

## ▼ IRIS FLOWER CLASSIFICATION

The Iris dataset is a widely used benchmark dataset in the field of machine learning and statistics for classification tasks.

This dataset consists of 150 samples of iris flowers, with each sample belonging to one of three species: setosa, versicolor, or virginica. Each sample comprises four features: sepal length, sepal width, petal length, and petal width, all measured in centimeters.

The purpose of this dataset is to classify iris flowers based on these four features. It is often used for teaching and practicing various machine learning algorithms, especially for tasks related to classification, clustering, and dimensionality reduction.

The Iris dataset is relatively small, making it easily manageable for testing and implementing machine learning algorithms. It is considered a good starting point for beginners due to its simplicity and clear classification task.

**iris setosa**



petal      sepal

**iris versicolor**



petal      sepal

**iris virginica**



petal      sepal

### Import the libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

### Load the dataset

```
df=pd.read_csv('/content/Iris.csv')
df
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	
<b>0</b>	1	5.1	3.5	1.4	0.2	Iris-setosa	
<b>1</b>	2	4.9	3.0	1.4	0.2	Iris-setosa	
<b>2</b>	3	4.7	3.2	1.3	0.2	Iris-setosa	
<b>3</b>	4	4.6	3.1	1.5	0.2	Iris-setosa	
<b>4</b>	5	5.0	3.6	1.4	0.2	Iris-setosa	
...	...	...	...	...	...	...	
<b>145</b>	146	6.7	3.0	5.2	2.3	Iris-virginica	
<b>146</b>	147	6.3	2.5	5.0	1.9	Iris-virginica	
<b>147</b>	148	6.5	3.0	5.2	2.0	Iris-virginica	
<b>148</b>	149	6.2	3.4	5.4	2.3	Iris-virginica	

Data Exploration

```
df.head()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	
<b>0</b>	1	5.1	3.5	1.4	0.2	Iris-setosa	
<b>1</b>	2	4.9	3.0	1.4	0.2	Iris-setosa	
<b>2</b>	3	4.7	3.2	1.3	0.2	Iris-setosa	
<b>3</b>	4	4.6	3.1	1.5	0.2	Iris-setosa	
<b>4</b>	5	5.0	3.6	1.4	0.2	Iris-setosa	

```
df.tail()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	
<b>145</b>	146	6.7	3.0	5.2	2.3	Iris-virginica	
<b>146</b>	147	6.3	2.5	5.0	1.9	Iris-virginica	
<b>147</b>	148	6.5	3.0	5.2	2.0	Iris-virginica	
<b>148</b>	149	6.2	3.4	5.4	2.3	Iris-virginica	

```
df.shape
```

```
(150, 6)
```

```
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
```

```
df.columns
```

```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

```
df.dtypes
```

```
Id                int64
SepalLengthCm    float64
SepalWidthCm     float64
PetalLengthCm    float64
PetalWidthCm     float64
Species          object
dtype: object
```

```
df.describe()
```

	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

```
df.dropna()
```

	<b>Id</b>	<b>SepalLengthCm</b>	<b>SepalWidthCm</b>	<b>PetalLengthCm</b>	<b>PetalWidthCm</b>	<b>Species</b>
<b>0</b>	1	5.1	3.5	1.4	0.2	Iris-setosa
<b>1</b>	2	4.9	3.0	1.4	0.2	Iris-setosa
<b>2</b>	3	4.7	3.2	1.3	0.2	Iris-setosa
<b>3</b>	4	4.6	3.1	1.5	0.2	Iris-setosa
<b>4</b>	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
<b>145</b>	146	6.7	3.0	5.2	2.3	Iris-virginica
<b>146</b>	147	6.3	2.5	5.0	1.9	Iris-virginica
<b>147</b>	148	6.5	3.0	5.2	2.0	Iris-virginica
<b>148</b>	149	6.2	3.4	5.4	2.3	Iris-virginica

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

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

```
df=df.drop(['Id'],axis=1)
df
```

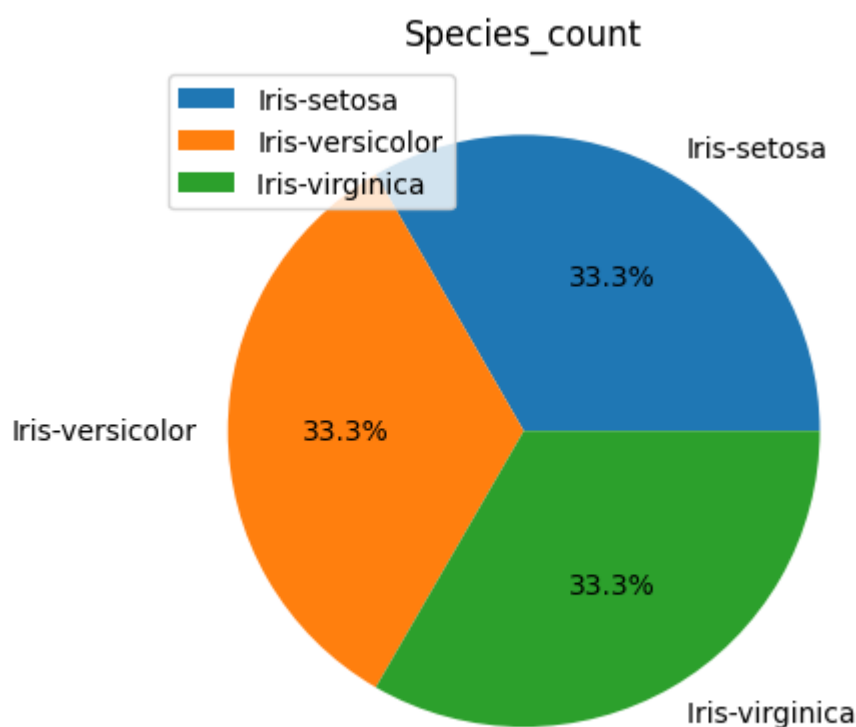
	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species	
0	5.1	3.5	1.4	0.2	Iris-setosa	
1	4.9	3.0	1.4	0.2	Iris-setosa	
2	4.7	3.2	1.3	0.2	Iris-setosa	

## Data Visualization

```
y_counts=df['Species'].value_counts()
y_counts
```

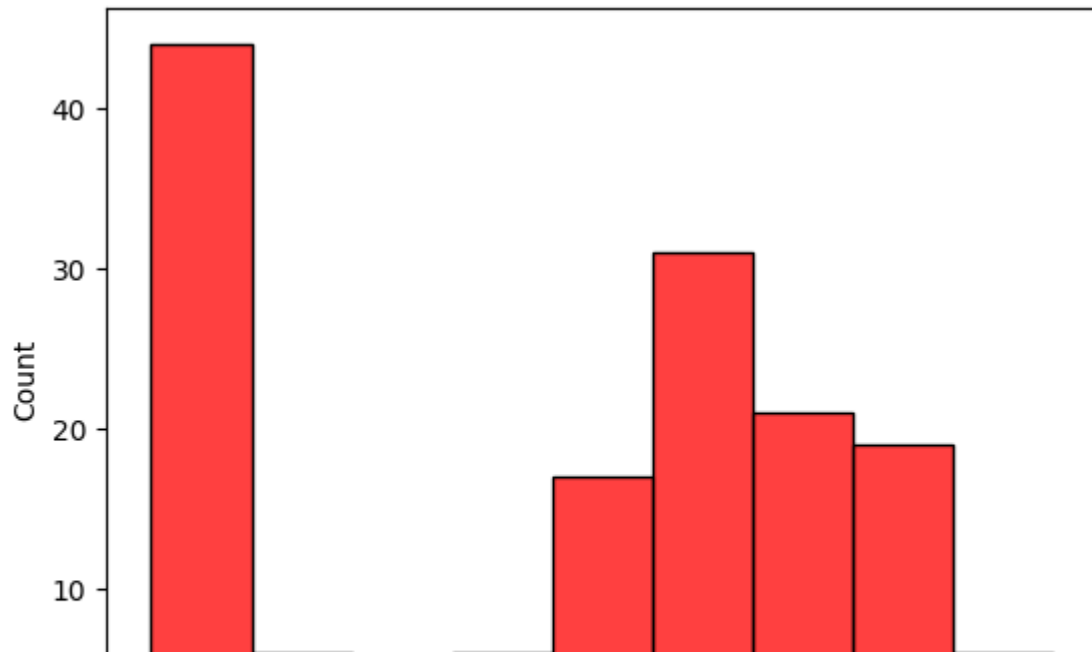
```
Iris-setosa      50
Iris-versicolor  50
Iris-virginica   50
Name: Species, dtype: int64
```

```
mylabels=['Iris-setosa','Iris-versicolor','Iris-virginica ']
plt.pie(y_counts,labels=mylabels,autopct="%1.1f%%")
plt.title('Species_count')
plt.legend(loc='upper left')
plt.show()
```



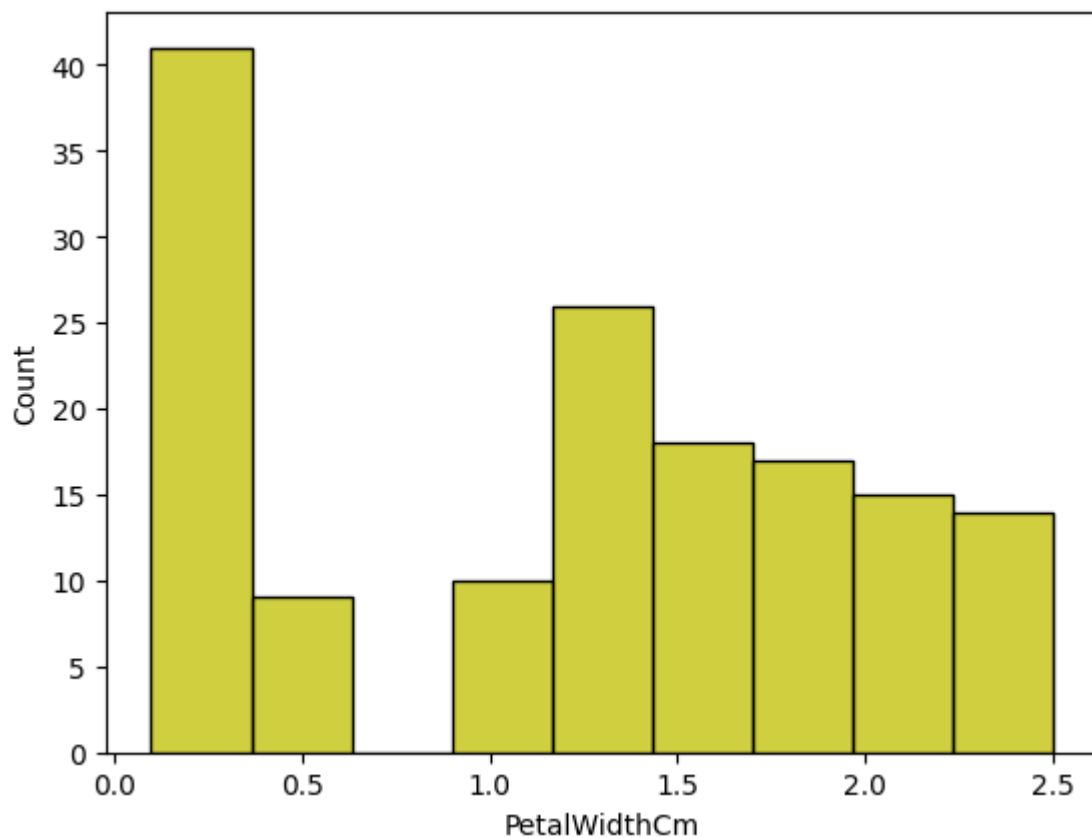
```
sns.histplot(df['PetalLengthCm'],color='r')
```

```
<Axes: xlabel='PetalLengthCm', ylabel='Count'>
```



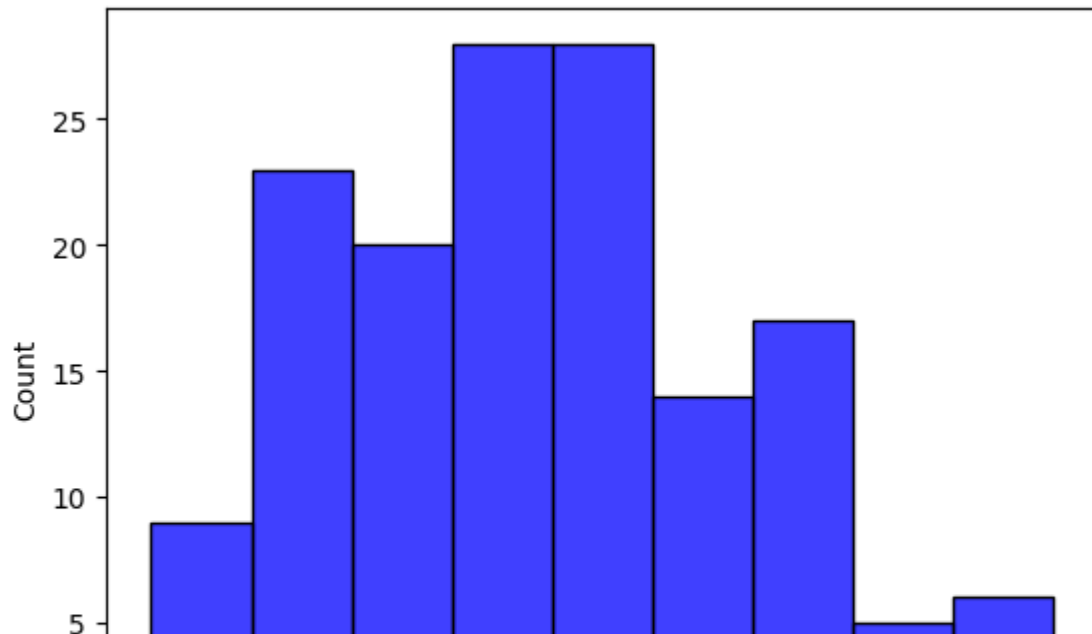
```
sns.histplot(df['PetalWidthCm'],color='y')
```

```
<Axes: xlabel='PetalWidthCm', ylabel='Count'>
```



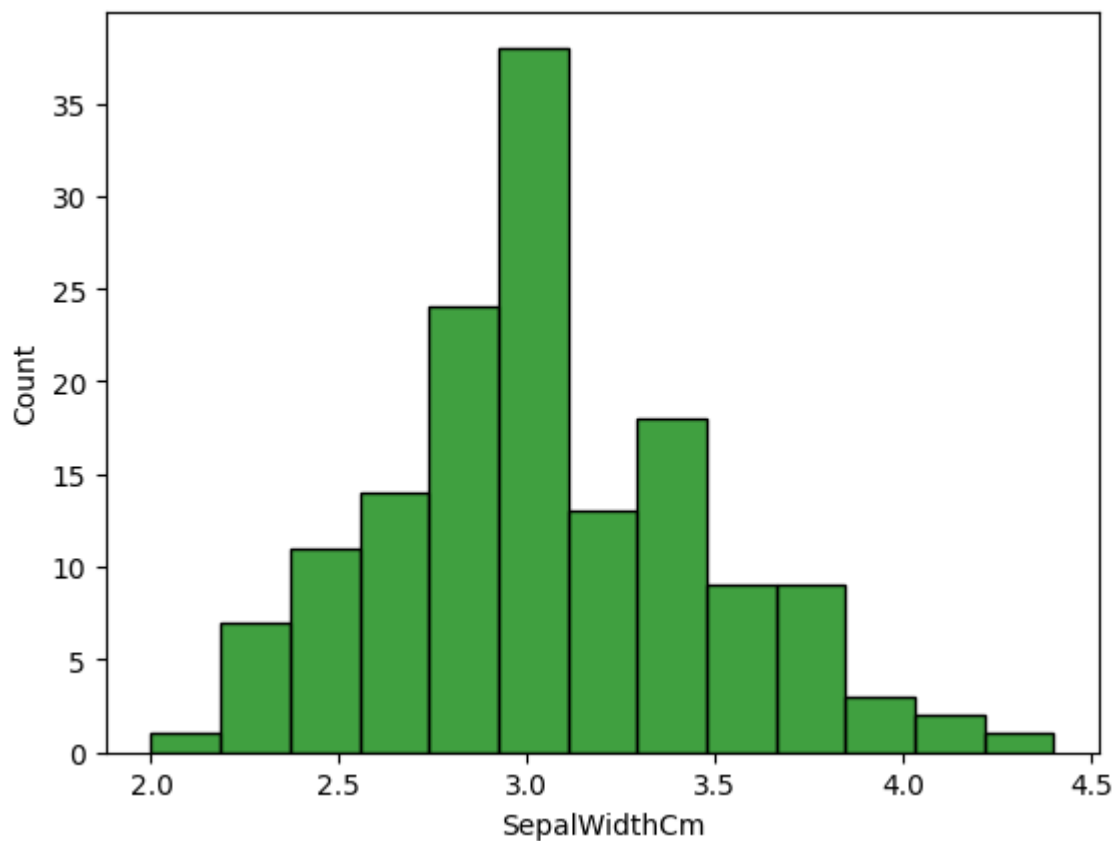
```
sns.histplot(df['SepalLengthCm'],color='b')
```

```
<Axes: xlabel='SepalLengthCm', ylabel='Count'>
```



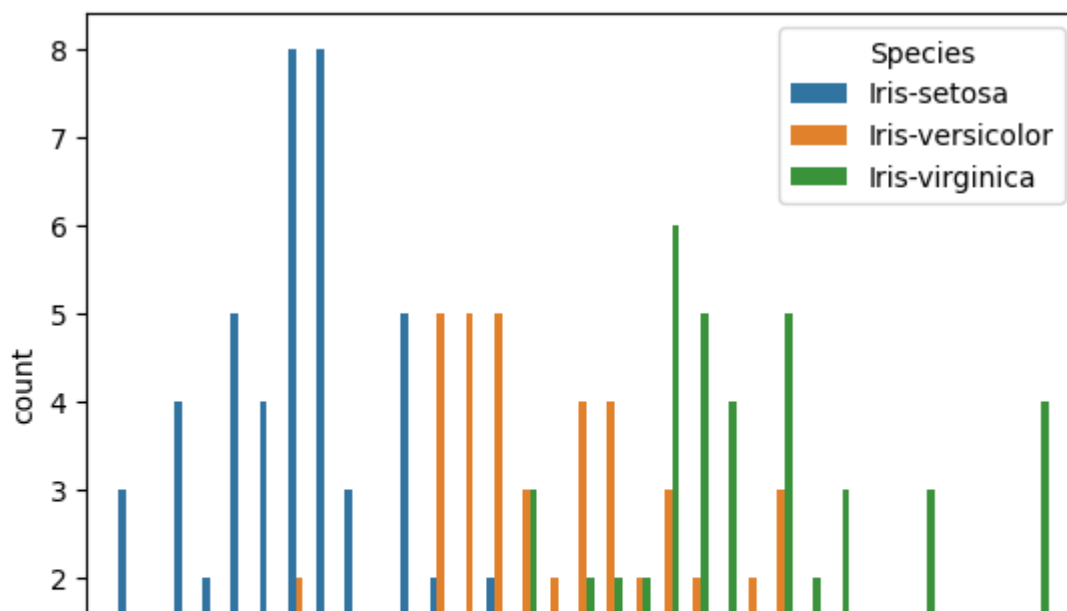
```
sns.histplot(df['SepalWidthCm'],color='g')
```

```
<Axes: xlabel='SepalWidthCm', ylabel='Count'>
```



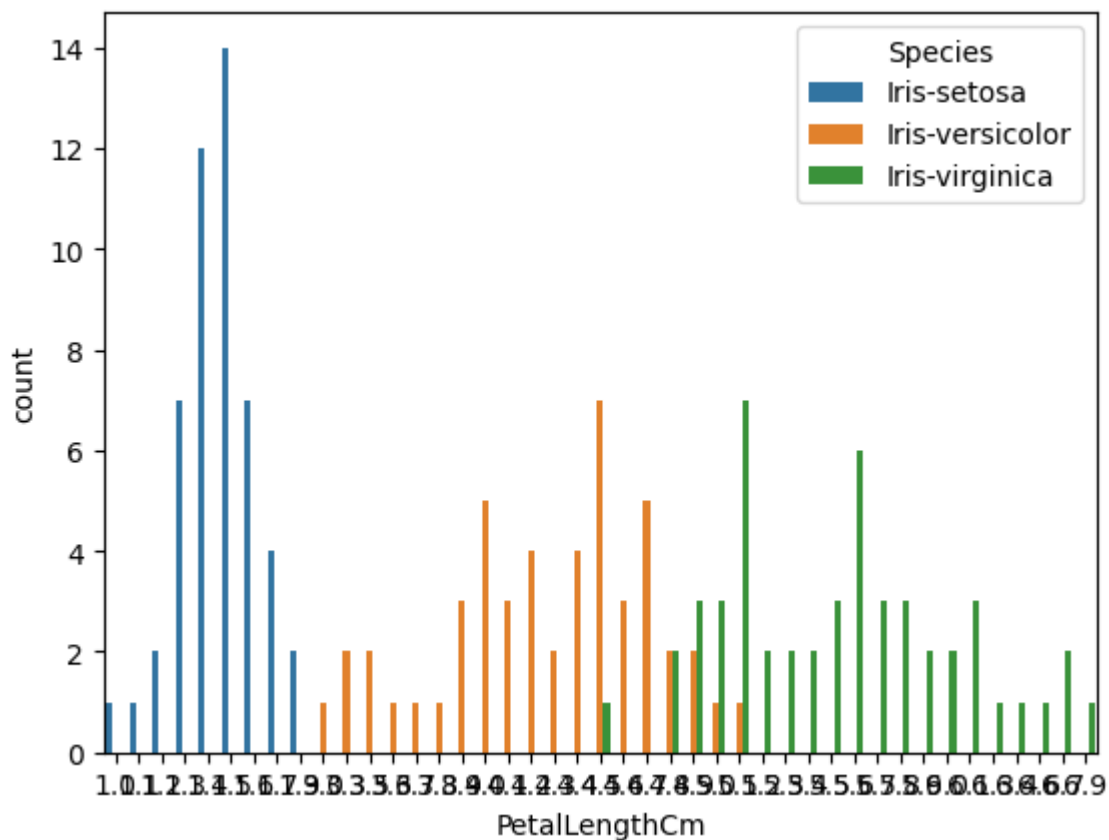
```
sns.countplot(x='SepalLengthCm',hue='Species',data=df)
```

<Axes: xlabel='SepalLengthCm', ylabel='count'>



```
sns.countplot(x='PetalLengthCm',hue='Species',data=df)
```

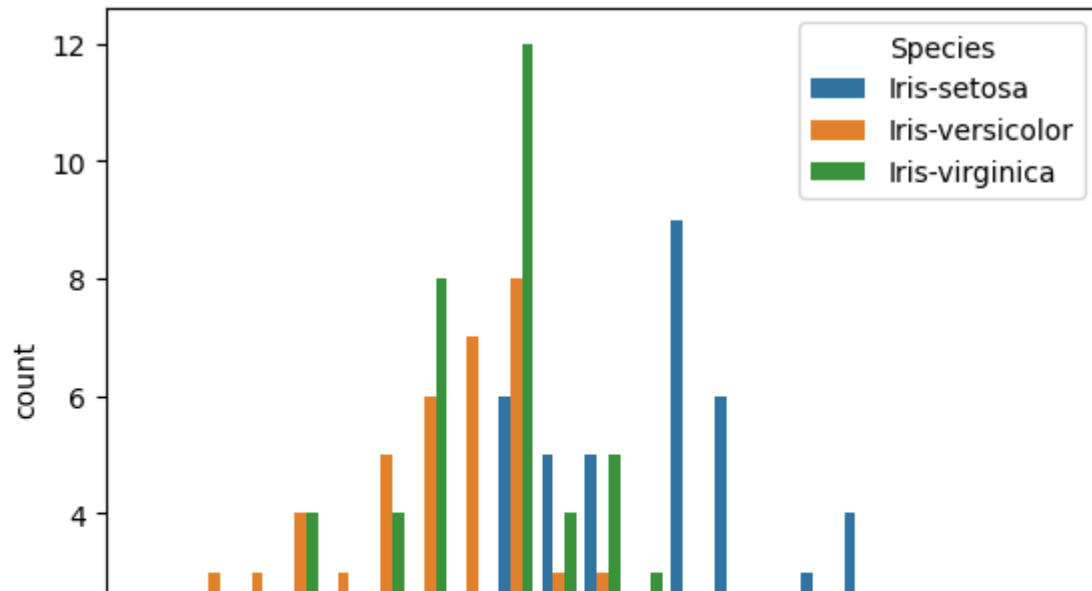
<Axes: xlabel='PetalLengthCm', ylabel='count'>



```
sns.countplot(x='SepalWidthCm',hue='Species',data=df)
```

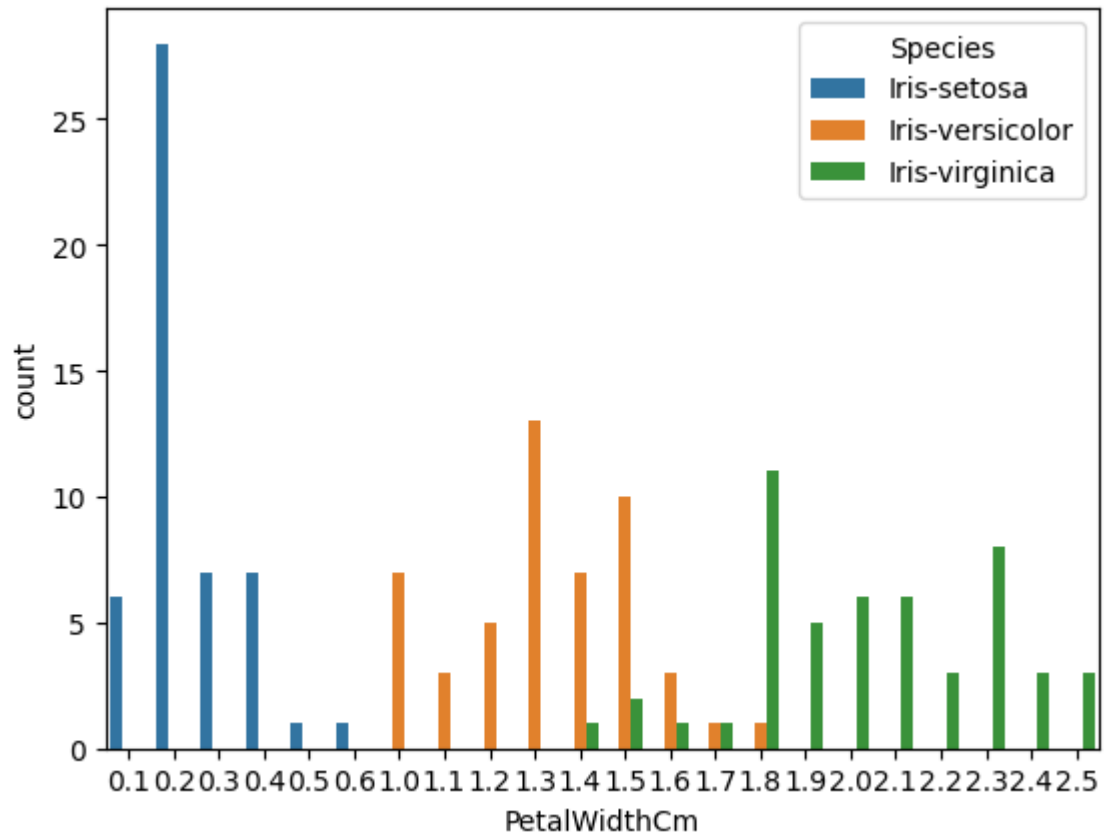


<Axes: xlabel='SepalWidthCm', ylabel='count'>



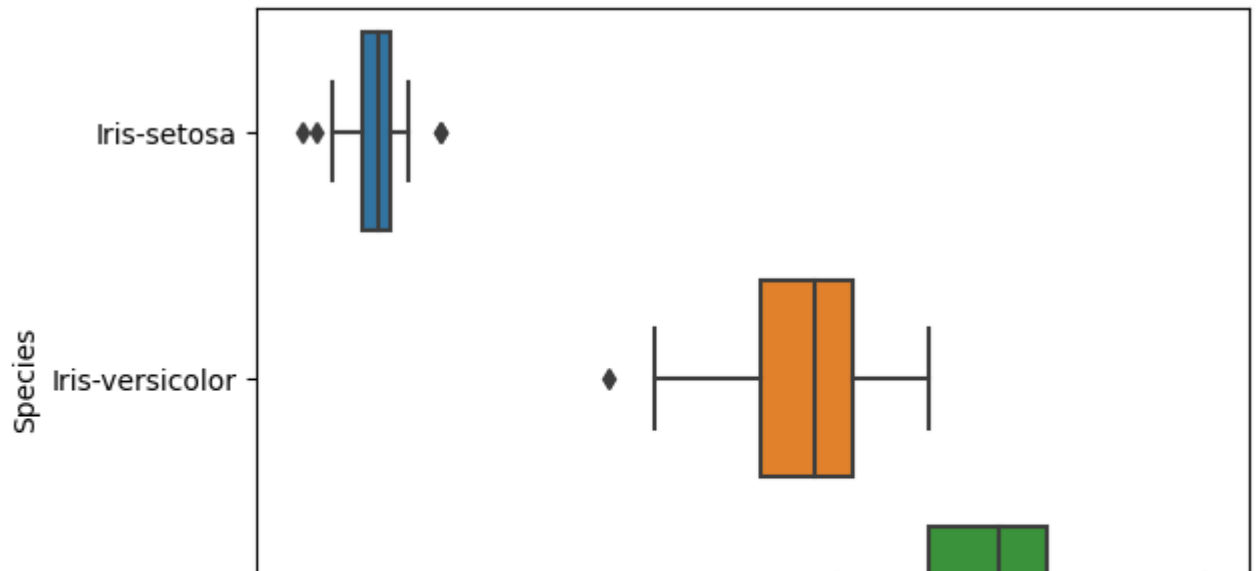
```
sns.countplot(x='PetalWidthCm',hue='Species',data=df)
```

<Axes: xlabel='PetalWidthCm', ylabel='count'>



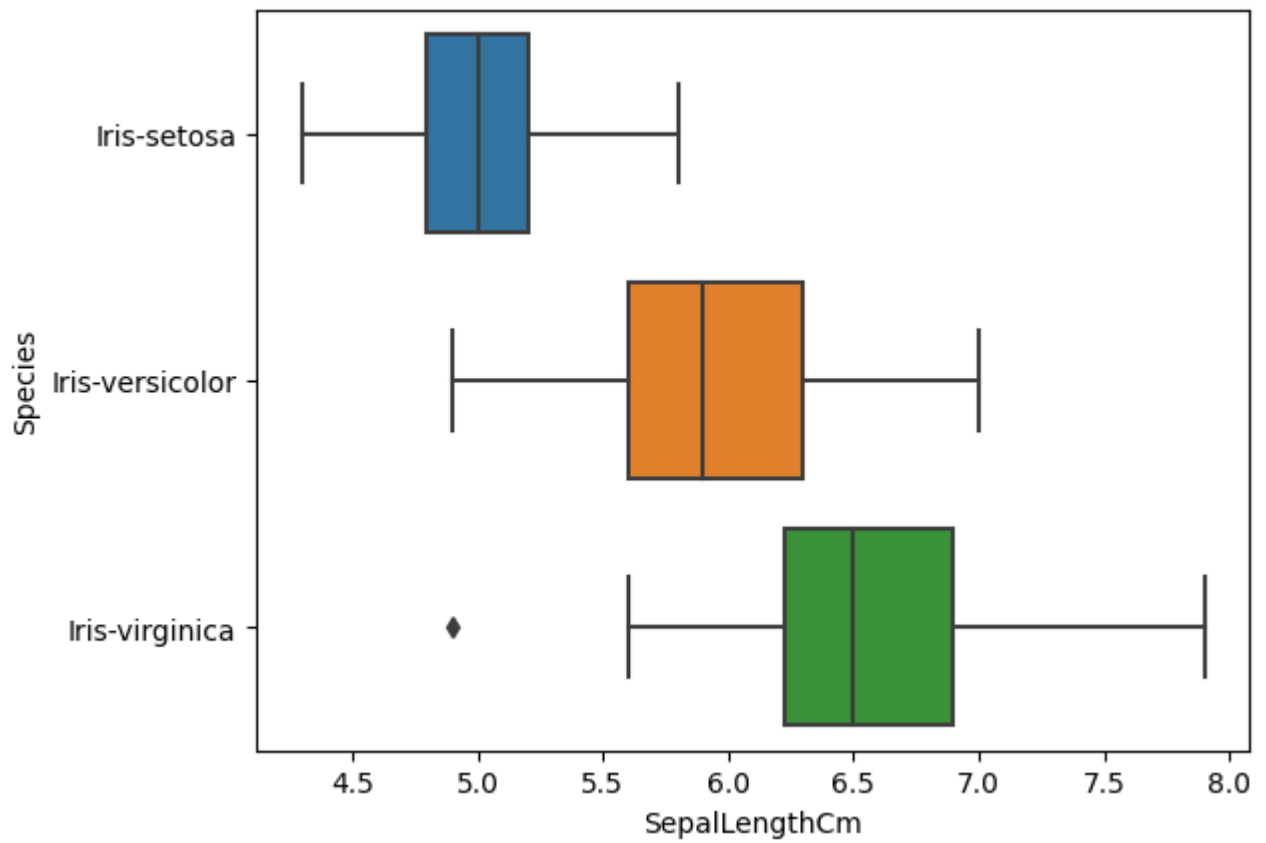
```
sns.boxplot(x=df['PetalLengthCm'],y=df['Species'])
```

<Axes: xlabel='PetalLengthCm', ylabel='Species'>



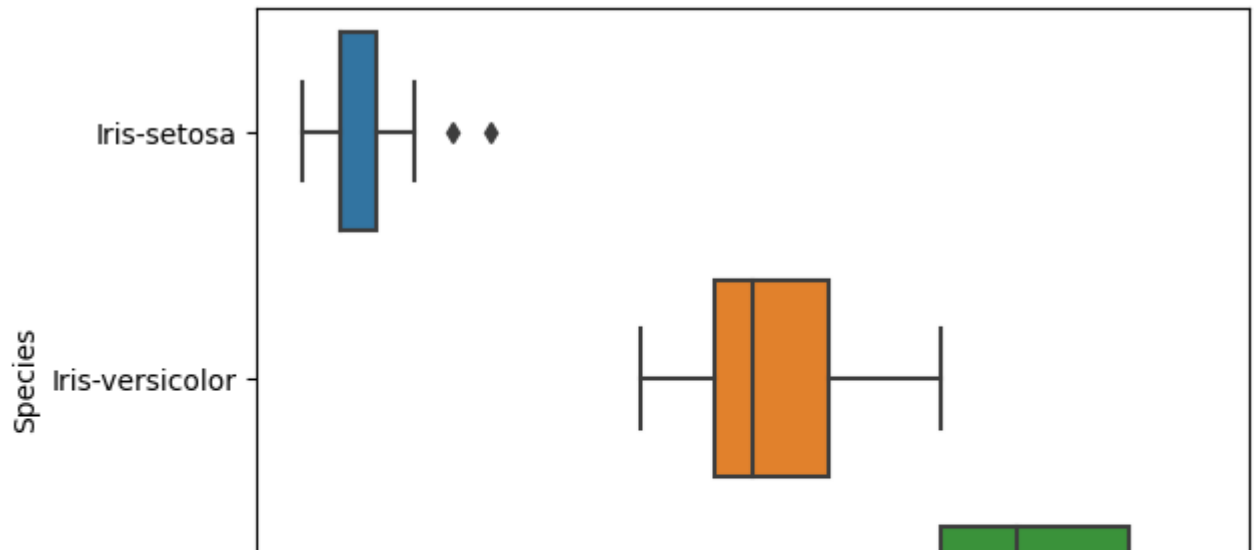
```
sns.boxplot(x=df['SepalLengthCm'],y=df['Species'])
```

<Axes: xlabel='SepalLengthCm', ylabel='Species'>



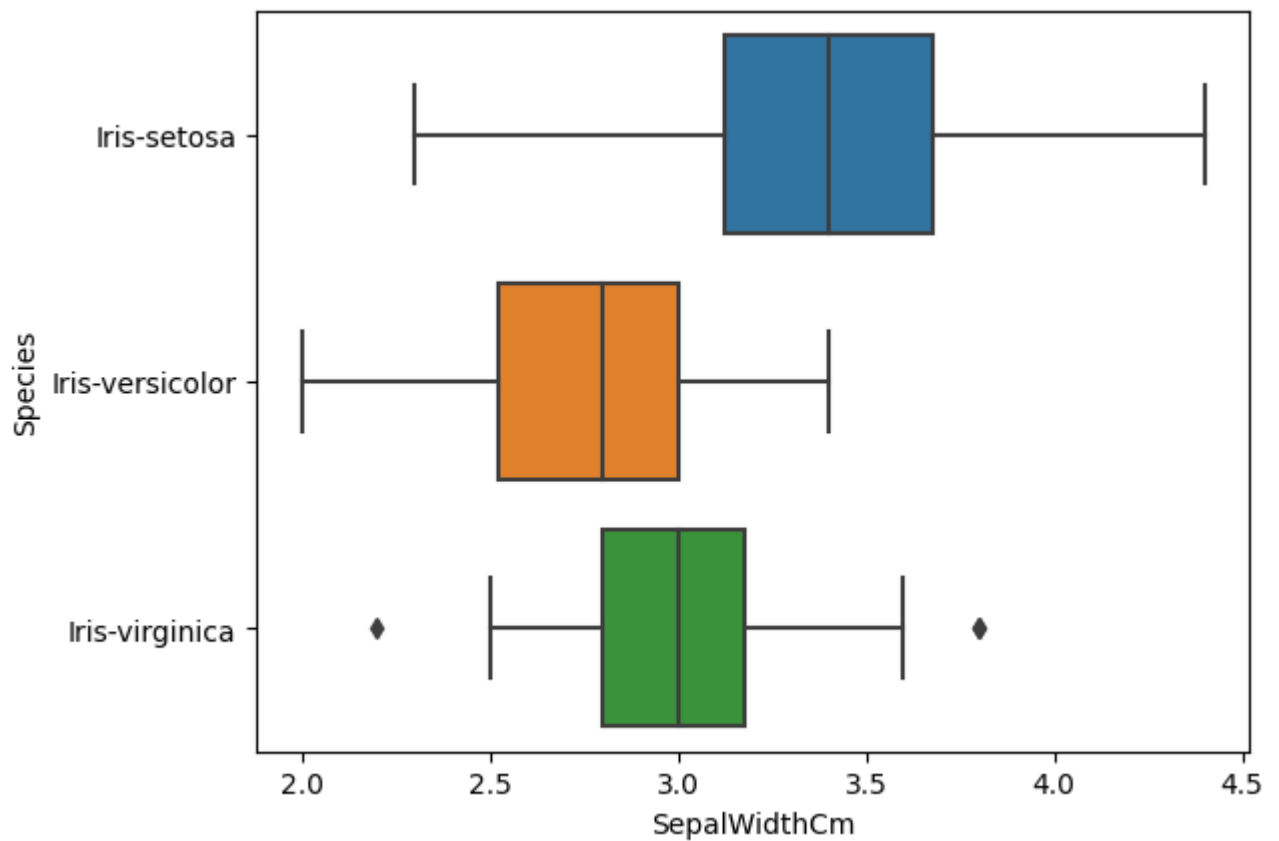
```
sns.boxplot(x=df['PetalWidthCm'],y=df['Species'])
```

<Axes: xlabel='PetalWidthCm', ylabel='Species'>



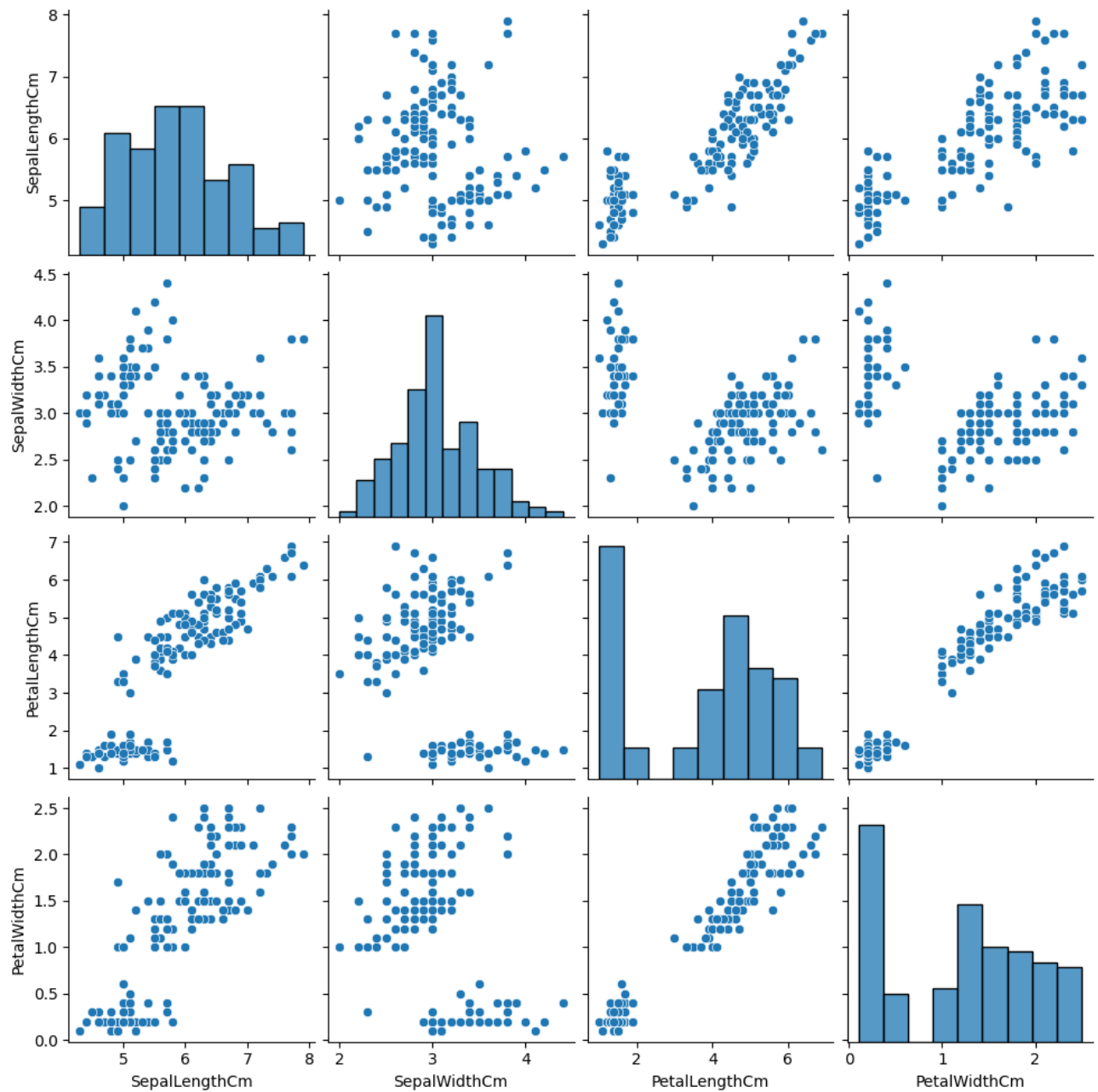
```
sns.boxplot(x=df['SepalWidthCm'],y=df['Species'])
```

<Axes: xlabel='SepalWidthCm', ylabel='Species'>



```
sns.pairplot(df)
```

<seaborn.axisgrid.PairGrid at 0x78a7a40fa950>



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

```
<ipython-input-28-8df7bcac526d>:1: FutureWarning: The default value of numeric_only :
sns.heatmap(df.corr(),annot=True)
<Axes: >
```



### Separating x and y

```
x=df.drop(['Species'],axis=1)
y=df['Species']
```

### Splitting 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=0.3,random_state=42)
```

```
x_train
```

```
[ -1.57805466, 0.47275953, -1.50218532, -1.40173942 ],
[ 0.3100623 , -0.25367584, 0.48403749, 0.21861991 ],
[ 0.79238143, -0.49582097, 0.42561917, 0.35364985 ],
[ 0.43064208, -0.49582097, 0.54245581, 0.75873969 ],
[ 1.39528035, 0.47275953, 0.48403749, 0.21861991 ],
[ 0.67180165, 0.47275953, 0.8345474 , 1.43388941 ],
[ -0.89573553, 1.92563026, -1.32693037, -1.40173942 ],
[ 1.27470056, 0.2306144 , 0.89296572, 1.16382952 ],
[ 0.06890273, -0.01153072, 0.1919459 , 0.35364985 ],
[ 0.79238143, -0.01153072, 0.77612908, 1.02879957 ],
[ -0.17225683, -0.98011121, -0.21698232, -0.32149987 ],
[ -0.77515575, -0.73796609, 0.01669095, 0.21861991 ],
[ 0.3100623 , -0.01153072, 0.42561917, 0.21861991 ],
[ -1.61921423, -1.70654658, -1.50218532, -1.26670948 ],
[ 0.91296121, -0.25367584, 0.42561917, 0.08358997 ],
[ -0.4134164 , -0.98011121, 0.30878254, -0.05143998 ],
[ -0.65457597, 1.68348514, -1.38534869, -1.40173942 ],
[ -0.29283662, -0.01153072, 0.13352758, 0.08358997 ],
[ 1.7570197 , -0.25367584, 1.41873058, 0.75873969 ],
[ 1.033541 , 0.71490465, 1.06822067, 1.16382952 ],
[ -0.89573553, 1.68348514, -1.38534869, -1.13167953 ],
[ -1.1368951 , -1.46440146, -0.33381896, -0.32149987 ],
[ 1.033541 , 0.71490465, 1.06822067, 1.7039493 ],
[ 1.63643991, -0.01153072, 1.12663899, 0.4886798 ],
[ -1.1368951 , 0.2306144 , -1.38534869, -1.53676936 ],
[ 1.033541 , 0.2306144 , 1.00980236, 1.56891935 ],
[ -1.1368951 , -0.01153072, -1.443767 , -1.40173942 ],
[ 1.27470056, 0.2306144 , 0.60087413, 0.35364985 ],
[ 1.87759948, -0.49582097, 1.30189395, 0.89376963 ],
[ 0.55122187, -0.25367584, 1.00980236, 0.75873969 ],
[ -0.17225683, -0.49582097, 0.13352758, 0.08358997 ],
[ 0.79238143, -0.01153072, 0.95138404, 0.75873969 ],
[ 0.55122187, -1.70654658, 0.30878254, 0.08358997 ],
[ 0.67180165, -0.25367584, 0.25036422, 0.08358997 ],
[ -0.29283662, -0.49582097, 0.60087413, 1.02879957 ],
[ 0.06890273, -0.01153072, 0.71771076, 0.75873969 ],
[ -0.53399618, 0.95704977, -1.26851205, -1.40173942 ],
[ 0.3100623 , -0.49582097, 0.07510927, 0.08358997 ],
[ -1.1368951 , -1.22225633, 0.36720086, 0.62370974 ],
[ -0.05167705, 2.40992051, -1.56060364, -1.40173942 ],
[ -0.05167705, -0.98011121, 0.07510927, -0.05143998 ],
[ 1.51586013, -0.01153072, 1.18505731, 1.16382952 ] ] )
```

x\_test

```
array([ [ 0.3100623 , -0.49582097, 0.48403749, -0.05143998 ],
[ -0.17225683, 1.92563026, -1.26851205, -1.26670948 ],
[ 2.23933883, -0.98011121, 1.76924049, 1.43388941 ],
[ 0.18948252, -0.25367584, 0.36720086, 0.35364985 ],
[ 1.15412078, -0.49582097, 0.54245581, 0.21861991 ],
[ -0.53399618, 0.95704977, -1.38534869, -1.13167953 ],
[ -0.29283662, -0.25367584, -0.15856401, 0.08358997 ],
[ 1.27470056, 0.2306144 , 0.71771076, 1.43388941 ],
[ 0.43064208, -1.9486917 , 0.36720086, 0.35364985 ],
[ -0.05167705, -0.73796609, 0.01669095, -0.05143998 ],
[ 0.79238143, 0.47275953, 0.71771076, 1.02879957 ],
[ -1.25747488, -0.01153072, -1.443767 , -1.53676936 ],
[ -0.4134164 , 1.19919489, -1.50218532, -1.40173942 ],
[ -1.1368951 , 0.2306144 , -1.38534869, -1.53676936 ],
[ -0.89573553, 1.92563026, -1.38534869, -1.26670948 ],
```

```
[ 0.55122187,  0.71490465,  0.48403749,  0.4886798 ],
[ 0.79238143, -0.01153072,  1.12663899,  1.29885946],
[-0.29283662, -1.22225633,  0.01669095, -0.18646992],
[-0.17225683, -0.49582097,  0.36720086,  0.08358997],
[ 0.67180165, -0.49582097,  1.00980236,  1.29885946],
[-1.37805466,  0.47275953, -1.32693037, -1.40173942],
[ 0.3100623 , -0.01153072,  0.60087413,  0.75873969],
[-1.01631531,  0.95704977, -1.32693037, -1.13167953],
[ 0.67180165, -0.49582097,  1.00980236,  1.16382952],
[ 2.4804984 ,  1.92563026,  1.4771489 ,  1.02879957],
[ 1.033541 , -0.01153072,  0.77612908,  1.43388941],
[ 1.033541 , -1.22225633,  1.12663899,  0.75873969],
[ 1.15412078,  0.47275953,  1.18505731,  1.43388941],
[-1.25747488, -0.01153072, -1.443767 , -1.26670948],
[-1.25747488,  0.2306144 , -1.32693037, -1.40173942],
[-1.49863445,  1.44134002, -1.67744028, -1.40173942],
[-0.17225683,  3.378501 , -1.38534869, -1.13167953],
[ 1.033541 ,  0.2306144 ,  0.30878254,  0.21861991],
[-1.25747488,  0.95704977, -1.32693037, -1.40173942],
[-1.73979401,  0.47275953, -1.50218532, -1.40173942],
[ 0.55122187, -1.22225633,  0.65929245,  0.89376963],
[ 0.67180165,  0.47275953,  0.36720086,  0.35364985],
[-0.77515575,  1.19919489, -1.38534869, -1.40173942],
[-1.01631531,  1.44134002, -1.443767 , -1.40173942],
[-0.77515575,  2.65206563, -1.38534869, -1.53676936],
[-0.05167705, -0.73796609,  0.71771076,  0.89376963],
[ 0.18948252,  0.95704977,  0.36720086,  0.4886798 ],
[ 1.033541 ,  0.2306144 ,  0.48403749,  0.35364985],
[-0.53399618,  2.16777538, -1.50218532, -1.13167953],
[-0.53399618,  1.68348514, -1.38534869, -1.40173942]]])
```

y\_train

```
81    Iris-versicolor
133    Iris-virginica
137    Iris-virginica
75    Iris-versicolor
109    Iris-virginica
...
71    Iris-versicolor
106    Iris-virginica
14    Iris-setosa
92    Iris-versicolor
102    Iris-virginica
Name: Species, Length: 105, dtype: object
```

y\_test

```
73    Iris-versicolor
18    Iris-setosa
118   Iris-virginica
78    Iris-versicolor
76    Iris-versicolor
31    Iris-setosa
64    Iris-versicolor
141   Iris-virginica
68    Iris-versicolor
82    Iris-versicolor
```

```
110    Iris-virginica
12      Iris-setosa
36      Iris-setosa
9       Iris-setosa
19      Iris-setosa
56    Iris-versicolor
104    Iris-virginica
69    Iris-versicolor
55    Iris-versicolor
132    Iris-virginica
29      Iris-setosa
127    Iris-virginica
26      Iris-setosa
128    Iris-virginica
131    Iris-virginica
145    Iris-virginica
108    Iris-virginica
143    Iris-virginica
45      Iris-setosa
30      Iris-setosa
22      Iris-setosa
15      Iris-setosa
65    Iris-versicolor
11      Iris-setosa
42      Iris-setosa
146    Iris-virginica
51    Iris-versicolor
27      Iris-setosa
4       Iris-setosa
32      Iris-setosa
142    Iris-virginica
85    Iris-versicolor
86    Iris-versicolor
16      Iris-setosa
10      Iris-setosa
Name: Species, dtype: object
```

## Performing Normalization

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
scaler.fit(x_train)
x_train=scaler.transform(x_train)
x_test=scaler.transform(x_test)
```

## Model Creation

```
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(x_train,y_train)
y_pred=knn.predict(x_test)
y_pred

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)
```

```
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix,Confus:
print("accuracy score is",accuracy_score(y_test,y_pred))
```

accuracy score is 1.0

```
print("classification report is",classification_report(y_test,y_pred))
```

classification report is			precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	19		
Iris-versicolor	1.00	1.00	1.00	13		
Iris-virginica	1.00	1.00	1.00	13		
accuracy			1.00	45		
macro avg	1.00	1.00	1.00	45		
weighted avg	1.00	1.00	1.00	45		

```
labels=['Iris-setosa','Iris-versicolor','Iris-virginica']
result=confusion_matrix(y_test,y_pred)
cmd=ConfusionMatrixDisplay(result,display_labels=labels)
cmd.plot()
print(result)
```

```
[[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
```

