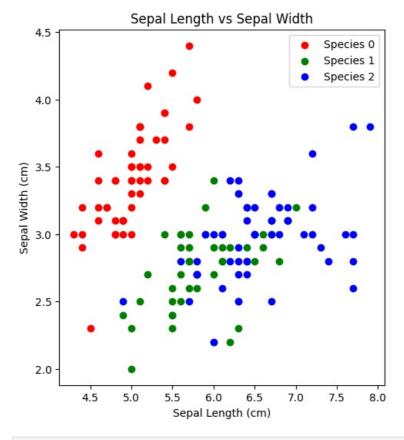
```
In [2]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         \textbf{from} \  \, \textbf{sklearn.model\_selection} \  \, \textbf{import} \  \, \textbf{train\_test\_split}, \  \, \textbf{GridSearchCV}, \  \, \textbf{cross\_val\_score}
         from sklearn.preprocessing import LabelEncoder
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
In [3]: # Load the dataset
         df = pd.read_csv("Iris.csv")
In [4]: df.head()
           Id SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm
                                                                         Species
Out[4]:
                                       3.5
                         5.1
                                                      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
                                                                   0.2 Iris-setosa
         4 5
                          5.0
                                        36
                                                      14
In [5]: df = df.drop("Id", axis =1)
In [6]: df
              Species
Out[6]:
                        5.1
                                      3.5
                                                     1.4
                                                                       Iris-setosa
                                                                  0.2
                        49
                                      3.0
                                                     14
                                                                       Iris-setosa
           1
           2
                        4.7
                                      3.2
                                                     1.3
                                                                  0.2
                                                                       Iris-setosa
                                                     1.5
                        4.6
                                      3.1
                                                                  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
In [7]: df.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
                                                 obiect
         dtypes: float64(4), object(1)
         memory usage: 6.0+ KB
In [8]: #Display the number of samples for each species
         df["Species"].value_counts()
Out[8]: Iris-setosa
                              50
         Iris-versicolor
                              50
         Iris-virginica
         Name: Species, dtype: int64
In [9]: # Convert class labels into numerical form
         le = LabelEncoder()
         df['Species'] = le.fit_transform(df['Species'])
         df["Species"]
```

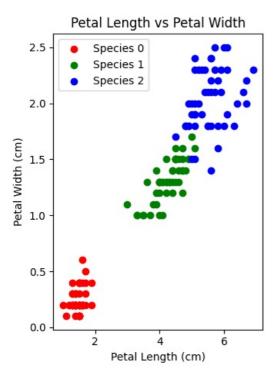
```
Out[9]: 0
         2
                0
         3
                0
         4
                0
                2
         145
         146
                2
         147
                2
         148
                2
         149
         Name: Species, Length: 150, dtype: int32
```

Visualization

```
In [10]: species_colors = {0: 'red', 1: 'green', 2: 'blue'}
In [11]: # Scatter plots for Sepal Length vs Sepal Width
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
for species, color in species_colors.items():
    subset = df[df['Species'] == species]
    plt.scatter(subset['SepalLengthCm'], subset['SepalWidthCm'], label=f'Species {species}', color=color)
plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.title('Sepal Length vs Sepal Width')
plt.legend()
```

Out[11]: <matplotlib.legend.Legend at 0x20325bfaa70>

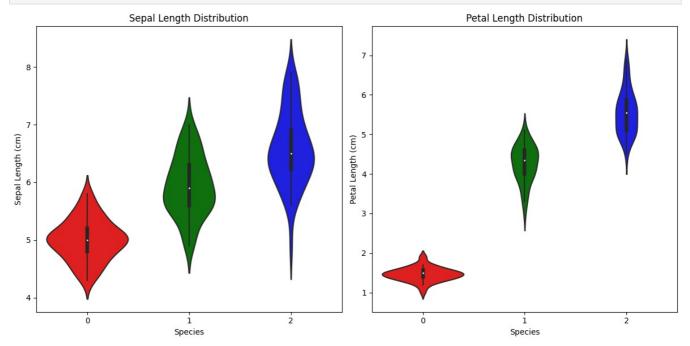




```
In [13]: # Violin plots for feature distributions
    plt.figure(figsize=(12, 6))
    plt.subplot(1, 2, 1)
    sns.violinplot(x='Species', y='SepalLengthCm', data=df, palette=species_colors)
    plt.xlabel('Species')
    plt.ylabel('Sepal Length (cm)')
    plt.title('Sepal Length Distribution')

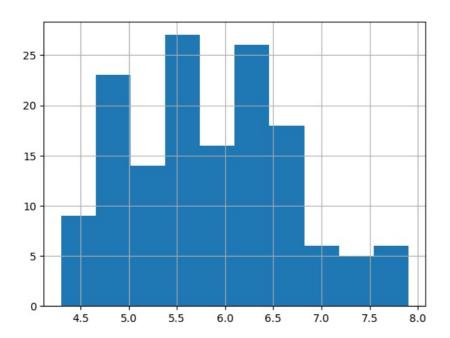
plt.subplot(1, 2, 2)
    sns.violinplot(x='Species', y='PetalLengthCm', data=df, palette=species_colors)
    plt.xlabel('Species')
    plt.ylabel('Petal Length (cm)')
    plt.title('Petal Length Distribution')

plt.tight_layout()
    plt.show()
```



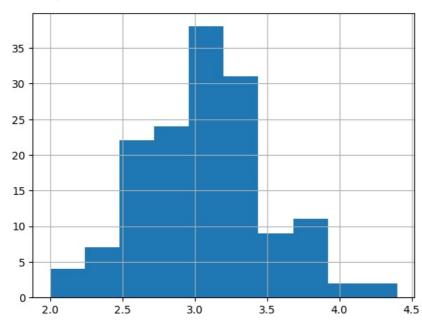
```
In [15]: # Plotting histogram for each feature
df['SepalLengthCm'].hist()
```

Out[15]: <AxesSubplot: >



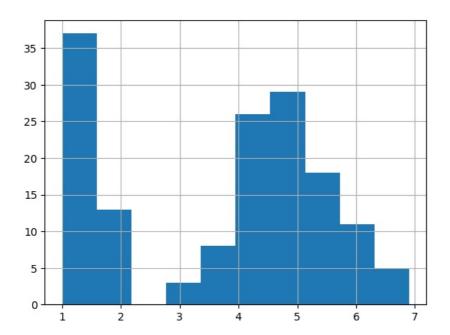
In [16]: df['SepalWidthCm'].hist()

Out[16]: <AxesSubplot: >



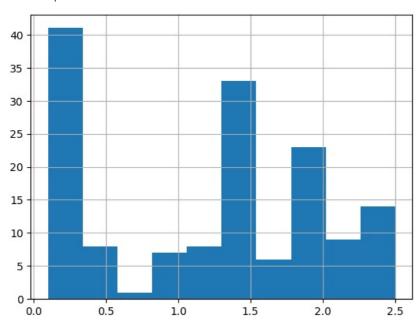
In [17]: df['PetalLengthCm'].hist()

Out[17]: <AxesSubplot: >

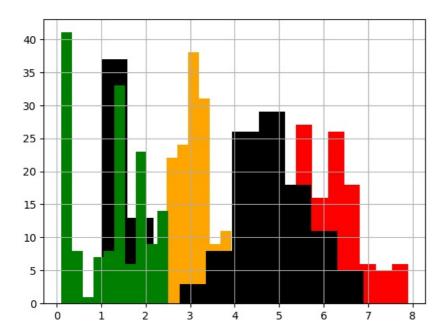


In [18]: df['PetalWidthCm'].hist()

Out[18]: <AxesSubplot: >



```
In [19]: #Plotting histogram for all the features together
    df['SepalLengthCm'].hist(color='red')
    df['SepalWidthCm'].hist(color='orange')
    df['PetalLengthCm'].hist(color='black')
    df['PetalWidthCm'].hist(color='green')
```

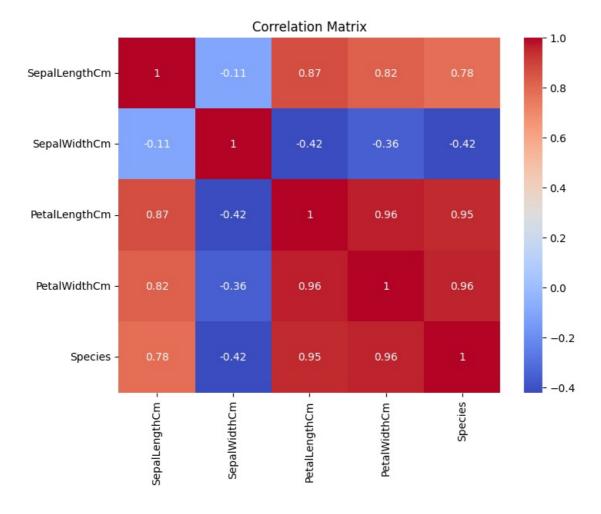


In [20]: # Finding the correlation matrix
df.corr()

Out[20]:

		SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
	SepalLengthCm	1.000000	-0.109369	0.871754	0.817954	0.782561
	SepalWidthCm	-0.109369	1.000000	-0.420516	-0.356544	-0.419446
	PetalLengthCm	0.871754	-0.420516	1.000000	0.962757	0.949043
	PetalWidthCm	0.817954	-0.356544	0.962757	1.000000	0.956464
	Species	0.782561	-0.419446	0.949043	0.956464	1.000000

```
In [21]: # Correlation matrix and heatmap
    corr = df.corr()
    plt.figure(figsize=(8, 6))
    sns.heatmap(corr, annot=True, cmap='coolwarm')
    plt.title('Correlation Matrix')
    plt.show()
```



Model Training

from sklearn.tree import DecisionTreeClassifier

model3 = DecisionTreeClassifier()
model3.fit(X_train, y_train)

```
In [22]: # Splitting the data into features (X) and target (y)
         X = df.drop('Species', axis=1)
         y = df["Species"]
         # Train-test split
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
In [23]: # Model 1: Logistic Regression
         from sklearn.linear_model import LogisticRegression
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import accuracy score
         # Step 1: Scale the data
         scaler = StandardScaler()
         X train scaled = scaler.fit transform(X train)
         X_test_scaled = scaler.transform(X_test)
         # Step 2: Create and train the Logistic Regression model with increased max_iter
         model1 = LogisticRegression(max iter=1000) # Increase max iter to an appropriate value
         model1.fit(X_train_scaled, y_train)
         # Step 3: Make predictions and calculate accuracy
         y pred1 = model1.predict(X test scaled)
         accuracy1 = accuracy_score(y_test, y_pred1)
         print("Accuracy (Logistic Regression): {:.2f}%".format(accuracy1 * 100))
         Accuracy (Logistic Regression): 95.56%
In [24]: # Model 2: K-nearest Neighbors (KNN)
         from sklearn.neighbors import KNeighborsClassifier
         model2 = KNeighborsClassifier()
         model2.fit(X train, y train)
         y_pred2 = model2.predict(X_test)
         accuracy2 = accuracy_score(y_test, y_pred2)
print("Accuracy (KNN): {:.2f}%".format(accuracy2 * 100))
         Accuracy (KNN): 97.78%
In [25]: # Model 3: Decision Tree
```

```
y_pred3 = model3.predict(X_test)
         accuracy3 = accuracy_score(y_test, y_pred3)
         print("Accuracy (Decision Tree): {:.2f}%".format(accuracy3 * 100))
         Accuracy (Decision Tree): 95.56%
In [26]: from sklearn.linear model import LogisticRegression
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.model selection import cross val score
         import numpy as np
         # Create your machine learning models
         model1 = LogisticRegression(max iter=1000) # Increased max iter
         model2 = KNeighborsClassifier()
         model3 = DecisionTreeClassifier()
         best_rf = RandomForestClassifier()
         # List of models
         models = [model1, model2, model3]
         model names = ["Logistic Regression", "KNN", "Decision Tree"]
         # Perform cross-validation and print results
         for i, model in enumerate(models):
             cv_scores = cross_val_score(model, X, y, cv=5)
             print(f"{model_names[i]} - Cross-Validation Accuracy: {np.mean(cv_scores):.2f}%")
         Logistic Regression - Cross-Validation Accuracy: 0.97%
         KNN - Cross-Validation Accuracy: 0.97%
         Decision Tree - Cross-Validation Accuracy: 0.96%
```

Logistic regression and KNN has the good accuracy

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