

PRACTICAL NO.4

To perform and analysis of Decision Trees Algorithm

Importing the Libraries

```
In [1]: import pandas as pd
import numpy as np
```

Data acquisitionuing Pandas

```
In [2]: import os

In [3]: os.getcwd()
Out[3]: 'C:\Users\SAICOM\Downloads'

In [4]: os.chdir('C:\Users\SAICOM\Downloads')

In [5]: data=pd.read_csv("heart.csv")

In [6]: data.head()

Out[6]:
```

	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

```
In [7]: data.tail()

Out[7]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
1020	59	1	1	140	221	0	1	164	1	0.0	2	0	2	1
1021	60	1	0	125	258	0	0	141	1	2.8	1	1	3	0
1022	47	1	0	110	275	0	0	118	1	1.0	1	1	2	0
1023	50	0	0	110	254	0	0	159	0	0.0	2	0	2	1
1024	54	1	0	120	188	0	1	113	0	1.4	1	1	3	0

```
In [8]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype
---  ---
 0   age         1025 non-null   int64
 1   sex         1025 non-null   int64
 2   cp          1025 non-null   int64
 3   trestbps    1025 non-null   int64
 4   chol        1025 non-null   int64
 5   fbs         1025 non-null   int64
 6   restecg     1025 non-null   int64
 7   thalach     1025 non-null   int64
 8   exang       1025 non-null   int64
 9   oldpeak     1025 non-null   float64
10  slope       1025 non-null   int64
11  ca          1025 non-null   int64
12  thal        1025 non-null   int64
13  target      1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB

In [9]: data.describe()

Out[9]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
count	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000
mean	54.434146	0.695610	0.942439	131.611707	246.000000	0.149268	0.529756	149.114146	0.336585	1.071512	1.385366	0.754146	2.323902	0.513171
std	9.072290	0.460373	1.029641	17.516718	51.59251	0.356527	0.527878	23.005724	0.472772	1.175053	0.617755	1.030798	0.620660	0.500070
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	48.000000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	132.000000	0.000000	0.000000	1.000000	0.000000	2.000000	0.000000
50%	56.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	152.000000	0.000000	0.800000	1.000000	0.000000	2.000000	1.000000
75%	61.000000	1.000000	2.000000	140.000000	275.000000	0.000000	1.000000	166.000000	1.000000	1.800000	2.000000	1.000000	3.000000	1.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000	3.000000	1.000000

```
In [10]: data.shape

Out[10]: (1025, 14)
```

```
In [11]: data.size

Out[11]: 14350
```

```
In [12]: data.ndim

Out[12]: 2
```

Data preprocessing *data cleaning* missing value treatment

```
In [13]: # check Missing Value by record
data.isna()

Out[13]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False
...
1020	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1021	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1022	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1023	False	False	False	False	False	False	False	False	False	False	False	False	False	False
1024	False	False	False	False	False	False	False	False	False	False	False	False	False	False

1025 rows x 14 columns

```
In [14]: data.isna().any()

Out[14]:
age          False
sex          False
cp           False
trestbps     False
chol         False
fbs          False
restecg      False
thalach      False
exang        False
oldpeak      False
slope        False
ca           False
thal         False
target       False
dtype: bool

In [15]: data.isna().sum()

Out[15]:
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
```

Removing duplicates

```
In [16]: data_dup =data.duplicated().any()

In [17]: data_dup
Out[17]: True

In [18]: data=data.drop_duplicates()

In [19]: data_dup =data.duplicated().any()

In [20]: data_dup
Out[20]: False
```

Splitting of DataSet into train and Test

```
In [21]: x=data.drop("target", axis=1)
y=data["target"]

In [22]: #splitting the data into training and testing data sets
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2 ,random_state=42)

In [23]: x_train

Out[23]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
163	48	1	0	124	274	0	0	166	0	0.5	1	0	3
291	58	1	0	128	259	0	0	130	1	3.0	1	2	3
280	45	0	1	130	234	0	0	175	0	0.6	1	0	2
85	44	1	1	120	220	0	1	170	0	0.0	2	0	2
239	62	0	0	150	244	0	1	154	1	1.4	1	0	2
...
267	67	1	0	120	237	0	1	71	0	1.0	1	0	2
77	63	1	0	140	187	0	0	144	1	4.0	2	2	3
125	60	0	3	150	240	0	1	171	0	0.9	2	0	2
522	67	0	2	152	277	0	1	172	0	0.0	2	1	2
119	42	1	1	120	295	0	1	162	0	0.0	2	0	2

241 rows x 13 columns

```
In [24]: x_test

Out[24]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
245	44	1	1	130	219	0	0	188	0	0.0	2	0	2
349	62	0	2	130	263	0	1	97	0	1.2	1	1	3
135	58	0	0	170	225	1	0	146	1	2.8	1	2	1
389	63	1	3	145	233	1	0	150	0	2.3	0	0	1
66	53	1	2	130	197	1	0	152	0	1.2	0	0	2
...
402	70	1	1	156	245	0	0	143	0	0.0	2	0	2
123	65	0	2	140	417	1	0	157	0	0.8	2	1	2
739	52	1	0	128	255	0	1	161	1	0.0	2	1	3
274	66	1	0	160	228	0	0	138	0	2.3	2	0	1
256	35	0	0	138	183	0	1	182	0	1.4	2	0	2

61 rows x 13 columns

```
In [25]: y_train

Out[25]:
163    0
291    0
280    1
85     1
239    0
...
267    0
77     0
125    1
522    1
119    1
Name: target, Length: 241, dtype: int64

In [26]: y_test

Out[26]:
245    1
349    0
135    0
389    1
66     1
...
402    1
123    1
739    0
274    1
256    1
Name: target, Length: 61, dtype: int64
```

Decision Trees Algorithm

```
In [27]: from sklearn.tree import DecisionTreeClassifier

In [28]: from sklearn.metrics import accuracy_score

In [29]: dt=DecisionTreeClassifier()

In [30]: dt.fit(x_train, y_train)

Out[30]: DecisionTreeClassifier()
DecisionTreeClassifier()

In [31]: y_pred5=dt.predict(x_test)

In [32]: accuracy_score (y_test,y_pred5)

Out[32]: 0.7049180327868853

In [33]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred5)

labels = np.unique(y_test) # Get unique class labels
cm_df = pd.DataFrame(cm, index=labels, columns=labels)

# Plot confusion matrix using seaborn
plt.figure(figsize=(6, 4))
sns.heatmap(cm_df, annot=True, fmt='d', cmap='Blues', linewidths=1, linecolor='black')

plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```

