Iris Dataset Analysis Documentation:

Approach and Methodologies:

1. Exploratory Data Analysis (EDA): Initial exploration of the Iris Dataset was conducted to understand the data's structure, patterns, and relationships between variables. This involved statistical techniques and visualization tools.

2. Power BI Report: The EDA findings were further analyzed and presented using Power BI, a business analytics tool. Power BI helped in creating interactive visualizations and deriving insights from the data.

3. Visualization Techniques: Various plots and graphs were utilized to visualize the relationships between different variables. This included scatter plots, histograms, density plots, and box plots.

4. Statistical Analysis: Statistical measures such as mean, median, and frequency distributions were calculated to understand the central tendencies and distributions of the data.

5. Correlation Analysis: Correlation coefficients were computed to quantify the relationships between different features. This helped in identifying patterns of association between variables.

Clear Explanations for Identified Patterns:

1. Sepal Characteristics by Species:

   - Setosa: Smaller sepal lengths but larger sepal widths.

   - Versicolor: Intermediate values for both sepal length and width.

   - Virginica: Larger sepal lengths but smaller sepal widths.

2. Petal Characteristics by Species:

   - Setosa: Smaller petal lengths and widths.

   - Versicolor: Intermediate values for both petal length and width.

   - Virginica: Largest petal lengths and widths.

3. Frequency Distribution:

   - Sepal Length: Peak frequency between 30 and 35.

   - Sepal Width: Peak frequency around 70.

   - Petal Length: Peak frequency around 50.

   - Petal Width: Peak frequency between 40 and 50.

4. Overlap Analysis:

   - Sepal Length: Significant overlap among species.

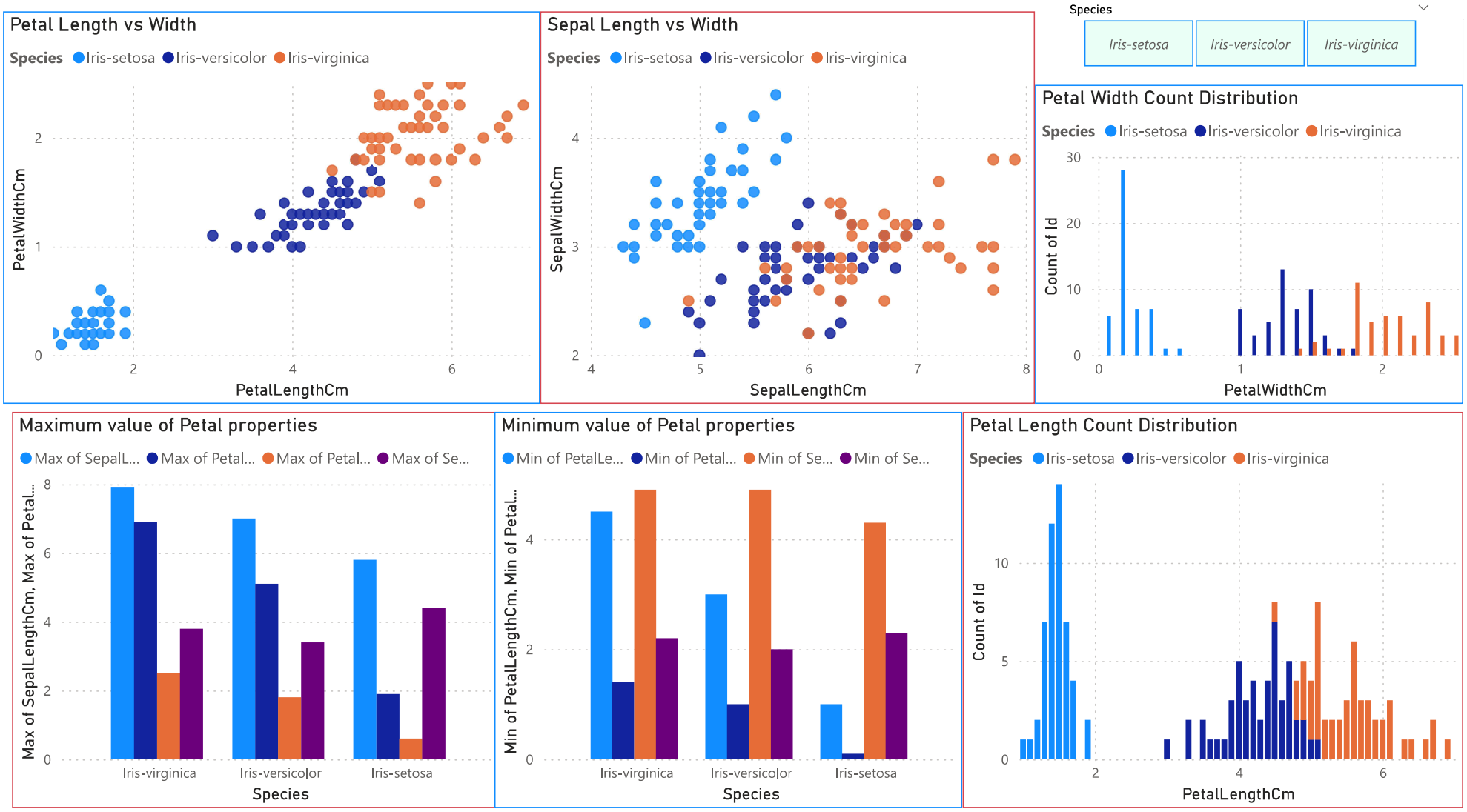
   - Sepal Width: High overlap among species.

   - Petal Length: Minimal overlap among species.

- Petal Width: Minimal overlap among species.

5. Correlation Analysis:
   - High correlation between petal width and length.
   - Good correlations between petal length and sepal width, and petal width and sepal length.
6. Species Distribution:
   - Setosa: Smallest features, less distributed with outliers.
   - Versicolor: Average features and distribution.
   - Virginica: Highly distributed with large number of values and features.
7. Classification Features:
   - Petal length and width are effective classification features due to minimal overlap among species.
   - Sepal dimensions (length and width) are not effective for classification due to significant overlap.
8. Thresholds for Species Identification:
   - Setosa: Petal length < 2.1.
   - Versicolor: 2.1 < Petal length < 4.8.
   - Virginica: Petal length > 4.8.

By employing these methodologies and analyses, clear patterns and insights about the Iris Dataset were obtained, aiding in better understanding and interpretation of the data.


Petal Length vs Width
Species Iris-setosa Iris-versicolor Iris-virginica
PetalWidthCm
PetalLengthCm
Sepal Length vs Width
Species Iris-setosa Iris-versicolor Iris-virginica
SepalWidthCm
SepalLengthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica
Petal Width Count Distribution
Species Iris-setosa Iris-versicolor Iris-virginica
Count of Id
PetalWidthCm
Maximum value of Petal properties
Max of SepalL... Max of Petal... Max of Petal... Max of Se...
Max of SepalLengthCm, Max of Petal...
Iris-virginica
Iris-versicolor
Iris-setosa
Species
Minimum value of Petal properties
Min of PetalLe... Min of Petal... Min of Se... Min of Se...
Min of PetalLengthCm, Min of Petal...
Iris-virginica
Iris-versicolor
Iris-setosa
Species
Petal Length Count Distribution
Species Iris-setosa Iris-versicolor Iris-virginica
Count of Id
PetalLengthCm

The Iris Dataset

This data sets consists of 3 different types of irises' (Setosa, Versicolour, and Virginica) petal and sepal length, stored in a 150x4 numpy.ndarray

Loading the iris dataset

```
from sklearn import datasets
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
sns.set()
```

```
# Reading the CSV file
df = pd.read_csv("Iris.csv")

# Printing top 5 rows
df.head()
```

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

```
df.shape
```

```
(150, 6)
```

We can see that the dataframe contains 6 columns and 150 rows.

```
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
```

We can see that only one column has categorical data and all the other columns are of the numeric type with non-Null entries.

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

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

We can see that no column as any missing value.

```
data = df.drop_duplicates(subset ="Species",)
data
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
50	51	7.0	3.2	4.7	1.4	Iris-versicolor
100	101	6.3	3.3	6.0	2.5	Iris-virginica

```
df.value_counts("Species")
```

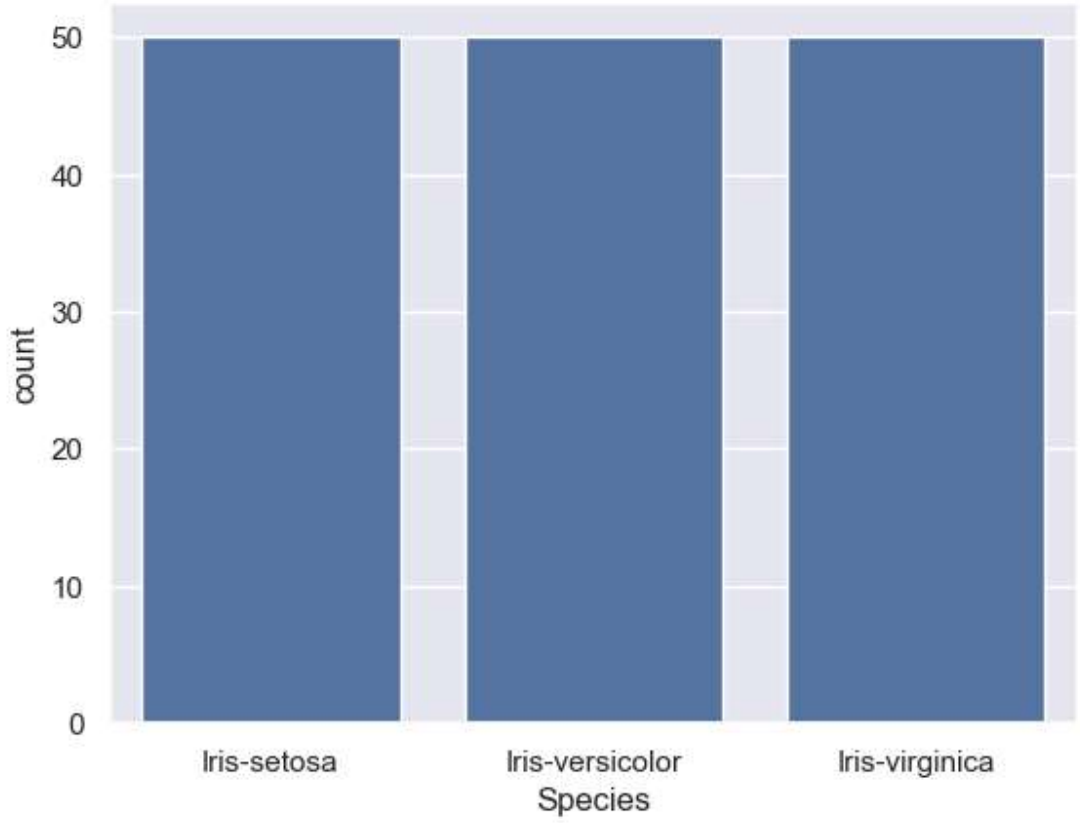
```
Species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: count, dtype: int64
```

We can see that all the species contain an equal amount of rows, so we should not delete any entries.

Visualizing the target column Our target column will be the Species column because at the end we will need the result according to the species only. Let’s see a countplot for species.

```
# importing packages
import seaborn as sns
import matplotlib.pyplot as plt


sns.countplot(x='Species', data=df, )
plt.show()
```

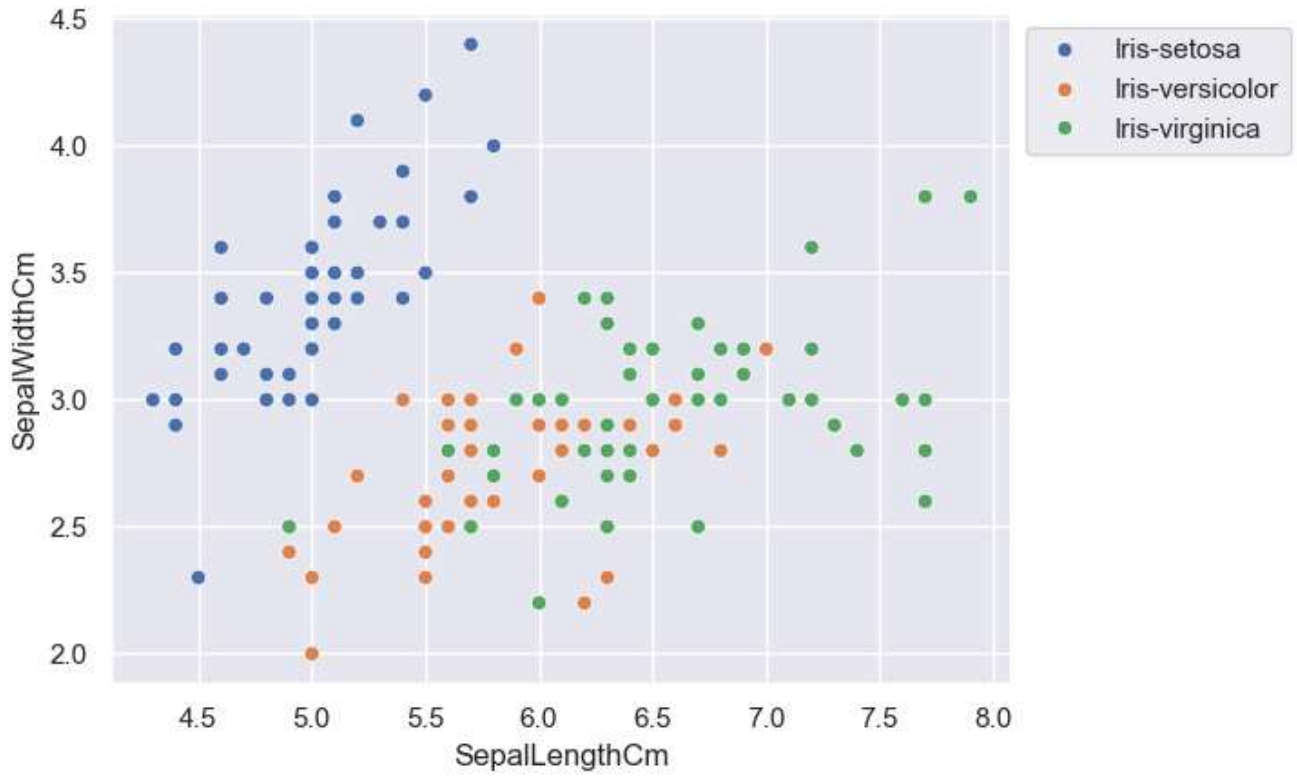


We will see the relationship between the sepal length and sepal width and also between petal length and petal width.

```
sns.scatterplot(x='SepalLengthCm', y='SepalWidthCm',
                hue='Species', data=df, )

# Placing Legend outside the Figure
plt.legend(bbox_to_anchor=(1, 1), loc=2)

plt.show()
```



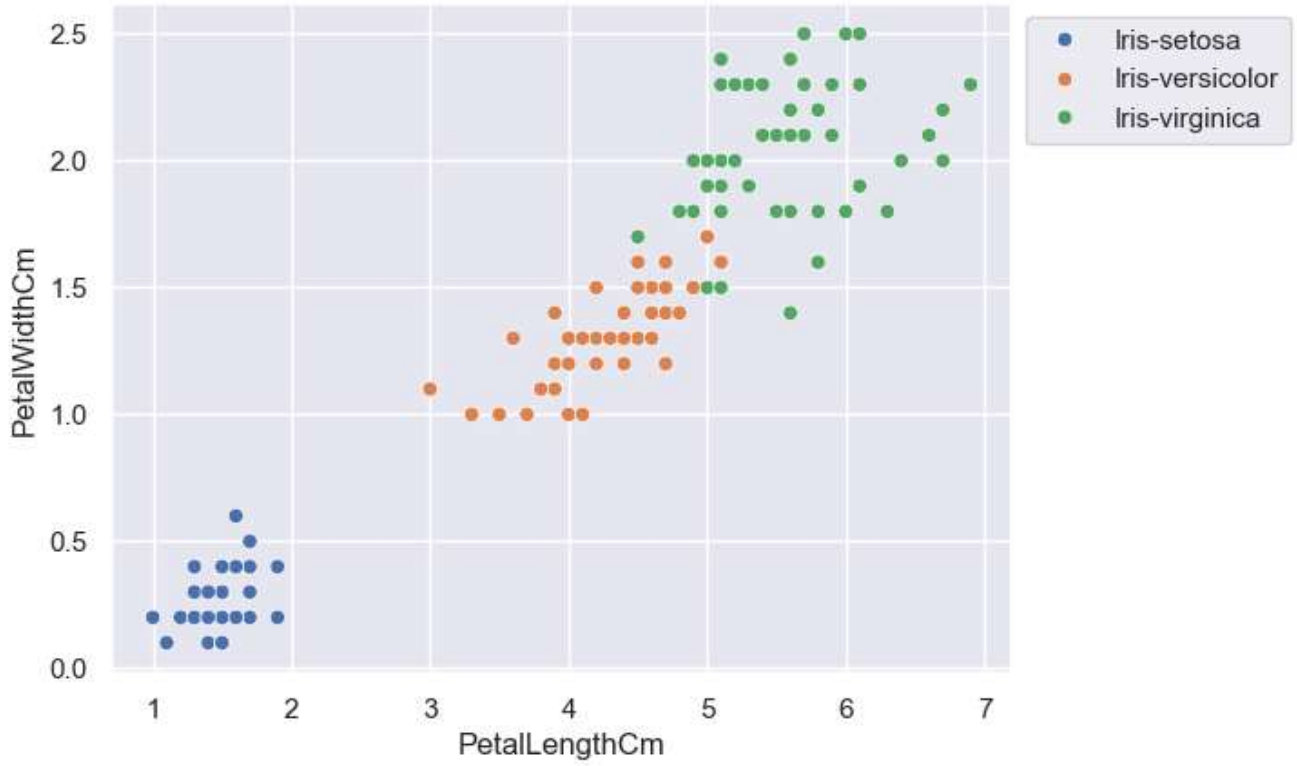
From the above plot, we can infer that –

Species Setosa has smaller sepal lengths but larger sepal widths. Versicolor Species lies in the middle of the other two species in terms of sepal length and width Species Virginica has larger sepal lengths but smaller sepal widths.

```
sns.scatterplot(x='PetalLengthCm', y='PetalWidthCm',
                hue='Species', data=df, )

# Placing Legend outside the Figure
plt.legend(bbox_to_anchor=(1, 1), loc=2)

plt.show()
```

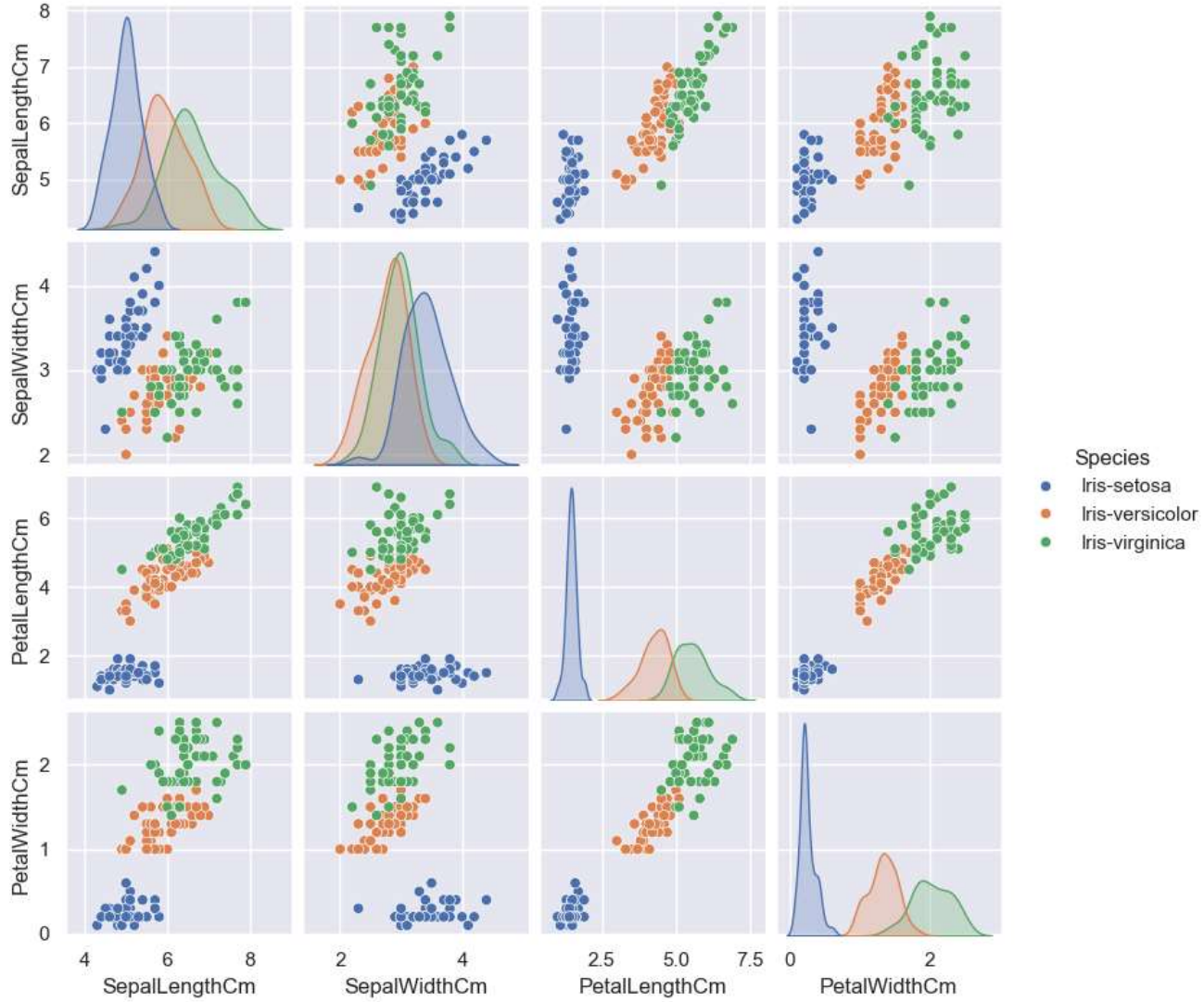


From the above plot, we can infer that –

Species Setosa has smaller petal lengths and widths. Versicolor Species lies in the middle of the other two species in terms of petal length and width Species Virginica has the largest of petal lengths and widths.

```
sns.pairplot(df.drop(['Id'], axis = 1),
             hue='Species', height=2)
```

```
<seaborn.axisgrid.PairGrid at 0x23a8fdcaed0>
```



We can see many types of relationships from this plot such as the species Setosa has the smallest of petals widths and lengths. It also has the smallest sepal length but larger sepal widths. Such information can be gathered about any other species.

Histograms allow seeing the distribution of data for various columns. It can be used for uni as well as bi-variate analysis.

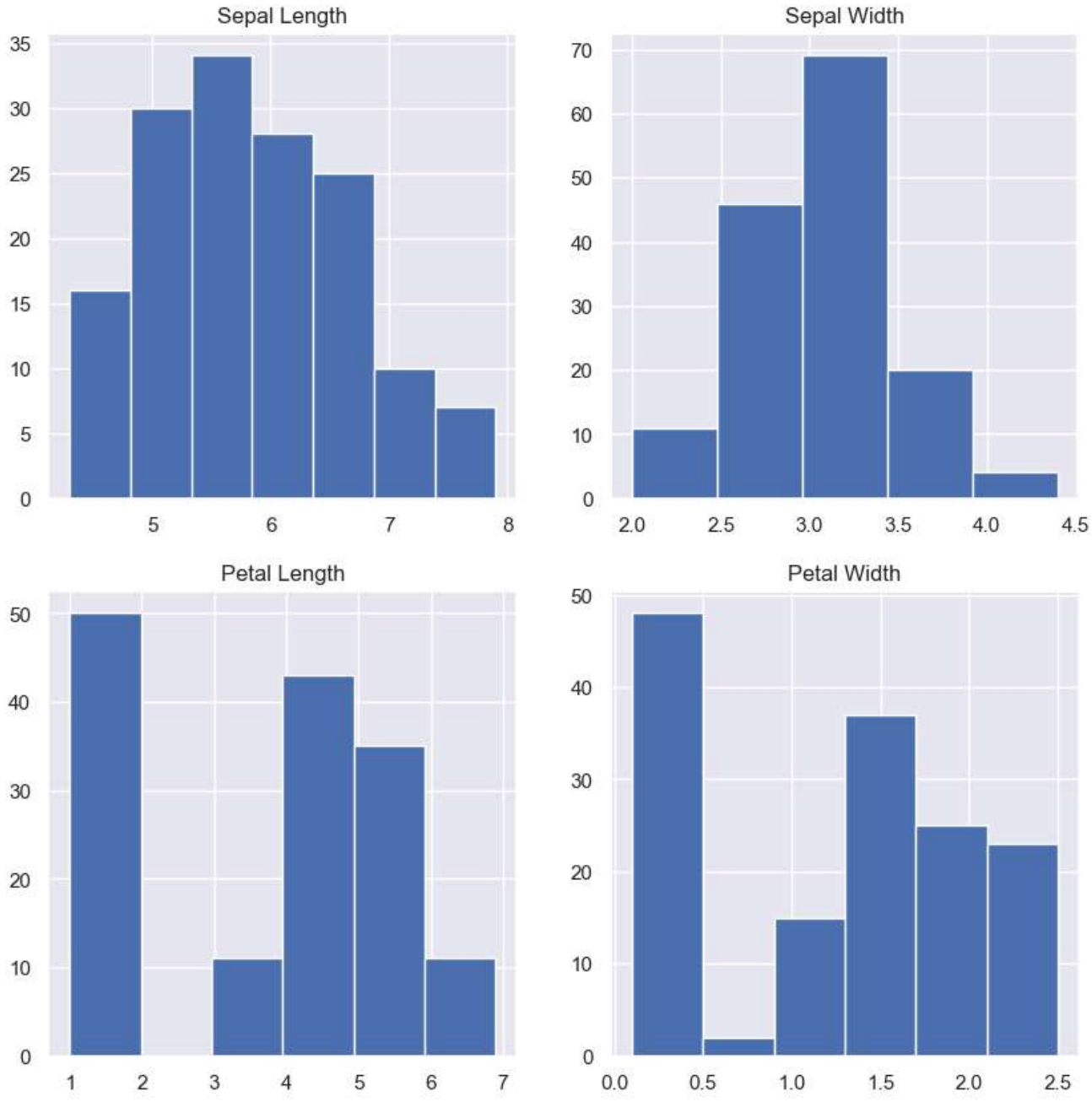
```
fig, axes = plt.subplots(2, 2, figsize=(10,10))

axes[0,0].set_title("Sepal Length")
axes[0,0].hist(df['SepalLengthCm'], bins=7)

axes[0,1].set_title("Sepal Width")
axes[0,1].hist(df['SepalWidthCm'], bins=5);

axes[1,0].set_title("Petal Length")
axes[1,0].hist(df['PetalLengthCm'], bins=6);

axes[1,1].set_title("Petal Width")
axes[1,1].hist(df['PetalWidthCm'], bins=6);
```



From the above plot, we can see that –

The highest frequency of the sepal length is between 30 and 35 which is between 5.5 and 6 The highest frequency of the sepal Width is around 70 which is between 3.0 and 3.5 The highest

frequency of the petal length is around 50 which is between 1 and 2 The highest frequency of the petal width is between 40 and 50 which is between 0.0 and 0.5

Histograms with Distplot Plot Distplot is used basically for the univariant set of observations and visualizes it through a histogram i.e. only one observation and hence we choose one particular column of the dataset.

```
plot = sns.FacetGrid(df, hue="Species")
plot.map(sns.distplot, "SepalLengthCm").add_legend()

plot = sns.FacetGrid(df, hue="Species")
plot.map(sns.distplot, "SepalWidthCm").add_legend()

plot = sns.FacetGrid(df, hue="Species")
plot.map(sns.distplot, "PetalLengthCm").add_legend()

plot = sns.FacetGrid(df, hue="Species")
plot.map(sns.distplot, "PetalWidthCm").add_legend()

plt.show()
```

```
C:\Users\anujk\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:854: U

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  func(*plot_args, **plot_kwargs)
C:\Users\anujk\AppData\Roaming\Python\Python311\site-packages\seaborn\axisgrid.py:854: U

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  func(*plot_args, **plot_kwargs)
```
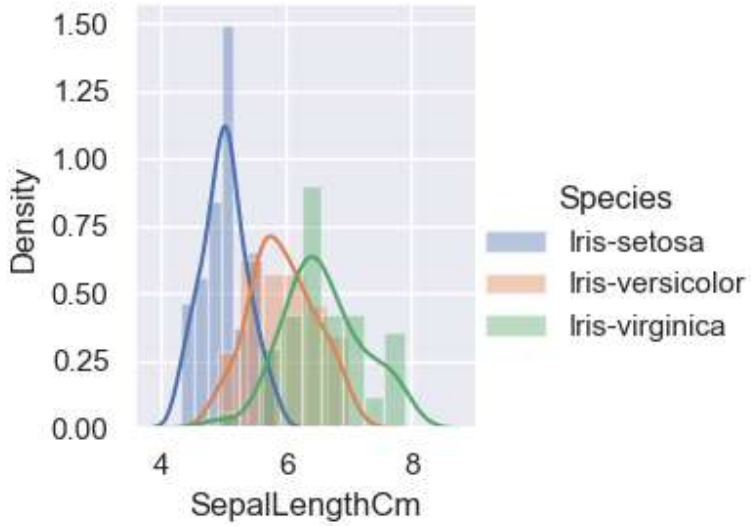
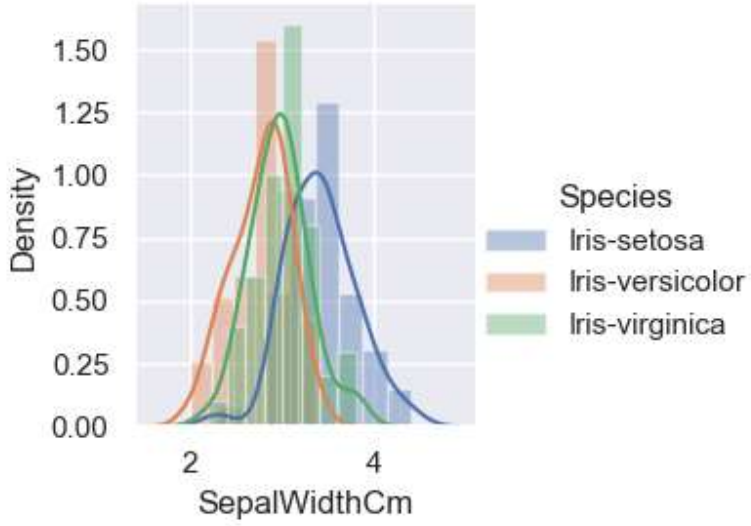
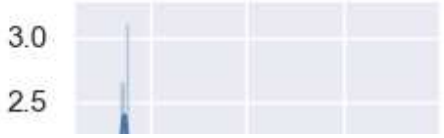
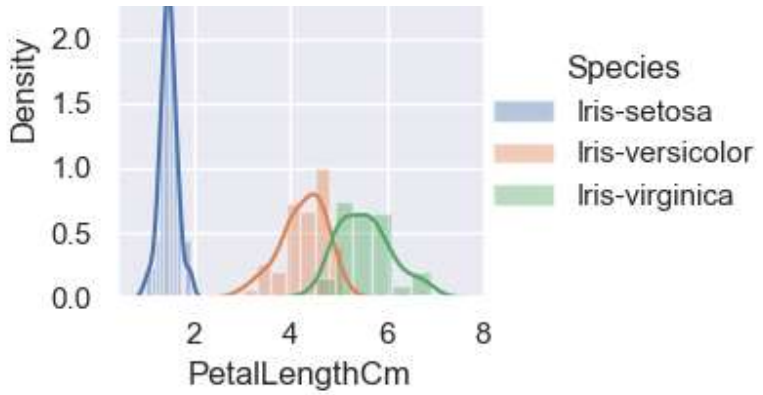
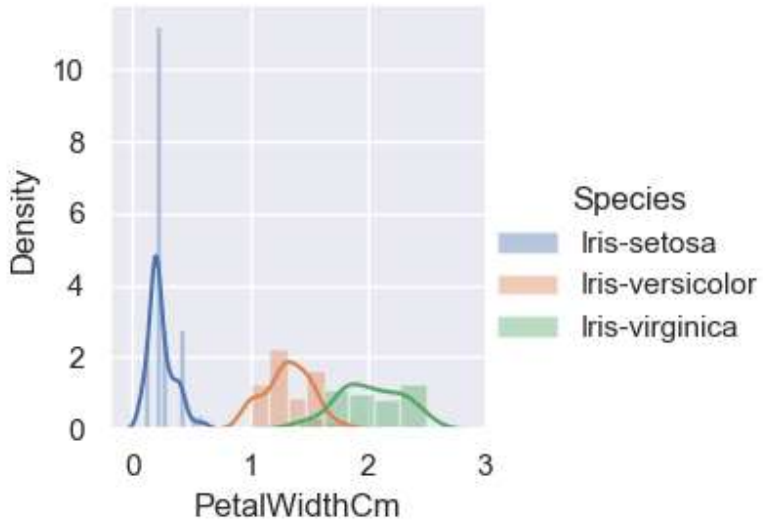











From the above plots, we can see that –

In the case of Sepal Length, there is a huge amount of overlapping. In the case of Sepal Width also, there is a huge amount of overlapping. In the case of Petal Length, there is a very little amount of overlapping. In the case of Petal Width also, there is a very little amount of overlapping. So we can use Petal Length and Petal Width as the classification feature.

Handling Correlation Pandas dataframe.corr() is used to find the pairwise correlation of all columns in the dataframe. Any NA values are automatically excluded. For any non-numeric data type columns in the dataframe it is ignored.

```
df['Species'].nunique()
```

```
3
```

```
from sklearn.preprocessing import LabelEncoder

# Assuming 'df' is your DataFrame and 'Species' is the column to be encoded
label_encoder = LabelEncoder()
df['Species'] = label_encoder.fit_transform(df['Species'])
```

```
df.head()
```

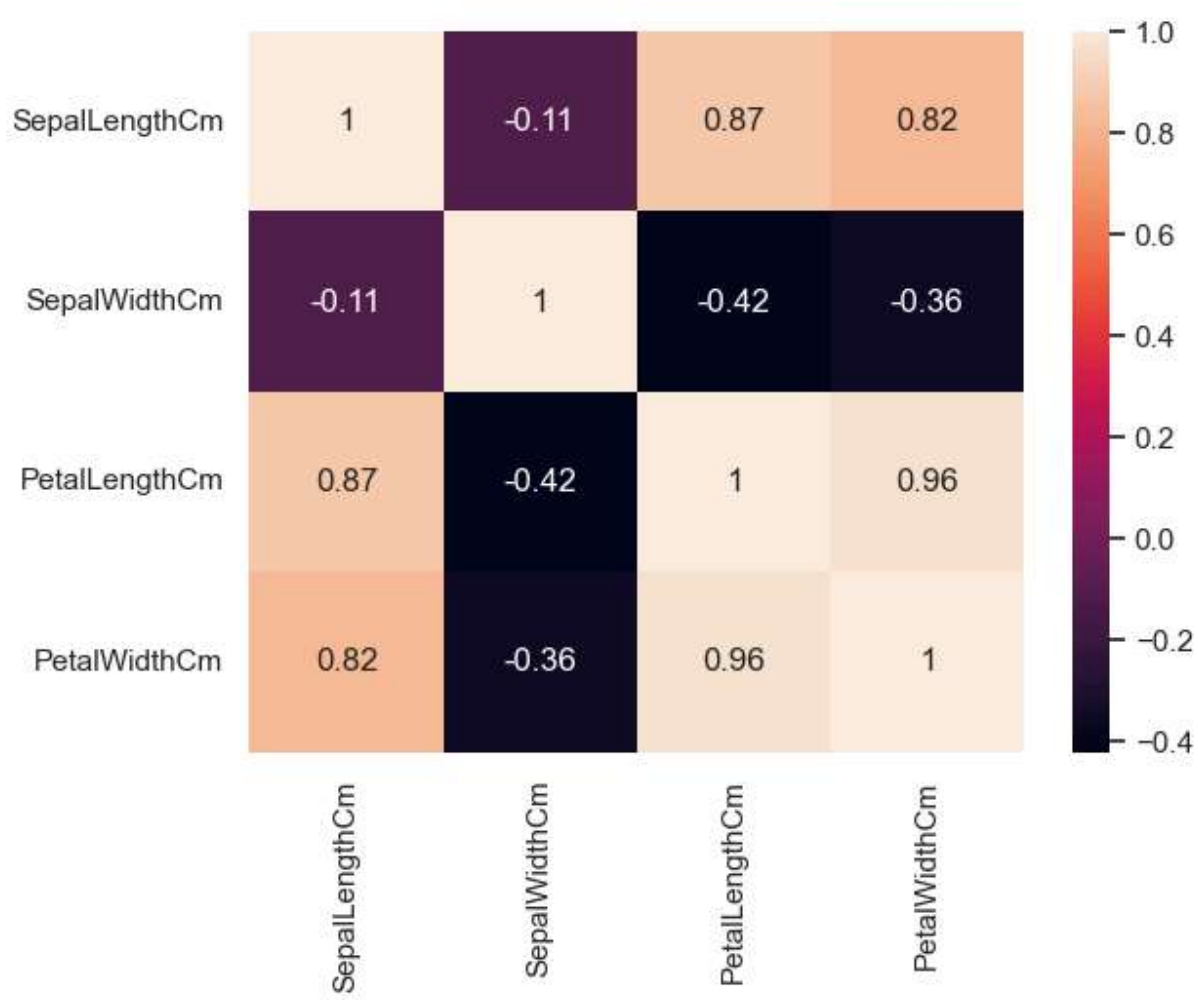
	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	0
1	2	4.9	3.0	1.4	0.2	0
2	3	4.7	3.2	1.3	0.2	0
3	4	4.6	3.1	1.5	0.2	0
4	5	5.0	3.6	1.4	0.2	0

```
df.corr(method='pearson')
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Spe
Id	1.000000	0.716676	-0.397729	0.882747	0.899759	0.9
SepalLengthCm	0.716676	1.000000	-0.109369	0.871754	0.817954	0.7
SepalWidthCm	-0.397729	-0.109369	1.000000	-0.420516	-0.356544	-0.4
PetalLengthCm	0.882747	0.871754	-0.420516	1.000000	0.962757	0.9
PetalWidthCm	0.899759	0.817954	-0.356544	0.962757	1.000000	0.9
Species	0.942830	0.782561	-0.419446	0.949043	0.956464	1.0

Heatmaps: The heatmap is a data visualization technique that is used to analyze the dataset as colors in two dimensions. Basically, it shows a correlation between all numerical variables in the dataset. In simpler terms, we can plot the above-found correlation using the heatmaps.

```
sns.heatmap(df.corr(method='pearson').drop( ['Id','Species'], axis=1).drop( ['Id','Species']

plt.show()
```

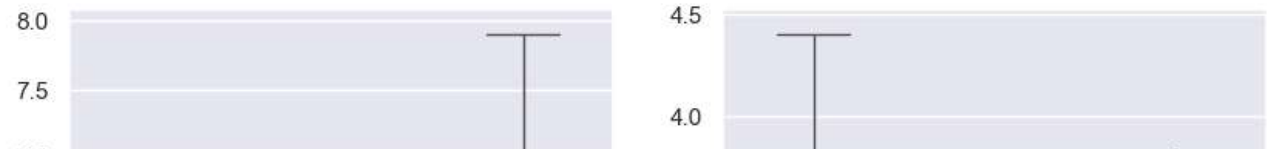


From the above graph, we can see that –

Petal width and petal length have high correlations. Petal length and sepal width have good correlations. Petal Width and Sepal length have good correlations.

Box Plots: We can use boxplots to see how the categorical value os distributed with other numerical values.

```
def graph(y):
    sns.boxplot(x="Species", y=y, data=df)

plt.figure(figsize=(10,10))

# Adding the subplot at the specified
# grid position
plt.subplot(221)
graph('SepalLengthCm')

plt.subplot(222)
graph('SepalWidthCm')

plt.subplot(223)
graph('PetalLengthCm')

plt.subplot(224)
graph('PetalWidthCm')

plt.show()
```

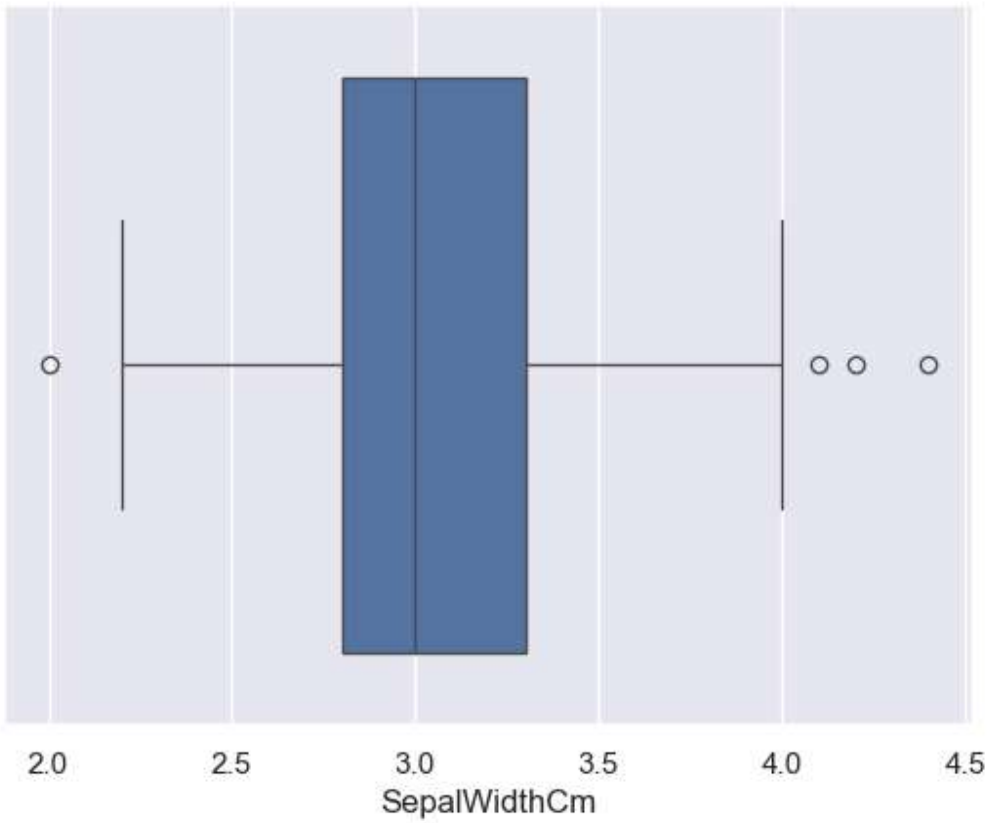


From the above graph, we can see that –

0 Species Setosa has the smallest features and less distributed with some outliers. 1 Species Versicolor has the average features. 2 Species Virginica has the highest features


```
sns.boxplot(x='SepalWidthCm', data=df)
```

```
<Axes: xlabel='SepalWidthCm'>
```



Scatter Plot of the Iris dataset

```
from sklearn import datasets

iris = datasets.load_iris()
```

```
import matplotlib.pyplot as plt

. ax = plt.subplots()
```