VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

SANTOSH B (1BM22CS243)

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 **Santosh B (1BM22CS243),** who is a 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.

Lab Faculty Incharge	
Name: **Ms. Saritha A N** Assistant Professor Department of CSE, BMSCE	**Dr. Kavitha Sooda** Professor & HOD Department of CSE, BMSCE

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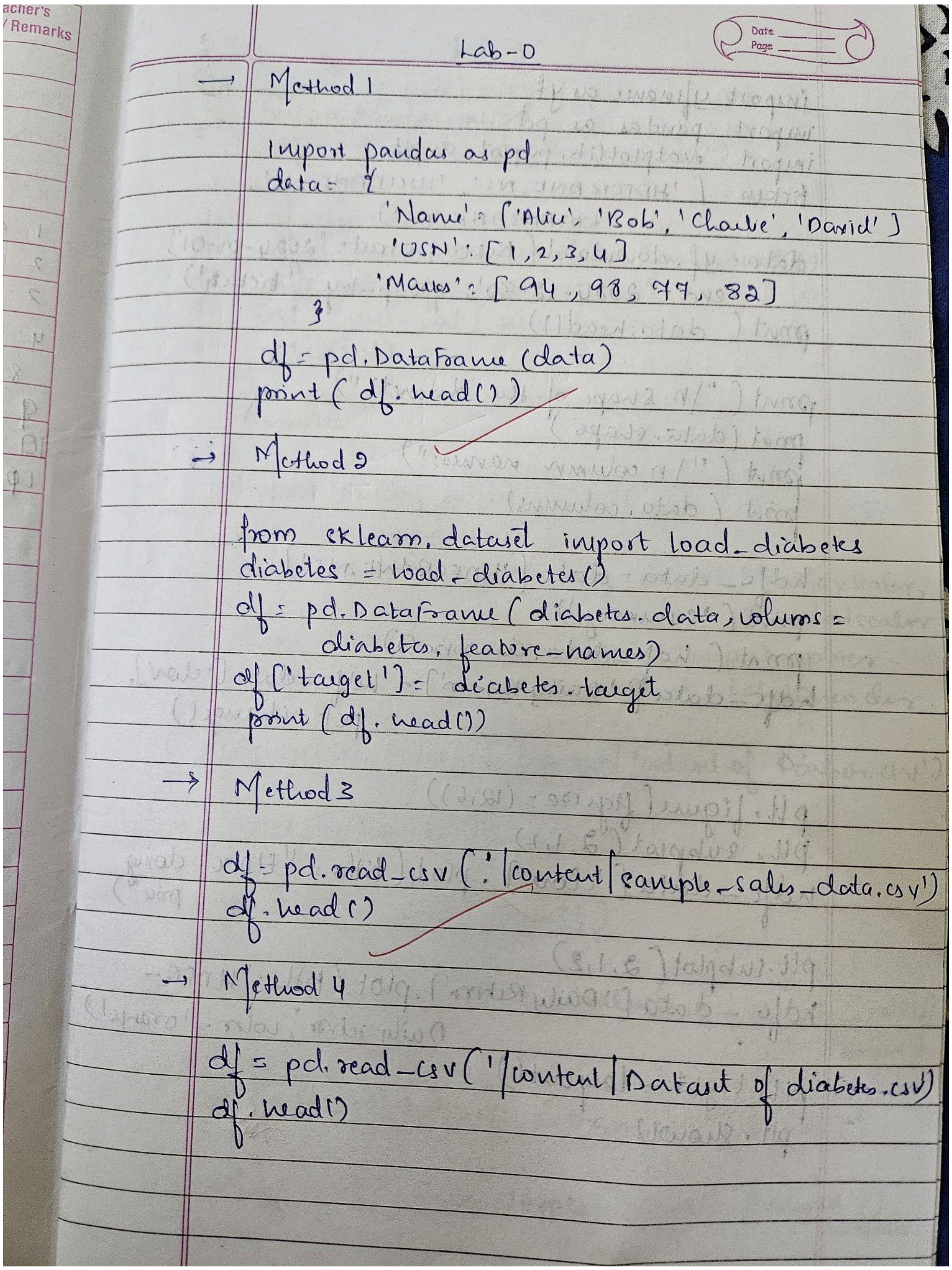
Github Link:

https://github.com/Santoshb2004/ML

Program 1

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

Screenshot



Lab-0

→ Method 1

```
import pandas as pd
data = {
        'Name': ['Alice', 'Bob', 'Charlie', 'David']
        'USN': [1,2,3,4]
        'Marks': [94, 98, 77, 82]
    }
df = pd.DataFrame (data)
print ( df.head() )
```

→ Method 2

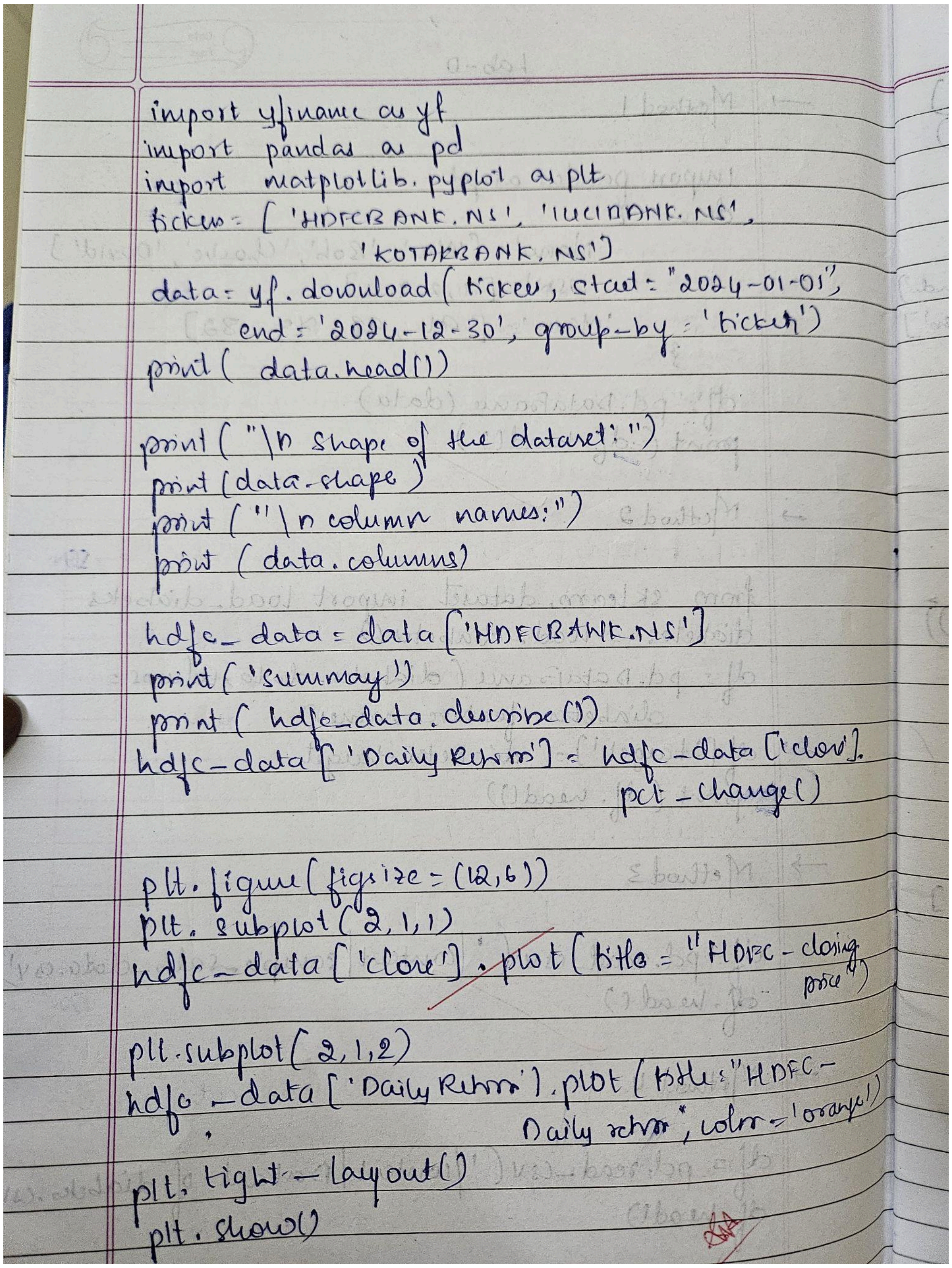
```
from sklearn.dataset import load_diabetes
diabetes = load_diabetes()
df = pd.DataFrame( diabetes.data, columns =
        diabetes.feature_names)
df['target'] = diabetes.target
print (df.head())
```

→ Method 3

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

→ Method 4

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



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

print("\n Shape of the dataset:")
print(data.shape)
print("\n column names:")
print (data.columns)

hdfc_data = data['HDFCBANK.NS']
print('summary')
print( hdfc_data.describe())
hdfc_data['Daily Return'] = hdfc_data['close'].
                               pct_change()

plt.figure(figsize=(12,6))
plt.subplot(2,1,1)
hdfc_data['close'].plot(title = "HDFC - closing
                                   price")

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

plt.tight_layout()
plt.show()
```

Code:

```
from sklearn.datasets import load_iris
import pandas as pd


iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['target'] = iris.target
```

```
print("sample data: ")
df.head()

# method 1
data = {
    'USN': ['A001', 'A002', 'A003', 'A004'],
    'Name': ['Amar', 'Akbar', 'Anthony', 'Venky'],
    'Marks': [34, 30, 31, 32]
}

df2 = pd.DataFrame(data)
df2

# method 2
from sklearn.datasets import load_diabetes
import pandas as pd

diabetes = load_diabetes()
df = pd.DataFrame(diabetes.data, columns=diabetes.feature_names)
df['target'] = diabetes.target
print("sample data: ")
df.head()
# method 3

# Load data from a CSV file (replace 'data.csv' with your file path)
file_path = '/content/industry.csv' # Ensure the file exists in the same
directory
df2 = pd.read_csv(file_path)
print("Sample data:")
df2.head()

# method 4

file_path = '/content/Dataset of Diabetes .csv'
data3 = pd.read_csv(file_path)
df3 = pd.DataFrame(data3)

df3

#Using the code given in the above slides, do the exercise of the “Stock
Market Data Analysis”, considering the follwoing
```

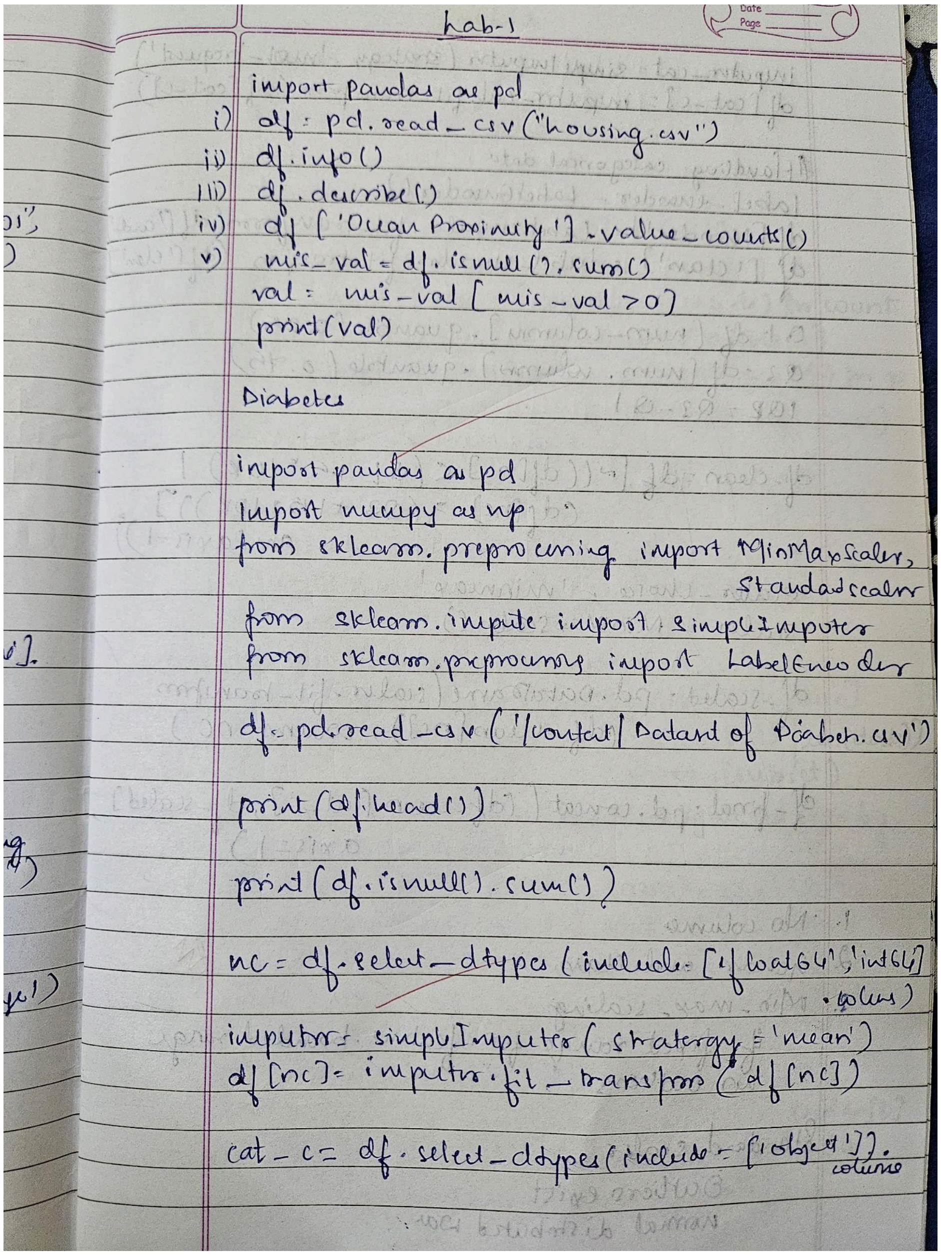
```
# 1. HDFC Bank Ltd. , ICICI Bank Ltd , Kotak Mahindra Bank Ltd.
# tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
# 2. Start date: 2024-01-01, End date: 2024-12-30

import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30",
group_by='ticker')
print("First 5 rows of the dataset:")
data.head()

print("\nShape of the dataset:")
print(data.shape)
print("\nColumn names:")
print(data.columns)
hdfc_data = data['HDFCBANK.NS']
print("\nSummary statistics for Reliance Industries:")
print(hdfc_data.describe())
hdfc_data['Daily Return'] = hdfc_data['Close'].pct_change()

# icici bank
icici_data = data['ICICIBANK.NS']
print(hdfc_data.describe())
icici_data['Daily Return'] = icici_data['Close'].pct_change()

# Kotak bank
kotak_data = data['KOTAKBANK.NS']
print(hdfc_data.describe())
kotak_data['Daily Return'] = kotak_data['Close'].pct_change()

plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
hdfc_data['Close'].plot(title="HDFC bank - Closing Price")
plt.subplot(2, 1, 2)
hdfc_data['Daily Return'].plot(title="HDFC bank - Daily Returns",
color='orange')
plt.tight_layout()
plt.show()
```

```
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
icici_data['Close'].plot(title="ICICI bank - Closing Price")
plt.subplot(2, 1, 2)
icici_data['Daily Return'].plot(title="ICICI bank - Daily Returns",
color='orange')
plt.tight_layout()
plt.show()

plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
kotak_data['Close'].plot(title="KOTAK bank - Closing Price")
plt.subplot(2, 1, 2)
kotak_data['Daily Return'].plot(title="KOTAK bank - Daily Returns",
color='orange')
plt.tight_layout()
plt.show()

# Save the Reliance data to a CSV file

hdfc_data.to_csv('hdfc_stock_data.csv')
icici_data.to_csv('icici_stock_data.csv')
kotak_data.to_csv('kotak_stock_data.csv')
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshot



Lab-1

```
import pandas as pd
i)   df = pd.read_csv("housing.csv")
ii)  df.info()
iii) df.describe()
iv)  df ['Ocean Proximity'] .value_counts()
v)   mis_val = df.isnull().sum()
     val = mis_val [ mis_val > 0 ]
     print(val)
```

Diabetes

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

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

print(df.head())

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

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

imputer = SimpleImputer ( strategy = 'mean')
df [nc] = imputer.fit_transform (df [nc])

cat_c = df.select_dtypes(include = ['object']).
                                          columns
```

```
imputer_cat = SimpleImputer(strategy='most_frequent')
df[cat_c] = imputer_cat.fit_transform(df[cat_c])

#Handling categorical data
label_encoder = LabelEncoder()
df['Gender'] = label_encoder.fit_transform(df['Gender'])
df['class'] = label_encoder.fit_transform(df['class'])

Q1 = df[num_columns].quantile(0.25)
Q3 = df[num_columns].quantile(0.75)
IQR = Q3 - Q1

df_clean = df[~((df[nc] < (Q1 - 1.5 * IQR)) |
                (df[nc] > (Q3 + 1.5 * IQR)))
                         .any(axis=1)]

scaler_choice = 'minmax'
scaler = MinMaxScaler()

df_scaled = pd.DataFrame(scaler.fit_transform
              (df_clean[nc]), columns=nc)

df_final = pd.concat([df_clean[cat_c], df_scaled],
                        axis=1)
```

1. No columns
2. Gender and class
3. Min_max_scaling
   if fixed range for feature bounded range
   no outliers

Standard scaler
   Outliers exist
   normal distributed data

code:

```
# -*- coding: utf-8 -*-
"""LAB-1.ipynb

Automatically generated by Colab.

Original file is located at
```

```
    https://colab.research.google.com/drive/1LFiPSjr6wkzvYXycyOlrEerHW0HtTTl2
"""

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

def createdata():
  data = {
      'Age': np.random.randint(18, 70, size=20),
      'Salary': np.random.randint(30000, 120000, size=20),
      'Purchased': np.random.choice([0, 1], size=20),
      'Gender': np.random.choice(['Male', 'Female'], size=20),
      'City': np.random.choice(['New York', 'San Francisco', 'Los Angeles'],
size=20)
  }

  df = pd.DataFrame(data)
  return df

df = createdata()
df.head(10)

df.shape

# Introduce some missing values for demonstration
df.loc[5, 'Age'] = np.nan
df.loc[10, 'Salary'] = np.nan
df.head(10)

# Basic information about the dataset
print(df.info())

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

```
#Code to Find Missing Values
# Check for missing values in each column
missing_values = df.isnull().sum()

# Display columns with missing values
print(missing_values[missing_values > 0])

#Set the values to some value (zero, the mean, the median, etc.).
# Step 1: Create an instance of SimpleImputer with the median strategy for
Age and mean stratergy for Salary
imputer1 = SimpleImputer(strategy="median")
imputer2 = SimpleImputer(strategy="mean")

df_copy=df

# Step 2: Fit the imputer on the "Age" and "Salary"column
# Note: SimpleImputer expects a 2D array, so we reshape the column
imputer1.fit(df_copy[["Age"]])
imputer2.fit(df_copy[["Salary"]])

# Step 3: Transform (fill) the missing values in the "Age" and "Salary"c
column
df_copy["Age"] = imputer1.transform(df[["Age"]])
df_copy["Salary"] = imputer2.transform(df[["Salary"]])

# Verify that there are no missing values left
print(df_copy["Age"].isnull().sum())
print(df_copy["Salary"].isnull().sum())

#Handling Categorical Attributes
#Using Ordinal Encoding for gender COlumn and One-Hot Encoding for City
Column# Initialize OrdinalEncoder
ordinal_encoder = OrdinalEncoder(categories=[["Male", "Female"]])
# Fit and transform the data
df_copy["Gender_Encoded"] =
ordinal_encoder.fit_transform(df_copy[["Gender"]])

# Initialize OneHotEncoder
onehot_encoder = OneHotEncoder()

# Fit and transform the "City" column
```

```
encoded_data = onehot_encoder.fit_transform(df[["City"]])

# Convert the sparse matrix to a dense array
encoded_array = encoded_data.toarray()

# Convert to DataFrame for better visualization
encoded_df = pd.DataFrame(encoded_array,
columns=onehot_encoder.get_feature_names_out(["City"]))
df_encoded = pd.concat([df_copy, encoded_df], axis=1)

df_encoded.drop("Gender", axis=1, inplace=True)
df_encoded.drop("City", axis=1, inplace=True)

df_encoded. head()

#Data Transformation
# Min-Max Scaler/Normalization (range 0-1)
#Pros: Keeps all data between 0 and 1; ideal for distance-based models.
#Cons: Can distort data distribution, especially with extreme outliers.
normalizer = MinMaxScaler()
df_encoded[['Salary']] = normalizer.fit_transform(df_encoded[['Salary']])
df_encoded.head()

# Standardization (mean=0, variance=1)
#Pros: Works well for normally distributed data; suitable for many models.
#Cons: Sensitive to outliers.
scaler = StandardScaler()
df_encoded[['Age']] = scaler.fit_transform(df_encoded[['Age']])
df_encoded.head()

#Removing Outliers
# Outlier Detection and Treatment using IQR.
#Pros: Simple and effective for mild outliers.
#Cons: May overly reduce variation if there are many extreme outliers.
df_encoded_copy1=df_encoded
df_encoded_copy2=df_encoded
df_encoded_copy3=df_encoded

Q1 = df_encoded_copy1['Salary'].quantile(0.25)
Q3 = df_encoded_copy1['Salary'].quantile(0.75)
IQR = Q3 - Q1
```

```
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df_encoded_copy1['Salary'] = np.where(df_encoded_copy1['Salary'] >
upper_bound, upper_bound,
                        np.where(df_encoded_copy1['Salary'] < lower_bound,
lower_bound, df_encoded_copy1['Salary']))

df_encoded_copy1.head()

#Removing Outliers
# Z-score method
#Pros: Good for normally distributed data.
#Cons: Not suitable for non-normal data; may miss outliers in skewed
distributions.

df_encoded_copy2['Salary_zscore'] = stats.zscore(df_encoded_copy2['Salary'])
df_encoded_copy2['Salary'] = np.where(df_encoded_copy2['Salary_zscore'].abs()
> 3, np.nan, df_encoded_copy2['Salary'])  # Replace outliers with NaN
df_encoded_copy2.head()

#Removing Outliers
# Median replacement for outliers
#Pros: Keeps distribution shape intact, useful when capping isn't feasible.
#Cons: May distort data if outliers represent real phenomena.
df_encoded_copy3['Salary_zscore'] = stats.zscore(df_encoded_copy3['Salary'])
median_salary = df_encoded_copy3['Salary'].median()
df_encoded_copy3['Salary'] = np.where(df_encoded_copy3['Salary_zscore'].abs()
> 3, median_salary, df_encoded_copy3['Salary'])
df_encoded_copy3.head()

'''
At the start of the Lab,  in the Observation book, Write python code for the
following considering  filename as "housing.csv"
 i. To load .csv file into the data frame
ii. To display information of all columns
iii. To display statistical information of all numerical
iv. To display the count of unique labels for "Ocean Proximity" column
v. To display which attributes (columns) in a dataset have missing values
count greater than zero
Step-2: Show the observation book to lab batch faculty incharge.
Step-3: Do the "To Do" tasks given in the PPT
```

```
Step-4: At the end of the lab,
i. Write the answers for questions given in the PPT and show it to  lab batch
faculty incharge
ii. Should upload the code in your respective GitHub account.
File name format:yourUSN_Lab-1-DataProcessing.ipynb
'''

filename = "/content/housing (1).csv"
df = pd.read_csv(filename)

print("Dataset Information:")
print(df.info())

print("\nStatistical Summary of Numerical Columns:")
print(df.describe())

if "ocean_proximity" in df.columns:
    print("\nUnique Value Counts for 'Ocean Proximity':")
    print(df["ocean_proximity"].value_counts())
else:
    print("\n'Ocean Proximity' column not found in the dataset.")

missing_values = df.isnull().sum()
missing_columns = missing_values[missing_values > 0]

if not missing_columns.empty:
    print("\nColumns with Missing Values:")
    print(missing_columns)
else:
    print("\nNo missing values found in the dataset.")

data2 = pd.read_csv("/content/Dataset_with_Nulls.csv")
data2.head()

data2.info()

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,
StandardScaler, MinMaxScaler
from scipy import stats

# Load dataset
file_path = "/content/Dataset_with_Nulls.csv"
df = pd.read_csv(file_path)

### Step 1: Handling Missing Values ###
# Identify missing values
print("Missing values before handling:\n", df.isnull().sum())

# Handling missing numerical columns - Median for 'Age', Mean for other
numerical values
num_imputer_median = SimpleImputer(strategy="median")
num_imputer_mean = SimpleImputer(strategy="mean")

df["AGE"] = num_imputer_median.fit_transform(df[["AGE"]])
for col in ["Urea", "Cr", "HbA1c", "Chol", "TG", "HDL", "LDL", "VLDL",
"BMI"]:
    df[col] = num_imputer_mean.fit_transform(df[[col]])

# Convert categorical columns to string type
df["Gender"] = df["Gender"].astype(str)
df["CLASS"] = df["CLASS"].astype(str)

# Handling missing categorical columns - Fill with Mode
cat_imputer = SimpleImputer(strategy="most_frequent")

df["Gender"] = cat_imputer.fit_transform(df[["Gender"]]).ravel()
df["CLASS"] = cat_imputer.fit_transform(df[["CLASS"]]).ravel()

print("Missing values after handling:\n", df.isnull().sum())

### Step 2: Handling Categorical Attributes ###
# Encode 'Gender' using Ordinal Encoding (Male = 0, Female = 1)
ordinal_encoder = OrdinalEncoder(categories=[["Male", "Female"]])
df['Gender'] = df['Gender'].replace({'F': 'Female', 'f': 'Female', 'M':
'Male'})  # Handle variations
# Replace NaN with Mode (most frequent) for Gender
df['Gender'] = df['Gender'].fillna(df['Gender'].mode()[0]) # Fill na with
```

```
mode if any

# Now apply ordinal encoding
ordinal_encoder = OrdinalEncoder(categories=[["Male", "Female"]])
# One-Hot Encoding for 'CLASS'
onehot_encoder = OneHotEncoder(sparse_output=False)
class_encoded = onehot_encoder.fit_transform(df[["CLASS"]])

# Convert to DataFrame
class_encoded_df = pd.DataFrame(class_encoded,
columns=onehot_encoder.get_feature_names_out(["CLASS"]))

# Merge One-Hot Encoded Data and drop original categorical columns
df = pd.concat([df, class_encoded_df], axis=1)
df.drop(["Gender", "CLASS"], axis=1, inplace=True)

### Step 3: Data Transformation ###
# Min-Max Scaling for Salary
minmax_scaler = MinMaxScaler()
df[["Urea", "Cr", "HbA1c", "Chol", "TG", "HDL", "LDL", "VLDL", "BMI"]] =
minmax_scaler.fit_transform(
    df[["Urea", "Cr", "HbA1c", "Chol", "TG", "HDL", "LDL", "VLDL", "BMI"]]
)

# Standardization for Age
standard_scaler = StandardScaler()
df[["AGE"]] = standard_scaler.fit_transform(df[["AGE"]])

### Step 4: Removing Outliers ###
# IQR Method for 'Salary' (Replacing Outliers with Boundaries)
for col in ["Urea", "Cr", "HbA1c", "Chol", "TG", "HDL", "LDL", "VLDL",
"BMI"]:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df[col] = np.where(df[col] > upper_bound, upper_bound, np.where(df[col] <
lower_bound, lower_bound, df[col]))

# Z-score method for 'AGE' (Replacing Outliers with NaN)
```

```
df["AGE_zscore"] = stats.zscore(df["AGE"])
df["AGE"] = np.where(df["AGE_zscore"].abs() > 3, np.nan, df["AGE"])

# Median Replacement for Outliers in 'AGE'
median_age = df["AGE"].median()
df["AGE"] = np.where(df["AGE"].isnull(), median_age, df["AGE"])

# Drop auxiliary columns
df.drop(columns=["AGE_zscore"], inplace=True)

df

print("Preprocessing Complete. Cleaned dataset saved!")
```

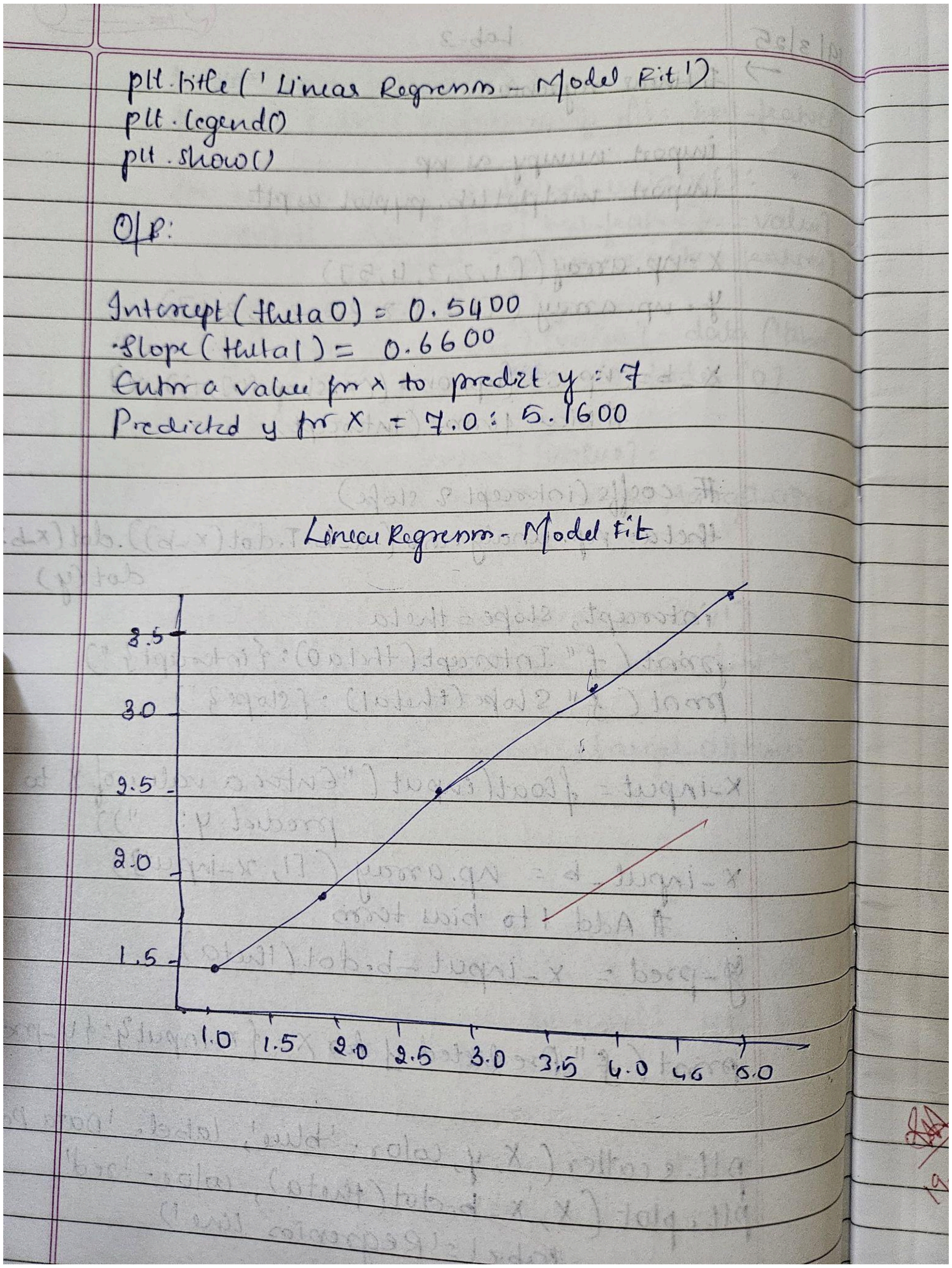
Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot

19/3/25 Lab-3

```
# Linear regression.

import numpy as np
import matplotlib.pyplot as plt

X = np.array([1,2,3,4,5])
y = np.array([1.2, 1.8, 2.6, 3.2, 3.8])

X_b = np.c_[np.ones((X.shape[0], 1)), X]
      # bias term (intercept)

# coeffs (intercept & slope)
theta = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).
                                         dot(y)
intercept, slope = theta
print(f"Intercept(theta0): {intercept} ")
print(f"Slope (theta1) : {slope}")

x_input = float(input("Enter a value of X to
                      predict y:  "))
x_input_b = np.array([1, x_input])
    # Add 1 to bias term
y_pred = x_input_b.dot(theta)

print(f"Predicted y for X = {x_input}: {y_pred}")

plt.scatter(X, y, color='blue', label='Data Points')
plt.plot(X, X_b.dot(theta), color='red',
         label='Regression line')
plt.xlabel('x')
plt.ylabel('y')
```



```
plt.title('Linear Regression - Model Fit')
plt.legend()
plt.show()
```

O/P:

```
Intercept (theta0) = 0.5400
Slope (theta1) = 0.6600
Enter a value for x to predict y: 7
Predicted y for x = 7.0: 5.1600
```


code:

```
import numpy as np
import matplotlib.pyplot as plt

def estimate_coef(x, y):
    # number of observations/points
    n = np.size(x)
```

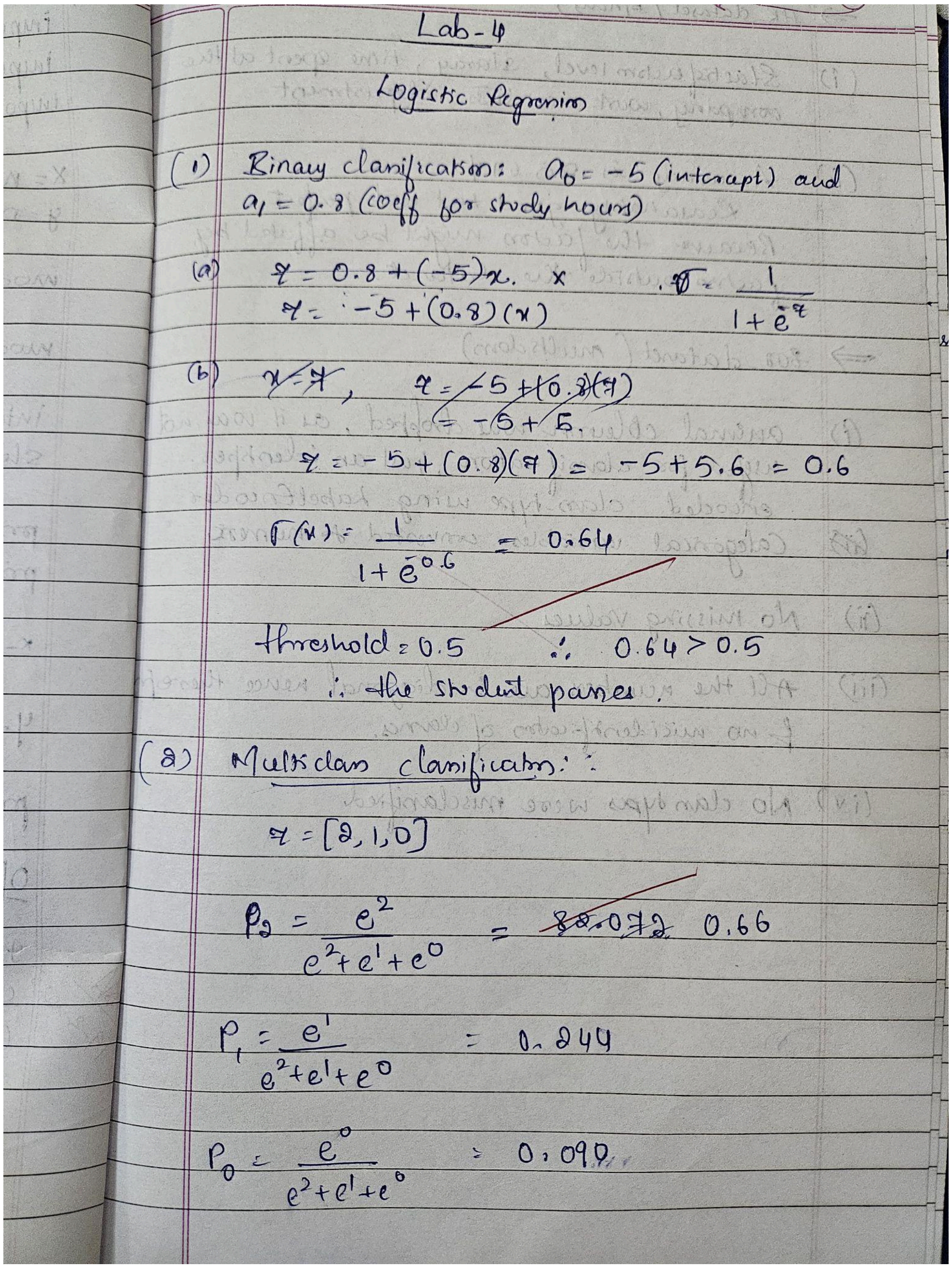
```
    # mean of x and y vector
    m_x = np.mean(x)
    m_y = np.mean(y)

    # calculating cross-deviation and deviation about x
    SS_xy = np.sum((x - m_x) * (y - m_y))
    SS_xx = np.sum((x - m_x) ** 2)

    # calculating regression coefficients
    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1 * m_x

    return (b_0, b_1)

def plot_regression_line(x, y, b):
    # plotting the actual points as scatter plot
    plt.scatter(x, y, color="m", marker="o", s=30)

    # predicted response vector
    y_pred = b[0] + b[1] * x

    # plotting the regression line
    plt.plot(x, y_pred, color="g")

    # putting labels
    plt.xlabel('x')
    plt.ylabel('y')
    plt.title("Linear Regression")
    plt.show()

x = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
y = np.array([1, 3, 2, 5, 7, 8, 8, 9, 10, 12])

# estimating coefficients
b = estimate_coef(x, y)
print(f"Estimated coefficients:\nb_0 = {b[0]} \nb_1 = {b[1]}")

# plot regression line
plot_regression_line(x, y, b)
```

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

def estimate_coef(x, y):
    n = np.size(x)
    m_x = np.mean(x)
    m_y = np.mean(y)
    SS_xy = np.sum((x - m_x) * (y - m_y))
    SS_xx = np.sum((x - m_x) ** 2)
    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1 * m_x
    return (b_0, b_1)

def plot_regression_line(x, y, b):
    plt.scatter(x, y, color="m", marker="o", s=30)
    y_pred = b[0] + b[1] * x
    plt.plot(x, y_pred, color="g")
    plt.xlabel('x')
    plt.ylabel('y')
    plt.title("Linear Regression")
    plt.show()

# Load dataset
file_path = input("Enter the path to the CSV file: ")
df = pd.read_csv(file_path)

# Assuming the dataset has two numerical columns: 'x' and 'y'
x = df.iloc[:, 0].values  # First column as x
y = df.iloc[:, 1].values  # Second column as y

b = estimate_coef(x, y)
print(f"Estimated coefficients:\nb_0 = {b[0]} \nb_1 = {b[1]}")
plot_regression_line(x, y, b)
```

Program 4

Build Logistic Regression Model for a given dataset

Screenshot



Lab-4

Logistic Regression

(1) Binary classification: $a_0 = -5$ (intercept) and $a_1 = 0.8$ (coeff for study hours)

(a) $\cancel{z = 0.8 + (-5)x}$ $\sigma = \frac{1}{1+e^{-z}}$

$z = -5 + (0.8)(x)$

(b) $\cancel{x = 7}$, $\cancel{z = -5 + (0.8)(7)}$ $\cancel{= -5 + 5.}$

$z = -5 + (0.8)(7) = -5 + 5.6 = 0.6$

$\sigma(x) = \frac{1}{1+e^{-0.6}} = 0.64$

threshold $= 0.5$ $\therefore$ $0.64 > 0.5$

$\therefore$ the student passes.

(2) Multiclass classification:

$z = [2, 1, 0]$

$P_2 = \frac{e^2}{e^2+e^1+e^0} = \cancel{88.072}\ 0.66$

$P_1 = \frac{e^1}{e^2+e^1+e^0} = 0.244$

$P_0 = \frac{e^0}{e^2+e^1+e^0} = 0.090$

code:

```
import numpy as np
import matplotlib.pyplot as plt
```

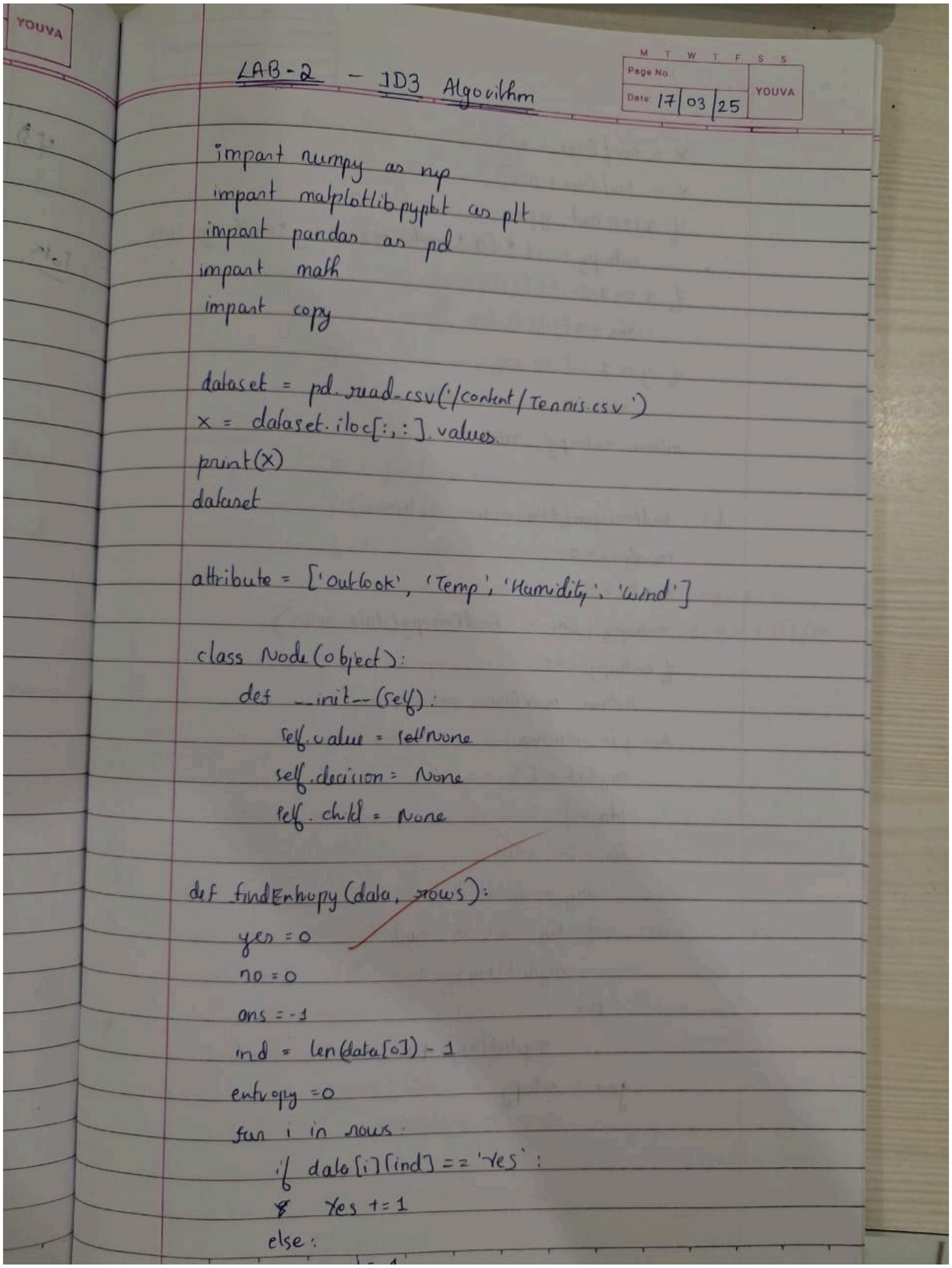
```python
def sigmoid(z):
    return 1 / (1 + np.exp(-z))

def compute_cost(X, y, theta):
    m = len(y)
    h = sigmoid(X @ theta)
    cost = (-1/m) * np.sum(y * np.log(h) + (1 - y) * np.log(1 - h))
    return cost

def gradient_descent(X, y, theta, alpha, iterations):
    m = len(y)
    cost_history = []

    for _ in range(iterations):
        gradient = (1/m) * X.T @ (sigmoid(X @ theta) - y)
        theta -= alpha * gradient
        cost_history.append(compute_cost(X, y, theta))

    return theta, cost_history

def predict(X, theta):
    return (sigmoid(X @ theta) >= 0.5).astype(int)

# Generate synthetic binary classification data
np.random.seed(42)
X = np.random.rand(100, 1) * 10  # Feature values between 0 and 10
y = (X > 5).astype(int).ravel()  # Label: 1 if X > 5, else 0

# Add intercept term
X_b = np.c_[np.ones((X.shape[0], 1)), X]

# Initialize parameters
theta = np.zeros(X_b.shape[1])
alpha = 0.1
iterations = 1000

# Train logistic regression using gradient descent
theta, cost_history = gradient_descent(X_b, y, theta, alpha, iterations)

# Make predictions
y_pred = predict(X_b, theta)
```

```
# Compute accuracy
accuracy = np.mean(y_pred == y)
print(f"Accuracy: {accuracy:.2f}")

# Plot the decision boundary
plt.scatter(X, y, color='blue', label='Actual Data')
plt.scatter(X, y_pred, color='red', marker='x', label='Predicted Labels')
plt.xlabel("Feature X")
plt.ylabel("Class (0 or 1)")
plt.legend()
plt.title("Logistic Regression Model (Without Scikit-learn)")
plt.show()
```

Program 5

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

Screenshot



LAB-2 - ID3 Algorithm

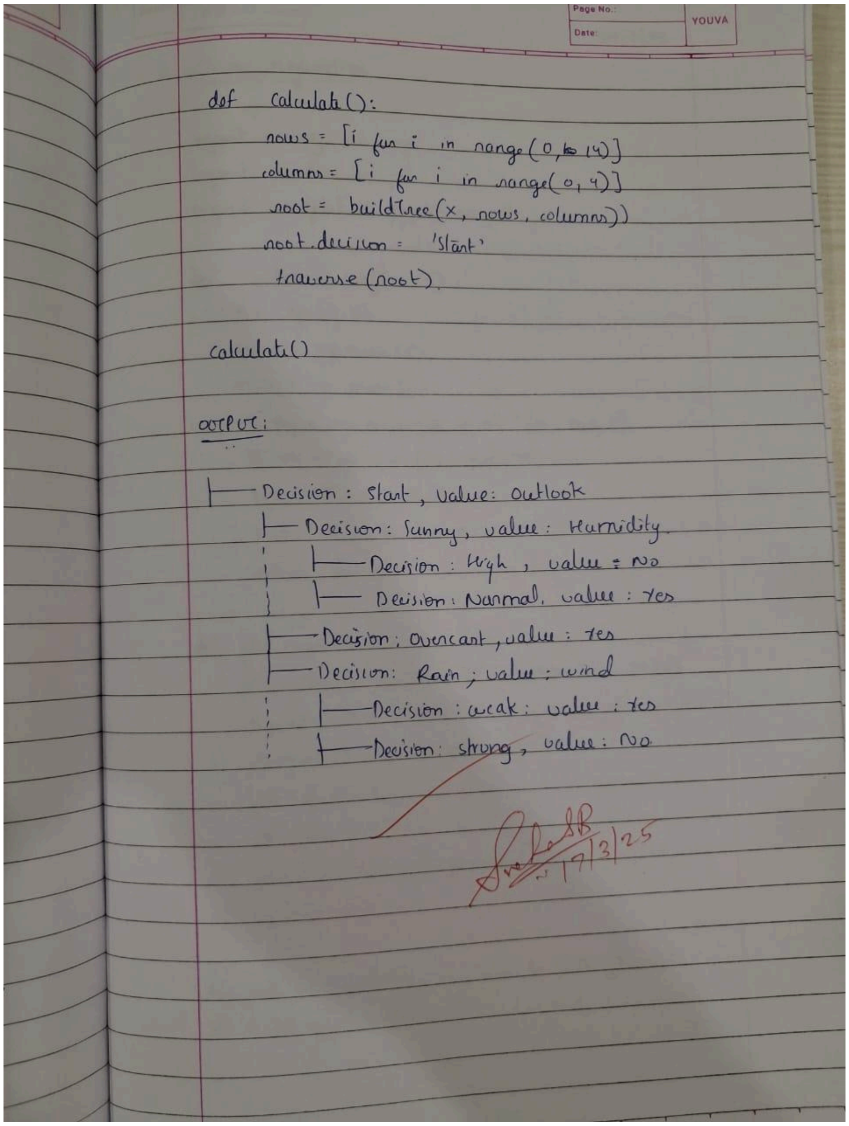
Date: 17/03/25

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import math
import copy

dataset = pd.read_csv('/content/Tennis.csv')
x = dataset.iloc[:,:].values
print(x)
dataset

attribute = ['Outlook', 'Temp', 'Humidity', 'wind']

class Node(object):
    def __init__(self):
        self.value = None
        self.decision = None
        self.child = None

def findEntropy(data, rows):
    yes = 0
    no = 0
    ans = -1
    ind = len(data[0]) - 1
    entropy = 0
    for i in rows:
        if data[i][ind] == 'Yes':
            yes += 1
        else:
```

og2 (y))

```
for key in mydict:
    yes = 0
    no = 0
    for k in rows:
        if data[k][j] == key:
            if data[k][-1] == 'Yes':
                yes += 1
            else:
                no += 1
    x = yes/(Yes+no)
    Y = no/(Yes+no)
    if x!=0 and y!=0:
        gain += (mydict[key] * (x*math.Log2(x) +
                                y*math.long2(y)))/14
if gain > maxGain:
    maxGain = gain
    retidx = j

return maxgain, retidx, ans

def buildTree(data, rows, columns):
    maxGain, idx, ans = findMaxGain(X, rows, columns)
    root = node()
    root.childs = []
    if maxGain == 0:
        if ans == 1:
            root.value = 'Yes'
        else:
            root.value = 'No'
        return root
```

```
x = Yes/(Yes + no)
y = No/(Yes + No)
if x!=0 and y!=0:
    entropy = -1 * (x * math.Log2(x) + y * math.log2(y))
if x == 1:
    ans = 1
if y == 1:
    ans = 0
return entropy, ans

def findMaxGain(data, rows, columns):
    maxGain = 0
    retidx = -1
    entropy, ans = findEntropy(data, rows)
    if entropy == 0:
        return maxGain, retidx, ans
    for j in columns:
        mydict = {}
        idx = j
        for i in rows:
            key = data[i][idx]
            if key not in mydict:
                mydict[key] = 1
            else:
                mydict[key] += 1
        gain = entropy
```



```
def calculate():
    rows = [i for i in range(0, 14)]
    columns = [i for i in range(0, 4)]
    root = buildTree(X, rows, columns)
    root.decision = 'Start'
    traverse(root)

calculate()
```

OUTPUT:

```
|—— Decision : Start , value: Outlook
    |—— Decision: Sunny, value: Humidity
    |   |—— Decision: High , value : No
    |   |—— Decision: Normal, value : Yes
    |—— Decision; Overcast ,value : Yes
    |—— Decision: Rain ; value : wind
    |   |—— Decision : weak : value : Yes
    |   |—— Decision: strong, value : No
```

17/3/25

code:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import math
import copy

dataset = pd.read_csv('/content/Tennis.csv')
X = dataset.iloc[:,:].values
print(X)

dataset

attribute = ['Outlook', 'Temp', 'Humidity', 'Wind']
```

```
class Node(object):
    def __init__(self):
        self.value = None
        self.decision = None
        self.child = None

def findEntropy(data, rows):
    yes=0
    no=0
    ans=-1
    idx=len(data[0])-1
    entropy=0

    for i in rows:
        if data[i][idx]=='Yes':
            yes=yes+1
        else:
            no=no+1

    x=yes/(yes+no)
    y=no/(yes+no)
    if x!=0 and y!=0:
        entropy= -1*(x*math.log2(x)+y*math.log2(y))
    if x==1:
        ans = 1
    if y==1:
        ans = 0
    return entropy, ans

def findMaxGain(data, rows, columns):
    maxGain = 0
    retidx = -1
    entropy, ans = findEntropy(data, rows)
    if entropy == 0:
        """if ans == 1:
            print("Yes")
        else:
            print("No")"""
        return maxGain, retidx, ans
    for j in columns:
```

```
        mydict = {}
        idx = j
        for i in rows:
            key = data[i][idx]
            if key not in mydict:
                mydict[key] = 1
            else:
                mydict[key] = mydict[key] + 1
        gain = entropy

        # print(mydict)
        for key in mydict:
            yes = 0
            no = 0
            for k in rows:
                if data[k][j] == key:
                    if data[k][-1] == 'Yes':
                        yes = yes + 1
                    else:
                        no = no + 1
            # print(yes, no)
            x = yes/(yes+no)
            y = no/(yes+no)
            # print(x, y)
            if x != 0 and y != 0:
                gain += (mydict[key] * (x*math.log2(x) + y*math.log2(y)))/14
        # print(gain)
        if gain > maxGain:
            # print("hello")
            maxGain = gain
            retidx = j

    return maxGain, retidx, ans

def buildTree(data, rows, columns):

    maxGain, idx, ans = findMaxGain(X, rows, columns)
    root = Node()
    root.childs = []
    # print(maxGain)
```

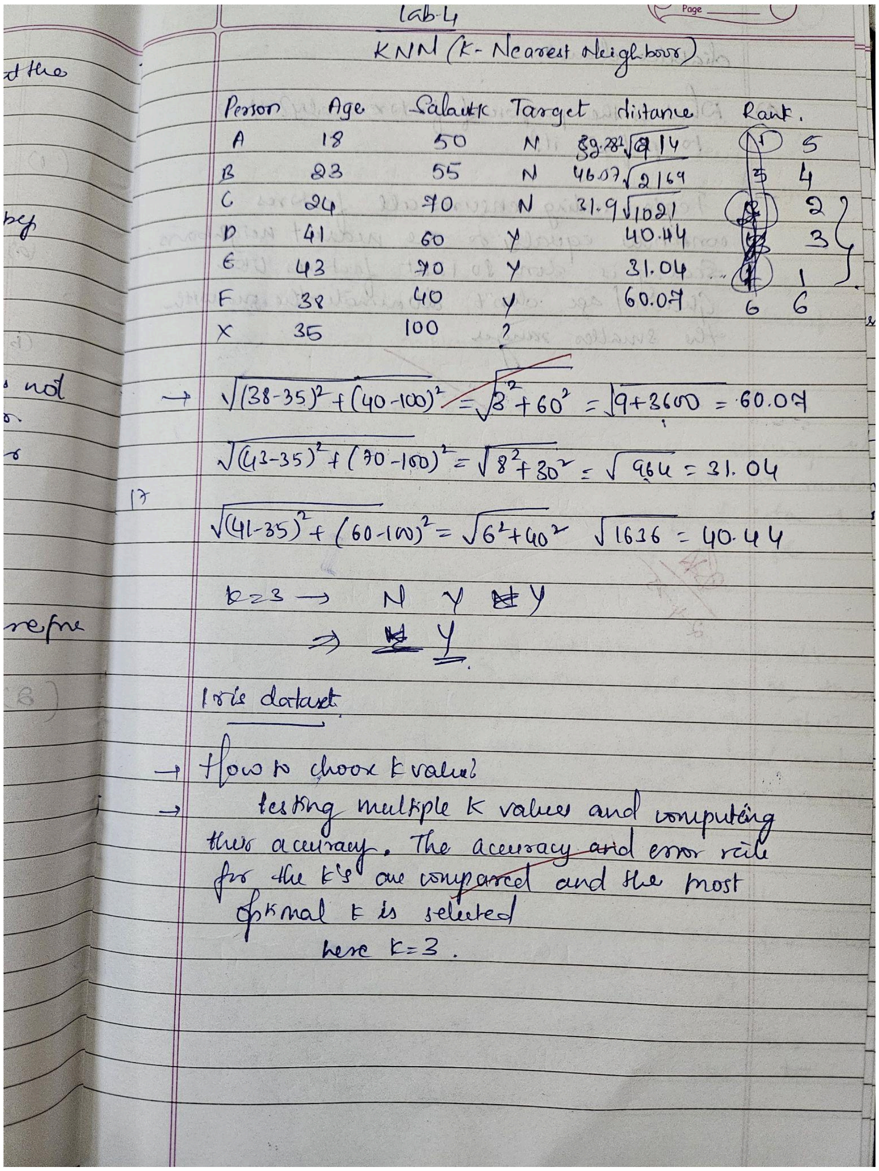
```
    if maxGain == 0:
        if ans == 1:
            root.value = 'Yes'
        else:
            root.value = 'No'
        return root

    root.value = attribute[idx]
    mydict = {}
    for i in rows:
        key = data[i][idx]
        if key not in mydict:
            mydict[key] = 1
        else:
            mydict[key] += 1

    newcolumns = copy.deepcopy(columns)
    newcolumns.remove(idx)
    for key in mydict:
        newrows = []
        for i in rows:
            if data[i][idx] == key:
                newrows.append(i)
        # print(newrows)
        temp = buildTree(data, newrows, newcolumns)
        temp.decision = key
        root.childs.append(temp)
    return root

def traverse(root, level=0):
    indent = "    " * level
    print(f"{indent}├── Decision: {root.decision}, Value: {root.value}")

    for i, child in enumerate(root.childs):
        # if i == len(root.childs) - 1:
        #     traverse(child, level + 1)
        # else:
        traverse(child, level + 1)

def calculate():
    rows = [i for i in range(0, 14)]
```

```
    columns = [i for i in range(0, 4)]
    root = buildTree(X, rows, columns)
    root.decision = 'Start'
    traverse(root)

calculate()

from graphviz import Source

dot_code = """
digraph G {
    edge [dir=forward]
    node [shape=box, style=bold]

    A [label="OUTLOOK"]
    B [label="HUMIDITY"]
    C [label="WIND"]

    D [label="NO", shape=plaintext]
    E [label="YES", shape=plaintext]
    F [label="YES", shape=plaintext]
    G [label="NO", shape=plaintext]

    A -> B [label="SUNNY"]
    A -> E [label="OVERCAST"]
    A -> C [label="RAIN"]

    B -> D [label="HIGH"]
    B -> F [label="NORMAL"]

    C -> F [label="WEAK"]
    C -> G [label="STRONG"]
}
"""

s = Source(dot_code, filename="decision_tree", format="png")
s.view()
```

Program 6

Build KNN Classification model for a given dataset

Screenshot



diabetes dataset.

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

→ Feature scaling ensures all features contribute equally to the nearest neighbours. Scaling is done so that features like Glucose / age don't dominate the one with the smaller ranges

code:

```
import math
import matplotlib.pyplot as plt

# Step 1: Distance calculation (Euclidean)
def distance(p1, p2):
    return math.sqrt((p1[0] - p2[0])**2 + (p1[1] - p2[1])**2)

# Step 2: KNN Function
def knn(training_data, test_point, k):
```

```
    distances = []
    for point, label in training_data:
        d = distance(point, test_point)
        distances.append((d, label))
    distances.sort()
    k_nearest = distances[:k]
    labels = [label for _, label in k_nearest]
    prediction = max(set(labels), key=labels.count)
    return prediction

# Step 3: Visualization Function
def visualize_knn(data, test_point, predicted_label, new_point=None,
new_label=None):
    colors = {'A': 'blue', 'B': 'red'}
    markers = {'A': 'o', 'B': 's'}

    # Plot training data
    for point, label in data:
        plt.scatter(point[0], point[1], color=colors[label],
marker=markers[label], label=label if f"train_{label}" not in
plt.gca().get_legend_handles_labels()[1] else "")

    # Plot test point
    plt.scatter(test_point[0], test_point[1], color='green', marker='*',
s=200, label=f'Test → {predicted_label}')

    # Plot new point if provided
    if new_point is not None and new_label is not None:
        plt.scatter(new_point[0], new_point[1], color='orange', marker='X',
s=150, label=f'New → {new_label}')

    plt.legend()
    plt.grid(True)
    plt.title("KNN Classification")
    plt.xlabel("Feature 1")
    plt.ylabel("Feature 2")
    plt.show()

# Step 4: Run everything
if __name__ == "__main__":
    # Training data
```

```
    data = [
        ([1, 2], 'A'),
        ([2, 3], 'A'),
        ([3, 1], 'A'),
        ([6, 5], 'B'),
        ([7, 7], 'B'),
        ([8, 6], 'B')
    ]

    # Test point
    test = [2, 2]
    result = knn(data, test, k=3)
    print("Predicted class for test:", result)

    # New point to classify
    new_point = [7, 5]
    new_result = knn(data, new_point, k=3)
    print("Predicted class for new point:", new_result)

    # Visualize
    visualize_knn(data, test, result, new_point=new_point,
new_label=new_result)
```

Program 7

Build Support vector machine model for a given dataset

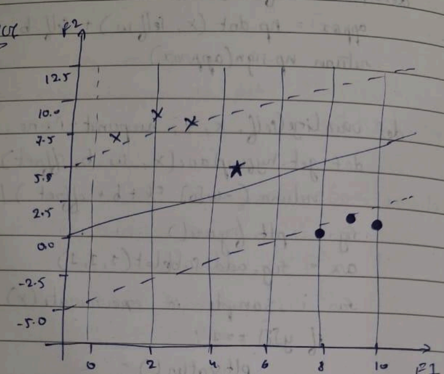
Screenshot

SVM:

```
import numpy as np
import matplotlib.pypot as plt

class SVM:
    def __init__(self, learning rate = 0.001, lambda_param
        = 0.01, n_iters = 1000):
        self. lr = learning_rate
        self. lambda = lambda
        self. n_iters = n_iters
        self. w = None
        self. b = None

    def fit(self, x, y):
        Y = np.where (y <= 0, -1, 1)
        n_samples, n_features = x.shape
        self.w = np.zeroes(n_features)
        self.b = 0
        for _ in range (self. n_iters):
            for idx, x_i in enumerate(x):
                condition = y[idx] * (np.dot(x_i, self.w)
                            + self.b ) >= 1
                if condition:
                self. w = -= self. lr * (2 * self. lambda
                                          * self.w)
                else:
                    self. w -= self. lr * (2 * self. lambda *
                                          self.w).
```

```
def predict(self, x):
    approx = np.dot(x, self.w) + self.b
    return np.sign(approx)

def visualize(self, x, y, newpoint=None, pred=None):
    def get_hyperplane(x, w, b, offset):
        return (-w[0] *x + b + offset) / w[1].
    fig = plt.figure()
    ax = fig.add_subplot(1, 1, 1)
    for i, sample in enumerate(x)
        if y[i] ==1:
            plt.scatter().
        else:
            plt.scatter(sample[0], sample[1])

if name == "__main__"
    x = np.array([[1, 7], [2, 8], [3, 8], [8, 1], [9, 2],
                  [10, 2]])
    y = np.array([0, 0, 0, 1, 1, 1])
    new_point = np.array([[5, 5]])
    svm = SVM()
    svm.fit(X, y)
    prediction = svm.predict(new_point)[0]
    svm.visualize(X, y, new_point = new_point[0],
                  pred = pred)
    print(new_point[0]).
```

OUTPUT



newpoint [5, 5] classified as: class 0.

code:

```
import numpy as np
import matplotlib.pyplot as plt

class SVM:
    def __init__(self, learning_rate=0.001, lambda_param=0.01, n_iters=1000):
        self.lr = learning_rate
        self.lambda_param = lambda_param
        self.n_iters = n_iters
        self.w = None
        self.b = None

    def fit(self, X, y):
        y = np.where(y <= 0, -1, 1)  # Convert labels to -1 and 1
        n_samples, n_features = X.shape
        self.w = np.zeros(n_features)
        self.b = 0

        for _ in range(self.n_iters):
            for idx, x_i in enumerate(X):
                condition = y[idx] * (np.dot(x_i, self.w) + self.b) >= 1
                if condition:
                    self.w -= self.lr * (2 * self.lambda_param * self.w)
                else:
                    self.w -= self.lr * (2 * self.lambda_param * self.w -
np.dot(x_i, y[idx]))
                    self.b += self.lr * y[idx]

    def predict(self, X):
        approx = np.dot(X, self.w) + self.b
        return np.sign(approx)

    def visualize(self, X, y, new_point=None, prediction=None):
        def get_hyperplane(x, w, b, offset):
            return (-w[0] * x + b + offset) / w[1]

        fig = plt.figure()
        ax = fig.add_subplot(1, 1, 1)

        # Plot existing data points
        for i, sample in enumerate(X):
```

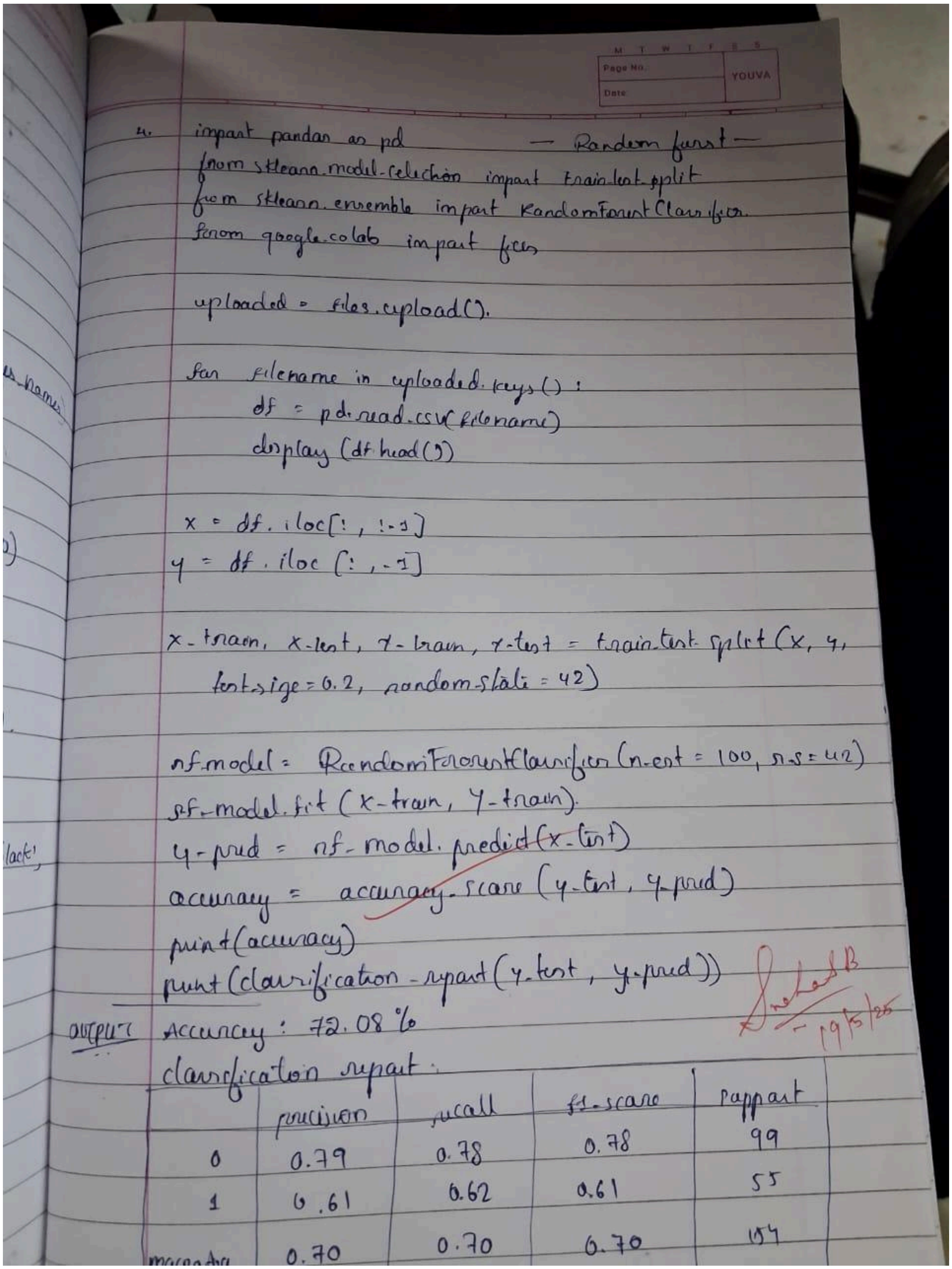
```
            if y[i] == 1:
                plt.scatter(sample[0], sample[1], marker='o', color='blue',
label='Class +1' if i == 0 else "")
            else:
                plt.scatter(sample[0], sample[1], marker='x', color='red',
label='Class -1' if i == 0 else "")

        # Plot decision boundary
        x0 = np.linspace(np.min(X[:, 0])-1, np.max(X[:, 0])+1, 100)
        x1 = get_hyperplane(x0, self.w, self.b, 0)
        x1_m = get_hyperplane(x0, self.w, self.b, -1)
        x1_p = get_hyperplane(x0, self.w, self.b, 1)

        ax.plot(x0, x1, 'k-', label='Decision Boundary')
        ax.plot(x0, x1_m, 'k--', label='Margins')
        ax.plot(x0, x1_p, 'k--')

        # Plot the new point
        if new_point is not None:
            color = 'green' if prediction == 1 else 'orange'
            label = f'New Point: Class {"1" if prediction == 1 else "0"}'
            plt.scatter(new_point[0], new_point[1], c=color, s=100,
edgecolors='black', label=label, marker='*')

        ax.legend()
        plt.xlabel("Feature 1")
        plt.ylabel("Feature 2")
        plt.title("SVM with New Point Prediction")
        plt.grid(True)
        plt.show()


# 🚀 Example usage
if __name__ == "__main__":
    # Training data
    X = np.array([
        [1, 7],
        [2, 8],
        [3, 8],
        [8, 1],
        [9, 2],
```

```
        [10, 2]
    ])
    y = np.array([0, 0, 0, 1, 1, 1])  # 0 -> -1, 1 -> +1

    # New point to classify
    new_point = np.array([[5, 5]])

    # Train and predict
    svm = SVM()
    svm.fit(X, y)
    prediction = svm.predict(new_point)[0]

    # Visualize
    svm.visualize(X, y, new_point=new_point[0], prediction=prediction)

    # Print prediction
    print(f"New point {new_point[0]} classified as: {'Class 1' if prediction
== 1 else 'Class 0'}")
```

Program 8

Implement Random forest ensemble method on a given dataset

Screenshot



4. — Random forest —

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from google.colab import files

uploaded = files.upload().

for filename in uploaded.keys():
    df = pd.read_csv(filename)
    display(df.head())

x = df.iloc[:, :-1]
y = df.iloc[:, -1]

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

rf_model = RandomForestClassifier(n_est = 100, r_s = 42)
rf_model.fit(x_train, y_train)
y_pred = rf_model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
print(accuracy)
print(classification_report(y_test, y_pred))
```

output Accuracy : 72.08 %

classification report :

	precision	recall	f1-score	support
0	0.79	0.78	0.78	99
1	0.61	0.62	0.61	55
macro avg	0.70	0.70	0.70	154

19/5/25

code:

```
#RANDOM FOREST
# STEP 1: Import required libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from google.colab import files

# STEP 2: Upload your dataset
uploaded = files.upload()

# STEP 3: Load the dataset (assuming it's a CSV)
for filename in uploaded.keys():
    df = pd.read_csv(filename)
    print(f"Data loaded from: {filename}")
    display(df.head())  # Display first 5 rows of data

# STEP 4: Preprocessing
# Assume the last column is the target variable (label)
X = df.iloc[:, :-1]  # Features (all rows, all columns except last)
y = df.iloc[:, -1]   # Target (last column)

# STEP 5: Split the 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=42)

# STEP 6: Initialize and train the Random Forest model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)  # 100
trees in the forest
rf_model.fit(X_train, y_train)

# STEP 7: Make predictions on the test set
y_pred = rf_model.predict(X_test)

# STEP 8: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of Random Forest Model: {accuracy * 100:.2f}%")
# STEP 9: Print classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

Program 9

Implement Boosting ensemble method on a given dataset

Screenshot

Lab 9. AdaBoost.

CGPA	Interactiveness	Practical Knowledge	Communication Skill	Job Profile
≥ 9	Yes	Good	Good	Yes
< 9	No	Good	Moderate	Yes
≥ 9	No	Average	Moderate	No
< 9	No	Average	Good	No
≥ 9	Yes	Good	Moderate	Yes
≥ 9	Yes	Good	Moderate	Yes

Decision stump for CGPA

if $> 9 \rightarrow$ Yes

$< 9 \rightarrow$ No

Weight for all $1/6$.

CGPA	Predicted	Actual Job Profile	weight
≥ 9	Yes	Yes	$1/6$
< 9	No	Yes	$1/6$
≥ 9	Yes	No	$1/6$
< 9	No	No	$1/6$
≥ 9	Yes	Yes	$1/6$
≥ 9	Yes	Yes	$1/6$

$\varepsilon_{CGPA} = 2 * 1/6 = 0.333$

$$\alpha_{CGPA} = \frac{1}{2} \ln \frac{(1-\varepsilon_{CGPA})}{\varepsilon_{CGPA}} = \frac{1}{2} \ln \frac{(1-0.333)}{0.333} = 0.347$$

Z_{CGPA} = wt correct * no. of correct * $e^{-\alpha_{CGPA}}$ + wt incorr * no. of incorr * $e^{+\alpha_{CGPA}}$

$$= \frac{1}{6}(4)(e^{-0.347}) + \frac{1}{6}(2)(e^{0.347})$$

$= 0.9428$

updated weight of

correct instance $= \frac{(wt)_{(int)\,upA} * e^{-\alpha_{upA}}}{Z_{upA}}$

$= \frac{1/6 * e^{-0.349}}{0.9428} = 0.1249$

incorrect instance $= \frac{(wt)_{upA(incnt)} * e^{+\alpha_{upA}}}{Z_{upA}}$

$= \frac{1/6 * e^{0.349}}{0.9428} = 0.2501$

For the 'income.csv' dataset

The best accuracy score obtained is 83.3%

confusion matrix is

		Predicted 0	Predicted 1
True	0	4106	308
True	1	1303	1052

The number of trees used are 50.

code:

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.datasets import make_classification
from sklearn.metrics import accuracy_score
from sklearn.decomposition import PCA

# Set up plot style
```

```
sns.set(style="whitegrid")

class AdaBoost:
    def __init__(self, n_estimators=50):
        self.n_estimators = n_estimators
        self.alphas = []  # Weights of each weak classifier
        self.models = []  # Weak classifiers (e.g., decision stumps)
        self.errors = []  # List to store error for each estimator

    def fit(self, X, y):
        # Initialize weights for each data point
        n_samples, n_features = X.shape
        w = np.ones(n_samples) / n_samples  # Equal weights initially

        for estimator in range(self.n_estimators):
            # Train weak classifier (decision stump)
            model = DecisionTreeClassifier(max_depth=1)  # Decision stump
            model.fit(X, y, sample_weight=w)
            y_pred = model.predict(X)

            # Calculate error rate
            err = np.sum(w * (y_pred != y)) / np.sum(w)
            self.errors.append(err)

            # Compute alpha (weight for the classifier)
            alpha = 0.5 * np.log((1 - err) / err) if err < 1 else 0
            self.alphas.append(alpha)
            self.models.append(model)

            # Update weights for misclassified samples
            w = w * np.exp(-alpha * y * y_pred)  # Update weights based on
classifier performance
            w = w / np.sum(w)  # Normalize the weights

    def predict(self, X):
        # Initialize the final prediction
        final_pred = np.zeros(X.shape[0])

        for model, alpha in zip(self.models, self.alphas):
            final_pred += alpha * model.predict(X)
```

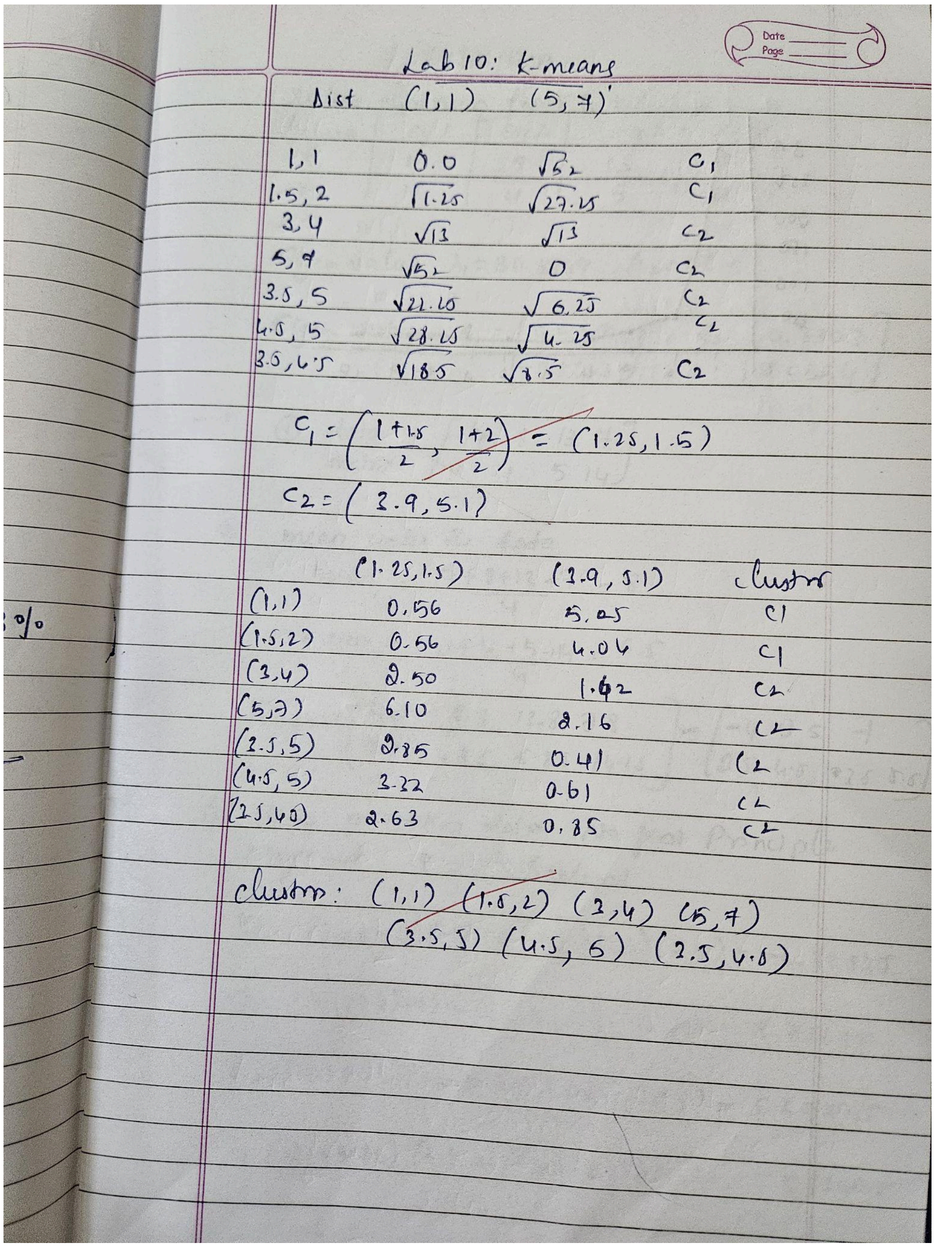
```
        # Return the sign of the final prediction
        return np.sign(final_pred)

    def score(self, X, y):
        # Return accuracy of the model
        return accuracy_score(y, self.predict(X))

# Generate a synthetic binary classification dataset with 2 informative
features
X, y = make_classification(n_samples=500, n_features=2, n_informative=2,
n_redundant=0, n_classes=2, random_state=42)

# Convert labels to -1 and 1 for AdaBoost
y = 2 * y - 1

# Create and train AdaBoost model
adaboost = AdaBoost(n_estimators=50)
adaboost.fit(X, y)

# Evaluate the model
accuracy = adaboost.score(X, y)
print(f"Model accuracy: {accuracy:.4f}")

# Plot error over iterations
plt.figure(figsize=(10, 6))
plt.plot(range(1, adaboost.n_estimators + 1), adaboost.errors, marker='o',
linestyle='-', color='b')
plt.title('Error vs. Number of Estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('Error')
plt.grid(True)
plt.show()

# Plot decision boundary for final model
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1

xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))
Z = adaboost.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
```

```
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, alpha=0.75, cmap='coolwarm')
plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', marker='o', s=50,
cmap='coolwarm')
plt.title('AdaBoost Decision Boundary')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()
```

Program 10

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

Screenshot



Lab 10: k-means

Dist	(1,1)	(5,7)	
1,1	0.0	$\sqrt{52}$	C1
1.5,2	$\sqrt{1.25}$	$\sqrt{27.25}$	C1
3,4	$\sqrt{13}$	$\sqrt{13}$	C2
5,7	$\sqrt{52}$	0	C2
3.5,5	$\sqrt{22.25}$	$\sqrt{6.25}$	C2
4.5,5	$\sqrt{28.25}$	$\sqrt{4.25}$	C2
3.5,4.5	$\sqrt{18.5}$	$\sqrt{6.5}$	C2

$C_1 = \left(\frac{1+1.5}{2}, \frac{1+2}{2}\right) = (1.25, 1.5)$

$C_2 = (3.9, 5.1)$

	(1.25,1.5)	(3.9,5.1)	cluster
(1,1)	0.56	5.02	C1
(1.5,2)	0.56	4.04	C1
(3,4)	2.50	1.42	C2
(5,7)	6.10	2.16	C2
(3.5,5)	2.85	0.41	C2
(4.5,5)	3.22	0.61	C2
(2.5,4.5)	2.63	0.85	C2

cluster: (1,1) (1.5,2) (3,4) (5,7)
(3.5,5) (4.5,5) (2.5,4.5)

code:

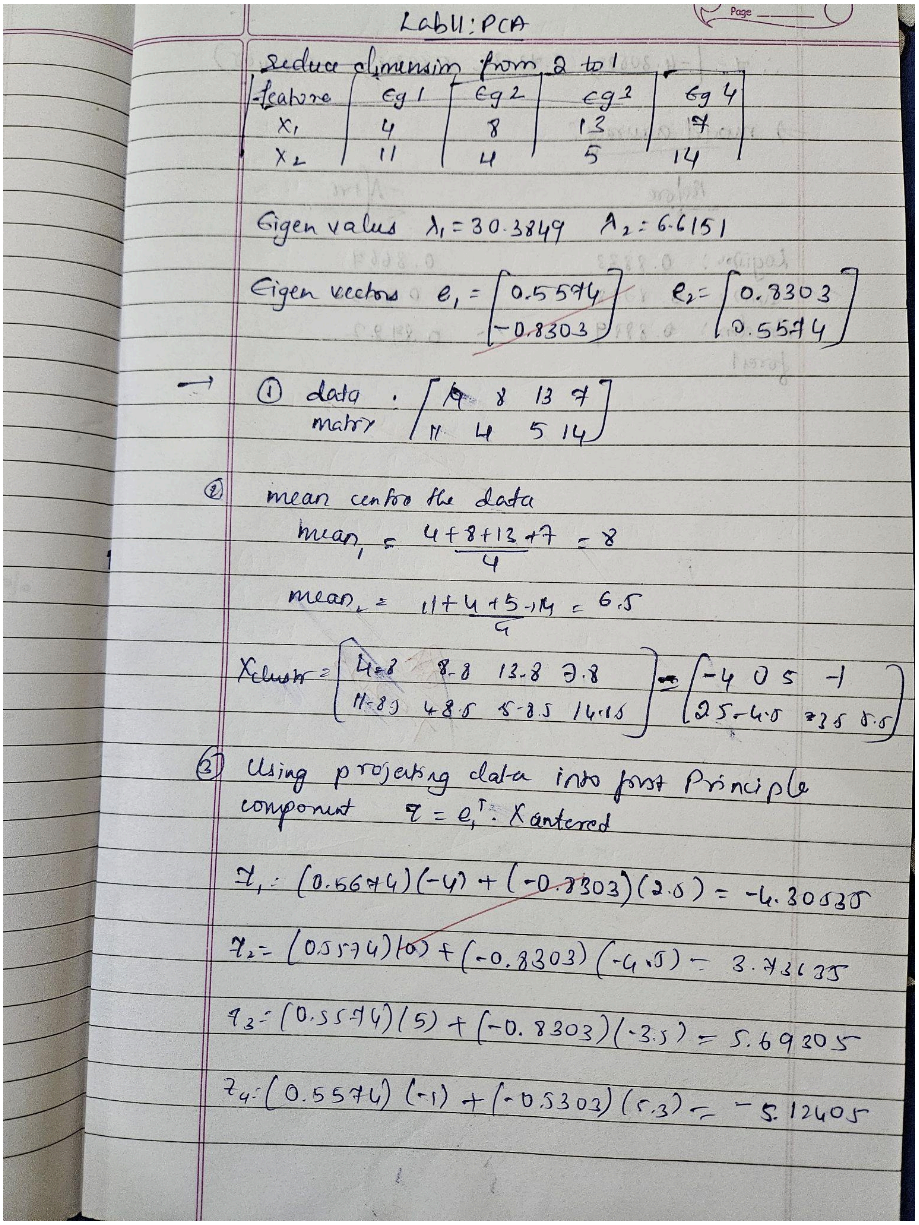
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets
import seaborn as sns
from sklearn.cluster import KMeans
```

```
iris = datasets.load_iris()
print("Dataset loaded successfully")

Data = pd.DataFrame(iris.data, columns = iris.feature_names)

#Top values of Dataset
# Data.head()
x=Data.iloc[:,0:3].values

css=[]

# # Finding inertia on various k values
# for i in range(1,8):
#     kmeans=KMeans(n_clusters = i, init = 'k-means++',
#                     max_iter = 100, n_init = 10, random_state = 0).fit(x)
#     css.append(kmeans.inertia_)
#Applying Kmeans classifier
kmeans = KMeans(n_clusters=3,init = 'k-means++', max_iter = 100, n_init = 10,
random_state = 0)
y_kmeans = kmeans.fit_predict(x)
kmeans.cluster_centers_
# Visualising the clusters - On the first two columns
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1],
            s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1],
            s = 100, c = 'blue', label = 'Iris-versicolour')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1],
            s = 100, c = 'green', label = 'Iris-virginica')

# Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1],
            s = 100, c = 'black', label = 'Centroids')
plt.legend()
```

Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Screenshot



Lab11: PCA

reduce dimension from 2 to 1

feature	Eg 1	Eg 2	Eg 3	Eg 4
X_1	4	8	13	7
X_2	11	4	5	14

Eigen values $\lambda_1 = 30.3849$ $\lambda_2 = 6.6151$

Eigen vectors $e_1 = \begin{bmatrix} 0.5574 \\ -0.8303 \end{bmatrix}$ $e_2 = \begin{bmatrix} 0.8303 \\ 0.5574 \end{bmatrix}$

① data matrix : $\begin{bmatrix} 4 & 8 & 13 & 7 \\ 11 & 4 & 5 & 14 \end{bmatrix}$

② mean centre the data

$mean_1 = \frac{4+8+13+7}{4} = 8$

$mean_2 = \frac{11+4+5+14}{4} = 6.5$

$X_{center} = \begin{bmatrix} 4-8 & 8-8 & 13-8 & 7-8 \\ 11-6.5 & 4-6.5 & 5-6.5 & 14-6.5 \end{bmatrix} = \begin{bmatrix} -4 & 0 & 5 & -1 \\ 4.5 & -2.5 & -1.5 & 7.5 \end{bmatrix}$

③ Using projecting data into first Principle component $z = e_1^T \cdot X_{centered}$

$z_1 = (0.5574)(-4) + (-0.8303)(4.5) = -4.30535$

$z_2 = (0.5574)(0) + (-0.8303)(-2.5) = 3.73635$

$z_3 = (0.5574)(5) + (-0.8303)(-1.5) = 5.69305$

$z_4 = (0.5574)(-1) + (-0.8303)(7.5) = -5.12405$

$\therefore z = [-4.30835,\ 3.73135,\ 5.69305,\ -5.12405]$

→ model accuracy?

	Before	After
Logistic:	0.8833	0.8667
SVM:	0.8778	0.8556
Random forest:	0.8889	0.8722

7-5-2025

code:

```
# STEP 1: Import packages
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
from google.colab import files
```

```python
# STEP 2: Upload the CSV file
uploaded = files.upload()

# STEP 3: Load the dataset
for filename in uploaded.keys():
    df = pd.read_csv(filename)
    print(f"✅ Uploaded: {filename}")
    display(df.head())

# STEP 4: Select numerical columns
numeric_df = df.select_dtypes(include=[np.number])
print("📊 Numerical features found:", list(numeric_df.columns))

# OPTIONAL: Manually select columns if needed
# selected_features = ['feature1', 'feature2', ...]
selected_features = numeric_df.columns  # use all numeric features for now

# STEP 5: Standardize data
X = numeric_df[selected_features].dropna()
X_scaled = StandardScaler().fit_transform(X)

# STEP 6: Apply PCA
pca = PCA(n_components=2)
principal_components = pca.fit_transform(X_scaled)

# STEP 7: Create DataFrame for components
pca_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])

# STEP 8: Visualize the first two principal components
plt.figure(figsize=(8,6))
plt.scatter(pca_df['PC1'], pca_df['PC2'], alpha=0.7)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('2D PCA Visualization')
plt.grid(True)
plt.show()

# STEP 9: Explained variance ratio
print("📈 Explained Variance Ratio:", pca.explained_variance_ratio_)
```

```python
print(f"Model accuracy: {accuracy:.4f}")
```