Name- Kore Pratiksha Jayant

Oasis Infobyte (Data Science)

Task-1 Iiris Flower Classification

INTRODUCTION_ In this notebook, we aim to perform Iris Flower Classification using machine learning techniques, training models on the measurements of iris flowers to accurately predict their species.

Import necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")
```

Loading dataset

In [2]:
```
data = pd.read_csv('C:\\Users\\stati\\OneDrive\\Desktop\\Iris.csv')
data
```

Out[2]:

	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
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

(EDA) Exploratory Data Analysis

In [3]:
```python
# To display column names
data.columns
```

Out[3]:
```
Index(['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

we can see there are 5 columns

In [4]:
```python
# To display data types of columns
data.dtypes
```

Out[4]:
```
SepalLengthCm    float64
SepalWidthCm     float64
PetalLengthCm    float64
PetalWidthCm     float64
Species           object
dtype: object
```

In [5]:
```python
# To display count of each species
data['Species'].value_counts()
```

Out[5]:
```
Species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: count, dtype: int64
```

In [6]:
```python
# To display summary statistics
data.describe()
```

Out[6]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
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 [7]:
```python
# To rename columns for better readability
updated_data = data.rename(columns={'SepalLengthCm':'Sepal_Length',
                                    'SepalWidthCm':'Sepal_Width',
                                    'PetalLengthCm':'Petal_Length',
                                    'PetalWidthCm':'Petal_Width',
                                    'Species':'Species'})
updated_data
```

Out[7]:

	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

Visualization

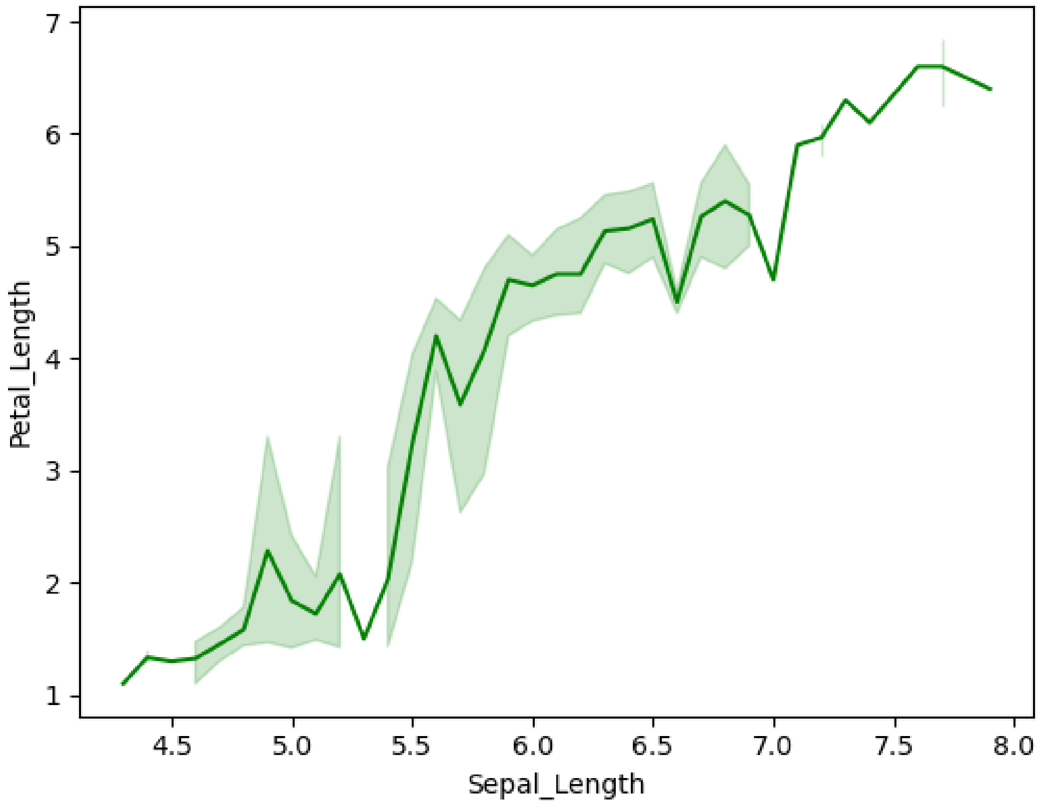
In [8]:

```
import seaborn as sns
import matplotlib.pyplot as plt
```

Visualizing the Relationship between Sepal Length and Petal Length

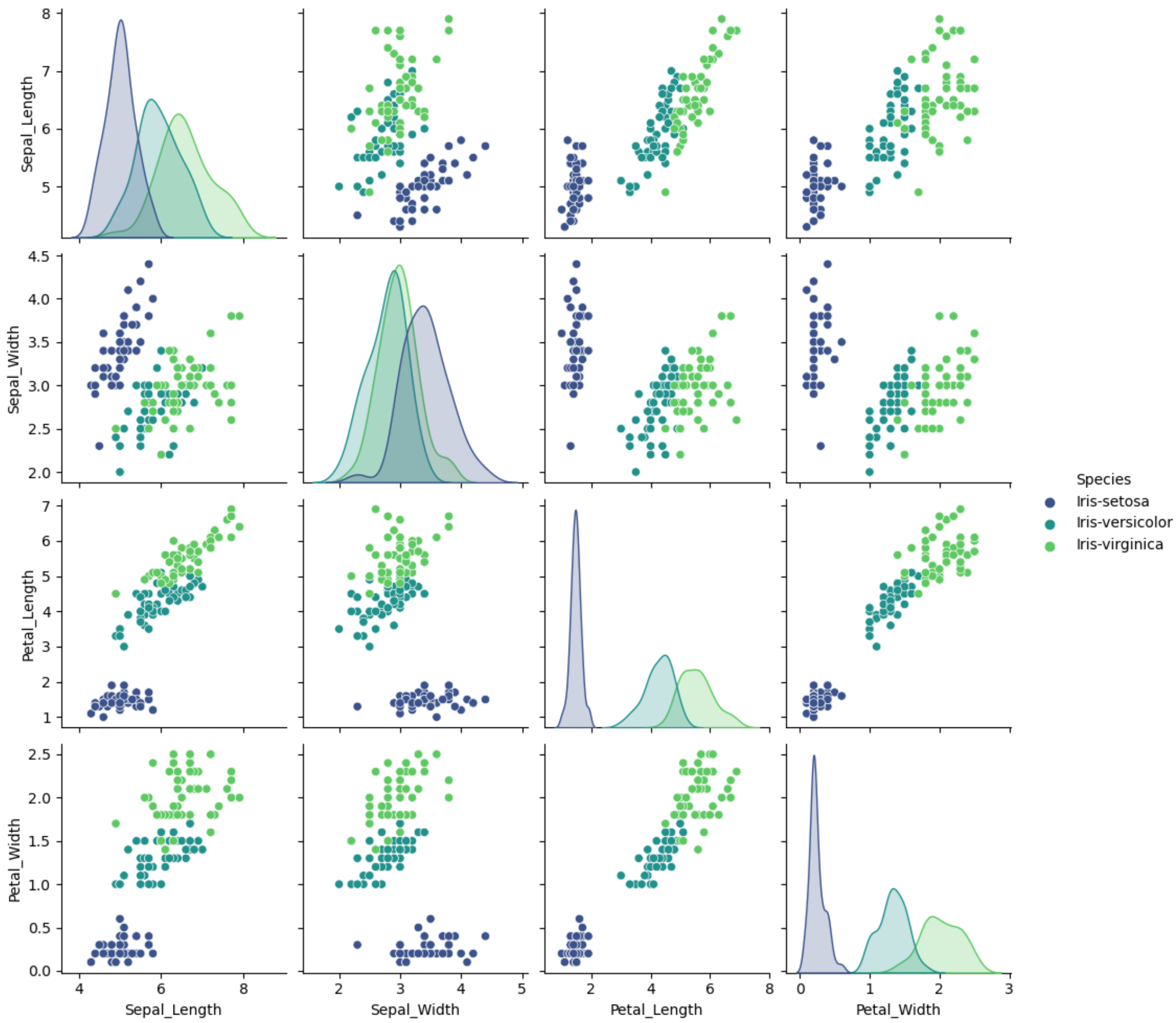
In [9]:

```
sns.lineplot(x=updated_data["Sepal_Length"],
             y=updated_data["Petal_Length"], color='Green')
plt.show()
```



Visualize pair plots with species differentiation

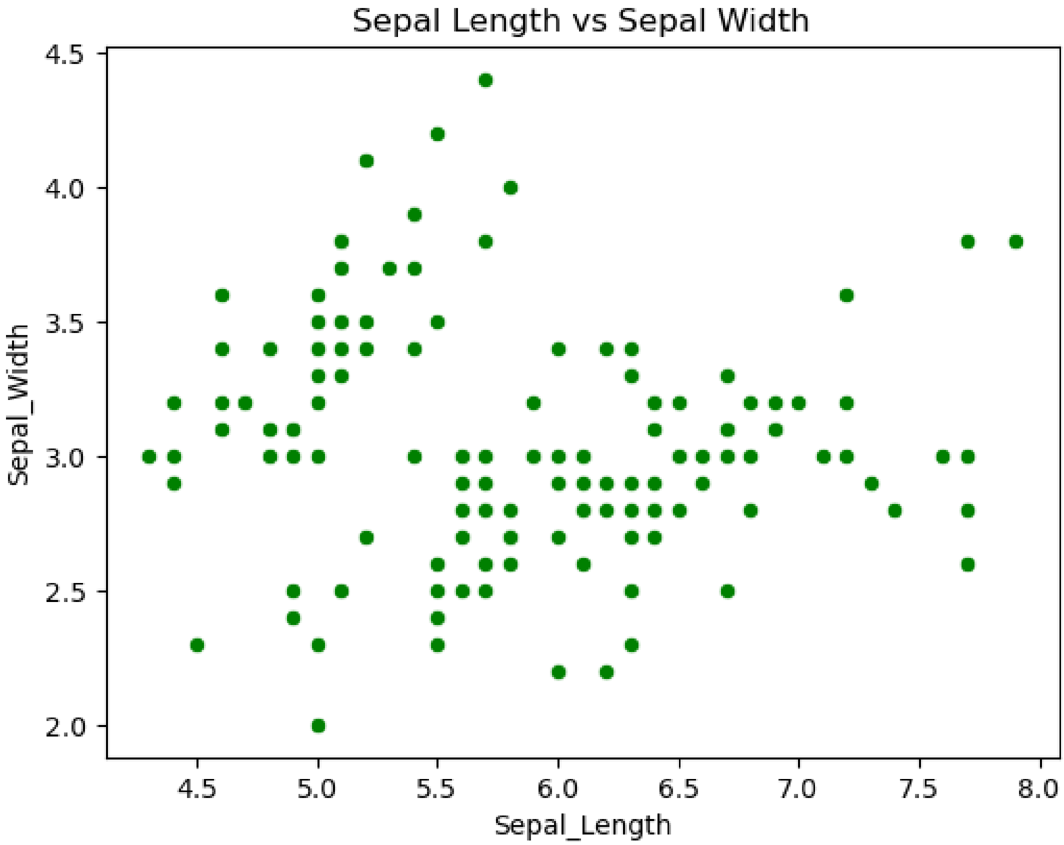
```
In [10]: sns.pairplot(updated_data, hue="Species", palette='viridis')
         plt.show()
```



After creating a pair plot for the features, it's evident that the pattern of relationships between different pairs of features for iris-setosa is noticeably unique compared to the other two species. However, there is some overlap in the patterns of relationships between features for iris-versicolor and iris-virginica.

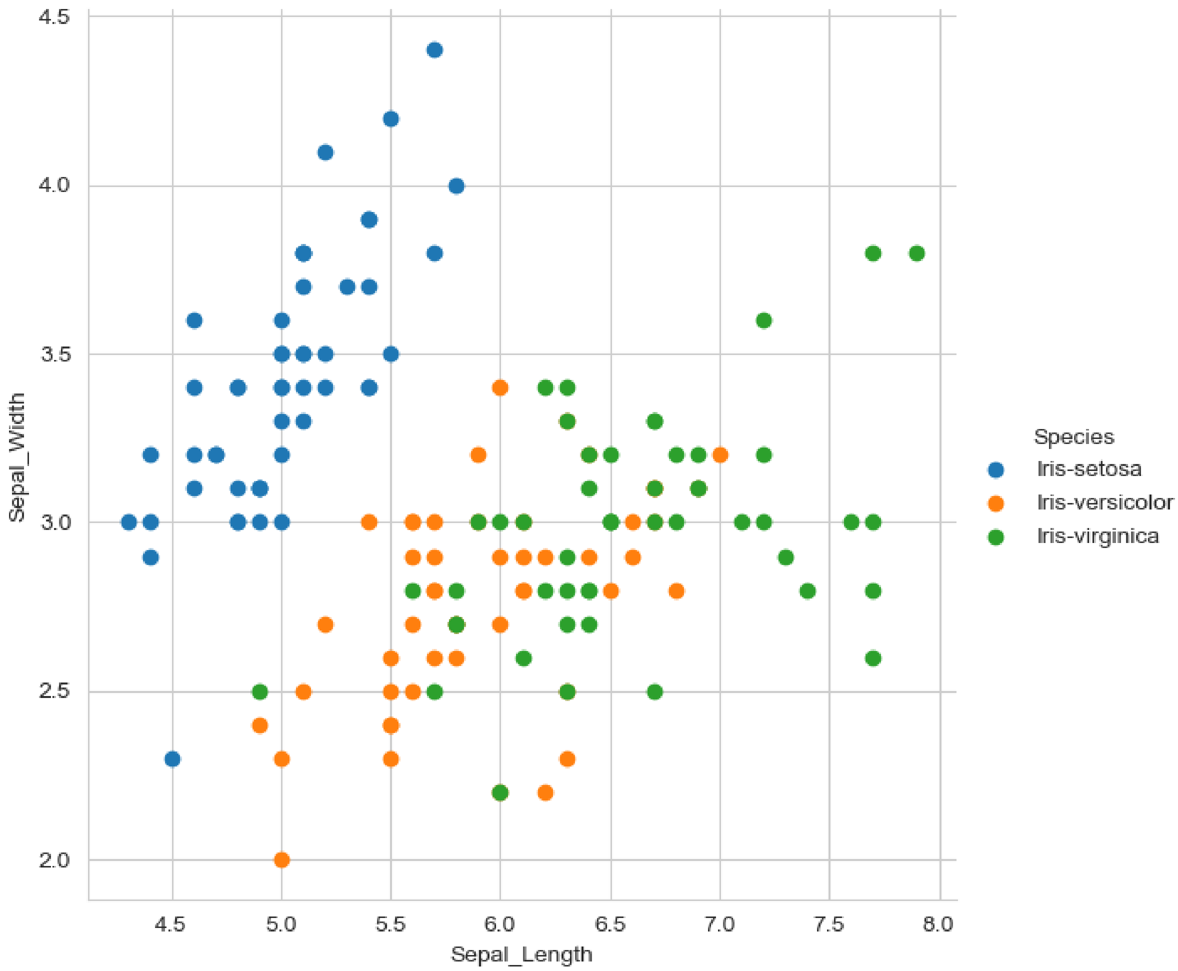
Visualize Sepal Length vs Sepal Width using scatter plot

In [11]:
```
sns.scatterplot(x=updated_data["Sepal_Length"],
                y=updated_data["Sepal_Width"],
                color='green')
plt.title("Sepal Length vs Sepal Width")
plt.show()
```



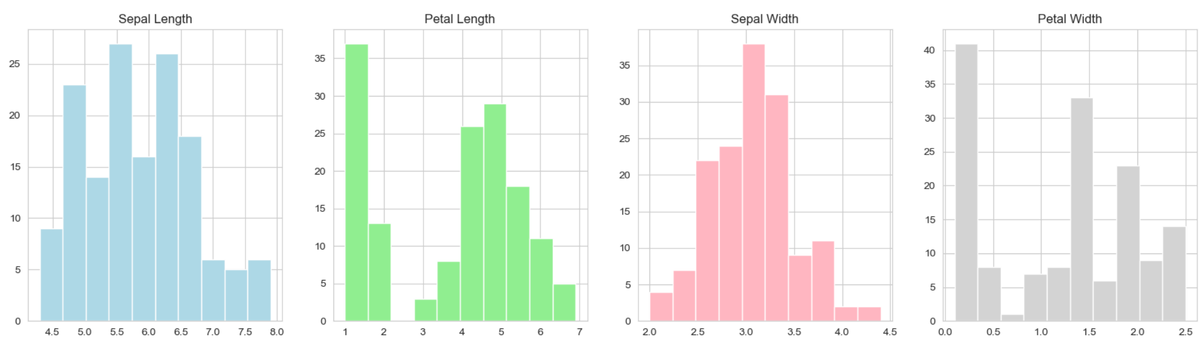
Visualize Sepal Length vs Sepal Width using FacetGrid

In [12]:
```
sns.set_style("whitegrid")
sns.FacetGrid(updated_data, hue="Species", height=6) \
    .map(plt.scatter, "Sepal_Length", "Sepal_Width") \
    .add_legend()
plt.show()
```



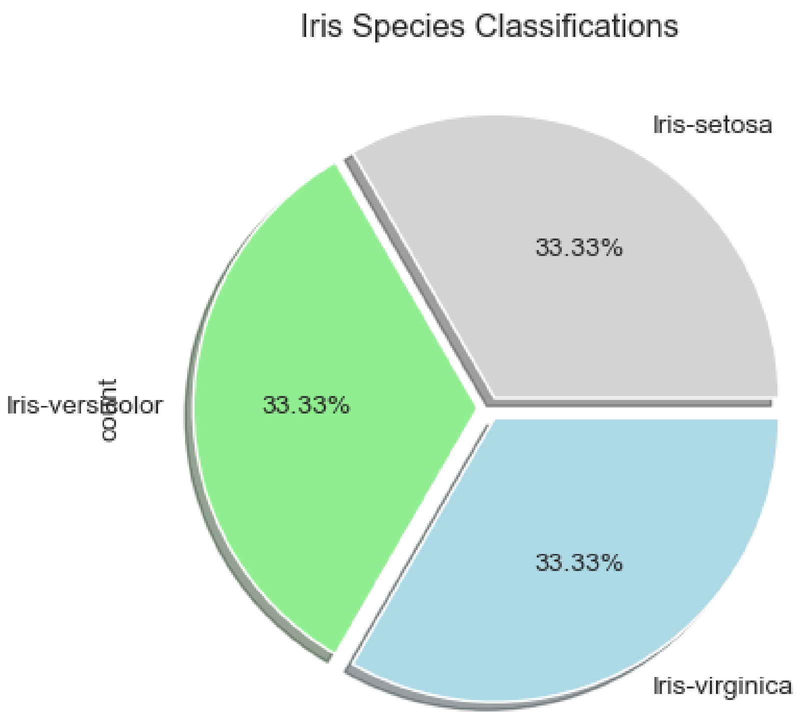
Create histograms for Sepal Length, Petal Length, Sepal Width, and Petal Width

In [13]:
```
fig, axes = plt.subplots(1, 4, figsize=(20, 5))

updated_data['Sepal_Length'].hist(ax=axes[0], color="lightblue")
axes[0].set_title("Sepal Length")

updated_data['Petal_Length'].hist(ax=axes[1], color="lightgreen")
axes[1].set_title("Petal Length")

updated_data['Sepal_Width'].hist(ax=axes[2], color="lightpink")
axes[2].set_title("Sepal Width")

updated_data['Petal_Width'].hist(ax=axes[3], color="lightgray")
axes[3].set_title("Petal Width")

plt.show()
```



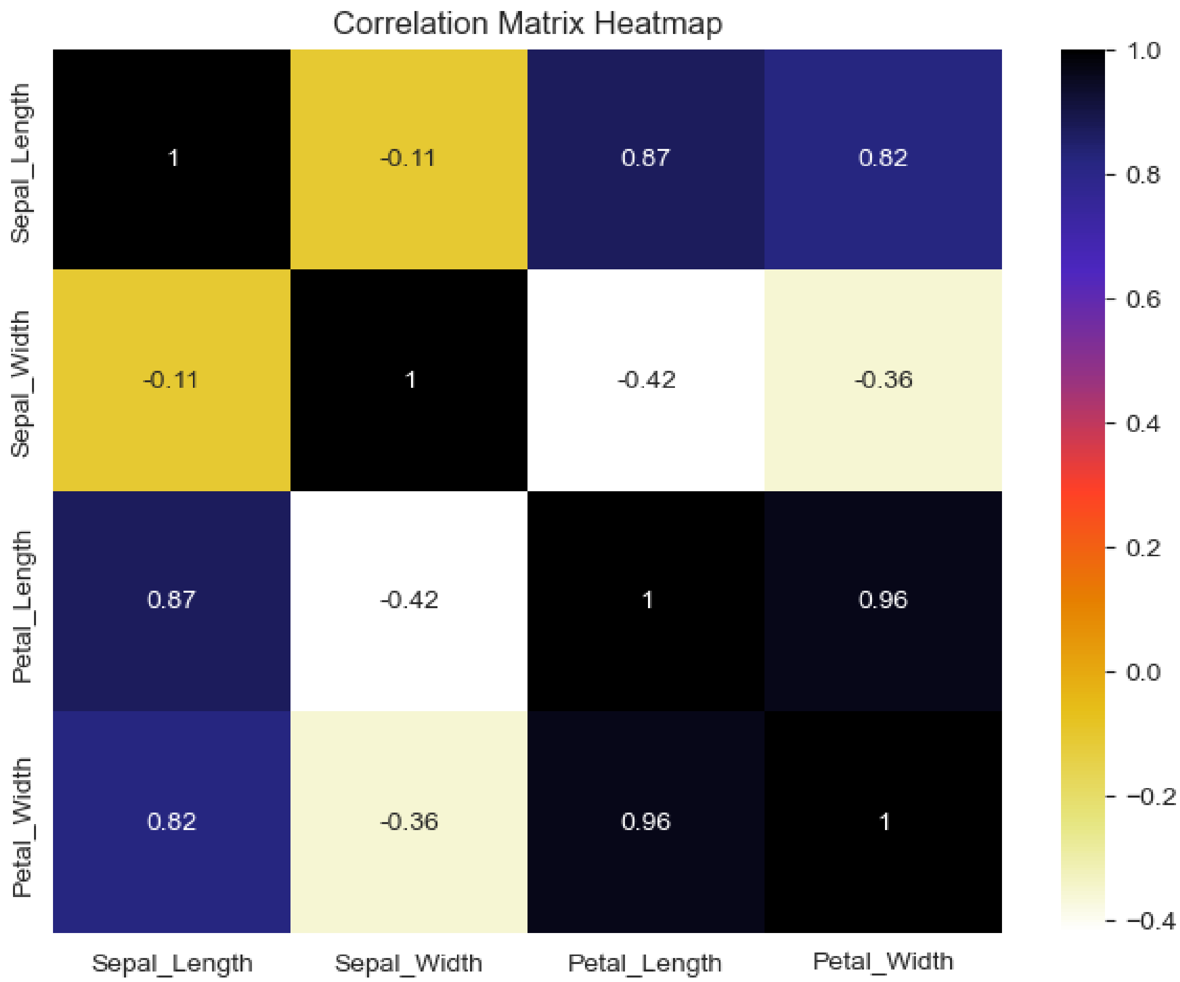
Pie chart for Iris Species Classifications

```
In [14]: species_counts = updated_data['Species'].value_counts()

         species_counts.plot.pie(explode=[0.04, 0.04, 0.04], autopct='%1.2f%%',
                                 colors=["lightgray", "lightgreen", "lightblue"],
                                 shadow=True)
         plt.title("Iris Species Classifications")
         plt.show()
```



Creating a Heatmap for the Correlation Matrix Numeric Columns

```
In [15]: numeric_columns = updated_data.select_dtypes(include=[np.number])

         plt.figure(figsize=(8, 6))
         sns.heatmap(numeric_columns.corr(), annot=True, cmap='CMRmap_r')
         plt.title("Correlation Matrix Heatmap")
         plt.show()
```



Data Processing

Dropping Duplicate Rows and Checking for Duplicates

In [16]:
```
updated_data.drop_duplicates(inplace=True)
print("Shape after removing duplicates:", updated_data.shape)
print("Any duplicates remaining:", updated_data.duplicated().any())
```

```
Shape after removing duplicates: (147, 5)
Any duplicates remaining: False
```

Preprocessing the 'Species' Column for Modeling

In [17]:
```
from sklearn import preprocessing
```

In [18]:
```
label_encoder = preprocessing.LabelEncoder()
updated_data['Species'] = label_encoder.fit_transform(updated_data['Species'])
updated_data['Species'].unique()
```

Out[18]:
```
array([0, 1, 2])
```

Now the value of this species has been converted into array

iris-setosa ==0

iris-versicolor ==1

iris-virginica ==2

In [19]:
```
updated_data['Species'].head()
```

Out[19]:
```
0    0
1    0
2    0
3    0
4    0
Name: Species, dtype: int32
```

Model Training

In [20]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
```

Spliting the data into training and testing sets

In [21]:
```
x = updated_data.drop(['Species'], axis=1)
y = updated_data['Species']

x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.2, random_state=45)
```

Train Linear Regression model

In [22]:
```
linear_model = LinearRegression()
linear_model.fit(x_train, y_train)

linear_accuracy = round(linear_model.score(x_test, y_test) * 100, 2)
print("Linear Regression Accuracy: {}%".format(linear_accuracy))
```

```
Linear Regression Accuracy: 92.53%
```

Train Logistic Regression model

In [23]:
```
logistic_model = LogisticRegression(max_iter=130)
logistic_model.fit(x_train, y_train)

logistic_accuracy = round(logistic_model.score(x_test, y_test) * 100, 2)
print("Logistic Regression Accuracy: {}%".format(logistic_accuracy))
```

```
Logistic Regression Accuracy: 96.67%
```

Train K-Nearest Neighbors (KNN) model

In [24]:
```
knn_model = KNeighborsClassifier(n_neighbors=3)
knn_model.fit(x_train, y_train)

knn_accuracy = round(accuracy_score(y_test, knn_model.predict(x_test)) * 100, 2)
print("KNN Accuracy: {}%".format(knn_accuracy))
```

```
KNN Accuracy: 96.67%
```

Model Evaluation

In [25]:
```python
# Evaluate Linear Regression model
linear_accuracy = round(linear_model.score(x_test, y_test) * 100, 2)
print("Linear Regression Accuracy: {}%".format(linear_accuracy))

# Evaluate Logistic Regression model
logistic_accuracy = round(logistic_model.score(x_test, y_test) * 100, 2)
print("Logistic Regression Accuracy: {}%".format(logistic_accuracy))

# Evaluate K-Nearest Neighbors (KNN) model
knn_accuracy = round(accuracy_score(y_test, knn_model.predict(x_test)) * 100, 2)
print("KNN Accuracy: {}%".format(knn_accuracy))
```

```
Linear Regression Accuracy: 92.53%
Logistic Regression Accuracy: 96.67%
KNN Accuracy: 96.67%
```

Logistic Regression and K-Nearest Neighbors (KNN) are both highly accurate at 96.67%, making them good choices for classifying iris species based on features. Linear Regression, with 92.53% accuracy, is less suitable for this task. Logistic Regression and KNN exhibit similar performance, providing flexibility in model selection.

Model Testing

In [26]:
```python
# Example of new data for testing
X_new = np.array([[5.1, 3.5, 1.4, 0.2],
                  [6.0, 3.0, 4.0, 1.3],
                  [7.3, 2.9, 6.3, 1.8]])
```

In [27]:
```python
# Testing with KNN model
knn_predictions = knn_model.predict(X_new)
print("KNN Predictions:", knn_predictions)
```

```
KNN Predictions: [0 1 2]
```

In [28]:
```python
# Testing with Logistic Regression model
logistic_predictions = logistic_model.predict(X_new)
print("Logistic Regression Predictions:", logistic_predictions)
```

```
Logistic Regression Predictions: [0 1 2]
```

In [29]:
```python
# Additional example for Logistic Regression
X_new_additional = np.array([[4.6, 3.4, 1.4, 0.3]])
additional_logistic_prediction = logistic_model.predict(X_new_additional)
print("Additional Logistic Regression Prediction:",
      additional_logistic_prediction)
```

```
Additional Logistic Regression Prediction: [0]
```

iris-setosa ==0

iris-versicolor ==1

iris-virginica ==2

END