IRIS

In [ ]:
```
**Data Description:** It is looks like a tabular dataset with four columns: "sepal

**Here's a brief description of each column:

**Sepal Length (cm):** This column represents the length of the sepal, which is one

**Sepal Width (cm):** This column represents the width of the sepal, measured in ce

**Petal Length (cm):** This column represents the length of the petal, which is anc

**Petal Width (cm):** This column represents the width of the petal, measured in ce

These measurements are commonly used in botany and particularly in the study of flc
```

In [3]:
```
#Loading necessary packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:
```
#Loading Datastet
from sklearn.datasets import load_iris
iris = load_iris()
```

In [5]:
```
#Assigns column names to it using the feature names from the Iris dataset
iris_df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
iris_df
```

Out[5]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
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 [7]:
```
#This line of code creates a new column in the iris_df DataFrame called 'species' c
iris_df['species'] = iris.target
iris_df['species'] = iris_df['species'].map({i: name for i, name in enumerate(iris.
print(iris_df)
```

```
     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
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

       species
0       setosa
1       setosa
2       setosa
3       setosa
4       setosa
..         ...
145  virginica
146  virginica
147  virginica
148  virginica
149  virginica

[150 rows x 5 columns]
```

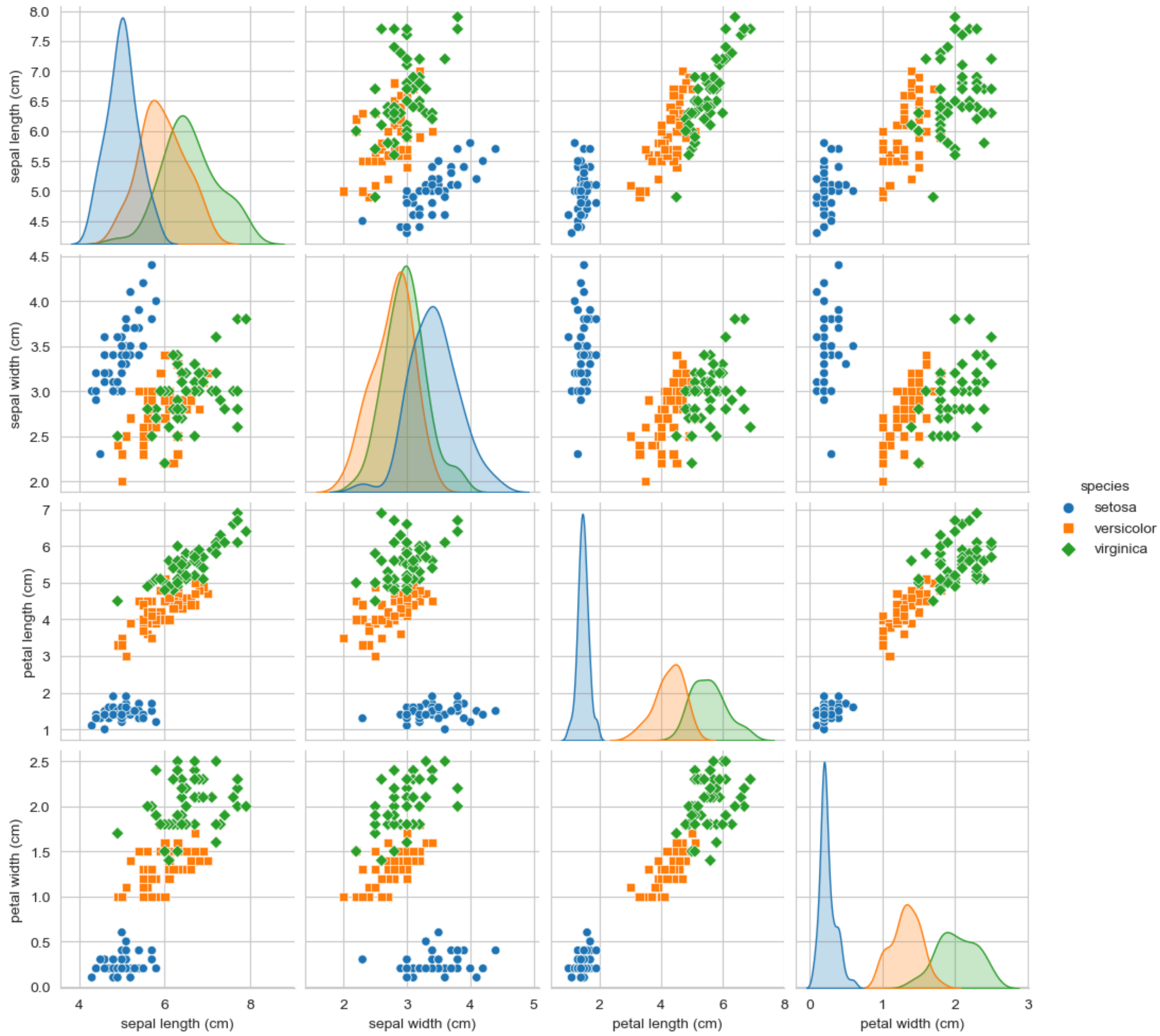
In [8]:

```
#Determine the x and y
X = iris.data  # Features
y = iris.target  # Labels
```

In [9]:

```
# Create a scatter plot using Seaborn
sns.set_style("whitegrid")
sns.pairplot(iris_df, hue="species", markers=["o", "s", "D"],  height=2.5)
plt.show()
```

```
C:\Users\SUJI\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: Th
e figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



In [13]:
```
#This code splits test and training dataset
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [14]:
```
#It creates a Support Vector Machine (SVM) classifier model with a linear kernel.

from sklearn.svm import SVC
model = SVC(kernel='linear')
```

In [15]:
```
# Import necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
```

In [16]:
```
#This line of code trains the SVM classifier model (model) using the training data
model.fit(X_train, y_train)
```

Out[16]:
```
▾ SVC
SVC(kernel='linear')
```

In [17]:
```
#This line of code uses the trained SVM classifier model (model) to predict the tar
y_pred = model.predict(X_test)
```

In [18]:
```
#Calculate the Accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 1.0
```

In [19]:
```
#It prints a classification report summarizing the performance of the classificatic
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=iris.target_names))
```

```
Classification Report:
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

In [20]:
```
#Perform cross-validation
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(model, X, y, cv=5)  # 5-fold cross-validation

# Print cross-validation scores
print("Cross-Validation Scores:", cv_scores)

# Calculate and print mean accuracy
print("Mean Accuracy:", np.mean(cv_scores))
```

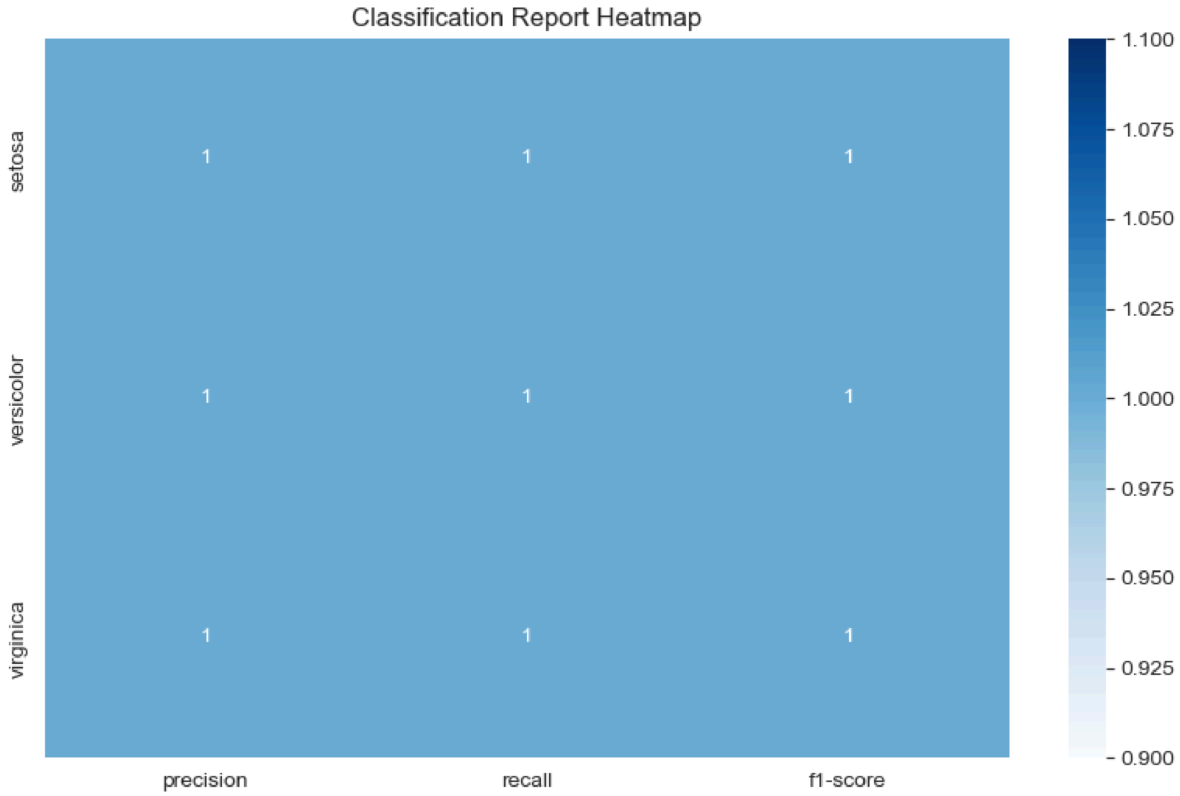
```
Cross-Validation Scores: [0.96666667 1.         0.96666667 0.96666667 1.        ]
Mean Accuracy: 0.9800000000000001
```

In [21]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report

# Generate the classification report
report = classification_report(y_test, y_pred, target_names=iris.target_names, outp

# Convert the report to a DataFrame
df_report = pd.DataFrame(report).transpose()

# Plot the heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(df_report.iloc[:-3, :-1], annot=True, cmap="Blues")
plt.title('Classification Report Heatmap')
plt.show()
```



**Observations:

Precision, Recall, and F1-score: For each class (setosa, versicolor, virginica), the precision, recall, and F1-score are all perfect, indicating that the model's predictions for each class are accurate. This suggests that the model performs well in distinguishing between different classes.

Support: The support column shows the number of samples for each class in the test set. It seems that there are 10 samples for setosa, 9 samples for versicolor, and 11 samples for virginica.

Accuracy: The overall accuracy of the model on the test set is 100%, indicating that all predictions made by the model match the actual labels in the test set.

Macro Average: The macro average for precision, recall, and F1-score is also 100%, suggesting that the model performs equally well across all classes.

Cross-Validation Scores: The cross-validation scores range from 0.966 to 1.0, with a mean accuracy of approximately 98.0%. This indicates that the model's performance is consistent across different subsets of the data.