

iris-flower-classification

November 2, 2023

1 IRIS DATASET

1.0.1 ABOUT THE DATASET

The Iris flower data set is a multivariate data set introduced by the British statistician and biologist Ronald Fisher in his 1936 paper The use of multiple measurements in taxonomic problems. It is sometimes called Anderson's Iris data set because Edgar Anderson collected the data to quantify the morphologic variation of Iris flowers of three related species. The data set consists of 50 samples from each of three species of Iris (Iris Setosa, Iris virginica, and Iris versicolor). Four features were measured from each sample: the length and the width of the sepals and petals, in centimeters. This dataset became a typical test case for many statistical classification techniques in machine learning such as support vector machines

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

```
[2]: #loading the dataset
df=pd.read_csv('/content/IRIS (1).csv')
df
```

```
[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 x 5 columns]

1.0.2 DATA PREPROCESSING

```
[3]: # Getting top 5 rows of Dataset
df.head()
```

```
[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
```

```
[4]: # Getting last 5 rows of Dataset
df.tail()
```

```
[4]:   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
```

```
[5]: #Getting all columns
df.columns
```

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

```
[6]: #check the descriptive statistics of numeric variables
df.describe()
```

```
[6]:   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
```

```
[7]: #view the dataset information
df.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

```
[8]: #checking for missing values
df.isna().sum()
```

```
[8]: sepal_length    0
      sepal_width    0
      petal_length   0
      petal_width    0
      species        0
      dtype: int64
```

```
[9]: #checking duplicates values
df.duplicated().sum()
```

```
[9]: 3
```

```
[10]: #removing duplicates rows
df.drop_duplicates(inplace=True)
```

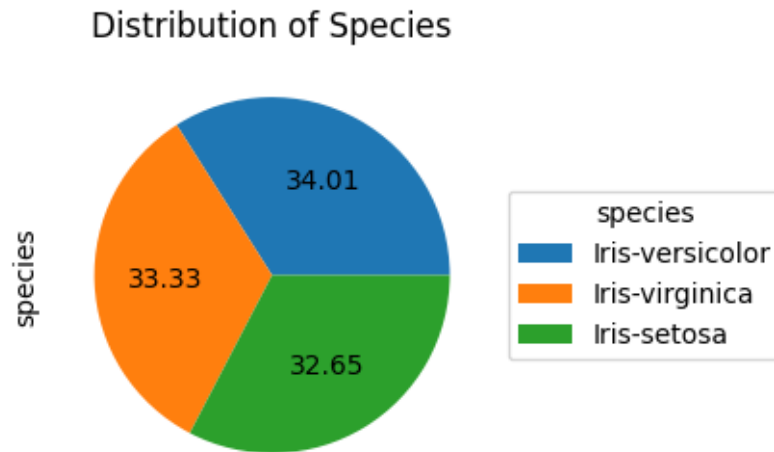
```
[11]: df.shape
```

```
[11]: (147, 5)
```

DATA VISUALIZATION

```
[12]: plt.figure(figsize=(5,3))
      df["species"].value_counts().plot(kind='pie',autopct='%.2f',labels=None)
      plt.legend(df["species"].value_counts().index, title="species", loc="center_␣
      ↪left", bbox_to_anchor=(1, 0.5))
      plt.title("Distribution of Species")
```

```
[12]: Text(0.5, 1.0, 'Distribution of Species')
```



```
[13]: plt.figure(figsize=(8,6));  
sns.scatterplot(x=df.sepal_length,y=df.sepal_width,hue=df.species).  
      ↪set_title("Sepal length and Sepal width distribution of three flowers")
```

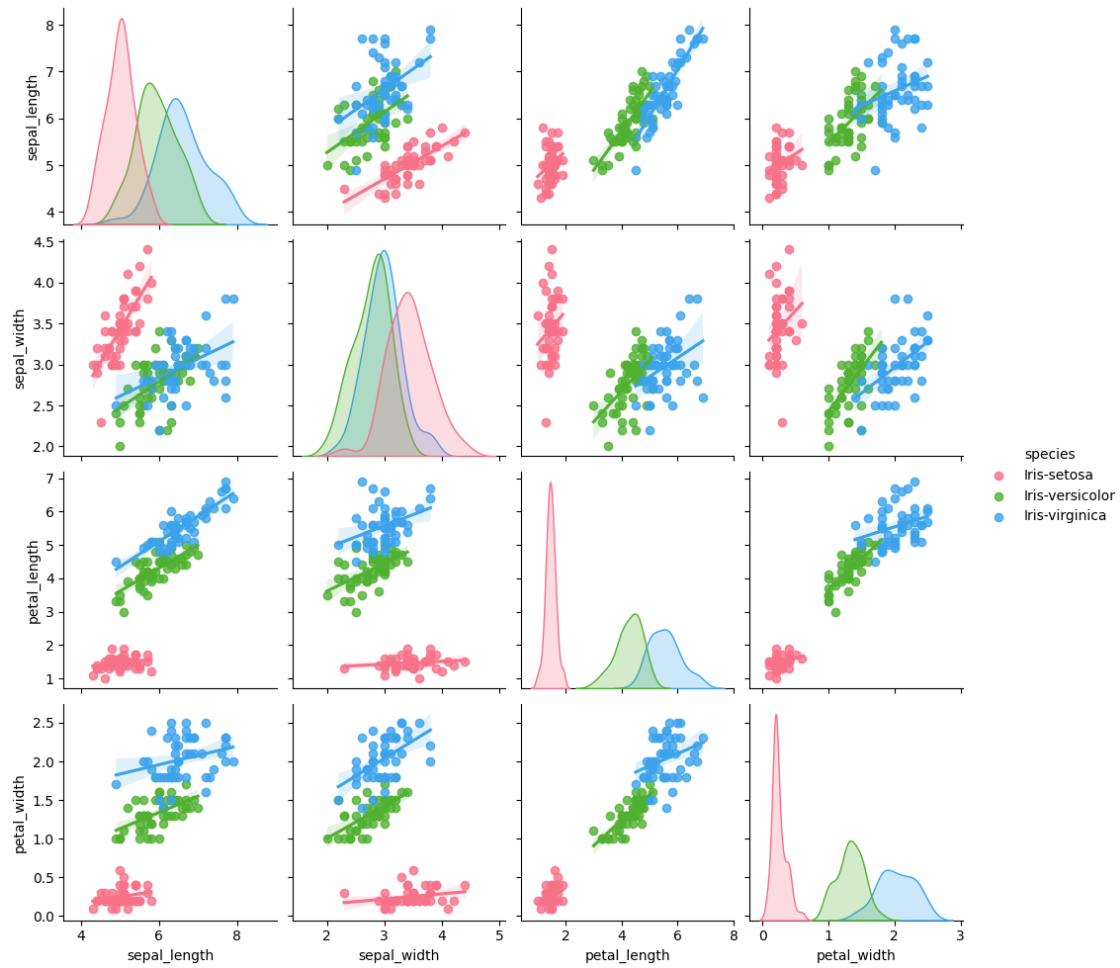
```
[13]: Text(0.5, 1.0, 'Sepal length and Sepal width distribution of three flowers')
```



```
[14]: plt.figure(figsize=(8,6));  
sns.pairplot(df,kind='reg',hue = 'species',palette="husl" )
```

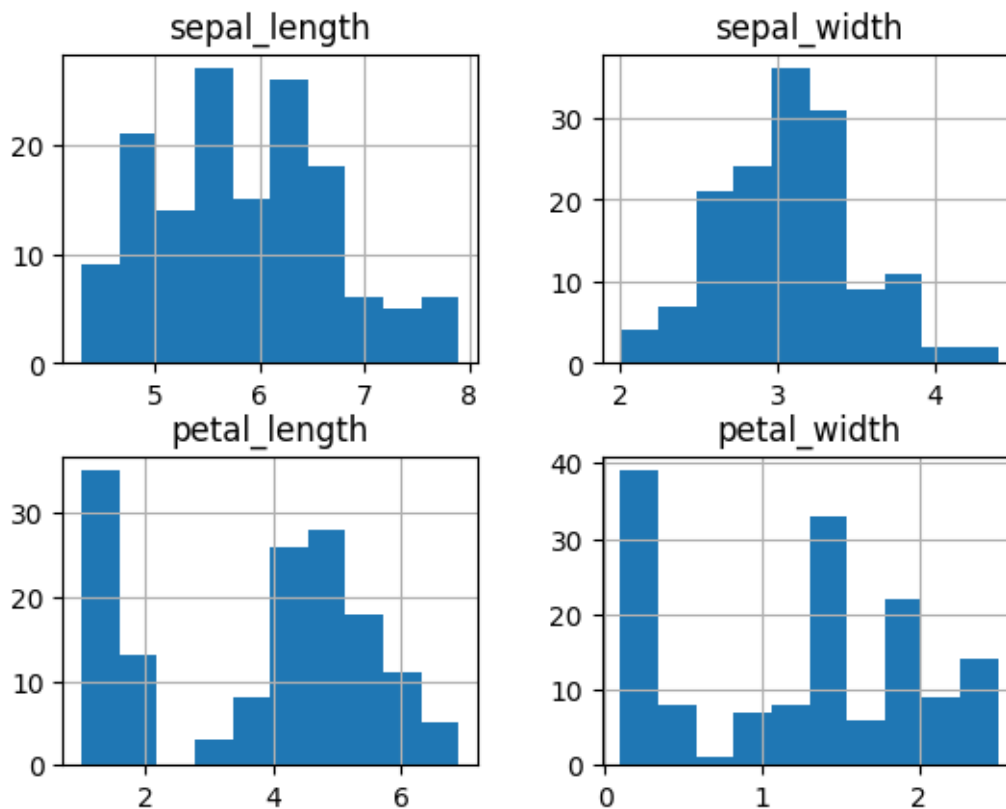
```
[14]: <seaborn.axisgrid.PairGrid at 0x7aae0d84be20>
```

```
<Figure size 800x600 with 0 Axes>
```



```
[15]: df.hist()
```

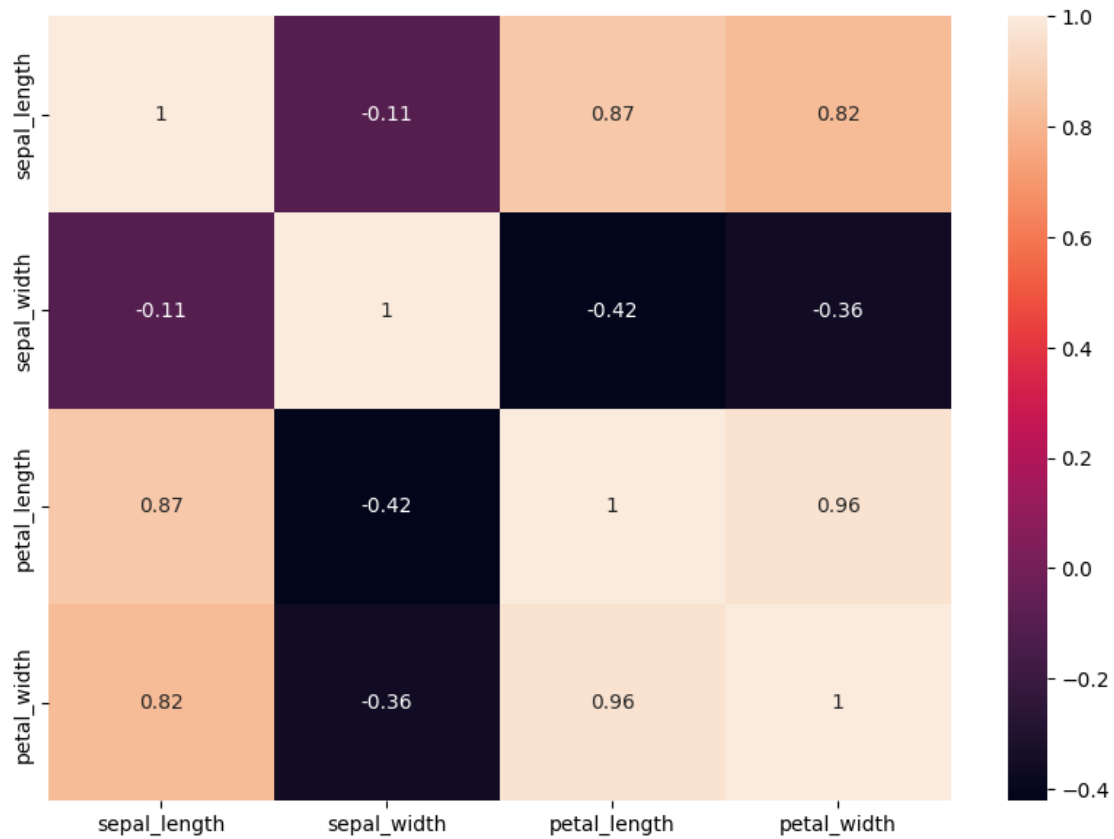
```
[15]: array([[<Axes: title={'center': 'sepal_length'}>,
<Axes: title={'center': 'sepal_width'}>],
[<Axes: title={'center': 'petal_length'}>,
<Axes: title={'center': 'petal_width'}>]], dtype=object)
```



```
[16]: plt.figure(figsize = (10,7))
sns.heatmap(df.corr(), annot = True)
plt.show()
```

<ipython-input-16-8e3c60167342>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df.corr(), annot = True)
```



1.0.3 Splitting Independent and Dependent Features

```
[17]: x=df.iloc[:, :-1].values
      x
```

```
[17]: 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],
 [5. , 3.2, 1.2, 0.2],
 [5.5, 3.5, 1.3, 0.2],
 [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],
[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]]

```
[18]: y=df.iloc[:,-1].values
      y
```

```
[18]: 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'])
```

[illegible]

1.0.4 MODEL SELECTION

```
[19]: 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)
```

```
[20]: x_train
```

```
[20]: array([[5.7, 3. , 4.2, 1.2],
             [6.8, 3.2, 5.9, 2.3],
             [6.5, 3.2, 5.1, 2. ],
             [5.1, 3.5, 1.4, 0.2],
             [6.6, 3. , 4.4, 1.4],
             [5.8, 2.7, 4.1, 1. ],
             [5.2, 3.4, 1.4, 0.2],
             [4.4, 3.2, 1.3, 0.2],
             [6. , 2.2, 4. , 1. ],
             [4.8, 3.4, 1.9, 0.2],
             [5. , 3. , 1.6, 0.2],
             [5.1, 3.3, 1.7, 0.5],
             [6. , 2.2, 5. , 1.5],
             [6.7, 3.1, 4.7, 1.5],
             [6.7, 3. , 5.2, 2.3],
             [5.1, 3.8, 1.6, 0.2],
             [5.7, 4.4, 1.5, 0.4],
             [6.3, 2.9, 5.6, 1.8],
             [4.5, 2.3, 1.3, 0.3],
             [5.9, 3.2, 4.8, 1.8],
             [6.5, 3. , 5.5, 1.8],
             [5. , 3.3, 1.4, 0.2],
             [5.7, 2.9, 4.2, 1.3],
             [6.8, 3. , 5.5, 2.1],
             [5.5, 4.2, 1.4, 0.2],
             [5.6, 3. , 4.1, 1.3],
             [6.3, 3.3, 6. , 2.5],
             [5.6, 2.9, 3.6, 1.3],
             [6.4, 2.8, 5.6, 2.1],
             [5.5, 2.4, 3.8, 1.1],
             [5.7, 2.8, 4.5, 1.3],
             [5.4, 3.9, 1.7, 0.4],
             [7.7, 2.8, 6.7, 2. ],
             [5.7, 2.8, 4.1, 1.3],
             [6.4, 3.2, 4.5, 1.5],
             [5.5, 3.5, 1.3, 0.2],
             [5.8, 2.7, 3.9, 1.2],
             [5.7, 2.6, 3.5, 1. ],
             [5. , 3.2, 1.2, 0.2],
             [5.7, 2.5, 5. , 2. ],
             [5. , 3.4, 1.5, 0.2],
             [4.8, 3. , 1.4, 0.3],
             [6.3, 2.5, 4.9, 1.5],
             [6.2, 2.9, 4.3, 1.3],
             [6. , 3.4, 4.5, 1.6],
```

[6.3, 2.8, 5.1, 1.5],
[6.1, 2.6, 5.6, 1.4],
[6.1, 3. , 4.6, 1.4],
[4.4, 2.9, 1.4, 0.2],
[4.3, 3. , 1.1, 0.1],
[6. , 3. , 4.8, 1.8],
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[4.6, 3.1, 1.5, 0.2],
[5.1, 3.5, 1.4, 0.3],
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[7.1, 3. , 5.9, 2.1],
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[6.7, 3.1, 4.4, 1.4],
[6.3, 3.3, 4.7, 1.6],
[7.2, 3.2, 6. , 1.8],
[6.9, 3.1, 4.9, 1.5],
[5.8, 2.8, 5.1, 2.4],
[5.3, 3.7, 1.5, 0.2],
[6.4, 3.2, 5.3, 2.3],
[6.1, 2.9, 4.7, 1.4],
[6.5, 3. , 5.2, 2.],
[5.5, 2.4, 3.7, 1.],
[5.9, 3. , 4.2, 1.5],
[5. , 2.3, 3.3, 1.],
[5. , 3.5, 1.6, 0.6],
[5. , 2. , 3.5, 1.],
[5.8, 2.6, 4. , 1.2],
[7. , 3.2, 4.7, 1.4],
[5.5, 2.6, 4.4, 1.2],
[7.2, 3.6, 6.1, 2.5],
[5.1, 3.7, 1.5, 0.4],
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[6.7, 3. , 5. , 1.7],
[5.2, 4.1, 1.5, 0.1],
[6.7, 3.3, 5.7, 2.5],
[5.1, 3.4, 1.5, 0.2],
[6.9, 3.1, 5.4, 2.1],
[4.9, 3. , 1.4, 0.2],
[6.5, 2.8, 4.6, 1.5],
[6.4, 2.8, 5.6, 2.2],
[7.6, 3. , 6.6, 2.1],
[5.8, 2.7, 5.1, 1.9],
[7.7, 2.6, 6.9, 2.3],

```

[5.5, 2.5, 4. , 1.3],
[6.8, 2.8, 4.8, 1.4],
[6.3, 2.7, 4.9, 1.8],
[5.9, 3. , 5.1, 1.8],
[5.4, 3.4, 1.7, 0.2],
[6.1, 2.8, 4.7, 1.2],
[6.7, 2.5, 5.8, 1.8],
[5.8, 4. , 1.2, 0.2],
[5.6, 2.7, 4.2, 1.3],
[6.5, 3. , 5.8, 2.2]])

```

```
[21]: x_test
```

```

[21]: array([[6.1, 3. , 4.9, 1.8],
 [5.5, 2.3, 4. , 1.3],
 [6.7, 3.1, 5.6, 2.4],
 [5.1, 3.8, 1.5, 0.3],
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 [4.9, 3.1, 1.5, 0.1],
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 [4.8, 3.1, 1.6, 0.2],
 [4.7, 3.2, 1.6, 0.2],
 [7.3, 2.9, 6.3, 1.8],
 [4.4, 3. , 1.3, 0.2],
 [6.9, 3.2, 5.7, 2.3],
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 [5.6, 3. , 4.5, 1.5],
 [7.7, 3. , 6.1, 2.3],
 [5.4, 3. , 4.5, 1.5],
 [4.8, 3.4, 1.6, 0.2],
 [6.4, 3.1, 5.5, 1.8],
 [4.6, 3.2, 1.4, 0.2],
 [5.6, 2.8, 4.9, 2. ],
 [5.2, 3.5, 1.5, 0.2],

```

```
[5. , 3.6, 1.4, 0.2],
[7.2, 3. , 5.8, 1.6],
[7.9, 3.8, 6.4, 2. ],
[6.2, 3.4, 5.4, 2.3],
[5.1, 3.8, 1.9, 0.4],
[5.4, 3.9, 1.3, 0.4],
[5.4, 3.7, 1.5, 0.2],
[7.7, 3.8, 6.7, 2.2],
[6.3, 2.3, 4.4, 1.3],
[6.9, 3.1, 5.1, 2.3],
[6.6, 2.9, 4.6, 1.3]])
```

```
[22]: y_train
```

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

```
[23]: y_test
```



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

1.0.5 SCALING/ NORMALIZATION

```
[24]: from sklearn.preprocessing import StandardScaler
      scalar=StandardScaler()
      scalar.fit(x_train)
      x_train=scalar.fit_transform(x_train)
      x_test=scalar.fit_transform(x_test)
```

```
[25]: x_train
```

```
[25]: array([[ -0.23690478, -0.08738704,  0.20877397, -0.03330265],
        [ 1.16208031,  0.38174338,  1.19788343,  1.46132027],
        [ 0.78053892,  0.38174338,  0.73242015,  1.05369584],
        [-0.99998756,  1.085439   , -1.42034749, -1.39205076],
        [ 0.90771938, -0.08738704,  0.32513979,  0.23844697],
        [-0.10972432, -0.79108266,  0.15059106, -0.30505227],
        [-0.8728071  ,  0.85087379, -1.42034749, -1.39205076],
        [-1.8902508  ,  0.38174338, -1.4785304  , -1.39205076],
        [ 0.14463661, -1.9639087  ,  0.09240815, -0.30505227],
        [-1.38152895,  0.85087379, -1.12943294, -1.39205076],
        [-1.12716803, -0.08738704, -1.30398167, -1.39205076],
        [-0.99998756,  0.61630858, -1.24579876, -0.98442633],
        [ 0.14463661, -1.9639087  ,  0.67423724,  0.37432178],
        [ 1.03489985,  0.14717817,  0.49968851,  0.37432178],
        [ 1.03489985, -0.08738704,  0.79060306,  1.46132027],
        [-0.99998756,  1.78913462, -1.30398167, -1.39205076],
        [-0.23690478,  3.19652586, -1.36216458, -1.12030114],
        [ 0.52617799, -0.32195225,  1.0233347  ,  0.78194622],
        [-1.76307034, -1.72934349, -1.4785304  , -1.25617595],
        [ 0.01745614,  0.38174338,  0.55787142,  0.78194622],
        [ 0.78053892, -0.08738704,  0.96515179,  0.78194622],
        [-1.12716803,  0.61630858, -1.42034749, -1.39205076],
```

[-0.23690478, -0.32195225, 0.20877397, 0.10257216],
 [1.16208031, -0.08738704, 0.96515179, 1.18957065],
 [-0.49126571, 2.72739545, -1.42034749, -1.39205076],
 [-0.36408525, -0.08738704, 0.15059106, 0.10257216],
 [0.52617799, 0.61630858, 1.25606633, 1.7330699],
 [-0.36408525, -0.32195225, -0.14032349, 0.10257216],
 [0.65335846, -0.55651745, 1.0233347 , 1.18957065],
 [-0.49126571, -1.49477828, -0.02395767, -0.16917746],
 [-0.23690478, -0.55651745, 0.3833227 , 0.10257216],
 [-0.61844617, 2.02369983, -1.24579876, -1.12030114],
 [2.30670448, -0.55651745, 1.6633467 , 1.05369584],
 [-0.23690478, -0.55651745, 0.15059106, 0.10257216],
 [0.65335846, 0.38174338, 0.3833227 , 0.37432178],
 [-0.49126571, 1.085439 , -1.4785304 , -1.39205076],
 [-0.10972432, -0.79108266, 0.03422524, -0.03330265],
 [-0.23690478, -1.02564787, -0.1985064 , -0.30505227],
 [-1.12716803, 0.38174338, -1.53671331, -1.39205076],
 [-0.23690478, -1.26021307, 0.67423724, 1.05369584],
 [-1.12716803, 0.85087379, -1.36216458, -1.39205076],
 [-1.38152895, -0.08738704, -1.42034749, -1.25617595],
 [0.52617799, -1.26021307, 0.61605433, 0.37432178],
 [0.39899753, -0.32195225, 0.26695688, 0.10257216],
 [0.14463661, 0.85087379, 0.3833227 , 0.5101966],
 [0.52617799, -0.55651745, 0.73242015, 0.37432178],
 [0.27181707, -1.02564787, 1.0233347 , 0.23844697],
 [0.27181707, -0.08738704, 0.44150561, 0.23844697],
 [-1.8902508 , -0.32195225, -1.42034749, -1.39205076],
 [-2.01743127, -0.08738704, -1.59489622, -1.52792557],
 [0.14463661, -0.08738704, 0.55787142, 0.78194622],
 [1.03489985, 0.61630858, 1.08151761, 1.18957065],
 [-1.63588988, 0.14717817, -1.36216458, -1.39205076],
 [-0.99998756, 1.085439 , -1.42034749, -1.25617595],
 [-1.12716803, 1.085439 , -1.4785304 , -1.25617595],
 [0.65335846, -0.32195225, 0.26695688, 0.10257216],
 [1.92516309, -0.55651745, 1.31424924, 0.91782103],
 [-1.63588988, 0.85087379, -1.42034749, -1.25617595],
 [0.65335846, -0.79108266, 0.84878597, 0.91782103],
 [1.5436217 , -0.08738704, 1.19788343, 1.18957065],
 [-1.50870941, 0.38174338, -1.4785304 , -1.39205076],
 [1.03489985, 0.14717817, 0.32513979, 0.23844697],
 [0.52617799, 0.61630858, 0.49968851, 0.5101966],
 [1.67080216, 0.38174338, 1.25606633, 0.78194622],
 [1.28926077, 0.14717817, 0.61605433, 0.37432178],
 [-0.10972432, -0.55651745, 0.73242015, 1.59719509],
 [-0.74562664, 1.55456941, -1.36216458, -1.39205076],
 [0.65335846, 0.38174338, 0.84878597, 1.46132027],
 [0.27181707, -0.32195225, 0.49968851, 0.23844697],

```
[ 0.78053892, -0.08738704,  0.79060306,  1.05369584],
[-0.49126571, -1.49477828, -0.08214058, -0.30505227],
[ 0.01745614, -0.08738704,  0.20877397,  0.37432178],
[-1.12716803, -1.72934349, -0.31487221, -0.30505227],
[-1.12716803,  1.085439   , -1.30398167, -0.84855152],
[-1.12716803, -2.43303911, -0.1985064  , -0.30505227],
[-0.10972432, -1.02564787,  0.09240815, -0.03330265],
[ 1.41644124,  0.38174338,  0.49968851,  0.23844697],
[-0.49126571, -1.02564787,  0.32513979, -0.03330265],
[ 1.67080216,  1.32000421,  1.31424924,  1.7330699 ],
[-0.99998756,  1.55456941, -1.36216458, -1.12030114],
[-0.8728071  , -0.79108266,  0.03422524,  0.23844697],
[ 1.03489985, -0.08738704,  0.67423724,  0.64607141],
[-0.8728071  ,  2.49283024, -1.36216458, -1.52792557],
[ 1.03489985,  0.61630858,  1.08151761,  1.7330699 ],
[-0.99998756,  0.85087379, -1.36216458, -1.39205076],
[ 1.28926077,  0.14717817,  0.90696888,  1.18957065],
[-1.25434849, -0.08738704, -1.42034749, -1.39205076],
[ 0.78053892, -0.55651745,  0.44150561,  0.37432178],
[ 0.65335846, -0.55651745,  1.0233347  ,  1.32544546],
[ 2.17952401, -0.08738704,  1.60516379,  1.18957065],
[-0.10972432, -0.79108266,  0.73242015,  0.91782103],
[ 2.30670448, -1.02564787,  1.77971252,  1.46132027],
[-0.49126571, -1.26021307,  0.09240815,  0.10257216],
[ 1.16208031, -0.55651745,  0.55787142,  0.23844697],
[ 0.52617799, -0.79108266,  0.61605433,  0.78194622],
[ 0.01745614, -0.08738704,  0.73242015,  0.78194622],
[-0.61844617,  0.85087379, -1.24579876, -1.39205076],
[ 0.27181707, -0.55651745,  0.49968851, -0.03330265],
[ 1.03489985, -1.26021307,  1.13970052,  0.78194622],
[-0.10972432,  2.25826503, -1.53671331, -1.39205076],
[-0.36408525, -0.79108266,  0.20877397,  0.10257216],
[ 0.78053892, -0.08738704,  1.13970052,  1.32544546]]])
```

[26]: `x_test`

```
[26]: array([[ 0.34307955, -0.21589908,  0.69064254,  0.78705882],
 [-0.31857387, -1.76154024,  0.19645486,  0.15908636],
 [ 1.00473297,  0.0049068  ,  1.07501074,  1.54062577],
 [-0.75967615,  1.55054796, -1.17628871, -1.09685856],
 [-0.98022729, -1.31992848,  0.47100357,  0.66146433],
 [-1.09050286, -0.21589908, -1.23119846, -1.34804755],
 [ 0.23280398, -0.43670496,  0.47100357,  0.41027534],
 [-0.42884944,  0.66732444, -1.17628871, -0.97126407],
 [ 0.23280398, -0.87831672,  0.80046203,  0.53586983],
 [-0.98022729,  0.0049068  , -1.17628871, -1.34804755],
 [-0.86995172,  0.66732444, -1.12137897, -0.97126407],
```

```

[-0.75967615, -1.31992848, -0.35264257, -0.09210263],
[ 0.56363069, -1.31992848,  0.74555229,  0.91265331],
[-0.2082983 , -1.31992848,  0.14154512, -0.09210263],
[ 0.56363069,  0.66732444,  1.07501074,  1.54062577],
[ 0.45335512, -1.98234612,  0.47100357,  0.41027534],
[-0.09802273,  1.55054796, -1.06646923, -1.09685856],
[ 0.34307955, -0.65751084,  0.19645486,  0.15908636],
[ 0.45335512, -0.65751084,  0.6357328 ,  0.78705882],
[-1.09050286,  0.0049068 , -1.12137897, -1.22245306],
[-1.20077843,  0.22571268, -1.12137897, -1.22245306],
[ 1.6663864 , -0.43670496,  1.45937894,  0.78705882],
[-1.53160514, -0.21589908, -1.2861082 , -1.22245306],
[ 1.22528412,  0.22571268,  1.12992049,  1.41503128],
[-0.98022729, -1.54073436, -0.18791334, -0.21769712],
[-1.311054 ,  1.1089362 , -1.45083743, -1.22245306],
[-0.2082983 , -0.21589908,  0.47100357,  0.41027534],
[ 2.10748868, -0.21589908,  1.34955946,  1.41503128],
[-0.42884944, -0.21589908,  0.47100357,  0.41027534],
[-1.09050286,  0.66732444, -1.12137897, -1.22245306],
[ 0.67390626,  0.0049068 ,  1.020101 ,  0.78705882],
[-1.311054 ,  0.22571268, -1.23119846, -1.22245306],
[-0.2082983 , -0.65751084,  0.69064254,  1.0382478 ],
[-0.64940058,  0.88813032, -1.17628871, -1.22245306],
[-0.86995172,  1.1089362 , -1.23119846, -1.22245306],
[ 1.55611083, -0.21589908,  1.18483023,  0.53586983],
[ 2.32803982,  1.55054796,  1.51428869,  1.0382478 ],
[ 0.45335512,  0.66732444,  0.96519126,  1.41503128],
[-0.75967615,  1.55054796, -0.95664974, -0.97126407],
[-0.42884944,  1.77135384, -1.2861082 , -0.97126407],
[-0.42884944,  1.32974208, -1.17628871, -1.22245306],
[ 2.10748868,  1.55054796,  1.67901792,  1.28943679],
[ 0.56363069, -1.76154024,  0.41609383,  0.15908636],
[ 1.22528412,  0.0049068 ,  0.80046203,  1.41503128],
[ 0.8944574 , -0.43670496,  0.52591332,  0.15908636]])

```

1.0.6 MODEL CREATION

1.0.7 1 Random Forest

```

[27]: from sklearn.ensemble import RandomForestClassifier
forest_model=RandomForestClassifier(n_estimators=100)
forest_model.fit(x_train,y_train)
y_pred=forest_model.predict(x_test)
y_pred

```

```

[27]: array(['Iris-virginica', 'Iris-versicolor', 'Iris-virginica',
        'Iris-setosa', 'Iris-versicolor', 'Iris-setosa', 'Iris-versicolor',

```

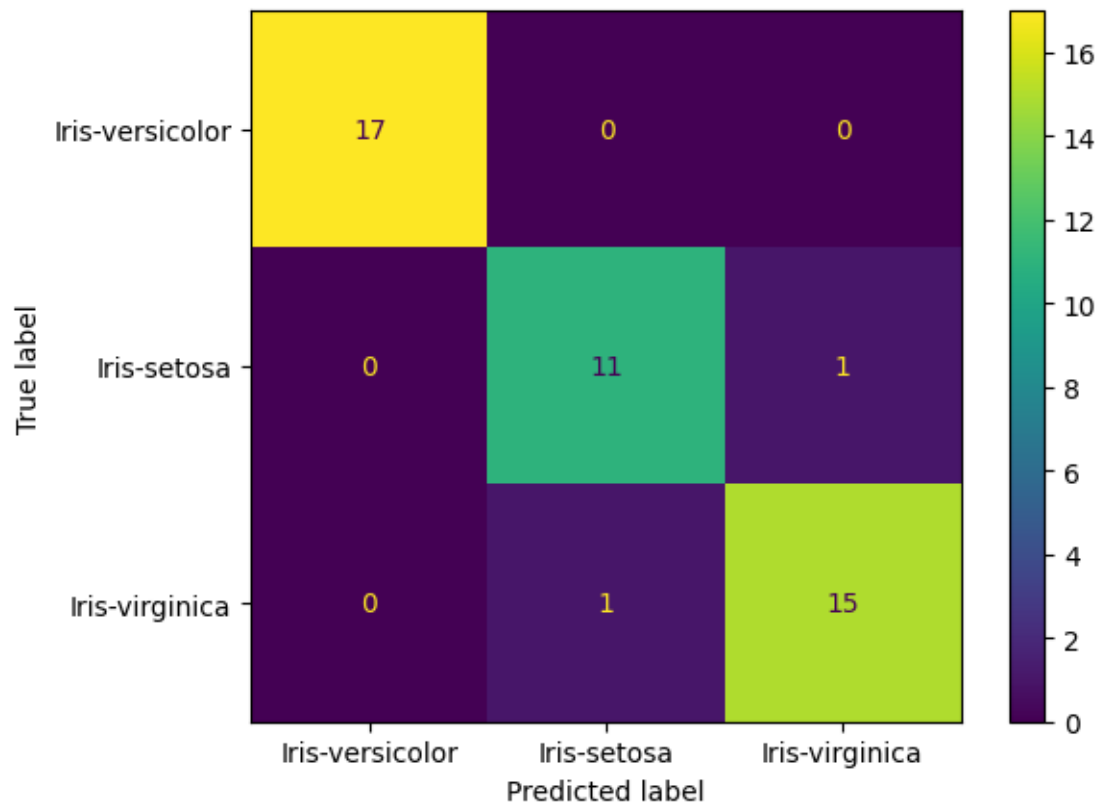
```
'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
'Iris-virginica', 'Iris-versicolor', 'Iris-setosa',
'Iris-versicolor', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
'Iris-virginica', 'Iris-setosa', 'Iris-virginica',
'Iris-versicolor',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

```
[28]: #confusion matrix
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
result=confusion_matrix(y_test,y_pred)
print(result)
labels=['Iris-versicolor', 'Iris-setosa', 'Iris-virginica']
cmd=ConfusionMatrixDisplay(result, display_labels=labels)
```

```
[[17  0  0]
 [ 0 11  1]
 [ 0  1 15]]
```

```
[29]: cmd.plot()
```

```
[29]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7aae455f4bb0>
```



```
[30]: #accuracy score and classification report
from sklearn.metrics import accuracy_score, classification_report
print('Accuracy', accuracy_score(y_test, y_pred)*100)
print(classification_report(y_test, y_pred))
```

Accuracy 95.55555555555556

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	17
Iris-versicolor	0.92	0.92	0.92	12
Iris-virginica	0.94	0.94	0.94	16
accuracy			0.96	45
macro avg	0.95	0.95	0.95	45
weighted avg	0.96	0.96	0.96	45

1.0.8 2 Logistic Regression

```
[31]: from sklearn.linear_model import LogisticRegression
model = LogisticRegression(max_iter=1000)
model.fit(x_train,y_train)
y_pred1=model.predict(x_test)
y_pred1
```

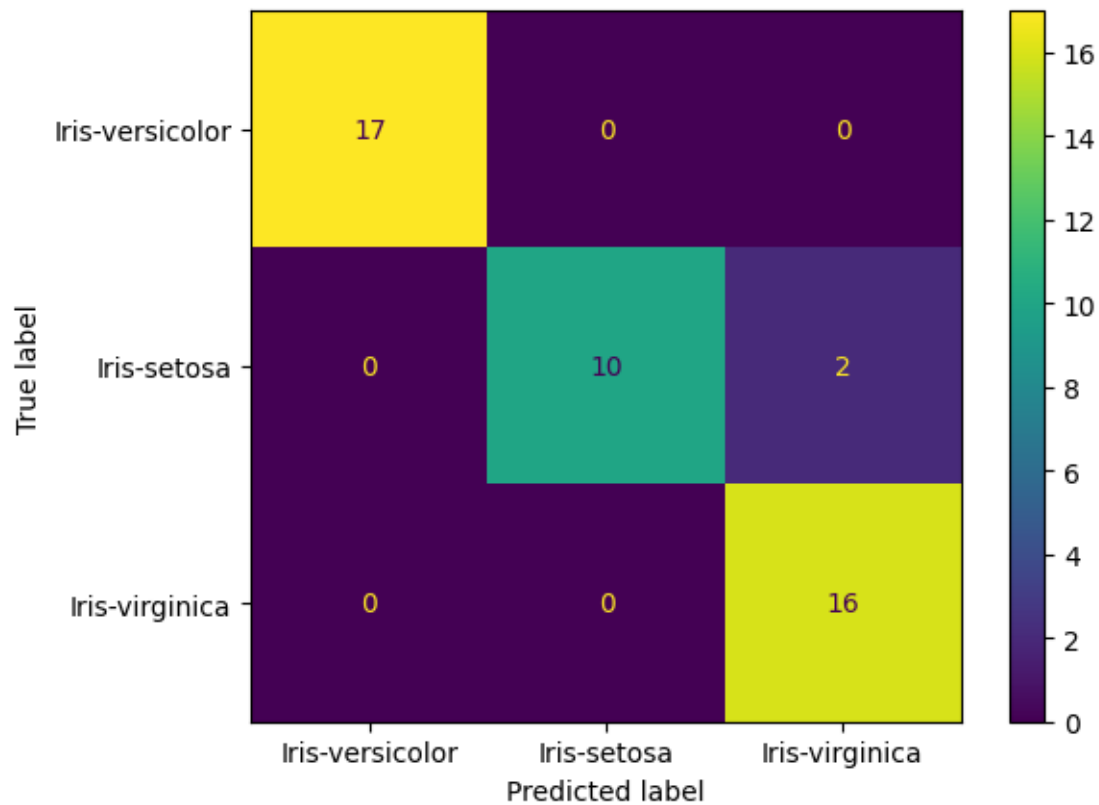
```
[31]: array(['Iris-virginica', 'Iris-versicolor', 'Iris-virginica',
        'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-versicolor',
        'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
        'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
        'Iris-virginica',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

```
[32]: #confusion matrix
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay
result=confusion_matrix(y_test,y_pred1)
print(result)
labels=['Iris-versicolor','Iris-setosa','Iris-virginica']
cmd=ConfusionMatrixDisplay(result,display_labels=labels)
```

```
[[17  0  0]
 [ 0 10  2]
 [ 0  0 16]]
```

```
[33]: cmd.plot()
```

```
[33]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7aae0722f8e0>
```



```
[34]: #accuracy score and classification report
from sklearn.metrics import accuracy_score, classification_report
print('Accuracy', accuracy_score(y_test, y_pred1) * 100)
print(classification_report(y_test, y_pred1))
```

Accuracy 95.55555555555556

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	17
Iris-versicolor	1.00	0.83	0.91	12
Iris-virginica	0.89	1.00	0.94	16
accuracy			0.96	45
macro avg	0.96	0.94	0.95	45
weighted avg	0.96	0.96	0.95	45

1.0.9 3 Decision Tree

```
[35]: from sklearn.tree import DecisionTreeClassifier, plot_tree
dt_model=DecisionTreeClassifier()
dt_model.fit(x_train,y_train)
y_pred2=dt_model.predict(x_test)
y_pred2
```

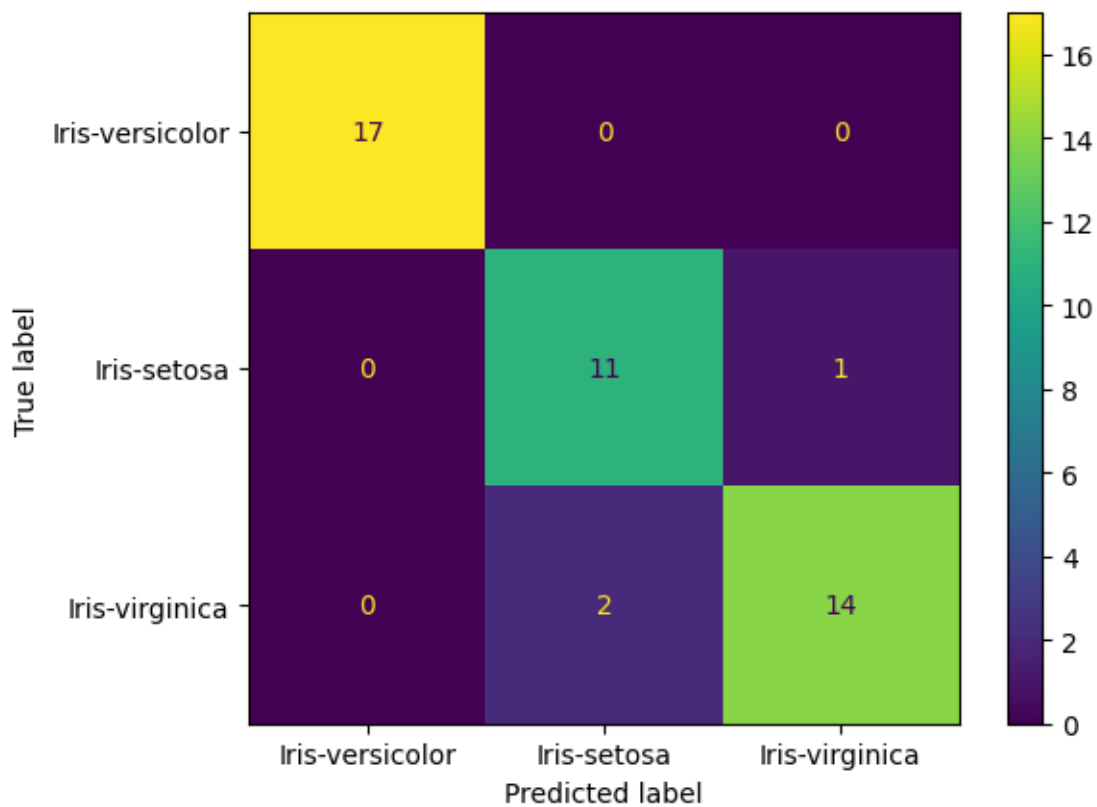
```
[35]: array(['Iris-versicolor', 'Iris-versicolor', 'Iris-virginica',
        'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-versicolor',
        'Iris-setosa', 'Iris-virginica', 'Iris-setosa', 'Iris-setosa',
        'Iris-versicolor', 'Iris-virginica', 'Iris-versicolor',
        'Iris-virginica',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

```
[36]: #confusion matrix
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay
result=confusion_matrix(y_test,y_pred2)
print(result)
labels=['Iris-versicolor','Iris-setosa','Iris-virginica']
cmd=ConfusionMatrixDisplay(result,display_labels=labels)
```

```
[[17  0  0]
 [ 0 11  1]
 [ 0  2 14]]
```

```
[37]: cmd.plot()
```

```
[37]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7aae07115480>
```



```
[38]: #accuracy score and classification report
from sklearn.metrics import accuracy_score, classification_report
print('Accuracy', accuracy_score(y_test, y_pred2) * 100)
print(classification_report(y_test, y_pred2))
```

Accuracy 93.33333333333333

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	17
Iris-versicolor	0.85	0.92	0.88	12
Iris-virginica	0.93	0.88	0.90	16
accuracy			0.93	45
macro avg	0.93	0.93	0.93	45
weighted avg	0.94	0.93	0.93	45