

STEP-1 LOAD AND EXPLORE THE DATA

1.1 importing the libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

1.2 Loading the Data

```
df = pd.read_csv("C:/Users/Harshit/Downloads/IRIS.csv")
df.head(10)
```

	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
5	5.4	3.9	1.7	0.4	Iris-setosa
6	4.6	3.4	1.4	0.3	Iris-setosa
7	5.0	3.4	1.5	0.2	Iris-setosa
8	4.4	2.9	1.4	0.2	Iris-setosa
9	4.9	3.1	1.5	0.1	Iris-setosa

1.3 Understanding the dataset structure

```
print("Dataset_shape: ", df.shape)

Dataset_shape:  (150, 5)

print("Dataset_Info" , df.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
Dataset_Info None

print("Dataset_Describe",df.describe())
```

Dataset_Describe	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

1.4 checking for thr missing value

```
print("MISSING_VALUES\n" ,df.isnull().sum())
```

```
MISSING_VALUES
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

1.5 check class Distribution(Target vriables)

```
df['species'].value_counts()
```

```
species
Iris-setosa      50
Iris-versicolor  50
Iris-virginica   50
Name: count, dtype: int64
```

```
print("Column_Dtypes",df.dtypes)
```

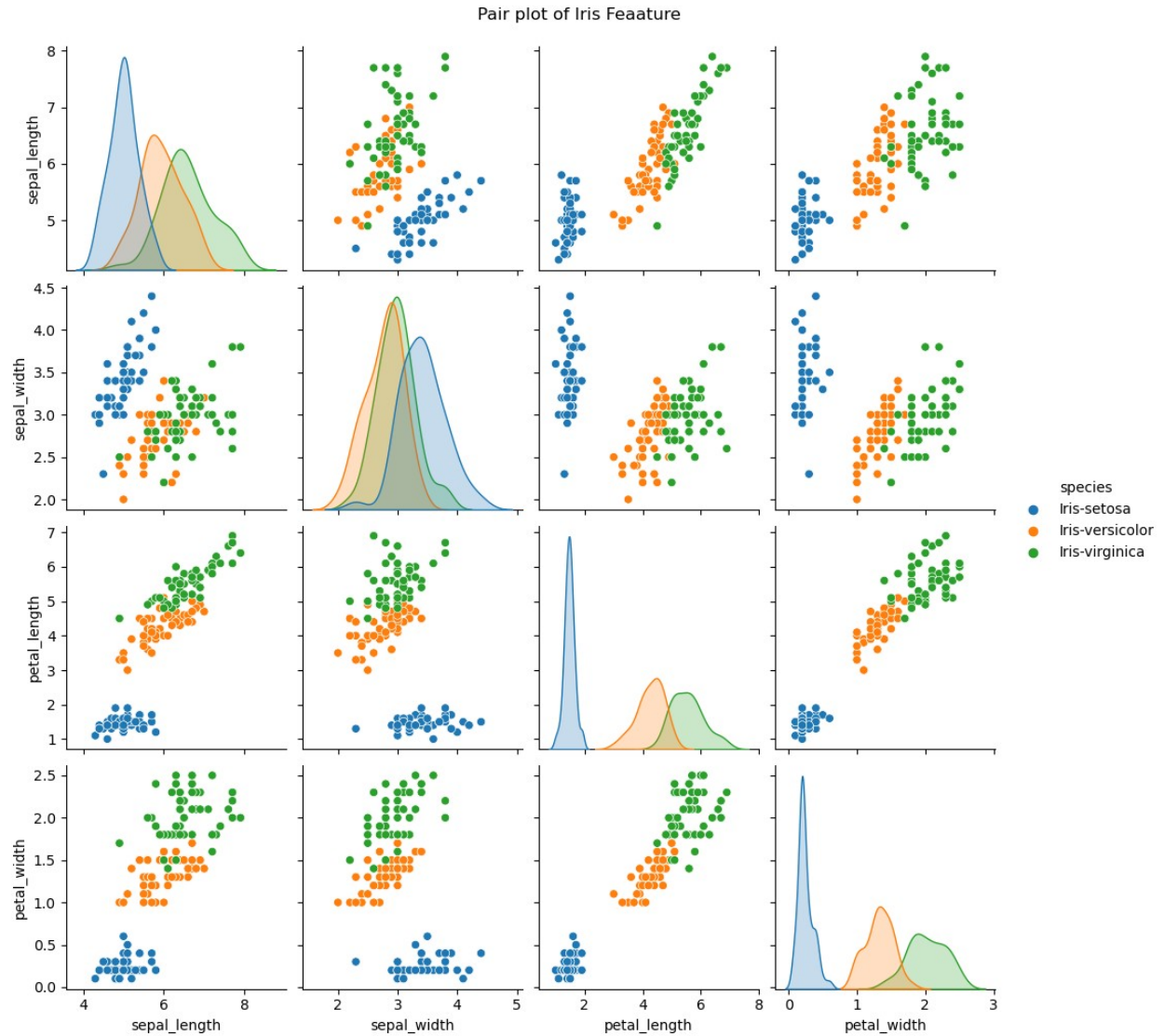
```
Column_Dtypes  sepal_length    float64
sepal_width    float64
petal_length    float64
petal_width    float64
species        object
dtype: object
```

STEP-2 DATA VISUALIZATION

2.1 Pair plot

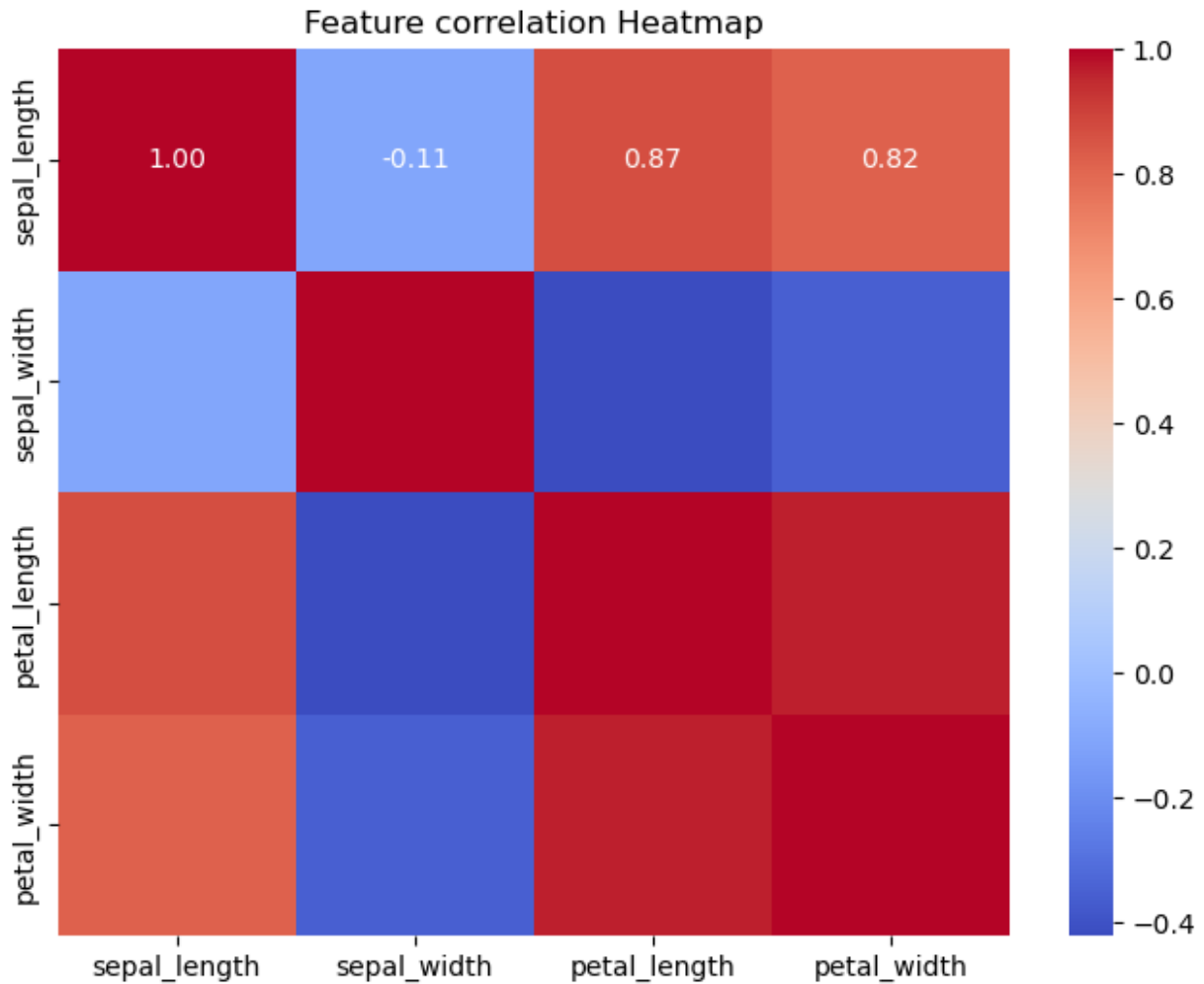
```
sns.pairplot(df,hue='species')
plt.suptitle("Pair plot of Iris Feaature", y = 1.02)
plt.show()
```

```
C:\Users\Harshit\anaconda3\anaconda_setup\Lib\site-packages\seaborn\
_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.
    with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Harshit\anaconda3\anaconda_setup\Lib\site-packages\seaborn\
_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.
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and will be removed in a future version. Convert inf values to NaN
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C:\Users\Harshit\anaconda3\anaconda_setup\Lib\site-packages\seaborn\
_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated
and will be removed in a future version. Convert inf values to NaN
before operating instead.
    with pd.option_context('mode.use_inf_as_na', True):
```



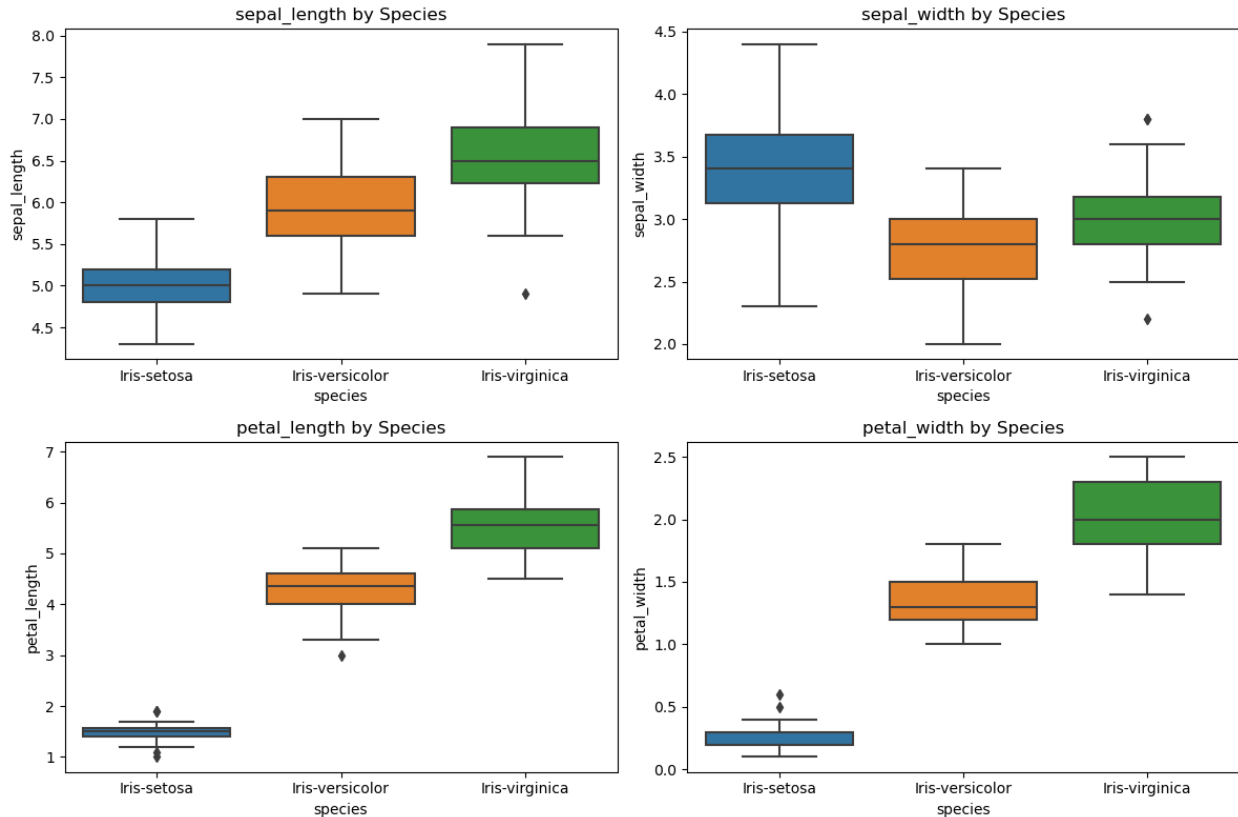
2.2 corelation Heatmap

```
plt.figure(figsize=(8,6))
sns.heatmap(df.drop('species',axis = 1).corr(),
annot=True,cmap='coolwarm',fmt=".2f")
plt.title("Feature correlation Heatmap")
plt.show()
```



2.3 Boxplot for feature Distribution

```
plt.figure(figsize=(12,8))
for idx, feature in enumerate(df.columns[:-1]):
    plt.subplot(2,2,idx+1)
    sns.boxplot(x='species', y=feature,data=df)
    plt.title(f"{feature} by Species")
plt.tight_layout()
plt.show()
```



STEP-3 FEATURE IMPORTANCE AND PREPARING DATA

3.1 split features and target

```
x= df.drop('species',axis = 1)
y=df['species']

print("After dropping column species\n:", x.head(10))
```

```
After dropping column species
:   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
5         5.4         3.9         1.7         0.4
6         4.6         3.4         1.4         0.3
7         5.0         3.4         1.5         0.2
8         4.4         2.9         1.4         0.2
9         4.9         3.1         1.5         0.1
```

3.2 Encode the target(species)

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
y_encoded = le.fit_transform(y)

label_mapping = dict(zip(le.classes_, le.transform(le.classes_)))
print("Label Encoding:\n",label_mapping)

Label Encoding:
{'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2}
```

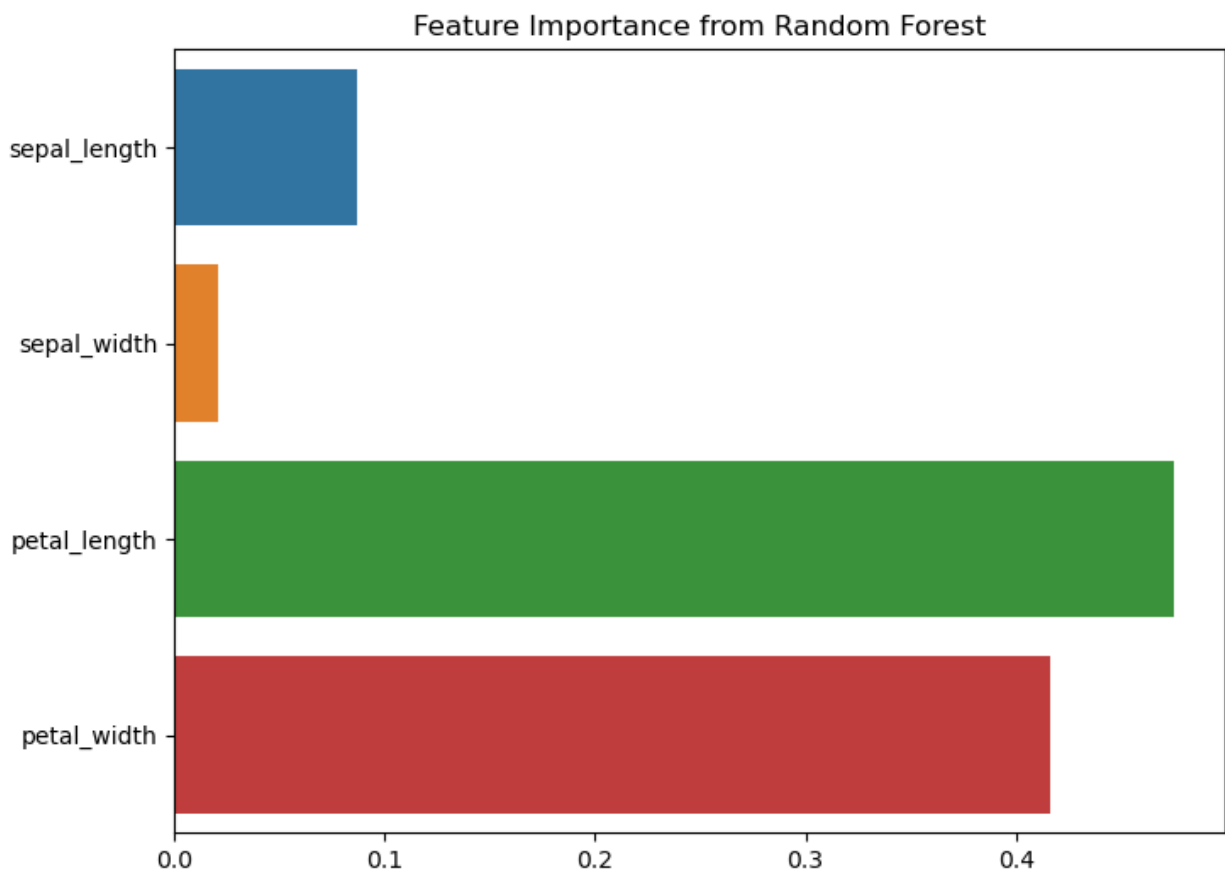
3.3 Random Forest

```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier()
model.fit(x,y_encoded)

importances = model.feature_importances_

plt.figure(figsize=(8,6))
sns.barplot(x = importances , y=x.columns)
plt.title("Feature Importance from Random Forest")
plt.show()
```



STEP-4 TRAIN-TEST SPLIT

```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(x,y_encoded,test_size
= 0.2,random_state=42)
```

STEP-5 TRAIN AND EVALUATE MULTIPLE MODELS

5.1 We will try different models ()

-Logistic Regression

-K-Nearest Neighbors (KNN)

-Decision Tree

-Random Forest

-Support Vector Machine (SVM)

```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
```

5.2 train and evaluate Model

```
models = {
    "Logistic Regression": LogisticRegression(max_iter=200),
    "KNN": KNeighborsClassifier(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "SVM": SVC()
}
for name, Model in models.items():
    model.fit(x_train, y_train)
    predictions = model.predict(x_test)

    print(f"\n===== {name} =====")
    print("Accuracy:", accuracy_score(y_test, predictions))
    print("confusion Matrix:\n", confusion_matrix(y_test,
predictions))
    print("Classification Report:\n", classification_report(y_test,
predictions, target_names=le.classes_))
```


==== Logistic Regression ====

Accuracy: 1.0

confusion Matrix:

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

Classification Report:

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-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

==== KNN ====

Accuracy: 1.0

confusion Matrix:

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

Classification Report:

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-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

==== Decision Tree ====

Accuracy: 1.0

confusion Matrix:

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

Classification Report:

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-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

===== Random Forest =====

Accuracy: 1.0

confusion Matrix:

```
[[10  0  0]
```

```
[ 0  9  0]
```

```
[ 0  0 11]]
```

Classification Report:

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-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

===== SVM =====

Accuracy: 1.0

confusion Matrix:

```
[[10  0  0]
```

```
[ 0  9  0]
```

```
[ 0  0 11]]
```

Classification Report:

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-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

5.3 Saving Trained model

```
import joblib
joblib.dump(model, 'iris_classifier.pkl')
print("Model saved successfully")
```

Model saved successfully