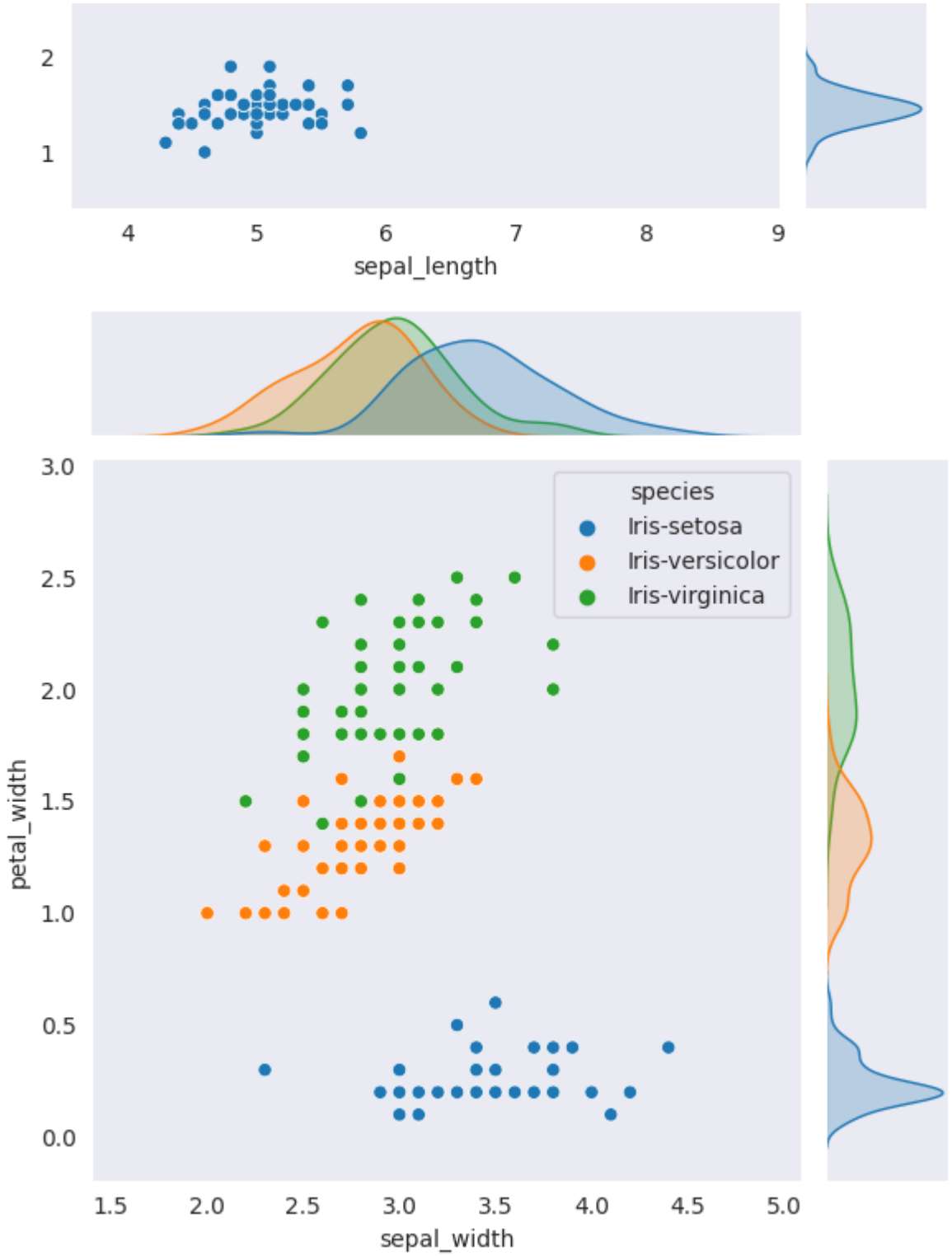





```
# jointplot
sns.jointplot(data=iris,x="sepal_length", y="petal_length",hue="species")
sns.jointplot(data=iris,x="sepal_width", y="petal_width",hue="species")
```

```
<seaborn.axisgrid.JointGrid at 0x7cab969bd1e0>
```

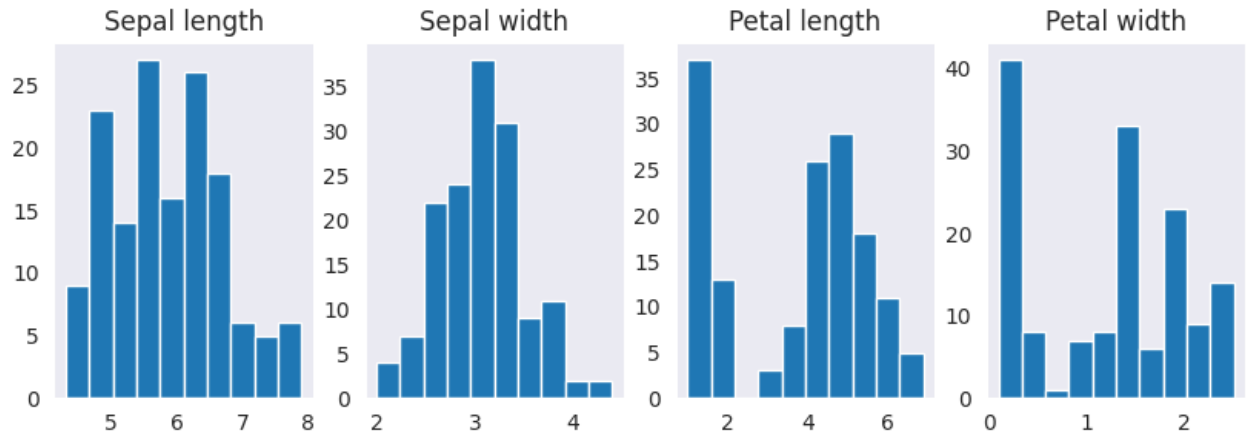





```
# histogram
plt.figure(figsize=(10,3))
plt.subplot(1,4,1)
plt.title("Sepal length")
plt.hist(iris['sepal_length'])
plt.subplot(1,4,2)
plt.title("Sepal width")
plt.hist(iris['sepal_width'])
plt.subplot(1,4,3)
plt.title("Petal length")
plt.hist(iris['petal_length'])
plt.subplot(1,4,4)
```

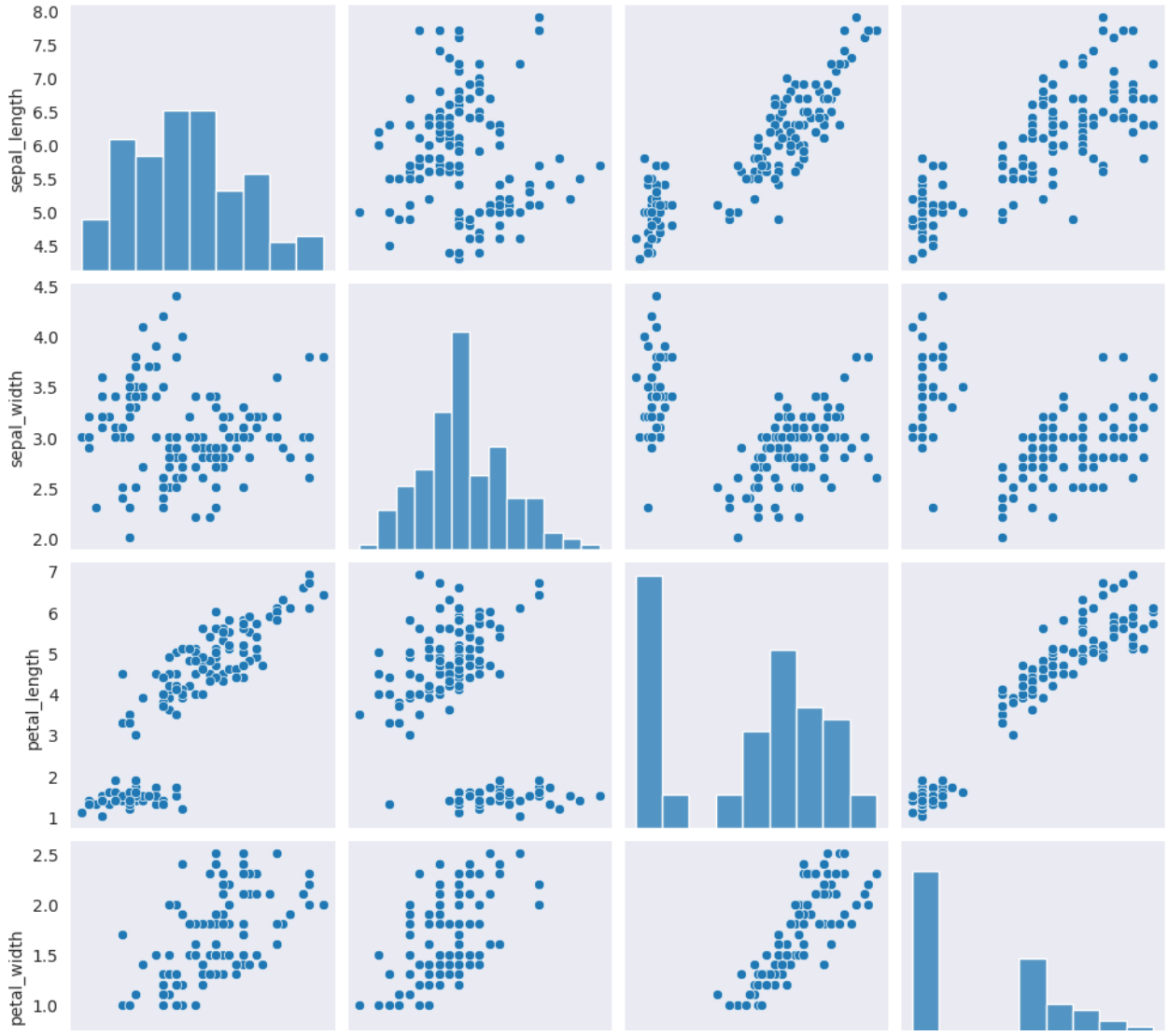
```
plt.title("Petal width")
plt.hist(iris['petal_width'])
```

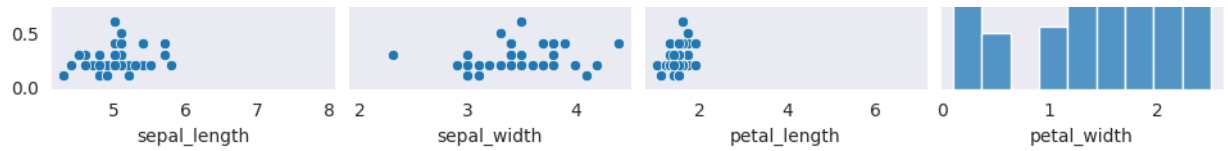
```
(array([41.,  8.,  1.,  7.,  8., 33.,  6., 23.,  9., 14.]),
 array([0.1 , 0.34, 0.58, 0.82, 1.06, 1.3 , 1.54, 1.78, 2.02, 2.26, 2.5 ]),
 <BarContainer object of 10 artists>)
```




```
sns.pairplot(data=iris)
```

```
<seaborn.axisgrid.PairGrid at 0x7cab94763b20>
```





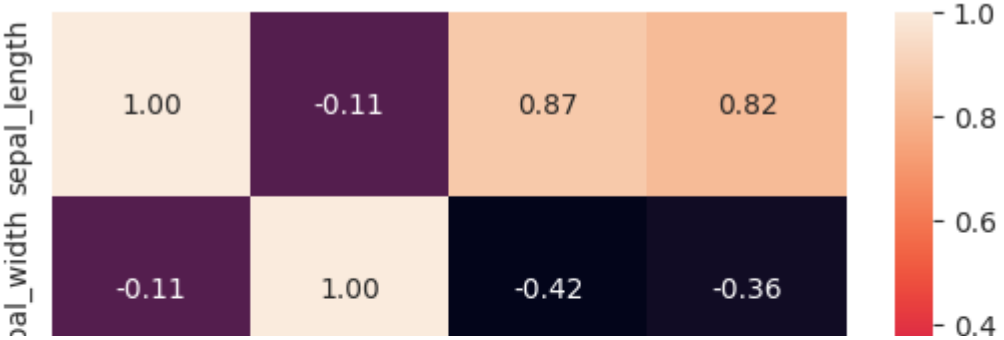

```
# relation between columns
iris.corr()
```

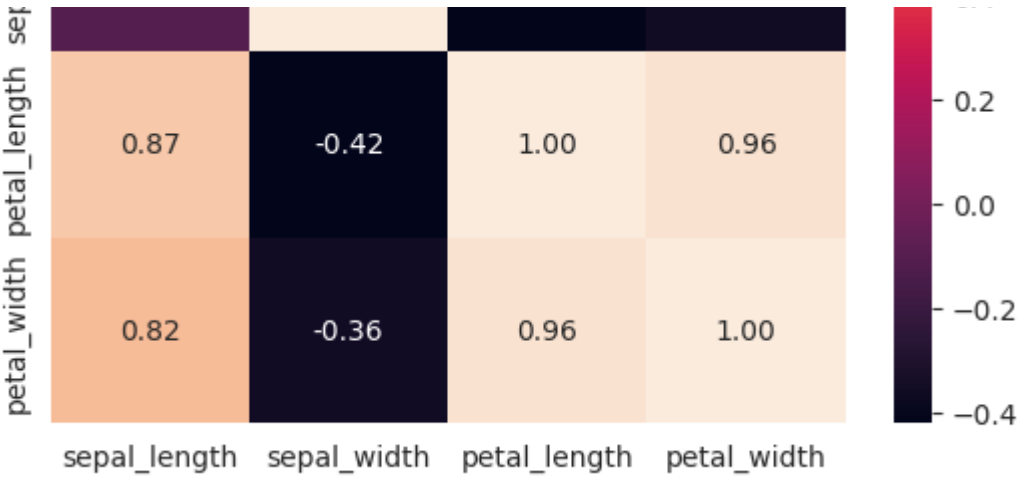
```
<ipython-input-23-58d4d0b42aac>:2: FutureWarning: The default value of numeric_onl
  iris.corr()
```

	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

```
# plotting correlation(heatmap)
sns.heatmap(iris.corr(),annot=True,fmt='.2f')
```

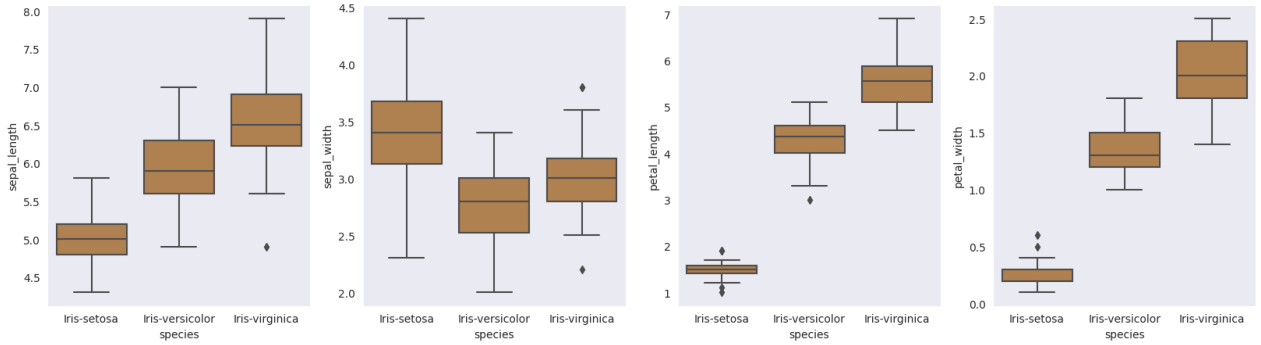
```
<ipython-input-24-01eb509bbb3c>:2: FutureWarning: The default value of numeric_onl
  sns.heatmap(iris.corr(),annot=True,fmt='.2f')
<Axes: >
```






```
# boxplot(checking outliers)
plt.figure(figsize=(20,5))
plt.subplot(1,4,1)
sns.boxplot(x=iris['species'],y=iris['sepal_length'],color='#bf8040')
plt.subplot(1,4,2)
sns.boxplot(x=iris['species'],y=iris['sepal_width'],color='#bf8040')
plt.subplot(1,4,3)
sns.boxplot(x=iris['species'],y=iris['petal_length'],color='#bf8040')
plt.subplot(1,4,4)
sns.boxplot(x=iris['species'],y=iris['petal_width'],color='#bf8040')
```

```
<Axes: xlabel='species', ylabel='petal_width'>
```




```
# splitting dataset into training and testing data
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=42)

x_train
```

```
_
    array([[5.5, 2.4, 3.7, 1. ],
           [6.3, 2.8, 5.1, 1.5],
           [6.4, 3.1, 5.5, 1.8],
           [6.6, 3. , 4.4, 1.4],
           [7.2, 3.6, 6.1, 2.5],
           [5.7, 2.9, 4.2, 1.3],
           [7.6, 3. , 6.6, 2.1],
           [5.6, 3. , 4.5, 1.5],
           [5.1, 3.5, 1.4, 0.2],
           [7.7, 2.8, 6.7, 2. ],
           [5.8, 2.7, 4.1, 1. ],
           [5.2, 3.4, 1.4, 0.2],
           [5. , 3.5, 1.3, 0.3],
           [5.1, 3.8, 1.9, 0.4],
           [5. , 2. , 3.5, 1. ],
           [6.3, 2.7, 4.9, 1.8],
           [4.8, 3.4, 1.9, 0.2],
           [5. , 3. , 1.6, 0.2],
           [5.1, 3.3, 1.7, 0.5],
           [5.6, 2.7, 4.2, 1.3],
           [5.1, 3.4, 1.5, 0.2],
           [5.7, 3. , 4.2, 1.2],
           [7.7, 3.8, 6.7, 2.2],
           [4.6, 3.2, 1.4, 0.2],
           [6.2, 2.9, 4.3, 1.3],
           [5.7, 2.5, 5. , 2. ],
           [5.5, 4.2, 1.4, 0.2],
           [6. , 3. , 4.8, 1.8],
           [5.8, 2.7, 5.1, 1.9],
           [6. , 2.2, 4. , 1. ],
           [5.4, 3. , 4.5, 1.5],
           [6.2, 3.4, 5.4, 2.3],
           [5.5, 2.3, 4. , 1.3],
           [5.4, 3.9, 1.7, 0.4],
           [5. , 2.3, 3.3, 1. ],
           [6.4, 2.7, 5.3, 1.9],
           [5. , 3.3, 1.4, 0.2],
           [5. , 3.2, 1.2, 0.2],
           [5.5, 2.4, 3.8, 1.1],
           [6.7, 3. , 5. , 1.7],
           [4.9, 3.1, 1.5, 0.1],
           [5.8, 2.8, 5.1, 2.4],
           [5. , 3.4, 1.5, 0.2],
           [5. , 3.5, 1.6, 0.6],
           [5.9, 3.2, 4.8, 1.8],
           [5.1, 2.5, 3. , 1.1],
           [6.9, 3.2, 5.7, 2.3],
           [6. , 2.7, 5.1, 1.6],
           [6.1, 2.6, 5.6, 1.4],
           [7.7, 3. , 6.1, 2.3],
           [5.5, 2.5, 4. , 1.3],
           [4.4, 2.9, 1.4, 0.2],
           [4.3, 3. , 1.1, 0.1],
           [6. , 2.2, 5. , 1.5],
           [7.2, 3.2, 6. , 1.8],
           [4.6, 3.1, 1.5, 0.2],
           [5.1, 3.5, 1.4, 0.3],
           [4.4, 3. , 1.3, 0.2],
```

```
x_test
```

```
array([[6.1, 2.8, 4.7, 1.2],
       [5.7, 3.8, 1.7, 0.3],
       [7.7, 2.6, 6.9, 2.3],
       [6. , 2.9, 4.5, 1.5],
       [6.8, 2.8, 4.8, 1.4],
       [5.4, 3.4, 1.5, 0.4],
       [5.6, 2.9, 3.6, 1.3],
       [6.9, 3.1, 5.1, 2.3],
       [6.2, 2.2, 4.5, 1.5],
       [5.8, 2.7, 3.9, 1.2],
       [6.5, 3.2, 5.1, 2. ],
       [4.8, 3. , 1.4, 0.1],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.1, 3.8, 1.5, 0.3],
       [6.3, 3.3, 4.7, 1.6],
       [6.5, 3. , 5.8, 2.2],
       [5.6, 2.5, 3.9, 1.1],
       [5.7, 2.8, 4.5, 1.3],
       [6.4, 2.8, 5.6, 2.2],
       [4.7, 3.2, 1.6, 0.2],
       [6.1, 3. , 4.9, 1.8],
       [5. , 3.4, 1.6, 0.4],
       [6.4, 2.8, 5.6, 2.1],
       [7.9, 3.8, 6.4, 2. ],
       [6.7, 3. , 5.2, 2.3],
       [6.7, 2.5, 5.8, 1.8],
       [6.8, 3.2, 5.9, 2.3],
       [4.8, 3. , 1.4, 0.3],
       [4.8, 3.1, 1.6, 0.2],
       [4.6, 3.6, 1. , 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [6.7, 3.1, 4.4, 1.4],
       [4.8, 3.4, 1.6, 0.2],
       [4.4, 3.2, 1.3, 0.2],
       [6.3, 2.5, 5. , 1.9],
       [6.4, 3.2, 4.5, 1.5],
       [5.2, 3.5, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
       [5.2, 4.1, 1.5, 0.1],
       [5.8, 2.7, 5.1, 1.9],
       [6. , 3.4, 4.5, 1.6],
       [6.7, 3.1, 4.7, 1.5],
       [5.4, 3.9, 1.3, 0.4],
       [5.4, 3.7, 1.5, 0.2]])
```

```
y_train
```

```
array(['Iris-versicolor', 'Iris-virginica', 'Iris-virginica',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
```

```
       'Iris-virginica', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-setosa', 'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
       'Iris-setosa', 'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-virginica', 'Iris-virginica', 'Iris-versicolor',
       'Iris-setosa', 'Iris-setosa', 'Iris-virginica', 'Iris-virginica',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-versicolor',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-virginica',
       'Iris-setosa', 'Iris-versicolor', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-virginica',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-virginica',
       'Iris-setosa', 'Iris-versicolor', 'Iris-virginica', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

```
y_test
```

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

```
# standardization technique used for normalization
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
ss.fit(x_train)
x_train=ss.transform(x_train)
x_test=ss.transform(x_test)
```

Model Creation

K-Nearest Neighbours

```
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=7)
```

```
knn.fit(x_train,y_train)
y_pred_knn=knn.predict(x_test)
y_pred_knn
```

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

```
# Performance Evaluation
from sklearn.metrics import confusion_matrix,accuracy_score
print("Confusion Matrix :\n",confusion_matrix(y_test,y_pred_knn))
print("Accuracy Score :",(accuracy_score(y_test,y_pred_knn)*100),"%")
```

```
Confusion Matrix :
 [[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
Accuracy Score : 100.0 %
```

Naive Bayes Classification

```
from sklearn.naive_bayes import GaussianNB
nb=GaussianNB()
nb.fit(x_train,y_train)
y_pred_nb=nb.predict(x_test)
y_pred_nb
```

```
array(['Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-virginica', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-virginica',
       'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa', 'Iris-setosa'], dtype='<U15')
```

```
# Performance Evaluation
print("Confusion Matrix :\n",confusion_matrix(y_test,y_pred_nb))
print("Accuracy Score :",(accuracy_score(y_test,y_pred_nb)*100),"%")
```

```
Confusion Matrix :
```

```
 [[19  0  0]
 [ 0 12  1]
 [ 0  0 13]]
Accuracy Score : 97.77777777777777 %
```

Support Vector Machine(SVM)

```
from sklearn.svm import SVC
svm=SVC()
svm.fit(x_train,y_train)
y_pred_svm=svm.predict(x_test)
y_pred_svm
```

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

```
# Performance Evaluation
print("Confusion Matrix :\n",confusion_matrix(y_test,y_pred_svm))
print("Accuracy Score :",(accuracy_score(y_test,y_pred_svm)*100),"%")
```

```
Confusion Matrix :
 [[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
Accuracy Score : 100.0 %
```

Decision Tree Classification

```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier(criterion='entropy')
dtc.fit(x_train,y_train)
y_pred_dtc=dtc.predict(x_test)
y_pred_dtc
```

```
array(['Iris-versicolor', 'Iris-setosa', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-virginica',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-virginica',
       'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
```

```
       'Iris-virginica', 'Iris-versicolor', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-virginica', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-setosa', 'Iris-setosa'], dtype=object)
```

```
# Performance Evaluation
print("Confusion Matrix :\n",confusion_matrix(y_test,y_pred_dtc))
print("Accuracy Score :",(accuracy_score(y_test,y_pred_dtc)*100),"%")
```

```
Confusion Matrix :
 [[19  0  0]
 [ 0 13  0]
 [ 0  2 11]]
Accuracy Score : 95.55555555555556 %
```

Random Forest Classification

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
y_pred_rfc=rfc.predict(x_test)
y_pred_rfc
```

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

```
# Performance Evaluation
print("Confusion Matrix :\n",confusion_matrix(y_test,y_pred_rfc))
print("Accuracy Score :",(accuracy_score(y_test,y_pred_rfc)*100),"%")
```

```
Confusion Matrix :
 [[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
Accuracy Score : 100.0 %
```