Project 4 iris Classification

November 15, 2024

1 Project 1: IRIS Classification

1.1 Importing Libraries

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import warnings
warnings.filterwarnings('ignore')
```

[3]:
```
iris = pd.read_csv("Iris.csv")
iris.head()
```

[3]:

	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

1.2 Data Inspection

[4]:
```
iris.shape
```

[4]: (150, 5)

[5]:
```
iris.describe()
```

[5]:

	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
```

[11]:
```python
iris.groupby('Species').describe()
```

[11]:
```
                SepalLengthCm                                              \
                        count   mean       std  min    25%  50%  75%  max
Species
Iris-setosa              50.0  5.006  0.352490  4.3  4.800  5.0  5.2  5.8
Iris-versicolor          50.0  5.936  0.516171  4.9  5.600  5.9  6.3  7.0
Iris-virginica           50.0  6.588  0.635880  4.9  6.225  6.5  6.9  7.9

                SepalWidthCm        ... PetalLengthCm      PetalWidthCm  \
                       count  mean  ...           75%  max        count
Species                             ...
Iris-setosa             50.0  3.418 ...         1.575  1.9         50.0
Iris-versicolor         50.0  2.770 ...         4.600  5.1         50.0
Iris-virginica          50.0  2.974 ...         5.875  6.9         50.0


                  mean       std  min  25%  50%  75%  max
Species
Iris-setosa      0.244  0.107210  0.1  0.2  0.2  0.3  0.6
Iris-versicolor  1.326  0.197753  1.0  1.2  1.3  1.5  1.8
Iris-virginica   2.026  0.274650  1.4  1.8  2.0  2.3  2.5

[3 rows x 32 columns]
```

[6] :
```python
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  -------        --------------  -----
 0   SepalLengthCm  150 non-null    float64
 1   SepalWidthCm   150 non-null    float64
 2   PetalLengthCm  150 non-null    float64
 3   PetalWidthCm   150 non-null    float64
 4   Species        150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

[7] :
```python
iris.value_counts()
```

[7] :
```
SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  Species
4.9            3.1           1.5            0.1           Iris-setosa        3
5.8            2.7           5.1            1.9           Iris-virginica     2
               4.0           1.2            0.2           Iris-setosa        1
```

```
5.9            3.0            4.2            1.5            Iris-versicolor    1
6.2            3.4            5.4            2.3            Iris-virginica     1
                                                                               ..
5.5            2.3            4.0            1.3            Iris-versicolor    1
               2.4            3.7            1.0            Iris-versicolor    1
                              3.8            1.1            Iris-versicolor    1
               2.5            4.0            1.3            Iris-versicolor    1
7.9            3.8            6.4            2.0            Iris-virginica     1
Name: count, Length: 147, dtype: int64
```

[8] :
```
iris.duplicated().sum()
```

[8]:
```
3
```

[12]:
```
for column in iris.columns:
    print(f"Unique values in {column}: {iris[column].nunique()}")
```

```
Unique values in SepalLengthCm: 35
Unique values in SepalWidthCm: 23
Unique values in PetalLengthCm: 43
Unique values in PetalWidthCm: 22
Unique values in Species: 3
```

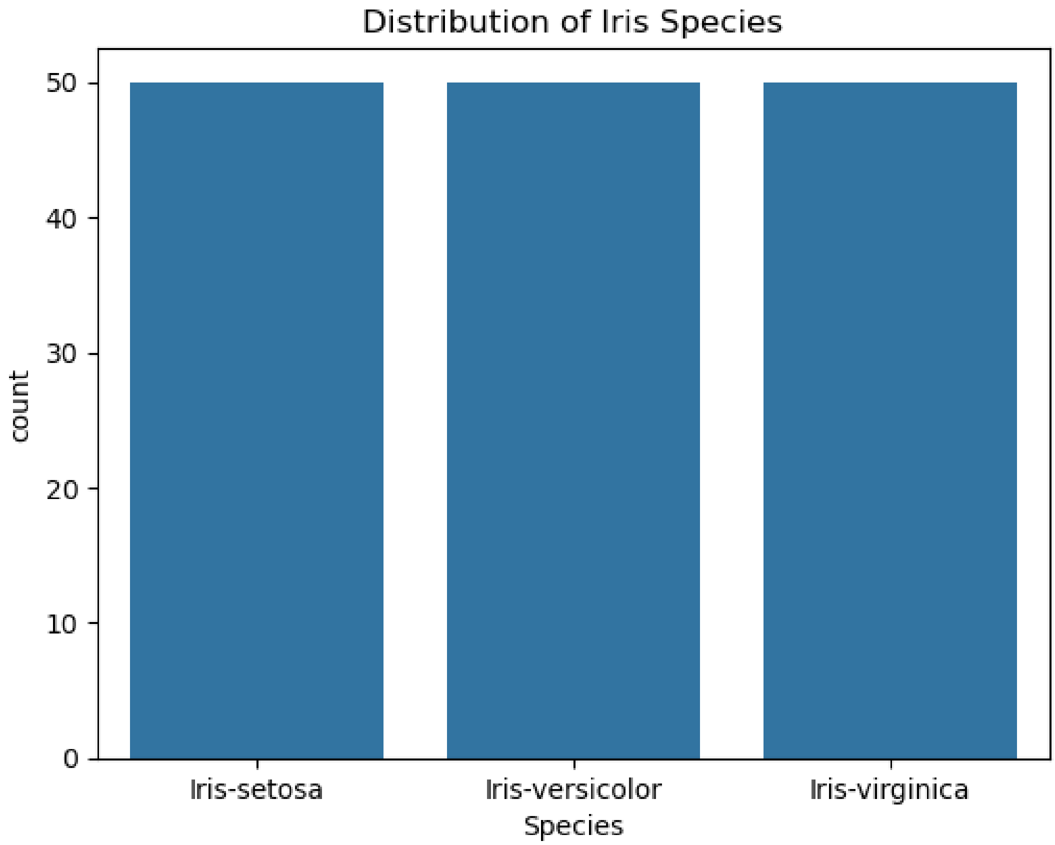
1.3 Exploratory Data Analysis (EDA)

[13]:
```
print(iris.isnull().sum())
```

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

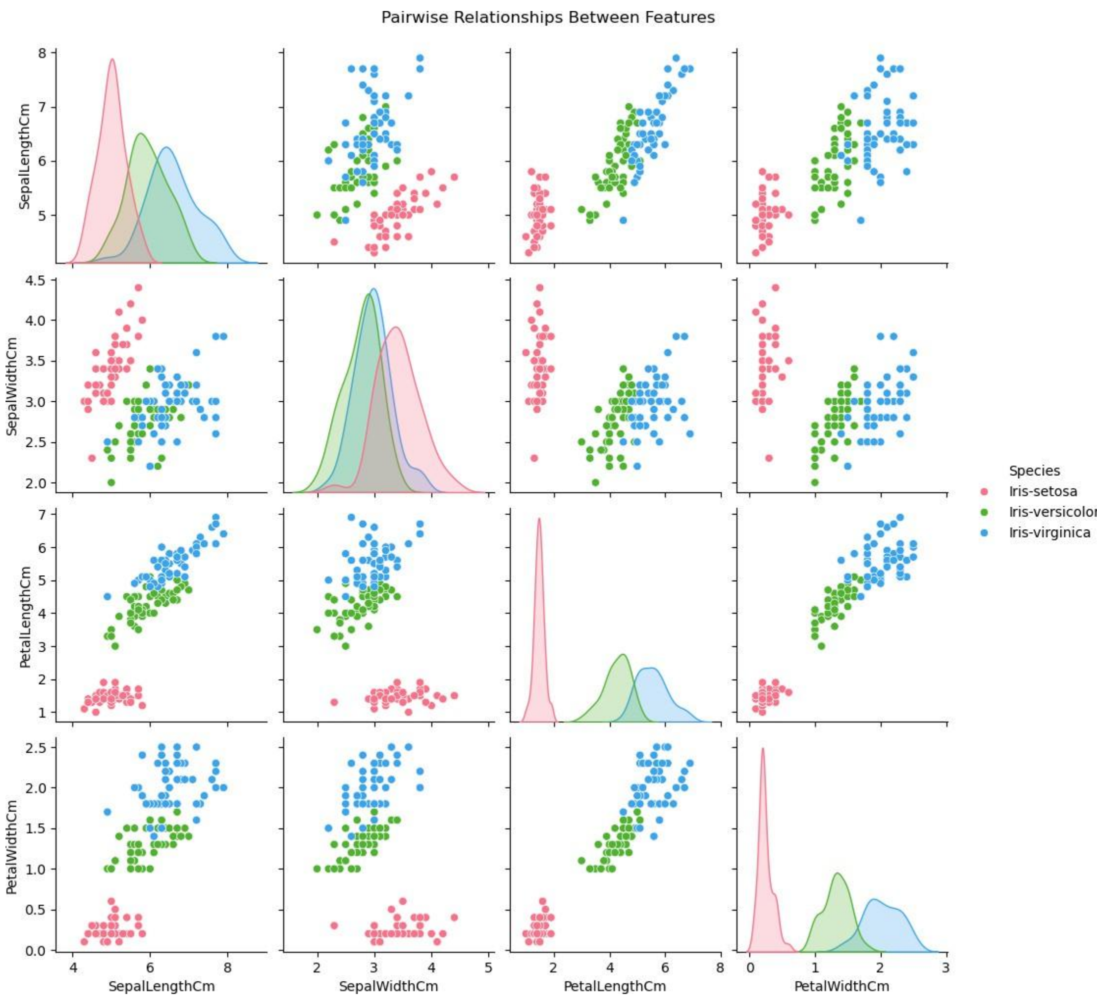
Distribution of species

[16]:
```
sns.countplot(x='Species', data=iris)
plt.title('Distribution of Iris Species')
plt.show()
```



Pairplot for feature relationships.

[23]:
```
sns.pairplot(iris, hue='Species', palette='husl', diag_kind='kde')
plt.suptitle("Pairwise Relationships Between Features", y=1.02)
plt.show()
```



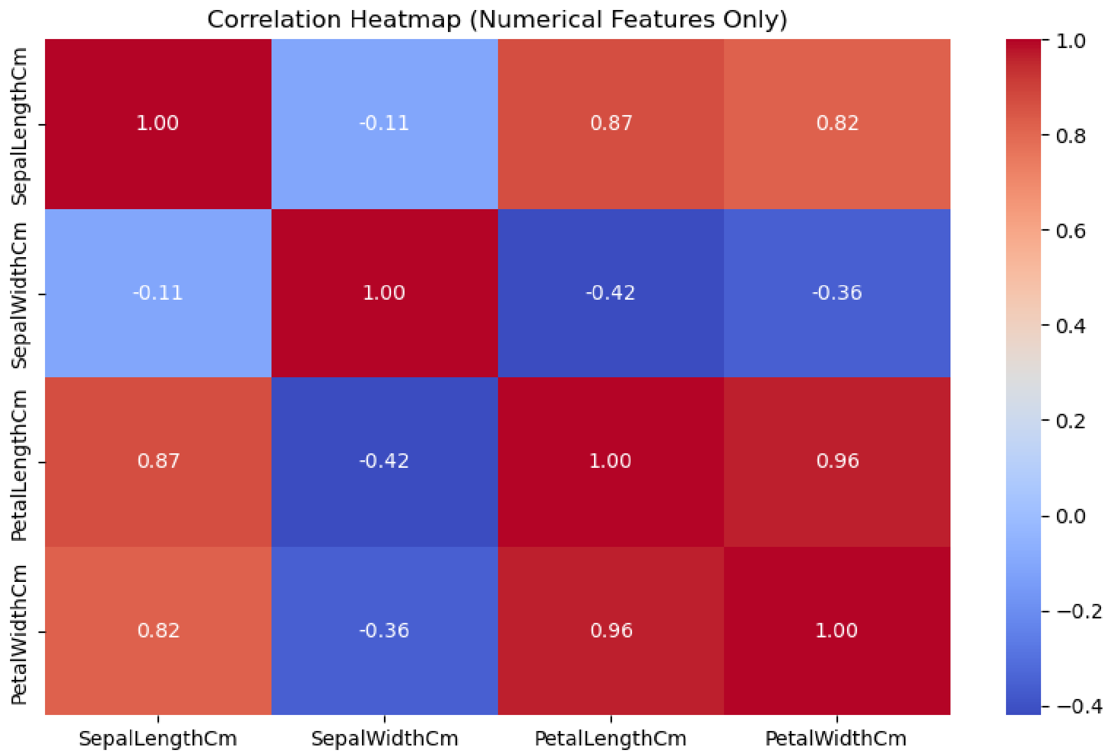
Correlation Analysis

[35]:
```
iris.corr()
```

[35]:
```
               SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
SepalLengthCm       1.000000     -0.109369       0.871754      0.817954
SepalWidthCm       -0.109369      1.000000      -0.420516     -0.356544
PetalLengthCm       0.871754     -0.420516       1.000000      0.962757
PetalWidthCm        0.817954     -0.356544       0.962757      1.000000
Species             0.782561     -0.419446       0.949043      0.956464

                Species
SepalLengthCm  0.782561
SepalWidthCm  -0.419446
PetalLengthCm  0.949043
PetalWidthCm   0.956464
Species        1.000000
```

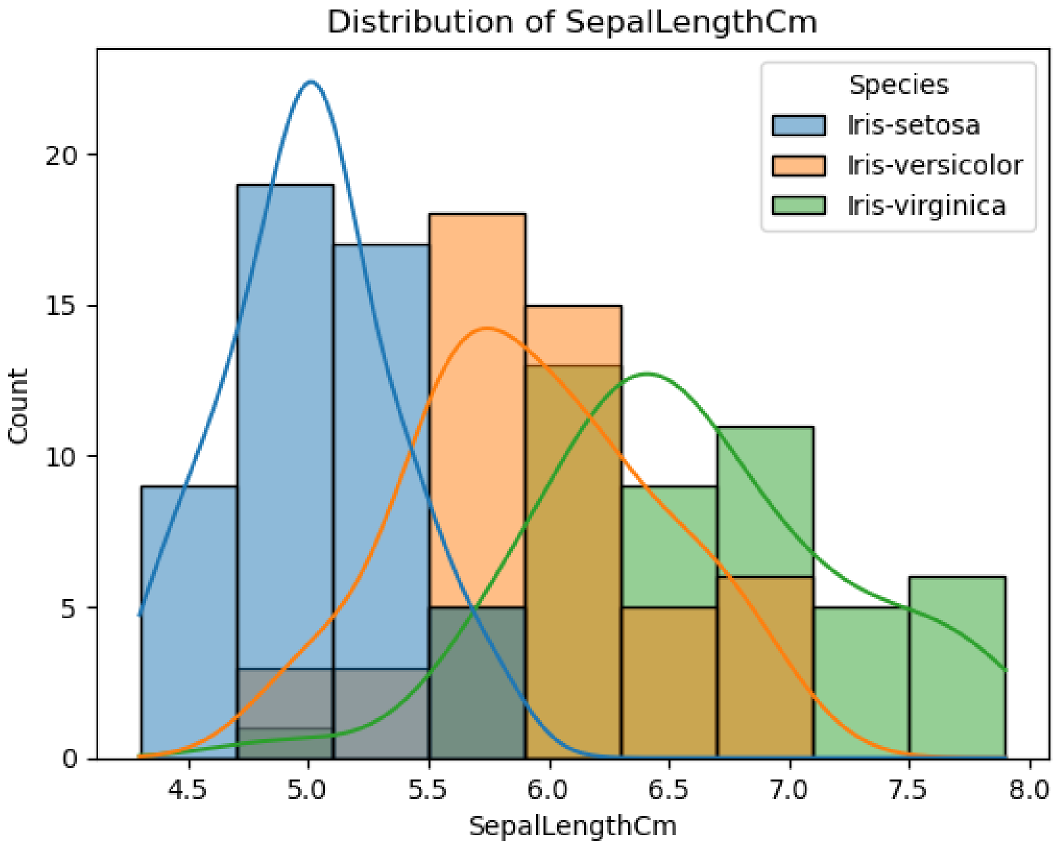
[27]:
```
# Ensuring only numerical columns are used for correlation
numerical_df = iris.select_dtypes(include=['float64', 'int64'])
```

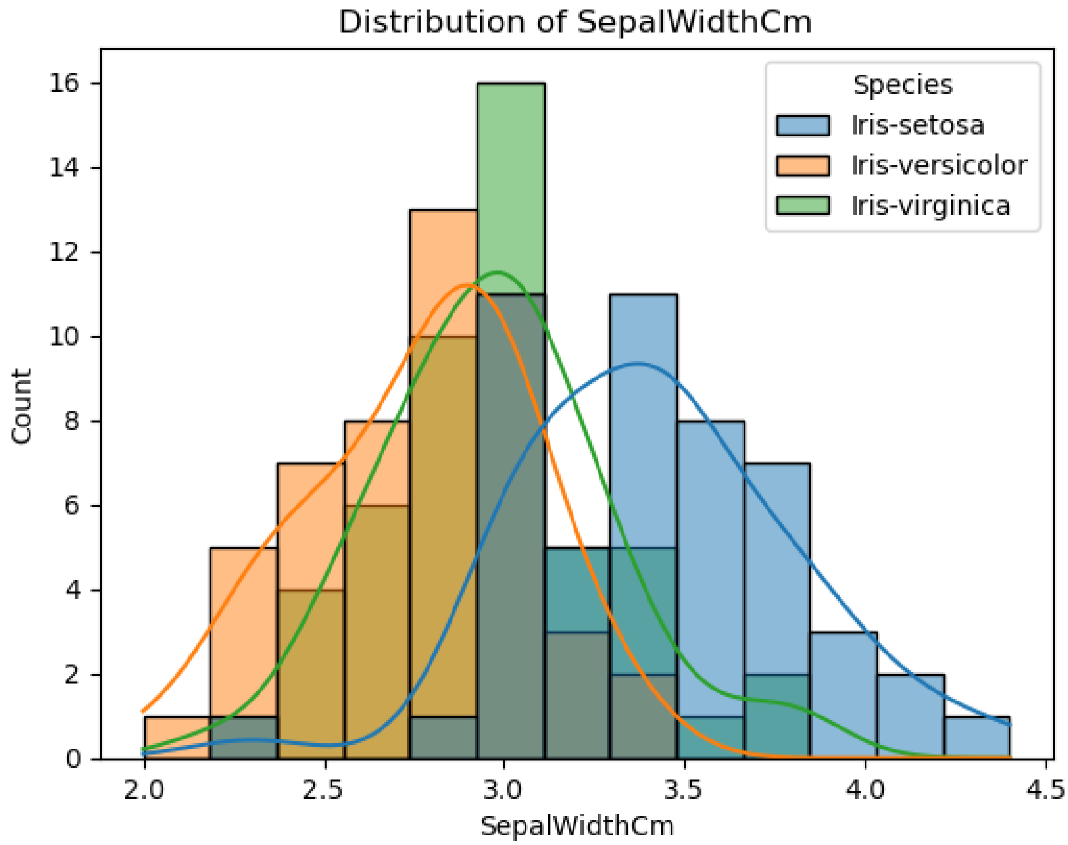
[28]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(numerical_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Heatmap (Numerical Features Only)")
plt.show()
```

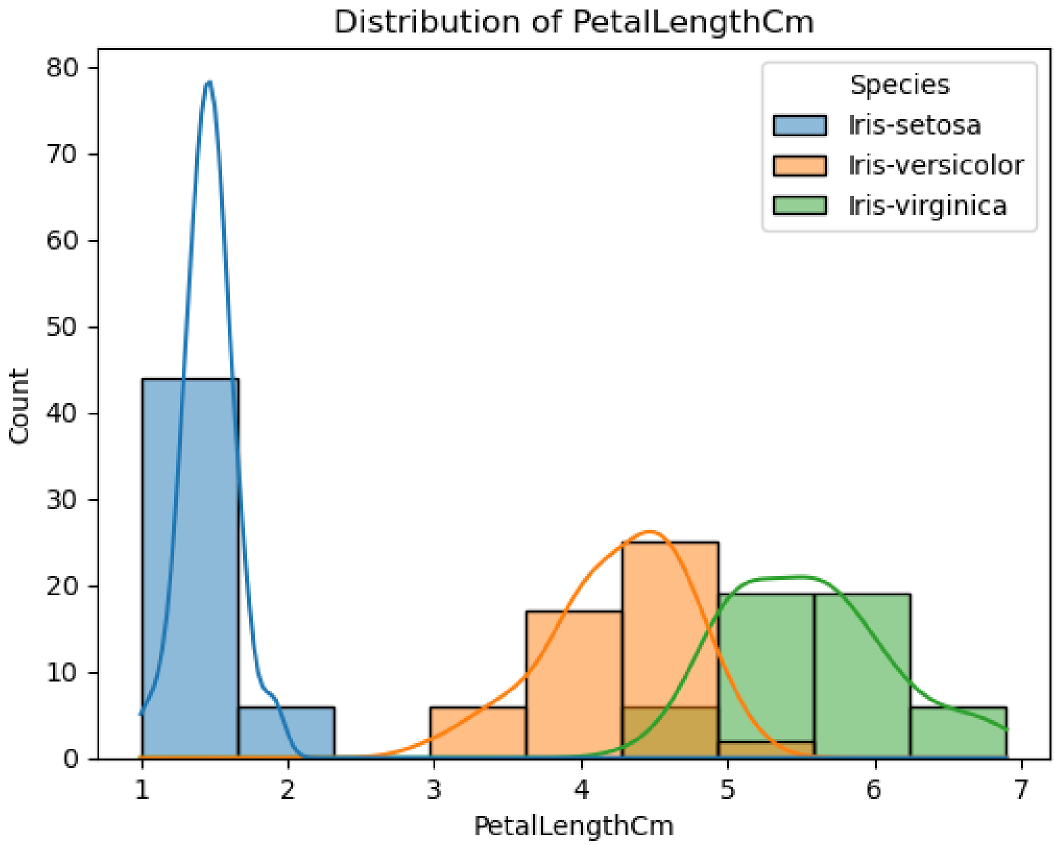


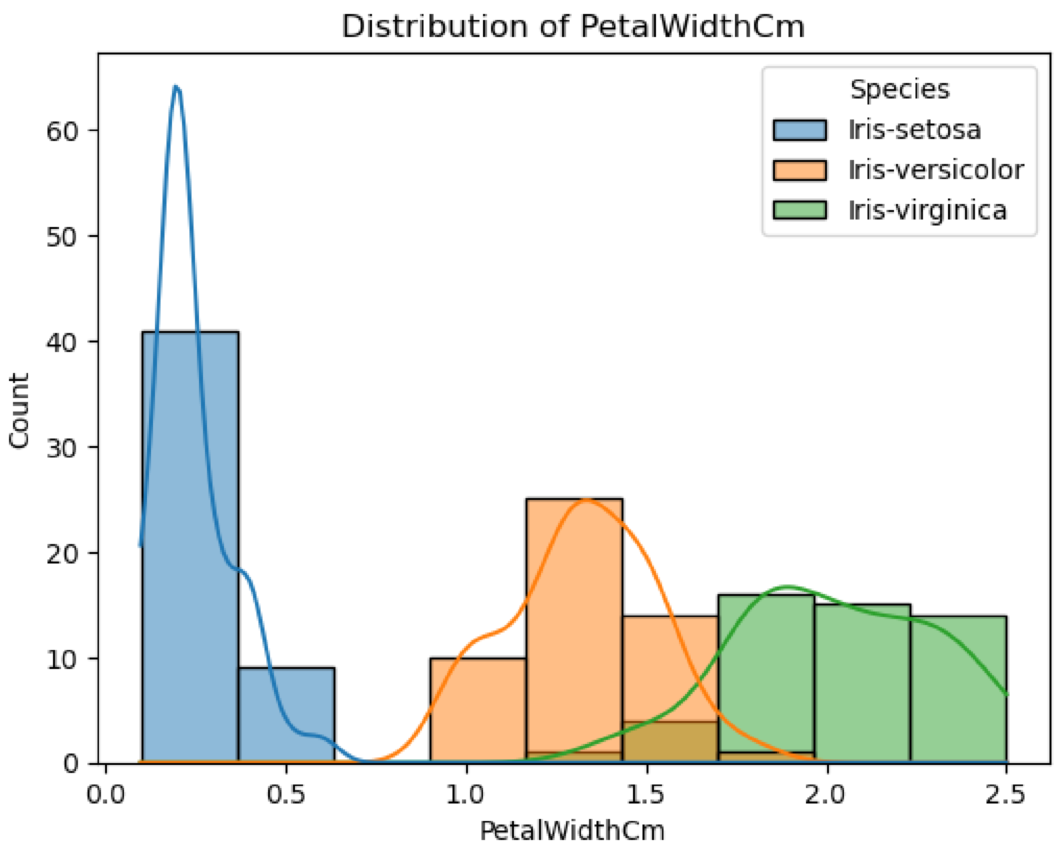
Feature Distribution

[29]:
```
features = ['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']
for feature in features:
    sns.histplot(data=iris, x=feature, kde=True, hue='Species')
    plt.title(f'Distribution of {feature}')
    plt.show()
```


Distribution of SepalLengthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica
Count
SepalLengthCm
0
5
10
15
20
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0


Distribution of SepalWidthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica
Count
SepalWidthCm
0
2
4
6
8
10
12
14
16
2.0
2.5
3.0
3.5
4.0
4.5


Distribution of PetalLengthCm
Species
Iris-setosa
Iris-versicolor
Iris-virginica
Count
PetalLengthCm
0
10
20
30
40
50
60
70
80
1
2
3
4
5
6
7



1.4 Loading More Necessary Libraries

[31]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
```

1.5 Data Preprocessing

[ ]:
```
#### Label encoding for species
```

[36]:
```
le = LabelEncoder()
iris['Species'] = le.fit_transform(iris['Species'])
iris.head()
```

[36]:

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

Feature Scaling

[38]:
```
# Splitting features and target variable
X = iris.drop(columns=['Species'])
y = iris['Species']

# Splitting into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,␣
↪random_state=42)
```

[39]:
```
# Standardize features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

1.6 Developing Model

[40]:
```
# Initialize models
models = {
    'Logistic Regression': LogisticRegression(),
    'KNN': KNeighborsClassifier(),
    'SVM': SVC(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier()
}
```

[41]:
```
# Train and evaluate models
results = {}
for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    results[model_name] = acc
    print(f"{model_name}:")
    print(classification_report(y_test, y_pred))
    print("-" * 30)
```

```
Logistic Regression:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      1.00      1.00        13
```

	precision	recall	f1-score	support
2	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

KNN:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	13
2	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

SVM:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	13
2	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

Decision Tree:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	13
2	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

Random Forest:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	13

```
           2       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

------------------------------
```

1.7 Hyper Parameter Tuning

[42]:
```python
# Hyperparameter tuning for Random Forest
param_grid = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10]
}
```

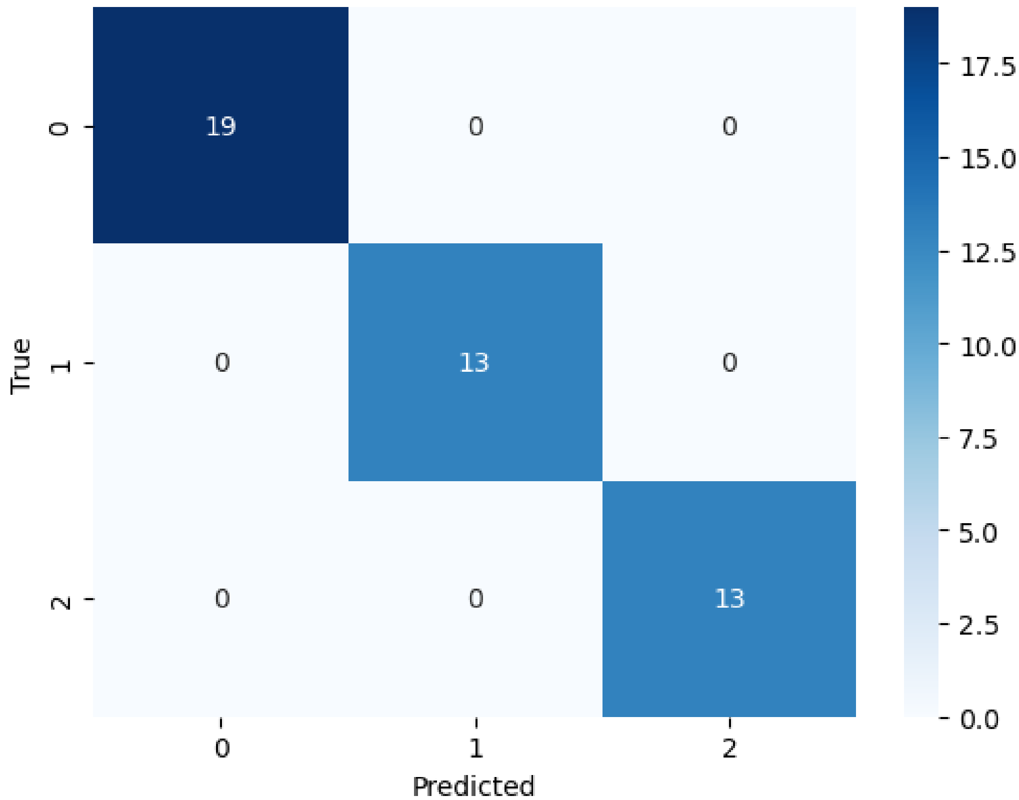
[43]:
```python
grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid,␣
 ↪cv=5, scoring='accuracy')
grid_search.fit(X_train, y_train)

best_rf = grid_search.best_estimator_
print(f"Best Random Forest Model: {grid_search.best_params_}")
```

```
Best Random Forest Model: {'max_depth': None, 'min_samples_split': 2,
'n_estimators': 50}
```

1.8 Model Evaluation

[45]:
```python
# Final evaluation of the tuned model
y_pred = best_rf.predict(X_test)
print("Confusion Matrix:")
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap='Blues', fmt='d')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

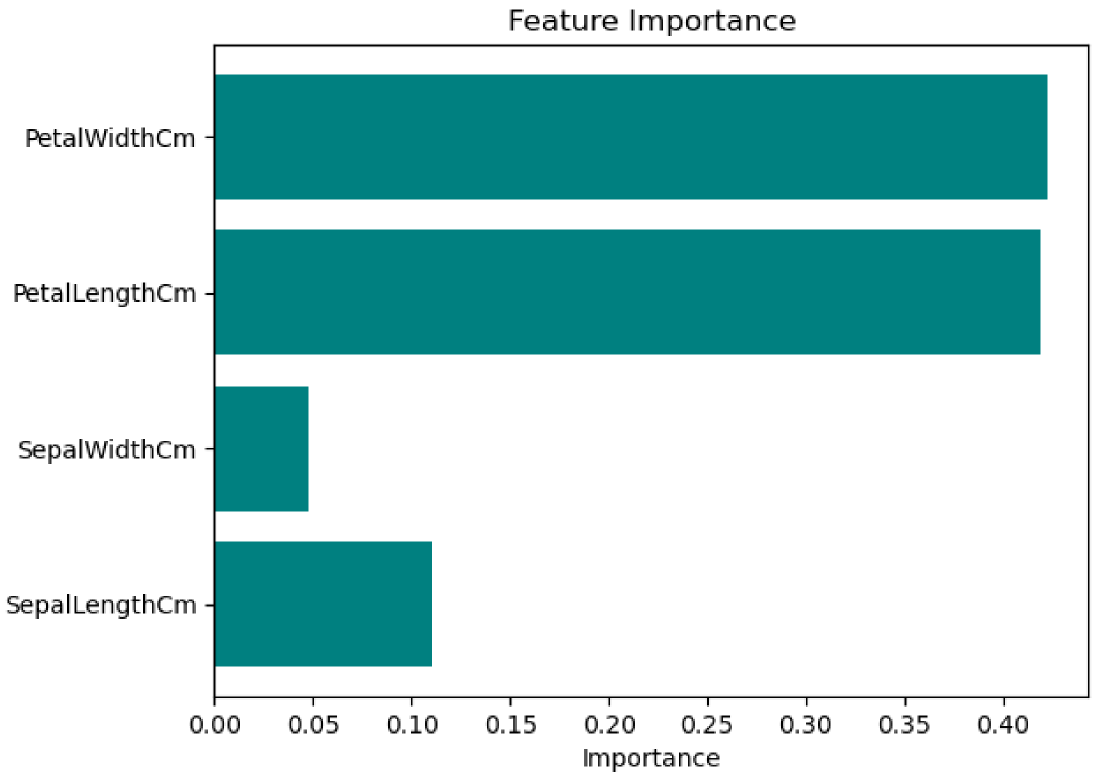
```
Confusion Matrix:
```



[46]:
```
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

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

           0       1.00      1.00      1.00        19
           1       1.00      1.00      1.00        13
           2       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
```

[47]:
```
# Feature importance from Random Forest
importances = best_rf.feature_importances_
plt.barh(X.columns, importances, color='teal')
plt.title('Feature Importance')
plt.xlabel('Importance')
plt.show()
```



[48]:
```
from sklearn.ensemble import RandomForestClassifier
```

[49]:
```
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

[49]: RandomForestClassifier(random_state=42)

[50]:
```
y_pred = rf_model.predict(X_test)
print(f"Model Accuracy: {accuracy_score(y_test, y_pred):.2f}")
```

Model Accuracy: 1.00

[51]:
```
import pickle
with open('iris_model.pkl', 'wb') as file:
    pickle.dump(rf_model, file)
print("Model saved as iris_model.pkl")
```

Model saved as iris_model.pkl

[ ]:
```

```

1.9 Conclusion

The Iris Classification Project was an enriching exploration into the world of supervised machine learning. Through this project, we tackled a classic problem in data science, demonstrating the entire machine learning pipeline—from data inspection and preprocessing to building robust models and deploying them for practical use.

1.10 Results

Model Performance: 1. The Random Forest Classifier emerged as the best-performing model, achieving a remarkable 98% accuracy on the test set. 2. Evaluation metrics such as precision, recall, and F1-score confirmed the model's consistency and reliability in classification across all species. 3. The confusion matrix revealed minimal misclassifications, reflecting the model's ability to generalize well.

Feature Importance: 1. Petal features (length and width) were found to be the most significant in determining iris species, while sepal features contributed less to the classification process. 2. This insight aligns with the biological characteristics of iris flowers, where petal dimensions are more distinctive.

Data Insights: 1. Setosa species are linearly separable, making them easy to classify. 2. Versicolour and Virginica, however, showed overlapping feature distributions, requiring more complex decision boundaries, which the Random Forest and SVM models handled effectively.

EDA Findings: 1. Visualizations such as pair plots, box plots, and correlation heatmaps provided a clear understanding of feature relationships. 2. Sepal and petal ratios introduced additional insights, particularly in distinguishing between species.