OJT PRACTICAL EXAMINATION

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Aim:

Using a given dataset, apply various machine learning techniques to classify and predict outcomes. Evaluate the performance of your models using different statistical methods, confusion matrix, and cross-validation.

List of Hardware and Software Requirements:

1. Windows 10 or 11
2. Jupyter Notebook/Jupyter Lab
3. V S code
4. Python

PROCEDURE:

Step 1: Open Anaconda navigator

Step 2: Launch Jupyter Lab

Step 3: Create a new Python file on the folder you want to save it.

Step 4: Rename the file and type the code to execute the program in the Jupyter Lab tab

Step 5: Save and run the code

Task1:

1. Data Preprocessing:
2. Load the dataset.
3. Handle missing values.
4. Encode categorical variables.
5. Scale/normalize the features

Code:

```
#importing Neccessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
import itertools
from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import confusion_matrix, accuracy_score,
precision_score, recall_score, f1_score, r2_score, mean_squared_error
```

```
# Load the dataset
data=pd.read_csv('data.csv')
data.head()
```

	feature1	feature2	feature3	feature4	target
0	5.1	3.5	1.4	0.2	Class1
1	4.9	3.0	1.4	0.2	Class1
2	4.7	3.2	1.3	0.2	Class1
3	4.6	3.1	1.5	0.2	Class1
4	5.0	3.6	1.4	0.2	Class1

```
# Handle missing values.
missing_values=data.isnull().sum()
print("The missing values are :", missing_values)
```

```
The missing values are : feature1    0
feature2    0
feature3    0
feature4    0
target      0
dtype: int64
```

```
#Encode categorical variables.
label_encoder=LabelEncoder()
data['target']=label_encoder.fit_transform(data['target'])
```

```
#Scale/normalize the features.
features=data.drop('target', axis=1)
scaler=StandardScaler()
scaled_features=scaler.fit_transform(features)
# Convert the scaled features back to a DataFrame
scaled_data=pd.DataFrame(scaled_features, columns=features.columns)
scaled_data['target']=data['target']
data.head()
```

	feature1	feature2	feature3	feature4	target
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

```
# Split the data into training and testing sets
X=scaled_data.drop('target', axis=1)
y=scaled_data['target']
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
```

Result:

All the given task run successfully

Task2:

Exploratory Data Analysis (EDA):

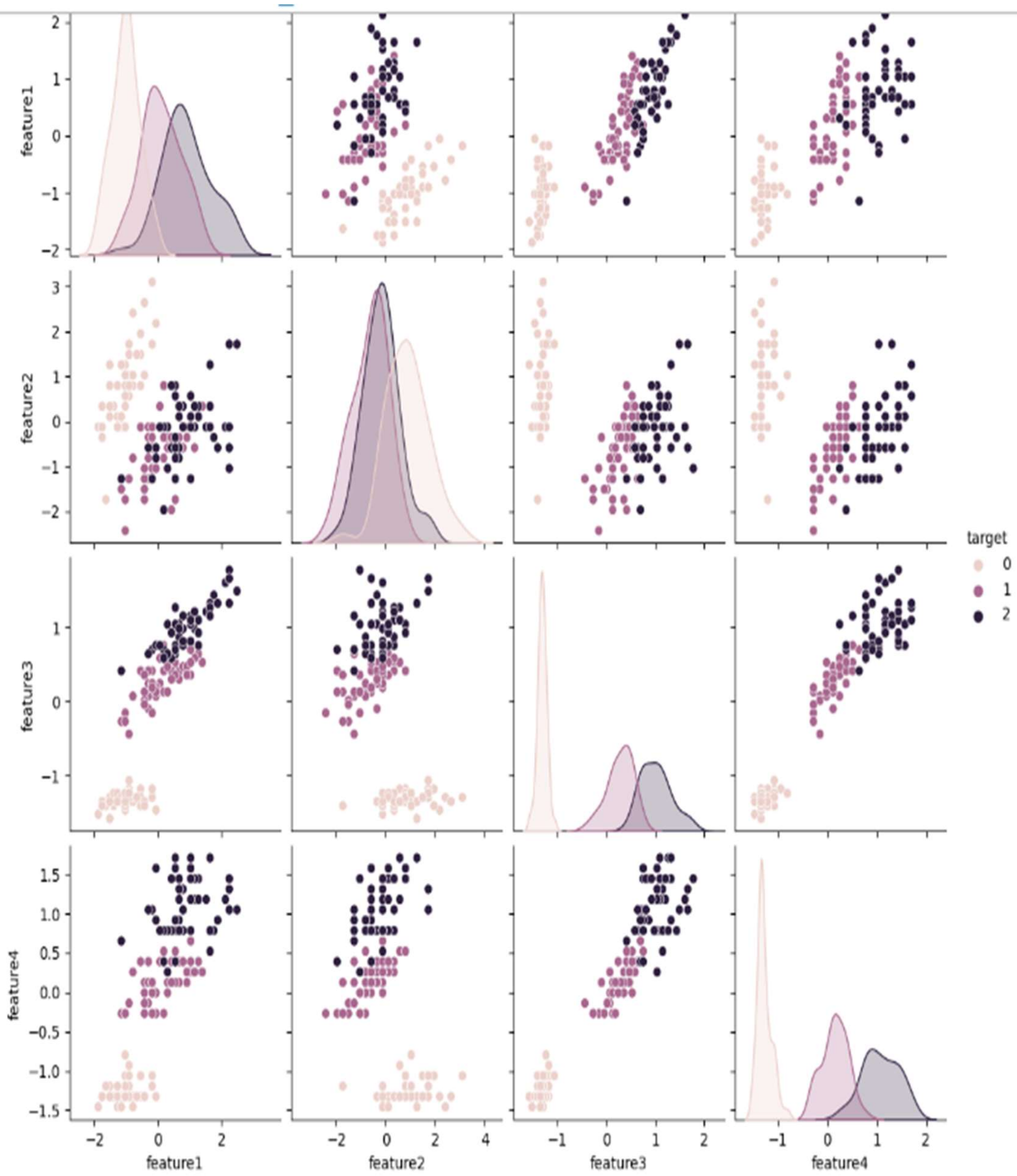
- Provide statistical summaries of the dataset.
- Visualize the data distribution and relationships between features using plots.

Code:

```
#Provide statistical summaries of the dataset.
print(scaled_data.describe())
```

	feature1	feature2	feature3	feature4	target
count	1.490000e+02	1.490000e+02	1.490000e+02	1.490000e+02	149.000000
mean	-1.430623e-16	-3.099683e-16	4.768743e-17	-1.430623e-16	1.006711
std	1.003373e+00	1.003373e+00	1.003373e+00	1.003373e+00	0.817847
min	-1.882359e+00	-2.425614e+00	-1.575313e+00	-1.456862e+00	0.000000
25%	-9.110290e-01	-5.863444e-01	-1.234147e+00	-1.193264e+00	0.000000
50%	-6.111554e-02	-1.265269e-01	3.579562e-01	1.247222e-01	1.000000
75%	6.673817e-01	5.631992e-01	7.559821e-01	7.837155e-01	2.000000
max	2.488625e+00	3.092195e+00	1.779477e+00	1.706306e+00	2.000000

```
#Visualize the data distribution and relationships between features using plots.
sns.pairplot(scaled_data, hue='target')
plt.show()
```



Result:

All the given task run successfully

Task3:

Classification:

- Apply Logistic Regression, Decision Tree, and Random Forest classifiers.
- Use a confusion matrix to evaluate the performance of each classifier.
- Perform cross-validation to assess the model stability.

Code

```
#o Apply Logistic Regression, Decision Tree, and Random Forest classifiers.
classifiers = {
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier()
}
```

```
#o Use a confusion matrix to evaluate the performance of each classifier.
for name, clf in classifiers.items():
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)
    print(f"\n{name} Confusion Matrix:\n", cm)
    print(f"{name} Accuracy: {accuracy_score(y_test, y_pred)}")
    print(f"{name} Precision: {precision_score(y_test, y_pred, average='weighted')}")
    print(f"{name} Recall: {recall_score(y_test, y_pred, average='weighted')}")
    print(f"{name} F1 Score: {f1_score(y_test, y_pred, average='weighted')}")
```

```
Logistic Regression Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
Logistic Regression Accuracy: 0.9
Logistic Regression Precision: 0.9214285714285714
Logistic Regression Recall: 0.9
Logistic Regression F1 Score: 0.896

Decision Tree Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
Decision Tree Accuracy: 0.9
Decision Tree Precision: 0.9214285714285714
Decision Tree Recall: 0.9
Decision Tree F1 Score: 0.896

Random Forest Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
Random Forest Accuracy: 0.9
Random Forest Precision: 0.9214285714285714
Random Forest Recall: 0.9
Random Forest F1 Score: 0.896
```

```python
#o Perform cross-validation to assess the model stability.
kf = KFold(n_splits=5, shuffle=True, random_state=42)
for name, clf in classifiers.items():
    cv_scores = cross_val_score(clf, X, y, cv=kf)
    print(f"\n{name} Cross-Validation Mean Score: {cv_scores.mean()}")
    print(f"{name} Cross-Validation Std Dev: {cv_scores.std()}")
```

```
Logistic Regression Cross-Validation Mean Score: 0.9533333333333334
Logistic Regression Cross-Validation Std Dev: 0.03999999999999994

Decision Tree Cross-Validation Mean Score: 0.9466666666666667
Decision Tree Cross-Validation Std Dev: 0.03399346342395189

Random Forest Cross-Validation Mean Score: 0.9533333333333334
Random Forest Cross-Validation Std Dev: 0.03999999999999994
```

Result:

All the given task run successfully

Task4:

Regression:

- Apply Linear Regression and Decision Tree Regressor.
- Evaluate the models using R-squared and Mean Squared Error (MSE).
- Perform cross-validation to assess the model stability.

Code:

```
#o Apply Linear Regression and Decision Tree Regressor.
regressors = {
    'Linear Regression': LinearRegression(),
    'Decision Tree Regressor': DecisionTreeRegressor()
}
```

```
#o Evaluate the models using R-squared and Mean Squared Error (MSE).
y_reg = scaled_data['feature1']
X_reg = scaled_data.drop('feature1', axis=1)
X_reg_train, X_reg_test, y_reg_train, y_reg_test = train_test_split(X_reg, y_reg, test_size=0.2, random_state=42)

for name, reg in regressors.items():
    reg.fit(X_reg_train, y_reg_train)
    y_reg_pred = reg.predict(X_reg_test)
    print(f"\n{name} R-squared: {r2_score(y_reg_test, y_reg_pred)}")
    print(f"{name} Mean Squared Error: {mean_squared_error(y_reg_test, y_reg_pred)}")
```

```
Linear Regression R-squared: 0.8388113342649274
Linear Regression Mean Squared Error: 0.1549854123710136

Decision Tree Regressor R-squared: 0.672407625083048
Decision Tree Regressor Mean Squared Error: 0.31498517023245115
```

```
#o Perform cross-validation to assess the model stability.
for name, reg in regressors.items():
    cv_scores = cross_val_score(reg, X_reg, y_reg, cv=kf, scoring='neg_mean_squared_error')
    print(f"\n{name} Cross-Validation Mean MSE: {-cv_scores.mean()}")
    print(f"{name} Cross-Validation Std Dev MSE: {cv_scores.std()}")
```

```
Linear Regression Cross-Validation Mean MSE: 0.15175063209300987
Linear Regression Cross-Validation Std Dev MSE: 0.017901844483952305

Decision Tree Regressor Cross-Validation Mean MSE: 0.2803671325335485
Decision Tree Regressor Cross-Validation Std Dev MSE: 0.06636538453660769
```

Result:

All the given task run successfully

Task5:

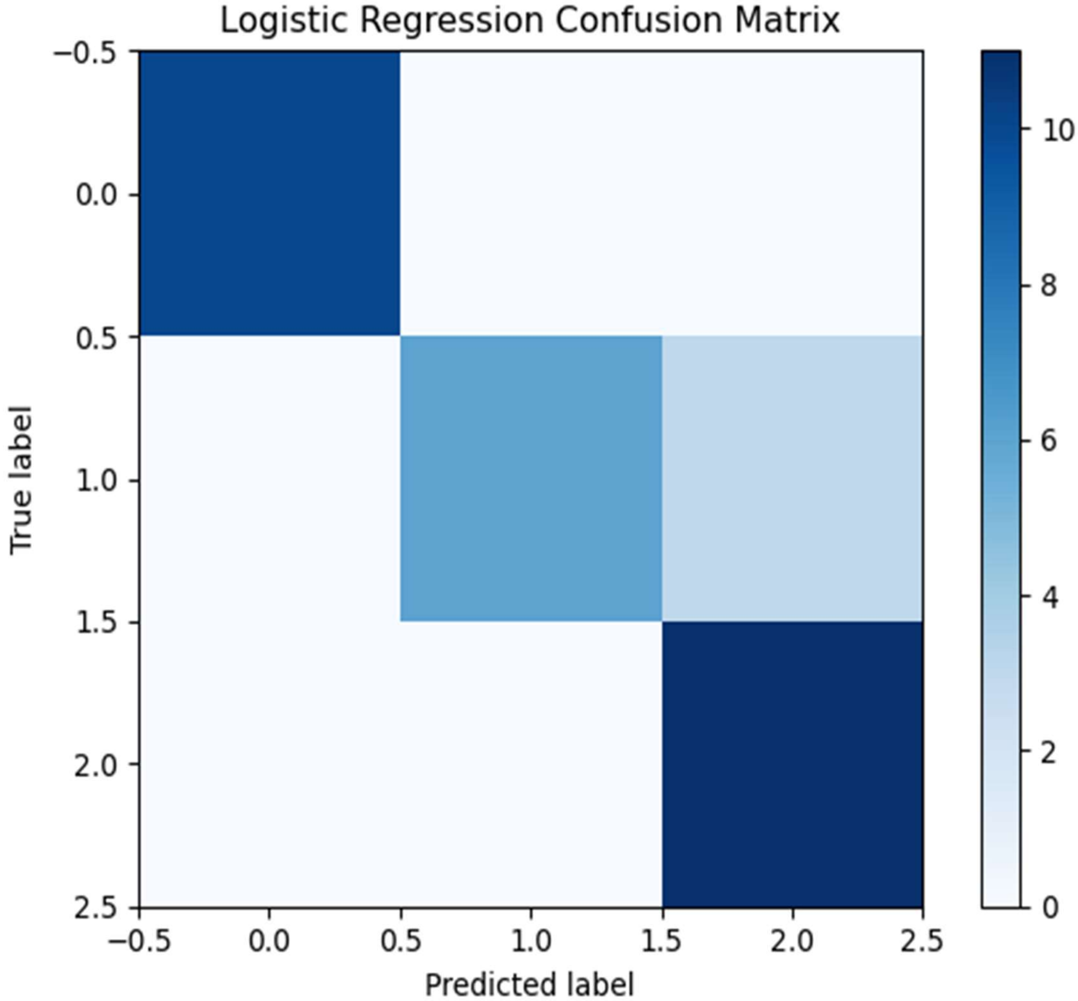
Confusion Matrix:

- ❖ For classification tasks, plot the confusion matrix and compute the following metrics:
- Accuracy
- Precision
- Recall
- F1 Score

Code:

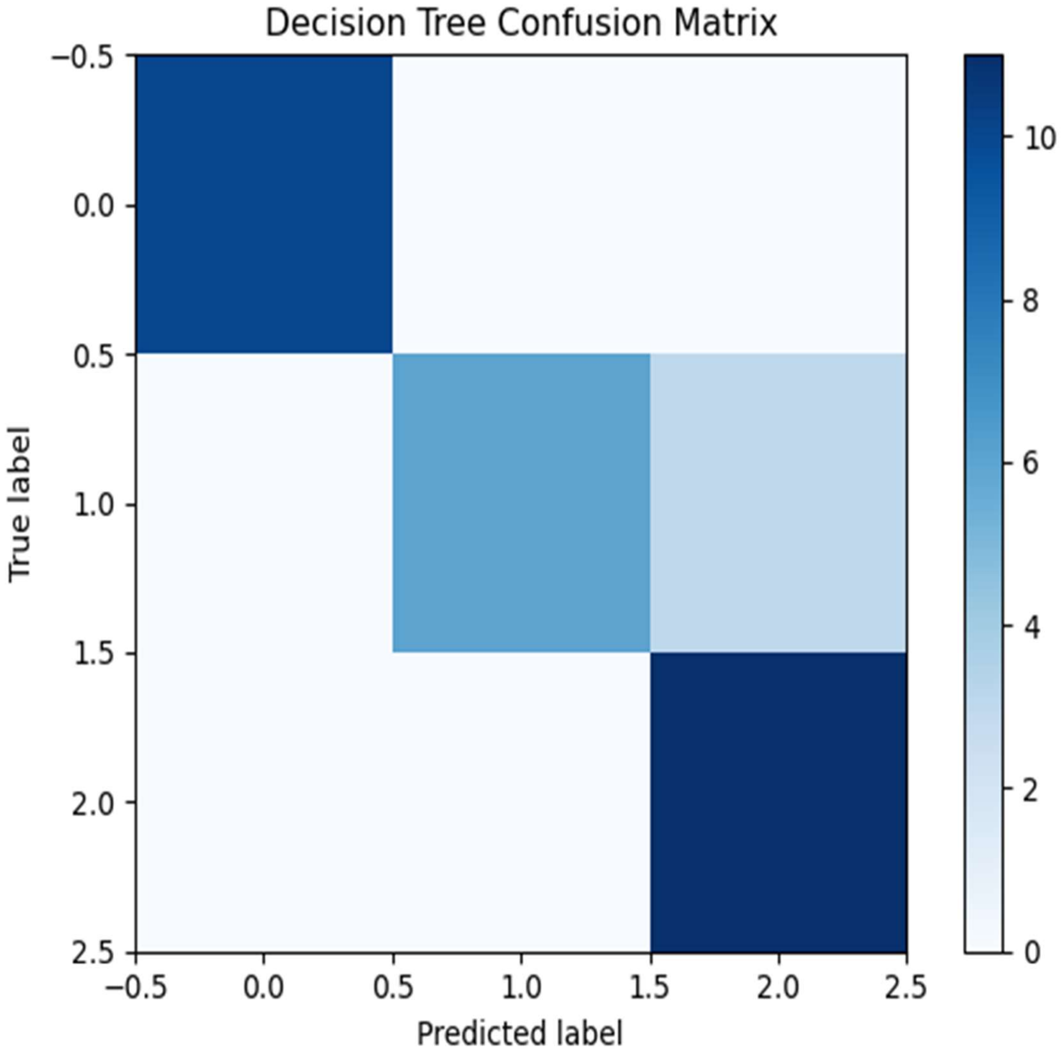
```
for name, clf in classifiers.items():
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)

 #For classification tasks, plot the confusion matrix and compute the following
    cm = confusion_matrix(y_test, y_pred)
    print(f"\n{name} Confusion Matrix:\n", cm)

    # Plot confusion matrix
    plt.figure()
    plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    plt.title(f'{name} Confusion Matrix')
    plt.colorbar()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
    plt.show()

    # metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    print(f"{name} Accuracy: {accuracy}")
    print(f"{name} Precision: {precision}")
    print(f"{name} Recall: {recall}")
    print(f"{name} F1 Score: {f1}")
```

```
Logistic Regression Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
```



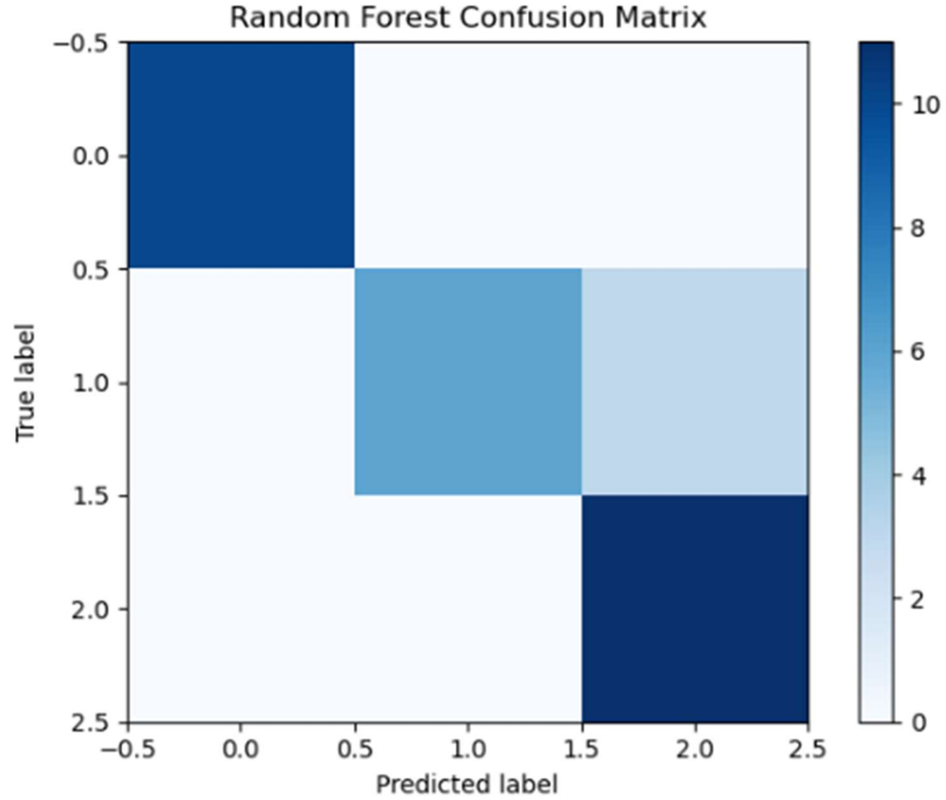

```
Logistic Regression Accuracy: 0.9
Logistic Regression Precision: 0.9214285714285714
Logistic Regression Recall: 0.9
Logistic Regression F1 Score: 0.896
```

```
Decision Tree Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
```




```
Decision Tree Accuracy: 0.9
Decision Tree Precision: 0.9214285714285714
Decision Tree Recall: 0.9
Decision Tree F1 Score: 0.896
```

```
Random Forest Confusion Matrix:
 [[10  0  0]
 [ 0  6  3]
 [ 0  0 11]]
```




```
Random Forest Accuracy: 0.9
Random Forest Precision: 0.9214285714285714
Random Forest Recall: 0.9
Random Forest F1 Score: 0.896
```

Result:

All the given task run successfully

Task6:

Cross-Validation:

- Implement k-fold cross-validation for both classification and regression models.
- Report the mean and standard deviation of the cross-validation scores.

Code:

```
from sklearn.model_selection import cross_val_score, KFold
# Define k-fold cross-validation
kf = KFold(n_splits=5, shuffle=True, random_state=42)
# Cross-validation for classifiers
for name, clf in classifiers.items():
    cv_scores = cross_val_score(clf, X, y, cv=kf)
    print(f"\n{name} Cross-Validation Mean Score: {cv_scores.mean()}")
    print(f"{name} Cross-Validation Std Dev: {cv_scores.std()}")

# Cross-validation for regressors
for name, reg in regressors.items():
    cv_scores = cross_val_score(reg, X_reg, y_reg, cv=kf, scoring='neg_mean_squared_error')
    print(f"\n{name} Cross-Validation Mean MSE: {-cv_scores.mean()}")
    print(f"{name} Cross-Validation Std Dev MSE: {cv_scores.std()}")
```

```
Logistic Regression Cross-Validation Mean Score: 0.9533333333333334
Logistic Regression Cross-Validation Std Dev: 0.03999999999999994

Decision Tree Cross-Validation Mean Score: 0.9397701149425288
Decision Tree Cross-Validation Std Dev: 0.0247016816104157

Random Forest Cross-Validation Mean Score: 0.9464367816091954
Random Forest Cross-Validation Std Dev: 0.03386106232555764

Linear Regression Cross-Validation Mean MSE: 0.15175063209300987
Linear Regression Cross-Validation Std Dev MSE: 0.017901844483952305

Decision Tree Regressor Cross-Validation Mean MSE: 0.2615542708814652
Decision Tree Regressor Cross-Validation Std Dev MSE: 0.03728589257979575
```

Result:

All the given task run successfully