VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

Anjali (1BM22CS042)

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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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 **Anjali (1BM22CS042),** who is bonafide student of **B.M.S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements in respect of an Machine Learning (23CS6PCMAL) work prescribed for the said degree.

Saritha A. N Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

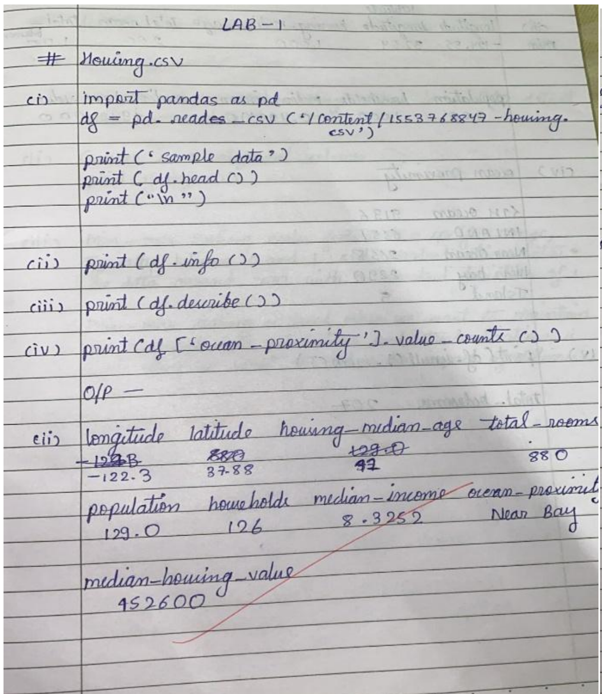
Index

Github Link: https://github.com/Anjali-042/ML_LAB

Program 1

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

Screenshot



LAB – 1

Housing.csv

(i) import pandas as pd
df = pd.readcs_csv ('/content/1553768847-housing.csv')
print ('sample data')
print (df.head ())
print ("\n")

(ii) print (df.info ())

(iii) print (df.describe ())

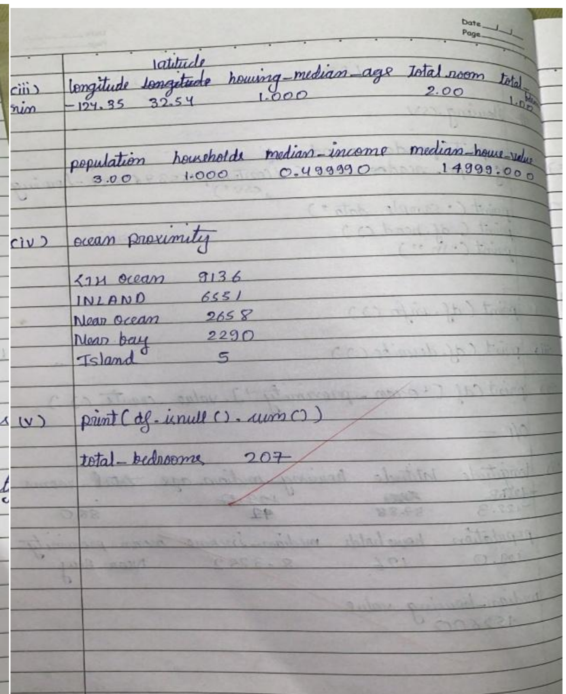
(iv) print (df ['ocean_proximity'].value_counts ())

O/P —

(i) longitude latitude housing_median_age total_rooms
~~-122.B~~ ~~880~~ ~~129.0~~ 880
-122.3 37.88 41

population households median_income ocean_proximity
129.0 126 8.3252 Near Bay

median_housing_value
452600



(iii) min
longitude latitude housing_median_age Total room total bedrooms
-124.35 32.54 1.000 2.00 1.00

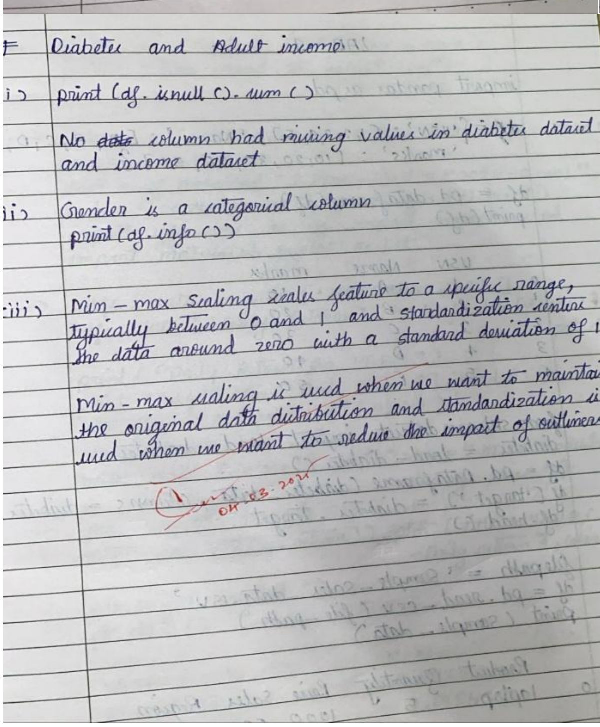
population households median_income median_house_value
3.00 1.000 0.499990 14999.000

(iv) ocean proximity

<1H Ocean 9136
INLAND 6551
Near Ocean 2658
Near bay 2290
Island 5

(v) print (df.isnull ().sum ())

total_bedrooms 207



Diabetes and Adult income

i) print (df.isnull ().sum ())

No ~~data~~ column had missing values in diabetes dataset and income dataset

ii) Gender is a categorical column
print (df.info ())

iii) Min – max Scaling scales feature to a specific range, typically between 0 and 1 and standardization centers the data around zero with a standard deviation of 1

Min - max scaling is used when we want to maintain the original data distribution and standardization is used when we want to reduce the impact of outliners

04.03.2024

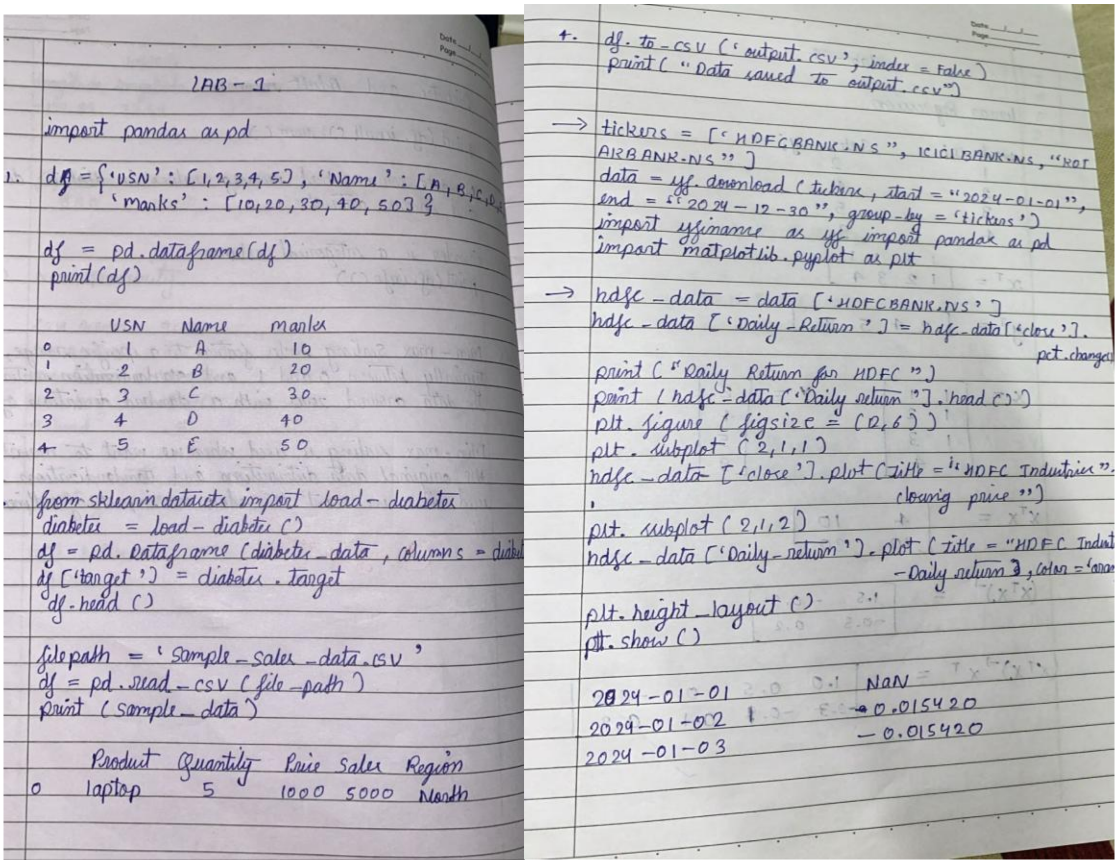
Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from scipy import stats

#**Diabetes Dataset**
df=pd.read_csv('/content/Dataset of Diabetes .csv')
df.head()
df.shape
print(df.info())
# Summary statistics
print(df.describe())
missing_values=df.isnull().sum()
print(missing_values[missing_values > 0])
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.")
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())

#**Adult Income Dataset**
df1=pd.read_csv('/content/adult.csv')
df1.head()
df1.shape
```

```
print(df1.info())
# Summary statistics
print(df.describe())
missing_values=df1.isnull().sum()
print(missing_values[missing_values > 0])
categorical_cols = df1.select_dtypes(include=['object']).columns
print("Categorical columns identified:", categorical_cols)
if len(categorical_cols) > 0:
    df1 = pd.get_dummies(df1, columns=categorical_cols, drop_first=True)
    print("\nDataFrame after one-hot encoding:")
    print(df.head())
else:
    print("\nNo categorical columns found in the dataset.")
from sklearn.preprocessing import MinMaxScaler, StandardScaler
import pandas as pd

numerical_cols = df1.select_dtypes(include=['number']).columns

scaler = MinMaxScaler()
df_minmax = df1.copy()  # Create a copy to avoid modifying the original
df_minmax[numerical_cols] = scaler.fit_transform(df1[numerical_cols])

scaler = StandardScaler()
df_standard = df1.copy()
df_standard[numerical_cols] = scaler.fit_transform(df1[numerical_cols])
print("\nDataFrame after Min-Max Scaling:")
print(df_minmax.head())
print("\nDataFrame after Standardization:")
print(df_standard.head())
```

PROGRAM 2 Demonstrate various data pre-processing techniques for a given dataset

Screenshot



LAB - 1

```
import pandas as pd

1. df = {'USN': [1,2,3,4,5], 'Name': [A,B,C,D,
        'marks': [10,20,30,40,50]}

df = pd.dataframe(df)
print(df)

     USN   Name   marks
0     1     A      10
1     2     B      20
2     3     C      30
3     4     D      40
4     5     E      50

from sklearn.datasets import load_diabetes
diabetes = load_diabetes()
df = pd.DataFrame(diabetes_data, columns = diab
df['target'] = diabetes.target
df.head()

filepath = 'Sample_sales_data.csv'
df = pd.read_csv(file_path)
print (sample_data)

     Product  Quantity  Price  Sales  Region
0    laptop     5       1000   5000   North
```

```
4. df.to_csv('output.csv', index = False)
print("Data saved to output.csv")

→ tickers = ["HDFCBANK.NS", ICICIBANK.NS, "KOTAKBANK.NS"]
data = yf.download(tickers, start = "2024-01-01",
end = "2024-12-30", group_by = 'tickers')
import yfinance as yf import pandas as pd
import matplotlib.pyplot as plt

→ hdfc_data = data['HDFCBANK.NS']
hdfc_data['Daily_Return'] = hdfc_data['close'].
                                        pct.change()

print("Daily Return for HDFC")
print(hdfc_data['Daily return'].head())
plt.figure(figsize = (12,6))
plt.subplot(2,1,1)
hdfc_data['close'].plot(title = "HDFC Industries".
                        closing price")

plt.subplot(2,1,2)
hdfc_data['Daily_return'].plot(title = "HDFC Indust
                        -Daily return", color = 'oran

plt.height_layout()
plt.show()

2024-01-01          NaN
2024-01-02       -0.015420
2024-01-03       -0.015420
```

Code

```
import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

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

df.head(2)

df.describe()

df.info()

sns.histplot(df['median_income'], kde=True, color='green')

sns.histplot(df['housing_median_age'])

from sklearn.model_selection import train_test_split


X = df.drop("median_house_value", axis=1)

y = df["median_house_value"]


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

X = df.drop("median_house_value", axis=1)

y = df["median_house_value"]

df["income_cat"] = pd.cut(df["median_house_value"],

bins=[0, 100000, 200000, 300000, 400000, np.inf],

labels=[1, 2, 3, 4, 5])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42,

stratify=df["income_cat"])
```

```
train_set = X_train.copy()

train_set["median_house_value"] = y_train

train_set.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,s=train_set["population"]/100,
label="population",figsize=(10,7), c="median_house_value", cmap=plt.get_cmap("jet"),

colorbar=True)

plt.legend()

numerical_columns = df.select_dtypes(include=['float64', 'int64'])

correlation_matrix = numerical_columns.corr()

print(correlation_matrix["median_house_value"].sort_values(ascending=False))

df.plot(kind="scatter", x="median_income", y="median_house_value", alpha=0.1)

# Combine 'median_income' and 'households'

df["income_households"] = df["median_income"] * df["households"]


numerical_columns = df.select_dtypes(include=['float64', 'int64'])

correlation_matrix = numerical_columns.corr()

print(correlation_matrix["median_house_value"].sort_values(ascending=False))

df.plot(kind="scatter", x="income_households", y="median_house_value", alpha=0.1)

plt.show()

missing_values = df.isnull().sum()

print(missing_values[missing_values > 0])

h=df

h.dropna(subset=["total_bedrooms"])

from sklearn.preprocessing import OneHotEncoder

df1=pd.read_csv('housing.csv')

hc=df1[["ocean_proximity"]]
```

```
encoder=OneHotEncoder()

hc_encoded=encoder.fit_transform(hc).toarray()

hc_1hot_df = pd.DataFrame(hc_encoded, columns=encoder.get_feature_names_out(hc.columns))

hc_1hot_df.head()
```

Feature scaling is crucial in machine learning for several reasons, particularly when using algorithms that are sensitive to the scale of features. Here's a breakdown of its importance:

1. Improved Performance of Distance-Based Algorithms:

2. Faster Convergence of Gradient Descent:

3. Improved Regularization:

4. Better Interpretation of Coefficients:

5. Numerical Stability:

```
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):

    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 = df1.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()),
```

```python
# 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)
```

PROGRAM 3 Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot

Lab - 4

Linear Regression

week x_i	Sales y_i
1	2
2	4
3	5
4	9

$$x^T = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 \end{bmatrix}$$

$$y^T = \begin{bmatrix} 2 & 4 & 5 & 9 \end{bmatrix}$$

$$X = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} \quad Y = \begin{bmatrix} 2 \\ 4 \\ 5 \\ 9 \end{bmatrix}$$

$$X^T X = \begin{bmatrix} 4 & 10 \\ 10 & 30 \end{bmatrix}$$

$$(X^T X)^{-1} = \begin{bmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{bmatrix}$$

$$(X^T X)^{-1} X^T = \begin{bmatrix} 1.0 & 0.5 & 0 & -0.5 \\ -0.3 & -0.1 & 0.1 & 0.3 \end{bmatrix}$$

$$((X^T X)^{-1} X^T)\, Y = \begin{bmatrix} 1.0 & 0.5 & 0 & -0.5 \\ -0.3 & -0.1 & 0.1 & 0.3 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \\ 5 \\ 9 \end{bmatrix}$$

$$= \begin{bmatrix} -0.5 \\ 2.2 \end{bmatrix}$$

$$y = a_0 + a_1 x_1 \cancel{+ a_2 x_2}$$

for $x = 5$

$$y = -0.5 + (2.2) \times 5$$
$$= 10.5$$

* Steps (algo)

1) import libraries
2) import data - distribution
3) Analyse data - distribution
4) Distribution plot - visualisation
5) Relationship b/w variables
6) Split the data
7) Train the model
8) Predict the result
9) Visualize prediction
10) Values of coefficient and intercept

11.03.25

⇒ linear Regression

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import linear regression
from sklearn.metrics import mean_squared error

file path = "/Content/Canada_per_capita_income.csv"
~~df = rea~~
df = pd.read_csv(file_path)
df.columns = ["year", "per_capita_income"]

X = df[["year"]]
Y = df["per_capita_income"]
model = LinearRegression()
model.fit(X, Y)

predited_income_2020 = model.predict([[2020]])

plt.scatter(X, Y, color = 'blue', label = 'Actual Data')
plt.plot(X, model.predict(X), color = 'red', label = 'Reg line
plt.xlabel("year")
plt.ylabel("per capita income")
plt.legend()
plt.show()

print(f"Predicted per capita income 2020: ${predicted
       income_2020[0]:.2f}")
```

1. O/P —
   Predicted_per capita income 2020: $ 41288.69

2. O/P —
   predicted salary for 12 years of experience: $139093.67

Multiple Regression

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

file_path = "/Content/hiring.csv"
df = pd.read_csv(file_path)

df.loc[:, "test_score (out of 10)"] = df["test_score (
 out of 10)"].fillna(df["test_score (out of 10")].mean

def Convert_experience(val):
    if instance(val, str):
        word_to_num = {"zero": 0, "one": 1, "two":
                       "three": 3, ... "Ten": 10}
        return word_to_num.get(val.lower(), 0)
    return val

df.loc[:, "experience"] = df["experience"].apply(
                                      Convert_experience

df.dropna(inplace = True)
X = df[["experience", "test_score(out of 10)",
       "interview_score (out of 10)"]]
y = df["salary($)"]

model = LinearRegression
model.fit(X, y)

candidates = pd.Dataframe([[2, 9, 6], [12, 10, 10]],
Columns = ["experince", "test_score (out of 10)",
           interview_score (out of 10)"])

for i, salary in enumerate(predited_salaries):
    print(f"Predited salary for Candidate {i+1}: $
          {salary:.2f}")
```

O/P —

1. Predited Salary for Candidate 1: $ 78581.11
   Predited Salary for Candidate 2: $ 56486.29

2. Predited Profit: $ 510570.99

3. Predicted Salary: $ 96,000

Q.1. Yes I performed data processing steps like Handling missing values and encoding categorical data to ensure the datasets are clean and ready for modeling.

2. Yes, I visualized the regression line.

   The regression line slopes upward, indicating that per capita income increases over time. There is a strong positive correlation between year and per capita income.

Yes, I encoded categorical values like state using one-hot Encoding to convert the categorical values into binary variable.

Code

```
# -*- coding: utf-8 -*-
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt

df = pd.read_csv('/content/housing_area_price.csv')
df
# Commented out IPython magic to ensure Python compatibility.
# %matplotlib inline
plt.xlabel('area')
plt.ylabel('price')
plt.scatter(df.area,df.price,color='red',marker='+')

new_df = df.drop('price',axis='columns')
new_df

price = df.price
price

# Create linear regression object
reg = linear_model.LinearRegression()
reg.fit(new_df,price)
```

```
"""(1) Predict price of a home with area = 3300 sqr ft"""

reg.predict([[3300]])

reg.coef_

reg.intercept_

"""Y = m * X + b (m is coefficient and b is intercept)"""

3300*135.78767123 + 180616.43835616432

"""(1) Predict price of a home with area = 5000 sqr ft"""

reg.predict([[5000]])
# -*- coding: utf-8 -*-
import pandas as pd
import numpy as np
from sklearn import linear_model

df = pd.read_csv('/content/homeprices_Multiple_LR.csv')
df
```

```
"""Data Preprocessing: Fill NA values with median value of a column"""

df.bedrooms.median()

df.bedrooms = df.bedrooms.fillna(df.bedrooms.median())
df

reg = linear_model.LinearRegression()
reg.fit(df.drop('price',axis='columns'),df.price)

reg.coef_

reg.intercept_

"""Find price of home with 3000 sqr ft area, 3 bedrooms, 40 year old"""

reg.predict([[3000, 3, 40]])

112.06244194*3000 + 23388.88007794*3 + -3231.71790863*40 + 221323.00186540384
import pandas as pd
from sklearn.linear_model import LinearRegression

# Load the dataset
df1 = pd.read_csv('/content/canada_per_capita_income.csv')
```

```
# Prepare the data
X = df1.year.values.reshape(-1, 1)  # Features (year)
y = df1['per capita income (US$)']   # Target (per capita income)

# Create and train the linear regression model
model = LinearRegression()
model.fit(X, y)

# Predict per capita income for 2020
year_2020 = [[2020]]
predicted_income = model.predict(year_2020)

print(f"Predicted per capita income for Canada in 2020: {predicted_income[0]:.2f}")

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

# Load the dataset (canada_per_capita_income.csv)
df1 = pd.read_csv('/content/canada_per_capita_income.csv')

# Prepare the data
X = df1.year.values.reshape(-1, 1)  # Features (year)
```

```
y = df1['per capita income (US$)']   # Target (per capita income)


# Create and train the linear regression model
model = LinearRegression()
model.fit(X, y)


# Create the plot
plt.figure(figsize=(8, 6))
plt.scatter(X, y, color='blue', label='Data Points') # Now using the correct X and y
plt.plot(X, model.predict(X), color='red', label='Regression Line')
plt.xlabel('Year')
plt.ylabel('Per Capita Income (US$)')
plt.title('Per Capita Income in Canada over Time')
plt.legend()
plt.grid(True)
plt.show()
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.impute import SimpleImputer


# Load the dataset
df = pd.read_csv('/content/salary.csv')


# Prepare the data
```

```
X = df.iloc[:, :-1].values  # Features (years of experience)
y = df.iloc[:, 1].values    # Target (salary)

# Impute missing values with the mean
imputer = SimpleImputer(strategy='mean') # Create an imputer object with strategy as mean
X = imputer.fit_transform(X) # Fit and transform the imputer on feature data 'X'

# Create and train the linear regression model
model = LinearRegression()
model.fit(X, y)

# Predict salary for 12 years of experience
years_experience = [[12]]
predicted_salary = model.predict(years_experience)

print(f"Predicted salary for 12 years of experience: {predicted_salary[0]:.2f}")
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.impute import SimpleImputer

# Load the dataset
df = pd.read_csv('/content/hiring.csv')

# Handle missing values
```

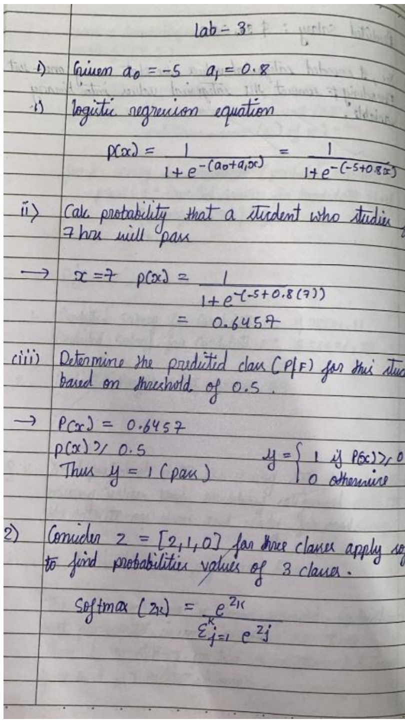
```
# Convert 'experience' column to numeric, replacing non-numeric with NaN
df['experience'] = pd.to_numeric(df['experience'], errors='coerce')

imputer = SimpleImputer(strategy='mean')
df['experience'] = imputer.fit_transform(df[['experience']])
df['test_score(out of 10)'] = imputer.fit_transform(df[['test_score(out of 10)']])

# Prepare the data
X = df.drop('salary($)', axis='columns')
y = df['salary($)']

# Create and train the linear regression model
model = LinearRegression()
model.fit(X, y)

# Predict salaries for the given candidates
candidate1 = [[2, 9, 6]]
candidate2 = [[12, 10, 10]]

predicted_salary1 = model.predict(candidate1)
predicted_salary2 = model.predict(candidate2)

print(f"Predicted salary for candidate 1: ${predicted_salary1[0]:.2f}")
print(f"Predicted salary for candidate 2: ${predicted_salary2[0]:.2f}")
```

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.compose import ColumnTransformer

# Load the dataset
df = pd.read_csv('/content/1000_Companies.csv')

# Separate features (X) and target (y)
X = df.iloc[:, :-1].values
y = df.iloc[:, 4].values

# Encode categorical data (State)
labelencoder = LabelEncoder()
X[:, 3] = labelencoder.fit_transform(X[:, 3])

ct = ColumnTransformer(
    transformers=[('encoder', OneHotEncoder(), [3])],
    remainder='passthrough'
)
X = ct.fit_transform(X)

# Avoid dummy variable trap (remove one encoded column)
```

```
X = X[:, 1:]


# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)


# Create and train the multiple linear regression model
regressor = LinearRegression()
regressor.fit(X_train, y_train)


# Predict profit for the given values
new_prediction = regressor.predict([[1, 0, 91694.48, 515841.3, 11931.24]])
print(f"Predicted Profit: {new_prediction[0]:.2f}")
```

PROGRAM 4 Build Logistic Regression Model for a given dataset

Screenshot



lab - 3:

1) Given $a_0 = -5$ $a_1 = 0.8$

i) logistic regression equation

$$p(x) = \frac{1}{1+e^{-(a_0+a_1x)}} = \frac{1}{1+e^{-(-5+0.8x)}}$$

ii) Calc probability that a student who studies 7 hrs will pass

→ $x = 7$ $p(x) = \frac{1}{1+e^{-(-5+0.8(7))}}$

$= 0.6457$

(iii) Determine the predicted class (P/F) for this stu[dent] based on threshold of 0.5.

→ $P(x) = 0.6457$

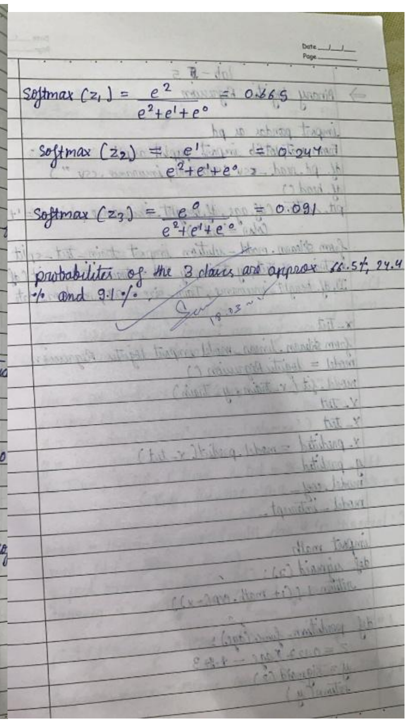
$p(x) \geq 0.5$

Thus $y = 1$ (pass)

$$y = \begin{cases} 1 & \text{if } P(x) \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

2) Consider $z = [2,1,0]$ for three classes apply so[ftmax] to find probabilities values of 3 classes.

$$\text{Softmax}(z_k) = \frac{e^{z_k}}{\sum_{j=1}^{k} e^{z_j}}$$



Date __/__/__

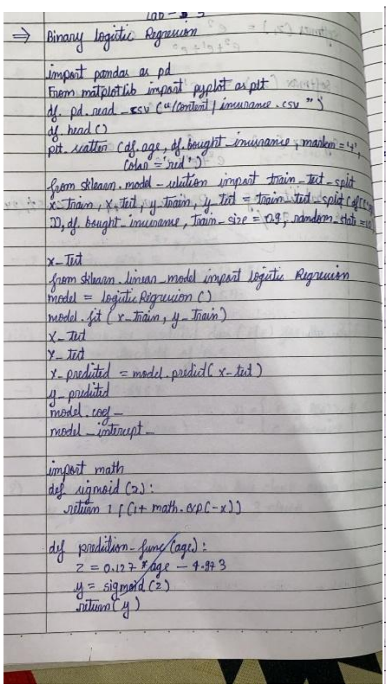
Page ____

$$\text{Softmax}(z_1) = \frac{e^2}{e^2+e^1+e^0} \doteq 0.665$$

$$\text{Softmax}(z_2) = \frac{e^1}{e^2+e^1+e^0} \doteq 0.244$$

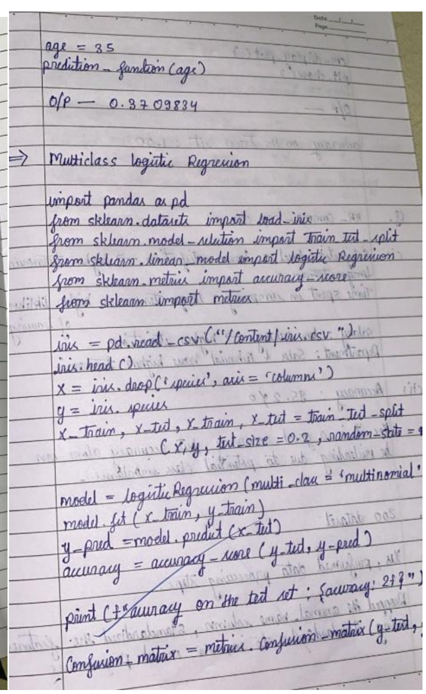
$$\text{Softmax}(z_3) = \frac{e^0}{e^2+e^1+e^0} \doteq 0.091$$

probabilities of the 3 classes are approx 66.5%, 24.4% and 9.1%.



⇒ Binary logistic Regression

```
import pandas as pd
From matplotlib import pyplot as plt
df. pd.read_csv ("/content/insurance.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_test
from sklearn.linear_model import logistic Regression
model = logisticRegression()
model.fit (x_train, y_train)
x_test
y_test
y_predicted = model.predict(x_test)
y_predicted
model.coef_
model.intercept_

import math
def sigmoid (x):
  return 1/(1+ math.exp(-x))

def prediction_func (age):
   z = 0.127 * age - 4.973
   y = sigmoid(z)
   return(y)
```



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Page ____

```
age = 35
prediction_function(age)
```

O/P — 0.37 09834

⇒ Multiclass logistic Regression

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import Train_test_split
from sklearn.linear_model import logistic Regression
from sklearn.metrics import accuracy_score
from sklearn import metrics

iris = pd.read_csv("/content/iris.csv")
iris.head()
x = iris.drop('species', axis='columns')
y = iris.species
x_train, x_test, y_train, y_test = train_test_split
              (x, y, test_size = 0.2, random_state =

model = logisticRegression (multi_class = 'multinomial'
model.fit (x_train, y_train)
y_pred = model.predict (x_test)
accuracy = accuracy_score (y_test, y_pred)

print (f"accuracy on the test set : {accuracy: 2f}")

Confusion_matrix = metrics.Confusion_matrix(y_test,
```

cm_display.plot()
plt.show()

O/P —

ccuracy on the train set : 1.00

HR_comma_sep.csv

atisfaction level : lower satisfaction → higher turnover
~~onger tenure~~ :
ime spent in company : longer tenure ⇒ higher likelihood of leaving

alary : low salary → higher attrition
partment : Sales & technical have higher turnover

ccuracy : 95.2%

it is a good accuracy, but accuracy alone can misleading due to potential class imbalance.

o dataset

, performed data processing steps.

ped the animal_name column, standardized the features g standardscaler to improve model performance g.

(ii) There were no missing or inconsistent values

(iii) The Confusion matrix showed achieved 95.2% accuracy.

(iv) Reptiles and amphibians were mostly misclassified classes. They share common features. Mammals and birds also as they had overlapping features.

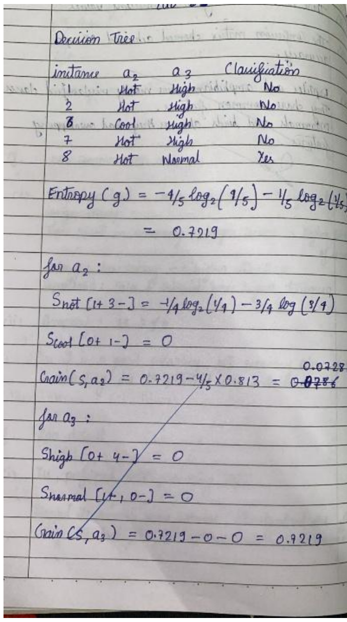
Code

```
import pandas as pd

import numpy as np

df=pd.read_csv("/content/HR_comma_sep.csv")

df.head(3)

print(df.isnull().sum())

print(df.groupby('left').mean(numeric_only=True))

print(df.groupby('salary').mean(numeric_only=True))

import matplotlib.pyplot as plt

pd.crosstab(df.salary,df.left).plot(kind='bar')

plt.title('Employee Retention vs Salary')

plt.xlabel('Salary')

plt.ylabel('Number of Employees')

plt.show()

pd.crosstab(df.Department,df.left).plot(kind='bar')

plt.title('Employee Retention vs Department')

plt.xlabel('Department')

plt.ylabel('Number of Employees')

plt.show()

salary_dummies = pd.get_dummies(df.salary, prefix="salary")

dept_dummies = pd.get_dummies(df.Department, prefix="dept")
```

```
df_with_dummies = pd.concat([df, salary_dummies, dept_dummies], axis=1)


df_with_dummies = df_with_dummies.drop(['salary', 'Department'], axis=1)


X_features = ['satisfaction_level', 'last_evaluation', 'number_project', 'average_montly_hours',
'time_spend_company', 'Work_accident', 'promotion_last_5years'] + list(salary_dummies.columns) +
list(dept_dummies.columns)

X = df_with_dummies[X_features]

y = df_with_dummies.left



from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)


from sklearn.linear_model import LogisticRegression

model = LogisticRegression()

model.fit(X_train, y_train)


from sklearn.metrics import accuracy_score

y_pred = model.predict(X_test)


accuracy = accuracy_score(y_test, y_pred)

print("Accuracy of the model:", accuracy)
```

PROGRAM 5 Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample.

Screenshot



Decision Tree

instance	a_2	a_3	Classification
1	Hot	High	No
2	Hot	High	No
3	Cool	High	No
7	Hot	High	No
8	Hot	Normal	Yes

$Entropy(g) = -4/5 \log_2(4/5) - 1/5 \log_2(1/5)$

$= 0.7219$

for a_2:

$S_{hot} [1+ 3-] = -1/4 \log_2(1/4) - 3/4 \log(3/4)$

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

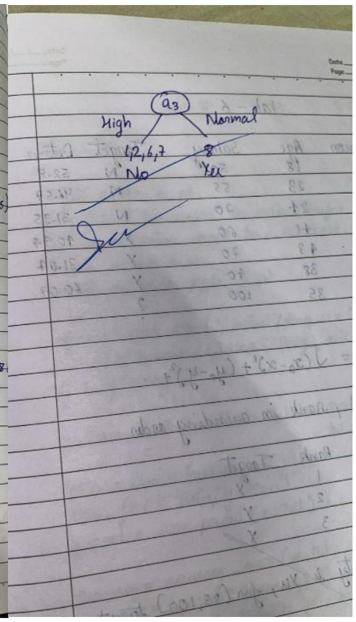
$Gain(S, a_2) = 0.7219 - 4/5 \times 0.813 = \cancel{0.0786}$ 0.0728

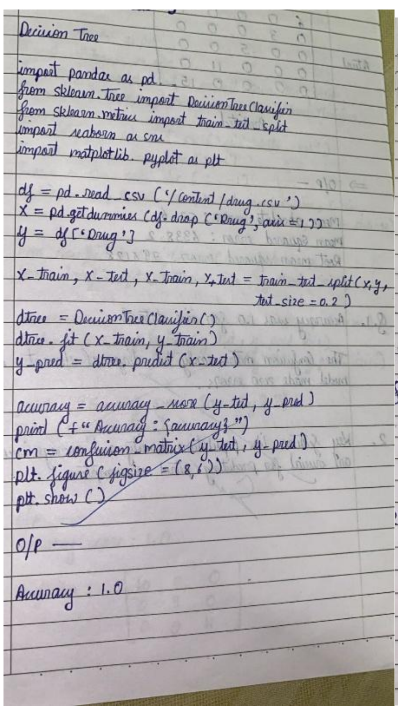
for a_3:

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

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

$Gain(S, a_3) = 0.7219 - 0 - 0 = 0.7219$



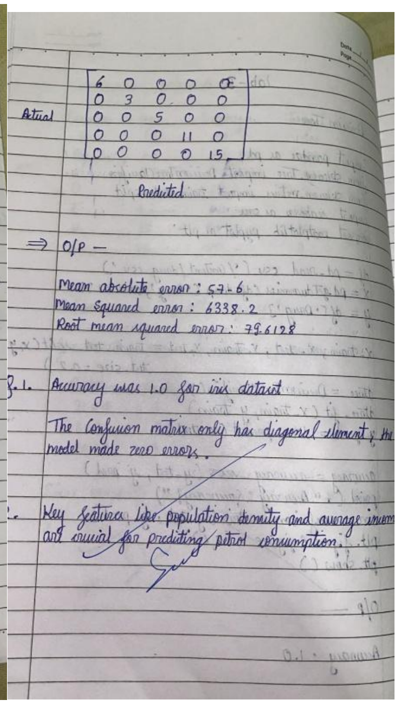


Decision Tree

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv('/content/drug.csv')
X = pd.get_dummies(df.drop('Drug', axis=1))
y = df['Drug']

X_train, X_test, Y_train, Y_test = train_test_split(X, y,
                                   test_size=0.2)
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
y_pred = dtree.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8,6))
plt.show()
```

O/P —

Accuracy : 1.0



$$\text{Actual} \begin{bmatrix} 6 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & 5 & 0 & 0 \\ 0 & 0 & 0 & 11 & 0 \\ 0 & 0 & 0 & 0 & 15 \end{bmatrix}$$

Predicted

⇒ O/P —

Mean absolute error : 57.6

Mean squared error : 6338.2

Root mean squared error : 79.6128

Q.1. Accuracy was 1.0 for iris dataset

The Confusion matrix only has diagonal elements, the model made zero errors.

2. Key features like population density and average income are crucial for predicting petrol consumption.

Code

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn import tree
import matplotlib.pyplot as plt

iris = load_iris()
X = iris.data
y = iris.target

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

clf = DecisionTreeClassifier()

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)

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

print("Accuracy:", accuracy)
```

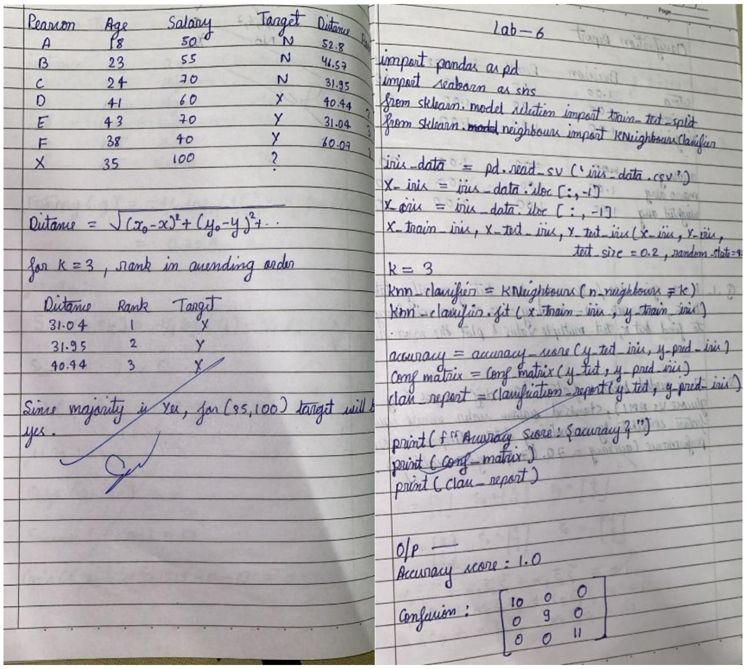
```
print("Confusion Matrix:\n", conf_matrix)



plt.figure(figsize=(12, 8))
tree.plot_tree(clf, feature_names=iris.feature_names, class_names=iris.target_names, filled=True)
plt.show()

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn import tree
import matplotlib.pyplot as plt

iris = load_iris()
X = iris.data
y = iris.target

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

clf = DecisionTreeClassifier()

clf.fit(X_train, y_train)
```

```
y_pred = clf.predict(X_test)

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

print("Accuracy:", accuracy)
print("Confusion Matrix:\n", conf_matrix)


plt.figure(figsize=(12, 8))
tree.plot_tree(clf, feature_names=iris.feature_names, class_names=iris.target_names, filled=True)
plt.show()

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np # import numpy

data = pd.read_csv("petrol_consumption.csv")

X = data[['Petrol_tax', 'Average_income', 'Paved_Highways',
          'Population_Driver_licence(%)']]
y = data['Petrol_Consumption']
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42)


regressor = DecisionTreeRegressor()


regressor.fit(X_train, y_train)


y_pred = regressor.predict(X_test)


mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)


print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt


plt.figure(figsize=(15, 10))
# Assuming 'data' is your original pandas DataFrame
plot_tree(regressor, feature_names=data[['Petrol_tax', 'Average_income', 'Paved_Highways',
'Population_Driver_licence(%)']].columns, filled=True, rounded=True)
plt.show()
```

PROGRAM 6 Build KNN Classification model for a given dataset.

Screenshot



Person	Age	Salary	Target	Distance
A	18	50	N	52.8
B	23	55	N	41.57
C	24	70	N	31.95
D	41	60	Y	40.44
E	43	70	Y	31.04
F	38	40	Y	60.07
X	35	100	?	

Distance = $\sqrt{(x_0-x)^2+(y_0-y)^2+\cdots}$

for K = 3, rank in ascending order

Distance	Rank	Target
31.04	1	Y
31.95	2	Y
40.44	3	Y

Since majority is Yes, for (35,100) target will be yes.

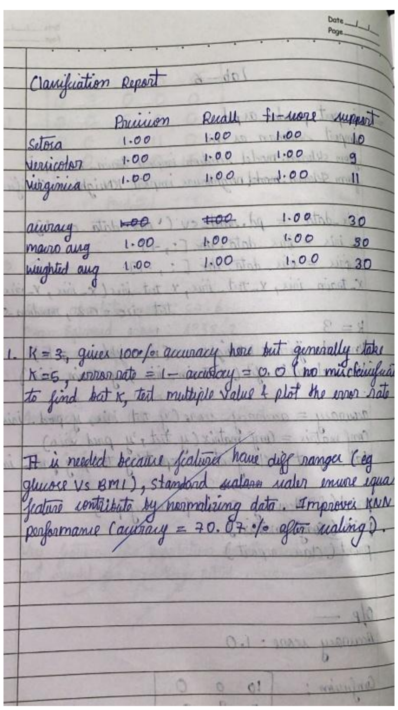
Lab – 6

```
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.neighbours import KNeighboursClassifier

iris_data = pd.read_csv('iris_data.csv')
X_iris = iris_data.iloc[:, -1]
Y_iris = iris_data.iloc[:, -1]
X_train_iris, X_test_iris, Y_test_iris(X_iris, Y_iris,
                          test_size = 0.2, random_state=42)
k = 3
knn_classifier = KNeighbours(n_neighbours = k)
knn_classifier.fit(x_train_iris, y_train_iris)

accuracy = accuracy_score(y_test_iris, y_pred_iris)
conf matrix = conf_matrix(y_test, y_pred_iris)
class_report = classification_report(y_test, y_pred_iris)

print(f"Accuracy Score: {accuracy}")
print(conf_matrix)
print(class_report)
```

O/P —

Accuracy score : 1.0

Confusion : $\begin{bmatrix} 10 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 11 \end{bmatrix}$



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~~	~~1.00~~	1.00	30
macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30

1. K = 3, gives 100% accuracy here but generally take K=5, error rate = 1 – accuracy = 0.0 (no misclassification) to find best K, test multiple value & plot the error rate

It is needed because features have diff ranges (eg glucose vs BMI), standard scalar scales ensure equal feature contribute by normalizing data. Improves KNN performance (accuracy = 70.87% after scaling).

Code

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt

try:
    data = pd.read_csv('/content/iris (1).csv')
except FileNotFoundError:
    print("Error: 'iris.csv' not found. Please upload the file to your Colab environment.")
    exit()

X = data.drop('species', axis=1)
y = data['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=knn.classes_, yticklabels=knn.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
import seaborn as sns
import matplotlib.pyplot as plt

try:
    diabetes = pd.read_csv('diabetes.csv')
except FileNotFoundError:
    print("Error: 'diabetes.csv' not found. Please ensure the file is in the current directory.")
```

```
    exit()


X = diabetes.drop('Outcome', axis=1)
y = diabetes['Outcome']


scaler = StandardScaler()
X = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)
sns.heatmap(cm, annot=True, fmt="d")
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()


print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler


try:

    heart = pd.read_csv('heart.csv')

except FileNotFoundError:

    print("Error: 'heart.csv' not found. Please ensure the file is in the current directory.")

    exit()


X = heart.drop('target', axis=1)

y = heart['target']


scaler = StandardScaler()

X = scaler.fit_transform(X)

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

best_k = 1

best_accuracy = 0
```

```
for k in range(1, 21):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_k = k

print(f"Best k: {best_k} with accuracy {best_accuracy}")
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)

sns.heatmap(cm, annot=True, fmt="d")
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
```

```
plt.show()


print("Classification Report:")

print(classification_report(y_test, y_pred))


import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.metrics import classification_report, confusion_matrix


cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")

plt.title("Confusion Matrix")

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.show()

print(classification_report(y_test, y_pred))


# prompt: For Iris dataset

# How to choose the k value? Demonstrate using accuracy rate and error

# rate. Give theory


import pandas as pd

from sklearn.model_selection import train_test_split
```

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler

# Load the Iris dataset
try:
    data = pd.read_csv('/content/iris (1).csv')
except FileNotFoundError:
    print("Error: 'iris (1).csv' not found. Please upload the file to your Colab environment.")
    exit()

# Prepare the data
X = data.drop('species', axis=1)
y = data['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the data (important for KNN)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Find the optimal k value
```

```
error_rates = []

for k in range(1, 31):  # Test k values from 1 to 30

    knn = KNeighborsClassifier(n_neighbors=k)

    knn.fit(X_train, y_train)

    y_pred = knn.predict(X_test)

    error_rates.append(1 - accuracy_score(y_test, y_pred)) # Error rate = 1 - accuracy


# Plot error rates

plt.figure(figsize=(10, 6))

plt.plot(range(1, 31), error_rates, color='blue', linestyle='dashed', marker='o',

         markerfacecolor='red', markersize=10)

plt.title('Error Rate vs. K Value')

plt.xlabel('K')

plt.ylabel('Error Rate')

plt.show()

# Theory for choosing k:

# The optimal 'k' value minimizes the error rate.

# Very small k (e.g., 1) can lead to overfitting, being too sensitive to noise.

# Very large k (e.g., 30) can lead to underfitting, smoothing out the decision boundaries too much.

# We seek a k that balances these extremes, as shown by the error rate plot.


#Select k based on the minimum error rate observed in the plot

best_k = error_rates.index(min(error_rates)) + 1  #Add 1 as the index starts from 0

# Train and evaluate the model with the best k
```

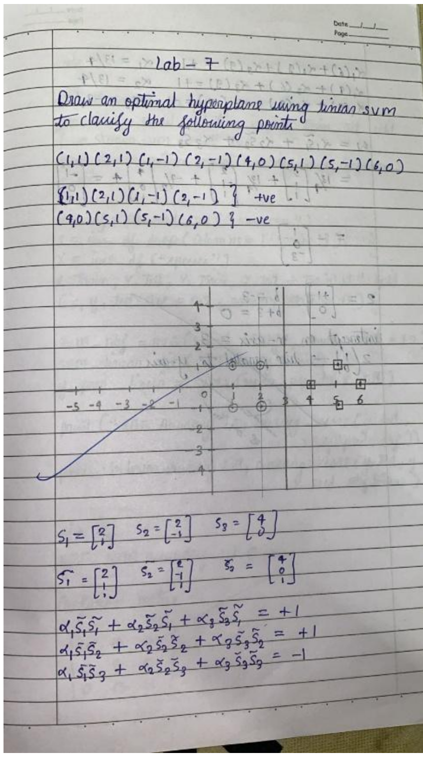
```
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

# Evaluate the model
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred)
print(cm)
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=knn.classes_, yticklabels=knn.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
```

```
import matplotlib.pyplot as plt

# Load data
df = pd.read_csv('/content/iris (1).csv')
X = df.iloc[:, :-1]
y = df.iloc[:, -1]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)

# Store accuracy and error rate
accuracy = []
error_rate = []

# Try k from 1 to 20
for k in range(1, 21):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    preds = knn.predict(X_test)
    acc = accuracy_score(y_test, preds)
    accuracy.append(acc)
    error_rate.append(1 - acc)

# Plot
```

```
plt.figure(figsize=(10,5))
plt.plot(range(1, 21), accuracy, label='Accuracy')
plt.plot(range(1, 21), error_rate, label='Error Rate')
plt.xlabel('K Value')
plt.ylabel('Rate')
plt.title('K vs Accuracy and Error Rate')
plt.legend()
plt.show()


import pandas as pd
from sklearn.preprocessing import StandardScaler


# Load data
df = pd.read_csv('/content/diabetes.csv')
X = df.drop('Outcome', axis=1)  # Features
y = df['Outcome']               # Target


# Perform scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)


# Convert back to DataFrame (optional)
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)
```

PROGRAM 7 Build Support vector machine model for a given dataset

Screenshot


lab - 7

Draw an optimal hyperplane using linear svm to classify the following points

(1,1) (2,1) (1,-1) (2,-1) (4,0) (5,1) (5,-1) (6,0)

{(1,1) (2,1) (1,-1) (2,-1)} +ve

(4,0) (5,1) (5,-1) (6,0) } -ve

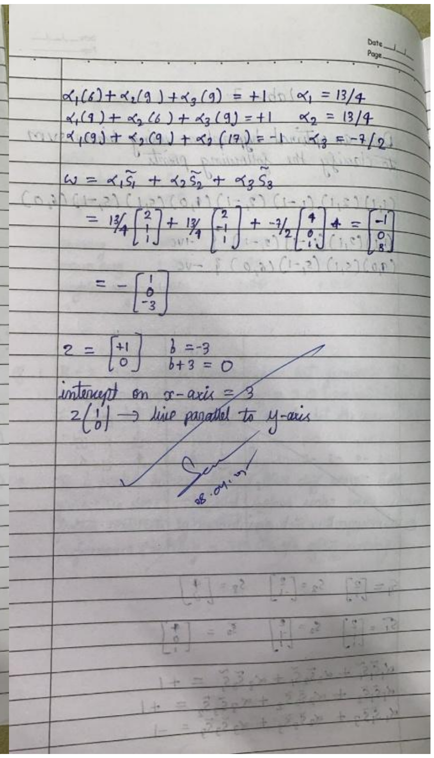
$s_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ $s_2 = \begin{bmatrix} 2 \\ -1 \end{bmatrix}$ $s_3 = \begin{bmatrix} 4 \\ 0 \end{bmatrix}$

$\tilde{s_1} = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix}$ $\tilde{s_2} = \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix}$ $\tilde{s_3} = \begin{bmatrix} 4 \\ 0 \\ 1 \end{bmatrix}$

$\alpha_1 \tilde{s_1}\tilde{s_1} + \alpha_2 \tilde{s_2}\tilde{s_1} + \alpha_3 \tilde{s_3}\tilde{s_1} = +1$

$\alpha_1 \tilde{s_1}\tilde{s_2} + \alpha_2 \tilde{s_2}\tilde{s_2} + \alpha_3 \tilde{s_3}\tilde{s_2} = +1$

$\alpha_1 \tilde{s_1}\tilde{s_3} + \alpha_2 \tilde{s_2}\tilde{s_3} + \alpha_3 \tilde{s_3}\tilde{s_3} = -1$


$\alpha_1(6) + \alpha_2(4) + \alpha_3(9) = +1$ $\alpha_1 = 13/4$

$\alpha_1(4) + \alpha_2(6) + \alpha_3(9) = +1$ $\alpha_2 = 13/4$

$\alpha_1(9) + \alpha_2(9) + \alpha_3(17) = -1$ $\alpha_3 = -7/2$

$\omega = \alpha_1 \tilde{s_1} + \alpha_2 \tilde{s_2} + \alpha_3 \tilde{s_3}$

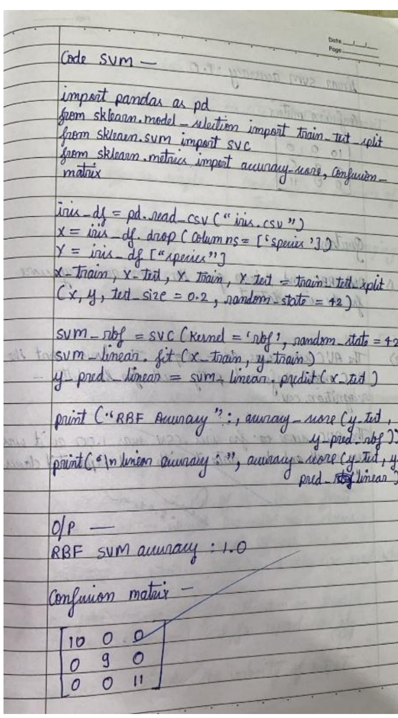
$= \frac{13}{4}\begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix} + \frac{13}{4}\begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix} + -\frac{7}{2}\begin{bmatrix} 4 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \\ 3 \end{bmatrix}$

$= -\begin{bmatrix} 1 \\ 0 \\ -3 \end{bmatrix}$

$\omega = \begin{bmatrix} +1 \\ 0 \end{bmatrix}$ $b = -3$, $b + 3 = 0$

intercept on x-axis = 3

$2\begin{pmatrix} 1 \\ 0 \end{pmatrix} \rightarrow$ line parallel to y-axis


Code SVM —

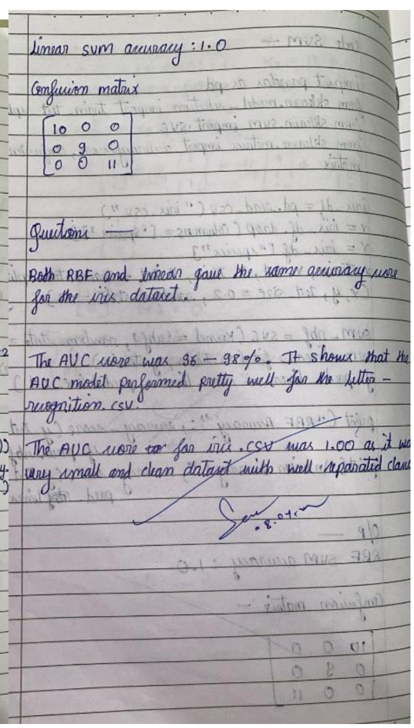
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix

iris_df = pd.read_csv("iris.csv")
X = iris_df.drop(columns=['species'])
Y = iris_df["species"]
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.2, random_state=42)

svm_rbf = SVC(kernel='rbf', random_state=42)
svm_linear.fit(X_train, y_train)
y_pred_linear = svm_linear.predict(X_test)

print("RBF Accuracy":, accuracy_score(y_test, y_pred_rbf))
print("\n linear accuracy:", accuracy_score(y_test, y_pred_linear))
```

O/P —

RBF SVM accuracy : 1.0

Confusion matrix —

$\begin{bmatrix} 10 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 11 \end{bmatrix}$


linear svm accuracy : 1.0

Confusion matrix

$\begin{bmatrix} 10 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 11 \end{bmatrix}$

Questions —

Both RBF and linear gave the same accuracy score for the iris dataset.

The AUC score was 96 – 98%. It shows that the AUC model performed pretty well for the letter-recognition.csv

The AUC score ~~for~~ for iris.csv was 1.00 as it was very small and clean dataset with well separated classes

Code

```
import numpy as np

import matplotlib.pyplot as plt



positive_class = np.array([[4, 1], [4, -1], [6, 0]])

negative_class = np.array([[1, 0], [0, 1], [0, -1]])



plt.figure(figsize=(8, 6))

plt.scatter(positive_class[:, 0], positive_class[:, 1], color='red', label='Positive Class', s=100,
edgecolors='black')

plt.scatter(negative_class[:, 0], negative_class[:, 1], color='blue', label='Negative Class', s=100,
edgecolors='black')



all_points = np.concatenate([positive_class, negative_class])

labels = ["(4,1)", "(4,-1)", "(6,0)", "(1,0)", "(0,1)", "(0,-1)"]



for i, txt in enumerate(labels):

    plt.annotate(txt, (all_points[i][0], all_points[i][1]), textcoords="offset points", xytext=(0,5),
ha='center', fontsize=10)



x_values = np.linspace(-1, 7, 100)

y_values = np.zeros_like(x_values)



plt.plot(x_values, y_values, color='black', linestyle='--', label='Optimal Hyperplane (y = 0)')
```

```
plt.plot(x_values, y_values + 1, color='gray', linestyle=':', label='Margin at y = 1')

plt.plot(x_values, y_values - 1, color='gray', linestyle=':', label='Margin at y = -1')


plt.title('Optimal Hyperplane for SVM (Visual Approximation)', fontsize=14)

plt.xlabel('x1')

plt.ylabel('x2')

plt.xlim(-1, 7)

plt.ylim(-2, 2)

plt.axhline(0, color='black',linewidth=0.5)

plt.axvline(0, color='black',linewidth=0.5)

plt.legend()


plt.grid(True)

plt.show()

import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.svm import SVC

from sklearn.metrics import accuracy_score, confusion_matrix

import seaborn as sns

import matplotlib.pyplot as plt


data = pd.read_csv('/content/iris (1) (1).csv')


X = data.drop('species', axis=1)
```

```
y = data['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

svm_rbf = SVC(kernel='rbf')
svm_rbf.fit(X_train, y_train)
y_pred_rbf = svm_rbf.predict(X_test)
accuracy_rbf = accuracy_score(y_test, y_pred_rbf)
cm_rbf = confusion_matrix(y_test, y_pred_rbf)

print("SVM with RBF Kernel:")
print("Accuracy:", accuracy_rbf)
print("Confusion Matrix:\n", cm_rbf)

plt.figure(figsize=(6, 4))
sns.heatmap(cm_rbf, annot=True, fmt='d', cmap='Blues',
            xticklabels=data['species'].unique(),
            yticklabels=data['species'].unique())
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (RBF Kernel)')
plt.show()

svm_linear = SVC(kernel='linear')
svm_linear.fit(X_train, y_train)
```

```
y_pred_linear = svm_linear.predict(X_test)
accuracy_linear = accuracy_score(y_test, y_pred_linear)
cm_linear = confusion_matrix(y_test, y_pred_linear)

print("\nSVM with Linear Kernel:")
print("Accuracy:", accuracy_linear)
print("Confusion Matrix:\n", cm_linear)

plt.figure(figsize=(6, 4))
sns.heatmap(cm_linear, annot=True, fmt='d', cmap='Blues',
            xticklabels=data['species'].unique(),
            yticklabels=data['species'].unique())
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (Linear Kernel)')
plt.show()
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, auc
import seaborn as sns
from sklearn.preprocessing import label_binarize
```

```
from sklearn.multiclass import OneVsRestClassifier


data = pd.read_csv('/content/letter-recognition.csv')  # Replace with the correct path if necessary


X = data.drop('letter', axis=1)

y = data['letter']


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


svm_classifier = SVC(kernel='rbf', probability=True) # probability=True is needed for ROC curve

svm_classifier.fit(X_train, y_train)


y_pred = svm_classifier.predict(X_test)


accuracy = accuracy_score(y_test, y_pred)

cm = confusion_matrix(y_test, y_pred)


print("SVM Classifier:")

print("Accuracy:", accuracy)

print("Confusion Matrix:\n", cm)


plt.figure(figsize=(10, 8))

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=np.unique(y),
yticklabels=np.unique(y))

plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

y_test_bin = label_binarize(y_test, classes=np.unique(y))
n_classes = y_test_bin.shape[1]

classifier = OneVsRestClassifier(SVC(kernel='rbf', probability=True))
classifier.fit(X_train, y_train)
y_score = classifier.predict_proba(X_test)

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

fpr["micro"], tpr["micro"], _ = roc_curve(y_test_bin.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])
plt.figure(figsize=(8, 6))
plt.plot(fpr["micro"], tpr["micro"],
         label='micro-average ROC curve (area = {0:0.2f})'
               ''.format(roc_auc["micro"]))
```

```
plt.plot([0, 1], [0, 1], 'k--')

plt.xlim([0.0, 1.0])

plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.title('Micro-averaged ROC Curve')

plt.legend(loc="lower right")

plt.show()

print(f"Micro-averaged AUC: {roc_auc['micro']}")
```

PROGRAM 8 Implement Random forest ensemble method on a given dataset.

Screenshot

Lab – 8

→ Difference between Decision tree and Random Forest

	DT	RF
1)	Model type is single tree	Model type is ensemble of trees
2)	Prone to overfitting	less prone due to averaging
3)	accuracy lower on complex data	accuracy higher due to ensemble learning
4)	Faster to train and predict	Slower due to multiple trees
5)	Low bias, high variance	low bias, reduced variance

→ Parameters of RF

n_estimators — No. of trees in the forest
class_weight — weight associated with classes
max_depth — max depth of each tree
bootstrap — whether bootstrap samples are used when building trees
n_jobs — no. of jobs to run in parallel
random_state — seed for reproducibility
verbose — controls the verbosity of output

→ Algorithm of random Forest

1) Input dataset D with features & class labels
2) Set the no. of trees n_estimators
3) for each tree i from 1 to n_estimators

Code :

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

iris = pd.read_csv('iris.csv')
x_axis = iris[['sepal_length', 'sepal_width', 'petal_len
y_axis = iris['species']

x_train, x_test, y_train, y_test, = train_test (x, y,
                   test_size = 0.2, random_state = 42)

rf_default = RandomForestClassifier (n_estimators = 10,
                   random_state = 42)
rf_default.fit (x_train, y_train)
y_pred_default = rf_default.predict [x_test]
accuracy_default = accuracy_score (y_test, y_pred_)
print (accuracy_default : 4f)
estimators = [10, 50, 100, 200, 500]
scores = []
print(scores)
print(best_n)
```

o/p – accuracy with n_estimators = 10 : 1.00
" = 50 : 1
" = 100 : 1
500 : 1

Best n_estimators : 10
best_accuracy_score : 1

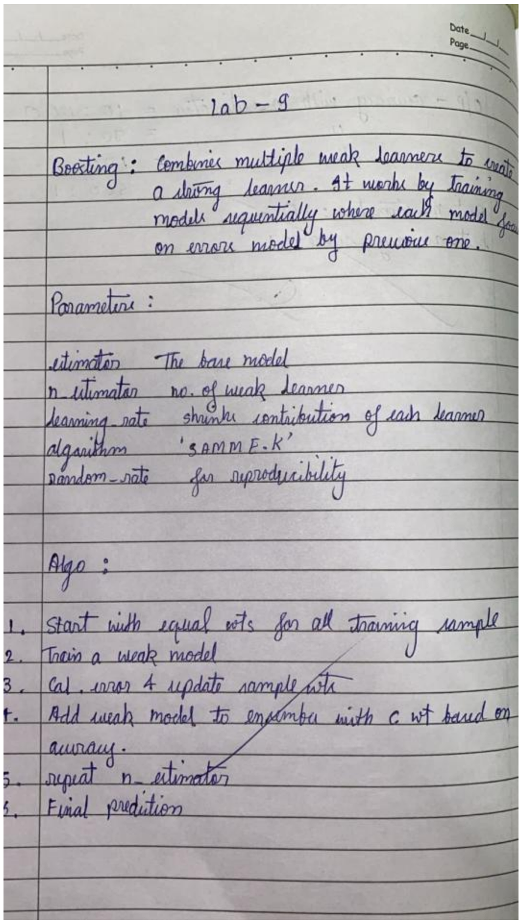
Code

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

# Load the dataset
df = pd.read_csv('/content/iris (1).csv')

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

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Build Random Forest with default n_estimators (10)
rf_default = RandomForestClassifier(n_estimators=10, random_state=42)
rf_default.fit(X_train, y_train)
y_pred_default = rf_default.predict(X_test)

# Measure accuracy
default_score = accuracy_score(y_test, y_pred_default)
```

```
print(f"Default RF accuracy (n_estimators=10): {default_score:.4f}")


# Fine-tune the number of trees
scores = []
n_range = range(1, 101)


for n in n_range:
    rf = RandomForestClassifier(n_estimators=n, random_state=42)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    score = accuracy_score(y_test, y_pred)
    scores.append(score)
# Find the best score and number of trees
best_score = max(scores)
best_n = n_range[scores.index(best_score)]
print(f"Best RF accuracy: {best_score:.4f} with n_estimators={best_n}")
# Optional: Plot accuracy vs number of estimators
plt.figure(figsize=(10, 6))
plt.plot(n_range, scores, marker='o')
plt.title('Random Forest Accuracy vs Number of Trees')
plt.xlabel('Number of Trees (n_estimators)')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()
```

PROGRAM 9 Implement Boosting ensemble method on a given dataset.

Screenshot



lab – 9

Boosting : Combines multiple weak learners to create a strong learner. It works by training models sequentially where each model focus on errors model by previous one.

Parameters :

estimator The base model
n_estimator no. of weak learner
learning_rate shrinks contribution of each learner
algorithm 'SAMME.R'
random_rate for reproducibility

Algo :

1. Start with equal wts for all training sample
2. Train a weak model
3. Cal. error & update sample wts
4. Add weak model to ensemble with c wt based on accuracy.
5. repeat n_estimator
6. Final prediction

Code

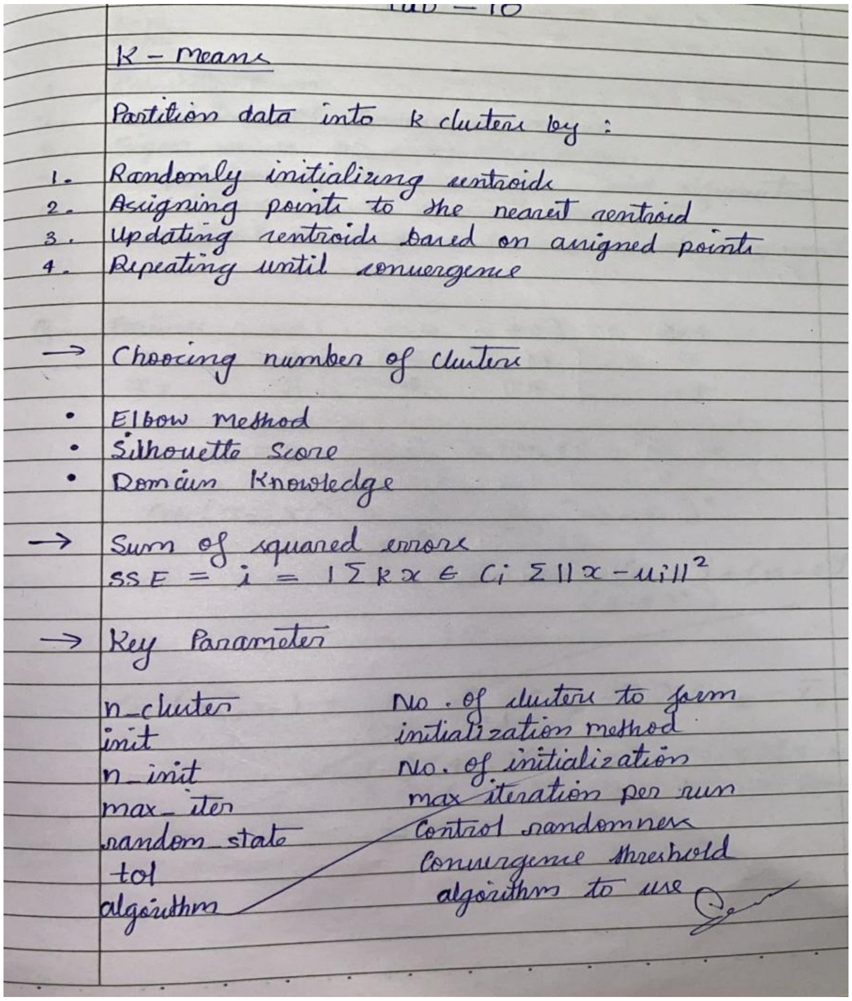
```
import pandas as pd

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder

from sklearn.ensemble import AdaBoostClassifier

from sklearn.metrics import accuracy_score

from sklearn.tree import DecisionTreeClassifier
```

```
# Load dataset
df = pd.read_csv("/content/income.csv")
# Drop rows with missing values
df.dropna(inplace=True)
# Encode categorical columns
label_encoders = {}
for column in df.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le
# Separate features and target
X = df.drop(columns=['income_level'], errors='ignore', axis=1)
y = df['income_level']
# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# AdaBoost with 10 estimators
model_10 = AdaBoostClassifier(n_estimators=10, random_state=42)
model_10.fit(X_train, y_train)
y_pred_10 = model_10.predict(X_test)
score_10 = accuracy_score(y_test, y_pred_10)
print(f"Accuracy with 10 estimators: {score_10:.4f}")
# Fine-tune number of estimators
best_score = 0
```

```
best_n = 0
estimators_range = list(range(10, 201, 10))
scores = []
for n in estimators_range:
    model = AdaBoostClassifier(n_estimators=n, random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    score = accuracy_score(y_test, y_pred)
    scores.append(score)
    print(f"n_estimators={n}, Accuracy={score:.4f}")
    if score > best_score:
        best_score = score
        best_n = n
print(f"\nBest Accuracy: {best_score:.4f} using {best_n} estimators")
# Plot accuracy vs number of estimators
plt.figure(figsize=(7, 4))
plt.plot(estimators_range, scores, marker='o', linestyle='-', color='blue')
plt.title("Accuracy vs Number of Estimators (AdaBoost)")
plt.xlabel("Number of Estimators (Trees)")
plt.ylabel("Accuracy")
plt.grid(True)
plt.xticks(estimators_range)
plt.tight_layout()
plt.show()
```

PROGRAM 10 Build k-Means algorithm to cluster a set of data stored in a .CSV file.

Screenshot



Lab – 10

K – Means

Partition data into k clusters by :

1. Randomly initializing centroids
2. Assigning points to the nearest centroid
3. Updating centroids based on assigned points
4. Repeating until convergence

→ Choosing number of clusters

- Elbow Method
- Silhouette Score
- Domain Knowledge

→ Sum of squared errors

SSE = i = 1 Σ k x ∈ Ci Σ || x − μi ||²

→ Key Parameter

n_cluster	No. of clusters to form
init	initialization method
n_init	No. of initialization
max_iter	max iteration per run
random_state	Control randomness
tol	Convergence threshold
algorithm	algorithm to use

Code

import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans

from sklearn.metrics import accuracy_score

```
from scipy.stats import mode
import matplotlib.pyplot as plt

# Step 1: Generate sample data and save to CSV
np.random.seed(42)
names = [f"Person_{i}" for i in range(50)]
ages = np.random.randint(20, 60, 50)
income = np.random.randint(30000, 120000, 50)

df = pd.DataFrame({'Name': names, 'Age': ages, 'Income': income})
df.to_csv("income.csv", index=False)

# Step 2: Load the data
data = pd.read_csv("income.csv")

# Drop 'Name' and extract features
X = data[['Age', 'Income']]

# Step 3: Split the data
X_train, X_test = train_test_split(X, test_size=0.2, random_state=42)

# Step 4: Perform scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
```

```
X_test_scaled = scaler.transform(X_test)

# Step 5: Plot SSE vs number of clusters (Elbow method)
sse = []
k_range = range(1, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_train_scaled)
    sse.append(kmeans.inertia_)

plt.figure(figsize=(8, 4))
plt.plot(k_range, sse, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('SSE (Inertia)')
plt.title('Elbow Method For Optimal k')
plt.grid(True)
plt.show()

# Step 6: Choose optimal number of clusters (say 3) and fit model
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans.fit(X_train_scaled)

# Predict on test data
```

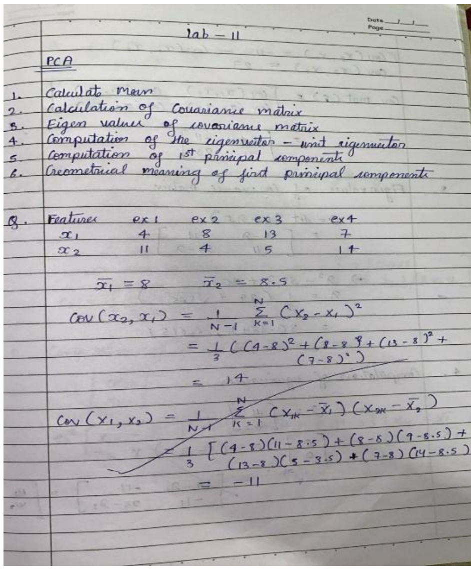
```
predictions = kmeans.predict(X_test_scaled)


# Note: There's no ground truth labels, but for demonstration,
# we can try assigning true clusters (via KMeans on full data)
# and see if predicted clusters align


# Fit on full data to assign pseudo-labels
full_kmeans = KMeans(n_clusters=optimal_k, random_state=42)
true_clusters = full_kmeans.fit_predict(scaler.fit_transform(X))


# Align predicted clusters using majority voting (only for demonstration)
# Match predicted labels to closest true labels
def map_clusters(true_labels, pred_labels):
    labels = np.zeros_like(pred_labels)
    for i in range(optimal_k):
        mask = (pred_labels == i)
        if np.sum(mask) == 0:
            continue
        labels[mask] = mode(true_labels[mask])[0]
    return labels


mapped_preds = map_clusters(true_clusters[X_test.index], predictions)
accuracy = accuracy_score(true_clusters[X_test.index], mapped_preds)
print(f"Approximate Clustering Accuracy: {accuracy:.2f}")
```

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

# Step 1: Load Iris dataset
iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['target'] = iris.target

# Keep only petal length and petal width
X = df[['petal length (cm)', 'petal width (cm)']].values

# Step 2: Check impact of scaling
# Try without scaling
sse_unscaled = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)
    sse_unscaled.append(kmeans.inertia_)
```

```
# Now scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

sse_scaled = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    sse_scaled.append(kmeans.inertia_)

# Step 3: Plot Elbow Comparison (Scaled vs Unscaled)
plt.figure(figsize=(10, 5))

plt.plot(range(1, 11), sse_unscaled, marker='o', label='Unscaled')
plt.plot(range(1, 11), sse_scaled, marker='s', label='Scaled')
plt.title('Elbow Method (Petal Features Only)')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('SSE (Inertia)')
plt.legend()
plt.grid(True)
plt.show()
```

PROGRAM 11 Implement Dimensionality reduction using Principal Component Analysis (PCA) method.

Screenshot



lab – 11

PCA

1. Calculate Mean
2. Calculation of Covariance matrix
3. Eigen values of covariance matrix
4. Computation of the eigenvector – unit eigenvector
5. Computation of 1st principal components
6. Geometrical meaning of first principal components

Q.

Features	ex 1	ex 2	ex 3	ex 4
x_1	4	8	13	7
x_2	11	4	5	14

$\bar{x}_1 = 8 \qquad \bar{x}_2 = 8.5$

$$\text{cov}(x_2, x_1) = \frac{1}{N-1} \sum_{K=1}^{N} (x_2 - x_1)^2$$

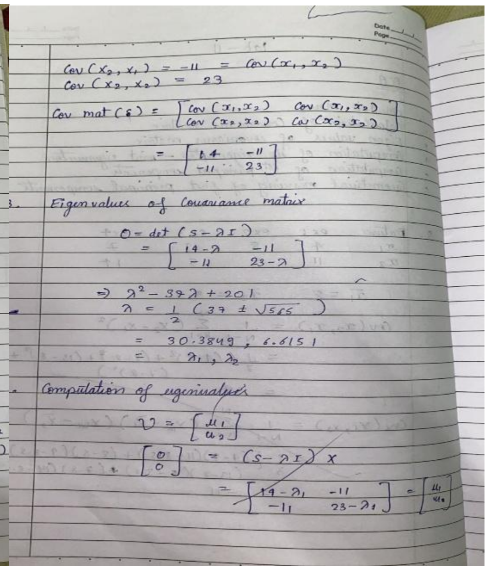
$$= \frac{1}{3}\left((4-8)^2 + (8-8)^2 + (13-8)^2 + (7-8)^2\right)$$

$$= 14$$

$$\text{cov}(x_1, x_2) = \frac{1}{N-1} \sum_{K=1}^{N} (x_{1K} - \bar{x}_1)(x_{2K} - \bar{x}_2)$$

$$= \frac{1}{3}\left[(4-8)(11-8.5) + (8-8)(4-8.5) + (13-8)(5-8.5) + (7-8)(14-8.5)\right]$$

$$= -11$$



$\text{cov}(x_2, x_1) = -11 = \text{cov}(x_1, x_2)$

$\text{cov}(x_2, x_2) = 23$

$$\text{Cov mat}(S) = \begin{bmatrix} \text{cov}(x_1, x_2) & \text{cov}(x_1, x_2) \\ \text{cov}(x_2, x_2) & \text{cov}(x_2, x_2) \end{bmatrix}$$

$$= \begin{bmatrix} 14 & -11 \\ -11 & 23 \end{bmatrix}$$

3. Eigenvalues of Covariance matrix

$$0 = \det(S - \lambda I)$$

$$= \begin{bmatrix} 14-\lambda & -11 \\ -11 & 23-\lambda \end{bmatrix}$$

$$\Rightarrow \lambda^2 - 37\lambda + 201$$

$$\lambda = \frac{1}{2}\left(37 \pm \sqrt{565}\right)$$

$$= 30.3849,\ 6.6151$$

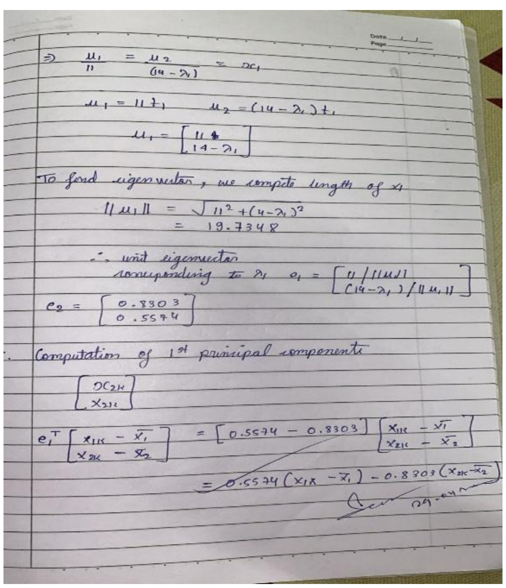
$$= \lambda_1, \lambda_2$$

Computation of eigenvalues

$$v = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = (S - \lambda I)\, x$$

$$= \begin{bmatrix} 14-\lambda_1 & -11 \\ -11 & 23-\lambda_1 \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$



$$\Rightarrow \frac{u_1}{11} = \frac{u_2}{(14-\lambda_1)} = x_1$$

$u_1 = 11 t_1 \qquad u_2 = (14-\lambda_1) t_1$

$$u_1 = \begin{bmatrix} 11 \\ 14-\lambda_1 \end{bmatrix}$$

To find eigenvector, we compute length of x_1

$$\|u_1\| = \sqrt{11^2 + (4-\lambda_1)^2}$$

$$= 19.7348$$

∴ unit eigenvector corresponding to λ_1 $\quad e_1 = \begin{bmatrix} 11/\|u_1\| \\ (14-\lambda_1)/\|u_1\| \end{bmatrix}$

$$e_2 = \begin{bmatrix} 0.8303 \\ 0.5574 \end{bmatrix}$$

Computation of 1st principal components

$$\begin{bmatrix} x_{2K} \\ x_{2K} \end{bmatrix}$$

$$e_1^T \begin{bmatrix} x_{1K} - \bar{x}_1 \\ x_{2K} - \bar{x}_2 \end{bmatrix} = \begin{bmatrix} 0.5574 & -0.8303 \end{bmatrix} \begin{bmatrix} x_{1K} - \bar{x}_1 \\ x_{2K} - \bar{x}_2 \end{bmatrix}$$

$$= 0.5574(x_{1K} - \bar{x}_1) - 0.8303(x_{2K} - \bar{x}_2)$$

Code

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score

# 1. Load data
df = pd.read_csv("heart.csv")

# 2. Label-encode binary text columns
le = LabelEncoder()
for col in ["Sex", "ExerciseAngina"]:
    df[col] = le.fit_transform(df[col])

# 3. Separate features and target
X = df.drop("HeartDisease", axis=1)
y = df["HeartDisease"]
```

```
# 4. Build preprocessing pipeline:
#    - One-hot for multi-category columns (using sparse_output=False)
#    - passthrough the rest
#    - then scale everything
cat_cols = ["ChestPainType", "RestingECG", "ST_Slope"]
preprocessor = Pipeline([
    ("onehot", ColumnTransformer([
        ("ohe", OneHotEncoder(sparse_output=False, drop="first"), cat_cols)
    ], remainder="passthrough")),
    ("scaler", StandardScaler())
])

# 5. Apply preprocessing
X_proc = preprocessor.fit_transform(X)

# 6. Train/test split
X_train, X_test, y_train, y_test = train_test_split(
    X_proc, y, test_size=0.2, random_state=42
)

# 7. Define models
models = {
    "SVM": SVC(random_state=42),
    "LogisticRegression": LogisticRegression(max_iter=1000, random_state=42),
```

```
    "RandomForest": RandomForestClassifier(random_state=42)
}

# 8. Train & evaluate before PCA
print("=== Accuracies BEFORE PCA ===")
scores_before = {}
for name, clf in models.items():
    clf.fit(X_train, y_train)
    preds = clf.predict(X_test)
    acc = accuracy_score(y_test, preds)
    scores_before[name] = acc
    print(f"{name:17s}: {acc:.4f}")

# 9. Apply PCA (retain 95% variance)
pca = PCA(n_components=0.95, random_state=42)
X_train_pca = pca.fit_transform(X_train)
X_test_pca  = pca.transform(X_test)
print(f"\nPCA retained {pca.n_components_} components, "
      f"explained variance = {pca.explained_variance_ratio_.sum():.4f}\n")
# 10. Train & evaluate after PCA
print("=== Accuracies AFTER PCA ===")
scores_after = {}
for name, clf in models.items():
    clf.fit(X_train_pca, y_train)
```

```
preds = clf.predict(X_test_pca)

acc = accuracy_score(y_test, preds)

scores_after[name] = acc

print(f"{name:17s}: {acc:.4f}")
```