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PRACTICAL EXAM

1. IMPORTING NECESSARY LIBRARIES

In [23]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler

from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split, RandomizedSearchCV
```

In [4]:
```
data = pd.read_csv("iris_dataset.csv")
data.head()
```

Out[4]:

	sepal_length	sepal_width	petal_length	petal_width	class
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

In [5]:
```
data.shape
```

Out[5]:
```
(150, 5)
```

In [6]:
```
data.describe()
```

Out[6]:

	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

In [7]:
```
data.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   class         150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

2. STANDARD SCALAR ON DATA

In [8]:
```
scalar = StandardScaler()
X = data.drop(["class"], axis = 1)
y = data[["class"]]

X, y
```

Out[8]:
```
(     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
 ..            ...          ...           ...          ...
 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 x 4 columns],
               class
 0       Iris-setosa
 1       Iris-setosa
 2       Iris-setosa
 3       Iris-setosa
 4       Iris-setosa
 ..              ...
 145  Iris-virginica
 146  Iris-virginica
 147  Iris-virginica
 148  Iris-virginica
 149  Iris-virginica

 [150 rows x 1 columns])
```

In [9]:
```python
X_scaled = scalar.fit_transform(X)
X_scaled[:5]
```

Out[9]:
```
array([[-0.90068117,  1.03205722, -1.3412724 , -1.31297673],
       [-1.14301691, -0.1249576 , -1.3412724 , -1.31297673],
       [-1.38535265,  0.33784833, -1.39813811, -1.31297673],
       [-1.50652052,  0.10644536, -1.2844067 , -1.31297673],
       [-1.02184904,  1.26346019, -1.3412724 , -1.31297673]])
```

In [10]:
```python
data_encoded = pd.get_dummies(data)
data_encoded.shape
```

Out[10]:
```
(150, 7)
```

In [11]:
```python
data_encoded.columns
```

Out[11]:
```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',
       'class_Iris-setosa', 'class_Iris-versicolor', 'class_Iris-virginica'],
      dtype='object')
```

3. ONE HOT ENCODING THE CATEGORICAL FEATURES

In [12]:
```python
Y_encoded = pd.get_dummies(y)
Y_encoded
```

Out[12]:

	class_Iris-setosa	class_Iris-versicolor	class_Iris-virginica
0	True	False	False
1	True	False	False
2	True	False	False
3	True	False	False
4	True	False	False
...	...	...	...
145	False	False	True
146	False	False	True
147	False	False	True
148	False	False	True
149	False	False	True

150 rows × 3 columns

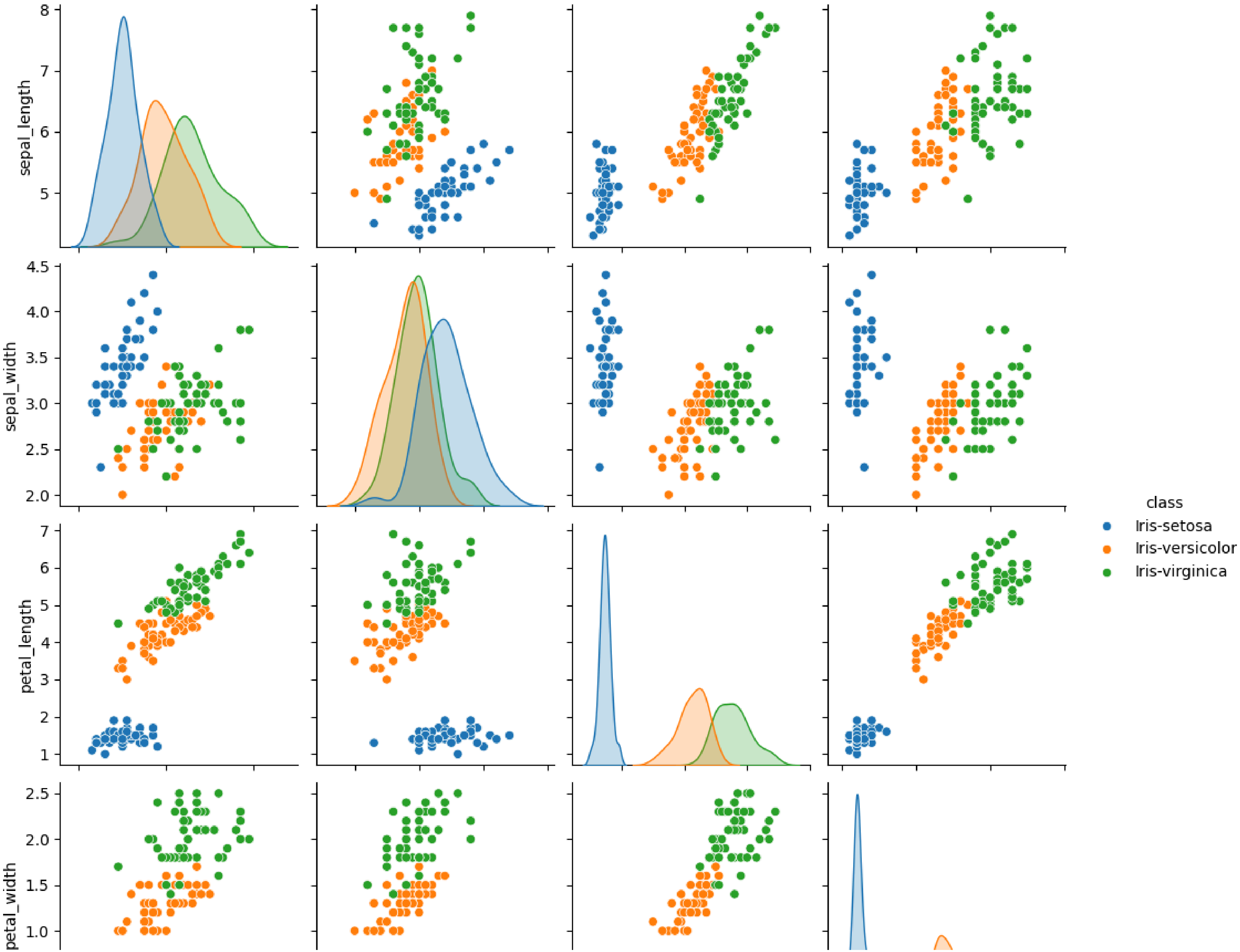
In [13]:

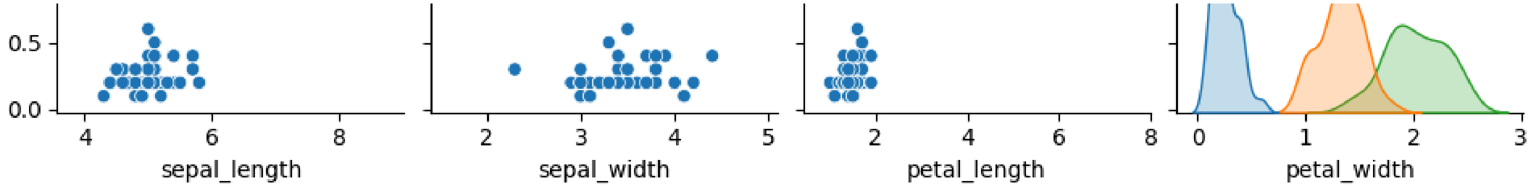
```
import warnings
warnings.filterwarnings("ignore")
```

4. EDA ON FEATURES

In [14]:

```
import seaborn as sns

_ = sns.pairplot(data, hue="class")
```


sepal_length
sepal_width
petal_length
petal_width
8
7
6
5
4.5
4.0
3.5
3.0
2.5
2.0
7
6
5
4
3
2
1
2.5
2.0
1.5
1.0
class
Iris-setosa
Iris-versicolor
Iris-virginica

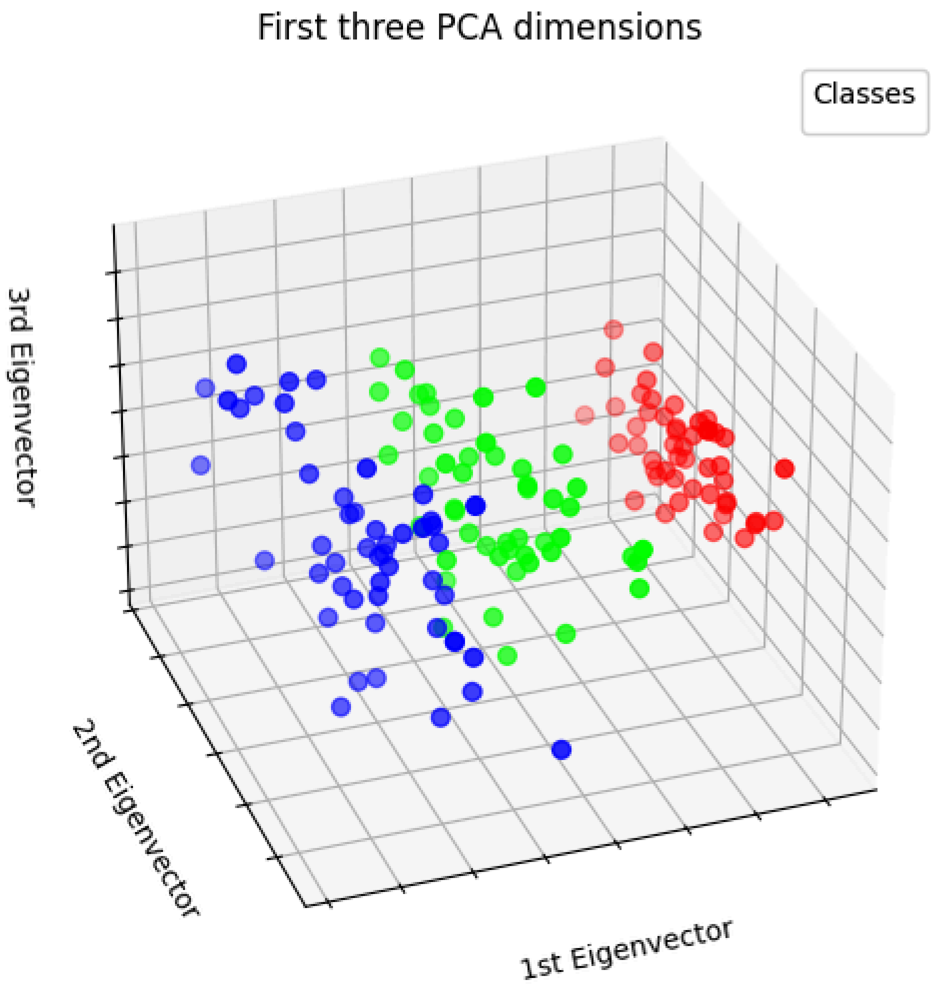


5. EDA + PCA

In [15]:

```
fig = plt.figure(1, figsize=(8, 6))
ax = fig.add_subplot(111, projection="3d", elev=-150, azim=110)

X_reduced = PCA(n_components=3).fit_transform(data_encoded[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']])
scatter = ax.scatter(
    X_reduced[:, 0],
    X_reduced[:, 1],
    X_reduced[:, 2],
    c=Y_encoded,
    s=40,
)

ax.set(
    title="First three PCA dimensions",
    xlabel="1st Eigenvector",
    ylabel="2nd Eigenvector",
    zlabel="3rd Eigenvector",
)
ax.xaxis.set_ticklabels([])
ax.yaxis.set_ticklabels([])
ax.zaxis.set_ticklabels([])

# Add a legend
legend1 = ax.legend(
    scatter.legend_elements()[0],
    Y_encoded,
    loc="upper right",
    title="Classes",
)
ax.add_artist(legend1)
```

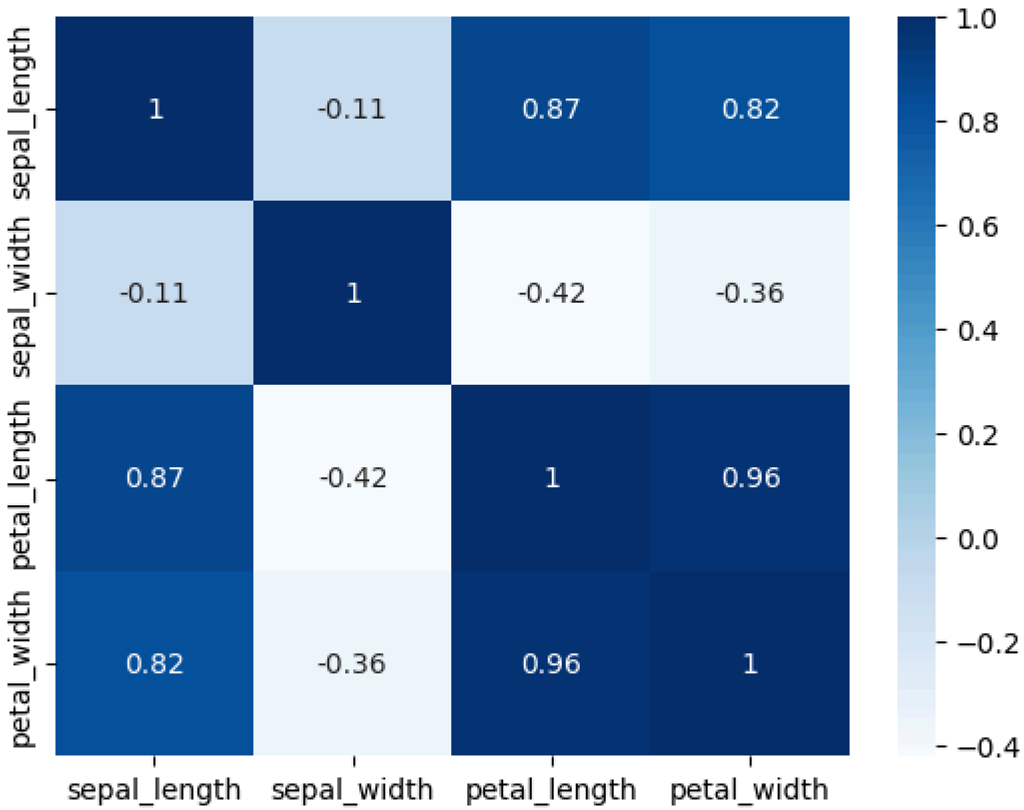
```
plt.show()
```



CORRELATION MATRIX

In [21]:
```
numeric_data = data_encoded.select_dtypes(include=[float, int])

numeric_data = data.drop(columns=['class'],)
```

```
sns.heatmap(numeric_data.corr(), annot=True, cmap='Blues')
plt.show()
```



6. TRAIN AND TEST SPLIT

In [17]:
```
X_train, X_test, y_train, y_test = train_test_split(X_reduced, y ,test_size=0.2, random_state=42)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[17]:
```
((120, 3), (30, 3), (120, 1), (30, 1))
```

7. SVM CLASSIFICATION WITHOUT HYPERPARAM TUNING BUT WITH PCA

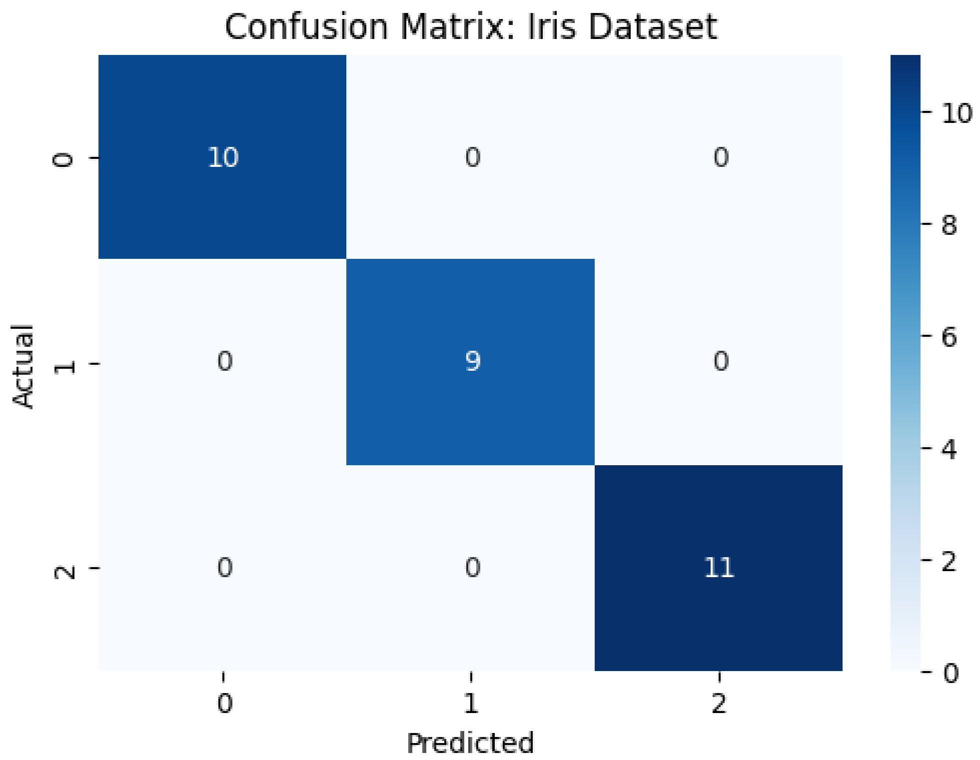
In [18]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

svc = SVC()
svc.fit(X_train, y_train)

y_pred = svc.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

print("SVC Accuracy:", accuracy)
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", class_report)
```

```
SVC 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
```

In [19]:
```
def plot_confusion_matrix(cm, title):
    plt.figure(figsize=(6, 4))
```

```
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(f'Confusion Matrix: {title}')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
```

In [20]:
```
plot_confusion_matrix(conf_matrix, 'Iris Dataset')
```



8. RANDOM SEARCH CV ALGORITHM WITH 5 FOLDS

In [22]:
```
param_grid = {
    'C': [0.1, 1, 10, 100],
    'gamma': [1, 0.1, 0.01, 0.001],
```

```
    'kernel': ['rbf', 'poly', 'sigmoid']
}
```

In [24]:
```
randomized_search = RandomizedSearchCV(svc, param_distributions=param_grid, n_iter=10, cv=5, scoring='accuracy')
randomized_search.fit(X_train, y_train)
```

Out[24]:
```
▸ RandomizedSearchCV
  ▸ best_estimator_: SVC
      ▸ SVC
```

In [25]:
```
randomized_search.best_params_
```

Out[25]:
```
{'kernel': 'poly', 'gamma': 0.1, 'C': 100}
```

In [26]:
```
randomized_search.best_score_
```

Out[26]:
```
0.9583333333333334
```

In [27]:
```
randomized_search.best_estimator_
```

Out[27]:
```
▾ SVC
SVC(C=100, gamma=0.1, kernel='poly')
```

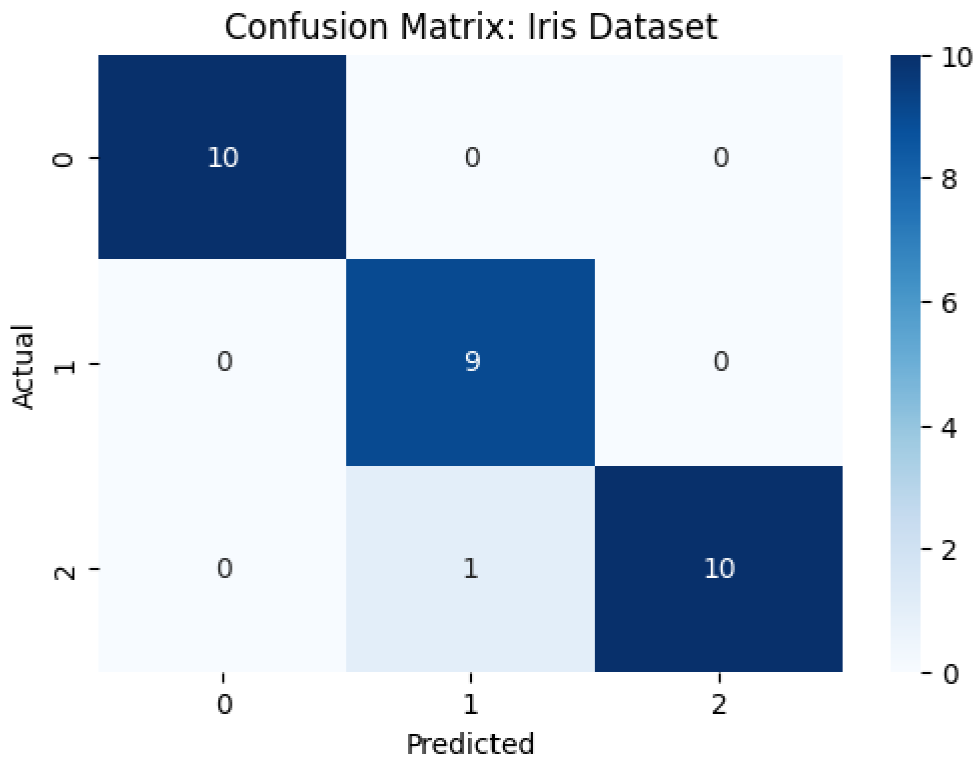
9. RESULTS FROM BEST ESTIMATOR OF RANDOM SEARCH CV ALGORITHM

In [28]:
```
y_preds = randomized_search.best_estimator_.predict(X_test)
```

In [29]:
```
class_report = classification_report(y_test, y_preds)
print(class_report)
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       0.90      1.00      0.95         9
 Iris-virginica       1.00      0.91      0.95        11

       accuracy                           0.97        30
      macro avg       0.97      0.97      0.97        30
   weighted avg       0.97      0.97      0.97        30
```

In [30]:
```python
conf_matrix = confusion_matrix(y_test, y_preds)
plot_confusion_matrix(conf_matrix, 'Iris Dataset')
```



10 CONCLUSION :

1. PCA AND HYPER PARAM TUNING HAS HUGE IMPACT ON MODEL'S PERFORMANCE.
2. CURSE OF DIMENTSIONALITY CAN BE REMOVED USING PCA.
3. AS WE KNOW THAT THE NOT ALL THE DATA POINTS CAN BE LINERALY SEPARABLE, IN SUCH CASES WE NEED NON LINEAR KERNELS ALSO, SUCH AS RBF OR POLY KERNEL.
4. DIFFERENT KERNEL BASED ON RESPECTIVE DATA POINTS CAN GIVE PERFECT DECISION BOUNDRIES SUCH THAT MODEL CAN CLEARLY CLASSIFY THE DATA POINT,