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
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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 **Abhishek Gouda (1BM22CS006),** who is Bonafide student of **B.M.S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements in respect of an Machine Learning (23CS6PCMAL) work prescribed for the said degree.

Dr. Seema Patil Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

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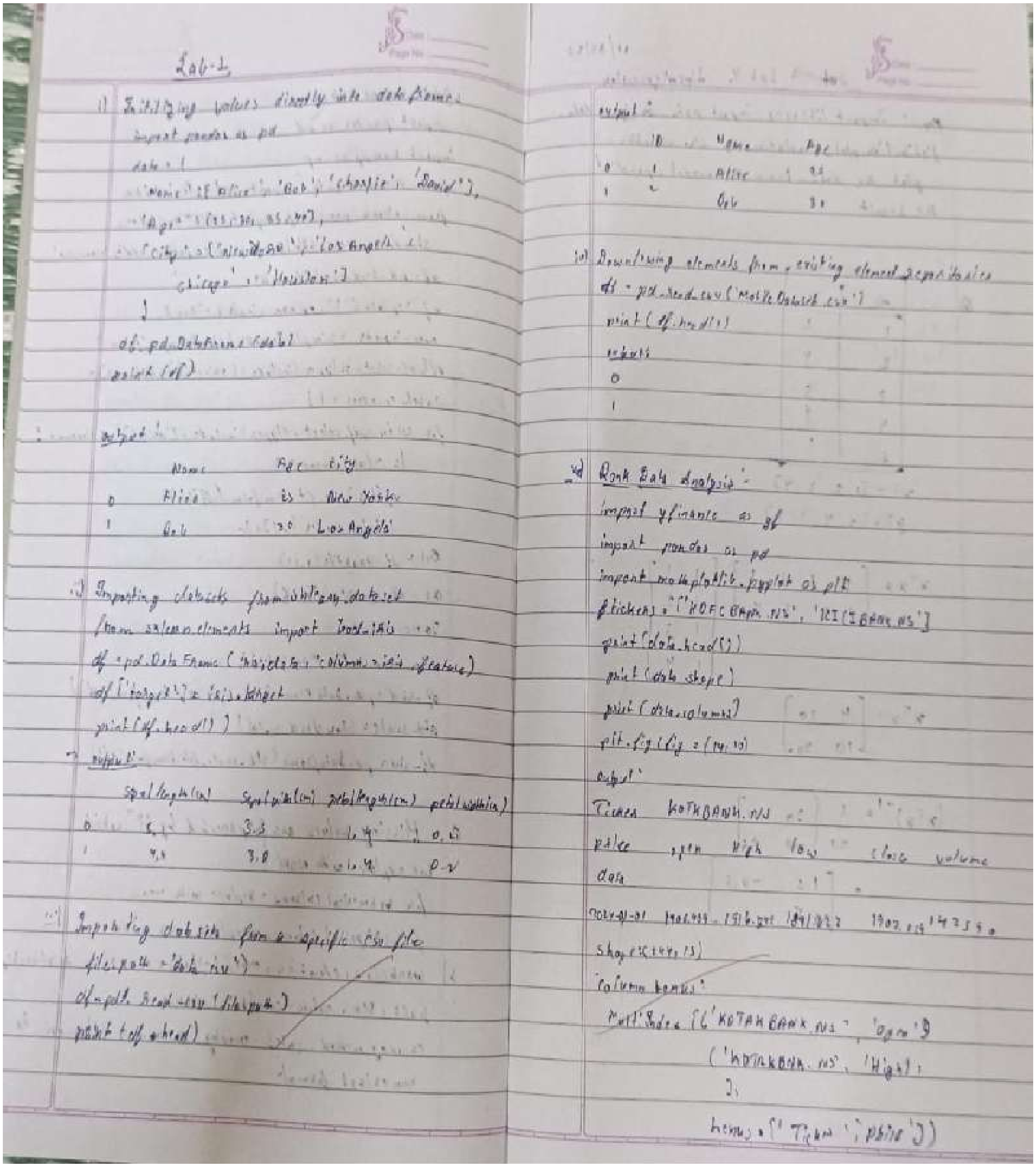
Github Link: https://github.com/Abhii2404/6thSem-ML-Lab

Program 1

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

Screenshot



Lab-1

i) Initializing values directly into dataframe

```
import pandas as pd
data = {
  'Name': ['Alice', 'Bob', 'Charlie', 'David'],
  'Age': [25, 30, 35, 40],
  'City': ['New York', 'Los Angeles',
       'Chicago', 'Houston']
  }
df = pd.DataFrame(data)
print(df)
```

output

```
     Name     Age   City
0    Alice    25    New York
1    Bob      30    Los Angeles
```

ii) Importing datasets from sklearn dataset

```
from sklearn.datasets import load_iris
df = pd.DataFrame(iris.data, columns = iris.feature)
df['target'] = iris.target
print(df.head())
```

output

```
   sepal length(cm)  sepal width(cm)  petal length(cm)  petal width(cm)
0       5.1              3.5              1.4              0.2
1       4.9              3.0              1.4              0.2
```

iii) Importing datasets from a specific csv file

```
filepath = 'data.csv'
df = pd.read_csv(filepath)
print(df.head)
```

output

```
      ID     Name     Age
0     1      Alice    25
1     2      Bob      30
```

iv) Downloading elements from existing element [illegible]

```
df = pd.read_csv('[illegible].csv')
print(df.head())
```

output

```
0
1
```

v) Bank Data Analysis

```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
tickers = ['HDFCBANK.NS', 'ICICIBANK.NS']
print(data.head())
print(data.shape)
print(data.columns)
plt.figure(figsize=(14, 10))
```

output

```
Ticker   KOTAKBANK.NS
Price    open   High   low   close   volume
date
2024-01-01  1906.499  1916.201  1891.823  1907.014  142350
Shape ((144, 15))
Column names
  MultiIndex([('KOTAKBANK.NS', 'Open'),
              ('KOTAKBANK.NS', 'High'),
             ],
  names = ['Ticker', 'Price'])
```

Code:

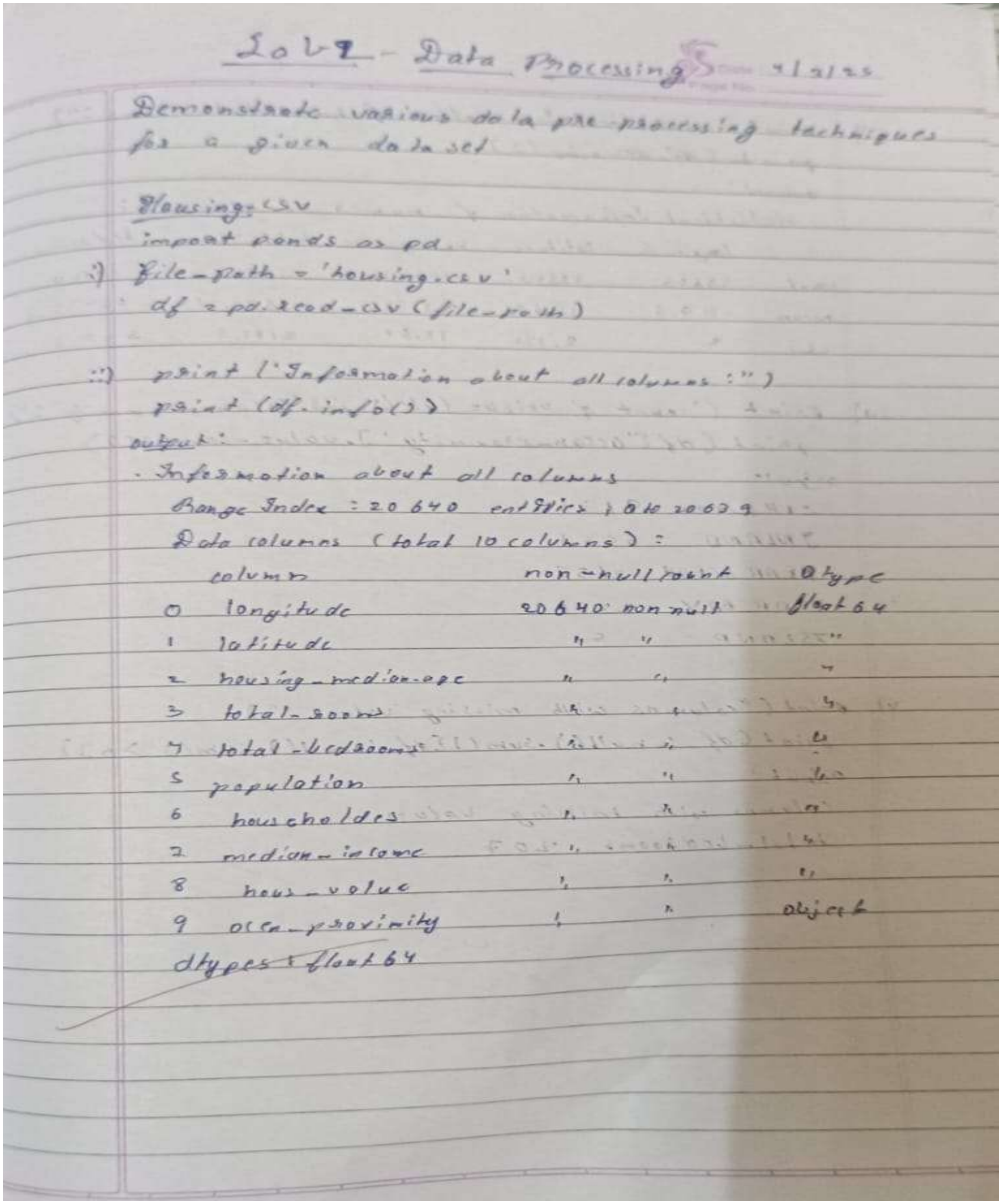
```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30", group_by='ticker')
print("First 5 rows of the dataset:")
print(data.head())
print("\nShape of the dataset:")
print(data.shape)
print("\nColumn names:")
print(data.columns)
hdfc_data = data['HDFCBANK.NS']
print("\nSummary statistics for HDFC Bank:")
print(hdfc_data.describe())
hdfc_data['Daily Return'] = hdfc_data['Close'].pct_change()
icici_data = data['ICICIBANK.NS']
print("\nSummary statistics for ICICI Bank:")
print(icici_data.describe())
icici_data['Daily Return'] = icici_data['Close'].pct_change()
kotak_data = data['KOTAKBANK.NS']
print("\nSummary statistics for Kotak Mahindra Bank:")
print(kotak_data.describe())
```

```
kotak_data['Daily Return'] = kotak_data['Close'].pct_change()
plt.figure(figsize=(14, 10))
plt.subplot(3, 2, 1)
hdfc_data['Close'].plot(title="HDFC Bank - Closing Price")
plt.subplot(3, 2, 2)
hdfc_data['Daily Return'].plot(title="HDFC Bank - Daily Returns", color='orange')
plt.subplot(3, 2, 3)
icici_data['Close'].plot(title="ICICI Bank - Closing Price")
plt.subplot(3, 2, 4)
icici_data['Daily Return'].plot(title="ICICI Bank - Daily Returns", color='orange')
plt.subplot(3, 2, 5)
kotak_data['Close'].plot(title="Kotak Mahindra Bank - Closing Price")
plt.subplot(3, 2, 6)
kotak_data['Daily Return'].plot(title="Kotak Mahindra Bank - Daily Returns", color='orange')
plt.tight_layout()
plt.show()


hdfc_data.to_csv('hdfc_bank_data.csv')
icici_data.to_csv('icici_bank_data.csv')
kotak_data.to_csv('kotak_bank_data.csv')


print("\nHDFC Bank data saved to 'hdfc_bank_data.csv'.")
print("ICICI Bank data saved to 'icici_bank_data.csv'.")
print("Kotak Bank data saved to 'kotak_bank_data.csv'.")
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshot



Lab 2 - Data Processing 21/2/25

Demonstrate various data pre-processing techniques for a given data set

Housing.csv

```
import pands as pd
i) file-path = 'housing.csv'
   df = pd.read-csv(file-path)

ii) print ("Information about all columns:")
    print (df.info())
```

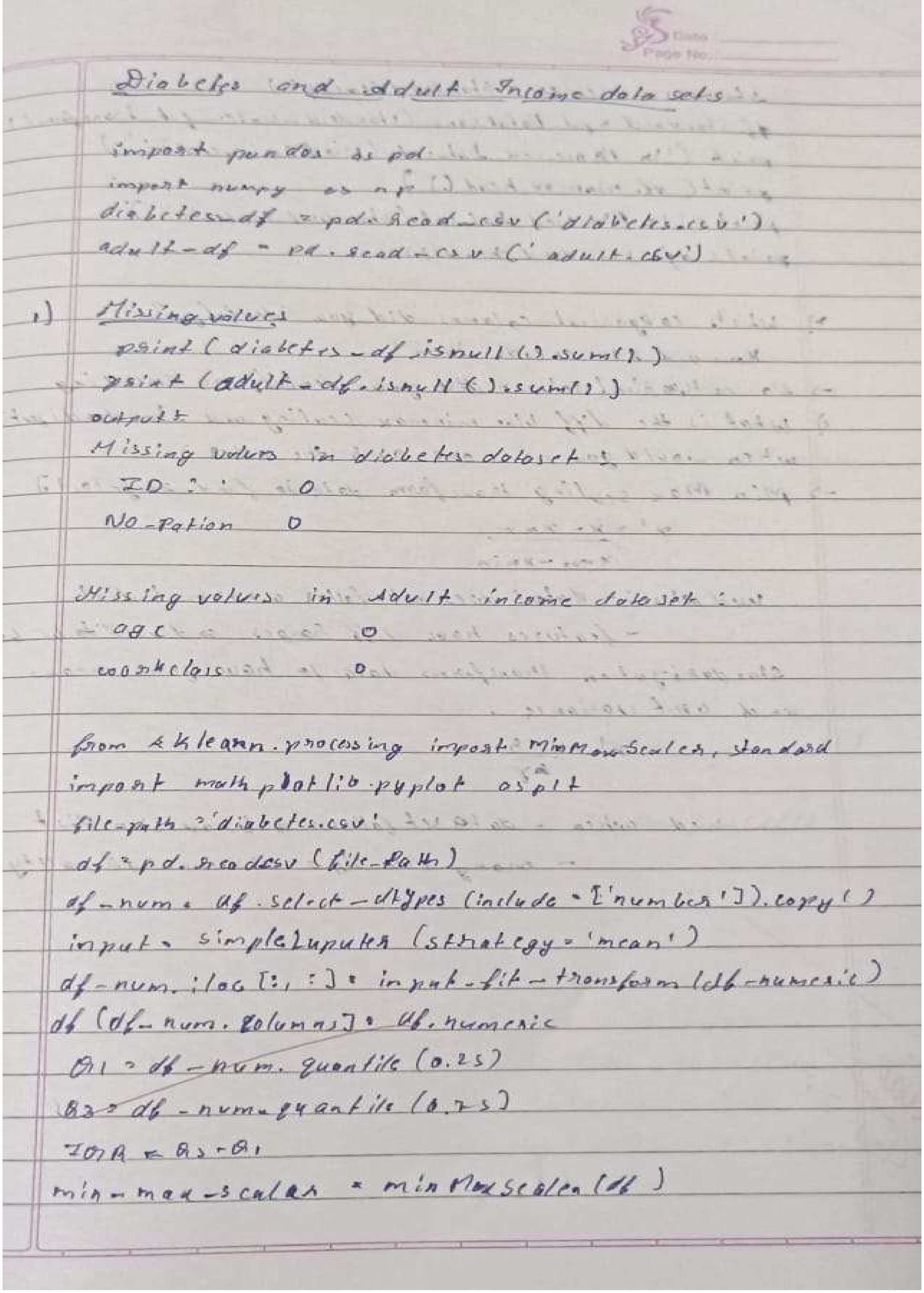
output:

```
. Information about all columns
   Range Index : 20640  entries ; 0 to 20639
   Data columns (total 10 columns) :
      column                     non-null count    Dtype
   0  longitude                  20640 non null    float64
   1  latitude                     "      "         "
   2  housing-median-age           "      "         "
   3  total-rooms                  "      "         "
   4  total-bedrooms               "      "         "
   5  population                   "      "         "
   6   householdes                 "      "         "
   7  median-income                "      "         "
   8   hous-value                  "      "         "
   9  ocen-proximity               "      "        object
   dtypes : float64
```

iii) print ("statistical Information of numerical columns :")
print (df.describe ())
output'
```
statistical Information of numerical columns ::
        longitude  latitude  housing_age  total_rooms  bed rooms
count   20640      20640     20640        20640        20640
mean    -119.5     35.631    28.639       2635.76      26433.1
std     2          2.173     12.58        2181.6       537.3
```

iv) Print ("count of unique labels for 'Ocean proximity':")
print (df['ocean_proximity'].value_counts())
output:
```
ZIHOcean   9136
INLAND     6551
NEAR OCEAN 2658
NEAR BAY   2290
ISLAND     5
```

v) print ("columns with missing values :")
print (df.isnull().sum()[df.isnull().sum() >0])
output'
```
columns with missing values :
total_bedrooms  207
```



Diabetes and Adult Income data sets

```
import pandas as pd
import numpy as np
diabetes_df = pd.read_csv('diabetes.csv')
adult_df = pd.read_csv('adult.csv')
```

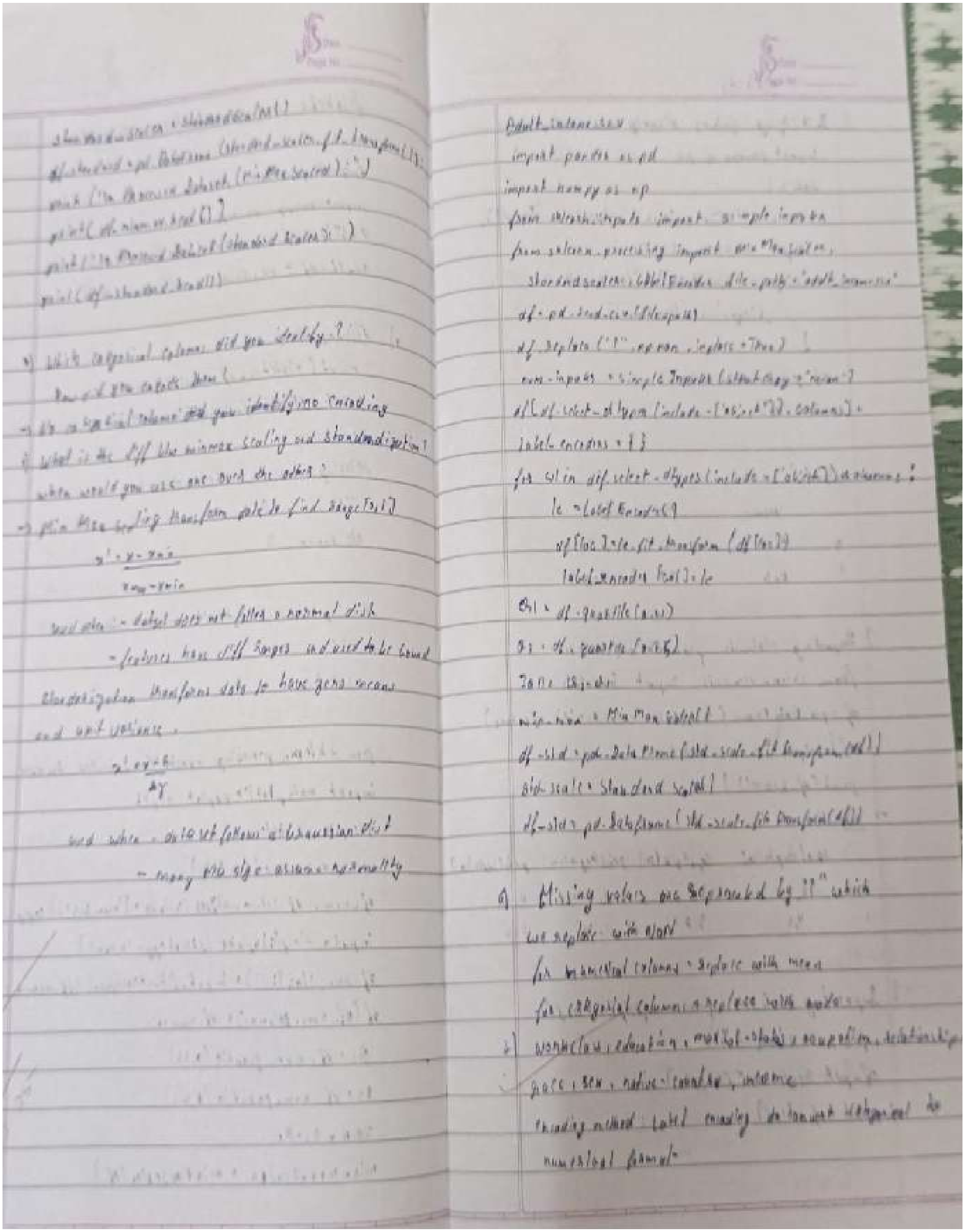
1) Missing values

```
print(diabetes_df.isnull().sum())
print(adult_df.isnull().sum())
```

output

```
Missing values in diabetes dataset :
 ID :     0
 No-Pation   0

Missing values in Adult income dataset :
 age        0
 workclass      0
```

```
from sklearn.processing import MinMaxScaler, standard
import mathplotlib.pyplot as plt
file_path = 'diabetes.csv'
df = pd.readcsv(file_path)
df_num = df.select_dtypes(include = ['number']).copy()
input = simpleInputer (strategy = 'mean')
df_num.iloc[:, :] = input.fit_transform(df_numeric)
df (df_num.columns] = df.numeric
Q1 = df_num.quantile (0.25)
Q3 = df_num.quantile (0.75)
IQR = Q3 - Q1
min_max_scaler = minMaxScaler(df )
```



```
standard_scaler = StandardScaler()
df_standard = pd.DataFrame(standard_scaler.fit_transform(df),
print("In Processed dataset (MinMax Scaled):")
print(df_minmax.head())
print("In Processed dataset (Standard Scaled):")
print(df_standard.head())
```

Q) Which categorical columns did you identify? How did you encode them?

→ the categorical columns did you identifying encoding

Q) What is the diff b/w minmax scaling and standardization? when would you use one over the other?

→ Min Max scaling transform data to find range [0,1]

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

used when :- dataset does not follow a normal dist.
- features have diff ranges and need to be bound

Standardization transforms data to have zero mean and unit variance.

$$x' = \frac{x - \mu}{\sigma}$$

used when - dataset follows a Gaussian dist
- many ML algo assume normality

Adult_income.csv

```
import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler,
  StandardScaler, LabelEncoder file_path = "adult_income.csv"
df = pd.read_csv(file_path)
df.replace("?", np.nan, inplace=True)
num_imputer = SimpleImputer(strategy="mean")
df[df.select_dtypes(include=["int64","float64"]).columns] =
label_encoders = {}
for col in df.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
min_max = MinMaxScaler()
df_std = pd.DataFrame(std_scaler.fit_transform(df))
std_scaler = StandardScaler()
df_std = pd.DataFrame(std_scaler.fit_transform(df))
```

a) Missing values are represented by "?" which we replace with NaN
for numerical columns : replace with mean
for categorical columns : replace with mode

b) workclass, education, marital-status, occupation, relationship, race, sex, native-country, income
Encoding method: Label encoding to convert categorical to numerical format.

Code:

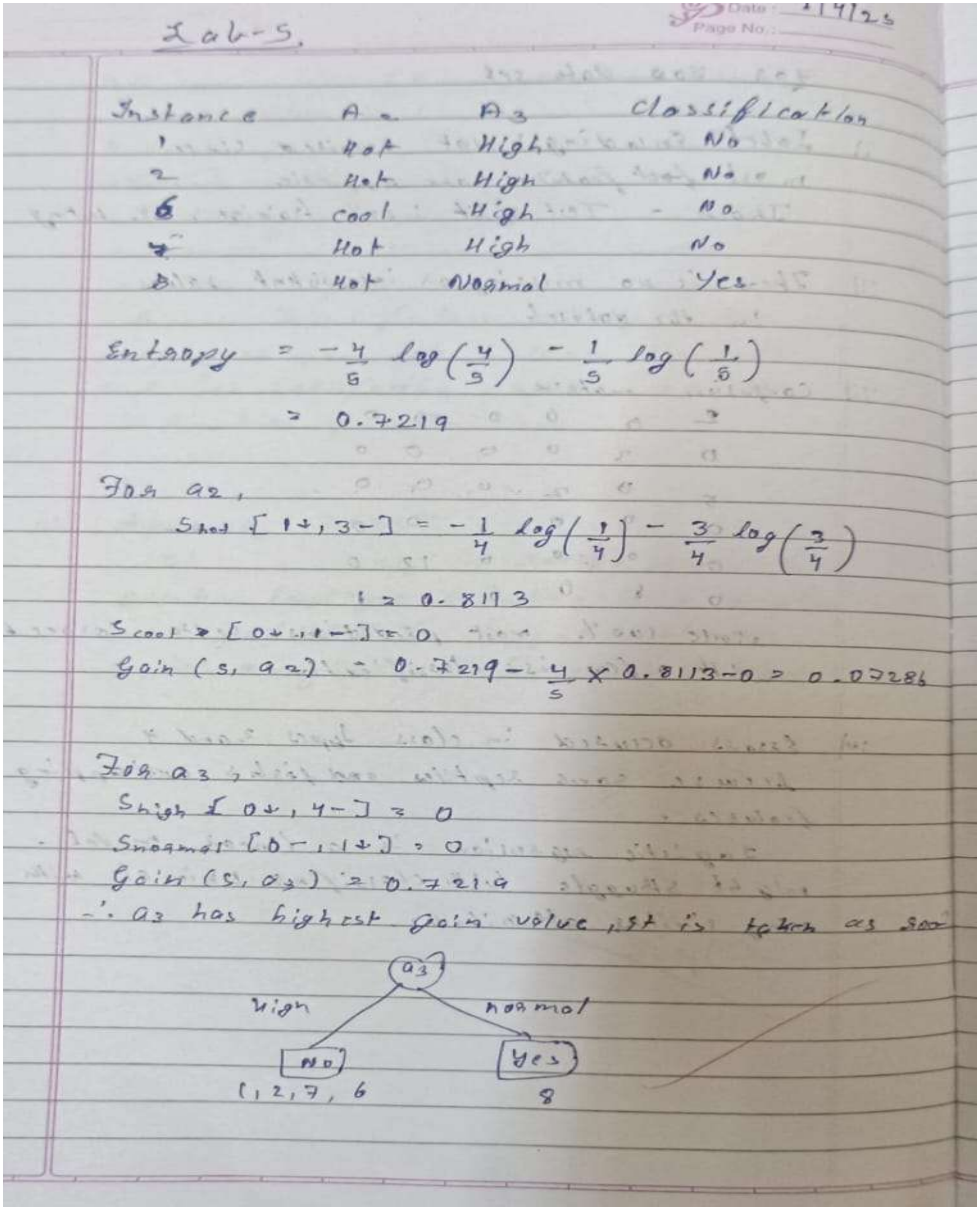
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
import matplotlib.pyplot as plt

diabetes_data = pd.read_csv('/content/Dataset of Diabetes .csv')
adult_income_data = pd.read_csv('/content/adult.csv')

print("Diabetes Dataset:")
print(diabetes_data.head())

print("\nAdult Income Dataset:")
print(adult_income_data.head())

diabetes_numerical_cols = diabetes_data.select_dtypes(include=[np.number]).columns
diabetes_categorical_cols = diabetes_data.select_dtypes(include=[object]).columns

diabetes_imputer_num = SimpleImputer(strategy='median')
diabetes_data[diabetes_numerical_cols] =
diabetes_imputer_num.fit_transform(diabetes_data[diabetes_numerical_cols])

diabetes_imputer_cat = SimpleImputer(strategy='most_frequent')
diabetes_data[diabetes_categorical_cols] =
diabetes_imputer_cat.fit_transform(diabetes_data[diabetes_categorical_cols])

adult_income_numerical_cols = adult_income_data.select_dtypes(include=[np.number]).columns
adult_income_categorical_cols = adult_income_data.select_dtypes(include=[object]).columns

adult_income_imputer_num = SimpleImputer(strategy='median')
adult_income_data[adult_income_numerical_cols] =
adult_income_imputer_num.fit_transform(adult_income_data[adult_income_numerical_cols])

adult_income_imputer_cat = SimpleImputer(strategy='most_frequent')
adult_income_data[adult_income_categorical_cols] =
adult_income_imputer_cat.fit_transform(adult_income_data[adult_income_categorical_cols])

categorical_columns_adult = adult_income_data.select_dtypes(include=['object']).columns
label_encoder = LabelEncoder()

for col in categorical_columns_adult:
    adult_income_data[col] = label_encoder.fit_transform(adult_income_data[col])
```

```
def detect_and_remove_outliers(df):
    numerical_df = df.select_dtypes(include=[np.number])
    Q1 = numerical_df.quantile(0.25)
    Q3 = numerical_df.quantile(0.75)
    IQR = Q3 - Q1
    return df[~((numerical_df < (Q1 - 1.5 * IQR)) | (numerical_df > (Q3 + 1.5 * IQR))).any(axis=1)]

diabetes_data_cleaned = detect_and_remove_outliers(diabetes_data)
adult_income_data_cleaned = detect_and_remove_outliers(adult_income_data)

min_max_scaler = MinMaxScaler()

diabetes_numerical_cols = diabetes_data_cleaned.select_dtypes(include=[np.number]).columns
diabetes_data_normalized = diabetes_data_cleaned.copy()

diabetes_data_normalized[diabetes_numerical_cols] =
min_max_scaler.fit_transform(diabetes_data_cleaned[diabetes_numerical_cols])

adult_income_numerical_cols =
adult_income_data_cleaned.select_dtypes(include=[np.number]).columns
adult_income_data_normalized = adult_income_data_cleaned.copy()

adult_income_data_normalized[adult_income_numerical_cols] =
min_max_scaler.fit_transform(adult_income_data_cleaned[adult_income_numerical_cols])

standard_scaler = StandardScaler()

diabetes_data_standardized = diabetes_data_cleaned.copy()
diabetes_data_standardized[diabetes_numerical_cols] =
standard_scaler.fit_transform(diabetes_data_cleaned[diabetes_numerical_cols])

adult_income_data_standardized = adult_income_data_cleaned.copy()
adult_income_data_standardized[adult_income_numerical_cols] =
standard_scaler.fit_transform(adult_income_data_cleaned[adult_income_numerical_cols])
```

Program 3

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

Screenshot:



Date: 1/4/25

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Lab-5.

Instance	A 2	A 3	Classification
1	Hot	High	No
2	Hot	High	No
6	cool	High	No
7	Hot	High	No
8	Hot	Normal	Yes

Entropy $= -\frac{4}{5}\log\left(\frac{4}{5}\right) - \frac{1}{5}\log\left(\frac{1}{5}\right)$

$= 0.7219$

For a2,

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

$= 0.8113$

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

Gain $(S, a2) = 0.7219 - \frac{4}{5} \times 0.8113 - 0 = 0.07286$

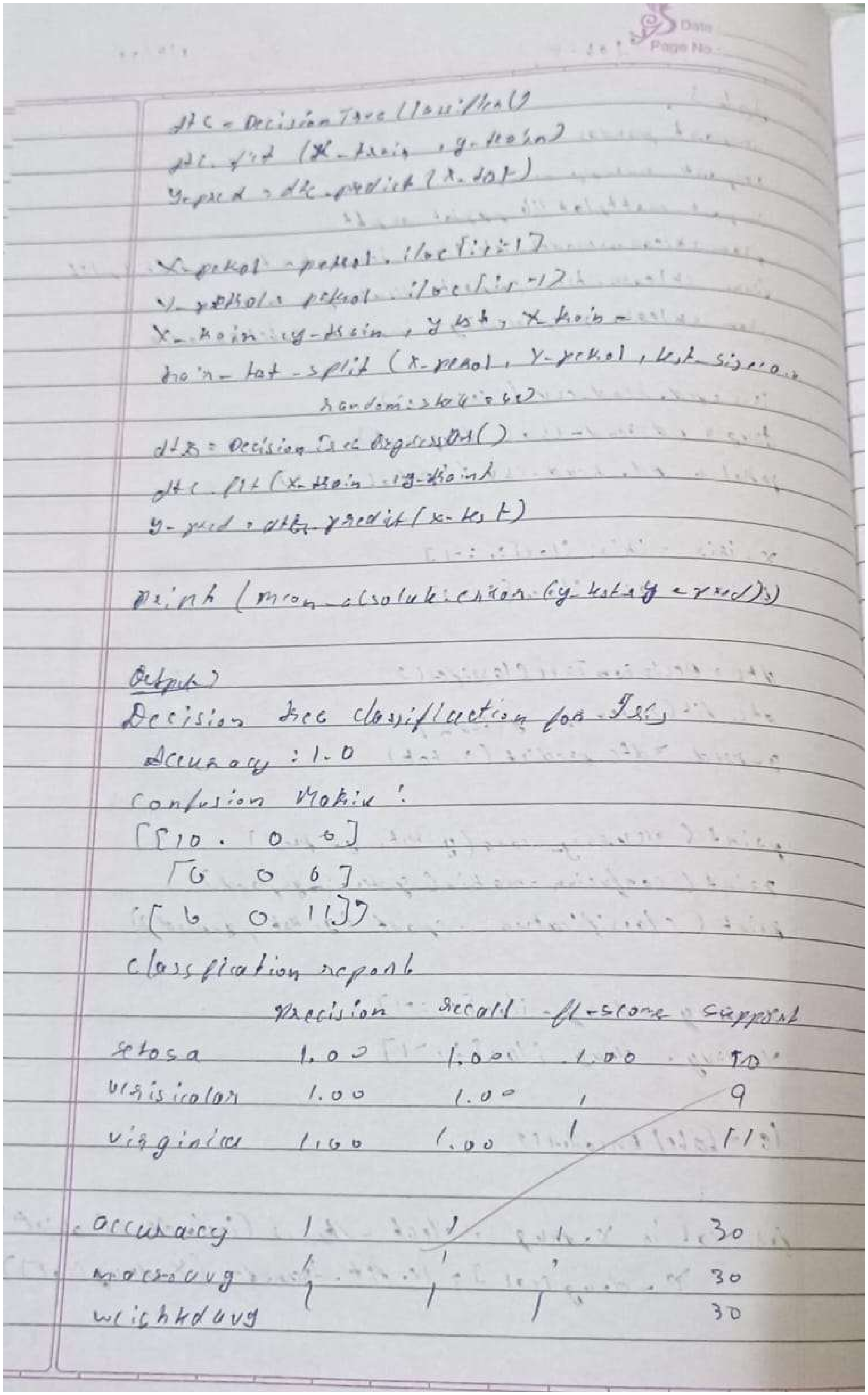
For a3,

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

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

Gain $(S, a_3) = 0.7219$

∴ a3 has highest gain value, it is taken as root



```
dtc = DecisionTreeClassifier()
dtc.fit (X_train , y_train)
y_pred = dtc.predict (x_test)

X_petrol = petrol.iloc[:,:-1]
y_petrol = petrol.iloc[:,-1]
X_train , y_train , y_test , X_train =
train_test_split (X_petrol , Y_petrol , test_size=0.2,
                  random_state=42)
dtr = DecisionTreeRegressor()
dtc.fit (X_train , y_train)
y_pred = dtr.predict (x_test)

print (mean_absolute_error (y_test , y_pred))
```

Output)

```
Decision tree classification for Iris
 Accuracy : 1.0
confusion Matrix :
[[10 . 0 0]
  [6  0  6]
 [6  0 11]]
classification report
            precision   recall   f1-score   support
setosa        1.00       1.00     1.00        10
versicolor    1.00       1.00     1           9
virginica     1.00       1.00     1           11

accuracy      1          1                    30
macro avg     1          1        1           30
weighted avg  1          1        1           30
```

Decision tree for drug:

Accuracy : 1.0

Confusion matrix

```
[[6 0 0 0 0]
 [0 3 0 0 0]
 [0 0 5 0 0]
 [0 0 0 11 0]
 [0 0 0 0 15]]
```

Classification Report:

```
              precision   recall   f1 score   support
 Drug A           1          1        1          6
      B           1          1        1          3
      C           1          1        1          5
      X           1          1        1         11
      Y           1          1        1         15

accuracy                              1         40
macro avg         1          1        1         40
weighted avg      1          1        1         40
```

Decision Tree regressor for Petrol consumption

Mean Absolute error : 91.9

Mean square Error : 17857.3

Root Mean square Squared Error : 133.6312089

Code:

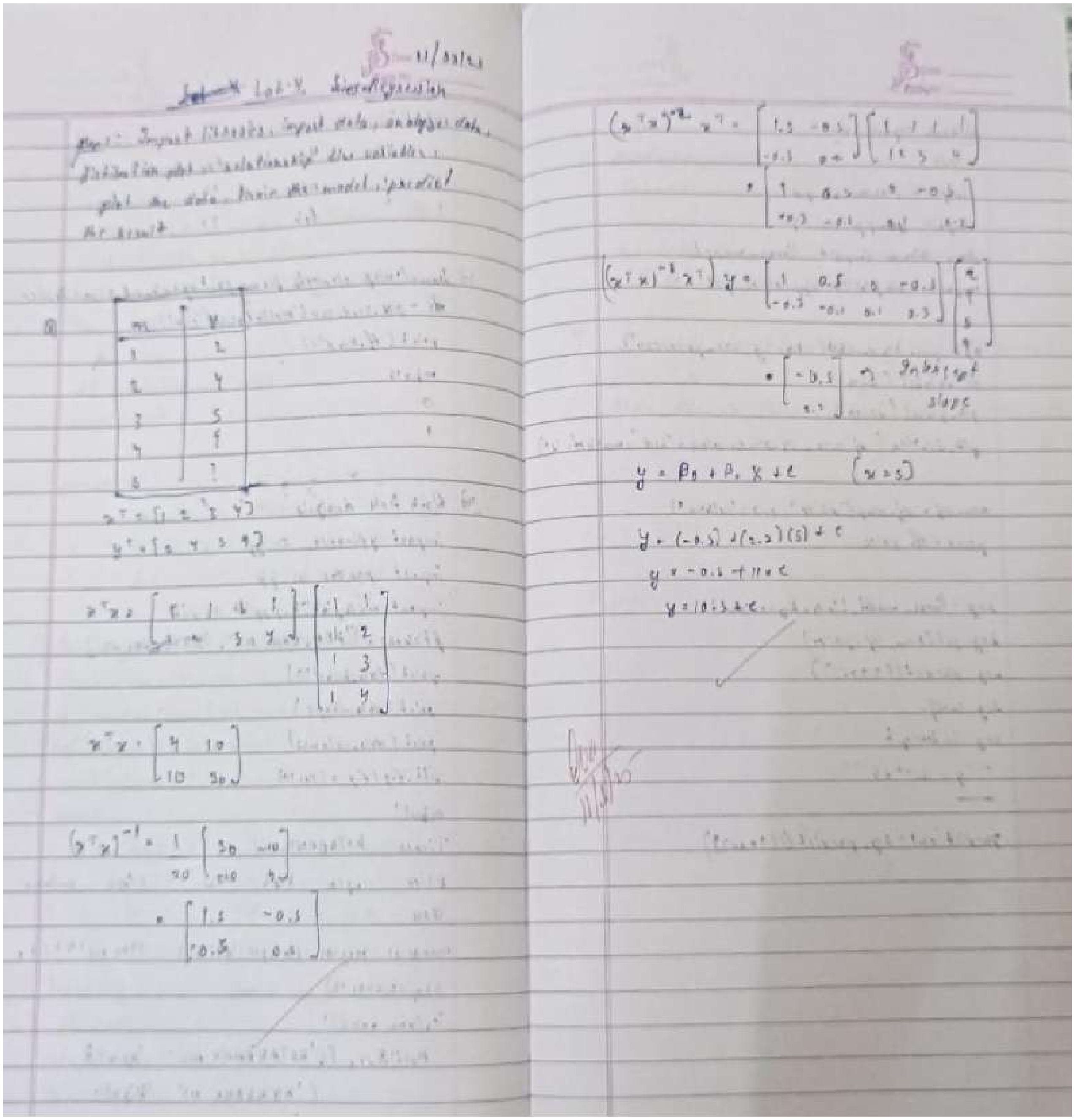
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report,
mean_absolute_error, mean_squared_error
from sklearn.preprocessing import LabelEncoder

iris = pd.read_csv("/content/iris (4).csv")
drug = pd.read_csv("/content/drug.csv")
petrol = pd.read_csv("/content/petrol_consumption.csv")

X_iris = iris.iloc[:, :-1]
y_iris = iris.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(X_iris, y_iris, test_size=0.2, random_state=42)

dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
y_pred = dtc.predict(X_test)

print("Decision Tree Classification for IRIS Dataset:")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))

X_drug = drug.iloc[:, :-1]
y_drug = drug.iloc[:, -1]

le = LabelEncoder()

for col in X_drug.select_dtypes(include=['object']).columns:
    X_drug[col] = le.fit_transform(X_drug[col])

X_train, X_test, y_train, y_test = train_test_split(X_drug, y_drug, test_size=0.2, random_state=42)

dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
y_pred = dtc.predict(X_test)

print("\nDecision Tree Classification for Drug Dataset:")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))

X_petrol = petrol.iloc[:, :-1]
```

```
y_petrol = petrol.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(X_petrol, y_petrol, test_size=0.2, random_state=42)

dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
y_pred = dtr.predict(X_test)

print("\nDecision Tree Regression for Petrol Consumption:")
print("Mean Absolute Error:", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error:", np.sqrt(mean_squared_error(y_test, y_pred)))
```

Program 4

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot



11/03/23

~~[illegible]~~ Lab-4 Linear Regression

Aim: Import libraries, import data, analyze data, visualize plot relationship b/w variables, plot the data, train the model, predict the result

①

x	y
1	2
2	4
3	5
4	4
5	[illegible]

$x^T = [1\ 2\ 3\ 4]$

$y^T = [2\ 4\ 5\ 4]$

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

$$x^Tx = \begin{bmatrix} 4 & 10 \\ 10 & 30 \end{bmatrix}$$

$$(x^Tx)^{-1} = \frac{1}{20}\begin{bmatrix} 30 & -10 \\ -10 & 4 \end{bmatrix}$$

$$= \begin{bmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{bmatrix}$$

$$(x^Tx)^{-1}x^T = \begin{bmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0.5 & 0 & -0.5 \\ -0.3 & -0.1 & 0.1 & 0.3 \end{bmatrix}$$

$$\left((x^Tx)^{-1}x^T\right) y = \begin{bmatrix} 1 & 0.5 & 0 & -0.5 \\ -0.3 & -0.1 & 0.1 & 0.3 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \\ 5 \\ 4 \end{bmatrix}$$

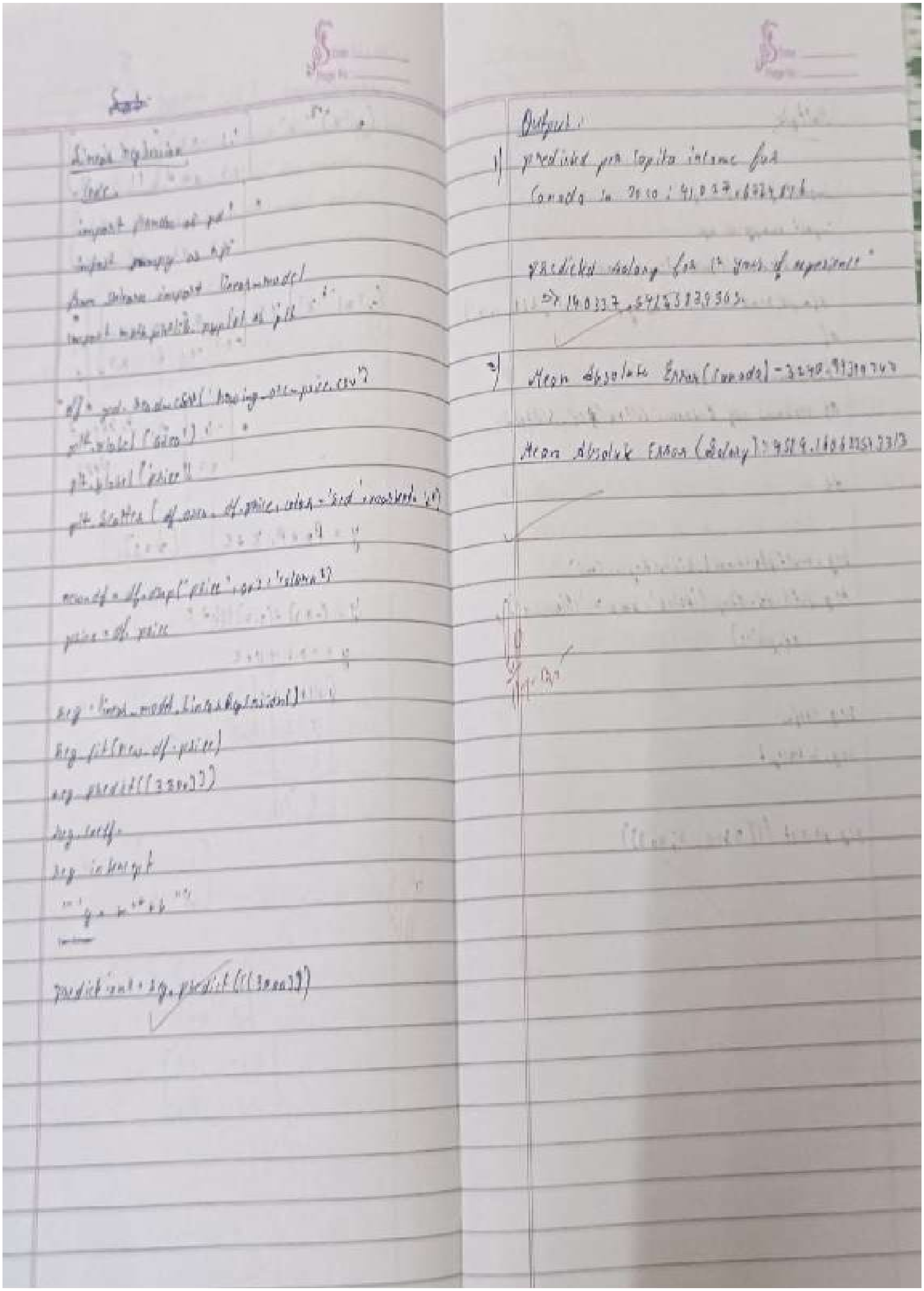
$$= \begin{bmatrix} -0.5 \\ 2.2 \end{bmatrix} \rightarrow \begin{matrix} \text{Intercept} \\ \text{slope} \end{matrix}$$

$y = \beta_0 + \beta_1 x + e \qquad (x = 5)$

$y = (-0.5) + (2.2)(5) + e$

$y = -0.5 + 11 + e$

$y = 10.5 + e$



[illegible]

Linear Regression

Code.

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

df = pd.read_csv('housing_area_price.csv')
plt.xlabel('area')
plt.ylabel('price')
plt.scatter(df.area, df.price, color='red', marker='+')

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

reg = linear_model.LinearRegression()
reg.fit(new_df, price)
reg.predict([[3300]])
reg.coef_
reg.intercept_
'''y = m*x + b'''

predict_val = reg.predict([[3000]])
```

Output:

1) predicted per capita income for Canada in 2020 : 41,037.6824,896

predicted salary for 12 years of experience
=> 140337.64153838303

2) Mean Absolute Error (Canada) - 3240.9939747

Mean Absolute Error (Salary): 4514.14062351733

Multiple

```
import pandas as pd
import numpy as np
from sklearn import linear_model
df = pd.read_csv('housing price Multiple.csv')
df
df.bedrooms.median()
df.bedrooms = df.bedrooms.fillna(df.bedrooms.
median())
df

reg = multiple-model.LinearRegression()
reg.fit(df.drop('price', axis = 'columns'),
      df.price)

reg.coef_
reg.intercept_

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

Output

1) predicted salary for candidate 1 (2 yr experience, 9 test score, 6 interview score)

   53562.500000001

2) Predicted salary for candidate 2 (12 yr experience, 10 test score, 10 interview score) = 92552.40999

3) Mean Absolute Error for salary prediction: 667

Predicted profit for the given inputs

(Florida State) 155400.6924852

Mean absolute for profit prediction:

1278.66744923337

10/15

Code:

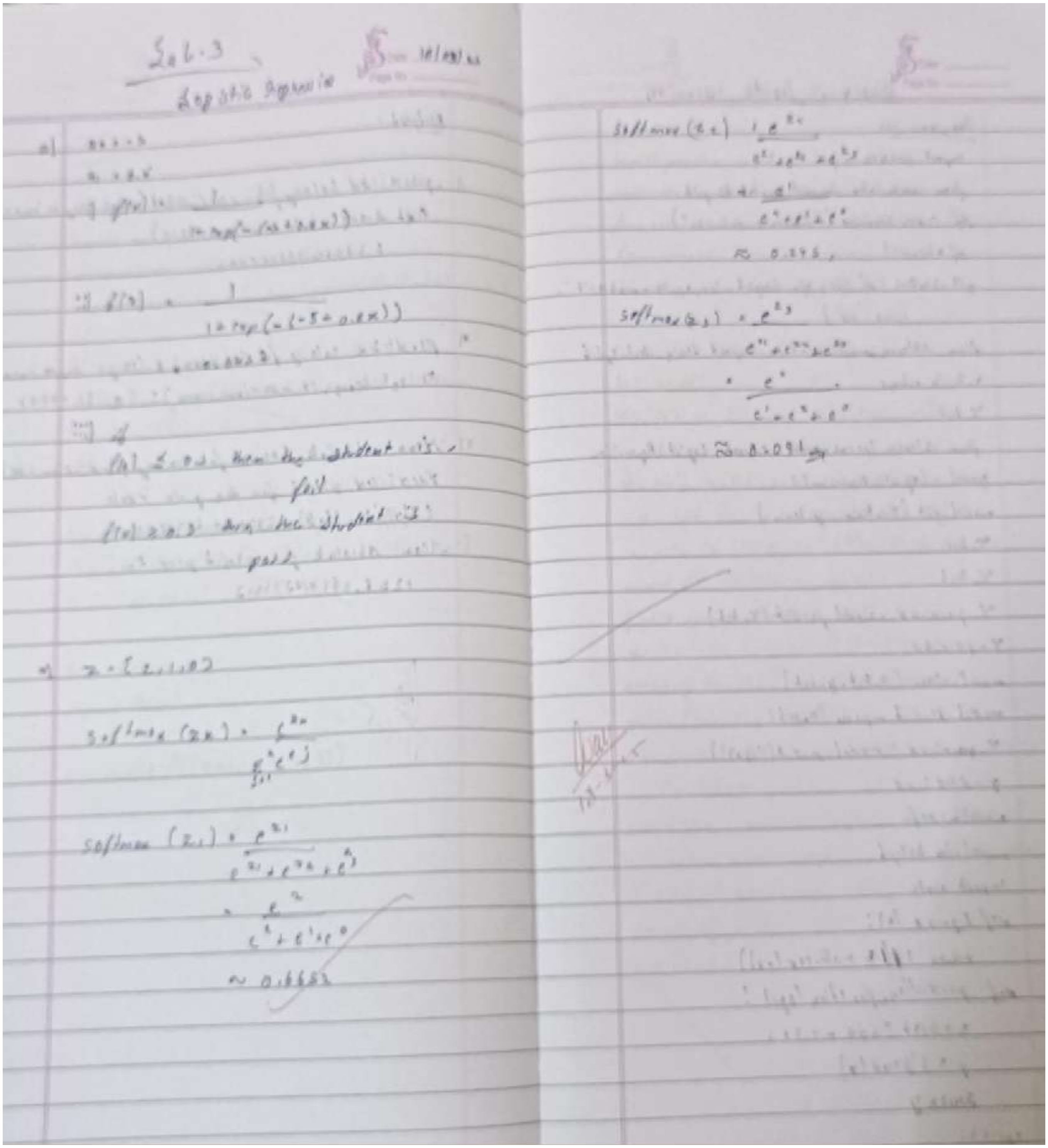
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import mean_absolute_error
import matplotlib.pyplot as plt

hiring_data = pd.read_csv('hiring.csv')
print(hiring_data.head())
hiring_data = hiring_data.dropna()

experience_mapping = {
    'one': 1, 'two': 2, 'three': 3, 'four': 4, 'five': 5, 'six': 6, 'seven': 7, 'eight': 8,
    'nine': 9, 'ten': 10, 'eleven': 11, 'twelve': 12, 'thirteen': 13, 'fourteen': 14,
}

hiring_data['experience'] = hiring_data['experience'].replace(experience_mapping)
hiring_data['experience'] = pd.to_numeric(hiring_data['experience'], errors='coerce')

if hiring_data['experience'].isnull().any():
    print("Warning: There are still non-numeric values in the 'experience' column.")
    hiring_data = hiring_data.dropna(subset=['experience'])

X_hiring = hiring_data[['experience', 'test_score(out of 10)', 'interview_score(out of 10)']]
y_hiring = hiring_data['salary($)']

X_train_hiring, X_test_hiring, y_train_hiring, y_test_hiring = train_test_split(X_hiring, y_hiring,
test_size=0.2, random_state=42)

regressor_hiring = LinearRegression()
regressor_hiring.fit(X_train_hiring, y_train_hiring)

candidate_1 = np.array([[2, 9, 6]])
candidate_2 = np.array([[12, 10, 10]])

salary_1 = regressor_hiring.predict(candidate_1)
salary_2 = regressor_hiring.predict(candidate_2)

print(f"Predicted salary for candidate 1 (2 yr experience, 9 test score, 6 interview score):
{salary_1[0]}")
print(f"Predicted salary for candidate 2 (12 yr experience, 10 test score, 10 interview score):
{salary_2[0]}")
```

```
companies_data = pd.read_csv('/content/1000_Companies.csv')
print(companies_data.head())
companies_data = companies_data.dropna()

label_encoder = LabelEncoder()
companies_data['State'] = label_encoder.fit_transform(companies_data['State'])

X_companies = companies_data[['R&D Spend', 'Administration', 'Marketing Spend', 'State']]
y_companies = companies_data['Profit']

X_train_companies, X_test_companies, y_train_companies, y_test_companies =
train_test_split(X_companies, y_companies, test_size=0.2, random_state=42)

regressor_companies = LinearRegression()
regressor_companies.fit(X_train_companies, y_train_companies)

input_data = np.array([[91694.48, 515841.3, 11931.24, label_encoder.transform(['Florida'])[0]]])
predicted_profit = regressor_companies.predict(input_data)

print(f"Predicted profit for the given inputs (Florida State): {predicted_profit[0]}")

y_pred_hiring = regressor_hiring.predict(X_test_hiring)
mae_hiring = mean_absolute_error(y_test_hiring, y_pred_hiring)
print(f"Mean Absolute Error for Salary Prediction: {mae_hiring}")

y_pred_companies = regressor_companies.predict(X_test_companies)
mae_companies = mean_absolute_error(y_test_companies, y_pred_companies)
print(f"Mean Absolute Error for Profit Prediction: {mae_companies}")
```

Program 5

Build Logistic Regression Model for a given dataset

Screenshot



Lab-3

Logistic Regression

1) $\beta_0 = -5$

$\beta_1 = 0.8$

i) $f(x) = \frac{1}{1+\exp(-(\beta_0+\beta_1 x))}$

ii) $f(x) = \frac{1}{1+\exp(-(-5+0.8x))}$

iii) If

$f(x) < 0.5$, then the student is fail

$f(x) \geq 0.5$ then the student is pass

2) $z = [2, 1, 0]$

$\text{softmax}(z_k) = \frac{e^{z_k}}{\sum_{j=1}^{3} e^{z_j}}$

$\text{softmax}(z_1) = \frac{e^{z_1}}{e^{z_1}+e^{z_2}+e^{z_3}}$

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

≈ 0.6652

$\text{softmax}(z_2) = \frac{e^{z_2}}{e^{z_1}+e^{z_2}+e^{z_3}}$

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

≈ 0.245

$\text{softmax}(z_3) = \frac{e^{z_3}}{e^{z_1}+e^{z_2}+e^{z_3}}$

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

≈ 0.091

Code:

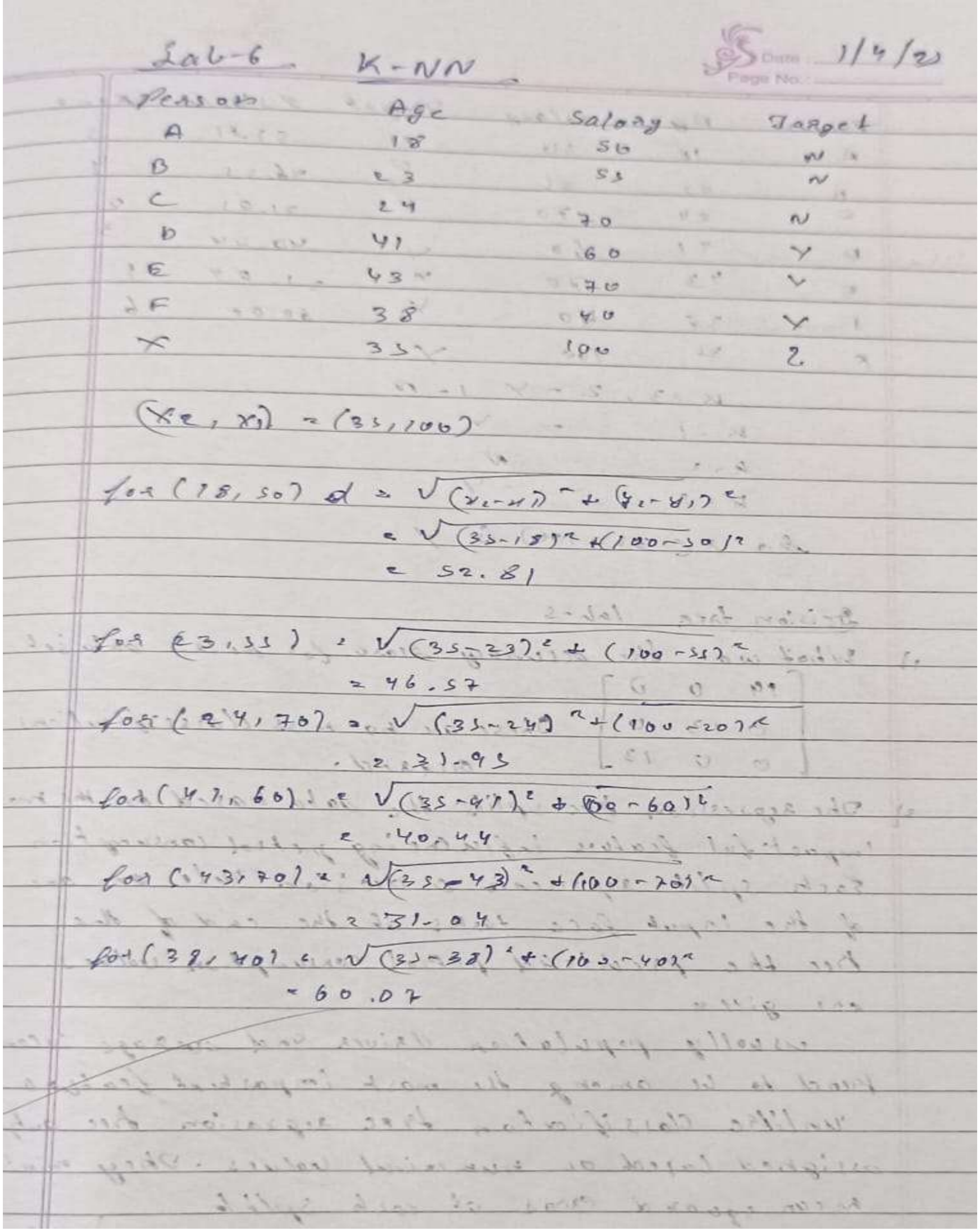
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix

file_path = 'HR_comma_sep.csv'
data = pd.read_csv(file_path)

print(data.info())

print(data.head())

print(data.describe())

plt.figure(figsize=(8, 5))
sns.countplot(x='salary', hue='left', data=data)
plt.title('Impact of Salary on Employee Retention')
plt.xlabel('Salary')
plt.ylabel('Count')
plt.legend(title='Employee Retention', labels=['Stayed', 'Left'])
plt.show()

plt.figure(figsize=(10, 6))
sns.countplot(x='Department', hue='left', data=data)
plt.title('Impact of Department on Employee Retention')
plt.xlabel('Department')
plt.ylabel('Count')
plt.legend(title='Employee Retention', labels=['Stayed', 'Left'])
plt.xticks(rotation=45)
plt.show()

data_encoded = pd.get_dummies(data, columns=['salary', 'Department'], drop_first=True)

print(data_encoded.info())

X = data_encoded.drop('left', axis=1)
y = data_encoded['left']

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

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
logreg = LogisticRegression(max_iter=1000)

logreg.fit(X_train_scaled, y_train)

y_pred = logreg.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the Logistic Regression Model: {accuracy * 100:.2f}%")

cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False, xticklabels=['Stayed', 'Left'],
yticklabels=['Stayed', 'Left'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

Program 6

Build KNN Classification model for a given dataset.

Screenshot



Lab-6 K-NN

Date 1/4/23

Person	Age	Salary	Target
A	18	50	N
B	23	55	N
C	24	70	N
D	41	60	Y
E	43	70	Y
F	38	40	Y
X	35	100	?

$(x_2, x_1) = (35, 100)$

for (18, 50) $d = \sqrt{(x_2-x_1)^2 + (y_2-y_1)^2}$

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

$= 52.81$

for (23, 55) $= \sqrt{(35-23)^2 + (100-55)^2}$

$= 46.57$

for (24, 70) $= \sqrt{(35-24)^2 + (100-20)^2}$

$= 31.95$

for (41, 60) $= \sqrt{(35-41)^2 + (100-60)^2}$

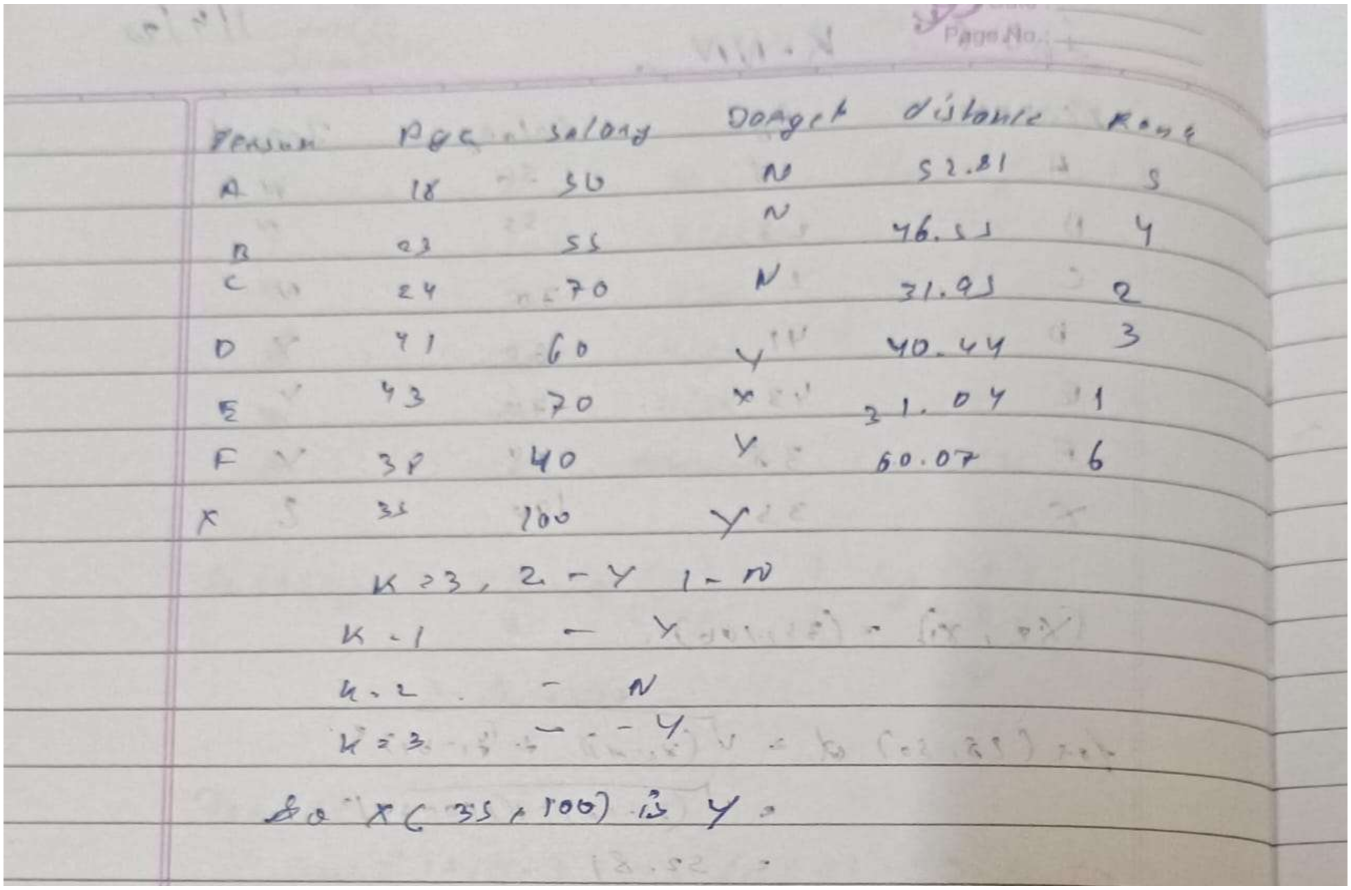
$= 40.44$

for (43, 70) $= \sqrt{(35-43)^2 + (100-70)^2}$

$= 31.04$

for (38, 40) $= \sqrt{(35-38)^2 + (100-40)^2}$

$= 60.07$



Page No.:

Person	Age	salary	Target	distance	Rank
A	18	50	N	52.81	5
B	23	55	N	46.51	4
C	24	70	N	31.93	2
D	41	60	Y	40.44	3
E	43	70	x	31.04	1
F	38	40	Y	60.07	6
X	35	100	Y		

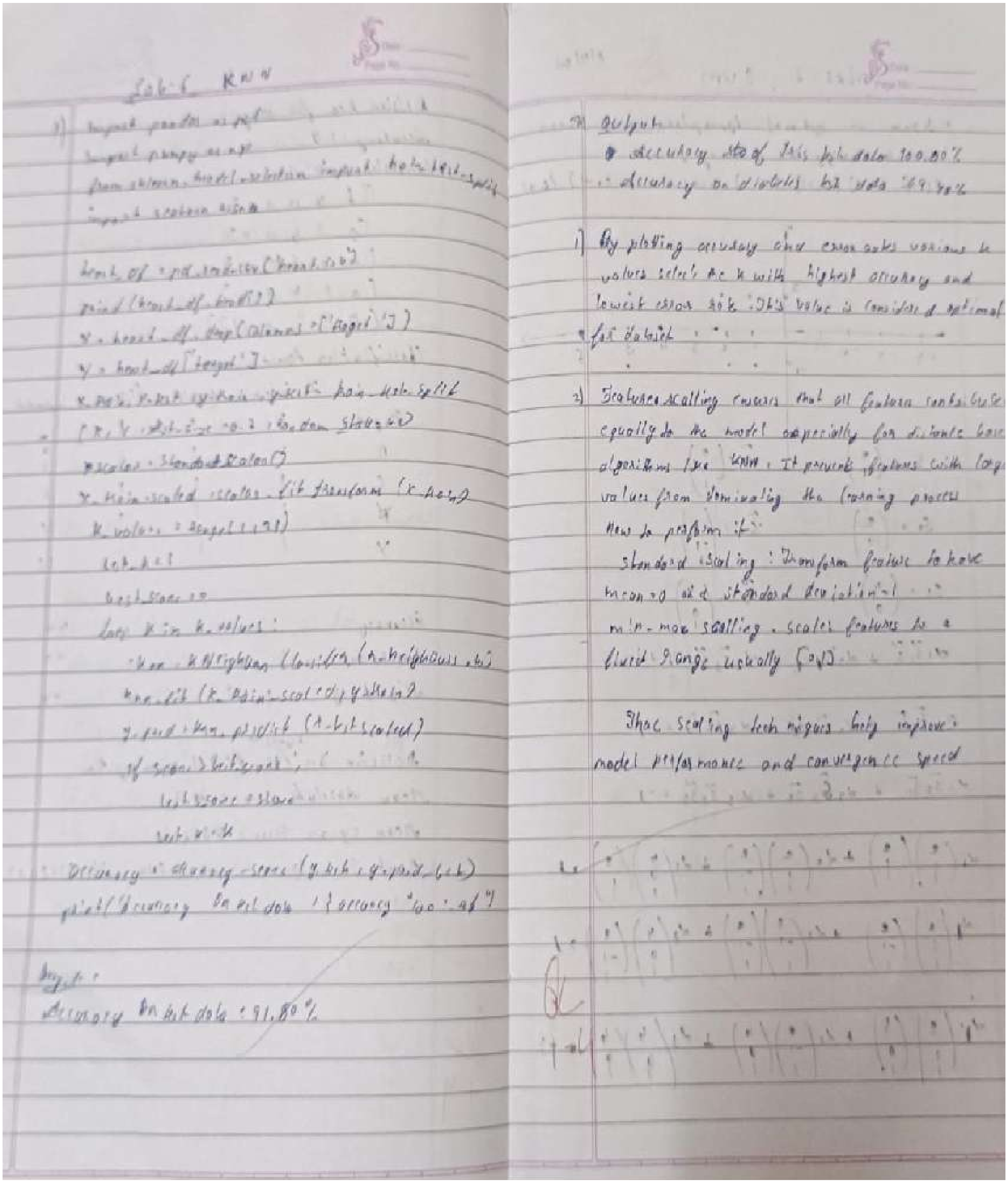
K = 3, 2 - Y 1 - N

K = 1 — Y

k = 2 — N

k = 3 — - Y

So X(35, 100) is Y.



Lab 6 KNN

1)
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import seaborn as sns

heart_df = pd.read_csv('heart.csv')
print(heart_df.head())
x = heart_df.drop(columns=['target'])
y = heart_df['target']
x_train, x_test, y_train, y_test = train_test_split
(x, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
 k_values = range(1,21)
  best_k = 1
  best_score = 0
  for k in k_values:
     knn = KNeighborsClassifier(n_neighbors=k)
     knn.fit(x_train_scaled, y_train)
     y_pred = knn.predict(x_test_scaled)
     if score > best_score:
        best_score = score
        best_k = k
accuracy = accuracy_score(y_test, y_pred_test)
print(f"Accuracy on test data: {accuracy*100:.2f}%")
```

Output:

Accuracy on test data: 91.80%

Output

- Accuracy on Iris test data 100.00%
- Accuracy on diabetes test data 79.70%

1) By plotting accuracy and error rate vs various k values select the k with highest accuracy and lowest error rate. This value is considered optimal for dataset.

2) Features scalling ensures that all features contribute equally to the model especially for distance based algorithms like KNN. It prevents features with large values from dominating the learning process.

How to perform it

Standard Scaling: Transform feature to have mean=0 and standard deviation=1

min-max scalling: scales features to a fixed range usually [0,1]

These scaling techniques help improve model performance and convergence speed

Code:

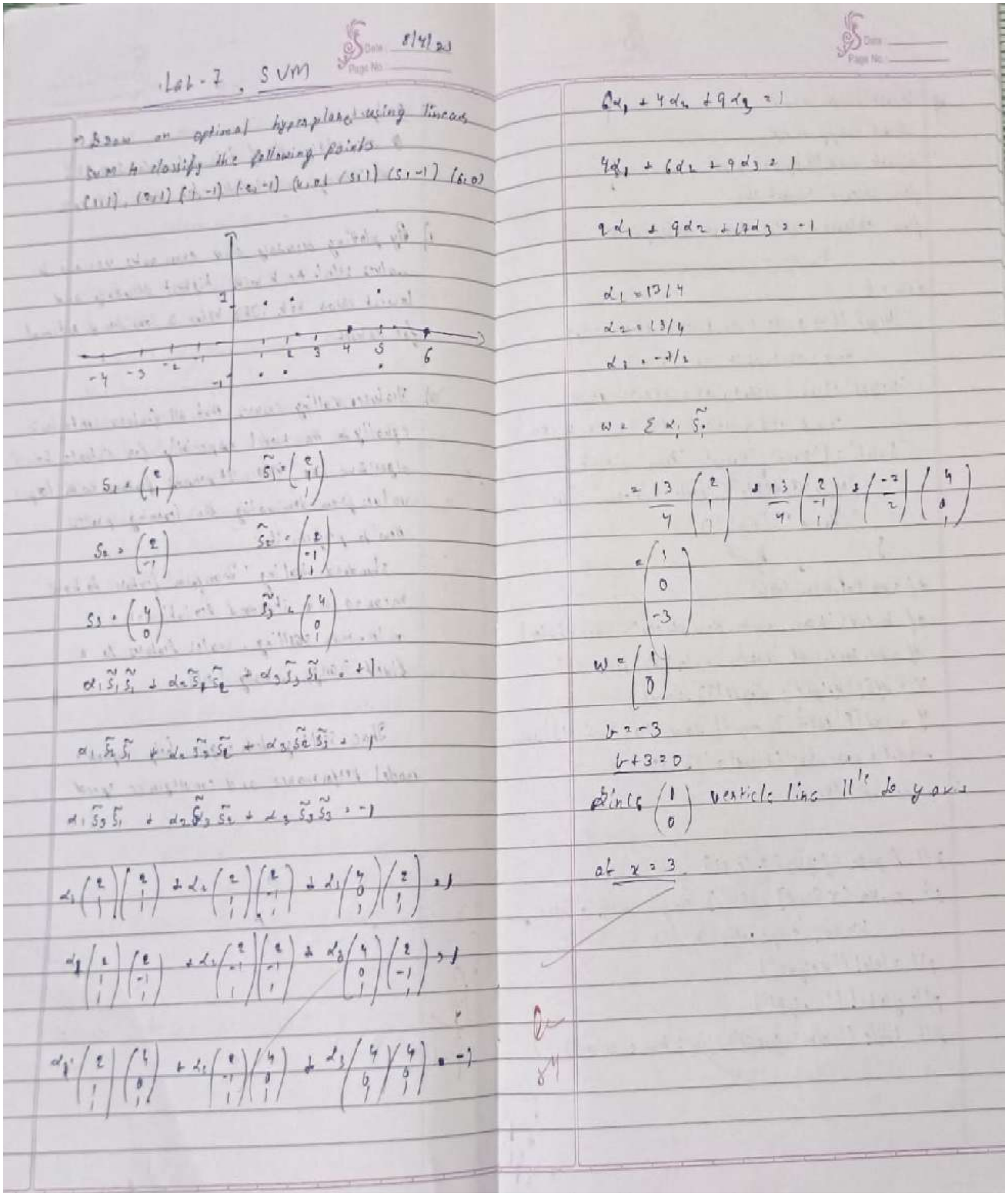
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot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

iris_df = pd.read_csv('/content/iris (3).csv')

print(iris_df.head())

X_iris = iris_df.drop(columns=['species'])
y_iris = iris_df['species']

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)

scaler = StandardScaler()
X_train_iris = scaler.fit_transform(X_train_iris)
X_test_iris = scaler.transform(X_test_iris)

knn_iris = KNeighborsClassifier(n_neighbors=3)

knn_iris.fit(X_train_iris, y_train_iris)

y_pred_iris = knn_iris.predict(X_test_iris)

accuracy_iris = accuracy_score(y_test_iris, y_pred_iris)
print(f"Accuracy on Iris test data: {accuracy_iris * 100:.2f}%")

cm_iris = confusion_matrix(y_test_iris, y_pred_iris)
sns.heatmap(cm_iris, annot=True, fmt="d", cmap="Blues", xticklabels=knn_iris.classes_,
yticklabels=knn_iris.classes_)
plt.title("Confusion Matrix for Iris Dataset")
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()

print("Classification Report for Iris Dataset:")
print(classification_report(y_test_iris, y_pred_iris))

diabetes_df = pd.read_csv('diabetes.csv')
print(diabetes_df.head())
```

```
X_diabetes = diabetes_df.drop(columns=['Outcome'])
y_diabetes = diabetes_df['Outcome']

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)

scaler = StandardScaler()
X_train_diabetes = scaler.fit_transform(X_train_diabetes)
X_test_diabetes = scaler.transform(X_test_diabetes)

knn_diabetes = KNeighborsClassifier(n_neighbors=5)

knn_diabetes.fit(X_train_diabetes, y_train_diabetes)

y_pred_diabetes = knn_diabetes.predict(X_test_diabetes)

accuracy_diabetes = accuracy_score(y_test_diabetes, y_pred_diabetes)
print(f"Accuracy on Diabetes test data: {accuracy_diabetes * 100:.2f}%")

cm_diabetes = confusion_matrix(y_test_diabetes, y_pred_diabetes)
sns.heatmap(cm_diabetes, annot=True, fmt="d", cmap="Blues", xticklabels=knn_diabetes.classes_,
yticklabels=knn_diabetes.classes_)
plt.title("Confusion Matrix for Diabetes Dataset")
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()

print("Classification Report for Diabetes Dataset:")
print(classification_report(y_test_diabetes, y_pred_diabetes))
```

Program 7

Build Support vector machine model for a given dataset

Screenshot



Date: 8/4/23

Lab - 7 . SVM

→ Draw an optimal hyperplane using linear SVM & classify the following points (1,1), (2,1) (1,-1) (2,-1) (4,0) (5,1) (5,-1) (6,0)

1
-1
-4
-3
-2
1
2
3
4
5
6

$S_1 = \begin{pmatrix}2\\1\end{pmatrix}$ $\tilde{S}_1 = \begin{pmatrix}2\\1\\1\end{pmatrix}$

$S_2 = \begin{pmatrix}2\\-1\end{pmatrix}$ $\tilde{S}_2 = \begin{pmatrix}2\\-1\\1\end{pmatrix}$

$S_3 = \begin{pmatrix}4\\0\end{pmatrix}$ $\tilde{S}_3 = \begin{pmatrix}4\\0\\1\end{pmatrix}$

$\alpha_1 \tilde{S}_1 \tilde{S}_1 + \alpha_2 \tilde{S}_2 \tilde{S}_2 + \alpha_3 \tilde{S}_3 \tilde{S}_1 = +1$

$\alpha_1 \tilde{S}_2 \tilde{S}_1 + \alpha_2 \tilde{S}_2 \tilde{S}_2 + \alpha_3 \tilde{S}_2 \tilde{S}_3 = 1$

$\alpha_1 \tilde{S}_3 \tilde{S}_1 + \alpha_2 \tilde{S}_3 \tilde{S}_2 + \alpha_3 \tilde{S}_3 \tilde{S}_3 = -1$

$\alpha_1 \begin{pmatrix}2\\1\end{pmatrix}\begin{pmatrix}2\\1\end{pmatrix} + \alpha_2 \begin{pmatrix}2\\1\\1\end{pmatrix}\begin{pmatrix}2\\-1\\1\end{pmatrix} + \alpha_1 \begin{pmatrix}4\\0\\1\end{pmatrix}\begin{pmatrix}2\\1\\1\end{pmatrix} = 1$

$\alpha_1 \begin{pmatrix}2\\1\\1\end{pmatrix}\begin{pmatrix}2\\-1\\1\end{pmatrix} + \alpha_2 \begin{pmatrix}2\\-1\\1\end{pmatrix}\begin{pmatrix}2\\-1\\1\end{pmatrix} + \alpha_3 \begin{pmatrix}4\\0\\1\end{pmatrix}\begin{pmatrix}2\\-1\\1\end{pmatrix} = 1$

$\alpha_1 \begin{pmatrix}2\\1\\1\end{pmatrix}\begin{pmatrix}4\\0\\1\end{pmatrix} + \alpha_2 \begin{pmatrix}2\\-1\\1\end{pmatrix}\begin{pmatrix}4\\0\\1\end{pmatrix} + \alpha_3 \begin{pmatrix}4\\0\\1\end{pmatrix}\begin{pmatrix}4\\0\\1\end{pmatrix} = -1$

8/4

$6\alpha_1 + 4\alpha_2 + 9\alpha_3 = 1$

$4\alpha_1 + 6\alpha_2 + 9\alpha_3 = 1$

$9\alpha_1 + 9\alpha_2 + 17\alpha_3 = -1$

$\alpha_1 = 13/4$

$\alpha_2 = 13/4$

$\alpha_3 = -7/2$

$w = \sum \alpha_i \tilde{S}_i$

$= \frac{13}{4}\begin{pmatrix}2\\1\\1\end{pmatrix} + \frac{13}{4}\begin{pmatrix}2\\-1\\1\end{pmatrix} + \left(\frac{-7}{2}\right)\begin{pmatrix}4\\0\\1\end{pmatrix}$

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

$w = \begin{pmatrix}1\\0\end{pmatrix}$

$b = -3$

$b + 3 = 0$

Since $\begin{pmatrix}1\\0\end{pmatrix}$ verticle line ||'l to y axis

at $x = 3$.

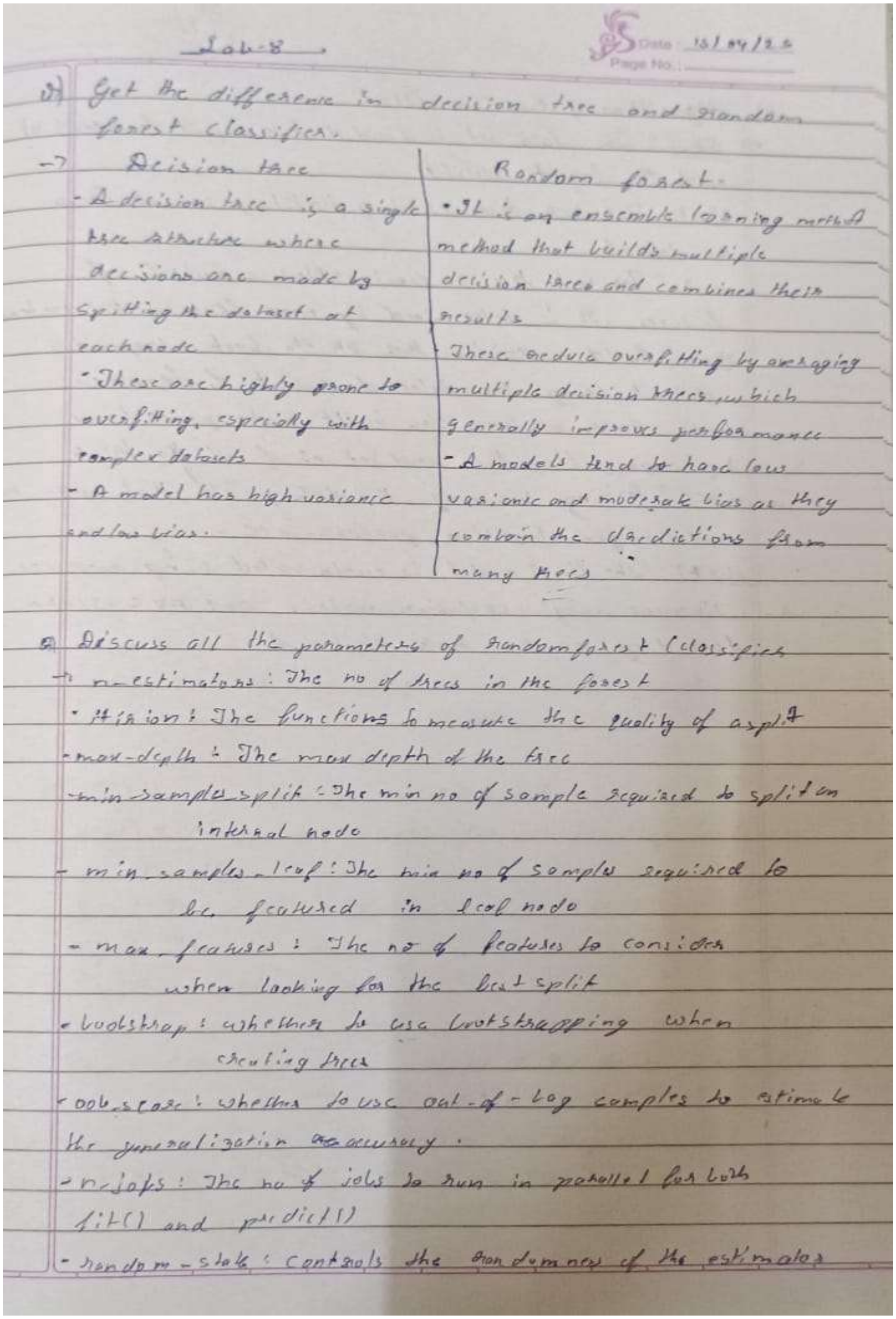
Code:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score, roc_curve
from sklearn.preprocessing import LabelEncoder, label_binarize
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

df = pd.read_csv("/content/letter-recognition.csv")

top_classes = df['letter'].value_counts().head(5).index.tolist()
df = df[df['letter'].isin(top_classes)]

X = df.iloc[:, 1:]
y = df.iloc[:, 0]

label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

y_bin = label_binarize(y_encoded, classes=np.unique(y_encoded))
n_classes = y_bin.shape[1]

X_train, X_test, y_train, y_test_bin = train_test_split(X, y_bin, test_size=0.2, random_state=42)

svm_model = SVC(kernel='linear', probability=True)
svm_model.fit(X_train, y_train.argmax(axis=1))
y_score = svm_model.predict_proba(X_test)

y_pred = svm_model.predict(X_test)
y_true = y_test_bin.argmax(axis=1)

print("Accuracy:", accuracy_score(y_true, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_true, y_pred))

plt.figure()
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    auc = roc_auc_score(y_test_bin[:, i], y_score[:, i])
    plt.plot(fpr, tpr, label=f"{label_encoder.inverse_transform([i])[0]} AUC={auc:.2f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve (Top 5 Classes)")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.tight_layout()
plt.show()

macro_auc = roc_auc_score(y_test_bin, y_score, average="macro")
print("Macro AUC Score:", macro_auc)
```

Program 8

Implement Random forest ensemble method on a given dataset.

Screenshot



Lab-8

Date: 18/04/24
Page No.:

Q1 Get the difference in decision tree and random forest classifier.

→

Decision tree	Random forest.
- A decision tree is a single tree structure where decisions are made by spiting the dataset at each node	• It is an ensemble learning method method that builds multiple decision trees and combines their results
• These are highly prone to overfitting, especially with complex datasets	These reduce overfitting by averaging multiple decision trees, which generally improves performance
- A model has high variance and low bias.	- A models tend to have low variance and moderate bias as they combain the predictions from many trees

Q2 Discuss all the parameters of randomforest (classifier

→ n-estimators: The no of trees in the forest

• criterion: The functions to measure the quality of a split

- max-depth: The max depth of the tree

- min-samples split: The min no of sample required to split an internal node

- min_samples_leaf: The min no of samples required to be featured in leaf node

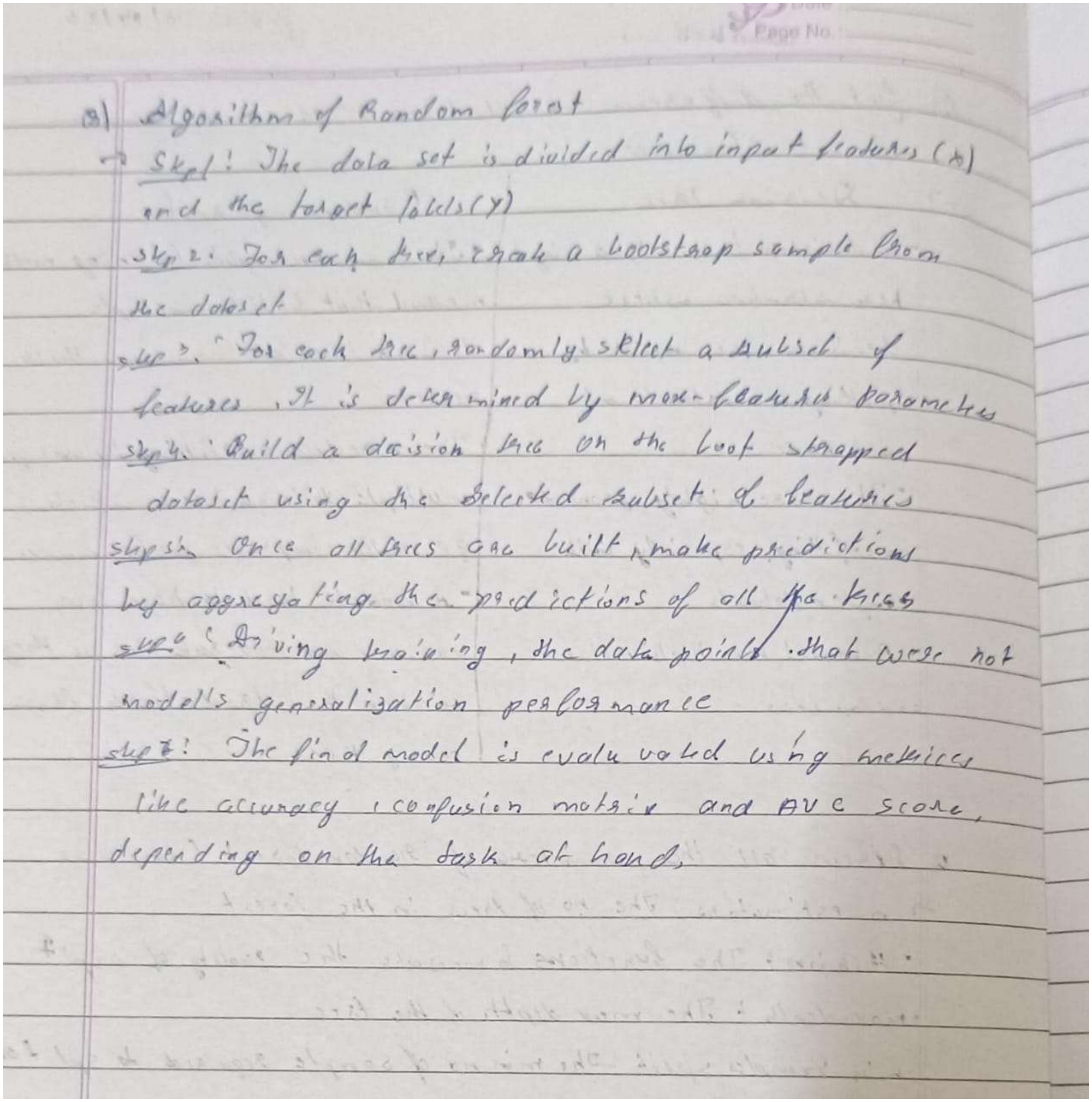
- max_features: The no of features to consider when looking for the best split

- bootstrap: whether to use bootstrapping when creating trees

- oob_score: whether to use out-of-bag samples to estimate the generalization accuracy.

- n_jobs: The no of jobs to run in parallel for both fit() and predict()

- random-state: controls the randomness of the estimator



Page No.

3) Algorithm of Random forest

→ Step1: The data set is divided into input features (x) and the target labels(y)

Step 2: For each tree, create a bootstrap sample from the dataset

Step 3: For each tree, randomly select a subset of features, It is determined by max-features parameters

Step4: Build a decision tree on the boot strapped dataset using the selected subset of features

Step5: Once all trees are built, make predictions by aggregating the predictions of all the trees

Step6: During training, the data points that were not model's generalization performance

Step7: The final model is evaluvated using metrics like accuracy, confusion matrix and AVC score, depending on the task at hand.

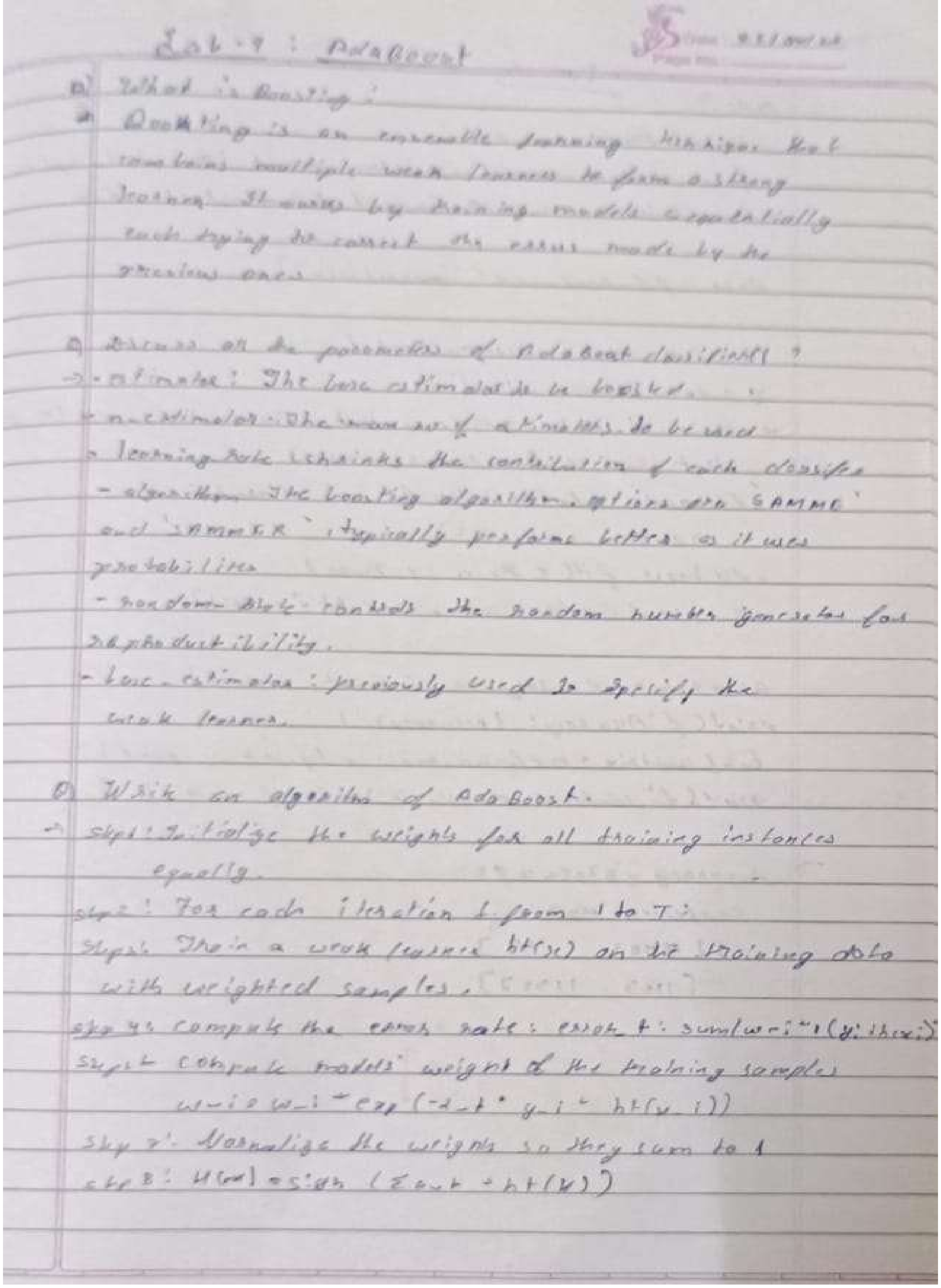
Code:

```
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
from sklearn import preprocessing

df = pd.read_csv('/content/train.csv')

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

for column in X.columns:
    if X[column].dtype == 'object':
      le = preprocessing.LabelEncoder()
      X[column] = le.fit_transform(X[column])

if y.dtype == 'object':
  le = preprocessing.LabelEncoder()
  y = le.fit_transform(y)

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

rf_classifier = RandomForestClassifier(random_state=42)
rf_classifier.fit(X_train, y_train)

y_pred = rf_classifier.predict(X_test)

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

print(f"Accuracy: {accuracy}")
print(f"Confusion Matrix:\n{conf_matrix}")
```

Program 9

Implement Boosting ensemble method on a given dataset.

Screenshot



Lab-9 : AdaBoost

Q) What is Boosting?

→ Boosting is an ensemble learning technique that combines multiple weak learners to form a strong learner. It works by training models sequentially each trying to correct the errors made by the previous ones.

Q) Discuss all the parameters of AdaBoost classifier?

→ - estimator: The base estimator to be boosted.
- n_estimators: The maximum no. of estimators to be used
- learning rate: shrinks the contribution of each classifier
- algorithm: The boosting algorithm, options are 'SAMME' and 'SAMME.R' ; typically performs better as it uses probabilities
- random_state: controls the random number generator for reproducibility.
- base_estimator: previously used to specify the weak learner.

Q) Write an algorithm of AdaBoost.

```
→ Step1: Initialize the weights for all training instances
        equally.
Step2: For each iteration t from 1 to T:
Step3: Train a weak learner ht(x) on the training data
   with weighted samples.
Step 4: compute the error rate: error_t = sum(w_i * I(y_i ≠ ht(x_i)))
Step 5: compute models' weight of the training samples
        w_i = w_i * exp(-α_t * y_i * ht(x_i))
Step 7: Normalize the weights so they sum to 1
Step 8: H(x) = sign (Σ α_t * ht(x))
```

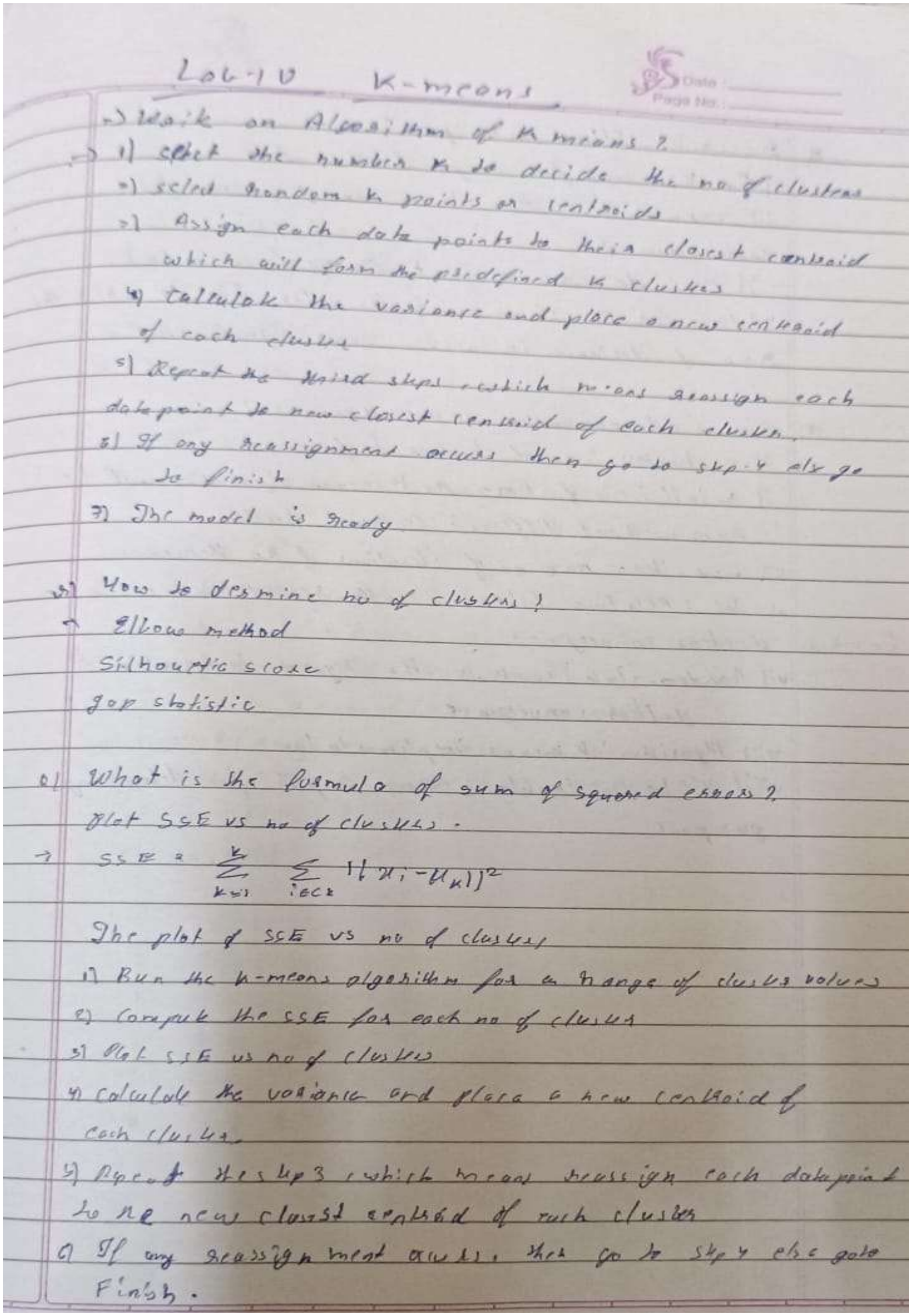
Code:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

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

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

results = []

n_estimators_list = [10, 50, 100]
learning_rates = [0.01, 0.1, 1]

for n in n_estimators_list:
    for lr in learning_rates:
        tree_base = DecisionTreeClassifier(max_depth=1)
        model = AdaBoostClassifier(estimator=tree_base, n_estimators=n, learning_rate=lr,
random_state=42)
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        acc = accuracy_score(y_test, y_pred)
        results.append({
            'Base': 'DecisionTree',
            'n_estimators': n,
            'learning_rate': lr,
            'Accuracy': acc
        })

for n in n_estimators_list:
    for lr in learning_rates:
        log_reg_base = LogisticRegression(max_iter=1000)
        model = AdaBoostClassifier(estimator=log_reg_base, n_estimators=n, learning_rate=lr,
random_state=42)
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        acc = accuracy_score(y_test, y_pred)
        results.append({
            'Base': 'LogisticRegression',
            'n_estimators': n,
            'learning_rate': lr,
            'Accuracy': acc
        })

results_df = pd.DataFrame(results)
print(results_df)

import seaborn as sns
plt.figure(figsize=(12, 6))
sns.barplot(x='n_estimators', y='Accuracy', hue='Base', data=results_df, ci=None)
plt.title('AdaBoost Accuracy with Different Estimators and n_estimators')
plt.show()
```

Program 10

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

Screenshot



Lab-10 K-means

Date :
Page No. :

→ Work on Algorithm of K means ?

→ 1) select the number K to decide the no of clusters

2) select random K points or centroids

3) Assign each data points to their closest centroid which will form the predefined K clusters

4) calculate the variance and place a new centroid of each cluster

5) Repeat the third steps which means reassign each datapoint to new closest centroid of each cluster.

6) If any reassignment occurs then go to step 4 else go to finish

7) The model is ready

Q) How to determine no of clusters ?

→ Elbow method

Silhouette score

gap statistic

Q) What is the formula of sum of squared errors ?
Plot SSE vs no of clusters.

→ $SSE = \sum_{k=1}^{k} \sum_{i \in C_k} ||x_i - \mu_k||^2$

The plot of SSE vs no of clusters

1) Run the k-means algorithm for a range of cluster values

2) Compute the SSE for each no of clusters

3) Plot SSE vs no of clusters

4) calculate the variance and place a new centroid of each cluster.

5) Repeat the step 3 which means reassign each datapoint to the new closest centroid of each cluster

6) If any reassignment occurs, then go to step 4 else goto Finish.

Date :
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Q Describe Elbow technique?

i] Run k-means for range of values of k

ii] compute the within cluster sum of squares for each values of k.

iii] Plot the w.c.s.s against the no of clusters (k)

iv] look for the elbow point - the value of k at which the rate of decrease in wcss slows significally

Q) Discuss all parameters used in kmeans()

3 i] n_clusters : no of clusters to form

ii] n-init : no of times the k-means algorithm will be run without different centroid seeds

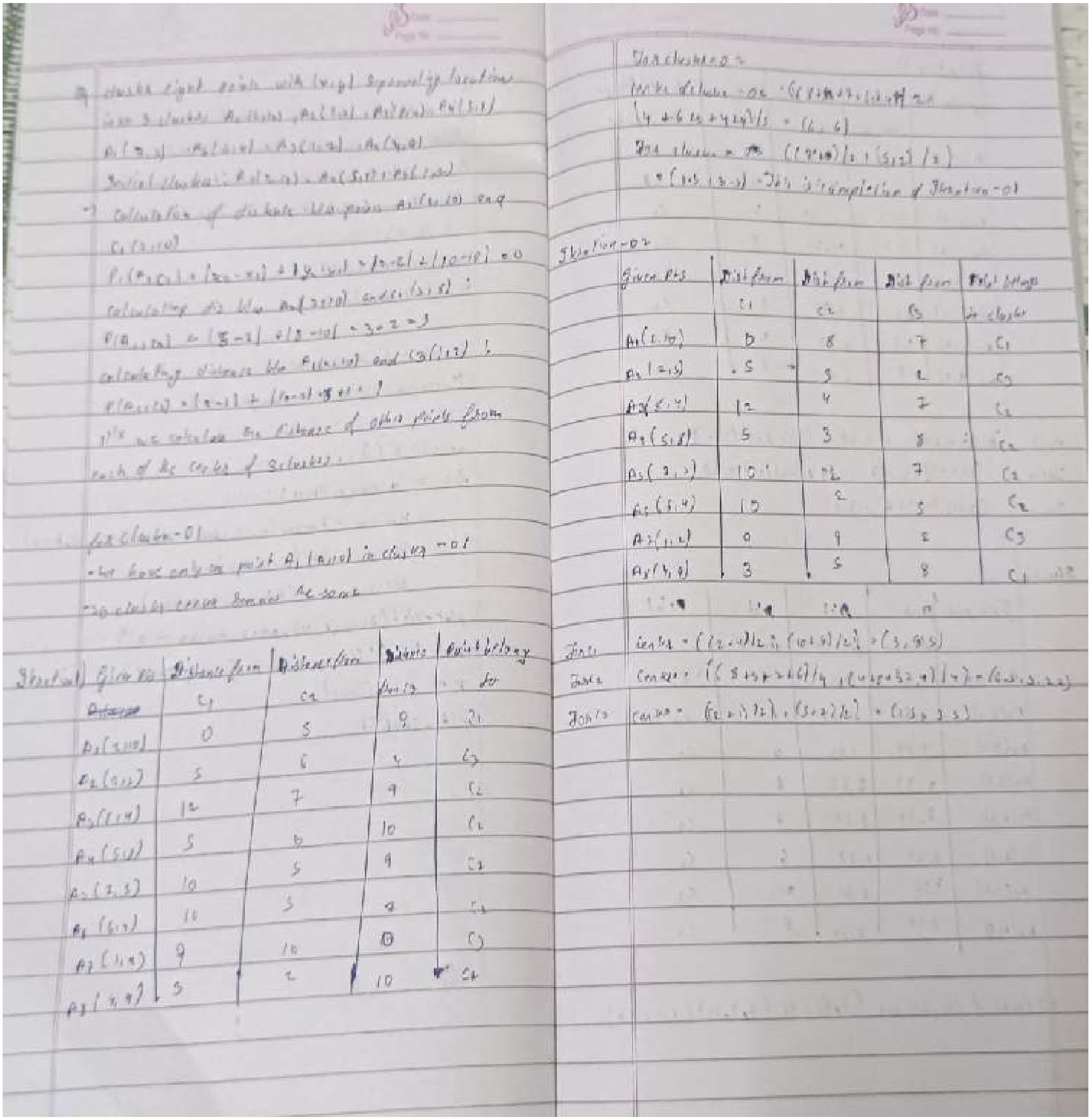
iii] max-iter : max no of iterations of the k-means.

v] tol : Relative tolerance with regards to inertia to declear convergence

vi] random-state : controls the regards to inertia to declear convergence

vii] Algorithm : k means implementation

viii] verbose : Enable verbose output for debugging purpose



Q Cluster eight points with (x,y) representing locations into 3 clusters A1(2,10), A2(2,5), A3(8,4), A4(5,8)
A5(7,5), A6(6,4), A7(1,2), A8(4,9)
Initial clusters: A1(2,10), A4(5,8), A7(1,2)

→ Calculation of distance b/w points A1(2,10) and C1(2,10)
P(A1,C1) = |x2 − x1| + |y2 − y1| = |2−2| + |10−10| = 0
Calculating dis b/w A1(2,10) and C2(5,8):
P(A1,C2) = |5−2| + |8−10| = 3+2 = 5
Calculating distance b/w A1(2,10) and C3(1,2):
P(A1,C3) = |1−2| + |2−10| = 1+8 = 9
Thly we calculate the distance of other points from each of the centre of 3 clusters.

For cluster-01
- we have only one point A1(2,10) in cluster-01
- so cluster centre remains the same

Iteration 1

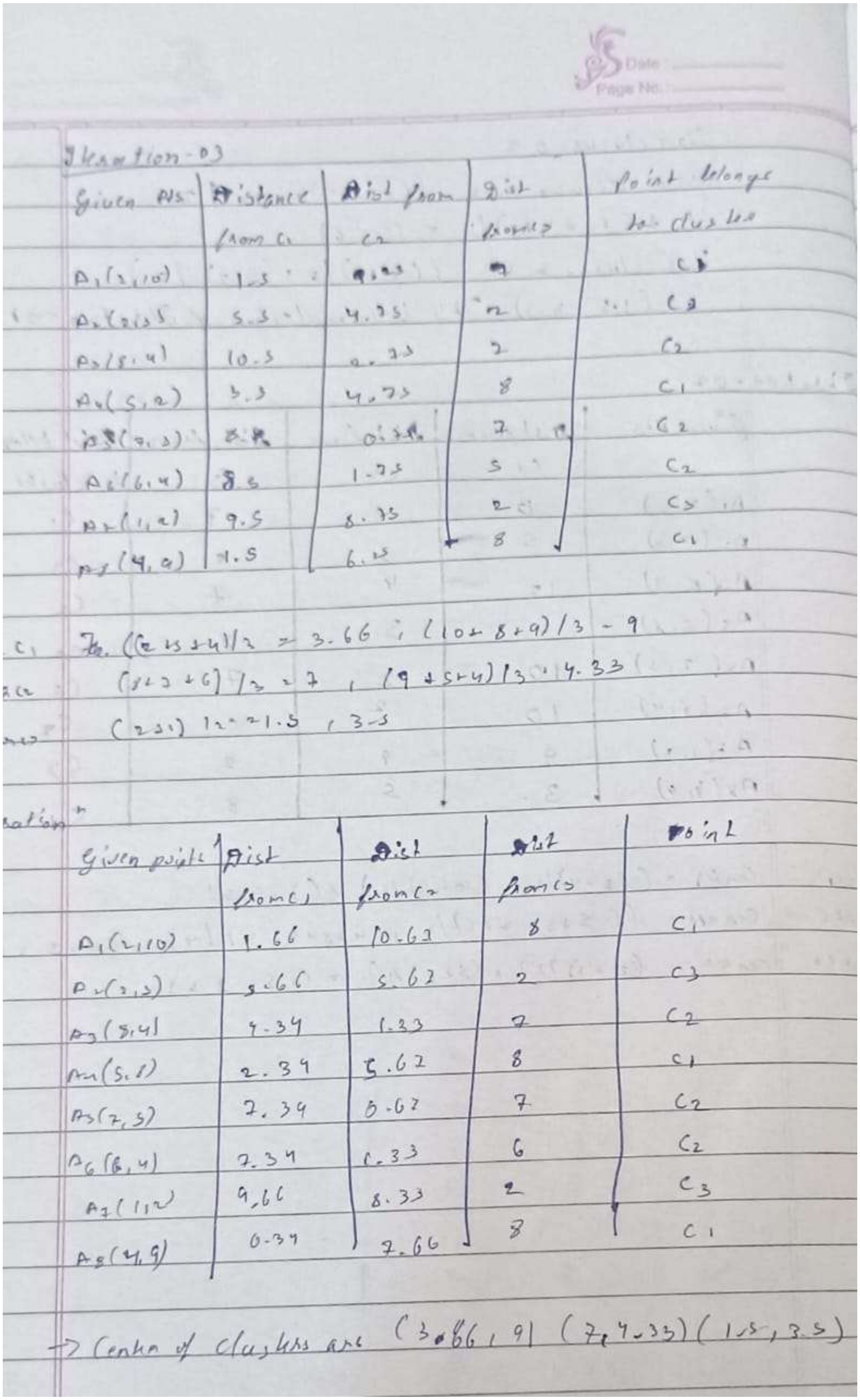
Given pts	Distance from C1	Distance from C2	Distance from C3	Point belong to
A1(2,10)	0	5	9	C1
A2(2,5)	5	6	4	C3
A3(8,4)	12	7	9	C2
A4(5,8)	5	0	10	C2
A5(7,5)	10	5	9	C2
A6(6,4)	10	3	7	C2
A7(1,2)	9	10	0	C3
A8(4,9)	3	2	10	C2

For cluster-02
centre of cluster-02 = ((8+5+7+6+4)/5, (4+8+5+4+9)/5) = (6, 6)
For cluster-03 = ((2+1)/2, (5+2)/2)
= (1.5, 3.5) This is completion of Iteration-01

Iteration-02

Given pts	Dist from C1	Dist from C2	Dist from C3	Point belongs in cluster
A1(2,10)	0	8	7	C1
A2(2,5)	5	5	2	C3
A3(8,4)	12	4	7	C2
A4(5,8)	5	3	8	C2
A5(7,5)	10	2	7	C2
A6(6,4)	10	2	5	C2
A7(1,2)	9	9	2	C3
A8(4,9)	3	5	8	C1

For C1 centre = ((2+4)/2, (10+9)/2) = (3, 9.5)
For C2 centre = ((8+5+7+6)/4, (4+8+5+4)/4) = (6.5, 5.25)
For C3 centre = ((2+1)/2, (5+2)/2) = (1.5, 3.5)



Iteration - 03

Given pts	Distance from C1	Dist from C2	Dist from C3	Point belongs to cluster
A1(2,10)	1.5	9.25	9	C1
A2(2,5)	5.3	4.75	2	C3
A3(8,4)	10.5	2.75	7	C2
A4(5,8)	3.3	4.75	8	C1
A5(7,5)	8.5	0.75	7	C2
A6(6,4)	8.5	1.75	5	C2
A7(1,2)	9.5	8.75	2	C3
A8(4,9)	1.5	6.25	8	C1

C1 For ((2+5+4)/3 = 3.66 ; (10+8+9)/3 = 9

C2 (8+7+6)/3 = 7 , (4+5+4)/3 = 4.33

C3 (2+1)/2 = 1.5 , 3.5

Given point	Dist from C1	Dist from C2	Dist from C3	Point
A1(2,10)	1.66	10.67	8	C1
A2(2,5)	5.66	5.67	2	C3
A3(8,4)	7.34	1.33	7	C2
A4(5,8)	2.34	5.67	8	C1
A5(7,5)	7.34	0.67	7	C2
A6(6,4)	7.34	1.33	6	C2
A7(1,2)	9.66	8.33	2	C3
A8(4,9)	0.34	7.66	8	C1

→ Centre of clusters are (3.66, 9) (7, 4.33) (1.5, 3.5)

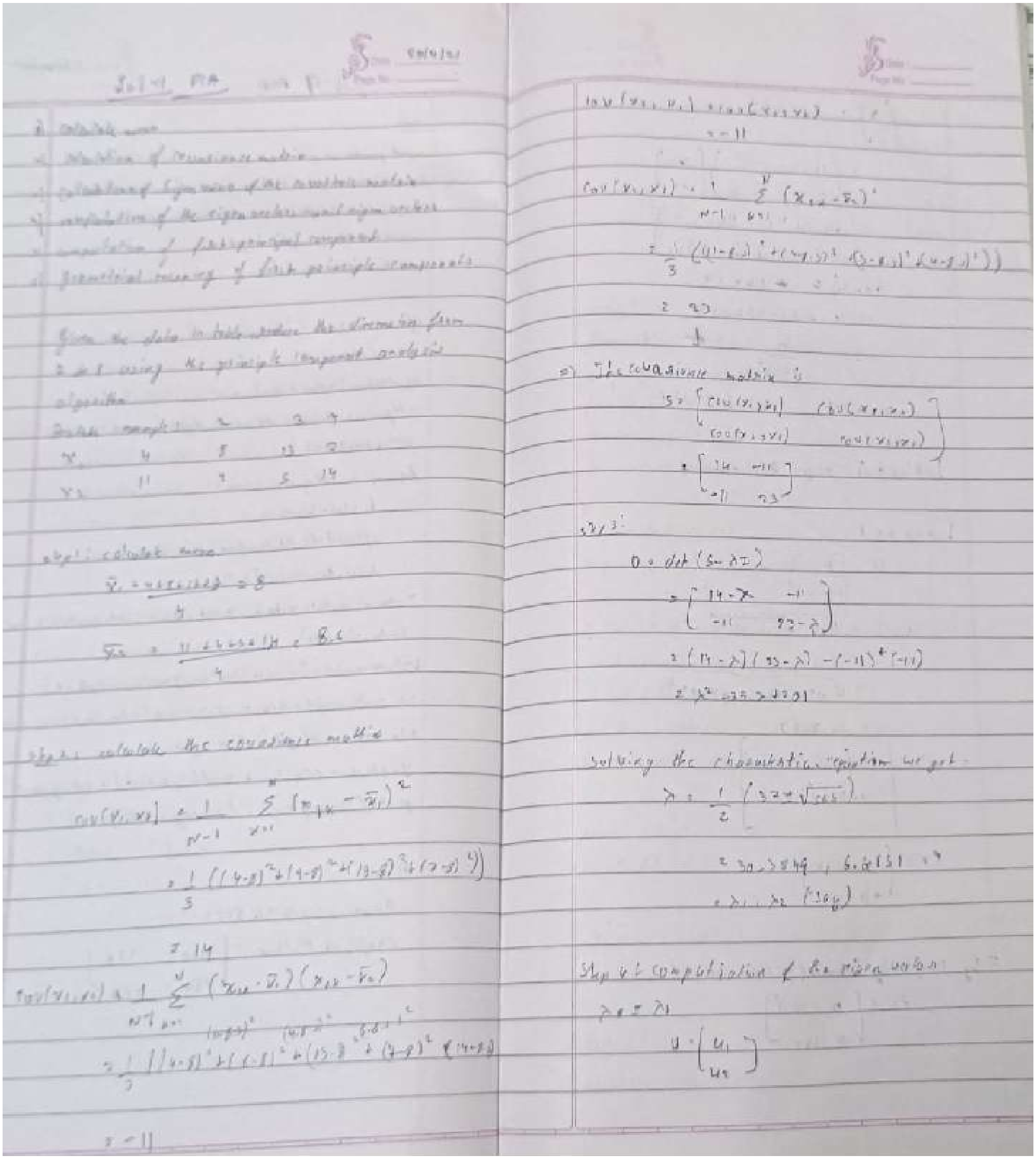
Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

data = {
    'Name': [f'Person_{i+1}' for i in range(50)],
    'Age': np.random.randint(18, 70, size=50),
    'Income': np.random.randint(20000, 120000, size=50)
}

df = pd.DataFrame(data)

df.to_csv('income.csv', index=False)

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

X = df[['Age', 'Income']]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

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

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

plt.plot(k_range, sse, marker='o')
plt.title('SSE vs Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Sum of Squared Errors (SSE)')
plt.show()

optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans.fit(X_train)
y_pred = kmeans.predict(X_test)

print(f'Predicted Clusters for Test Data: {y_pred}')
```

Program 11

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

Screenshot



Date 20/4/21

3.1.4 PCA

1) Calculate mean
2) Calculation of covariance matrix
3) Calculation of eigen values of the covariance matrix
4) computation of the eigen vectors and eigen vectors
5) computation of first principal component
6) geometrical meaning of first principle components

Given the data in table reduce the dimension from 2 to 1 using the principle component analysis algorithm

Feature	Example 1	2	3	4
X_1	4	8	13	7
X_2	11	4	5	14

step 1: calculate mean

$\bar{x}_1 = \frac{4+8+13+7}{4} = 8$

$\bar{x}_2 = \frac{11+4+5+14}{4} = 8.5$

step 2: calculate the covariance matrix

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

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

$= 14$

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

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

$= -11$

$cov(x_2, x_1) = cov(x_1, x_2)$

$= -11$

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

$= \frac{1}{3} ((11-8.5)^2 + (4-8.5)^2 + (5-8.5)^2 + (14-8.5)^2)$

$= 23$

2) The covariance matrix is

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

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

step 3:

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

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

$= (14-\lambda)(23-\lambda) - (-11) \times (-11)$

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

solving the characteristic equation we get

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

$= 30.3849, 6.6151$

$= \lambda_1, \lambda_2$ (say)

Step 4: computation of the eigen vectors

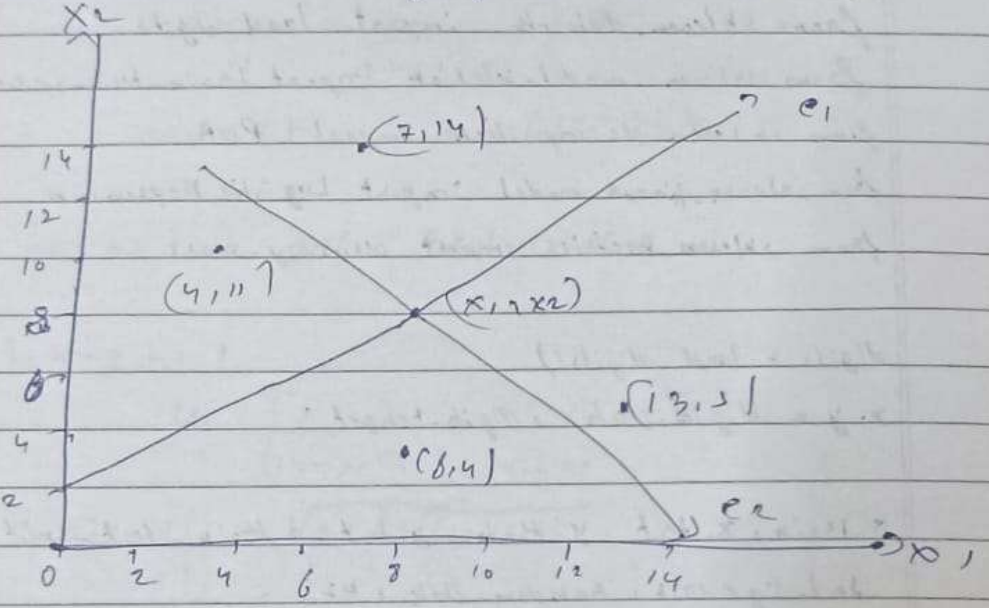
$\lambda = \lambda_1$

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

Q) Define PCA ?

→ It is a dimensionality reduction and ML method used to a simplify a large data set into a smaller set while still maintaining significant patterns and trends

Step 6: Geometrical meaning of first principal component



Code:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.decomposition import PCA
from scipy import stats

df = pd.read_csv('heart (2).csv')

z_scores = np.abs(stats.zscore(df.select_dtypes(include=[np.number])))
df_no_outliers = df[(z_scores < 3).all(axis=1)]

df_cleaned = df_no_outliers.copy()
for col in df_cleaned.select_dtypes(include='object').columns:
    df_cleaned[col] = LabelEncoder().fit_transform(df_cleaned[col])

X = df_cleaned.drop('HeartDisease', axis=1)
y = df_cleaned['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,
stratify=y)

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

print("Accuracy without PCA:")
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    print(f"{name}: {acc:.4f}")

pca = PCA(n_components=5)
X_pca = pca.fit_transform(X_scaled)
X_train_pca, X_test_pca, y_train, y_test = train_test_split(X_pca, y, test_size=0.2, random_state=42,
stratify=y)
```

```
print("\nAccuracy with PCA:")
for name, model in models.items():
    model.fit(X_train_pca, y_train)
    y_pred = model.predict(X_test_pca)
    acc = accuracy_score(y_test, y_pred)
    print(f"{name}: {acc:.4f}")
```