VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum- 590014, Karnataka.

LAB REPORT

on

Machine Learning (23CS6PCMAL)

Submitted by

Maanas Sajeev (1BM22CS139)

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING

(Autonomous Institution under VTU)

BENGALURU - 560019

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B.M.S. College of Engineering

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning (23CS6PCMAL)" carried out by **Maanas Sajeev (1BM22CS139),** who is bonafide student of **B.M.S. College of Engineering.** It is in partial fulfilment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Laboratory report has been approved as it satisfies the academic requirements in respect of an Machine Learning (23CS6PCMAL) work prescribed for the said degree.

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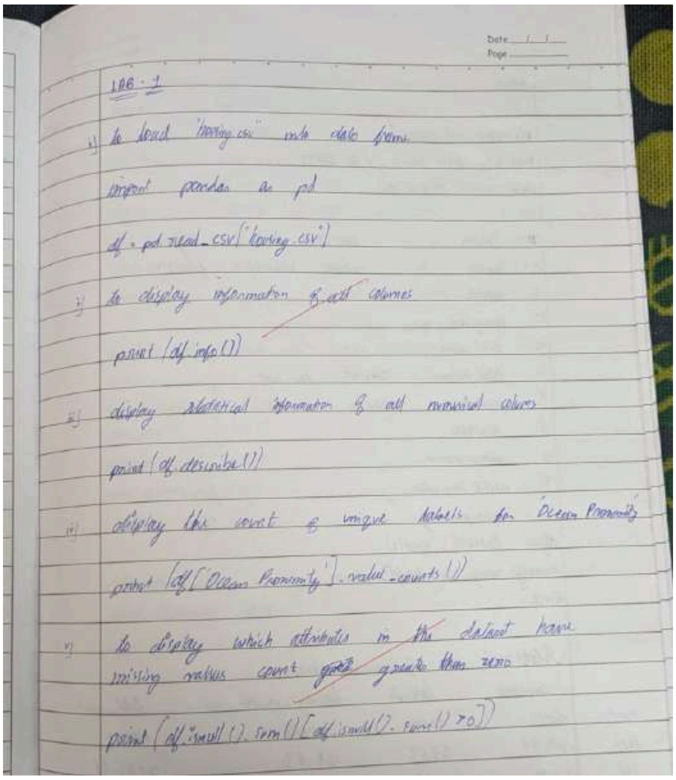
Github Link: https://github.com/maanas-sajeev/6thSem-ML-LAB

LABORATORY PROGRAM – 1

Write a python program to import and export data using Pandas library functions

OBSERVATION BOOK


LAB - 1

1) to load 'housing.csv' into data frame

import pandas as pd

df = pd.read_csv('housing.csv')

2) to display information of all columns

print(df.info())

3) display statistical information of all numerical columns

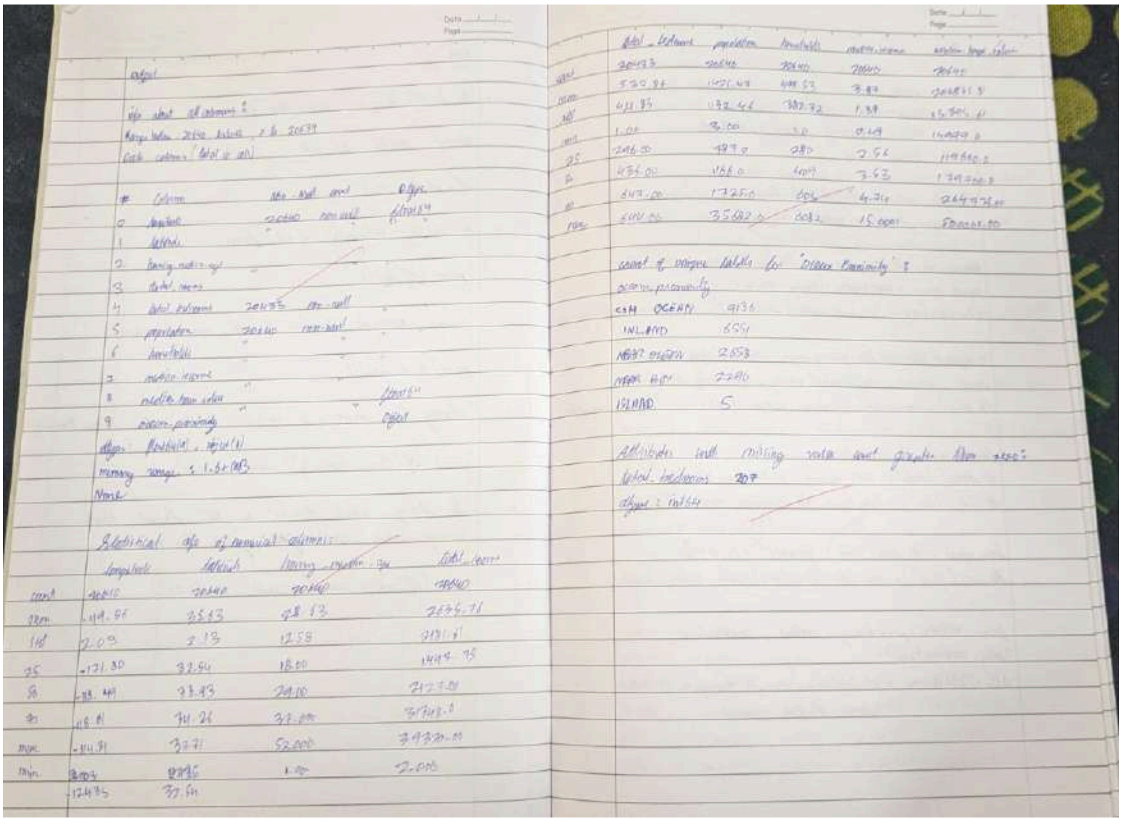
print(df.describe())

4) display the count of unique labels for 'Ocean Proximity'

print(df['Ocean Proximity'].value_counts())

5) to display which attributes in the dataset have missing values count greater than zero

print(df.isnull().sum()[df.isnull().sum() > 0])


output

count of unique labels for 'Ocean Proximity':

ocean_proximity

<1H OCEAN	9136
INLAND	6551
NEAR OCEAN	2658
NEAR BAY	2290
ISLAND	5

Attributes with missing value count greater than zero:

total_bedrooms 207

dtype: int64

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EDA

```
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
import numpy as np

db_data = pd.read_csv('diabetes_dataset.csv')
a_data = pd.read_csv('adult.csv')

numeric_cols = db_data.select_dtypes(include=['float64', 'int64']).columns
imputer_numeric = SimpleImputer(strategy='median')
db_data[numeric_cols] = imputer_numeric.fit_transform(db_data[numeric_cols])

categorical_cols = db_data.select_dtypes(include=['object']).columns
imputer_categorical = SimpleImputer(strategy='most_frequent')
db_data[categorical_cols] = imputer_categorical.fit_transform(db_data[categorical_cols])

label_encoder = LabelEncoder()
db_data['Gender'] = label_encoder.fit_transform(db_data['Gender'])
db_data['Class'] = label_encoder.fit_transform(db_data['Class'])

lower_upper = db_data['Urea'].quantile([0.01, 0.99])
db_data['Urea'] = np.clip(db_data['Urea'], lower, upper)

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
db_scaled_minmax = pd.DataFrame(scaler.fit_transform(db_data),
                 columns=db_data.columns)
```

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```
numeric_cols_adult = adult_mean_data.select_dtypes(include=['float64','int64']).columns
imputer_numeric_adult = SimpleImputer(strategy='median')
adult_mean_data[numeric_cols_adult] = imputer_numeric_adult.fit_transform(
        adult_mean_data[numeric_cols_adult])

categorical_cols_adult = adult_mean_data.select_dtypes(include=['object']).columns
imputer_categorical_adult = SimpleImputer(strategy='most_frequent')
adult_mean_data[categorical_cols_adult] = imputer_categorical_adult.
        fit_transform(adult_mean_data[categorical_cols_adult])

for col in categorical_cols_adult:
    adult_mean_data[col] = label_encoder.fit_transform(adult_mean_data[col])

lower, upper = adult_mean_data['age'].quantile([0.01, 0.99])
adult_mean_data['age'] = np.clip(adult_mean_data['age'], lower, upper)

adult_mean_scaled_minmax = pd.DataFrame(scaler.fit_transform(adult_mean_data),
        columns=adult_mean_data.columns)

print(db_scaled_minmax.head())
print(adult_mean_scaled_minmax.head())
```

Diabetes Dataset after Min-Max Scaling

	ID	No_Pation	Gender	Age	Urea
0	0.627	0.00073	0.0	0.508475	0.1631
1	0.918	0.000452	0.5	0.101	0.1329
2	0.571	0.000671	0.0	0.508475	0.143617
3	0.341	0.00116	0.0	0.508475	0.143617
4	0.61	0.000412	0.5	0.220339	0.272727

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Adult Income after Min-Max Scaling

	age	workclass	fnlwgt	education	education_num
0	0.1403	0.5	0.1451	0.0667	0.40000
1	0.3809	0.5	0.0524	0.7333	0.7333
2	0.1429	0.75	0.2196	0.6667	0.7333
3	0.4736	0.5	0.1001	1.000	0.6000
4	0.0174	0.0	0.06703	1.000	0.6000

1) Which column had missing values and how was it handled

Diabetes - BMI
Chol

Adult - Workclass
Occupation

2) Which categorical columns did you identify in the dataset. How did you encode them

Diabetes - Gender
Class

Adult - Education
Marital Status

Date ___
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3) diff. b/w Min-Max Scaling and Standardization

min-max Scaling: $\frac{x - min(x)}{max(x) - min(x)}$

Standardization: $\frac{x - \mu}{\sigma}$

3-3-25

CODE WITH OUTPUT

Diabetes Dataset

```
df=pd.read_csv('/content/Dataset of Diabetes .csv')
df.head()
```

	ID	No_Pation	Gender	AGE	Urea	Cr	HbA1c	Chol	TG	HDL	LDL	VLDL	BMI	CLASS
0	502	17975	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	N
1	735	34221	M	26	4.5	62	4.9	3.7	1.4	1.1	2.1	0.6	23.0	N
2	420	47975	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	N
3	680	87656	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	N
4	504	34223	M	33	7.1	46	4.9	4.9	1.0	0.8	2.0	0.4	21.0	N

```
df.shape
```

```
(1000, 14)
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   ID         1000 non-null   int64
 1   No_Pation  1000 non-null   int64
 2   Gender     1000 non-null   object
 3   AGE        1000 non-null   int64
 4   Urea       1000 non-null   float64
 5   Cr         1000 non-null   int64
 6   HbA1c      1000 non-null   float64
 7   Chol       1000 non-null   float64
 8   TG         1000 non-null   float64
 9   HDL        1000 non-null   float64
 10  LDL        1000 non-null   float64
 11  VLDL       1000 non-null   float64
 12  BMI        1000 non-null   float64
 13  CLASS      1000 non-null   object
dtypes: float64(8), int64(4), object(2)
memory usage: 109.5+ KB
None
```

```python
# Summary statistics
print(df.describe())
```

```
                ID    No_Pation          AGE         Urea           Cr  \
count  1000.000000  1.000000e+03  1000.000000  1000.000000  1000.000000
mean    340.500000  2.705514e+05    53.528000     5.124743    68.943000
std     240.397673  3.380758e+06     8.799241     2.935165    59.984747
min       1.000000  1.230000e+02    20.000000     0.500000     6.000000
25%     125.750000  2.406375e+04    51.000000     3.700000    48.000000
50%     300.500000  3.439550e+04    55.000000     4.600000    60.000000
75%     550.250000  4.538425e+04    59.000000     5.700000    73.000000
max     800.000000  7.543566e+07    79.000000    38.900000   800.000000

             HbA1c         Chol           TG          HDL          LDL  \
count  1000.000000  1000.000000  1000.000000  1000.000000  1000.000000
mean      8.281160     4.862820     2.349610     1.204750     2.609790
std       2.534003     1.301738     1.401176     0.660414     1.115102
min       0.900000     0.000000     0.300000     0.200000     0.300000
25%       6.500000     4.000000     1.500000     0.900000     1.800000
50%       8.000000     4.800000     2.000000     1.100000     2.500000
75%      10.200000     5.600000     2.900000     1.300000     3.300000
max      16.000000    10.300000    13.800000     9.900000     9.900000

              VLDL          BMI
count  1000.000000  1000.000000
mean      1.854700    29.578020
std       3.663599     4.962388
min       0.100000    19.000000
25%       0.700000    26.000000
50%       0.900000    30.000000
75%       1.500000    33.000000
max      35.000000    47.750000
```

```python
missing_values=df.isnull().sum()
print(missing_values[missing_values > 0])
```

```
Series([], dtype: int64)
```

```python
categorical_cols = df.select_dtypes(include=['object']).columns
print("Categorical columns identified:", categorical_cols)
if len(categorical_cols) > 0:
    df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
    print("\nDataFrame after one-hot encoding:")
    print(df.head())
else:
    print("\nNo categorical columns found in the dataset.")
```

```
Categorical columns identified: Index(['Gender', 'CLASS'], dtype='object')

DataFrame after one-hot encoding:
    ID  No_Pation  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL   BMI  \
0  502      17975   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
1  735      34221   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6  23.0
2  420      47975   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
3  680      87656   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
4  504      34223   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4  21.0

   Gender_M  Gender_f  CLASS_N  CLASS_P  CLASS_Y  CLASS_Y
0     False     False    False    False    False    False
1      True     False    False    False    False    False
2     False     False    False    False    False    False
3     False     False    False    False    False    False
4      True     False    False    False    False    False
```

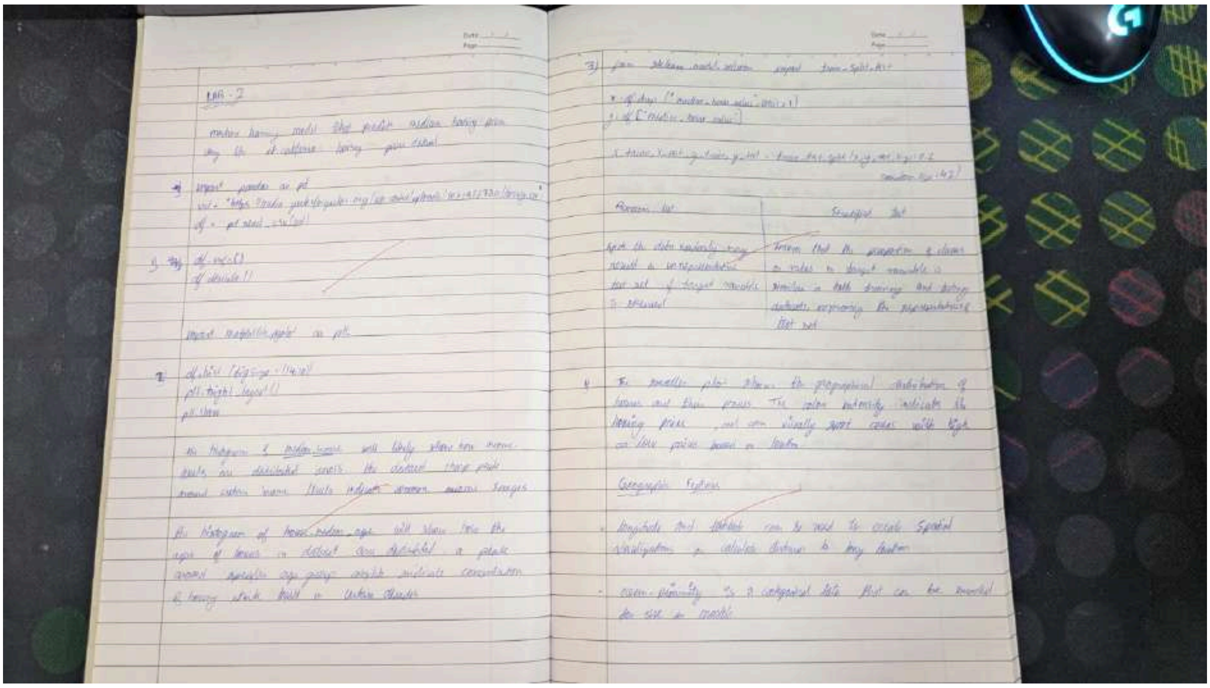
```python
from sklearn.preprocessing import MinMaxScaler, StandardScaler
import pandas as pd

numerical_cols = df.select_dtypes(include=['number']).columns

scaler = MinMaxScaler()
df_minmax = df.copy()  # Create a copy to avoid modifying the original
df_minmax[numerical_cols] = scaler.fit_transform(df[numerical_cols])

scaler = StandardScaler()
df_standard = df.copy()
df_standard[numerical_cols] = scaler.fit_transform(df[numerical_cols])
print("\nDataFrame after Min-Max Scaling:")
print(df_minmax.head())
print("\nDataFrame after Standardization:")
print(df_standard.head())
```

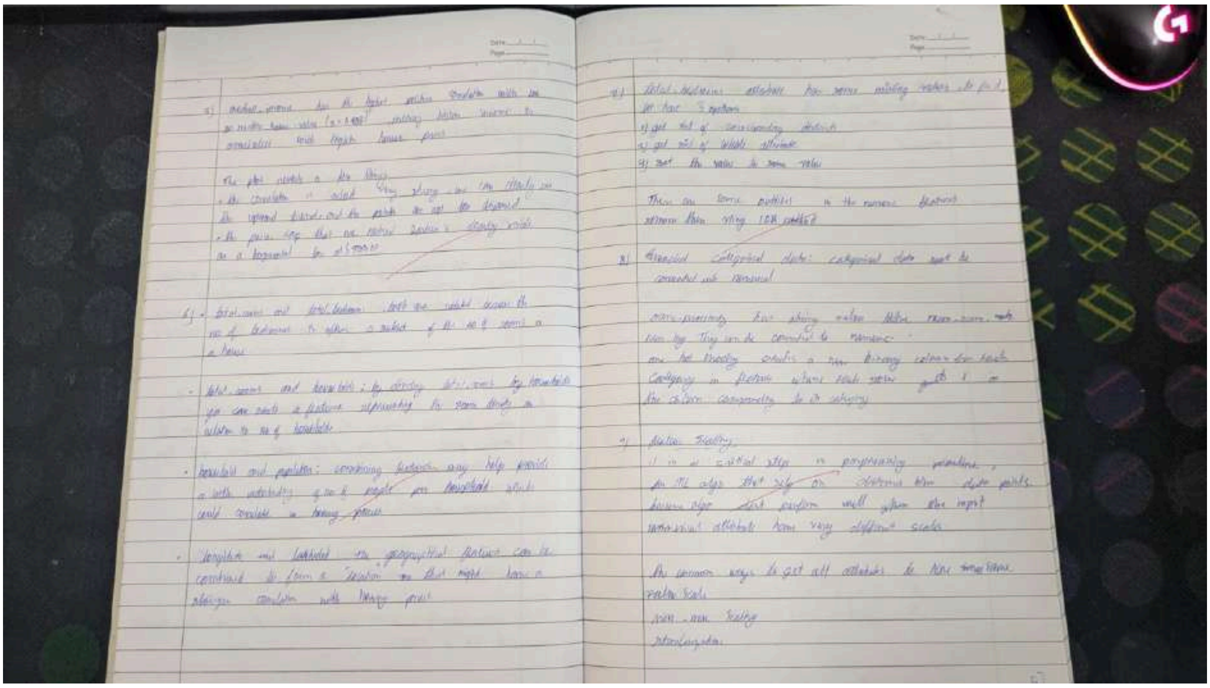
```
DataFrame after Min-Max Scaling:
         ID  No_Pation       AGE      Urea        Cr     HbA1c      Chol  \
0  0.627034   0.000237  0.508475  0.109375  0.050378  0.264901  0.407767
1  0.918648   0.000452  0.101695  0.104167  0.070529  0.264901  0.359223
2  0.524406   0.000634  0.508475  0.109375  0.050378  0.264901  0.407767
3  0.849812   0.001160  0.508475  0.109375  0.050378  0.264901  0.407767
4  0.629537   0.000452  0.220339  0.171875  0.050378  0.264901  0.475728

         TG       HDL       LDL      VLDL       BMI  Gender_M  Gender_f  \
0  0.044444  0.226804  0.114583  0.011461  0.173913     False     False
1  0.081481  0.092784  0.187500  0.014327  0.139130      True     False
2  0.044444  0.226804  0.114583  0.011461  0.173913     False     False
3  0.044444  0.226804  0.114583  0.011461  0.173913     False     False
4  0.051852  0.061856  0.177083  0.008596  0.069565      True     False

   CLASS_N  CLASS_P  CLASS_Y  CLASS_Y
0    False    False    False    False
1    False    False    False    False
2    False    False    False    False
3    False    False    False    False
4    False    False    False    False

DataFrame after Standardization:
         ID  No_Pation       AGE      Urea        Cr     HbA1c      Chol  \
0  0.672140  -0.074747 -0.401144 -0.144781 -0.382672 -1.334983 -0.509436
1  1.641852  -0.069940 -3.130017 -0.212954 -0.115804 -1.334983 -0.893730
2  0.330868  -0.065869 -0.401144 -0.144781 -0.382672 -1.334983 -0.509436
3  1.412950  -0.054126 -0.401144 -0.144781 -0.382672 -1.334983 -0.509436
4  0.680463  -0.069939 -2.334096  0.673299 -0.382672 -1.334983  0.028576

         TG       HDL       LDL      VLDL       BMI  Gender_M  Gender_f  \
0 -1.035084  1.810756 -1.085457 -0.369958 -1.124622     False     False
1 -0.678063 -0.158692 -0.457398 -0.342649 -1.326239      True     False
2 -1.035084  1.810756 -1.085457 -0.369958 -1.124622     False     False
3 -1.035084  1.810756 -1.085457 -0.369958 -1.124622     False     False
4 -0.963680 -0.613180 -0.547121 -0.397267 -1.729472      True     False

   CLASS_N  CLASS_P  CLASS_Y  CLASS_Y
0    False    False    False    False
1    False    False    False    False
2    False    False    False    False
3    False    False    False    False
4    False    False    False    False
```

LABORATORY PROGRAM – 2

Demonstrate various data pre-processing techniques for a given dataset

OBSERVATION BOOK





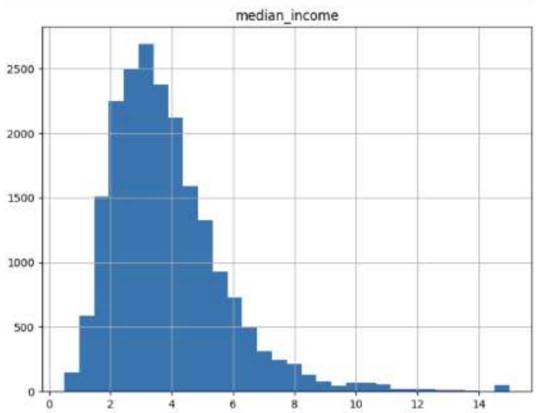
10) a ML pipeline with custom transformations encoding custom scaling, sequentially prepare data by applying custom changes to features converting categorical to numeric. and scaling numerical to ensure equal contribution

CODE WITH OUTPUT

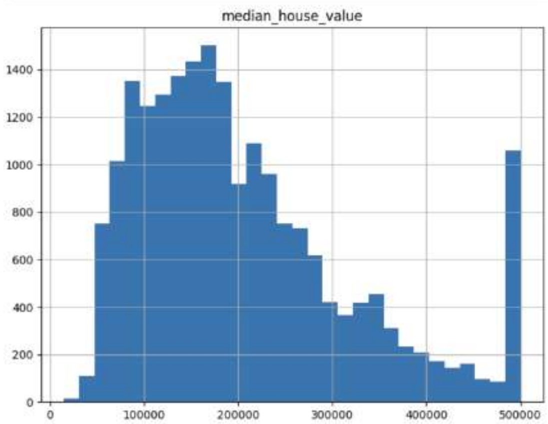
```python
# Load the dataset into a pandas DataFrame
df = pd.read_csv('housing.csv')

# Display descriptive statistics
df.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populatior
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.00000(
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.47674
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.46212
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.00000(
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.00000(
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.00000(
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.00000(
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.00000(

```python
import matplotlib.pyplot as plt
df.hist(column="median_income", bins=30, figsize=(8,6))
plt.show()
```




```python
import matplotlib.pyplot as plt
df.hist(column="median_house_value", bins=30, figsize=(8,6))
plt.show()
```

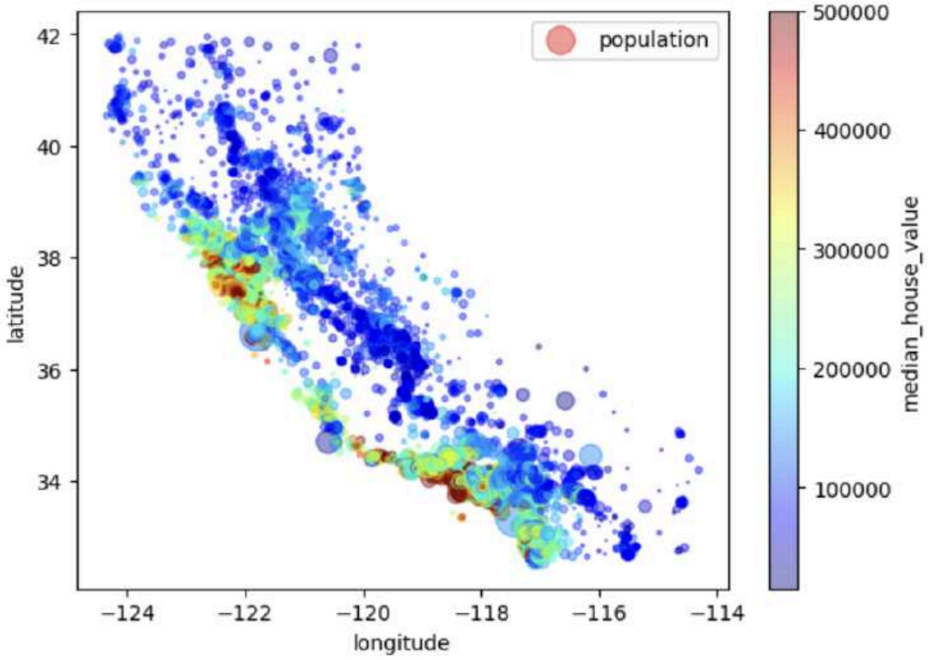



```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, StratifiedShuffleSplit

# Load the dataset
housing = pd.read_csv('housing.csv')

# For this demonstration, consider only 'median_income' and 'median_house_value'
```

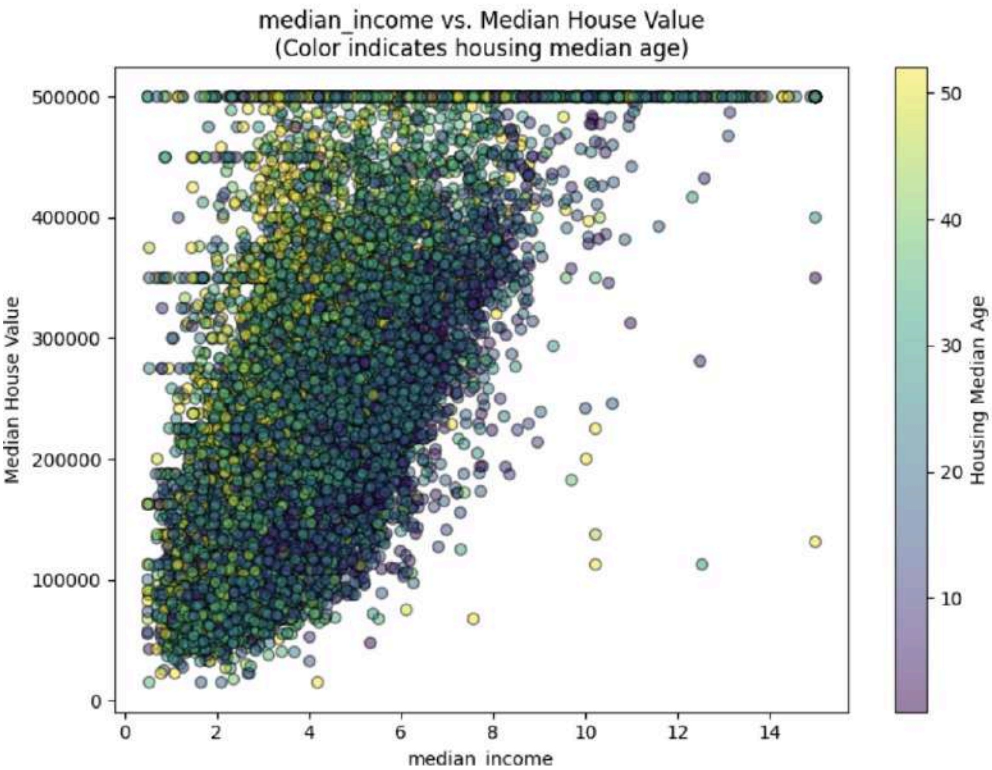
```
housing_selected = housing[['median_income', 'median_house_value']].copy()

# Random split: This splits the data randomly without preserving any specific distribution.
train_set_random, test_set_random = train_test_split(housing_selected, test_size=0.2, random_state=42)

# For stratified sampling, first create an income category.
housing_selected['income_cat'] = pd.cut(housing_selected['median_income'],
                                        bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                                        labels=[1, 2, 3, 4, 5])

# Use StratifiedShuffleSplit to ensure the income distribution is preserved in both sets.
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing_selected, housing_selected['income_cat']):
    strat_train_set = housing_selected.loc[train_index]
    strat_test_set = housing_selected.loc[test_index]

# Remove the temporary income category attribute.
for dataset in (strat_train_set, strat_test_set):
    dataset.drop("income_cat", axis=1, inplace=True)
```

```
import matplotlib.pyplot as plt
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
             s=housing["population"]/100, label="population", figsize=(7,5),
             c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,)
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7e55a2076b10>
```



```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8,6))
# Differentiate by using 'housing_median_age' for the color
scatter = plt.scatter(housing_numeric[max_feature],
                      housing_numeric["median_house_value"],
                      alpha=0.5,
                      c=housing_numeric["housing_median_age"],
                      cmap='viridis',
                      edgecolor='k')
plt.xlabel(max_feature)
plt.ylabel("Median House Value")
plt.title(f"{max_feature} vs. Median House Value\n(Color indicates housing median age)")
# Add a colorbar to explain the color mapping
cbar = plt.colorbar(scatter)
cbar.set_label("Housing Median Age")
plt.tight_layout()
plt.show()
```



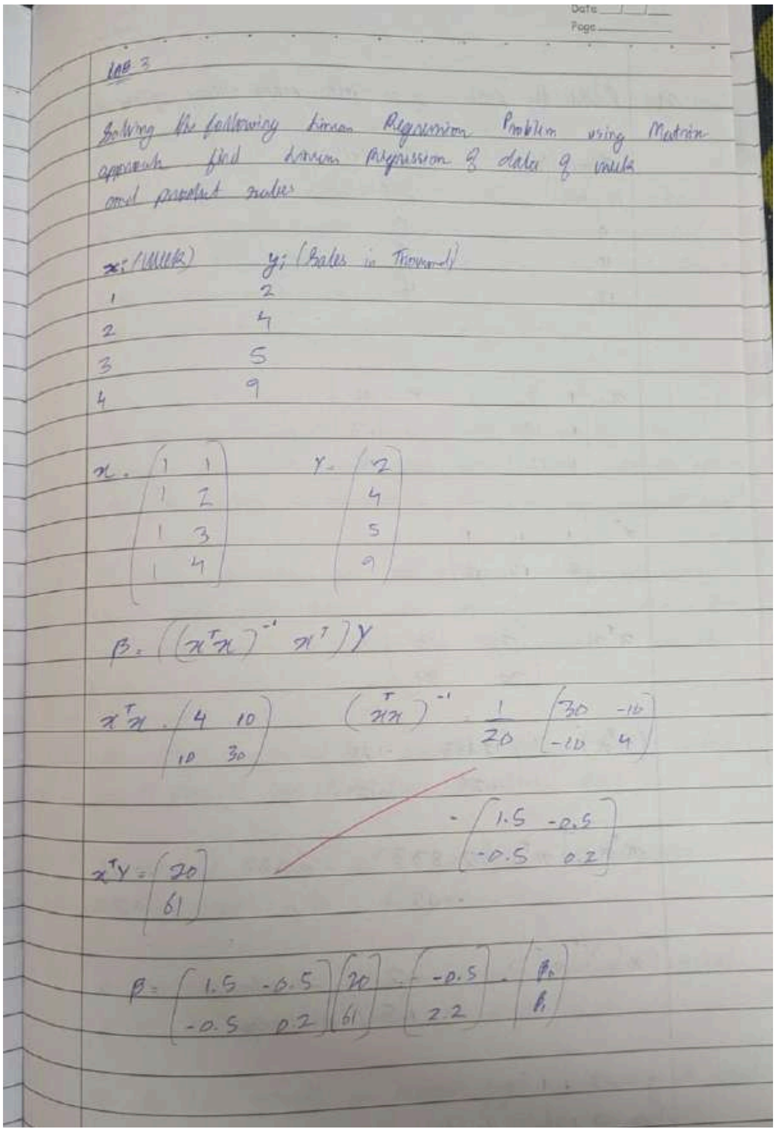

```
from sklearn.preprocessing import OneHotEncoder

# Extract the categorical attribute
housing_cat = housing[["ocean_proximity"]]

# Perform one-hot encoding
encoder = OneHotEncoder()
housing_cat_1hot = encoder.fit_transform(housing_cat).toarray()

# Create a DataFrame for the encoded features
housing_cat_1hot_df = pd.DataFrame(housing_cat_1hot,
                                   columns=encoder.get_feature_names_out(["ocean_proximity"]))
housing_cat_1hot_df.head()
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler

# Custom transformer to add engineered attributes
class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
```

```python
    def __init__(self, add_bedrooms_per_room=True):
        self.add_bedrooms_per_room = add_bedrooms_per_room
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        # Assumes X is a NumPy array with the following columns:
        # total_rooms (index 3), total_bedrooms (index 2), population (index 4), households (index 5)
        rooms_per_household = X[:, 3] / X[:, 5]
        population_per_household = X[:, 4] / X[:, 5]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, 2] / X[:, 3]
            return np.c_[X, rooms_per_household, population_per_household, bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household, population_per_household]

# Identify numerical and categorical columns
num_attribs = housing.drop("ocean_proximity", axis=1).columns  # All numeric columns
cat_attribs = ["ocean_proximity"]

# Build numerical pipeline: impute missing values, add new attributes, then scale
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()),
])

# Build the full pipeline combining numerical and categorical processing
full_pipeline = ColumnTransformer([
    ("num", num_pipeline, num_attribs),
    ("cat", OneHotEncoder(), cat_attribs),
])

# Process the dataset using the pipeline
housing_prepared = full_pipeline.fit_transform(housing)
print("Shape of processed data:", housing_prepared.shape)
```

LABORATORY PROGRAM – 3

Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample.

OBSERVATION BOOK



Lab 3

Solving the following Linear Regression Problem using Matrix approach find Linear Regression of data of week and product sales

x: (week)	y: (Sales in Thousand)
1	2
2	4
3	5
4	9

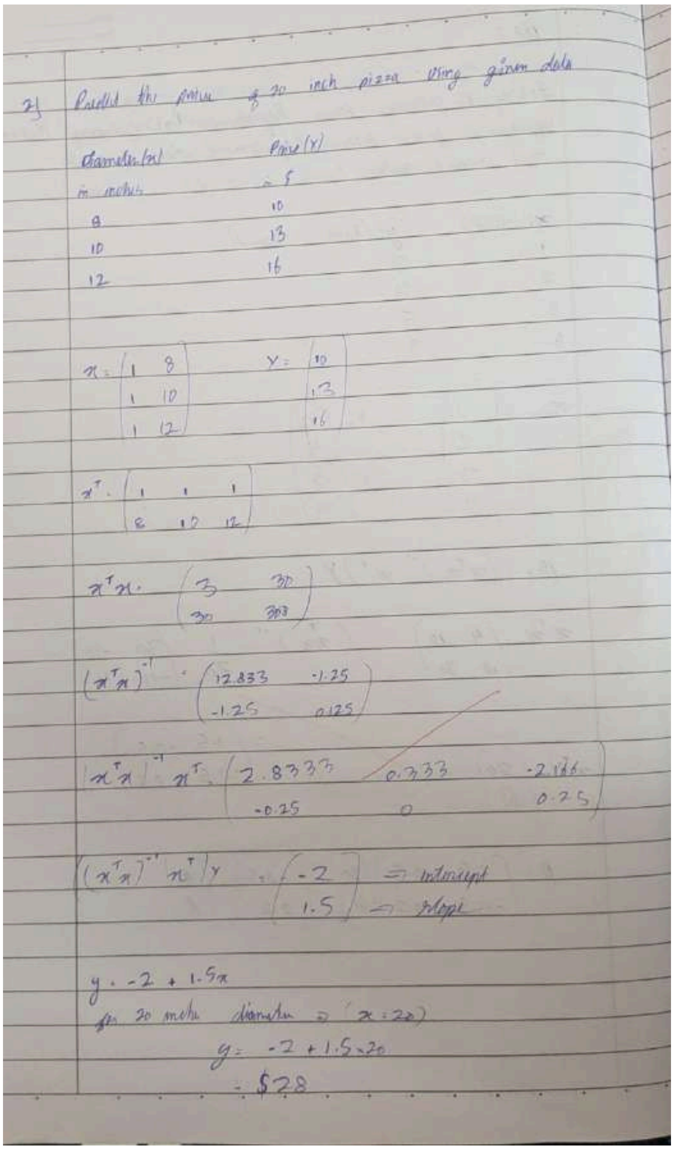
$$x = \begin{pmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{pmatrix} \qquad Y = \begin{pmatrix} 2 \\ 4 \\ 5 \\ 9 \end{pmatrix}$$

$$\beta = \left((x^T x)^{-1} x^T\right) Y$$

$$x^T x = \begin{pmatrix} 4 & 10 \\ 10 & 30 \end{pmatrix} \qquad (x^T x)^{-1} = \frac{1}{20}\begin{pmatrix} 30 & -10 \\ -10 & 4 \end{pmatrix} = \begin{pmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{pmatrix}$$

$$x^T Y = \begin{pmatrix} 20 \\ 61 \end{pmatrix}$$

$$\beta = \begin{pmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{pmatrix}\begin{pmatrix} 20 \\ 61 \end{pmatrix} = \begin{pmatrix} -0.5 \\ 2.2 \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}$$



2) Predict the price of 20 inch pizza using given data

diameter (x) in inches	Price (y)
8	10
10	13
12	16

$$x = \begin{pmatrix} 1 & 8 \\ 1 & 10 \\ 1 & 12 \end{pmatrix} \qquad Y = \begin{pmatrix} 10 \\ 13 \\ 16 \end{pmatrix}$$

$$x^T = \begin{pmatrix} 1 & 1 & 1 \\ 8 & 10 & 12 \end{pmatrix}$$

$$x^T x = \begin{pmatrix} 3 & 30 \\ 30 & 303 \end{pmatrix}$$

$$(x^T x)^{-1} = \begin{pmatrix} 12.833 & -1.25 \\ -1.25 & 0.125 \end{pmatrix}$$

$$(x^T x)^{-1} x^T = \begin{pmatrix} 2.8333 & 0.333 & -2.166 \\ -0.25 & 0 & 0.25 \end{pmatrix}$$

$$\left((x^T x)^{-1} x^T\right) Y = \begin{pmatrix} -2 \\ 1.5 \end{pmatrix} \begin{matrix} \Rightarrow \text{intercept} \\ \Rightarrow \text{slope} \end{matrix}$$

$y = -2 + 1.5x$

for 20 inch diameter $\Rightarrow (x = 20)$

$y = -2 + 1.5 \times 20$

$= \$28$

Date __/__/__
Page ______

1) considering 3 data .csv files (canada per-capita income, salary, hiring)
did you perform any data preprocessing steps

→ data preprocessing steps like handling missing values by dropping rows with dropna() and encoding categorical variable (like "State") using LabelEncoder to convert them into numeric values. No scaling was applied as features weren't significantly different in magnitude

2) For canada-per-capita-income.csv, did you visualize the regression line along with data points? What does the plot tell you about the relationship b/w year and per capita income?

→ Yes, the regression line was visualized along with data points. The plot shows an upward trend indicating that per capita income in Canada has been increasing over the years.

3) for hiring.csv, what is predicted salary for a candidate with 12 years of exp, 10 test score, 10 interview score

→ The predicted salary for a candidate ~~with 12 years experience~~ is $92,562.50

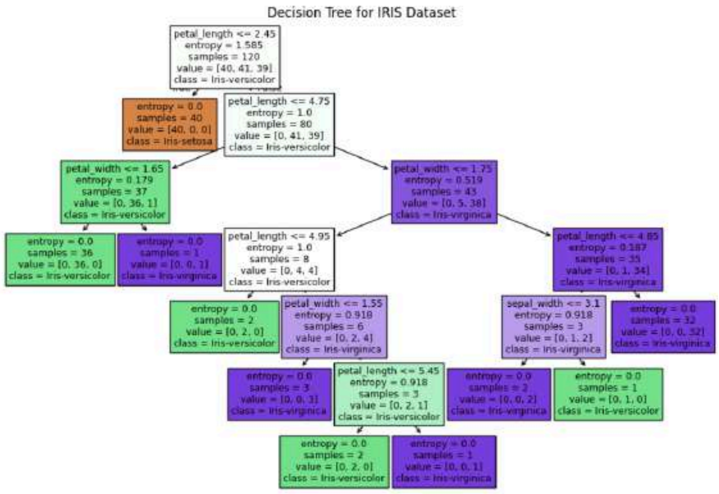
4) for 1000-companies.csv, did you encode categorical variables if yes, how? did you scale the features? if yes, why?

Yes, the "State" variable was encoded using LabelEncoder to convert it into numeric values. The State column has data like "Florida", "NY", "California". Categorical variables like state names, need to be encoded, but they do not require scaling.

CODE WITH OUTPUT

```
import pandas as pd
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
from sklearn.tree import plot_tree

# Load the iris dataset (make sure iris.csv is in the working directory)
iris = pd.read_csv("iris.csv")
# Assuming the last column is the target (species) and the rest are features.
X = iris.iloc[:, :-1]
y = iris.iloc[:, -1]

# Split data into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train the Decision Tree classifier
clf_iris = DecisionTreeClassifier(criterion='entropy', random_state=42)
clf_iris.fit(X_train, y_train)

# Make predictions and evaluate the model
y_pred_iris = clf_iris.predict(X_test)
accuracy_iris = accuracy_score(y_test, y_pred_iris)
conf_matrix_iris = confusion_matrix(y_test, y_pred_iris)

print("IRIS Dataset Decision Tree Classifier")
print("Accuracy:", accuracy_iris)
print("Confusion Matrix:\n", conf_matrix_iris)
print("Classification Report:\n", classification_report(y_test, y_pred_iris))

# Visualize the decision tree
plt.figure(figsize=(12, 8))
plot_tree(clf_iris, filled=True, feature_names=X.columns, class_names=clf_iris.classes_)
plt.title("Decision Tree for IRIS Dataset")
plt.show()
```

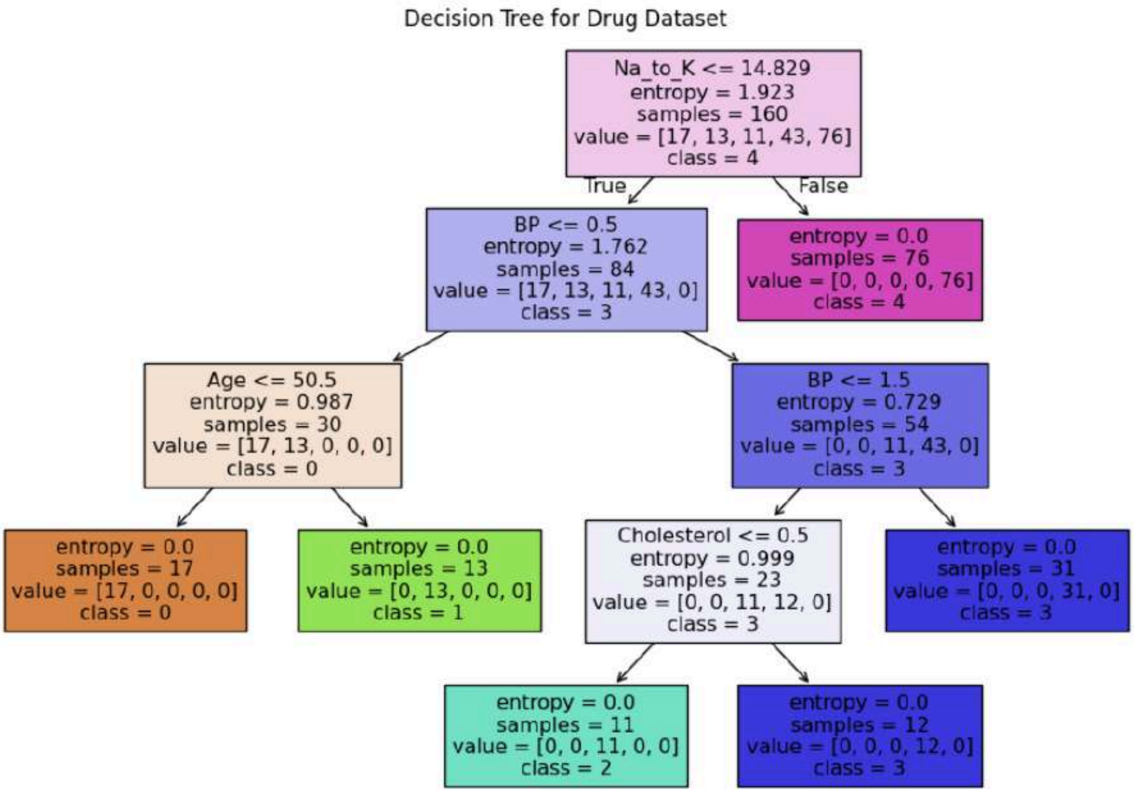
```
IRIS Dataset Decision Tree Classifier
Accuracy: 1.0
Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
Classification Report:
                  precision    recall  f1-score   support

    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
```




```python
import pandas as pd
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
from sklearn.tree import plot_tree

# Load the drug dataset (make sure drug.csv is in the working directory)
drug = pd.read_csv("drug.csv")

# Since the target column is 'Drug', drop it from the features
X_drug = drug.drop('Drug', axis=1)
y_drug = drug['Drug']

# If there are categorical features, perform necessary encoding
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
# Encode features that are categorical
for col in X_drug.select_dtypes(include='object').columns:
    X_drug[col] = le.fit_transform(X_drug[col])
# Also encode the target variable if necessary
y_drug = le.fit_transform(y_drug)

# Split the data (80% training, 20% testing)
X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_drug, y_drug, test_size=0.2, random_state=42)

# Initialize and train the Decision Tree classifier using entropy criterion
clf_drug = DecisionTreeClassifier(criterion='entropy', random_state=42)
clf_drug.fit(X_train_d, y_train_d)

# Make predictions and evaluate the model
y_pred_drug = clf_drug.predict(X_test_d)
accuracy_drug = accuracy_score(y_test_d, y_pred_drug)
conf_matrix_drug = confusion_matrix(y_test_d, y_pred_drug)

print("Drug Dataset Decision Tree Classifier")
print("Accuracy:", accuracy_drug)
```

```
print("Confusion Matrix:\n", conf_matrix_drug)
print("Classification Report:\n", classification_report(y_test_d, y_pred_drug))

# Visualize the decision tree
plt.figure(figsize=(12, 8))
plot_tree(clf_drug, filled=True, feature_names=X_drug.columns,
          class_names=[str(cls) for cls in clf_drug.classes_])
plt.title("Decision Tree for Drug Dataset")
plt.show()
```

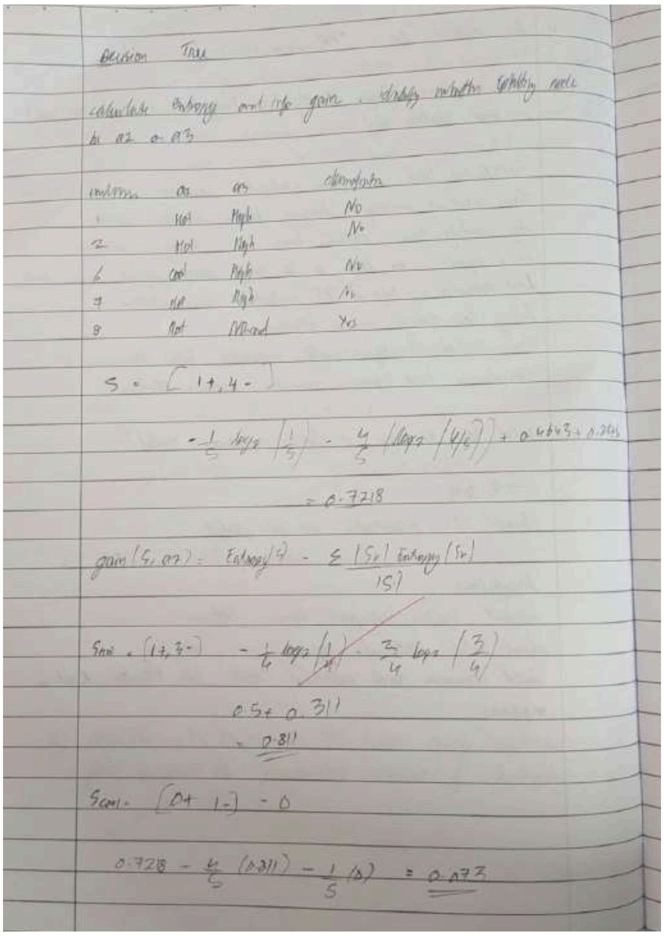
```
Drug Dataset Decision Tree Classifier
Accuracy: 1.0
Confusion Matrix:
 [[ 6  0  0  0  0]
 [ 0  3  0  0  0]
 [ 0  0  5  0  0]
 [ 0  0  0 11  0]
 [ 0  0  0  0 15]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00         6
           1       1.00      1.00      1.00         3
           2       1.00      1.00      1.00         5
           3       1.00      1.00      1.00        11
           4       1.00      1.00      1.00        15

    accuracy                           1.00        40
   macro avg       1.00      1.00      1.00        40
weighted avg       1.00      1.00      1.00        40
```



LABORATORY PROGRAM – 4

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

OBSERVATION BOOK



Decision Tree

calculate Entropy and info gain ... splitting node b/w a2 & a3

instance	a2	a3	classification
1	Hot	High	No
2	Hot	High	No
6	Cool	High	No
7	Hot	High	No
8	Hot	Normal	Yes

$S = [1+, 4-]$

$-\frac{1}{5}\log_2\left(\frac{1}{5}\right) - \frac{4}{5}\left(\log_2(4/5)\right) + 0.4643 + 0.2575$

$= 0.7218$

$gain(S, a2) = Entropy(S) - \sum \frac{|S_v|}{|S|} Entropy(S_v)$

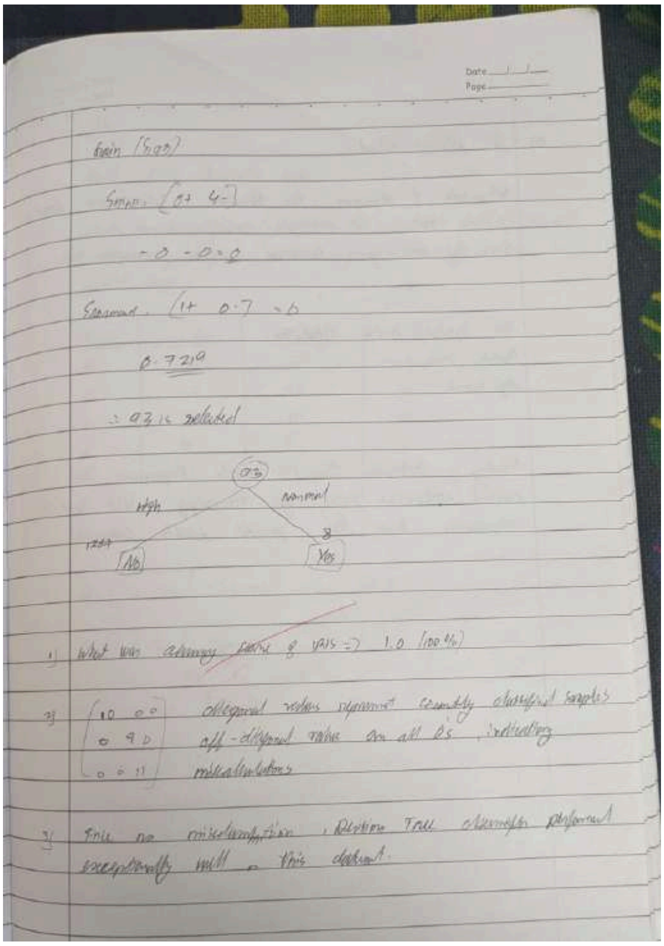
$S_{hot} = (1+, 3-)$ $-\frac{1}{4}\log_2\left(\frac{1}{4}\right) - \frac{3}{4}\log_2\left(\frac{3}{4}\right)$

$0.5 + 0.311$

$= 0.811$

$S_{cool} = [0+, 1-] = 0$

$0.728 - \frac{4}{5}(0.811) - \frac{1}{5}(0) = 0.073$



Gain (S, a3)

$S_{high} = [0+, 4-]$

$= 0 - 0 = 0$

$S_{normal} = [1+, 0-] = 0$

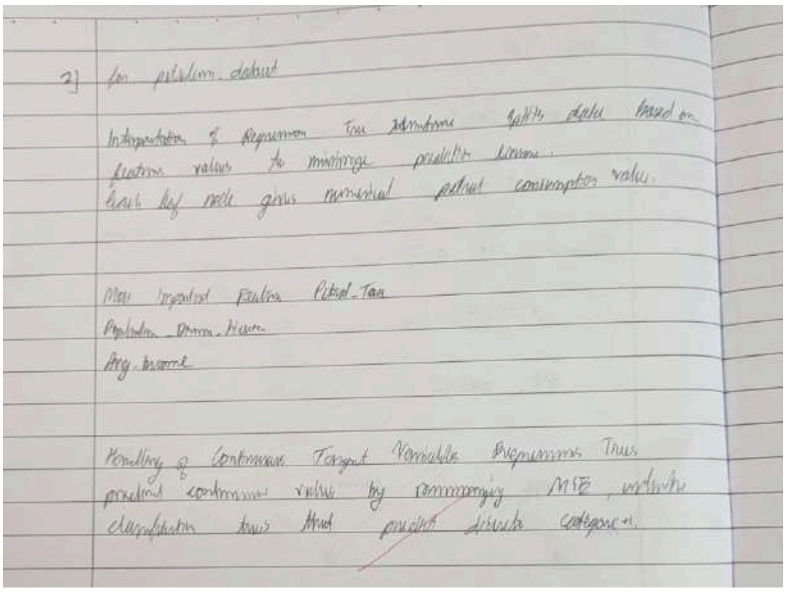
0.7219

$\therefore$ a3 is selected

1) What was accuracy ... 1.0 (100%)

2) $\begin{bmatrix} 10 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 11 \end{bmatrix}$ diagonal values represent correctly classified samples off-diagonal value are all 0s, indicating misclassifications

3) Thus no misclassification, Decision Tree classifier performed exceptionally well on this dataset.



2) for petroleum dataset

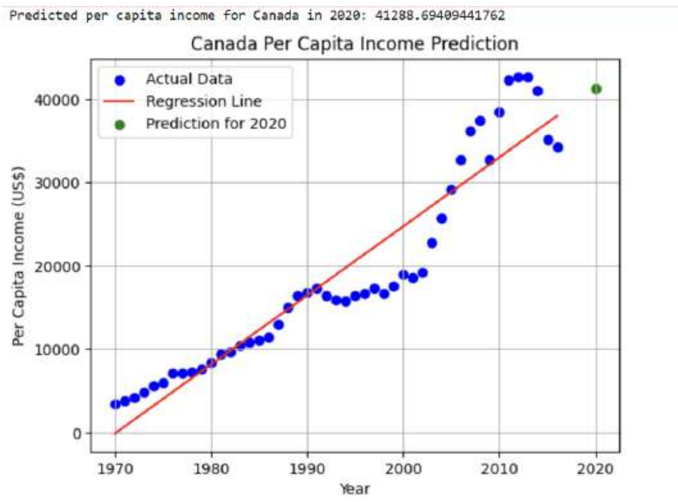
Interpretation of Regression Tree structure splits data based on feature values to minimize prediction error. Each leaf node gives numerical petrol consumption value.

Most important feature Petrol_Tax
Population_Driver_licence
Avg_income

Handling of Continuous Target Variable Regression Trees predict continuous value by minimizing MSE, while classification trees that predict discrete categories.

CODE WITH OUTPUT

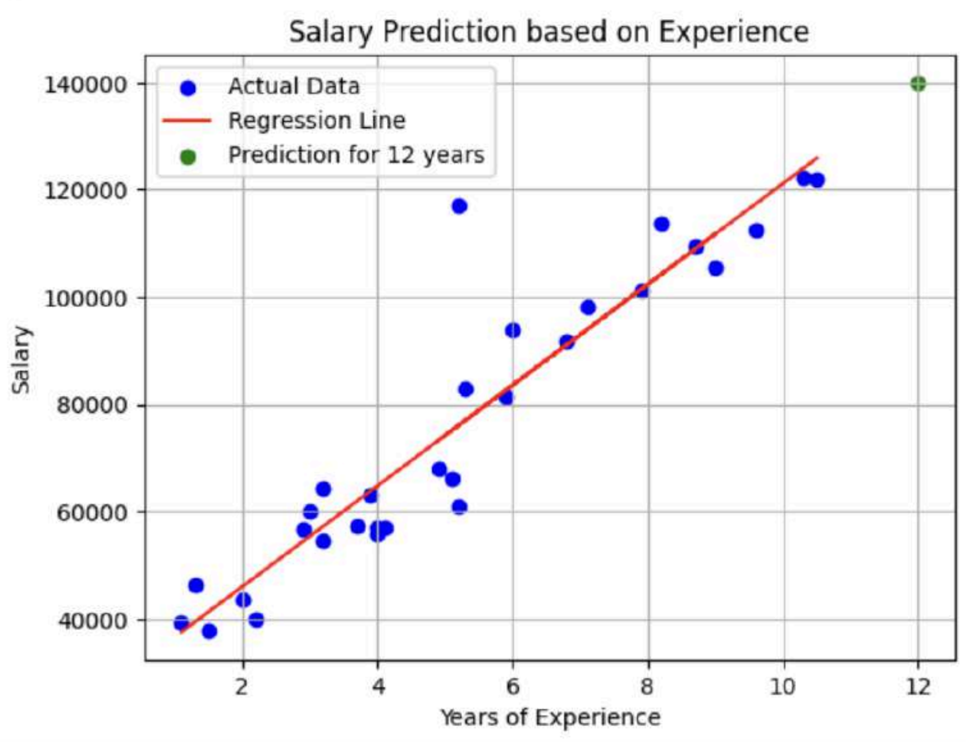
```
import pandas as pd
from sklearn.linear_model import LinearRegression
# Load the data
income_data = pd.read_csv("canada_per_capita_income.csv")
# Assumed data columns: 'Year' and 'PerCapitaIncome'
print("Canada Income Data Head:")
print(income_data.head())
# Prepare feature and target
X_income = income_data[["year"]]     # Predictor variable: Year
y_income = income_data["per capita income (US$)"]
# Build and train the linear regression model
model_income = LinearRegression()
model_income.fit(X_income, y_income)

# Predict per capita income for the year 2020
predicted_income = model_income.predict([[2020]])

print("\nPredicted per capita income for Canada in 2020:", predicted_income[0])

# Plot the data points and the regression line
plt.scatter(X_income, y_income, color='blue', label='Actual Data')
plt.plot(X_income, model_income.predict(X_income), color='red', label='Regression Line')

# Plot the prediction for 2020
plt.scatter(2020, predicted_income[0], color='green', label='Prediction for 2020')

# Customize the plot
plt.xlabel('Year')
plt.ylabel('Per Capita Income (US$)')
plt.title('Canada Per Capita Income Prediction')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```




```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.linear_model import LinearRegression

# Load the salary data
salary_data = pd.read_csv("salary.csv")
print(income_data.head())
```

```
# Prepare feature and target
X_salary = salary_data[["YearsExperience"]]  # Predictor variable: Years of Experience
y_salary = salary_data["Salary"]


# Build and train the linear regression model
model_salary = LinearRegression()
model_salary.fit(X_salary, y_salary)

import matplotlib.pyplot as plt
# Plot the data points and the regression line
plt.scatter(X_salary, y_salary, color='blue', label='Actual Data')
plt.plot(X_salary, model_salary.predict(X_salary), color='red', label='Regression Line')

# Plot the prediction for 12 years of experience
plt.scatter(12, predicted_salary[0], color='green', label='Prediction for 12 years')

# Customize the plot
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.title('Salary Prediction based on Experience')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```

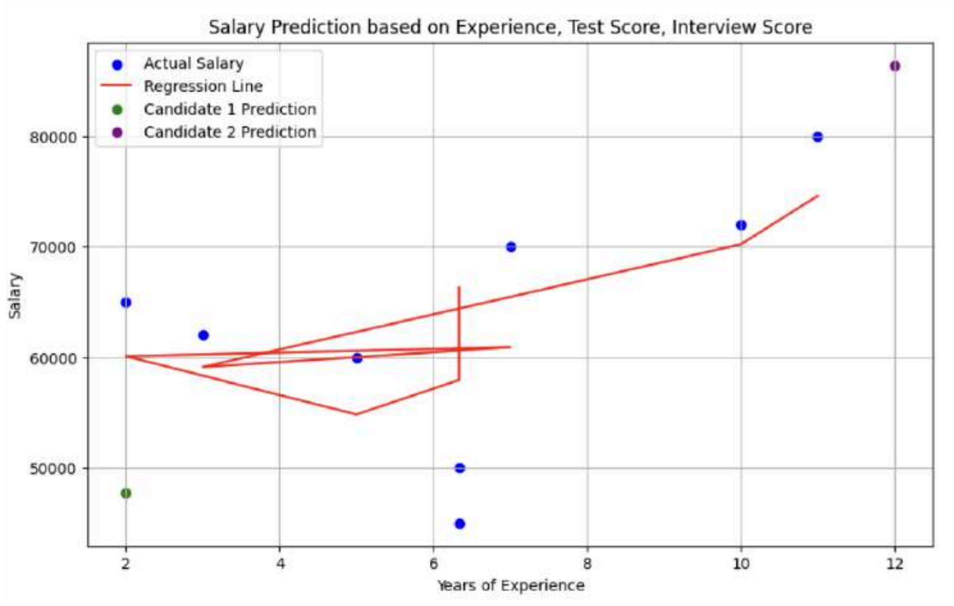
```
Predicted salary for an employee with 12 years of experience: 139980.88923969213
```




```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression

# Read the CSV file (ensure the file is uploaded in your Colab environment)
df = pd.read_csv("hiring.csv")

# Rename columns for convenience
df.columns = ['experience', 'test_score', 'interview_score', 'salary']
```

```
print("Original Data:")
print(df)
# Function to convert experience values to numeric
def convert_experience(x):
    try:
        return float(x)
    except:
        x_lower = str(x).strip().lower()
        return num_map.get(x_lower, np.nan)

# Convert the 'experience' column using the mapping
df['experience'] = df['experience'].apply(convert_experience)

# Convert 'test_score', 'interview_score', and 'salary' to numeric (coerce errors to NaN)
df['test_score'] = pd.to_numeric(df['test_score'], errors='coerce')
df['interview_score'] = pd.to_numeric(df['interview_score'], errors='coerce')
df['salary'] = pd.to_numeric(df['salary'], errors='coerce')

print("\nData After Conversion:")
print(df)

# Fill missing values in numeric columns using the column mean
df['experience'].fillna(df['experience'].mean(), inplace=True)
df['test_score'].fillna(df['test_score'].mean(), inplace=True)
df['interview_score'].fillna(df['interview_score'].mean(), inplace=True)

print("\nData After Filling Missing Values:")
print(df)

# Prepare the feature matrix X and target vector y
X = df[['experience', 'test_score', 'interview_score']]
y = df['salary']

# Build and train the Multiple Linear Regression model
model = LinearRegression()
model.fit(X, y)

# Predict salaries for the given candidate profiles
# Candidate 1: 2 years of experience, 9 test score, 6 interview score
candidate1 = np.array([[2, 9, 6]])
predicted_salary1 = model.predict(candidate1)

# Candidate 2: 12 years of experience, 10 test score, 10 interview score
candidate2 = np.array([[12, 10, 10]])
predicted_salary2 = model.predict(candidate2)


print("\nPredicted Salary for Candidate (2 yrs, 9 test, 6 interview): $", round(predicted_salary1[0], 2))
print("Predicted Salary for Candidate (12 yrs, 10 test, 10 interview): $", round(predicted_salary2[0], 2))
import matplotlib.pyplot as plt

# Create the plot
plt.figure(figsize=(10, 6))  # Adjust figure size for better visualization
plt.scatter(df['experience'], y, color='blue', label='Actual Salary') #Plot actual salary against years of experience

# Plot the regression line (this is an approximation since it's a multi-variable regression)
# You can visualize a single feature against the predicted salary
plt.plot(df['experience'], model.predict(X), color='red', label='Regression Line')

# Highlight predictions
plt.scatter(candidate1[0, 0], predicted_salary1, color='green', label='Candidate 1 Prediction')
plt.scatter(candidate2[0, 0], predicted_salary2, color='purple', label='Candidate 2 Prediction')

# Add labels and title
plt.xlabel("Years of Experience")
plt.ylabel("Salary")
plt.title("Salary Prediction based on Experience, Test Score, Interview Score")
```

```
# Add a legend
plt.legend()
plt.grid(True)
plt.show()
```



LABORATORY PROGRAM – 5

Build Logistic Regression Model for a given dataset

OBSERVATION BOOK

LAB-4

1) consider a binary classification problem where we want to predict whether a student will pass or fail based on their study hours. The logis regression model has been trained, and the learned parameters are a0 = -5 (intercept) and a1 = 0.8 (coefficient)

a) Logistic Regression eqn

$$p(\text{pass} \mid x) = \frac{1}{1+e^{-(-5+0.8x)}}$$

b) probability that student who studies for 7hrs will pass

$$z = -5 + 0.8 \times 7 = 0.6$$

$$p(\text{pass} \mid 7) = \frac{1}{1+e^{-0.6}} = 0.6457$$

c) determine the predicted class

$$0.6457 > 0.6$$

Pass.

1) for dataset file "HR_comma_sep.csv"

i) which variables did you identify as having direct and clear impact on emp retention? why?

Satisfaction level - Lower satisfaction increases ~~retention~~ attrition
Time spend in company - longer tenure increases attrition
Avg monthly Hours - extreme hours lead to higher attrition
no of projects - too few or too many ~~people~~ projects increase attrition
Last evaluation - high or low evaluation increases attrition
Salary - low salary increases attrition
Work accident - Employees with accidents leave less
Promotion in last 5 years - promotion reduces attrition

ii) what was accuracy of logistic regression model?

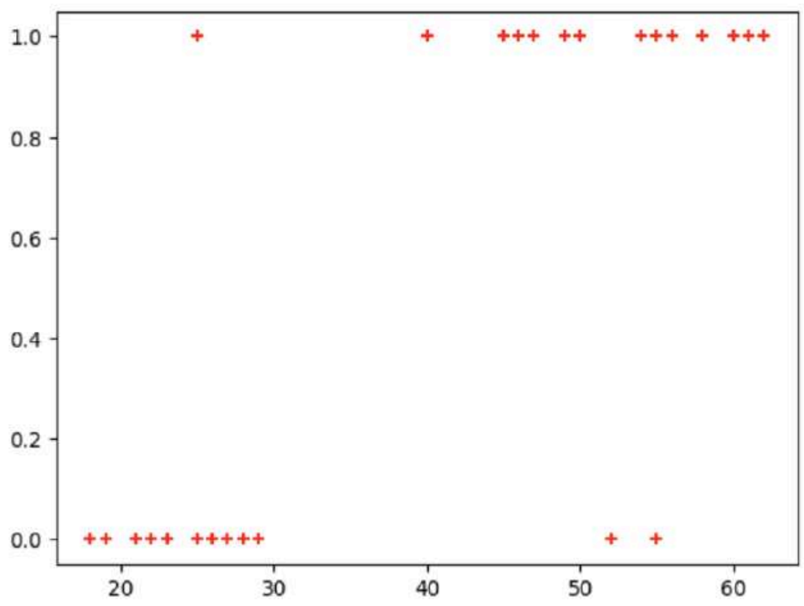
=> 78-80%
Good? Yes, reasonable but not perfect

Limitations
doesn't capture complex human behaviour
doesn't include external factors
could improve with advanced models like Random Forest or XGBoost

CODE WITH OUTPUT

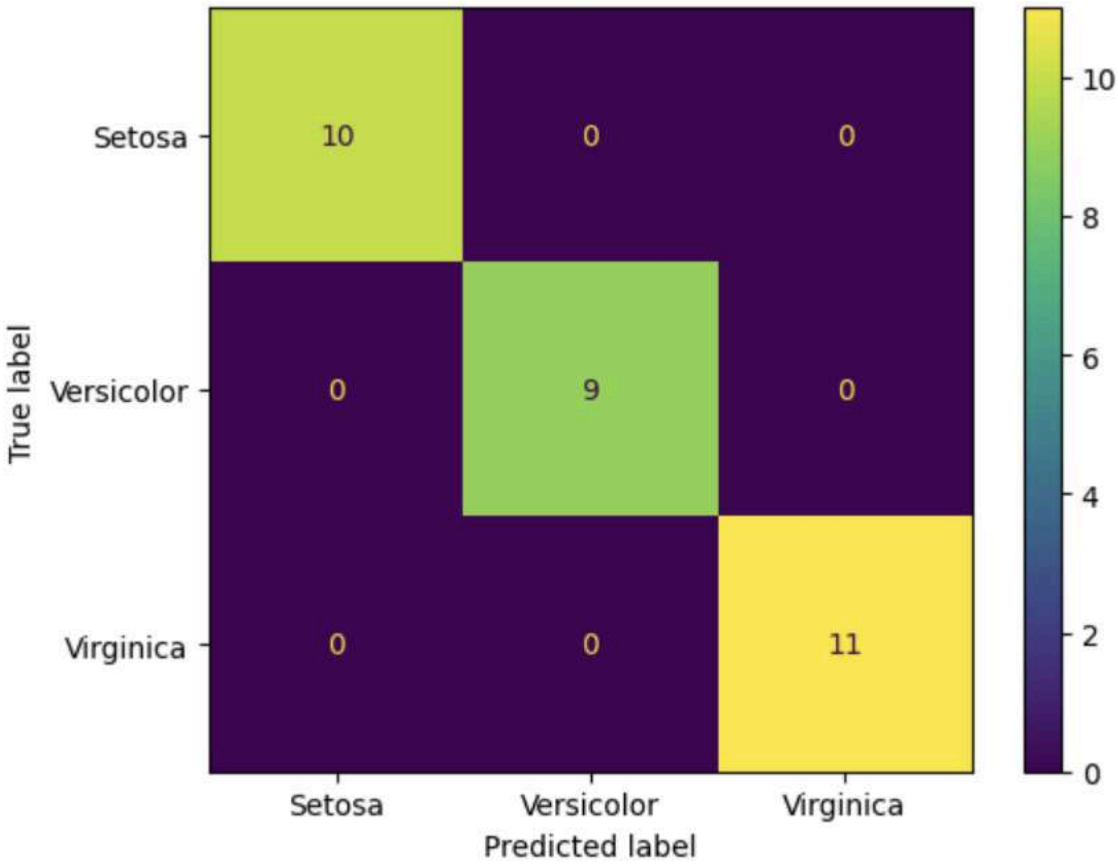
```
import pandas as pd
from matplotlib import pyplot as plt
# %matplotlib inline
#"%matplotlib inline" will make your plot outputs appear and be stored within the notebook.

df = pd.read_csv("insurance_data.csv")
df.head()

plt.scatter(df.age,df.bought_insurance,marker='+',color='red')

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df[['age']],df.bought_insurance,train_size=0.9,random_state=10)
X_train.shape

X_test

from sklearn.linear_model import LogisticRegression
model = LogisticRegression()

model.fit(X_train, y_train)

X_test

y_test

y_predicted = model.predict(X_test)
y_predicted

model.score(X_test,y_test)

model.predict_proba(X_test)

y_predicted = model.predict([[60]])
y_predicted

#model.coef_ indicates value of m in y=m*x + b equation
model.coef_

#model.intercept_ indicates value of b in y=m*x + b equation
model.intercept_

#Lets defined sigmoid function now and do the math with hand
import math
def sigmoid(x):
 return 1 / (1 + math.exp(-x))

def prediction_function(age):
  z = 0.127 * age - 4.973 # 0.12740563 ~ 0.0127 and -4.97335111 ~ -4.97
  y = sigmoid(z)
  return y

age = 35
prediction_function(age)

"""0.37 is less than 0.5 which means person with 35 will not buy the insurance"""
```

'0.37 is less than 0.5 which means person with 35 will not buy the insurance'




```
# Import necessary libraries
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn import metrics
import matplotlib.pyplot as plt

# Load the Iris dataset
iris =  pd.read_csv("iris.csv")
iris.head()

X=iris.drop('species',axis='columns')# Features (sepal length, sepal width, petal length, petal width)
y = iris.species # Target labels (0: Setosa, 1: Versicolor, 2: Virginica)

# Split the dataset into 80% training and 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the Multinomial Logistic Regression model
# Use 'multinomial' for multi-class classification and 'lbfgs' solver
model = LogisticRegression(multi_class='multinomial')

# Train the model on the training data
model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = model.predict(X_test)

# Calculate the accuracy of the model on the test data
accuracy = accuracy_score(y_test, y_pred)

# Display the accuracy
print(f"Accuracy of the Multinomial Logistic Regression model on the test set: {accuracy:.2f}")

confusion_matrix = metrics.confusion_matrix(y_test, y_pred)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels = ["Setosa",
"Versicolor", "Virginica"])

cm_display.plot()
plt.show()
```

```
Accuracy of the Multinomial Logistic Regression model on the test set: 1.00
```



LABORATORY PROGRAM – 6

Build KNN Classification model for a given dataset.

OBSERVATION BOOK

Lab - 5

Build KNN Classification model

consider the following dataset, k=3 and test data (x, 35,100) as (Person, Age, Salary K) solve using KNN classification model and predict target

Person	Age	Salary k	Target
A	18	50	N
B	23	55	N
C	24	70	N
D	41	60	Y
E	43	70	Y
F	33	40	Y
x	35	100	?

$A = \sqrt{(18-35)^2 \; (50-100)^2} = 52.8$

$B = \sqrt{(23-35)^2 \; (55-100)^2} \quad 46.6$

$C = \sqrt{(24-35)^2 \; (70-100)^2} \quad 31.3$

$D = \sqrt{(41-35)^2 \; (60-100)^2} \quad 40.4$

$E = \sqrt{(43-35)^2 \; (70-100)^2} \quad 31.1$

3 nearest neighbours

$F = \sqrt{(33-35)^2 \; (40-100)^2} \quad 60.1$

Majority is Y

x = (35,100) is Y

For Iris dataset

How to choose K value? Demonstrate using accuracy rate and error rate

The value of K in KNN algorithm determines how many neighbours influence classification. To choose the best k, test multiple k values and compare their accuracy and error rate. The optimal k is the one where accuracy is highest and error rate is lowest

For Diabetes dataset

What is the purpose of feature scaling? How to perform it?

Feature scaling ensures all features contribute equally to model training by bringing them to a common scale. This is especially important for distance-based algorithm like KNN or gradient descent-based models. It is commonly done by using Standardization (Z-Score) or Normalization (Min-Max Scaling)

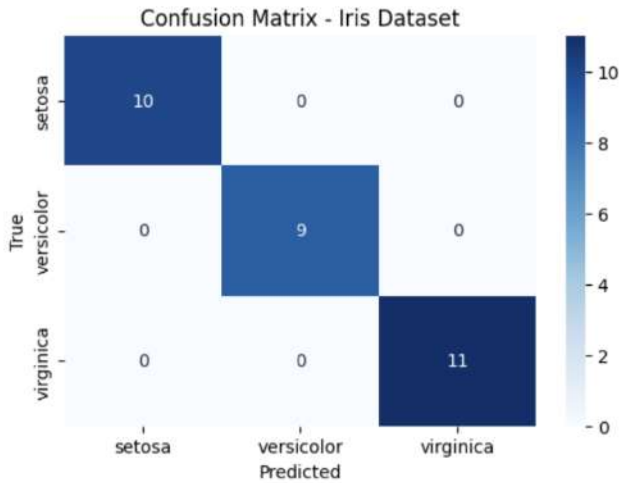
CODE WITH OUTPUT

```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
# For model building and evaluation
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# -------------------------- Part 1: IRIS Dataset -------------------------- #
# Load the iris dataset (ensure iris.csv is in the same directory or provide correct path)
iris_df = pd.read_csv("iris.csv")

# Separate features and target
X_iris = iris_df.drop("species", axis=1)
y_iris = iris_df["species"]

# Split the data (80% training, 20% testing)
X_train_iris, X_test_iris, y_train_iris, y_test_iris = train_test_split(
    X_iris, y_iris, test_size=0.2, random_state=42
)

# Choose a value for k; here K=3 is used as an example.
knn_iris = KNeighborsClassifier(n_neighbors=3)

# Train the model on training data
knn_iris.fit(X_train_iris, y_train_iris)

# Predict on test data
y_pred_iris = knn_iris.predict(X_test_iris)

# Calculate accuracy score
acc_iris = accuracy_score(y_test_iris, y_pred_iris)
print("IRIS Dataset Accuracy Score:", acc_iris)
# Compute confusion matrix and classification report
cm_iris = confusion_matrix(y_test_iris, y_pred_iris)
print("\nIRIS Dataset Confusion Matrix:\n", cm_iris)
```

```python
cr_iris = classification_report(y_test_iris, y_pred_iris)
print("\nIRIS Dataset Classification Report:\n", cr_iris)
```

```
IRIS Dataset Classification Report:
               precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   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
```

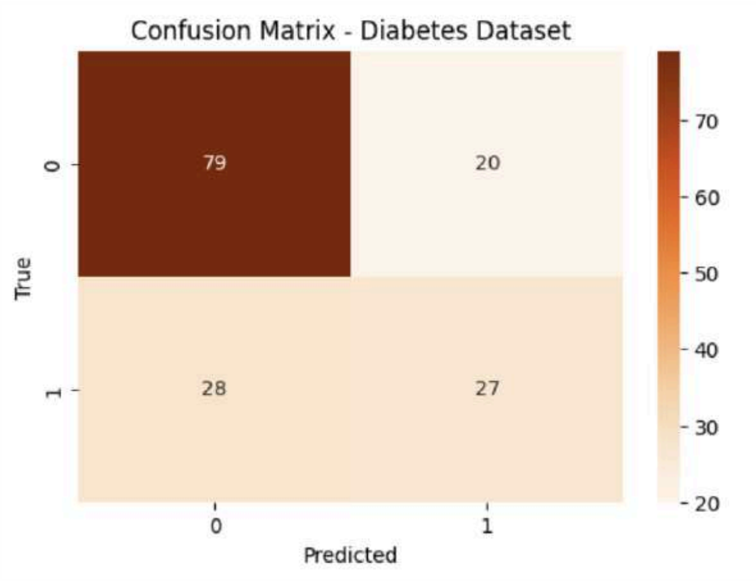



```python
# ---------------------- Part 2: Diabetes Dataset ------------------------ #
# Load the diabetes dataset (ensure diabetes.csv is in the same directory or provide correct path)
diabetes_df = pd.read_csv("diabetes.csv")

# Separate features and target (Outcome column is assumed to be the target)
X_diabetes = diabetes_df.drop("Outcome", axis=1)
y_diabetes = diabetes_df["Outcome"]

# Perform feature scaling on the features
scaler = StandardScaler()
X_scaled_diabetes = scaler.fit_transform(X_diabetes)

# Split the scaled data (80% training, 20% testing)
X_train_diab, X_test_diab, y_train_diab, y_test_diab = train_test_split(
    X_scaled_diabetes, y_diabetes, test_size=0.2, random_state=42
)

# Choose a value for k; here K=5 is used as an example.
knn_diabetes = KNeighborsClassifier(n_neighbors=5)

# Train the model on training data
knn_diabetes.fit(X_train_diab, y_train_diab)

# Predict on test data
y_pred_diab = knn_diabetes.predict(X_test_diab)

# Calculate accuracy score
acc_diab = accuracy_score(y_test_diab, y_pred_diab)
print("Diabetes Dataset Accuracy Score:", acc_diab)

# Compute confusion matrix and classification report
cm_diab = confusion_matrix(y_test_diab, y_pred_diab)
print("\nDiabetes Dataset Confusion Matrix:\n", cm_diab)
```

```
cr_diab = classification_report(y_test_diab, y_pred_diab)
print("\nDiabetes Dataset Classification Report:\n", cr_diab)
```

Diabetes Dataset Classification Report:

	precision	recall	f1-score	support
0	0.74	0.80	0.77	99
1	0.57	0.49	0.53	55
accuracy			0.69	154
macro avg	0.66	0.64	0.65	154
weighted avg	0.68	0.69	0.68	154




```
# ------------------------- Load the Dataset ------------------------- #
# Load heart.csv (make sure the file is in your working directory)
heart_df = pd.read_csv("heart.csv")

# Display the first few rows to check the data
heart_df.head()

# ------------------------- Data Preparation ------------------------- #
# Separate features and target
X_heart = heart_df.drop("target", axis=1)
y_heart = heart_df["target"]

# Perform feature scaling (important for distance-based algorithms like KNN)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_heart)

# Split data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_heart, test_size=0.2, random_state=42)
# ------------------------- Finding the Best k ------------------------- #
# We will try a range of k values (neighbors) and select the one with maximum accuracy.
k_range = range(1, 21)
accuracy_scores = []

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
```

```
accuracy_scores.append(acc)
print(f"k = {k} --> Accuracy: {acc:.4f}")
```

```
k = 1 --> Accuracy: 0.8525
k = 2 --> Accuracy: 0.8197
k = 3 --> Accuracy: 0.8689
k = 4 --> Accuracy: 0.8852
k = 5 --> Accuracy: 0.9180
k = 6 --> Accuracy: 0.9344
k = 7 --> Accuracy: 0.9180
k = 8 --> Accuracy: 0.8525
k = 9 --> Accuracy: 0.8852
k = 10 --> Accuracy: 0.8852
k = 11 --> Accuracy: 0.8852
k = 12 --> Accuracy: 0.8689
k = 13 --> Accuracy: 0.8852
k = 14 --> Accuracy: 0.8689
k = 15 --> Accuracy: 0.9016
k = 16 --> Accuracy: 0.8852
k = 17 --> Accuracy: 0.8852
k = 18 --> Accuracy: 0.9016
k = 19 --> Accuracy: 0.8852
k = 20 --> Accuracy: 0.8852
```

```
# Determine the best k value
best_k = k_range[np.argmax(accuracy_scores)]
print("\nBest k value:", best_k)
```

```
Best k value: 6
```

```
# ------------------------- Train Final Model with Best k ------------------------- #
best_knn = KNeighborsClassifier(n_neighbors=best_k)
best_knn.fit(X_train, y_train)
y_pred_best = best_knn.predict(X_test)
```

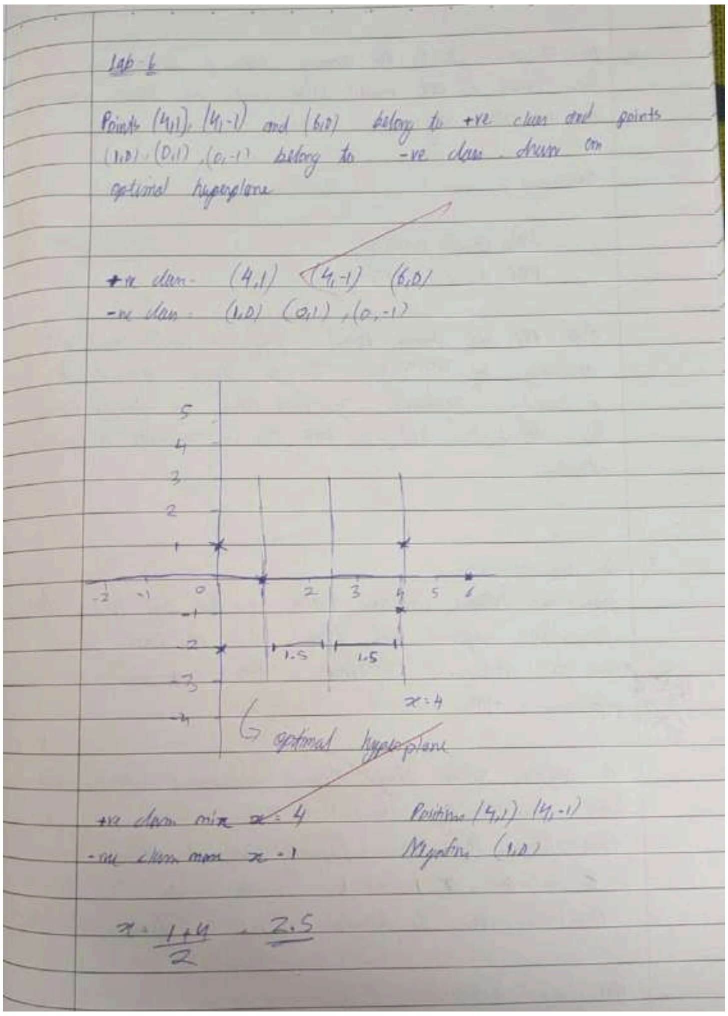
```
# Compute final accuracy, confusion matrix and classification report
final_accuracy = accuracy_score(y_test, y_pred_best)
cm = confusion_matrix(y_test, y_pred_best)
cr_text = classification_report(y_test, y_pred_best)
print("\nFinal Accuracy Score:", final_accuracy)
print("\nConfusion Matrix:\n", cm)
print("\nClassification Report:\n", cr_text)
```

```
Final Accuracy Score: 0.9344262295081968

Confusion Matrix:
 [[28  1]
 [ 3 29]]

Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.97      0.93        29
           1       0.97      0.91      0.94        32

    accuracy                           0.93        61
   macro avg       0.93      0.94      0.93        61
weighted avg       0.94      0.93      0.93        61
```

LABORATORY PROGRAM – 7

Build Support vector machine model for a given dataset

OBSERVATION BOOK


Lab 6

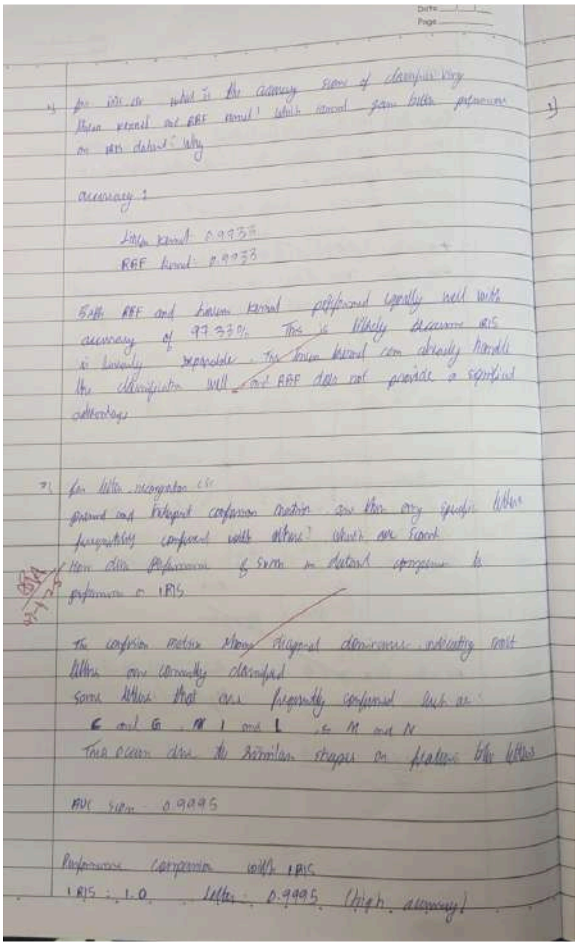
Points (4,1), (4,-1) and (6,0) belong to +ve class and points (1,0), (0,1), (0,-1) belong to -ve class. draw an optimal hyperplane

+ve class (4,1) (4,-1) (6,0)
-ve class (1,0) (0,1), (0,-1)

+ve class min x = 4
-ve class max x = 1

Positive (4,1) (4,-1)
Negative (1,0)

$x = \frac{1+4}{2} = 2.5$


accuracy :

Linear kernel 0.9733
RBF kernel 0.9733

Both RBF and linear kernel performed equally well with accuracy of 97.33%.

7) for letter recognition csv

The confusion matrix shows diagonal dominance indicating most letters are correctly classified

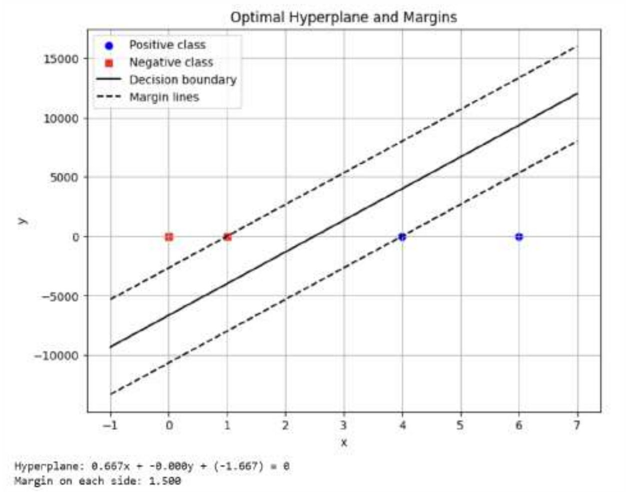
Some letters that are frequently confused such as E and G, I and L, M and N

AUC score 0.9995

Performance comparison with IRIS
IRIS : 1.0   letter : 0.9995 (high accuracy)

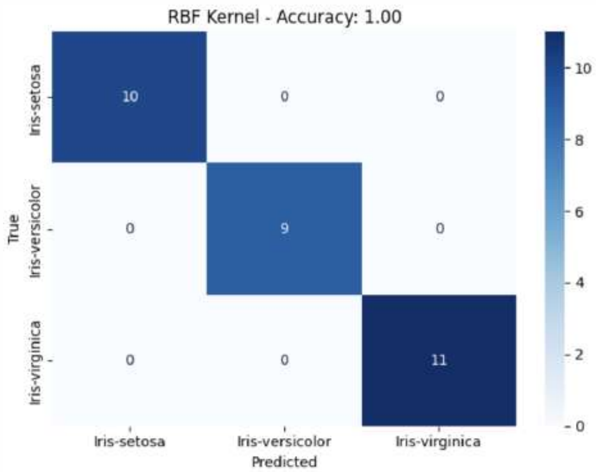
CODE WITH OUTPUT

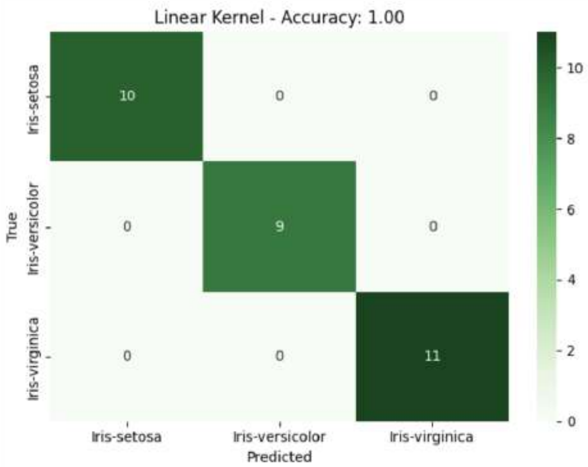
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.svm import SVC

# Data points
X = np.array([[4, 1], [4, -1], [6, 0], [1, 0], [0, 1], [0, -1]])
y = np.array([1, 1, 1, -1, -1, -1])

# Fit linear SVM with a very large C to approximate hard-margin
clf = SVC(kernel='linear', C=1e6)
clf.fit(X, y)

# Extract model parameters
w = clf.coef_[0]
b = clf.intercept_[0]

# Compute decision boundary and margins
xx = np.linspace(-1, 7, 500)
yy = -(w[0] * xx + b) / w[1]

# Margin offset: distance = 1/||w||
margin = 1 / np.linalg.norm(w)
yy_down = yy - np.sqrt(1 + (w[0] / w[1])**2) * margin
yy_up   = yy + np.sqrt(1 + (w[0] / w[1])**2) * margin

# Plotting
plt.figure(figsize=(8, 6))
plt.scatter(X[y == 1, 0], X[y == 1, 1], c='blue', marker='o', label='Positive class')
plt.scatter(X[y == -1, 0], X[y == -1, 1], c='red', marker='s', label='Negative class')
plt.plot(xx, yy, 'k-', label='Decision boundary')
plt.plot(xx, yy_down, 'k--', label='Margin lines')
plt.plot(xx, yy_up, 'k--')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.title('Optimal Hyperplane and Margins')
plt.grid(True)
plt.show()

# Print hyperplane equation
print(f"Hyperplane: {w[0]:.3f}x + {w[1]:.3f}y + ({b:.3f}) = 0")
print(f"Margin on each side: {margin:.3f}")
```




```
import pandas as pd

# Load both datasets
```

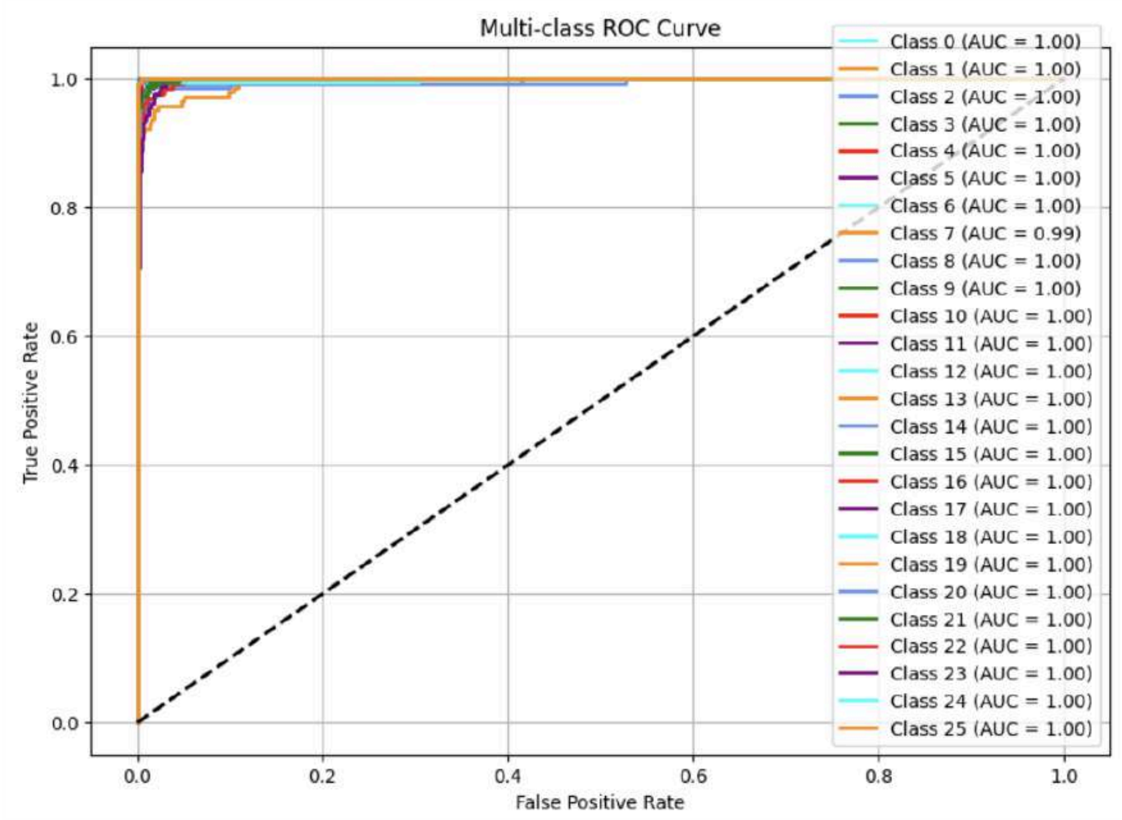
```
iris_df = pd.read_csv("/content/iris.csv")
# 1. IRIS DATASET - SVM with RBF and Linear Kernels
X_iris = iris_df.drop("species", axis=1)
y_iris = iris_df["species"]

# Encode labels
le_iris = LabelEncoder()
y_iris_encoded = le_iris.fit_transform(y_iris)

# Split dataset
X_train_iris, X_test_iris, y_train_iris, y_test_iris = train_test_split(X_iris, y_iris_encoded, test_size=0.2, random_state=42)

# Train models
svm_rbf = SVC(kernel='rbf')
svm_linear = SVC(kernel='linear')

svm_rbf.fit(X_train_iris, y_train_iris)
svm_linear.fit(X_train_iris, y_train_iris)

# Predictions
y_pred_rbf = svm_rbf.predict(X_test_iris)
y_pred_linear = svm_linear.predict(X_test_iris)

# Accuracy and Confusion Matrix
acc_rbf = accuracy_score(y_test_iris, y_pred_rbf)
acc_linear = accuracy_score(y_test_iris, y_pred_linear)
cm_rbf = confusion_matrix(y_test_iris, y_pred_rbf)
cm_linear = confusion_matrix(y_test_iris, y_pred_linear)
```






```
# Load dataset
letter_df = pd.read_csv("/content/letter-recognition.csv")  # Update path if needed
```

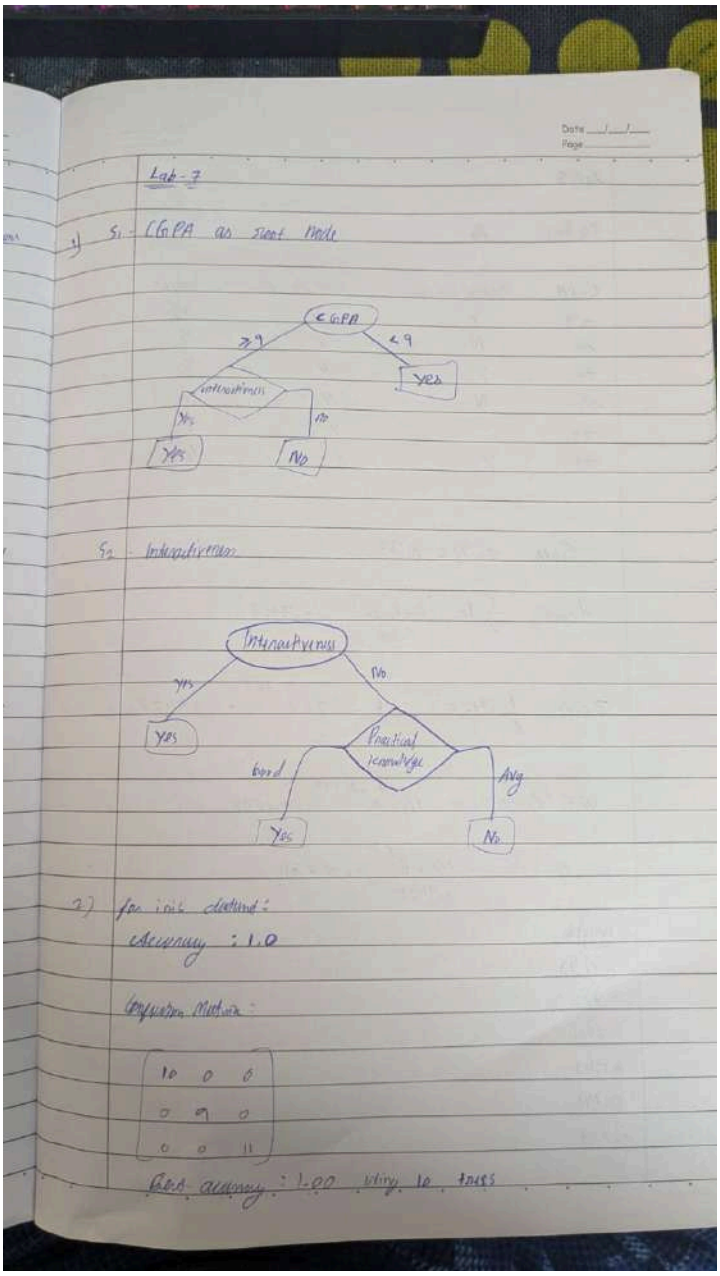
```python
letter_df['letter'] = LabelEncoder().fit_transform(letter_df['letter'])

# Split features and labels
X = letter_df.drop('letter', axis=1)
y = letter_df['letter']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train SVM
svm = SVC(kernel='rbf', probability=True)
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
y_prob = svm.predict_proba(X_test)

# Accuracy and Confusion Matrix
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

# ROC and AUC (one-vs-rest)
y_test_bin = label_binarize(y_test, classes=np.unique(y))
n_classes = y_test_bin.shape[1]

fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC Curve
plt.figure(figsize=(10, 7))
colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'green', 'red', 'purple'])

for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f'Class {i} (AUC = {roc_auc[i]:0.2f})')

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Multi-class ROC Curve")
plt.legend(loc="lower right")
plt.grid()
plt.show()
```


Multi-class ROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Class 0 (AUC = 1.00)
Class 1 (AUC = 1.00)
Class 2 (AUC = 1.00)
Class 3 (AUC = 1.00)
Class 4 (AUC = 1.00)
Class 5 (AUC = 1.00)
Class 6 (AUC = 1.00)
Class 7 (AUC = 0.99)
Class 8 (AUC = 1.00)
Class 9 (AUC = 1.00)
Class 10 (AUC = 1.00)
Class 11 (AUC = 1.00)
Class 12 (AUC = 1.00)
Class 13 (AUC = 1.00)
Class 14 (AUC = 1.00)
Class 15 (AUC = 1.00)
Class 16 (AUC = 1.00)
Class 17 (AUC = 1.00)
Class 18 (AUC = 1.00)
Class 19 (AUC = 1.00)
Class 20 (AUC = 1.00)
Class 21 (AUC = 1.00)
Class 22 (AUC = 1.00)
Class 23 (AUC = 1.00)
Class 24 (AUC = 1.00)
Class 25 (AUC = 1.00)

LABORATORY PROGRAM – 8

Implement Random forest ensemble method on a given dataset.

OBSERVATION BOOK

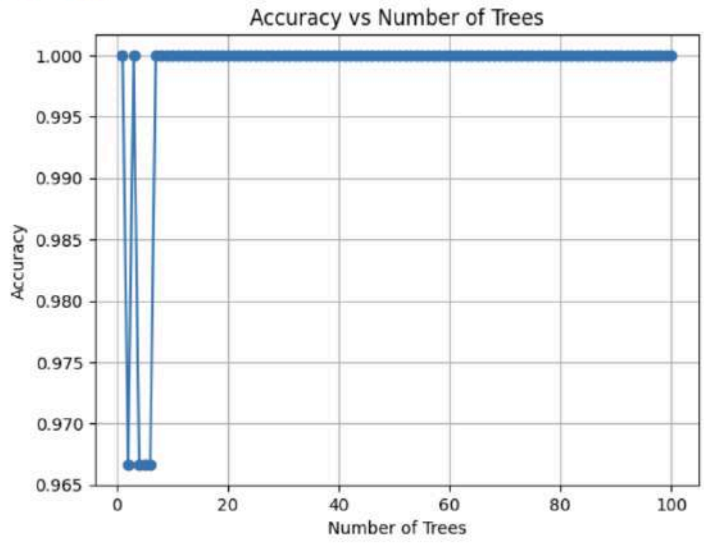


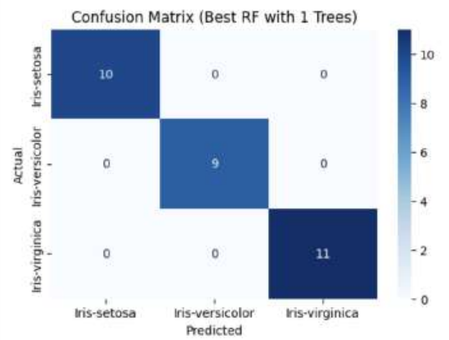
CODE WITH OUTPUT

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
```

```python
# Load the dataset
df = pd.read_csv("iris.csv")  # Adjust filename if needed

# Prepare data
X = df.drop(columns=["species"])  # Assuming 'species' is the target column
y = df["species"]

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Default Random Forest with 10 trees
rf_default = RandomForestClassifier(n_estimators=10, random_state=42)
rf_default.fit(X_train, y_train)
y_pred_default = rf_default.predict(X_test)
acc_default = accuracy_score(y_test, y_pred_default)
conf_matrix_default = confusion_matrix(y_test, y_pred_default)

print(f"Default RF (10 trees) Accuracy: {acc_default}")
print("Confusion Matrix:\n", conf_matrix_default)

# Try different numbers of trees to find the best
best_acc = 0
best_n = 10
acc_list = []

for n in range(1, 101):
    rf = RandomForestClassifier(n_estimators=n, random_state=42)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    acc_list.append((n, acc))
    if acc > best_acc:
        best_acc = acc
        best_n = n
        best_conf_matrix = confusion_matrix(y_test, y_pred)

print(f"\nBest Accuracy: {best_acc} using {best_n} trees")
print("Best Confusion Matrix:\n", best_conf_matrix)
# Plot accuracy vs number of trees
x_vals, y_vals = zip(*acc_list)
plt.plot(x_vals, y_vals, marker='o')
plt.title("Accuracy vs Number of Trees")
plt.xlabel("Number of Trees")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
```

```
Default RF (10 trees) Accuracy: 1.0
Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]

Best Accuracy: 1.0 using 1 trees
Best Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

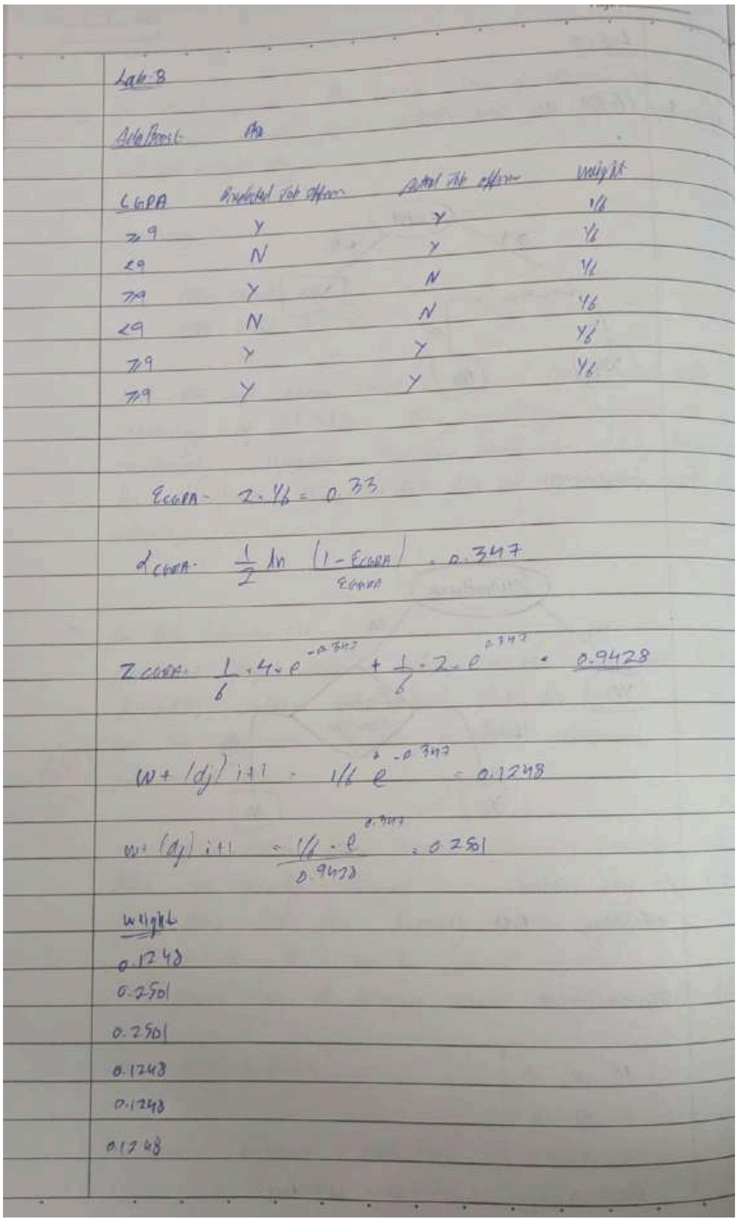




LABORATORY PROGRAM – 9

Implement Boosting ensemble method on a given dataset.

OBSERVATION BOOK



Lab-8

AdaBoost

CGPA	Predicted Job offer	Actual Job offer	weight
≥9	Y	Y	1/6
<9	N	Y	1/6
≥9	Y	N	1/6
<9	N	N	1/6
≥9	Y	Y	1/6
≥9	Y	Y	1/6

$\varepsilon_{CGPA} = 2 \cdot 1/6 = 0.33$

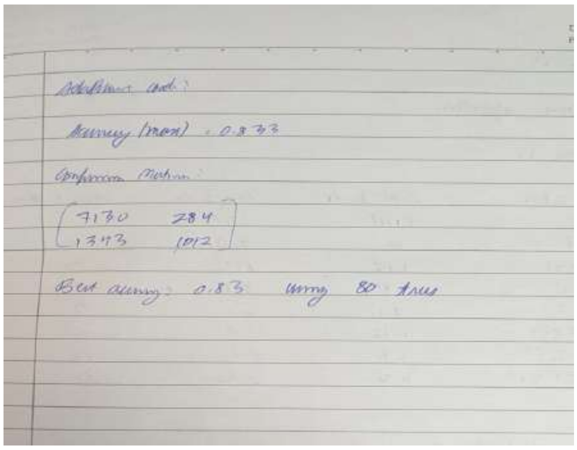
$\alpha_{CGPA} = \frac{1}{2} \ln \left(\frac{1-\varepsilon_{CGPA}}{\varepsilon_{CGPA}} \right) = 0.347$

$Z_{CGPA} = \frac{1}{6} \cdot 4 \cdot e^{-0.347} + \frac{1}{6} \cdot 2 \cdot e^{0.347} = 0.9428$

$w_t(d_j)_{i+1} = 1/6 \, e^{-0.347} = 0.1248$

$w_t(d_j)_{i+1} = \frac{1/6 \cdot e^{0.347}}{0.9428} = 0.2501$

weight
0.1248
0.2501
0.2501
0.1248
0.1248
0.1248



AdaBoost and:

Accuracy (mean) : 0.833

Confusion Matrix:

$$\begin{bmatrix} 7130 & 284 \\ 1343 & 1012 \end{bmatrix}$$

Best accuracy : 0.83 using 80 trees

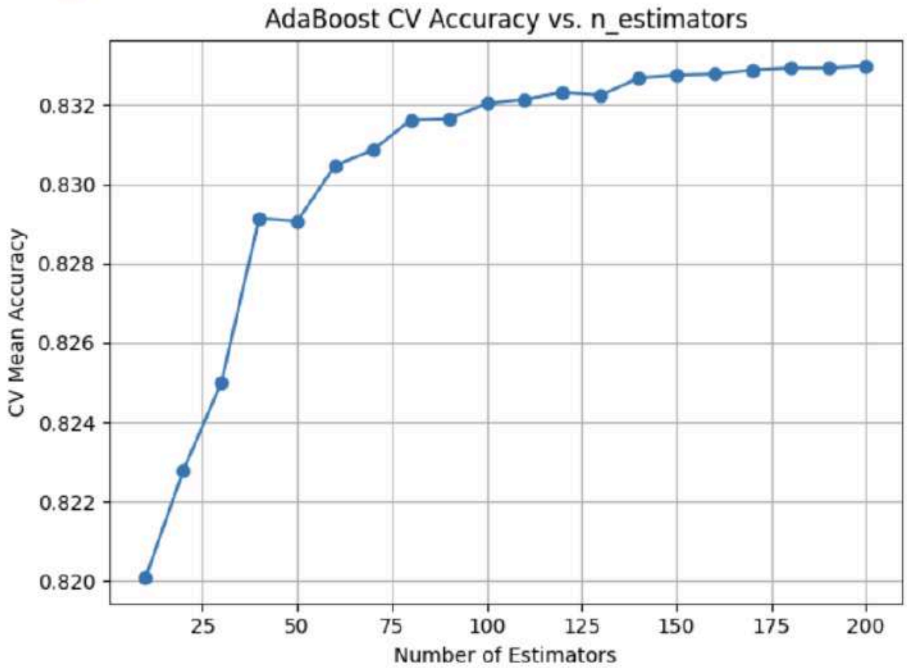
CODE WITH OUTPUT

```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
```

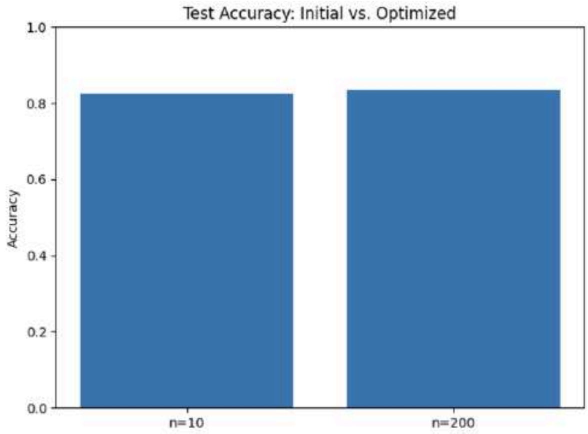
```python
# Load dataset
data = pd.read_csv('income.csv')

# Display basic info
print("First five rows:")
print(data.head())
print(f"\nDataset shape: {data.shape}")

# Define features and target
target_column = 'income_level'
y = data[target_column]
X = data.drop(columns=[target_column])

# Identify categorical vs numerical columns
categorical_cols = X.select_dtypes(include=['object', 'category']).columns.tolist()
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
print(f"\nNumerical columns: {numerical_cols}")
print(f"Categorical columns: {categorical_cols}")

# Preprocessor: scale numericals, one-hot encode categoricals
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
    ]
)

# Initial AdaBoost model with 10 estimators
pipeline = Pipeline([
    ('preprocess', preprocessor),
    ('clf', AdaBoostClassifier(n_estimators=10, random_state=42))
])

# Split into train/test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Train and evaluate initial model
pipeline.fit(X_train, y_train)
y_pred = pipeline.predict(X_test)
initial_acc = accuracy_score(y_test, y_pred)
print(f"Initial test accuracy (n_estimators=10): {initial_acc:.4f}")

# Hyperparameter tuning: find best n_estimators
tree_counts = list(range(10, 201, 10))  # 10,20,...,200
cv_scores = []
for n in tree_counts:
    model = Pipeline([
        ('preprocess', preprocessor),
        ('clf', AdaBoostClassifier(n_estimators=n, random_state=42))
    ])
    scores = cross_val_score(
        model, X_train, y_train, cv=5, scoring='accuracy', n_jobs=-1
    )
    mean_score = scores.mean()
    cv_scores.append(mean_score)
    print(f"n_estimators={n}: CV mean accuracy={mean_score:.4f}")

# Plot CV accuracy vs. number of estimators
plt.figure()
plt.plot(tree_counts, cv_scores, marker='o')
plt.title('AdaBoost CV Accuracy vs. n_estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('CV Mean Accuracy')
plt.grid(True)
plt.tight_layout()
```

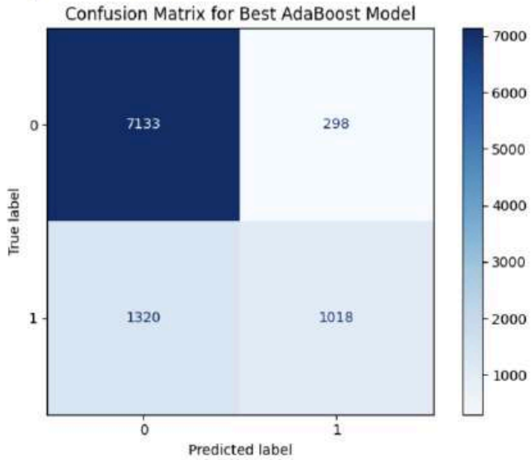
```
plt.show()

# Determine optimal number of trees
best_score = max(cv_scores)
best_n = tree_counts[cv_scores.index(best_score)]
print(f"\nBest CV accuracy={best_score:.4f} with n_estimators={best_n}")

# Retrain and evaluate best model
best_model = Pipeline([
    ('preprocess', preprocessor),
    ('clf', AdaBoostClassifier(n_estimators=best_n, random_state=42))
])
best_model.fit(X_train, y_train)
y_best = best_model.predict(X_test)
best_test_acc = accuracy_score(y_test, y_best)
print(f"Test accuracy with best n_estimators ({best_n}): {best_test_acc:.4f}")

# Plot comparison of initial vs. best test accuracy
plt.figure()
plt.bar(['n=10', f'n={best_n}'], [initial_acc, best_test_acc])
plt.title('Test Accuracy: Initial vs. Optimized')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.tight_layout()
plt.show()

# Plot confusion matrix for best model
cm = confusion_matrix(y_test, y_best)
labels = best_model.named_steps['clf'].classes_
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
plt.figure()
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for Best AdaBoost Model')
plt.tight_layout()
plt.show()
```

```
Dataset shape: (48842, 7)

Numerical columns: ['age', 'fnlwgt', 'education_num', 'capital_gain', 'capital_loss', 'hours_per_week']
Categorical columns: []
Initial test accuracy (n_estimators=10): 0.8257
n_estimators=10: CV mean accuracy=0.8201
n_estimators=20: CV mean accuracy=0.8228
n_estimators=30: CV mean accuracy=0.8250
n_estimators=40: CV mean accuracy=0.8291
n_estimators=50: CV mean accuracy=0.8291
n_estimators=60: CV mean accuracy=0.8305
n_estimators=70: CV mean accuracy=0.8309
n_estimators=80: CV mean accuracy=0.8316
n_estimators=90: CV mean accuracy=0.8316
n_estimators=100: CV mean accuracy=0.8320
n_estimators=110: CV mean accuracy=0.8321
n_estimators=120: CV mean accuracy=0.8323
n_estimators=130: CV mean accuracy=0.8322
n_estimators=140: CV mean accuracy=0.8327
n_estimators=150: CV mean accuracy=0.8327
n_estimators=160: CV mean accuracy=0.8328
n_estimators=170: CV mean accuracy=0.8329
n_estimators=180: CV mean accuracy=0.8329
n_estimators=190: CV mean accuracy=0.8329
n_estimators=200: CV mean accuracy=0.8330
```




```
Best CV accuracy=0.8330 with n_estimators=200
Test accuracy with best n_estimators (200): 0.8344
```

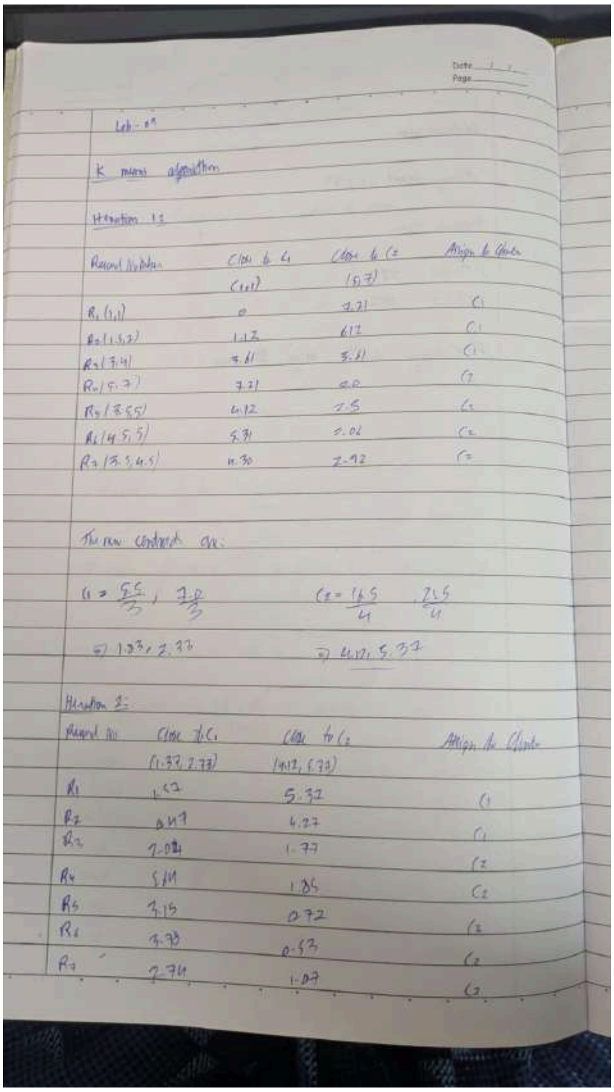

Test Accuracy: Initial vs. Optimized
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
n=10
n=200


Confusion Matrix for Best AdaBoost Model
7133
298
1320
1018
True label
Predicted label
0
1
0
1
7000
6000
5000
4000
3000
2000
1000

LABORATORY PROGRAM – 10

Build k-Means algorithm to cluster a set of data stored in a .CSV file.

OBSERVATION BOOK



Lab-10

K means algorithm

Iteration 1:

Record Number	Close to C1 (1,1)	Close to C2 (5,7)	Assign to Cluster
R1 (1,1)	0	7.21	C1
R2 (1.5,2)	1.12	6.12	C1
R3 (3,4)	3.61	3.61	C1
R4 (5,7)	7.21	0.0	C2
R5 (3.5,5)	4.72	2.5	C2
R6 (4.5,5)	5.31	2.06	C2
R7 (3.5,4.5)	4.30	2.92	C2

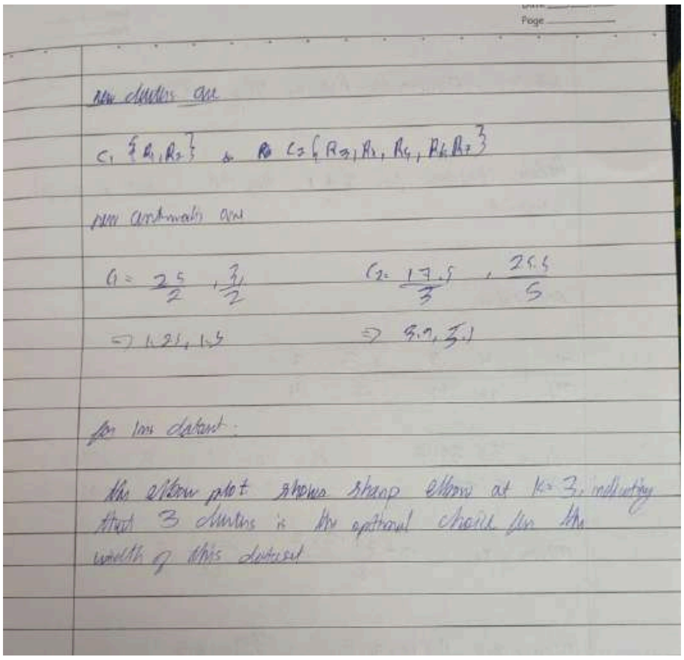
The new centroids are:

$C_1 = \frac{5.5}{3}, \frac{7.0}{3}$ $\Rightarrow 1.83, 2.33$

$C_2 = \frac{16.5}{4}, \frac{21.5}{4}$ $\Rightarrow 4.12, 5.37$

Iteration 2:

Record No	Close to C1 (1.83, 2.33)	Close to C2 (4.12, 5.37)	Assign the Cluster
R1	1.57	5.32	C1
R2	0.47	4.27	C1
R3	2.04	1.77	C2
R4	5.64	1.85	C2
R5	3.15	0.72	C2
R6	3.78	0.53	C2
R7	2.74	1.07	C2



New clusters are

$C_1 \{R_1, R_2\}$ & $C_2 \{R_3, R_4, R_5, R_6, R_7\}$

new centroids are

$C_1 = \frac{2.5}{2}, \frac{3}{2}$ $\Rightarrow 1.25, 1.5$

$C_2 = \frac{17.5}{3}, \frac{25.5}{5}$ $\Rightarrow 3.9, 5.1$

For Iris dataset:

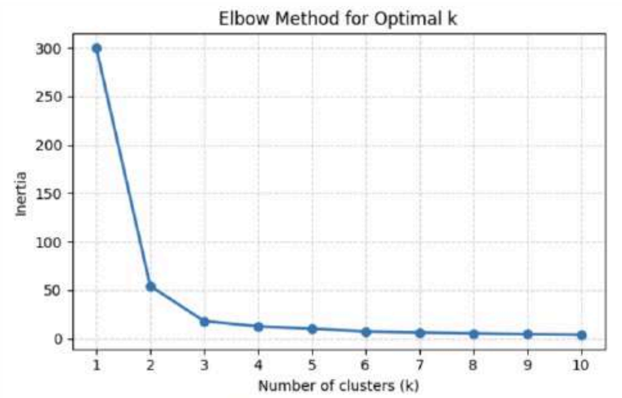
The elbow plot shows sharp elbow at k=3, indicating that 3 clusters is the optimal choice for the width of this dataset

CODE WITH OUTPUT

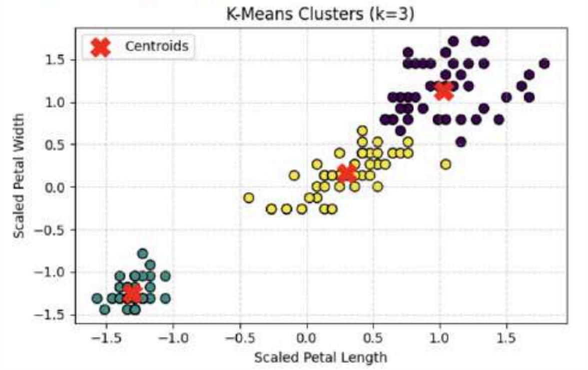
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

def load_data(csv_path='iris.csv'):
    """
    Try loading from csv_path; if not found, load via sklearn.
    Expects columns: sepal_length, sepal_width, petal_length, petal_width, species.
    Returns DataFrame with a 'species' column.
    """
    try:
        df = pd.read_csv(csv_path)
```

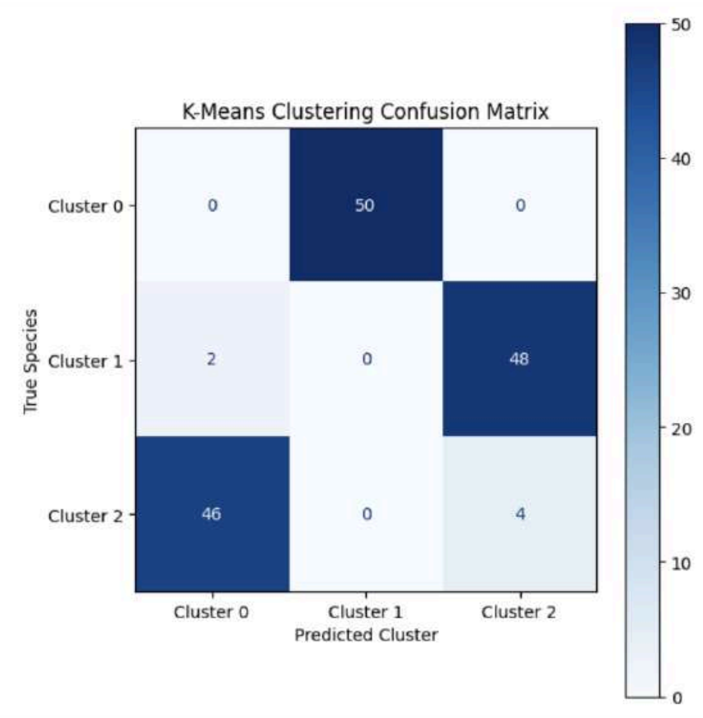
```
        # Fixed typo here: use c.strip().replace, not ace()
        df.columns = [c.strip().replace(' ', '_') for c in df.columns]
    except FileNotFoundError:
        iris = load_iris()
        df = pd.DataFrame(
            data=np.c_[iris['data'], iris['target']],
            columns=iris['feature_names'] + ['target']
        )
        df.columns = [c.strip().replace(' (cm)', '').replace(' ', '_')
                      for c in df.columns]
        df['species'] = df['target'].map(lambda x: iris['target_names'][int(x)])
    return df

def preprocess(df):
    """
    Select only petal_length & petal_width, then standard-scale.
    Returns scaled numpy array.
    """
    X = df[['petal_length', 'petal_width']].values
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    return X_scaled, scaler

def plot_elbow(X_scaled, max_k=10):
    """
    Compute KMeans inertia for k=1..max_k and plot the elbow curve.
    Returns list of inertias.
    """
    inertias = []
    ks = range(1, max_k + 1)
    for k in ks:
        km = KMeans(n_clusters=k, random_state=42)
        km.fit(X_scaled)
        inertias.append(km.inertia_)
    plt.figure(figsize=(6, 4))
    plt.plot(ks, inertias, 'o-', linewidth=2)
    plt.xlabel('Number of clusters (k)')
    plt.ylabel('Inertia')
    plt.title('Elbow Method for Optimal k')
    plt.xticks(ks)
    plt.grid(True, linestyle='--', alpha=0.5)
    plt.tight_layout()
    plt.show()
    return inertias

def run_kmeans(X_scaled, k):
    """
    Fit KMeans with k clusters, return labels and fitted model.
    """
    km = KMeans(n_clusters=k, random_state=42)
    labels = km.fit_predict(X_scaled)
    return km, labels

def plot_confusion(df, labels, k):
    """
    Builds and displays a confusion matrix comparing true species vs. cluster.
    """
    species_names = df['species'].unique()
    species_to_num = {name: idx for idx, name in enumerate(species_names)}
    true_nums = df['species'].map(species_to_num)

    cm = confusion_matrix(true_nums, labels)
    disp = ConfusionMatrixDisplay(
        confusion_matrix=cm,
        display_labels=[f"Cluster {i}" for i in range(k)]
    )
    fig, ax = plt.subplots(figsize=(6, 6))
```

```
    disp.plot(ax=ax, cmap='Blues', colorbar=True)
    ax.set_xlabel('Predicted Cluster')
    ax.set_ylabel('True Species')
    plt.title('K-Means Clustering Confusion Matrix')
    plt.tight_layout()
    plt.show()

    cm_df = pd.DataFrame(
        cm,
        index=[f"True: {name}" for name in species_names],
        columns=[f"Cluster {i}" for i in range(k)]
    )
    print("\nConfusion Matrix (counts):")
    print(cm_df)

def main():
    # 1) Load data
    df = load_data('iris.csv')
    if 'species' not in df.columns:
        print("Error: 'species' column not found.")
        return

    # 2) Preprocess
    X_scaled, scaler = preprocess(df)

    # 3) Elbow plot to decide k
    print("Generating elbow plot to find optimal k...")
    inertias = plot_elbow(X_scaled, max_k=10)

    # 4) From the elbow you'll typically see a bend at k=3
    optimal_k = 3
    print(f"Choosing k = {optimal_k} (you can adjust this based on the plot).")

    # 5) Run K-Means and assign clusters
    km_model, labels = run_kmeans(X_scaled, optimal_k)
    df['cluster'] = labels

    # 6) Visualize clusters in feature space
    plt.figure(figsize=(6, 4))
    plt.scatter(
        X_scaled[:, 0], X_scaled[:, 1],
        c=labels, cmap='viridis', edgecolor='k', s=50
    )
    centroids = km_model.cluster_centers_
    plt.scatter(
        centroids[:, 0], centroids[:, 1],
        marker='X', c='red', s=200, label='Centroids'
    )
    plt.xlabel('Scaled Petal Length')
    plt.ylabel('Scaled Petal Width')
    plt.title(f'K-Means Clusters (k={optimal_k})')
    plt.legend()
    plt.grid(True, linestyle='--', alpha=0.5)
    plt.tight_layout()
    plt.show()

    # 7) Confusion matrix vs. true species
    plot_confusion(df, labels, optimal_k)

if __name__ == "__main__":
    main()
```



Choosing k = 3 (you can adjust this based on the plot).

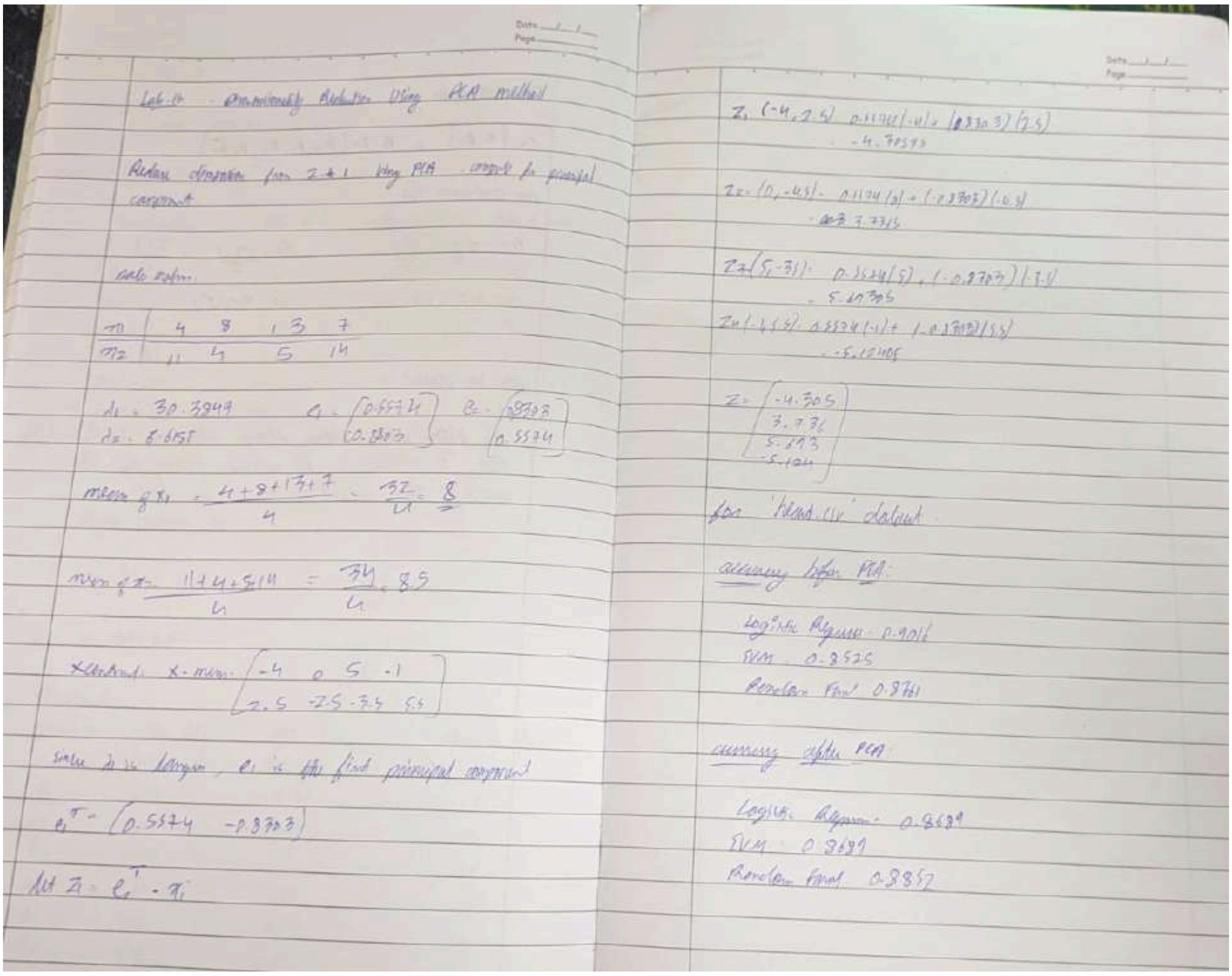




LABORATORY PROGRAM – 11

Implement Dimensionality reduction using Principle Component Analysis (PCA) method.

OBSERVATION BOOK



CODE WITH OUTPUT

```
import pandas as pd

df = pd.read_csv("heart.csv")

# Step 3: Split Features and Target
X = df.drop("target", axis=1)
y = df["target"]

# Step 4: Preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

categorical_features = ["cp", "thal", "slope"]
numerical_features = [col for col in X.columns if col not in categorical_features]

preprocessor = ColumnTransformer(transformers=[
    ("num", StandardScaler(), numerical_features),
```

```python
    ("cat", OneHotEncoder(), categorical_features)
])

# Step 5: Train/Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 6: Models
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "SVM": SVC(),
    "Random Forest": RandomForestClassifier()
}

# Step 7: Train and Evaluate Models (Before PCA)
print("Accuracy Before PCA:")
results = {}
for name, model in models.items():
    pipeline = Pipeline(steps=[
        ("preprocessor", preprocessor),
        ("classifier", model)
    ])
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    results[name] = acc
    print(f"{name}: {acc:.4f}")

from sklearn.decomposition import PCA

print("\nAccuracy After PCA (n_components=5):")
pca_results = {}

for name, model in models.items():
    pipeline_pca = Pipeline(steps=[
        ("preprocessor", preprocessor),
        ("pca", PCA(n_components=5)),
        ("classifier", model)
    ])
    pipeline_pca.fit(X_train, y_train)
    y_pred_pca = pipeline_pca.predict(X_test)
    acc_pca = accuracy_score(y_test, y_pred_pca)
    pca_results[name] = acc_pca
    print(f"{name}: {acc_pca:.4f}")
```

```
📋 Accuracy Before PCA:
Logistic Regression: 0.9016
SVM: 0.8525
Random Forest: 0.8361

📉 Accuracy After PCA (n_components=5):
Logistic Regression: 0.8689
SVM: 0.8689
Random Forest: 0.8852
```