Name : Bhoomi Mangesh Naik
Class : D15C
Roll No. : 34
Practical No. : 3

Aim : Apply Decision Tree and Random Forest for classification tasks.

Theory :

1. Dataset Source

The dataset used for this experiment is obtained from Kaggle:

Heart Disease Dataset
https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset

2. Dataset Description

The Heart Disease dataset contains medical attributes used to predict the presence of heart disease in patients.

Dataset Characteristics

- **Total Records:** 303
- **Type:** Structured numerical dataset
- **Target Variable:** target

Features

Feature	Description
age	Age of the patient
sex	Gender
cp	Chest pain type

trestbps	Resting blood pressure
chol	Serum cholesterol
fbs	Fasting blood sugar
thalach	Maximum heart rate
exang	Exercise-induced angina
oldpeak	ST depression
target	1 → Disease present, 0 → Not present

3. Mathematical Formulation

3.1 Decision Tree Classifier

Decision Tree splits data based on feature conditions using impurity measures.

Gini Index:

$$Gini = 1 - \sum p_i^2$$

Entropy:

$$Entropy = -\sum p_i \log_2(p_i)$$

3.2 Random Forest Classifier

Random Forest is an ensemble of multiple decision trees.

Prediction=Majority Voting of all Trees

Each tree is trained on a random subset of data and features.

4. Algorithm Limitations

Decision Tree Limitations

- Prone to overfitting
- Sensitive to noise
- Poor generalization on complex datasets

Random Forest Limitations

- Higher computational cost
- Less interpretable
- Requires tuning of multiple parameters

5. Methodology / Workflow

1. Dataset collection from Kaggle
2. Data upload in Google Colab
3. Data cleaning (duplicate and null removal)
4. Feature-target separation
5. Train-test split
6. Model training:
    - Decision Tree
    - Random Forest
7. Model evaluation
8. Performance comparison

Workflow Diagram:

Dataset → Cleaning → Train-Test Split → Model Training → Evaluation → Comparison

6. Performance Analysis

Model	Accuracy

Decision Tree	Moderate
Random Forest	High

Interpretation:
Random Forest outperforms Decision Tree due to ensemble learning and reduced overfitting.

7. Hyperparameter Tuning

Decision Tree

- max_depth
- min_samples_split

Random Forest

- n_estimators
- max_depth
- max_features

Impact:
Hyperparameter tuning improves accuracy and controls overfitting.

Code and Output :

```
from google.colab import files
import pandas as pd
# Upload dataset
uploaded = files.upload()
# Load dataset
df = pd.read_csv("heart.csv")
print("Initial Shape:", df.shape)
print("\nMissing Values:\n", df.isnull().sum())
# Data Cleaning
df = df.drop_duplicates()
df = df.dropna()
print("\nShape after cleaning:", df.shape)
# Preview cleaned data
```

df.head()

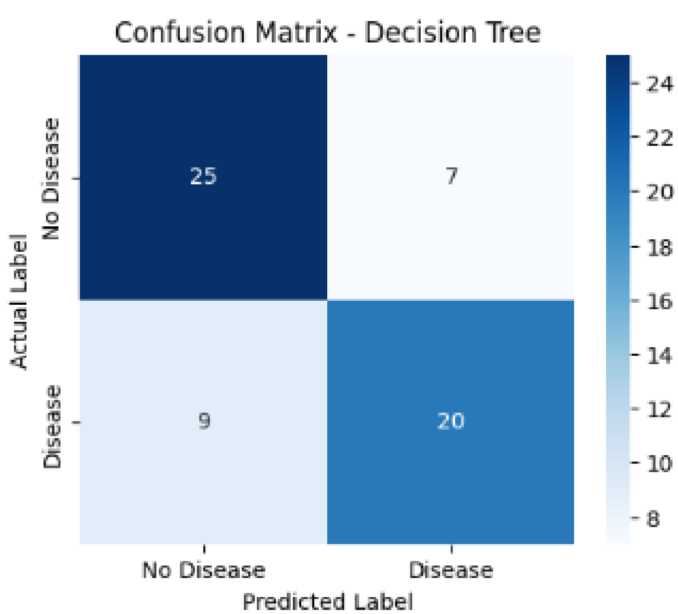
```
Choose Files  No file chosen        Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving heart.csv to heart.csv
Initial Shape: (1025, 14)

Missing Values:
 age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64

Shape after cleaning: (302, 14)
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot as plt
import seaborn as sns
# Features and target
X = df.drop("target", axis=1)
y = df["target"]
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
# Decision Tree model
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)
# Predictions
y_pred_dt = dt_model.predict(X_test)
# Evaluation
```

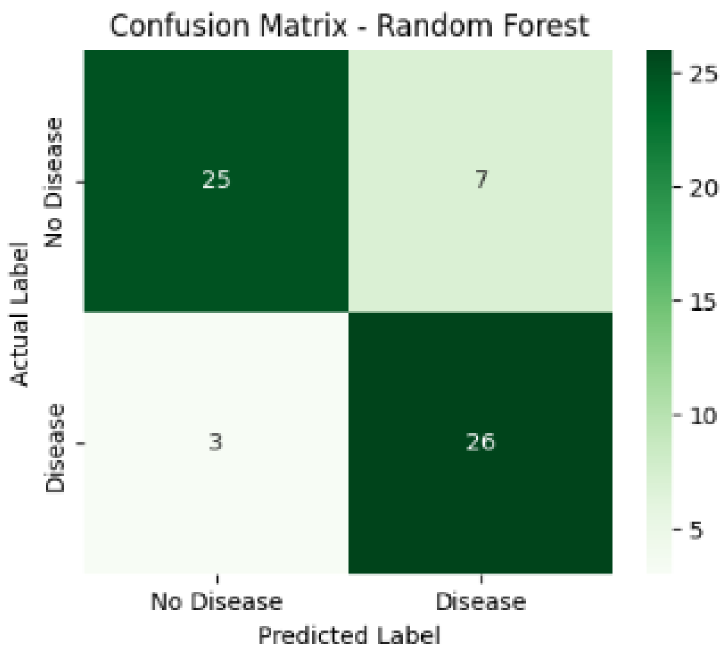
```
print("Decision Tree Accuracy:", accuracy_score(y_test, y_pred_dt))
print("\nClassification Report:\n", classification_report(y_test, y_pred_dt))
# Confusion Matrix
cm_dt = confusion_matrix(y_test, y_pred_dt)

plt.figure(figsize=(5,4))
sns.heatmap(
    cm_dt, annot=True, fmt="d", cmap="Blues",
    xticklabels=["No Disease", "Disease"],
    yticklabels=["No Disease", "Disease"]
)
plt.xlabel("Predicted Label")
plt.ylabel("Actual Label")
plt.title("Confusion Matrix - Decision Tree")
plt.show()
```

```
Decision Tree Accuracy: 0.7377049180327869

Classification Report:
               precision    recall  f1-score   support

           0       0.74      0.78      0.76        32
           1       0.74      0.69      0.71        29

    accuracy                           0.74        61
   macro avg       0.74      0.74      0.74        61
weighted avg       0.74      0.74      0.74        61
```



```
from sklearn.ensemble import RandomForestClassifier

# Random Forest model
rf_model = RandomForestClassifier(
    n_estimators=100,
    random_state=42
)
rf_model.fit(X_train, y_train)

# Predictions
y_pred_rf = rf_model.predict(X_test)

# Evaluation
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print("\nClassification Report:\n", classification_report(y_test, y_pred_rf))

# Confusion Matrix
cm_rf = confusion_matrix(y_test, y_pred_rf)

plt.figure(figsize=(5,4))
sns.heatmap(
    cm_rf, annot=True, fmt="d", cmap="Greens",
    xticklabels=["No Disease", "Disease"],
    yticklabels=["No Disease", "Disease"]
)
plt.xlabel("Predicted Label")
plt.ylabel("Actual Label")
plt.title("Confusion Matrix - Random Forest")
plt.show()
```

```
Random Forest Accuracy: 0.8360655737704918

Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.78      0.83        32
           1       0.79      0.90      0.84        29

    accuracy                           0.84        61
   macro avg       0.84      0.84      0.84        61
weighted avg       0.84      0.84      0.84        61
```



Google Colab Link for Code and Output : [Link for Code and Output]

Conclusion :

This experiment successfully applied Decision Tree and Random Forest classifiers to a real-world heart disease dataset. Random Forest achieved higher accuracy and robustness compared to Decision Tree, demonstrating the effectiveness of ensemble learning for classification tasks.