

Iris Flower Classification

Importing Libraries

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

import warnings
warnings.filterwarnings('ignore')
```

```
In [2]: iris_data = pd.read_csv("IRIS Dataset.csv")
iris_data.head()
```

```
Out[2]:
```

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

```
In [3]: iris_data.tail()
```

```
Out[3]:
```

| | 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 |

Statistical Data Analysis

```
In [4]: iris_data.describe()
```

```
Out[4]:
```

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

```
In [6]: #Length of Data
iris_data.shape
```

```
Out[6]: (150, 5)
```

summary of a DataFrame

```
In [7]: iris_data.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
```

```
In [8]: #Checking null value
iris_data.isnull().sum()
```

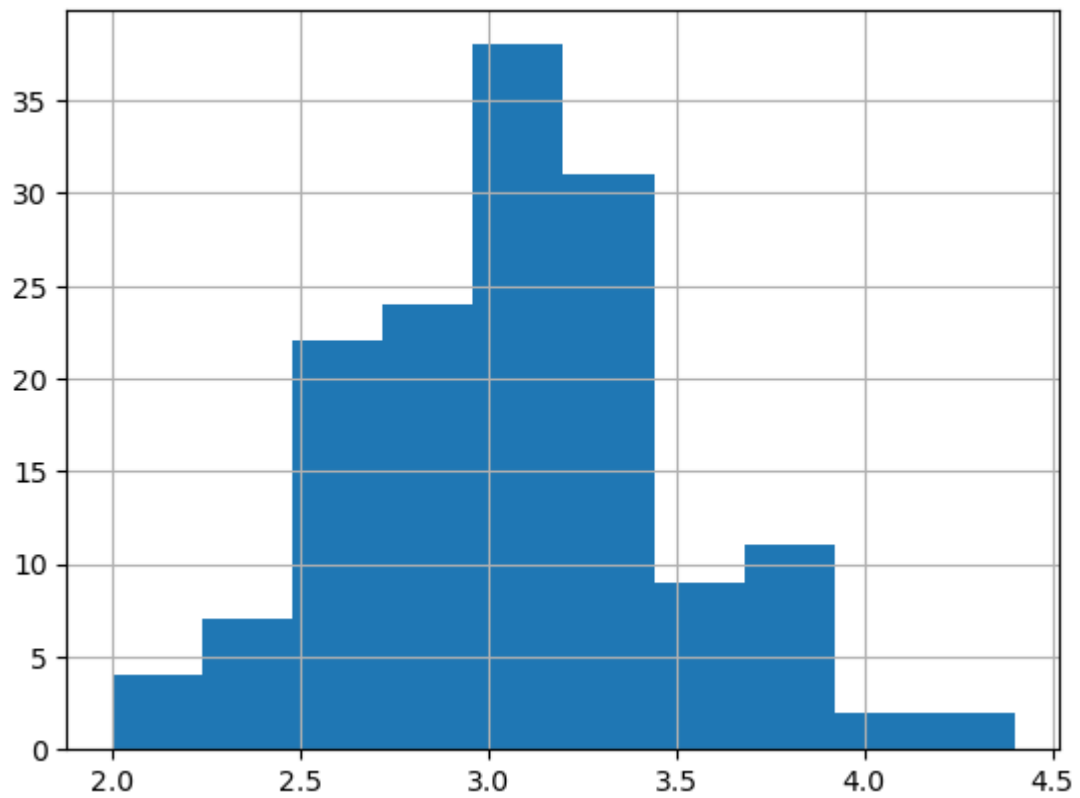
```
Out[8]: sepal_length    0
sepal_width    0
petal_length    0
petal_width    0
species        0
dtype: int64
```

```
In [9]: iris_data['species'].value_counts()
```

```
Out[9]: Iris-setosa      50
Iris-versicolor    50
Iris-virginica      50
Name: species, dtype: int64
```

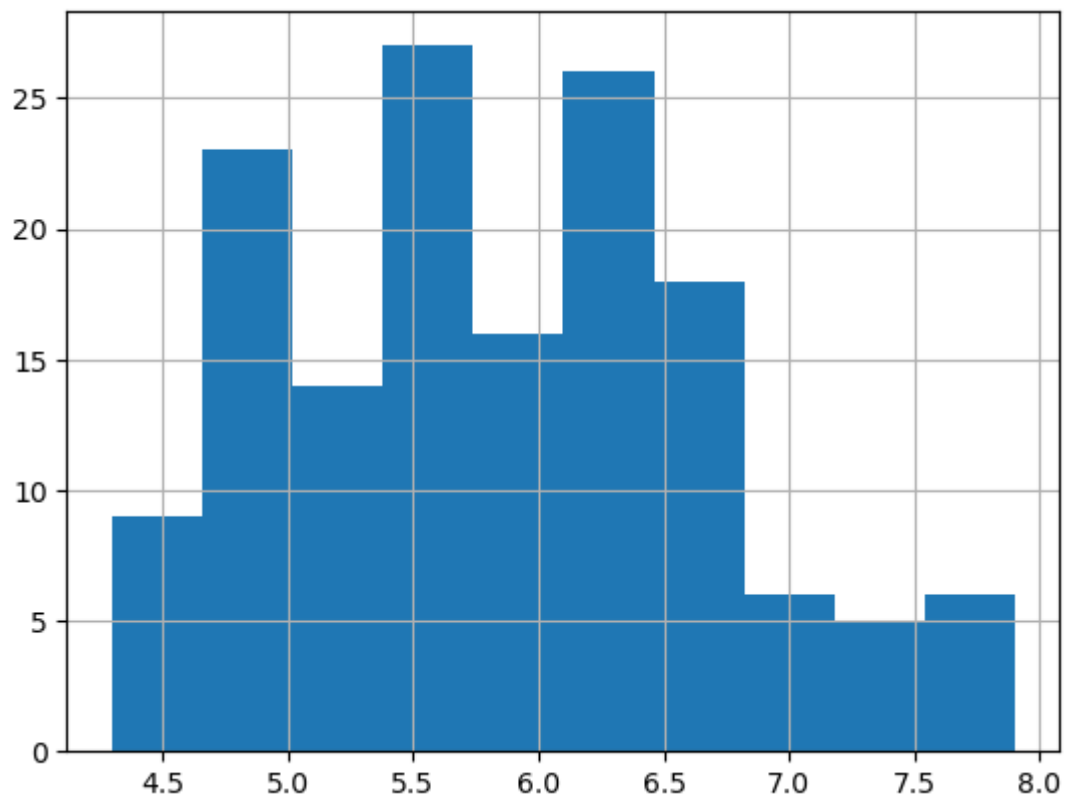
```
In [10]: iris_data['sepal_width'].hist()
```

```
Out[10]: <Axes: >
```



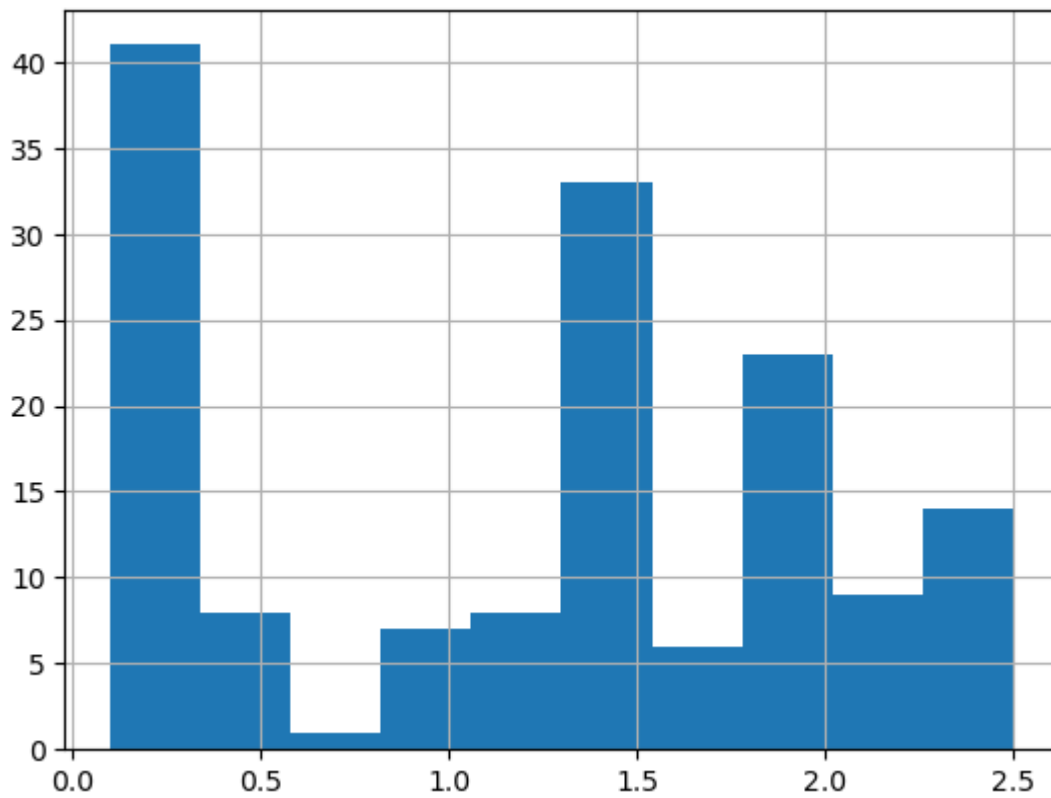
```
In [11]: iris_data['sepal_length'].hist()
```

```
Out[11]: <Axes: >
```



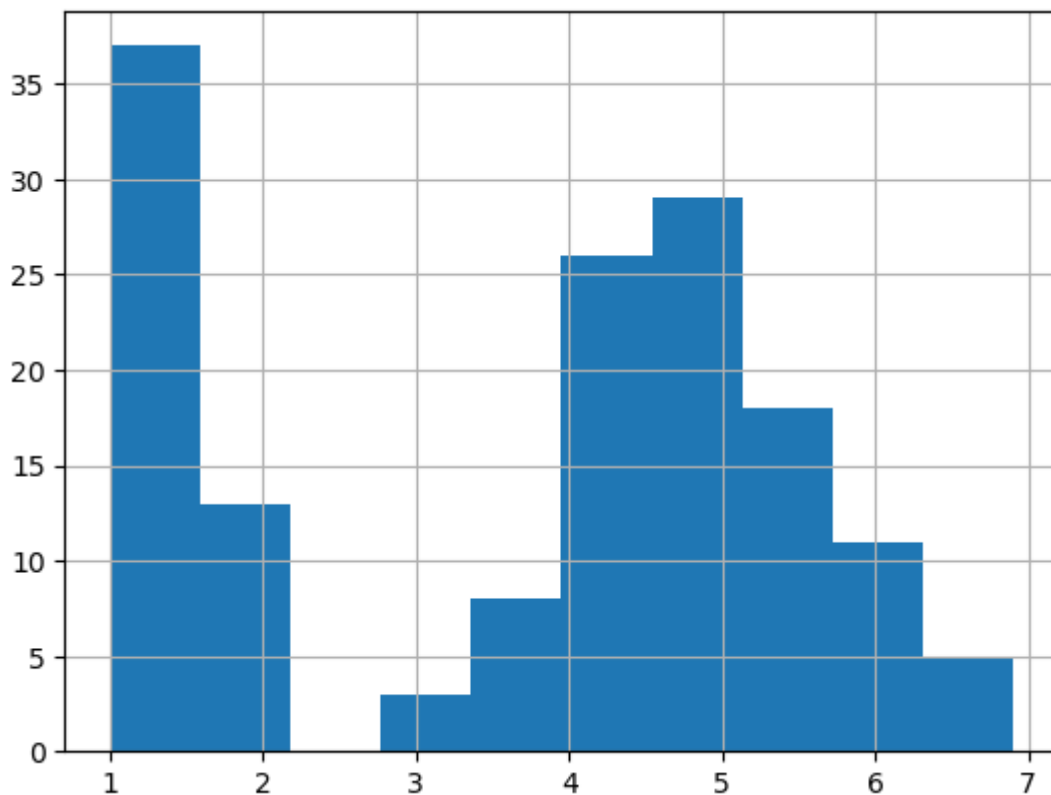
```
In [12]: iris_data['petal_width'].hist()
```

```
Out[12]: <Axes: >
```

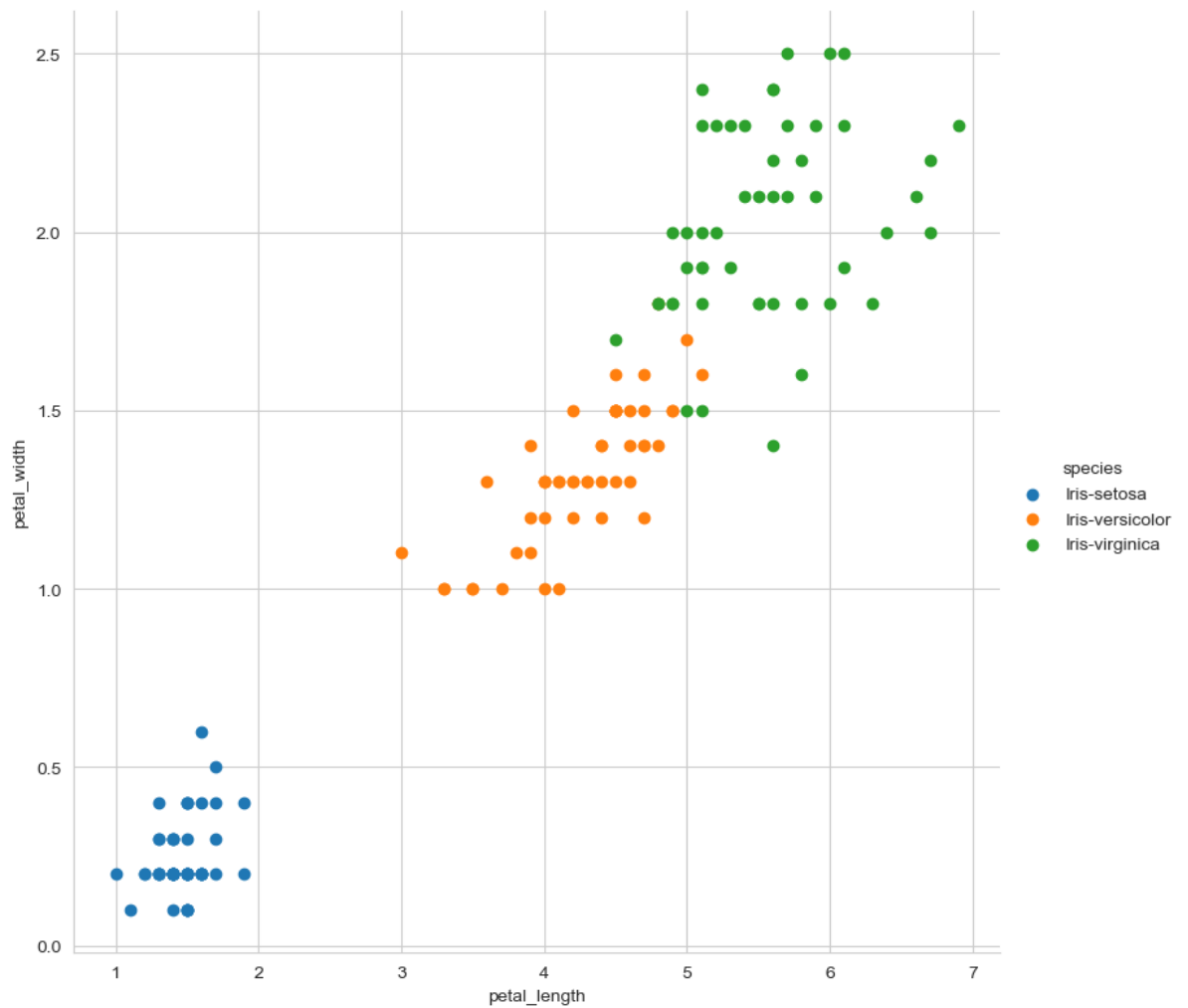


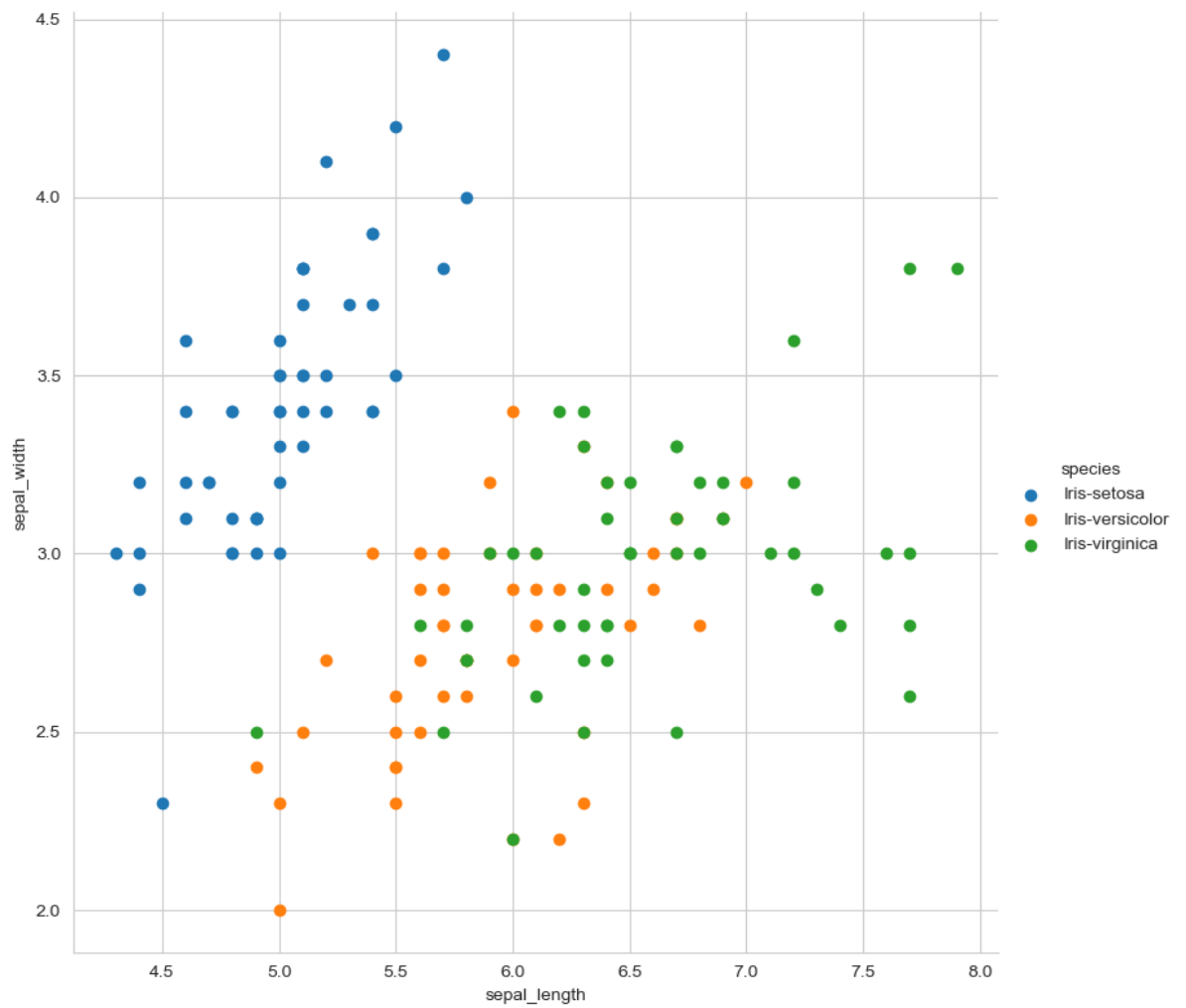
```
In [13]: iris_data['petal_length'].hist()
```

```
Out[13]: <Axes: >
```

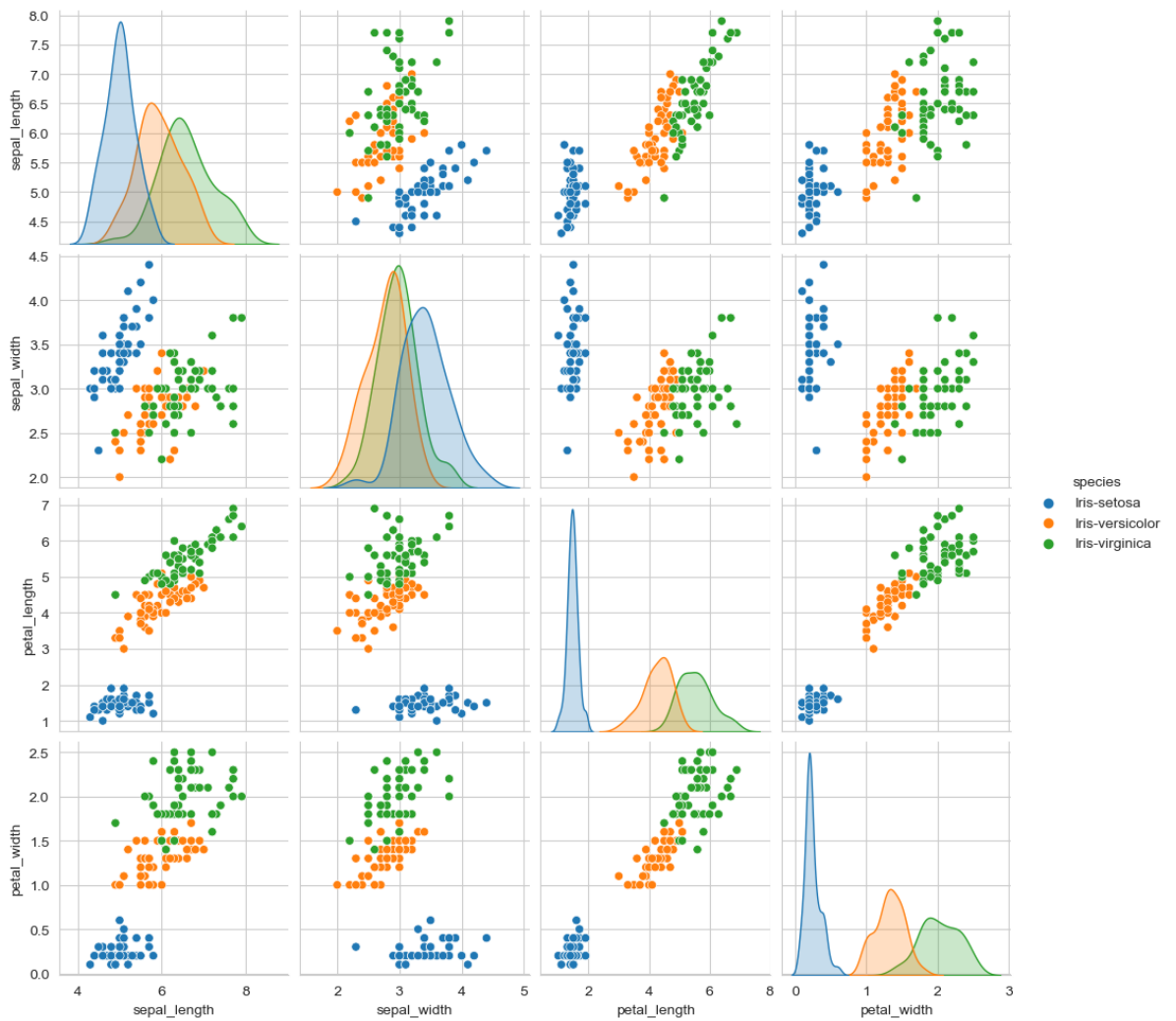


```
In [18]: s = sns.FacetGrid(iris_data, height=8, hue="species")
s.map(plt.scatter, "petal_length", "petal_width")
s.add_legend()
sns.set_style("whitegrid")
plt.show()
```

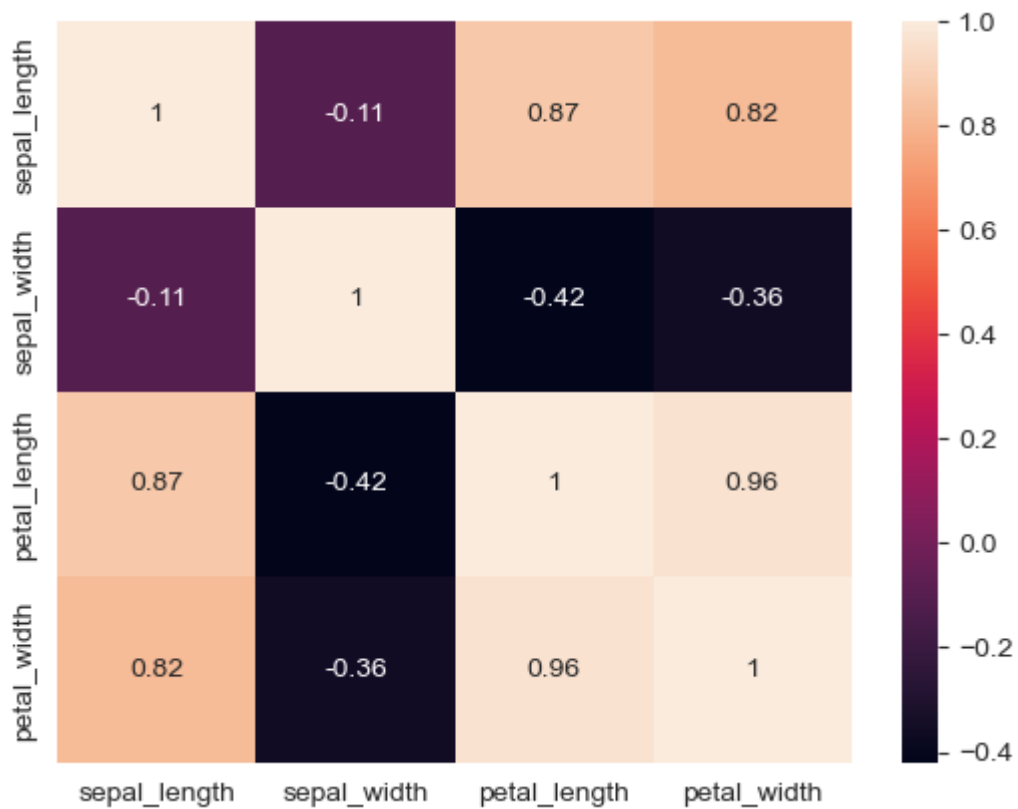




```
In [22]: sns.pairplot(iris_data, height=2.5, hue="species")  
plt.show()
```



```
In [25]: #Checking Correlation use of Heatmap
sns.heatmap(iris_data.corr(), annot=True)
plt.show()
```



Split the data into training and testing

```
In [30]: from sklearn.model_selection import train_test_split
```

```
X = iris_data[["sepal_length", "sepal_width", "petal_length", "petal_width"]]
y = iris_data["species"]
```

```
In [31]: X
```

```
Out[31]:
```

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

150 rows × 4 columns

```
In [32]: y
```

```
Out[32]:
```

| | |
|-----|----------------|
| 0 | Iris-setosa |
| 1 | Iris-setosa |
| 2 | Iris-setosa |
| 3 | Iris-setosa |
| 4 | Iris-setosa |
| ... | ... |
| 145 | Iris-virginica |
| 146 | Iris-virginica |
| 147 | Iris-virginica |
| 148 | Iris-virginica |
| 149 | Iris-virginica |

Name: species, Length: 150, dtype: object

```
In [38]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_st
```

Logistic regression model

```
In [34]: from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
```

```
In [35]: model.fit(X_train, y_train)
```



```
Out[35]: ▾ LogisticRegression
LogisticRegression()
```

```
In [39]: #metrics to get performance
print('Accuracy',model.score(X_test,y_test)*100)

Accuracy 97.77777777777777
```

K-Nearest Neighbours model

```
In [40]: from sklearn.neighbors import KNeighborsClassifier
model=KNeighborsClassifier()
```

```
In [41]: model.fit(X_train,y_train)
```

```
Out[41]: ▾ KNeighborsClassifier
KNeighborsClassifier()
```

```
In [42]: #metrics to get performance
print('Accuracy',model.score(X_test,y_test)*100)

Accuracy 97.77777777777777
```

Decision tree model

```
In [43]: from sklearn.tree import DecisionTreeClassifier
model=DecisionTreeClassifier()
```

```
In [44]: model.fit(X_train,y_train)
```

```
Out[44]: ▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

```
In [45]: #metrics to get performance
print('Accuracy',model.score(X_test,y_test)*100)

Accuracy 97.77777777777777
```

You can find this project on [GitHub](#).