VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
(Autonomous Institution under VTU)
BENGALURU-560019
Sep-2024 to Jan-2025

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 **,** who is bonafide student **Shivaraj Kallappa Pujari(1BM22CS259)** 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. Swathi Sridaran** Assistant Professor Department of CSE, BMSCE	 **Dr. Kavitha Sooda** Professor & HOD Department of CSE, BMSCE

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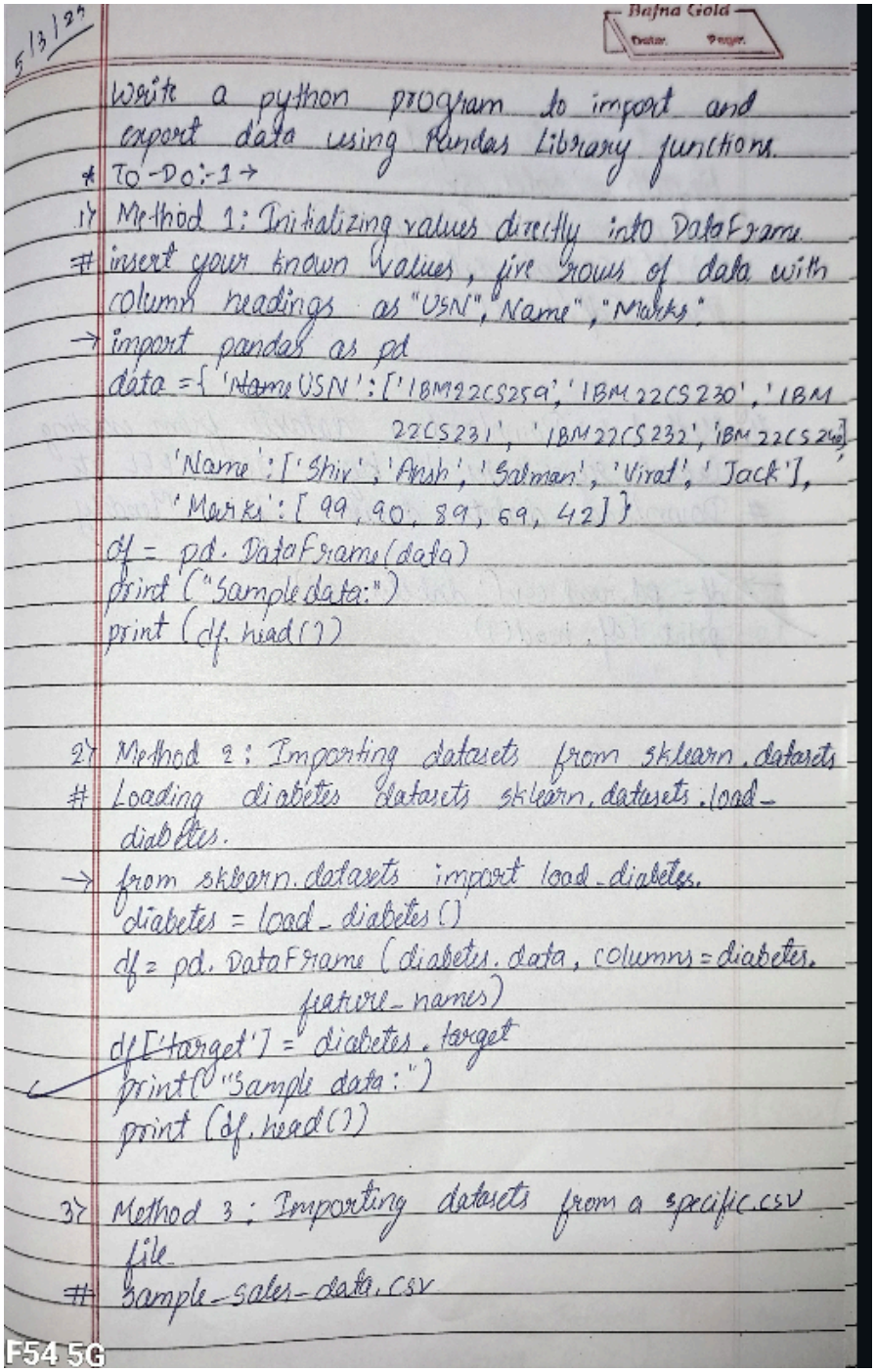
Github Link:
https://github.com/Shivarajpujari2004/1BM22CS259_ML-LAB

Program 1

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

Screenshot:



→ import pandas as pd
file_path = 'sales.csv'
df = pd.read_csv(file_path)
print("Sample data:")
print(df.head())

4) Method 4: Downloading datasets from existing dataset repositories like kaggle, UCI, KEEL etc
Download diabetes datasets from Mendely

→ df = pd.read_csv('diabetes.csv')
print(df.head())

A To DO :-

1) HDFC Bank Ltd., ICICI Bank Ltd., Kotak Mahindra Bank Ltd.

tickers = ["HDFCBANK.NS", "ICICI.NS", "KOTAK.NS"]

→ import pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt

tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]

2) Start date: 2024-01-01, End date: 2024-12-30

→ data = yf.download(tickers, start="2024-01-01", end="2024-12-30", groupby='ticker')

3) Plot the closing price & daily returns for all the 3 banks mentioned.

→ print(data.head())
print(data.shape)
print(data.columns)

hdfc_bank_data = data['HDFCBANK.NS']
print("HDFCBANK Statistics")
print(hdfc_bank_data.describe())
hdfc_bank_data['Daily Return'] = hdfc_bank_data['Close'].pct_change()

plt.figure(figsize=(12,6))
plt.subplot(2,1,1)
hdfc_data['Close'].plot(title='Reliance 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()

hdfc_data.to_csv('HDFC.csv')
print("\n HDFC bank data saved to 'hdfc.csv'.")

icicibank_data = data['ICICIBANK.NS']
print("ICICI stats")
print(icicibank_data.describe())
icicibank_data['Daily Return'] = icicibank_data['Close'].
                                 pct_change()
icicidata['Daily Return'] = icicidata
plt.figure(12,6)
plt.subplot(2,1,1)
icicidata['Close'].plot(title="ICICI")
plt.subplot(2,1,2)
icidata['Daily Return'].plot(title="ICICI - DR",
                             color='orange')
plt.tight_layout()
plt.show()
icici_data.to_csv('icici_data.csv')


kotak = data['KOTAKBANK.NS']
print("Kotak stats")
print(kotak.describe())
kotak_data['Daily Return'] = kotak['Close'].pct_chang
```

```
plt.figure(figsize=(12,6))
plt.subplot(2,1,1)
kotak['Close'].plot(title="Kotak Bank")
plt.subplot(2,1,2)
kotak['Daily Return'].plot(title="Kotak-DR",
                           color='orange')

plt.tight_layout()
plt.show()
kotak_data.to_csv('Kotak.csv')

print("\nBSE\n & Kotak Bank data saved\n")
```

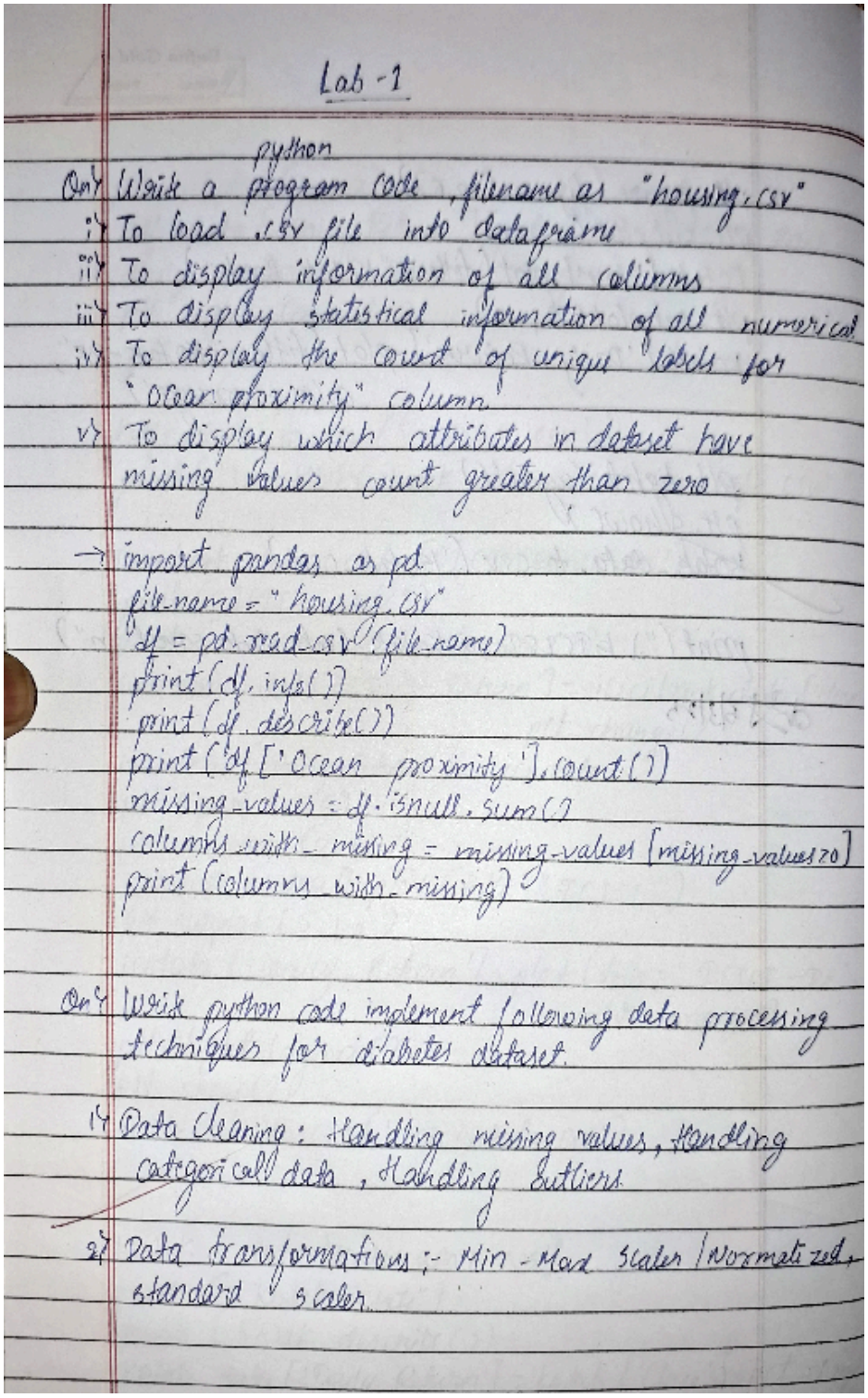
Code:

```
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')

hdfc_data = data['HDFCBANK.NS']
print("\nSummary statistics for HDFC bank :")
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 bank - Closing Price")
plt.subplot(2, 1, 2)
hdfc_data['Daily Return'].plot(title="Reliance Industries - Daily
Returns", color='orange')
plt.tight_layout()
plt.show()


icici_data = data['ICICIBANK.NS']
print("\nSummary statistics for ICICI bank :")
print(icici_data.describe())

icici_data['Daily Return'] = icici_data['Close'].pct_change()
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()
```

```
    kotak_data = data['KOTAKBANK.NS']
    print("\nSummary statistics for KOTAK bank :")
    print(kotak_data.describe())

    kotak_data['Daily Return'] = kotak_data['Close'].pct_change()
    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()
```

Program 2

Screenshot:



Lab - 1

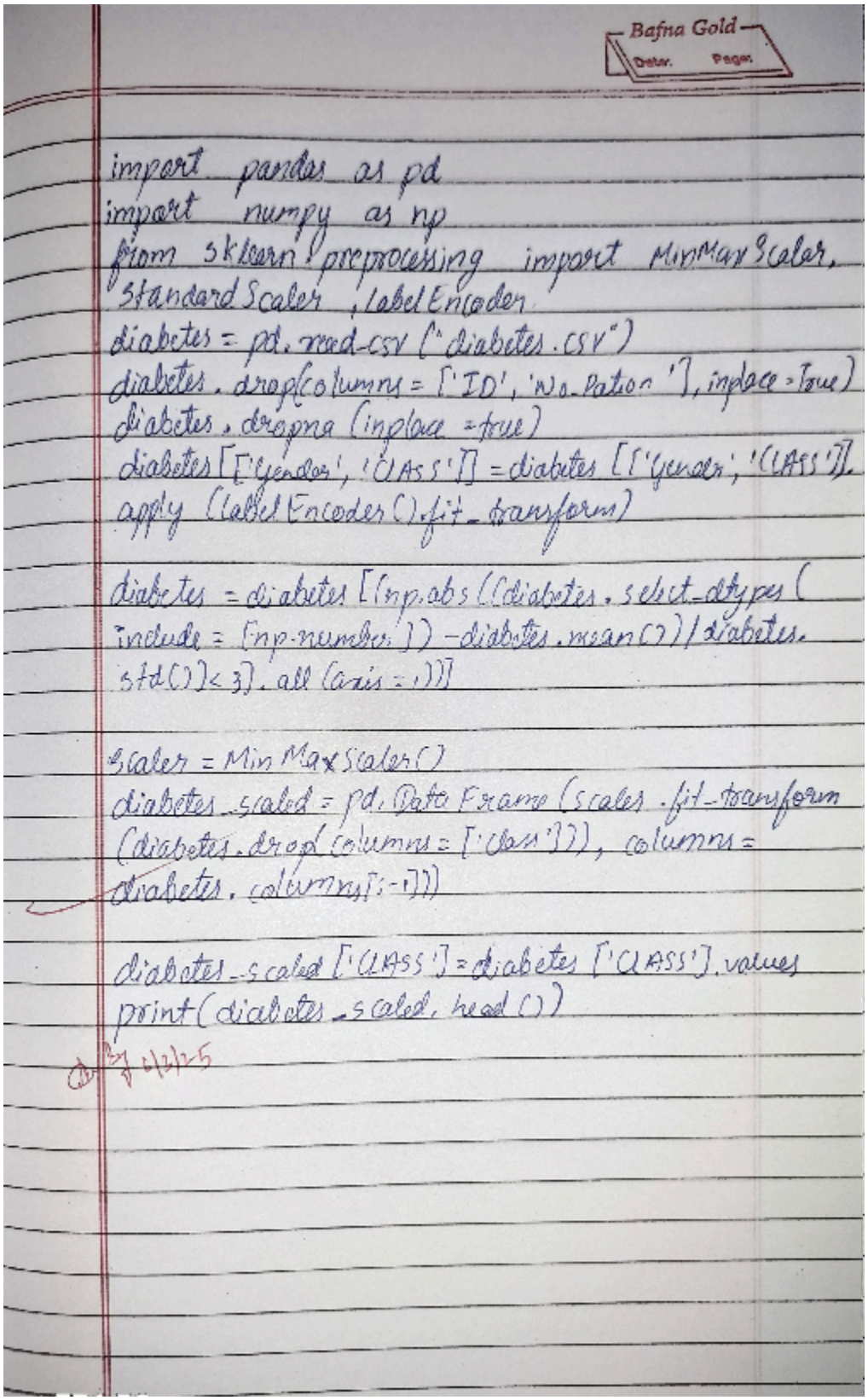
python

Q1) Write a program code, filename as "housing.csv"
i) To load .csv file into dataframe
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 in dataset have missing values count greater than zero

→
```
import pandas as pd
file_name = "housing.csv"
df = pd.read_csv(file_name)
print(df.info())
print(df.describe())
print(df['Ocean proximity'].count())
missing_values = df.isnull().sum()
columns_with_missing = missing_values[missing_values>0]
print(columns_with_missing)
```

Q2) Write python code implement following data processing techniques for diabetes dataset.

1) Data cleaning: Handling missing values, Handling categorical data, Handling outliers
2) Data transformations: Min-Max scaler / Normalized, standard scaler



```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler,
StandardScaler, LabelEncoder
diabetes = pd.read_csv("diabetes.csv")
diabetes.drop(columns=['ID', 'No_Pation'], inplace=True)
diabetes.dropna(inplace=True)
diabetes['Gender', 'CLASS'] = diabetes[['Gender', 'CLASS']].
apply(LabelEncoder().fit_transform)

diabetes = diabetes[(np.abs((diabetes.select_dtypes(
include=[np.number])) - diabetes.mean())/diabetes.
std())<3).all(axis=1)]

Scaler = MinMaxScaler()
diabetes_scaled = pd.DataFrame(scales.fit_transform
(diabetes.drop(columns=['Class'])), columns=
diabetes.columns[:-1])

diabetes_scaled['CLASS'] = diabetes['CLASS'].values
print(diabetes_scaled.head())
```

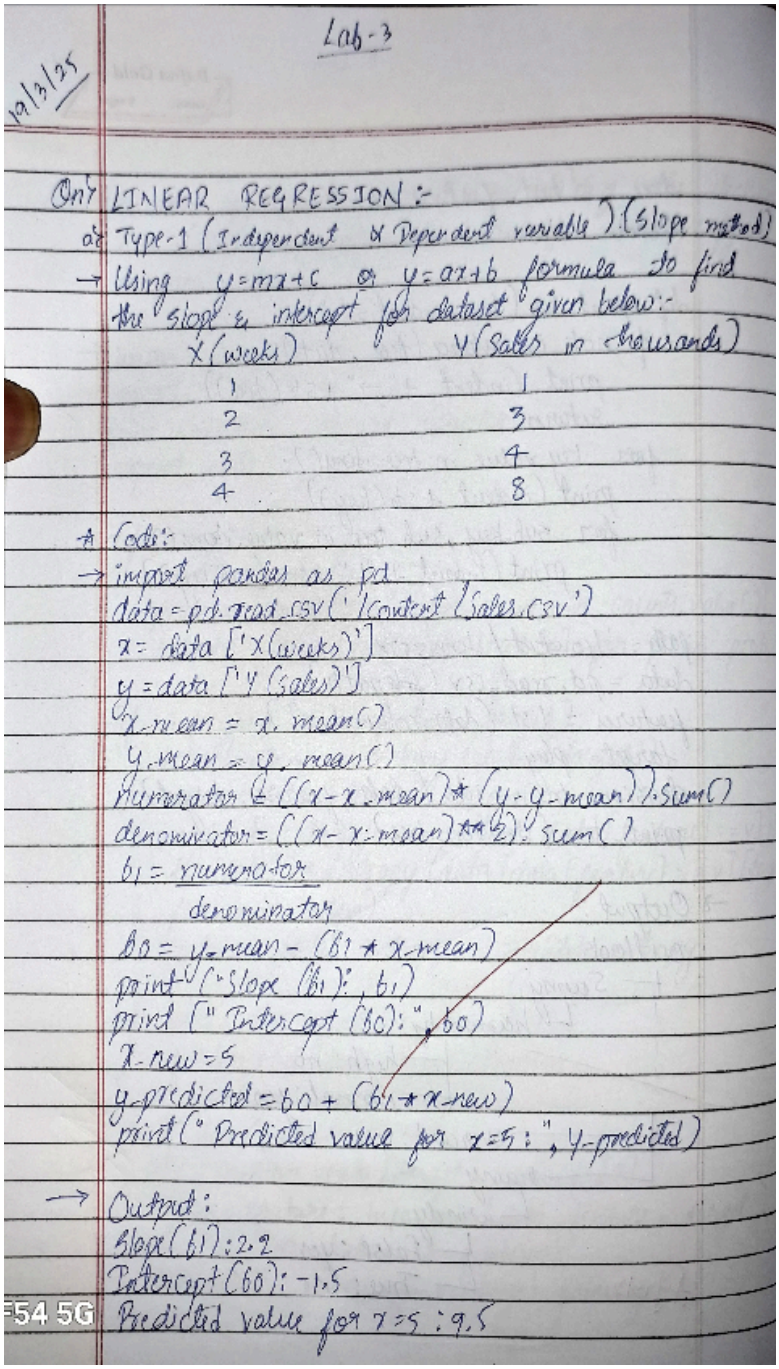
Code:

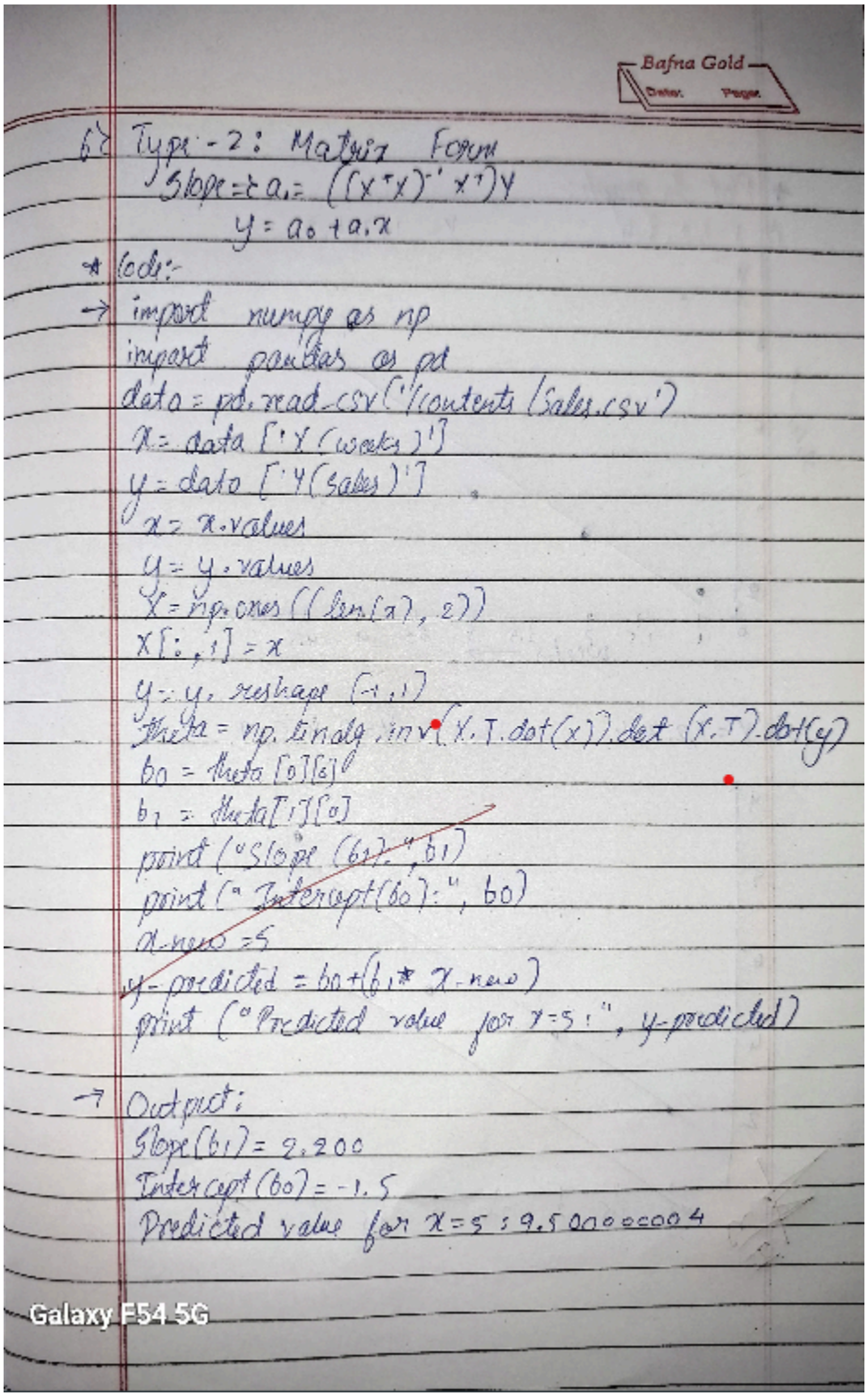
```
import pandas as pd

import numpy as np

from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder



# Load dataset

diabetes = pd.read_csv('diabetes.csv')  # Replace with actual file path



diabetes.drop(columns=['ID', 'No_Pation'], inplace=True)  # Drop unnecessary
columns



diabetes.dropna(inplace=True)  # Handle missing values



diabetes[['Gender', 'CLASS']] = diabetes[['Gender',
'CLASS']].apply(LabelEncoder().fit_transform)  # Encode categorical data



diabetes = diabetes[(np.abs((diabetes.select_dtypes(include=[np.number]) -
diabetes.mean()) / diabetes.std()) < 3).all(axis=1)]  # Remove outliers



scaler = MinMaxScaler()

diabetes_scaled =
pd.DataFrame(scaler.fit_transform(diabetes.drop(columns=['CLASS'])),
columns=diabetes.columns[:-1])

diabetes_scaled['CLASS'] = diabetes['CLASS'].values  # Add target column back
```

```
print(diabetes_scaled.head())
```

Program 3

Screenshot:





b) Type - 2 : Matrix Form

Slope = $a_1 = ((X^T X)^{-1} X^T) Y$

$y = a_0 + a_1 x$

* Code :-

→

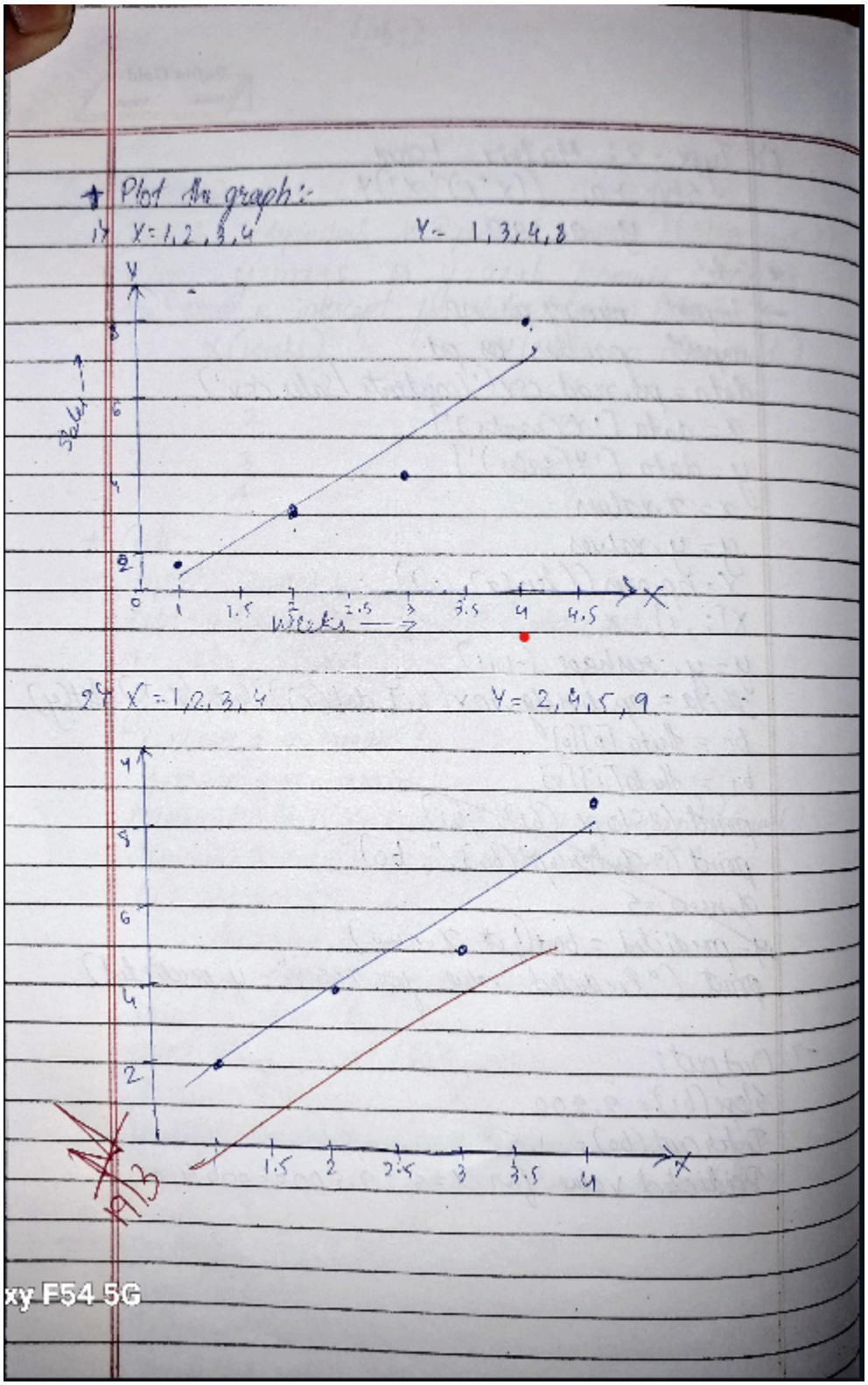
```
import numpy as np
import pandas as pd
data = pd.read_csv('/content/Sales.csv')
x = data['X(works)']
y = data['Y(Sales)']
x = x.values
y = y.values
X = np.ones((len(x), 2))
X[:, 1] = x
y = y.reshape(-1, 1)
theta = np.linalg.inv(X.T.dot(x)).dot(X.T).dot(y)
b0 = theta[0][0]
b1 = theta[1][0]
print("Slope (b1):", b1)
print("Intercept(b0):", b0)
x_new = 5
y_predicted = b0+(b1* x_new)
print("Predicted value for x=5 :", y_predicted)
```

→ Output :

Slope(b_1) = 2.200

Intercept(b_0) = -1.5

Predicted value for $x = 5$: 9.500000000004


Plot the graph:-
1) X=1,2,3,4
Y= 1,3,4,8
Y
Sales
Weeks
2) X=1,2,3,4
Y= 2,4,5,9
xy F54 5G

Code:

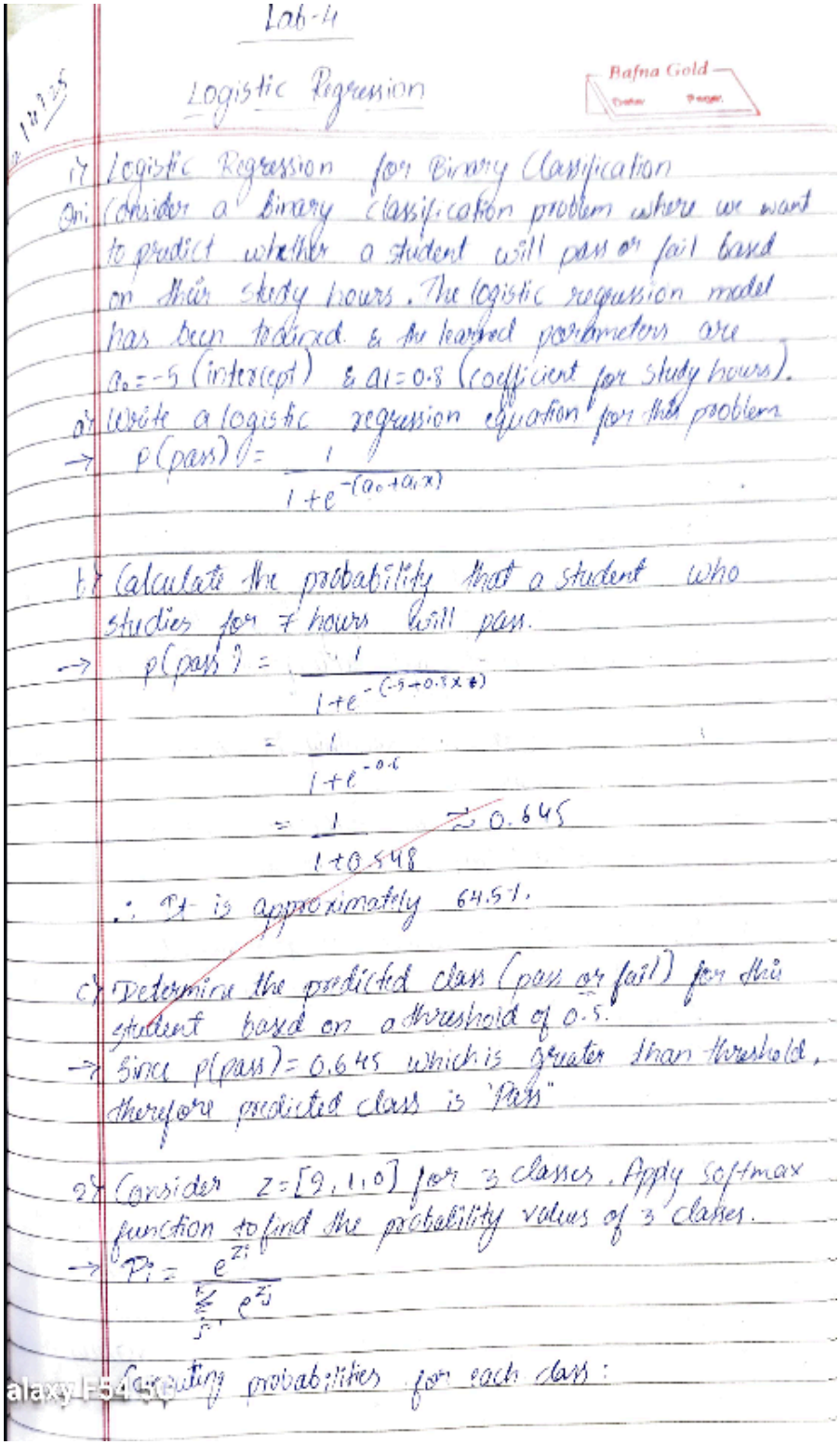
```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt



# Load the dataset from CSV file

dataset = pd.read_csv('/content/sales.csv')



# Display the first few rows of the dataset

print(dataset.head())



# Assuming the CSV has columns 'Week' and 'Sales' (adjust based on your
actual column names)

weeks = dataset['xi(week)'].values

sales = dataset['yi(Sales in thousands)'].values



# Reshaping weeks for matrix operations (make it a column vector)

X = weeks.reshape(-1, 1)

y = sales.reshape(-1, 1)



# Add a column of ones to X to account for the intercept (b)

X_b = np.c_[np.ones((len(X), 1)), X]  # The "1" is for the bias term
(intercept)
```

```
# Compute theta using the normal equation: θ = (X^T X)^(-1) X^T y
theta = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)

# Extract slope (m) and intercept (b) from theta
b = theta[0]
m = theta[1]

# Print the regression line equation
print(f"The regression equation is: y = {m[0]:.2f}x + {b[0]:.2f}")

# Predict the sales for 7th and 9th weeks
week_7 = 7
week_9 = 9

predicted_sales_7 = m * week_7 + b
predicted_sales_9 = m * week_9 + b

print(f"Predicted sales for the 7th week: {predicted_sales_7[0]:.2f}
thousand")
print(f"Predicted sales for the 9th week: {predicted_sales_9[0]:.2f}
thousand")
```

```
# Plot the data points and the regression line

plt.scatter(weeks, sales, color='blue', label='Data Points')

plt.plot(weeks, m * weeks + b, color='red', label=f'Linear Regression: y =
{m[0]:.2f}x + {b[0]:.2f}')

plt.xlabel('Weeks')

plt.ylabel('Sales (in thousands)')

plt.title('Sales Data and Linear Regression')

plt.legend()

plt.show()
```

Program 4

Screenshot:



Lab-4

Logistic Regression

Rafna Gold

1) Logistic Regression for Binary Classification

Q1: Consider a binary classification problem where we want to predict whether a student will pass or fail based on their study hours. The logistic regression model has been trained & the learned parameters are $\theta_0 = -5$ (intercept) & $\theta_1 = 0.8$ (coefficient for study hours).

a) Write a logistic regression equation for this problem

→ $p(\text{pass}) = \frac{1}{1+e^{-(\theta_0+\theta_1 x)}}$

b) Calculate the probability that a student who studies for 7 hours will pass.

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

$= \frac{1}{1+e^{-0.6}}$

$= \frac{1}{1+0.548} \approx 0.645$

∴ It is approximately 64.5%.

c) Determine the predicted class (pass or fail) for this student based on a threshold of 0.5.

→ Since p(pass) = 0.645 which is greater than threshold, therefore predicted class is "Pass"

2) Consider $z = [9, 1, 0]$ for 3 classes. Apply softmax function to find the probability values of 3 classes.

→ $P_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$

Calculating probabilities for each class:

$P_1 = \frac{e^2}{11.107} = \frac{7.389}{11.107} \approx 0.665$

$P_2 = \frac{e^1}{11.107} = \frac{2.718}{11.107} \approx 0.245$

$P_3 = \frac{e^0}{11.107} = \frac{1}{11.107} \approx 0.090$

2) Multiclass Classification:

Qn: i) For dataset files "HR_comma_sep.csv"

ii) Which variables did you identify as having a direct and clear impact on employee retention? Why?

→ * satisfaction_level → lower satisfaction increases attrition.

* number_project and avg_monthly_hours → Overworking leads to burnout.

* promotion_last_5years and salary → lack of growth opportunities impacts retention.

ii) What was the accuracy of your model? Do you think this is a good accuracy? Why or Why not?

→ Accuracy → 76.48%

→ It is good since it captures key patterns & relationships.

2) For Zoo dataset

i) Did you perform any data preprocessing steps? If Yes, what were they and why were they necessary?

ii) Were there any missing or inconsistent values in the dataset? How did you handle them?

Bafna Gold
Date: Page:

iii) What does the confusion matrix tell you about the performance of your model?

iv) Which class types were most frequently misclassified? Why do you think this happened?

→ i) Data preprocessing:
* Removed animal_name
* Standardized numerical features
* Split dataset (80% train, 20% test)

ii) Handling missing data
→ no missing or inconsistent values found.

iii) Confusion matrix insights
→ Achieved 100% accuracy, no misclassifications.

iv) Misclassified class types
→ None due to well-separated data features.

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Code:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score



# Load dataset

file_path = "/content/HR_comma_sep"

df = pd.read_csv(file_path)



# Exploratory Data Analysis

# Plot bar chart showing impact of salaries on retention

plt.figure(figsize=(8, 5))

sns.countplot(data=df, x='salary', hue='left')

plt.title("Impact of Salary on Employee Retention")

plt.xlabel("Salary Level")

plt.ylabel("Number of Employees")

plt.legend(["Stayed", "Left"])

plt.show()
```

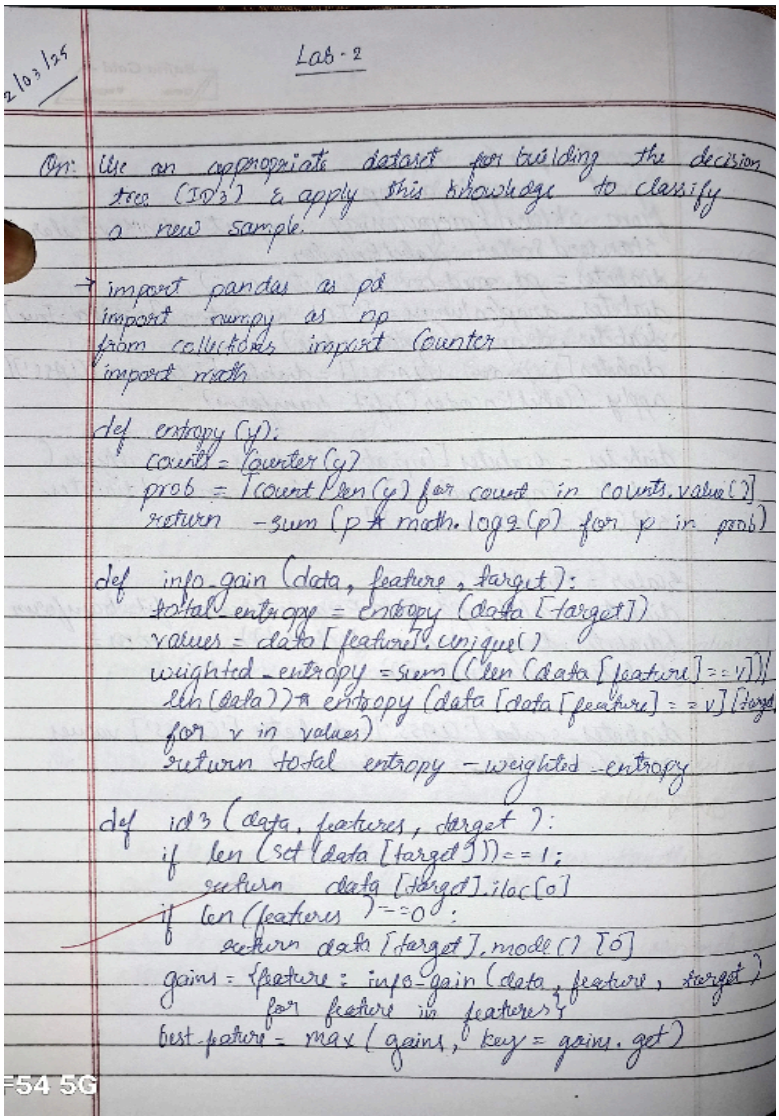
```
# Plot bar chart showing correlation between department and employee
retention

plt.figure(figsize=(10, 5))

sns.countplot(data=df, x='Department', hue='left')

plt.title("Department-wise Employee Retention")

plt.xlabel("Department")

plt.ylabel("Number of Employees")

plt.xticks(rotation=45)

plt.legend(["Stayed", "Left"])

plt.show()



# Selecting key features based on analysis

X = df[['satisfaction_level', 'time_spend_company', 'Work_accident',
'salary']]

X = pd.get_dummies(X, columns=['salary'], drop_first=True)  # Convert
categorical 'salary' to numerical

y = df['left']



# Splitting data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.9,
random_state=10)



# Train logistic regression model

model = LogisticRegression(max_iter=1000)
```

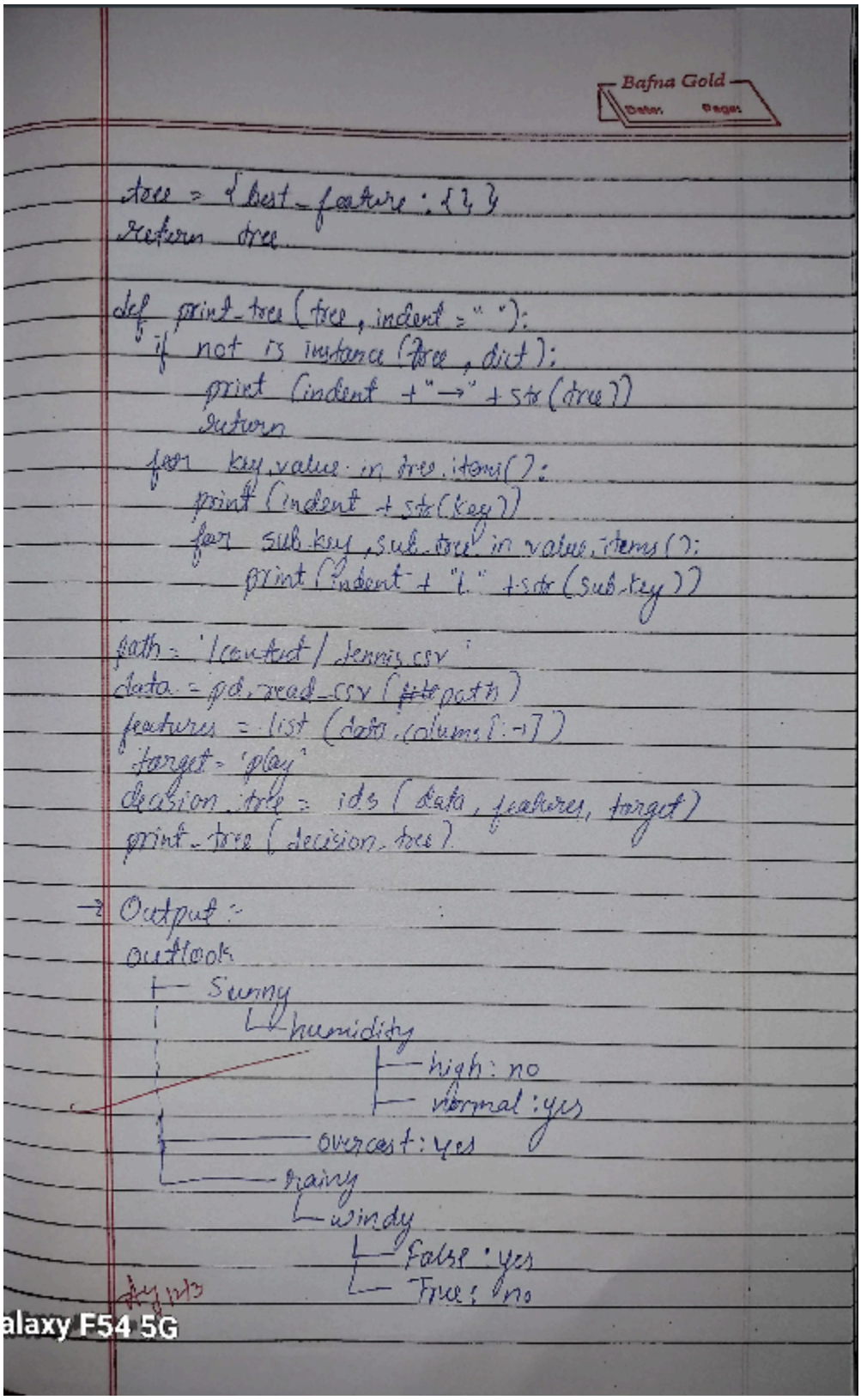
```
model.fit(X_train, y_train)



# Predictions

y_predicted = model.predict(X_test)



# Model accuracy

accuracy = accuracy_score(y_test, y_predicted)

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



# Plotting actual vs predicted values

plt.figure(figsize=(6, 4))

sns.heatmap(pd.crosstab(y_test, y_predicted), annot=True, fmt='d',
cmap='Blues')

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Confusion Matrix")

plt.show()



# Predict probability of an employee leaving

def predict_leave_probability(features):

    return model.predict_proba([features])[0][1]  # Probability of leaving



# Example prediction
```

```
example_employee = [[0.5, 3, 0, 1, 0]]  # Sample feature values with one-hot
encoded salary

probability = predict_leave_probability(example_employee[0])

print(f"Probability of leaving: {probability:.4f}")
```

Program 5

Screenshot:




Bafna Gold
tree = {best_feature : {}}
return tree
def print_tree(tree, indent = " "):
if not isinstance(tree, dict):
print(indent + "→" + str(tree))
return
for key, value in tree.items():
print(indent + str(key))
for sub_key, sub_tree in value.items():
print(indent + " " + str(sub_key))
path = 'Iris dataset/Tennis.csv'
data = pd.read_csv(path)
features = list(data.columns[:-1])
target = 'play'
decision_tree = ids(data, features, target)
print_tree(decision_tree)
→ Output :
outlook
Sunny
humidity
high : no
normal : yes
overcast : yes
rainy
windy
False : yes
True : no
alaxy F54 5G

Code:

```
import pandas as pd

import numpy as np



# Sample weather dataset

data = {

    'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Rain',
'Overcast', 'Sunny', 'Sunny', 'Rain', 'Sunny', 'Overcast', 'Overcast',
'Rain'],

    'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool',
'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'],

    'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal',
'Normal', 'High', 'Normal', 'Normal', 'Normal', 'High', 'Normal', 'High'],

    'Windy': ['No', 'Yes', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'No',
'Yes', 'Yes', 'No', 'Yes'],

    'Play Tennis?': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No',
'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']

}



# Convert to DataFrame

df = pd.DataFrame(data)



# Function to calculate entropy

def entropy(target):
```

```
    # Get the counts of each class
    class_counts = target.value_counts()
    # Calculate the entropy using the formula
    probabilities = class_counts / len(target)
    return -np.sum(probabilities * np.log2(probabilities))


# Function to calculate information gain
def information_gain(data, feature, target):
    # Calculate the entropy of the whole dataset
    entropy_before = entropy(target)

    # Get the unique values of the feature
    feature_values = data[feature].unique()

    # Calculate the weighted entropy after the split
    weighted_entropy = 0
    for value in feature_values:
        subset = target[data[feature] == value]
        weighted_entropy += (len(subset) / len(target)) * entropy(subset)

    # Information gain is the reduction in entropy
    return entropy_before - weighted_entropy
```

```
# Function to print entropy and information gain for each feature
def print_entropy_and_gain(data, features, target):
    print("\nEntropy and Information Gain for each feature:")
    for feature in features:
        gain = information_gain(data, feature, target)
        ent = entropy(target)
        print(f"Feature: {feature} | Entropy: {ent:.4f} | Information Gain: {gain:.4f}")

# Function to build the decision tree recursively
def build_tree(data, target, features):
    # Base case: If all target values are the same, return a leaf node
    if len(target.unique()) == 1:
        return target.iloc[0]

    # Base case: If no features left to split, return the majority class
    if len(features) == 0:
        return target.mode()[0]

    # Calculate information gain for each feature
    gains = {feature: information_gain(data, feature, target) for feature in features}
```

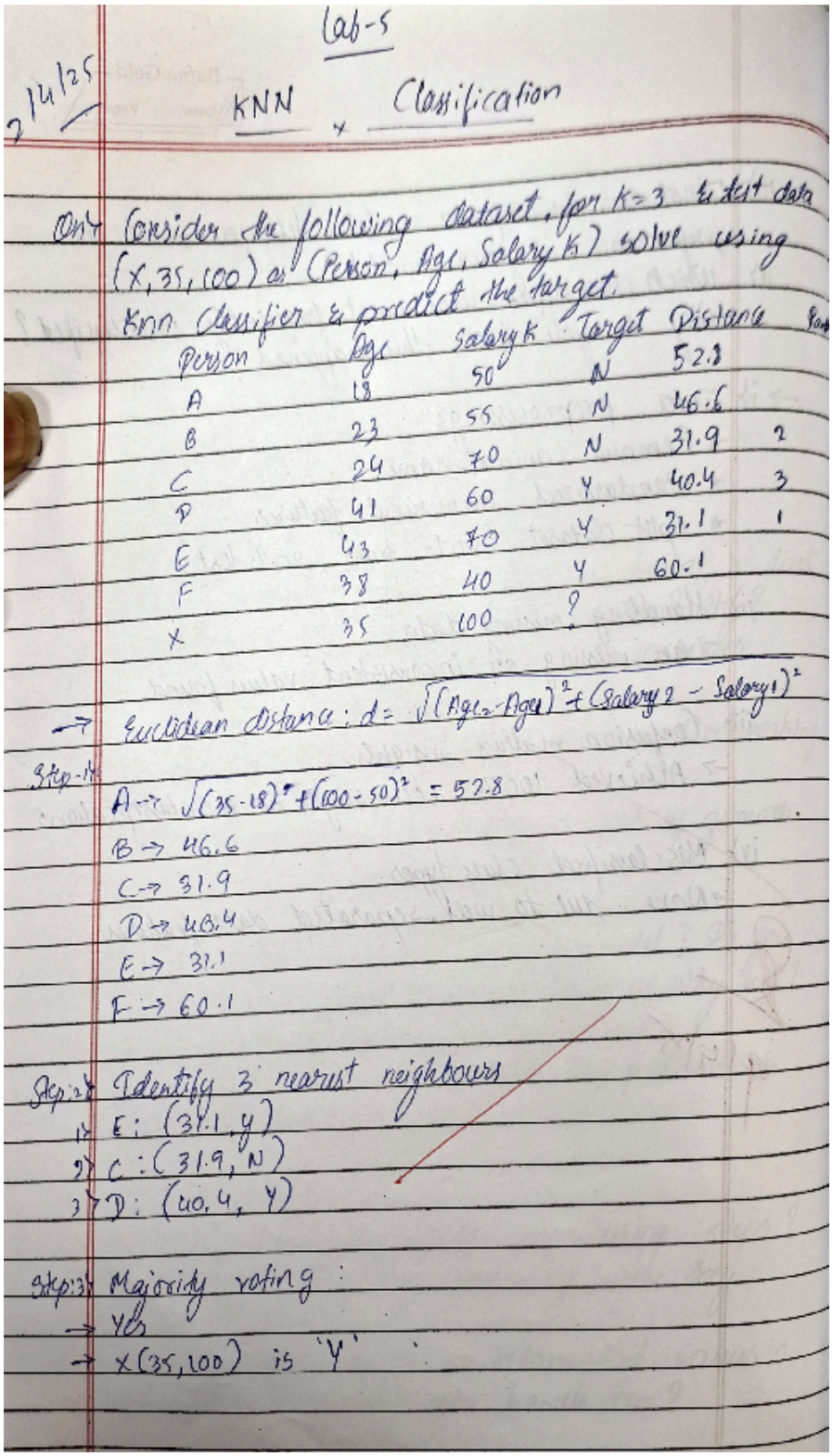
```
    # Find the feature with the highest information gain
    best_feature = max(gains, key=gains.get)

    # Create the tree node with the best feature
    tree = {best_feature: {}}

    # Get the unique values of the best feature
    feature_values = data[best_feature].unique()

    # Recursively build the tree for each subset of the data
    for value in feature_values:
        subset_data = data[data[best_feature] == value]
        subset_target = target[data[best_feature] == value]

        # Remove the best feature from the list of features for the next
level
        remaining_features = [f for f in features if f != best_feature]

        # Build the subtree for the subset
        subtree = build_tree(subset_data, subset_target, remaining_features)

        # Add the subtree to the tree
```

```
        tree[best_feature][value] = subtree



    return tree



# Function to print the tree in a visually structured way

def print_tree(tree, indent=""):

    if isinstance(tree, dict):

        for feature, branches in tree.items():

            print(f"{indent}{feature}:")

            for value, subtree in branches.items():

                print(f"{indent}  {value} ->", end=" ")

                print_tree(subtree, indent + "    ")

    else:

        print(f"{indent}{tree}")



# Target variable

target = df['Play Tennis?']



# Features

features = ['Outlook', 'Temperature', 'Humidity', 'Windy']



# Step 1: Print entropy and information gain for each feature
```

```
print_entropy_and_gain(df, features, target)



# Step 2: Build the decision tree

tree = build_tree(df, target, features)



# Step 3: Print the decision tree (formatted)

print("\nDecision Tree:")

print_tree(tree, indent="    ")
```

Program 6

Screenshot:



Lab-5

2 14/25

KNN & Classification

Q1) Consider the following dataset. for K=3 & test data (X, 35, 100) as (Person, Age, Salary K) solve using Knn classifier & predict the target.

Person	Age	Salary K	Target	Distance	Rank
A	18	50	N	52.8	
B	23	55	N	46.6	
C	24	70	N	31.9	2
D	41	60	Y	40.4	3
E	43	70	Y	31.1	1
F	38	40	Y	60.1	
X	35	100	?		

→ Euclidean distance: $d = \sqrt{(Age_2 - Age_1)^2 + (Salary_2 - Salary_1)^2}$

Step-1:

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

B → 46.6

C → 31.9

D → 40.4

E → 31.1

F → 60.1

Step-2: Identify 3 nearest neighbours

1) E: (31.1, Y)

2) C: (31.9, N)

3) D: (40.4, Y)

Step-3: Majority voting:

→ Yes

→ X(35, 100) is 'Y'

Bafna Gold
Date: Page:

Qn:1) For iris dataset
i) How to choose the K value? Demonstrate using accuracy rate & error rate.

Qn:2) For diabetes dataset.
What is the purpose of feature scaling? How to perform it?

→1) * Train KNN with different K values (eg. 1 to 20)
* Measure accuracy (higher is better) & error rate (lower is better)
* The best K is where accuracy is highest & error rate is lowest (typically 5-40)

→2) * KNN relies on distance, so large scaling features can dominate the smaller ones.
* Standardization ensures all features contribute equally.
* Scaling improves accuracy & prevents biased predictions.

9/4/25

Code:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report



# Load the Iris dataset

iris = pd.read_csv("/content/iris.csv")

X_iris = iris.drop(columns=['species'])

y_iris = iris['species']



# Split the dataset into training and testing sets

X_train_iris, X_test_iris, y_train_iris, y_test_iris =
train_test_split(X_iris, y_iris, test_size=0.2, random_state=42)



# Choose the best k value (testing k from 1 to 20)

k_values = range(1, 21)

accuracy_list = []
```

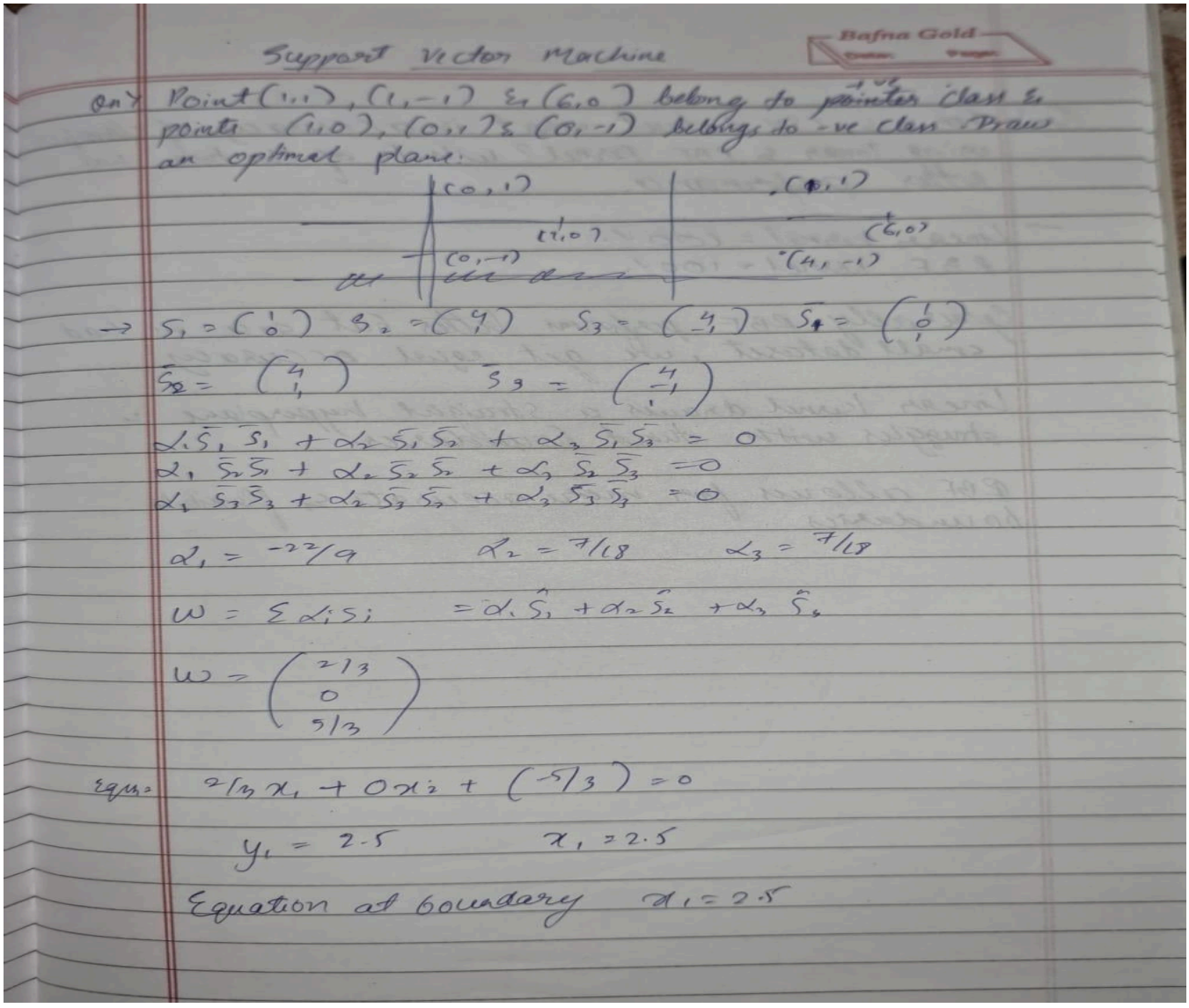
```
for k in k_values:

    knn = KNeighborsClassifier(n_neighbors=k)

    knn.fit(X_train_iris, y_train_iris)

    y_pred = knn.predict(X_test_iris)

    accuracy_list.append(accuracy_score(y_test_iris, y_pred))



best_k_iris = k_values[np.argmax(accuracy_list)]

print(f"Optimal k value for Iris dataset: {best_k_iris}")



# Train KNN with the best k value

knn_iris = KNeighborsClassifier(n_neighbors=best_k_iris)

knn_iris.fit(X_train_iris, y_train_iris)

y_pred_iris = knn_iris.predict(X_test_iris)



# Display Accuracy and Confusion Matrix for Iris dataset

print("Iris Dataset Accuracy:", accuracy_score(y_test_iris, y_pred_iris))

print("Confusion Matrix for Iris:")

print(confusion_matrix(y_test_iris, y_pred_iris))

print("Classification Report for Iris:")

print(classification_report(y_test_iris, y_pred_iris))



# Load the Diabetes dataset
```

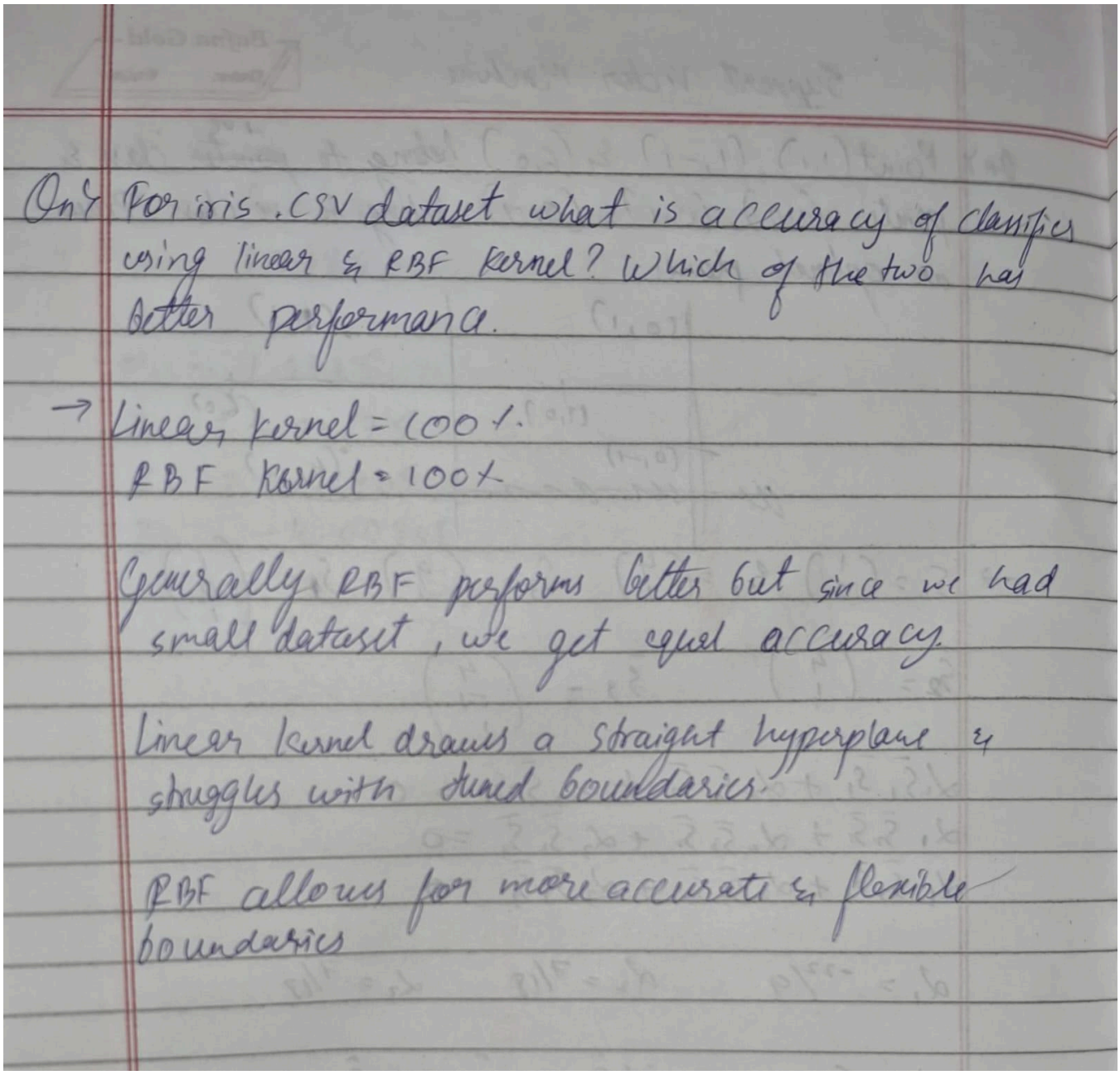
```
diabetes = pd.read_csv("/content/diabetes.csv")

X_diabetes = diabetes.drop(columns=['Outcome'])

y_diabetes = diabetes['Outcome']



# Split into training and testing

X_train_diabetes, X_test_diabetes, y_train_diabetes, y_test_diabetes =
train_test_split(X_diabetes, y_diabetes, test_size=0.2, random_state=42)



# Feature Scaling

scaler = StandardScaler()

X_train_diabetes = scaler.fit_transform(X_train_diabetes)

X_test_diabetes = scaler.transform(X_test_diabetes)



# Train KNN Classifier for Diabetes dataset

best_k_diabetes = 7  # Assume 7 as a reasonable k value (can be tuned
further)

knn_diabetes = KNeighborsClassifier(n_neighbors=best_k_diabetes)

knn_diabetes.fit(X_train_diabetes, y_train_diabetes)

y_pred_diabetes = knn_diabetes.predict(X_test_diabetes)



# Display Accuracy and Confusion Matrix for Diabetes dataset

print("Diabetes Dataset Accuracy:", accuracy_score(y_test_diabetes,
y_pred_diabetes))

print("Confusion Matrix for Diabetes:")
```

```
print(confusion_matrix(y_test_diabetes, y_pred_diabetes))

print("Classification Report for Diabetes:")

print(classification_report(y_test_diabetes, y_pred_diabetes))
```

Program 7

Screenshot:





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)
```

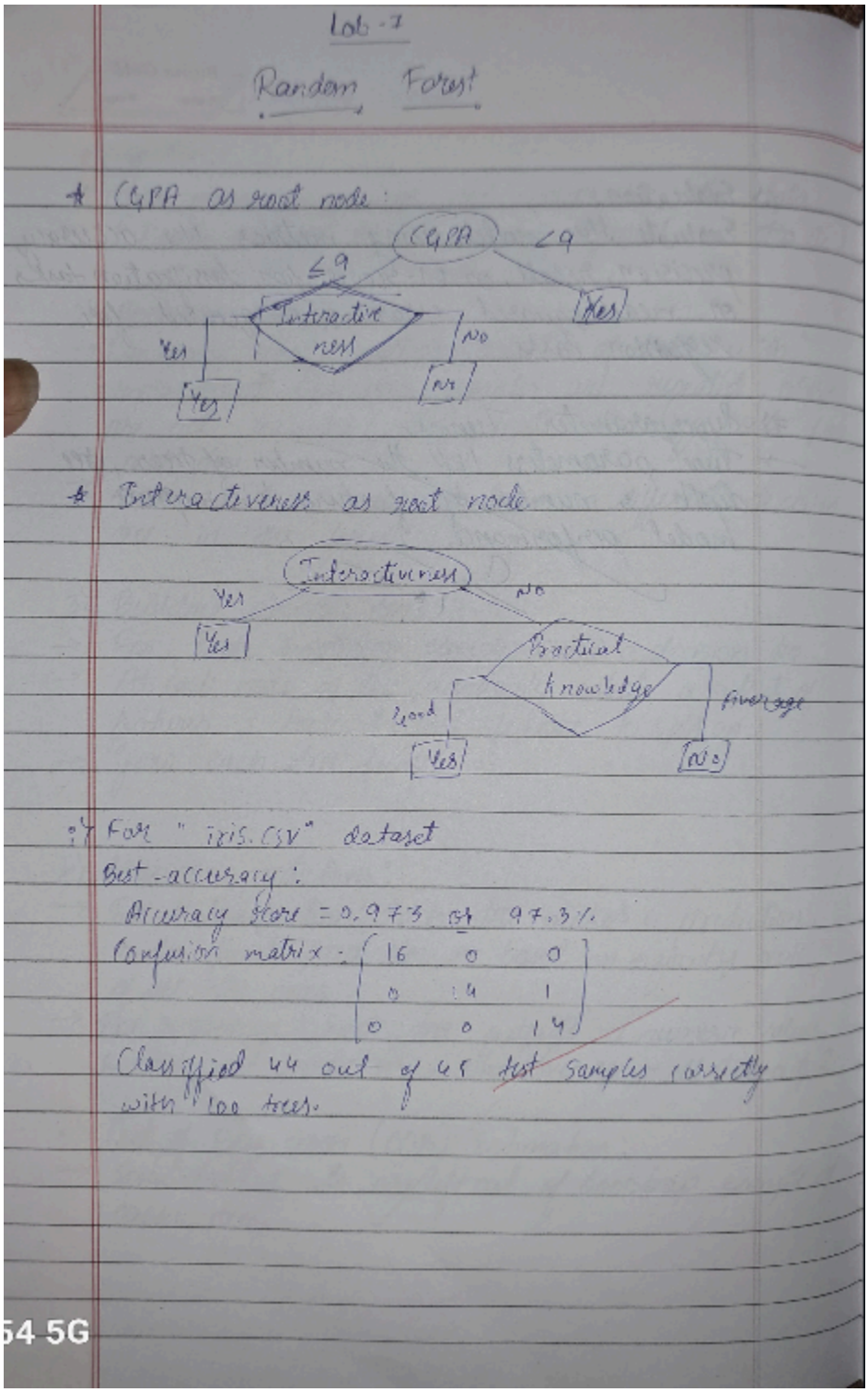
```
        x1_p = get_hyperplane(x0, self.w, self.b, 1)



        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()







if __name__ == "__main__":
```

```
# Training data
X = np.array([
    [1, 0],
    [0, 1],
    [0, -1],
    [4, -1],
    [4, 1],
    [6, 0]
])
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

Screenshot:



Code:

```
import pandas as pd
```

```
from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score, confusion_matrix

import matplotlib.pyplot as plt

import seaborn as sns



# Load dataset

df = pd.read_csv("/content/iris (4).csv")



# Features and target

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=0.2,
random_state=42)



# ------------------------------------------

# 1. Default Random Forest with 10 estimators

# ------------------------------------------

clf_default = RandomForestClassifier(n_estimators=10, random_state=42)

clf_default.fit(X_train, y_train)

y_pred_default = clf_default.predict(X_test)
```

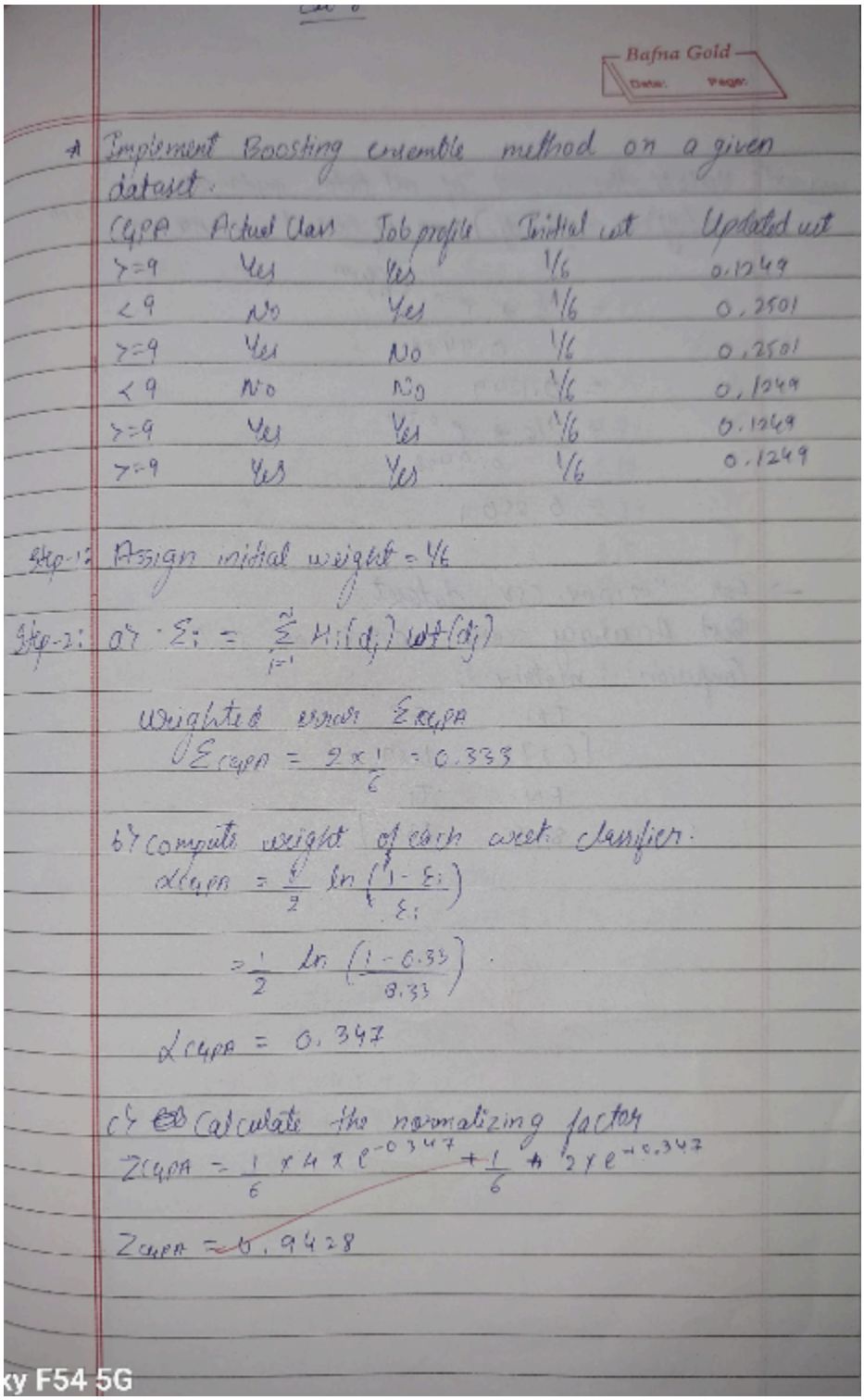
```
default_accuracy = accuracy_score(y_test, y_pred_default)

default_cm = confusion_matrix(y_test, y_pred_default)



print("=== Default Model (10 trees) ===")

print(f"Accuracy: {default_accuracy:.4f}")

print("Confusion Matrix:")

print(default_cm)



# ------------------------------------------

# 2. Fine-tune number of trees for best accuracy

# ------------------------------------------

best_score = 0

best_n = 0

best_model = None

best_cm = None



scores = []

n_estimators_range = range(1, 101)



for n in n_estimators_range:

    clf = RandomForestClassifier(n_estimators=n, random_state=42)

    clf.fit(X_train, y_train)
```

```
    y_pred = clf.predict(X_test)
    score = accuracy_score(y_test, y_pred)
    scores.append(score)

    if score > best_score:
        best_score = score
        best_n = n
        best_model = clf
        best_cm = confusion_matrix(y_test, y_pred)

# Print best result
print("\n=== Tuned Model ===")
print(f"Best Accuracy: {best_score:.4f}")
print(f"Best Number of Trees: {best_n}")
print("Confusion Matrix:")
print(best_cm)

# Plot accuracy vs number of trees
plt.figure(figsize=(8, 5))
plt.plot(n_estimators_range, scores, marker='o')
plt.xlabel("Number of Trees")
plt.ylabel("Accuracy")
```

```
plt.title("Random Forest Accuracy vs Number of Trees")

plt.grid(True)

plt.show()



# Plot best confusion matrix

plt.figure(figsize=(6, 4))

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

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Best Confusion Matrix")

plt.show()
```

Program 9

Screenshot:



Bafna Gold
Date: Page:

Implement Boosting ensemble method on a given dataset.

CGPA	Actual Class	Job profile	Initial wt	Updated wt
>=9	Yes	Yes	1/6	0.1249
<9	No	Yes	1/6	0.2501
>=9	Yes	No	1/6	0.2501
<9	No	No	1/6	0.1249
>=9	Yes	Yes	1/6	0.1249
>=9	Yes	Yes	1/6	0.1249

Step-1: Assign initial weight = 1/6

Step-2: a) $\varepsilon_i = \sum_{j=1}^{n} w_i(d_j)\, wt(d_j)$

Weighted error ε_{CGPA}

$\varepsilon_{CGPA} = 2 \times \frac{1}{6} = 0.333$

b) Compute weight of each weak classifier.

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

$= \frac{1}{2} \ln\left(\frac{1-0.33}{0.33}\right)$

$\alpha_{CGPA} = 0.347$

c) Calculate the normalizing factor

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

$Z_{CGPA} = 0.9428$

d) Update the weight of all data instances

$$wt(d_j)_{i+1} = \frac{wt(d_j) \text{ of correct instance} * e^{-\alpha_{i}}}{Z}$$

$$= \frac{1/6 * e^{-0.347}}{0.9428}$$

$$= 0.1249$$

$$= \frac{1/6 * e^{0.347}}{0.9428}$$

$$= 0.2501$$

→ For "income.csv" dataset

Best Accuracy score : 0.86 or 86%

Confusion matrix :

TN	FP
6873	419
FN	TP
845	1328

Code:

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.ensemble import AdaBoostClassifier

from sklearn.metrics import accuracy_score, confusion_matrix

import matplotlib.pyplot as plt

import seaborn as sns



# Load dataset

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



# Feature and target split

X = df.iloc[:, :-1]

y = df.iloc[:, -1]



# Handle categorical variables (if any)

X = pd.get_dummies(X)

y = pd.factorize(y)[0]



# Train/test split

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

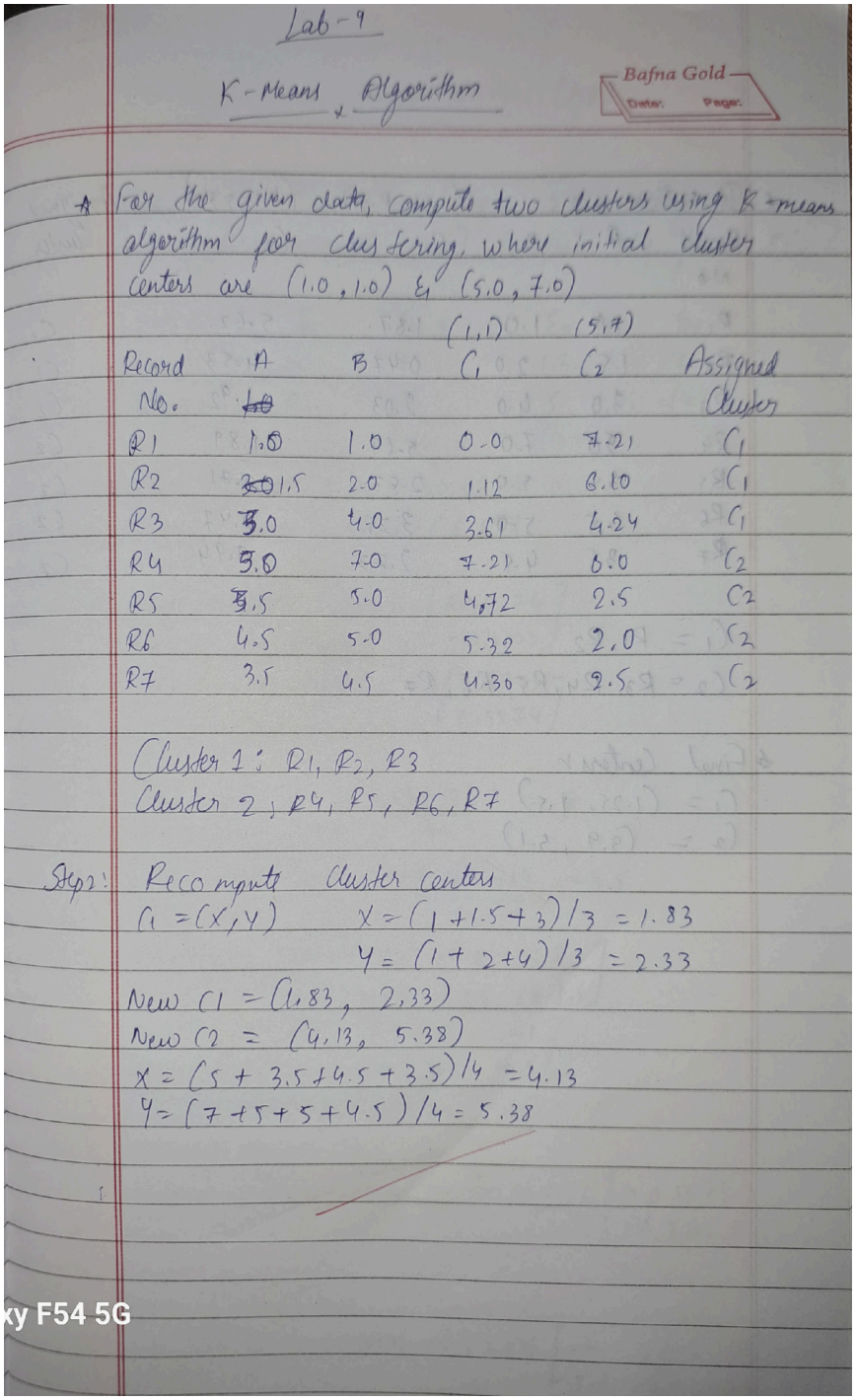
```
# ------------------------

# 1. Default AdaBoost model (10 estimators)

# ------------------------

clf_default = AdaBoostClassifier(n_estimators=10, random_state=42)

clf_default.fit(X_train, y_train)

y_pred_default = clf_default.predict(X_test)

default_accuracy = accuracy_score(y_test, y_pred_default)

default_cm = confusion_matrix(y_test, y_pred_default)



print("=== Default AdaBoost Model (10 estimators) ===")

print(f"Accuracy: {default_accuracy:.4f}")

print("Confusion Matrix:")

print(default_cm)



# ------------------------

# 2. Fine-tune n_estimators

# ------------------------

best_score = 0

best_n = 0

best_cm = None

scores = []
```

```
for n in range(1, 101):

    clf = AdaBoostClassifier(n_estimators=n, random_state=42)

    clf.fit(X_train, y_train)

    y_pred = clf.predict(X_test)

    score = accuracy_score(y_test, y_pred)

    scores.append(score)



    if score > best_score:

        best_score = score

        best_n = n

        best_cm = confusion_matrix(y_test, y_pred)



print("\n=== Best AdaBoost Model ===")

print(f"Best Accuracy: {best_score:.4f}")

print(f"Best Number of Estimators: {best_n}")

print("Confusion Matrix:")

print(best_cm)



# Plot accuracy vs number of estimators

plt.figure(figsize=(8, 5))

plt.plot(range(1, 101), scores, marker='o')

plt.xlabel("Number of Estimators")
```

```
plt.ylabel("Accuracy")

plt.title("AdaBoost Accuracy vs Number of Estimators")

plt.grid(True)

plt.show()



# Plot best confusion matrix

plt.figure(figsize=(6, 4))

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

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Best Confusion Matrix")

plt.show()
```

Program 10

Screenshot:



Lab-9

K-Means Algorithm

Bafna Gold

Date: Page:

For the given data, compute two clusters using K-means algorithm for clustering, where initial cluster centers are (1.0, 1.0) & (5.0, 7.0)

Record No.	A	B	C_1 (1,1)	C_2 (5,7)	Assigned Cluster
R1	1.0	1.0	0.0	7.21	C_1
R2	1.5	2.0	1.12	6.10	C_1
R3	3.0	4.0	3.61	4.24	C_1
R4	5.0	7.0	7.21	0.0	C_2
R5	3.5	5.0	4.72	2.5	C_2
R6	4.5	5.0	5.32	2.0	C_2
R7	3.5	4.5	4.30	2.5	C_2

Cluster 1: R1, R2, R3

Cluster 2: R4, R5, R6, R7

Step 2: Recompute cluster centers

$C_1 = (x, y)$ $x = (1 + 1.5 + 3)/3 = 1.83$

$y = (1 + 2 + 4)/3 = 2.33$

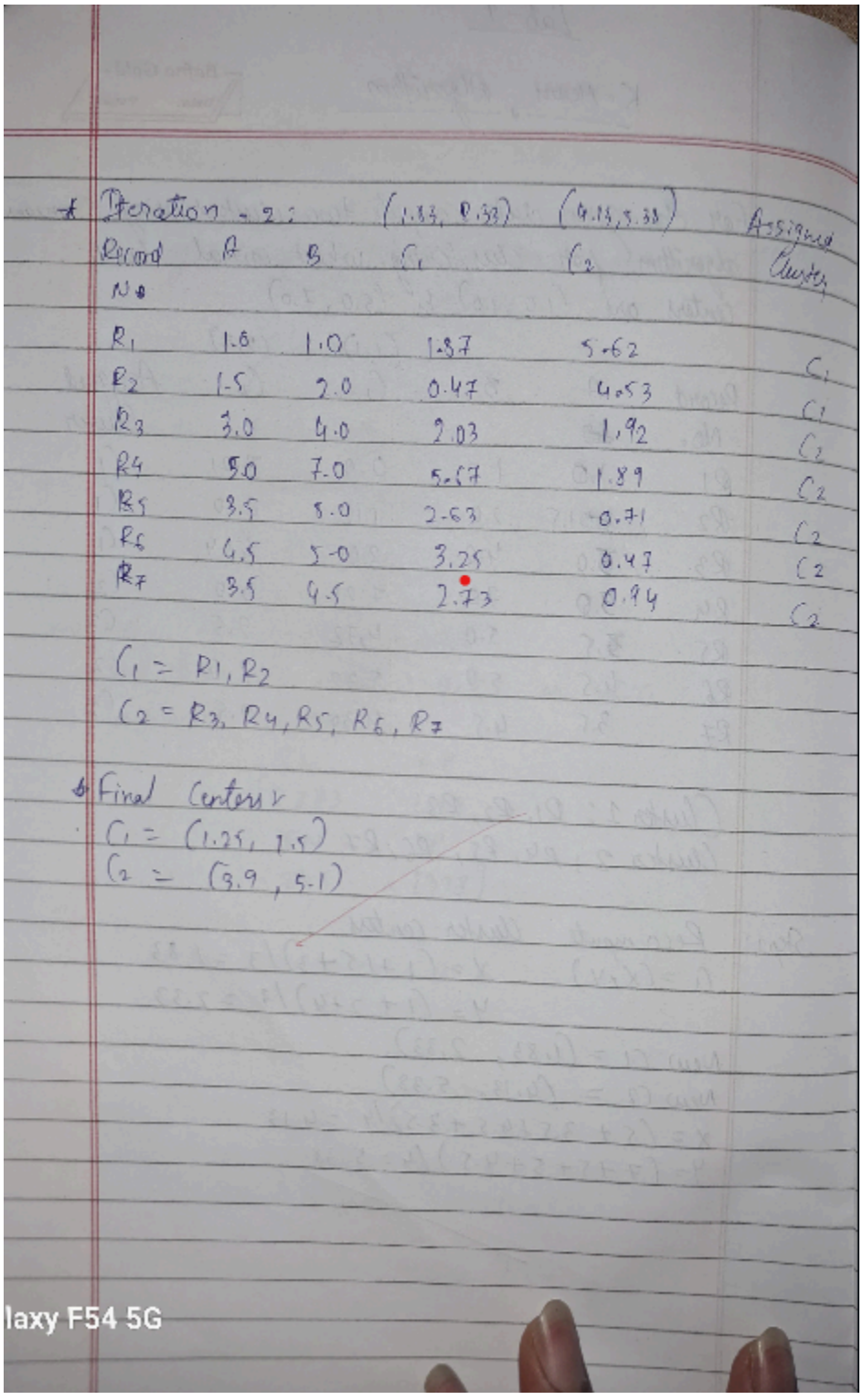
New $C_1 = (1.83, 2.33)$

New $C_2 = (4.13, 5.38)$

$x = (5 + 3.5 + 4.5 + 3.5)/4 = 4.13$

$y = (7 + 5 + 5 + 4.5)/4 = 5.38$

xy F54 5G



* Iteration - 2 :

Record No	A	B	C_1 (1.33, 0.33)	C_2 (4.13, 5.38)	Assigned Cluster
R_1	1.0	1.0	1.37	5.62	C_1
R_2	1.5	2.0	0.47	4.53	C_1
R_3	3.0	4.0	2.03	1.92	C_2
R_4	5.0	7.0	5.57	1.89	C_2
R_5	3.5	5.0	2.63	0.71	C_2
R_6	4.5	5.0	3.25	0.47	C_2
R_7	3.5	4.5	2.73	0.94	C_2

$C_1 = R1, R_2$

$C_2 = R_3, R_4, R_5, R_6, R_7$

* Final Centers

$C_1 = (1.25, 1.5)$

$C_2 = (3.9, 5.1)$

laxy F54 5G

Code:

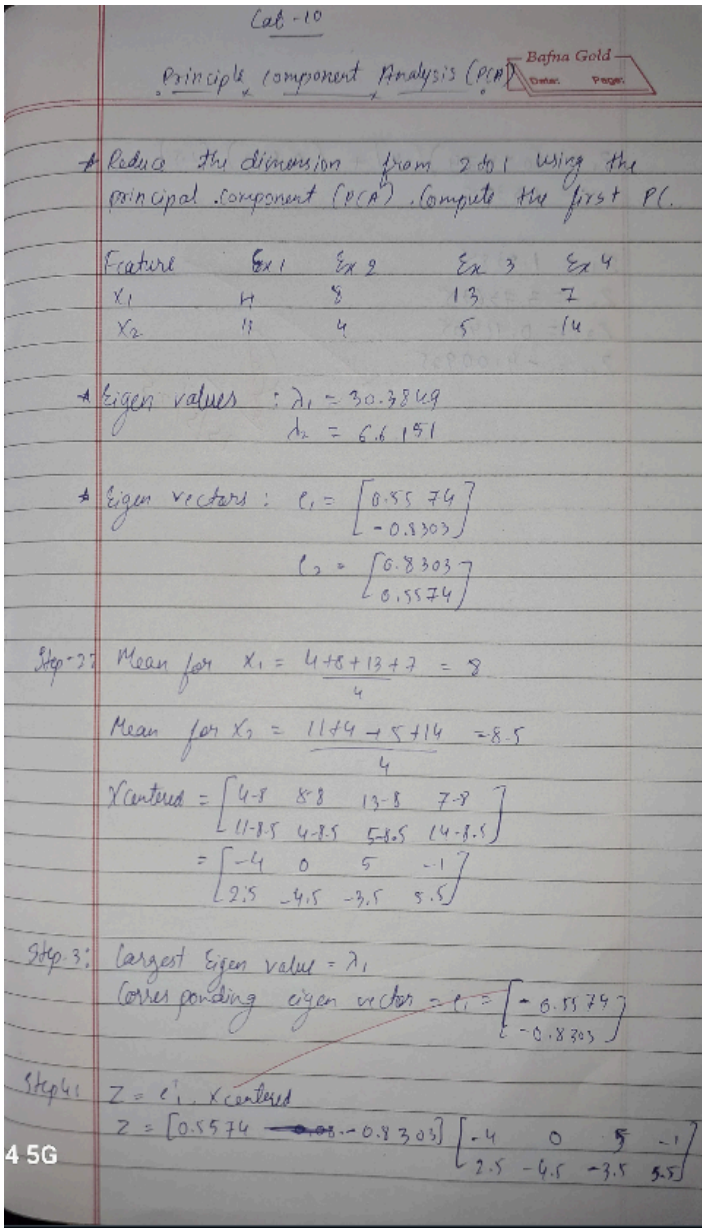
```
import pandas as pd

import matplotlib.pyplot as plt

from sklearn.cluster import KMeans

from sklearn.preprocessing import StandardScaler

import numpy as np



# Load dataset

df = pd.read_csv("iris (4).csv")  # Replace with your actual filename if
needed



# Use only petal length and petal width

X = df[['petal_length', 'petal_width']]



# Feature scaling

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)



# Elbow method to find optimal K

inertia = []

k_range = range(1, 11)

for k in k_range:

    kmeans = KMeans(n_clusters=k, random_state=42)
```

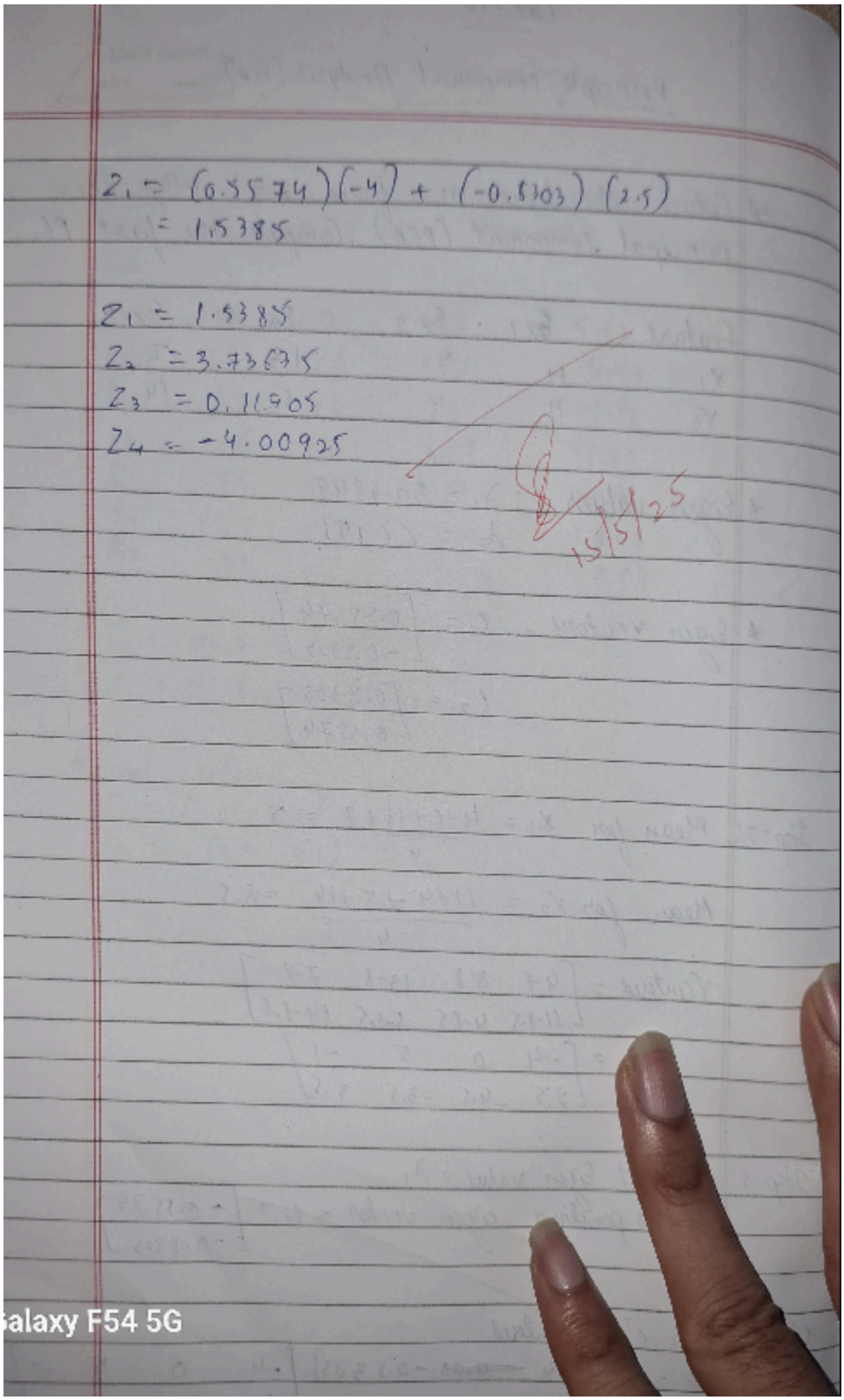
```
    kmeans.fit(X_scaled)

    inertia.append(kmeans.inertia_)



# Automatically determine the elbow point (optional)

diff = np.diff(inertia)

diff_r = np.diff(diff)

optimal_k = np.argwhere(diff_r > -0.1)[0][0] + 2  # add 2 due to second
derivative shift



# Plot elbow graph with optimal K marked

plt.figure(figsize=(8, 5))

plt.plot(k_range, inertia, 'bo-')

plt.axvline(x=optimal_k, color='red', linestyle='--', label=f'Optimal k =
{optimal_k}')

plt.xlabel('Number of Clusters (k)')

plt.ylabel('Inertia')

plt.title('Elbow Method For Optimal k')

plt.legend()

plt.grid(True)

plt.tight_layout()

plt.show()



# Output the optimal k
```

```
print(f"Optimal number of clusters (k): {optimal_k}")
```

Program 11

Screenshot:




$Z_1 = (0.5574)(-4) + (-0.8303)(2.5)$
$= 1.5385$
$Z_1 = 1.5385$
$Z_2 = 3.73675$
$Z_3 = 0.11905$
$Z_4 = -4.00925$
Galaxy F54 5G

Code:

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.decomposition import PCA

from sklearn.svm import SVC

from sklearn.linear_model import LogisticRegression

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score




df = pd.read_csv("heart (1).csv")




categorical_cols = ['Sex', 'ChestPainType', 'RestingECG', 'ExerciseAngina',
'ST_Slope']

df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)




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

y = df["HeartDisease"]
```

```
scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)



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



models = {

    "SVM": SVC(),

    "Logistic Regression": LogisticRegression(max_iter=1000),

    "Random Forest": RandomForestClassifier()

}



accuracy_before_pca = {}

for name, model in models.items():

    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)

    accuracy_before_pca[name] = accuracy_score(y_test, y_pred)



pca = PCA(n_components=0.95)

X_pca = pca.fit_transform(X_scaled)



X_train_pca, X_test_pca, y_train_pca, y_test_pca = train_test_split(X_pca, y,
test_size=0.2, random_state=42)
```

```
accuracy_after_pca = {}
for name, model in models.items():
    model.fit(X_train_pca, y_train_pca)
    y_pred_pca = model.predict(X_test_pca)
    accuracy_after_pca[name] = accuracy_score(y_test_pca, y_pred_pca)


print(" Accuracy BEFORE PCA:")
for name, acc in accuracy_before_pca.items():
    print(f"{name}: {acc:.4f}")


print("\nAccuracy AFTER PCA:")
for name, acc in accuracy_after_pca.items():
    print(f"{name}: {acc:.4f}")


print(f"\nOriginal features: {X.shape[1]}")
print(f"Features after PCA: {X_pca.shape[1]}")
```