VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

Setu Mishra (1BM22CS250)

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 **Setu Mishra (1BM22CS250),** 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 a Machine Learning (23CS6PCMAL) work prescribed for the said degree.

Lab Faculty Incharge Name:**Shravya AR** Assistant Professor Department of CSE, BMSCE	 **Dr. Kavitha Sooda** Professor & HOD Department of CSE, BMSCE

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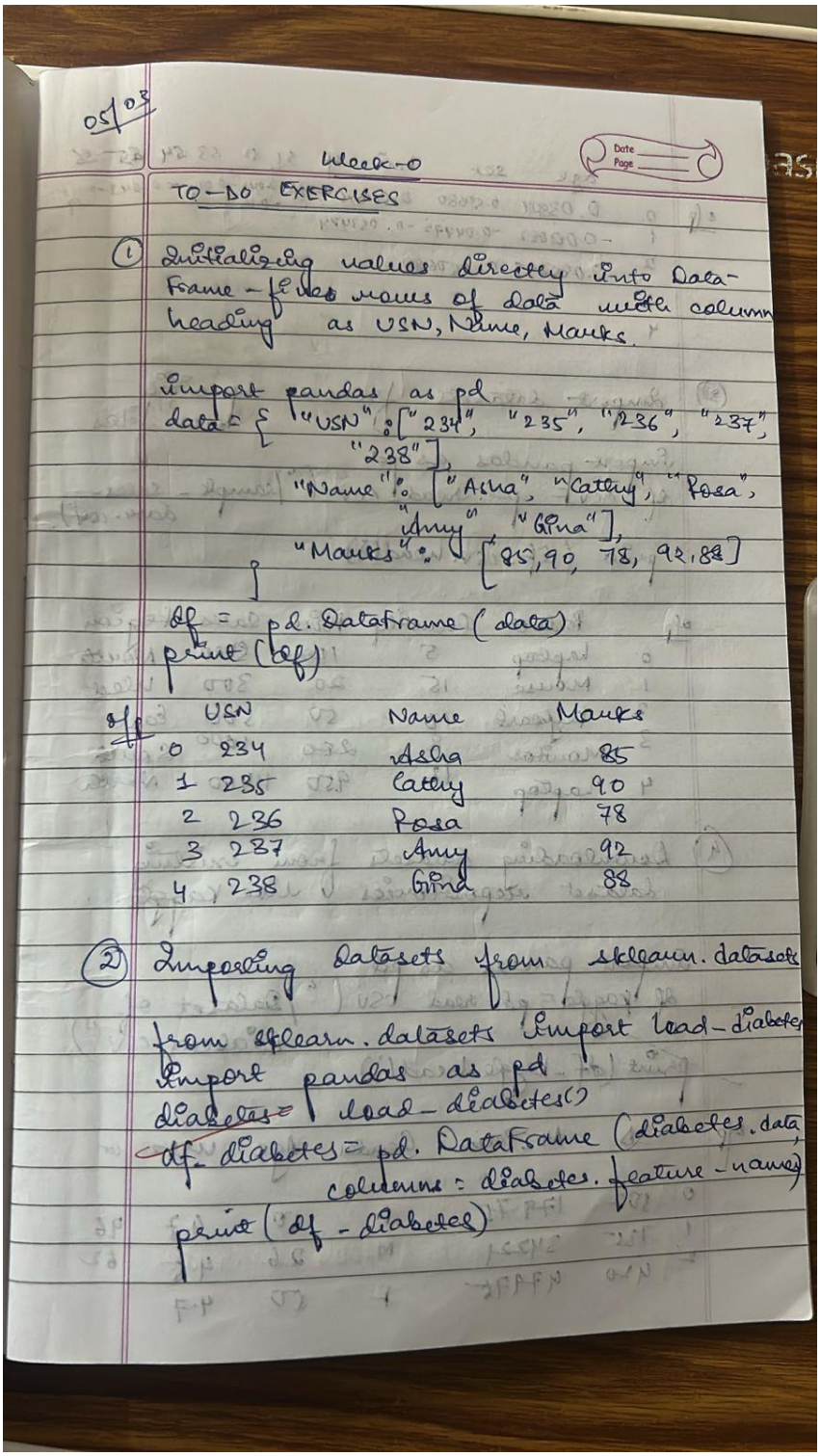
Github Link:

https://github.com/setu-mishra/ML

Program 1

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

Screenshot



05/08

Week-0

Date
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TO-DO EXERCISES

(1) Initializing values directly into DataFrame - fields names of data with column heading as USN, Name, Marks.

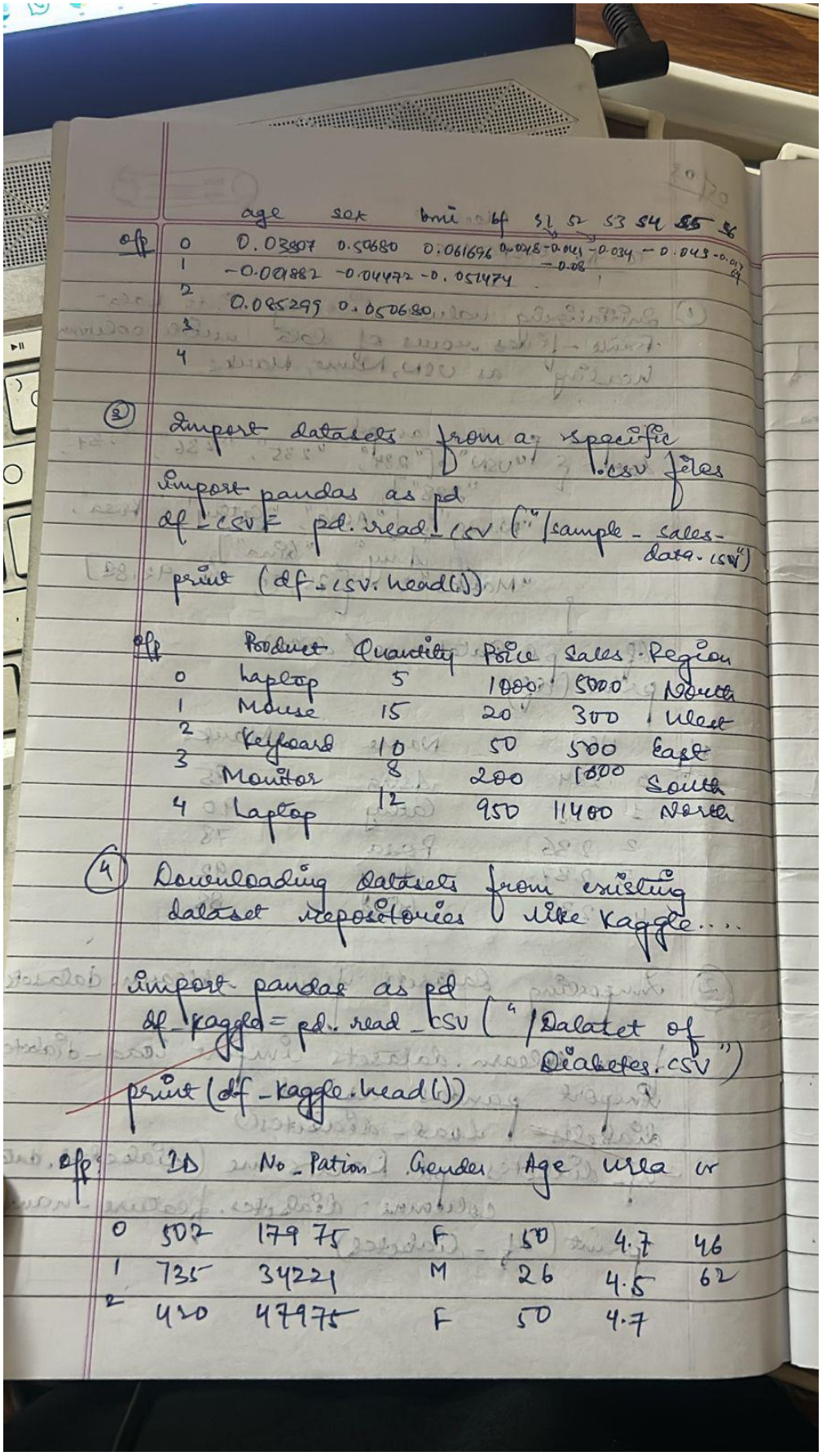
```
import pandas as pd
data = { "USN": ["234", "235", "236", "237",
                 "238"],
         "Name": ["Asha", "Cathy", "Rosa",
                  "Amy", "Gina"],
         "Marks": [85, 90, 78, 92, 88] }
df = pd.DataFrame(data)
print(df)
```

df

	USN	Name	Marks
0	234	Asha	85
1	235	Cathy	90
2	236	Rosa	78
3	237	Amy	92
4	238	Gina	88

(2) Importing datasets from sklearn.datasets

```
from sklearn.datasets import load_diabetes
import pandas as pd
diabetes = load_diabetes()
df_diabetes = pd.DataFrame(diabetes.data,
              columns = diabetes.feature_names)
print(df_diabetes)
```



	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6
0	0.03807	0.50680	0.061696	0.0218	-0.044	-0.034	-0.043	-0.002		
1	-0.001882	-0.04472	-0.051474				-0.08			
2	0.085299	0.050680								
3										
4										

(2) Import datasets from a specific .csv files

```
import pandas as pd
df = csv.pd.read_csv("/sample - sales - data.csv")
print (df.csv.head())
```

	Product	Quantity	Price	Sales	Region
0	laptop	5	1000	5000	North
1	Mouse	15	20	300	West
2	Keyboard	10	50	500	East
3	Monitor	8	200	1600	South
4	Laptop	12	950	11400	North

(4) Downloading datasets from existing dataset repositories like kaggle....

```
import pandas as pd
df_kaggle = pd.read_csv("/Dataset of Diabetes.csv")
print (df_kaggle.head())
```

	ID	No_Patient	Gender	Age	Urea	Cr
0	502	17975	F	50	4.7	46
1	735	34221	M	26	4.5	62
2	420	47975	F	50	4.7	

	BMI	CLASS
0	24.0	N
1	23.0	N
2	24.0	N
3	24.0	N
4	21.0	N

TO-DO

Stock Market Data Analysis

1. ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
2. start data and end date
3. Plot the closing price and daily returns for all three banks

```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
tickers = ["HDFC.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(5))
print("\n shape of dataset")
print(data.shape)
print("\n Column names")
print(data.columns)
hdfc_data = data["HDFCBANK.NS"]
```

```
print ("\n Summary statistics for
        HDFC Industries")

print (hdfc_data.describe())

hdfc_data['Daily Return'] = hdfc_data
                    ['Case'].pct_change()

plt.figure(figsize=(12,6))

plt.subplot(2,1,1)

hdfc_data['Daily_Return'].plot
        (title="HDFC Industries" Daily
                Returns," color_range)

plt.tight_layout()

plt.show()
```

Code:

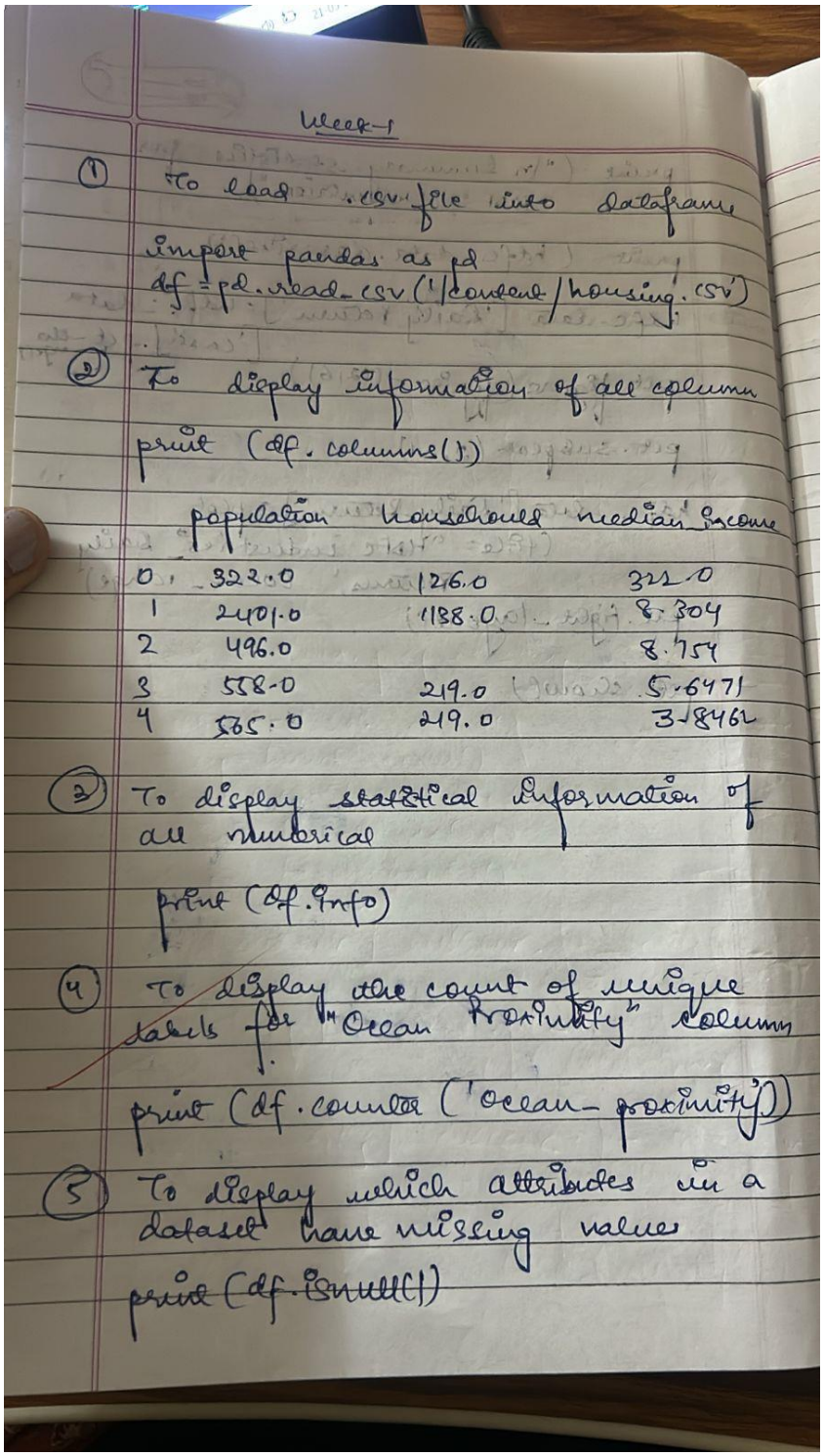
```
import pandas as pd

data={
   'USN':['1BM22CS001','1BM22CS002','1BM22CS003','1BM22CS004','1BM22CS005'],
   'Name':['Ankita','Anita','Amit','Anish','Arun'],
   'Marks':[99,56,96,85,45]
}

df=pd.DataFrame(data)
print(df)

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

path=r"/content/sample_sales_data.csv"
df=pd.read_csv(path)
print(df)


path=r"/content/Dataset of Diabetes .csv"
df=pd.read_csv(path)
print(df.head())


import yfinance as yf
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=tickers)
print(data)

#HDFCBANK
HDFC=data['HDFCBANK.NS']
HDFC['Daily Return']=HDFC['Close'].pct_change()
print(HDFC)

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

```
plt.show()

#ICICIBANK
ICICI=data['ICICIBANK.NS']
ICICI['Daily Return']=ICICI['Close'].pct_change()
print(ICICI)

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

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshot



Week-1

(1) To load .csv file into dataframe

```
import pandas as pd
df = pd.read_csv('/content/housing.csv')
```

(2) To display information of all column

```
print (df.columns())
```

	population	households	median income
0	322.0	126.0	322.0
1	2401.0	1188.0	8.304
2	496.0		8.754
3	558.0	219.0	5.6471
4	565.0	219.0	3.8462

(3) To display statistical information of all numerical

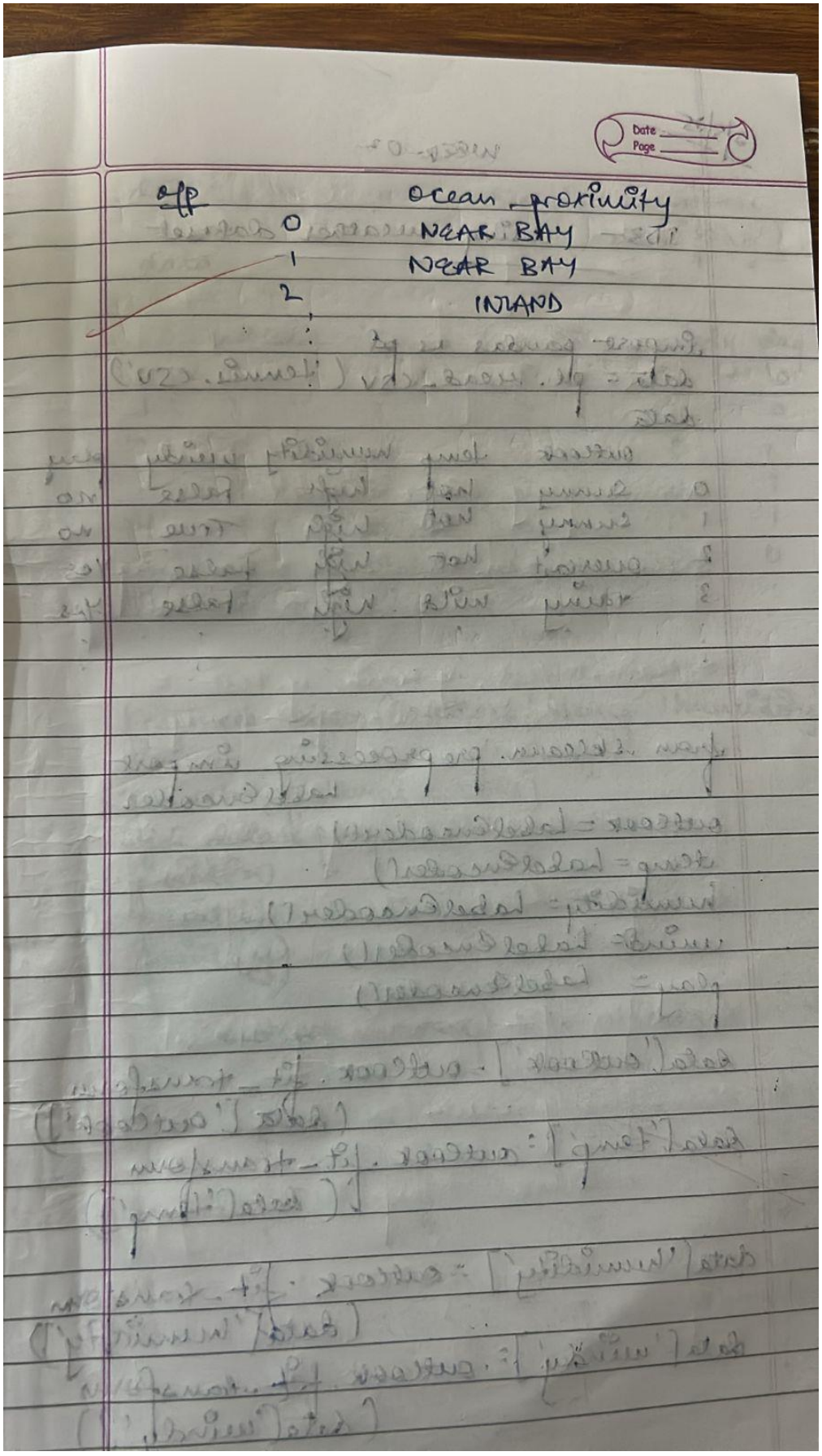
```
print (df.info)
```

(4) To display the count of unique labels for "Ocean Proximity" column

```
print (df.counter ('ocean_proximity'))
```

(5) To display which attributes in a dataset have missing value

```
print (df.isnull())
```


Date
Page
o/p
ocean_proximity
0
NEAR BAY
1
NEAR BAY
2
INLAND

Code:

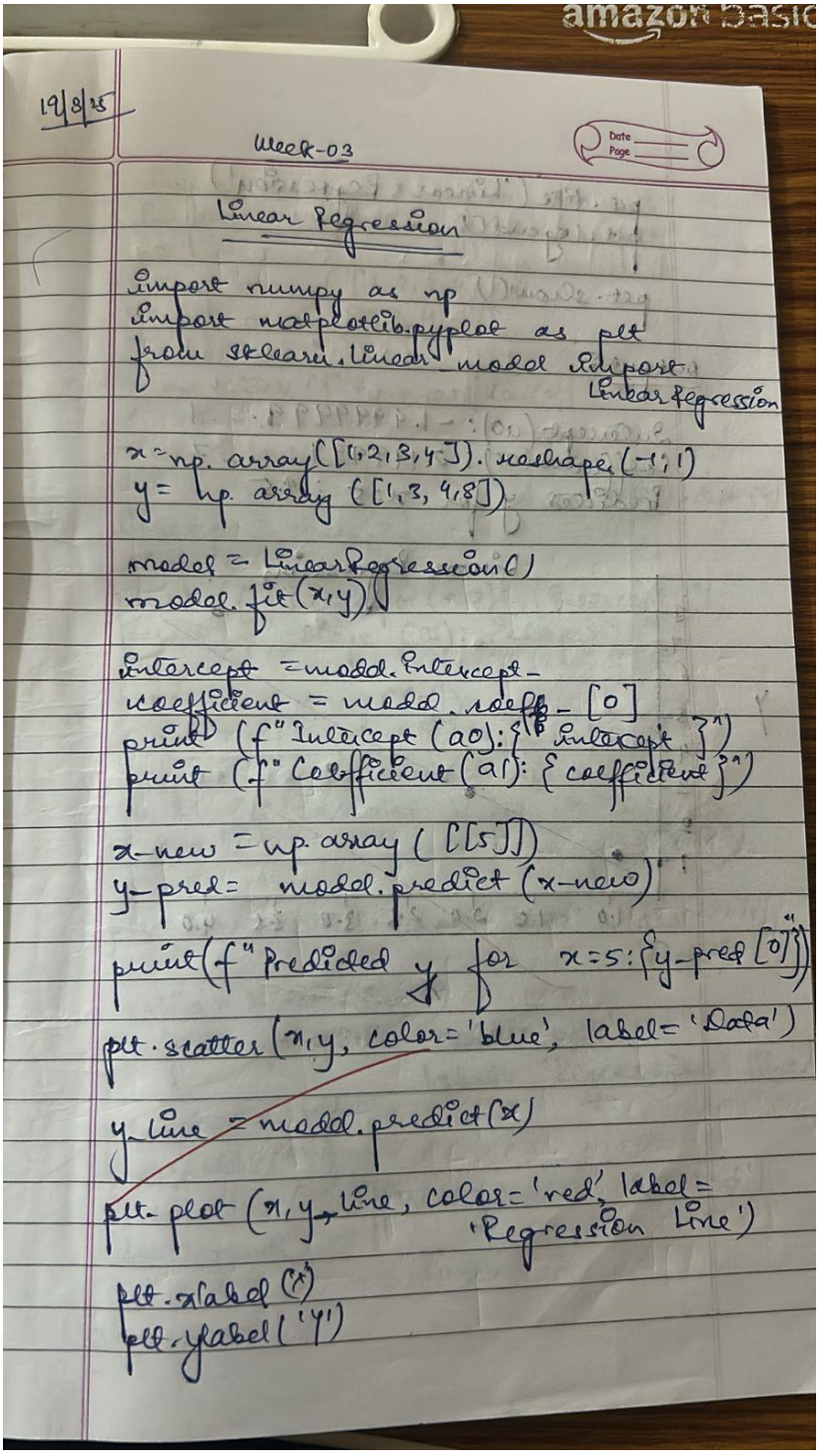
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from scipy import stats
df = pd.read_csv(r"/content/Dataset of Diabetes .csv")
df.head(10)
df.shape
print(df.info())
print(df.describe())
missing_values = df.isnull().sum()

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

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

df_copy=df

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

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

# Verify that there are no missing values left
print(df_copy["AGE"].isnull().sum())
print(df_copy["BMI"].isnull().sum())
#Handling Categorical Attributes
#Using Ordinal Encoding for gender COlumn and One-Hot Encoding for City Column

# Initialize OrdinalEncoder
ordinal_encoder = OrdinalEncoder(categories=[["M", "F","f"]])
# Fit and transform the data
df_copy["Gender_Encoded"] = ordinal_encoder.fit_transform(df_copy[["Gender"]])
```

```
# Initialize OneHotEncoder
onehot_encoder = OneHotEncoder()

# Fit and transform the "City" column
encoded_data = onehot_encoder.fit_transform(df[["CLASS"]])

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

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

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

print(df_encoded. head())
normalizer = MinMaxScaler()
df_encoded[['BMI']] = normalizer.fit_transform(df_encoded[['BMI']])
df_encoded.head()
scaler = StandardScaler()
df_encoded[['AGE']] = scaler.fit_transform(df_encoded[['AGE']])
df_encoded.head()
df_encoded_copy1=df_encoded
df_encoded_copy2=df_encoded
df_encoded_copy3=df_encoded

Q1 = df_encoded_copy1['BMI'].quantile(0.25)
Q3 = df_encoded_copy1['BMI'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
df_encoded_copy1['BMI'] = np.where(df_encoded_copy1['BMI'] > upper_bound, upper_bound,
                np.where(df_encoded_copy1['BMI'] < lower_bound, lower_bound, df_encoded_copy1['BMI']))

print(df_encoded_copy1.head())
df_encoded_copy2['BMI_zscore'] = stats.zscore(df_encoded_copy2['BMI'])
df_encoded_copy2['BMI'] = np.where(df_encoded_copy2['BMI_zscore'].abs() > 3, np.nan, df_encoded_copy2['BMI'])
# Replace outliers with NaN
print(df_encoded_copy2.head())
df_encoded_copy3['BMI_zscore'] = stats.zscore(df_encoded_copy3['BMI'])
median_salary = df_encoded_copy3['BMI'].median()
df_encoded_copy3['BMI'] = np.where(df_encoded_copy3['BMI_zscore'].abs() > 3, median_salary,
df_encoded_copy3['BMI'])
print(df_encoded_copy3.head())
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot



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Week-03

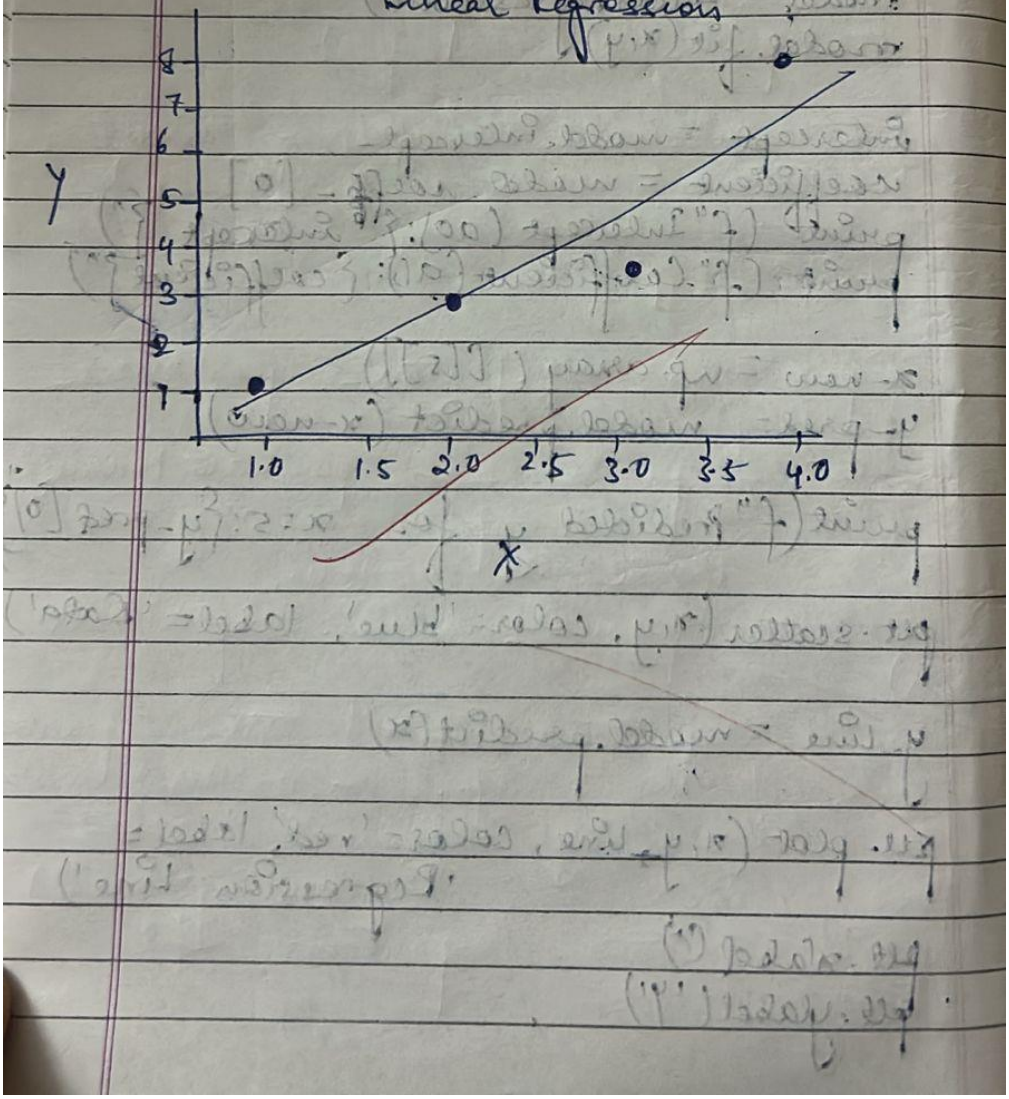
Linear Regression

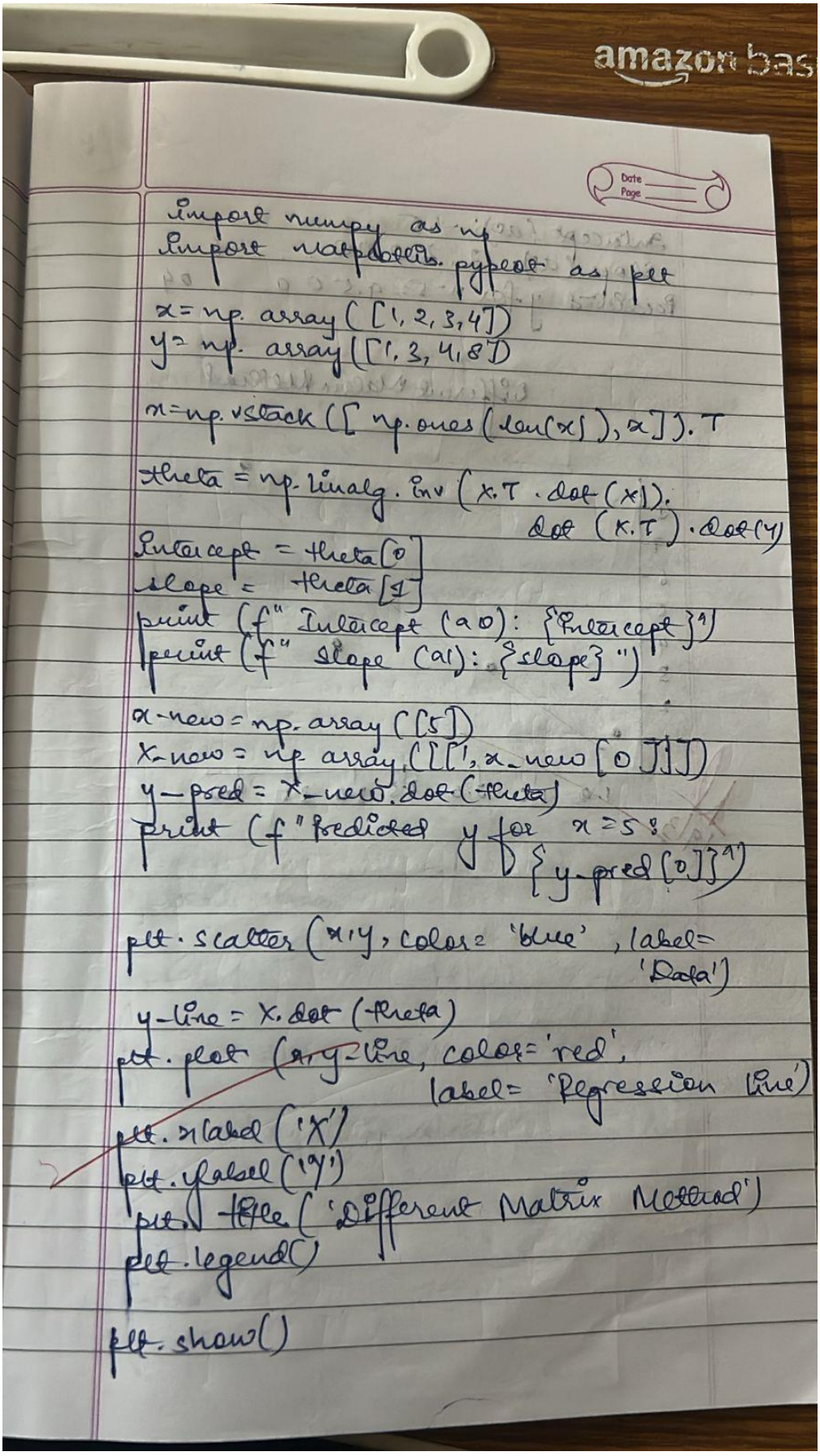
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

x = np.array([1,2,3,4]).reshape(-1,1)
y = np.array([1,3,4,8])

model = LinearRegression()
model.fit(x,y)

intercept = model.intercept_
coefficient = model.coef_[0]
print(f"Intercept (a0): {intercept}")
print(f"Coefficient (a1): {coefficient}")

x_new = np.array([[5]])
y_pred = model.predict(x_new)
print(f"Predicted y for x=5: {y_pred[0]}")

plt.scatter(x,y, color='blue', label='Data')

y_line = model.predict(x)

plt.plot(x,y_line, color='red', label='Regression Line')

plt.xlabel('x')
plt.ylabel('y')
```

plt.title('Linear Regression')
plt.legend()
plt.show()

Output:

Intercept (a0): -1.4999999...1
Coefficient (a1): 2.199999...7
Predicted y for x=5 : 9.5

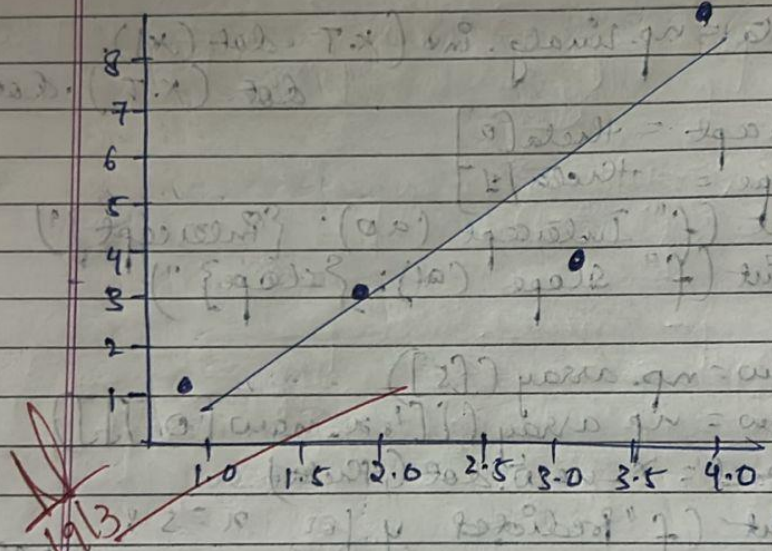




```
import numpy as np
import matplotlib.pyplot as plt
x = np.array([1, 2, 3, 4])
y = np.array([1, 3, 4, 8])

x = np.vstack([np.ones(len(x)), x]).T

theta = np.linalg.inv(x.T.dot(x)).
                dot(x.T).dot(y)
Intercept = theta[0]
slope = theta[1]
print(f"Intercept (a0): {Intercept}")
print(f"Slope (a1): {slope}")

x_new = np.array([5])
X_new = np.array([[1, x_new[0]]])
y_pred = X_new.dot(theta)
print(f"Predicted y for x=5:
                {y_pred[0]}")

plt.scatter(x1, y, color='blue', label=
                'Data')
y_line = X.dot(theta)
plt.plot(x1, y_line, color='red',
                label='Regression line')
plt.xlabel('X')
plt.ylabel('Y')
plt.title('Different Matrix Method')
plt.legend()

plt.show()
```

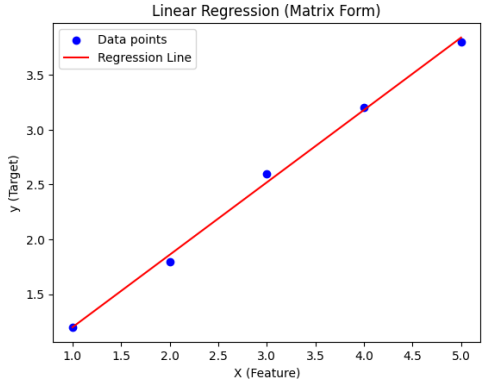
Intercept (a0): -1.5
Slope (a1): 2.2000
Predicted y for x=5: 9.5000

Different Matrix Method

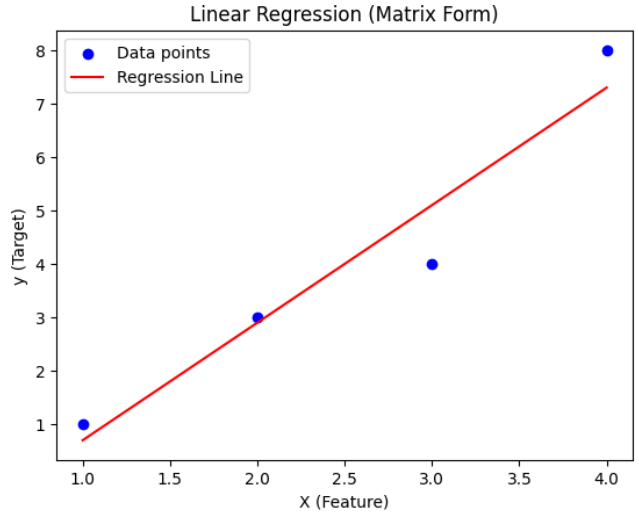


Code:

```
import pandas as pd
import matplotlib.pyplot as plt

data={"X":[1,2,3,4,5],
      "Y":[1.2,1.8,2.6,3.2,3.8]}
df=pd.DataFrame(data)
df

Xi=df["X"].mean()
Yi=df["Y"].mean()

df["Xi^2"]=[Xi**2 for Xi in df["X"]]
Xisq=df["Xi^2"].mean()

xiyi=[]
x=df["X"]
y=df["Y"]
for i in range(len(x)):
  xiyi.append(x[i]*y[i])
df["XiYi"]=xiyi
print(df["XiYi"])
XiYi2=df["XiYi"].mean()
print(XiYi2)
a1 = (df["XiYi"].sum() - len(df) * Xi * Yi) / (df["X"].apply(lambda x: x**2).sum() - len(df) * Xi**2)
a0 = Yi - a1 * Xi

x=9
Y=a0+a1*x
print(Y)
plt.scatter(df["X"], df["Y"], color='blue', label='Data points')  # Scatter plot of original data
plt.plot(df["X"], a0 + a1 * df["X"], color='red', label='Regression Line')  # Correct regression line
plt.title('Linear Regression (Matrix Form)')
plt.xlabel('X (Feature)')
plt.ylabel('y (Target)')
plt.legend()
plt.show()
```



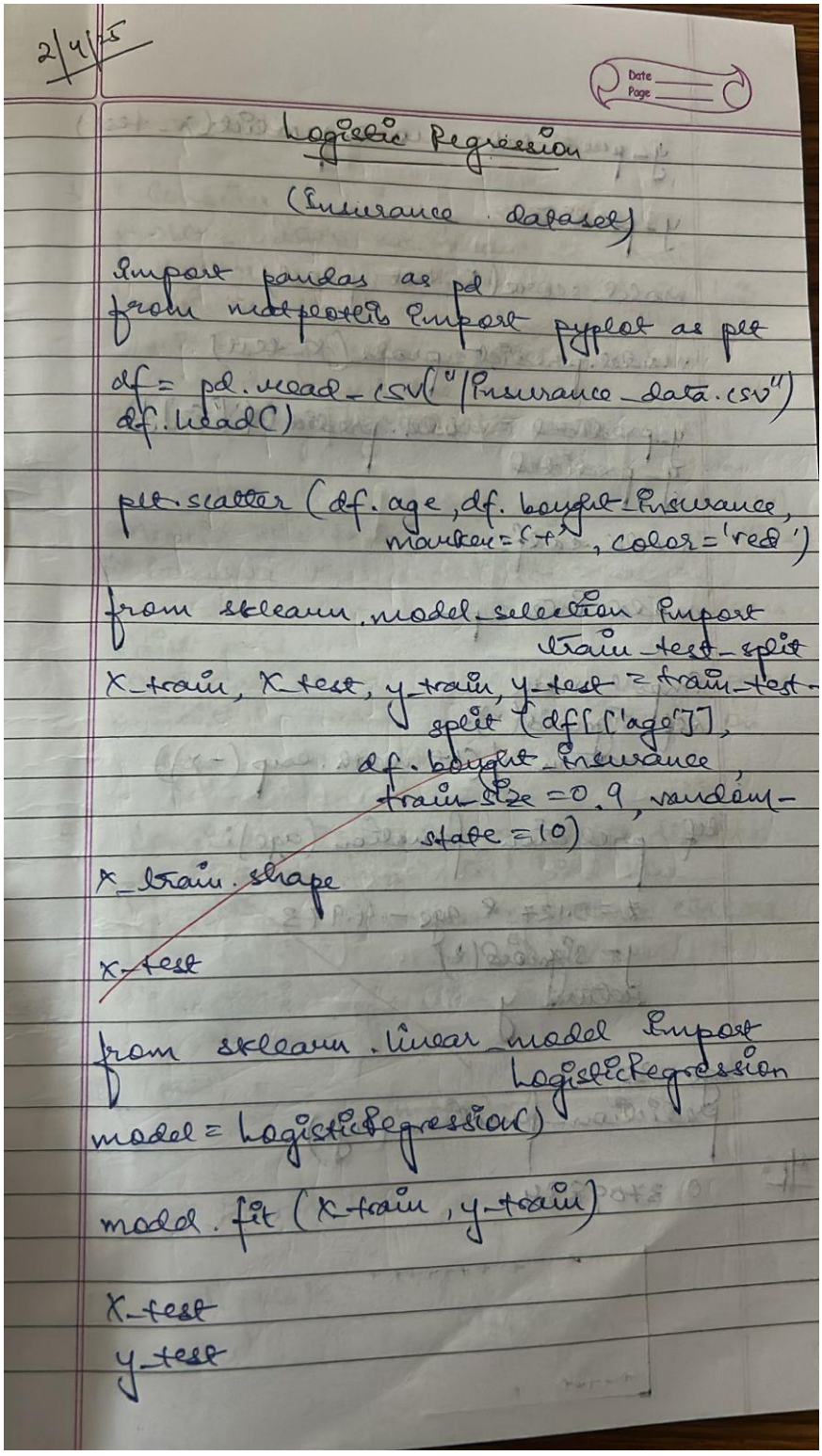
```
import numpy as np
import matplotlib.pyplot as plt

X = np.array([1, 2, 3, 4])
y = np.array([1,3,4,8])

X_matrix = np.c_[np.ones(len(X)), X]

theta = np.linalg.inv(X_matrix.T @ X_matrix) @ X_matrix.T @ y

b, m = theta


y_pred = m * X + b
print(f"Slope (m): {m}")
print(f"Intercept (b): {b}")

Slope (m): 2.2000000000000006
Intercept (b): -1.5

plt.scatter(X, y, color='blue', label='Data points')
plt.plot(X, y_pred, color='red', label='Regression Line')
plt.title('Linear Regression (Matrix Form)')
plt.xlabel('X (Feature)')
plt.ylabel('y (Target)')
plt.legend()
plt.show()
```



Program 4

Build Logistic Regression Model for a given dataset

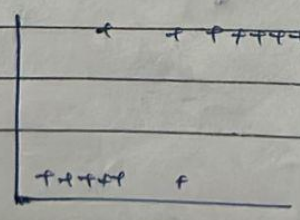
Screenshot



```
y_predicted = model.predict(x_test)
y_predicted
model.score(x_test, y_test)
model.predict_proba(x_test)
y_predicted = model.predict([[60]])
y_predicted
model.coef_
model.intercept_
import math
def sigmoid(x):
    return 1/(1+math.exp(-x))
def prediction_function(age):
    z = 0.127 * age - 4.973
    y = sigmoid(z)
    return y
age = 35
prediction_function(age)
```

o/p:

0.3709834



To do:

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, and the learned parameters are $a_0 = -5$ (intercept) and $a_1 = 0.8$ (coeff for study hours)

a) Write the logistic regression eqn for this.

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

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

2) Consider $z = [2, 1, 0]$ for three classes. Apply Softmax func^n to find the probability values of three classes.

Soln a) logistic regression Equation

$$P(\text{pass}) = \frac{1}{1 + e^{-(a_0 + a_1 x)}}$$

$a_0 = -5, a_1 = 0.8$

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

by x=7

$$P(\text{pass}) = \frac{1}{1+e^{-(-5+0.8\times7)}}$$

$$= \frac{1}{1+e^{-0.6}} = 0.646$$

∴ probability = 0.646 (64.66%)

by Predicted class : pass

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

$$P_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

Class1 (z=2) = 0.665 (66.52%)

Class2 (z=1) = 0.245 (24.47%)

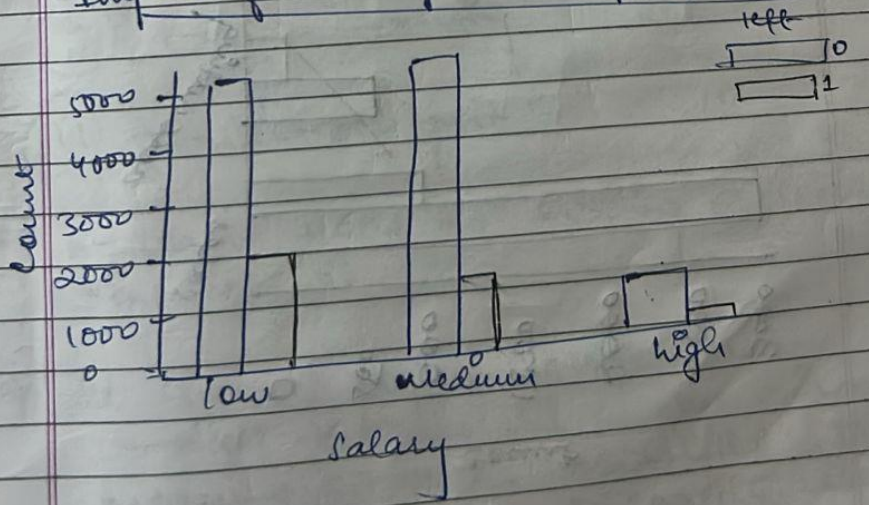
Class3 (z=0) = 0.090 (9.00%)

To do: Implementation – Logistic Regression (Binary classification)

Dataset = (HR_comma_sep.csv)

1. satisfaction_level – strong negative correlation
2. time_spent_in_the_company
3. Average_monthly_hours
4. No_of_projects
5. last_evaluation_score
6. Salary_level
7. Salary_level
8. Department

24 Impact of salary on employee retention



3)
Department vs employee retention
Count
3000
2500
2000
1500
1000
500
0
sales
accounting
hr
technical
support
management
IT
product_mng
marketing
RandD
Department

Model Accuracy = 0.75866...67

	precision	recall	f1-score	support
0	0.80	0.92	0.85	2294
1	0.47	0.23	0.31	706

Q1.) HR_comma_sep.csv :-

(i) employee retention has direct impact on/with satisfaction level

(ii) Accuracy: 0.758
It is good because generally it ranges from 0.75 and 0.85

Q2.) Zoo dataset:

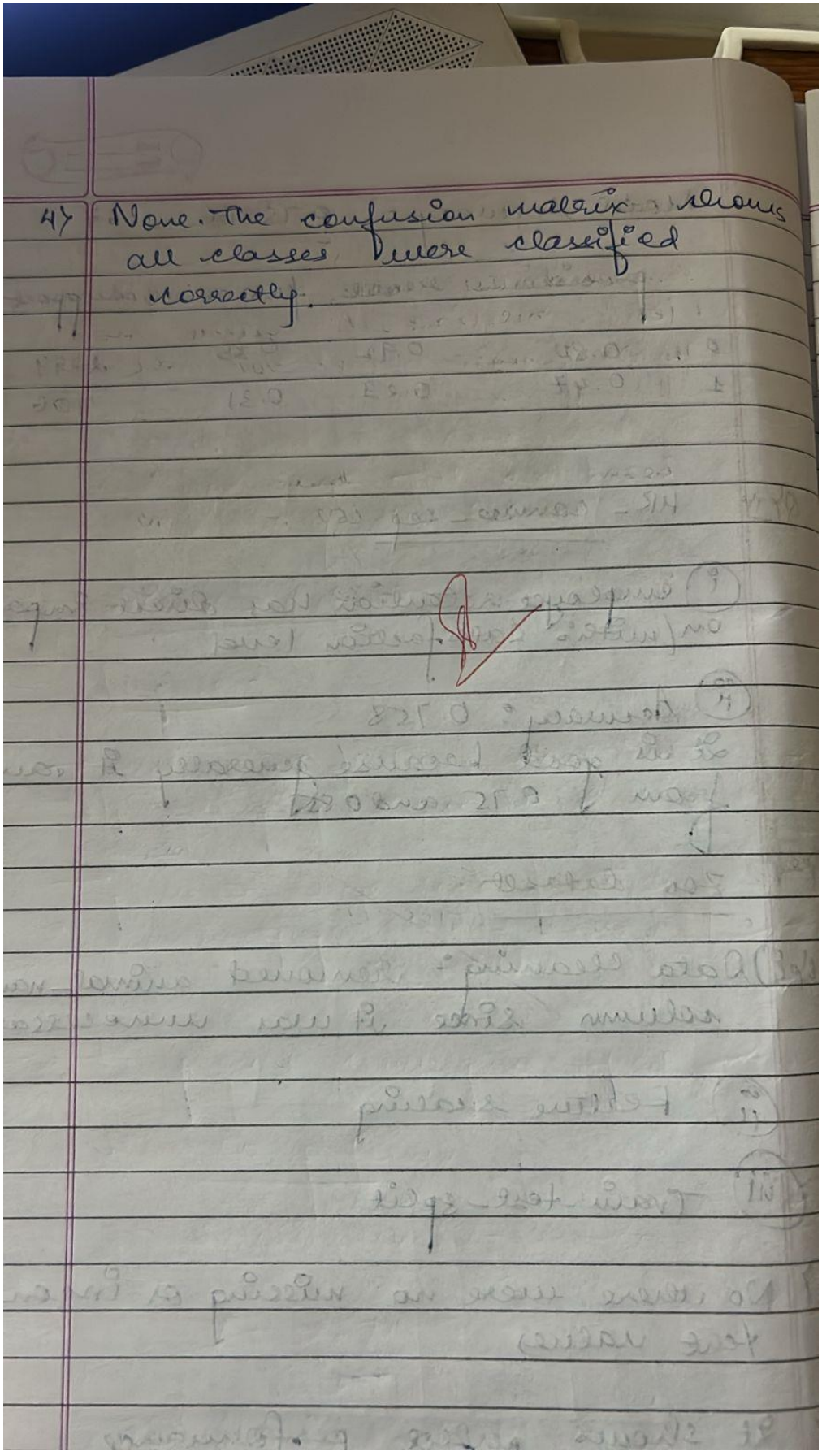
(i) Data cleaning: removed animal_name column since it was unnecessary

(ii) Feature scaling

(iii) Train_test_split

2) No there were no missing or inconsistent values

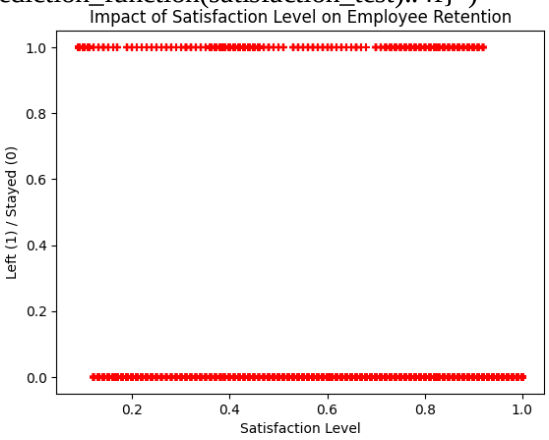
3) It shows perfect performance
→ all entries lie on the diagonal, meaning correctly classified into respective classes


4) None. The confusion matrix shows
all classes were classified
correctly.

Code:

```
import pandas as pd
import matplotlib.pyplot as plt
import math
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

# Load dataset
df = pd.read_csv("/content/HR_comma_sep (2).csv")

# Scatter plot: Employee satisfaction vs Retention
plt.scatter(df.satisfaction_level, df.left, marker='+', color='red')
plt.xlabel("Satisfaction Level")
plt.ylabel("Left (1) / Stayed (0)")
plt.title("Impact of Satisfaction Level on Employee Retention")
plt.show()

# Define features (X) and target (y)
X = df[['satisfaction_level']]
y = df['left']

# Split dataset (90% train, 10% test)
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()
model.fit(X_train, y_train)

# Predictions
y_predicted = model.predict(X_test)

# Model Accuracy
print(f"Model Accuracy: {model.score(X_test, y_test):.4f}")

# Probability predictions
print("Predicted Probabilities:")
print(model.predict_proba(X_test))

# Predict for a specific satisfaction level (e.g., 0.4)
predicted_status = model.predict([[0.4]])
print(f"Prediction for Satisfaction Level 0.4: {'Left' if predicted_status[0] == 1 else 'Stayed'}")

# Logistic function
def sigmoid(x):
    return 1 / (1 + math.exp(-x))
```

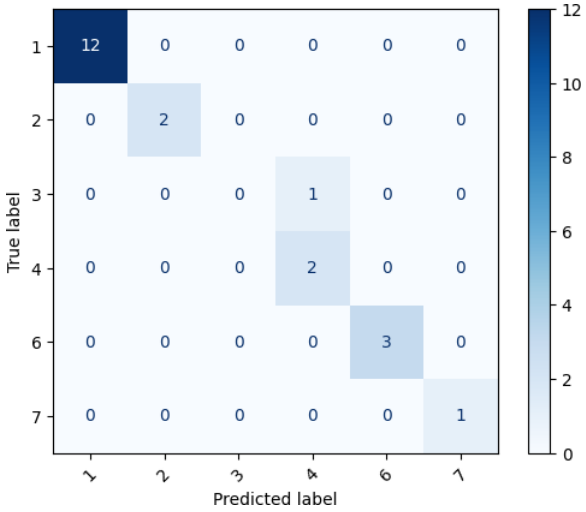
```
# Custom prediction function
m, b = model.coef_[0][0], model.intercept_[0]
def prediction_function(satisfaction):
    z = m * satisfaction + b
    y = sigmoid(z)
    return y

satisfaction_test = 0.4
print(f"Sigmoid Prediction for Satisfaction Level {satisfaction_test}:
{prediction_function(satisfaction_test):.4f}")
```




```
Model Accuracy: 0.7707
Predicted Probabilities:
[[0.81879598 0.18120402]
 [0.64435551 0.35564449]
 [0.67008191 0.32991809]
 ...
 [0.85026544 0.14973456]
 [0.93858587 0.06141413]
 [0.90306111 0.09693889]]
Prediction for Satisfaction Level 0.4: Stayed
Sigmoid Prediction for Satisfaction Level 0.4: 0.3644

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

# Load the Zoo dataset
file_path = "/content/zoo-data (1).csv"
zoo_data = pd.read_csv(file_path)

# Drop the 'animal_name' column as it is not a relevant feature
X = zoo_data.drop(['animal_name', 'class_type'], axis=1)  # Features
y = zoo_data['class_type']  # Target variable
```

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

# Initialize the Logistic Regression model for multi-class classification
model = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=200)
# Train the model
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the Multinomial Logistic Regression model: {accuracy:.2f}")

# Compute confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Adjust display labels to match actual present labels in the test set
unique_classes_in_test = sorted(y_test.unique())

# Display confusion matrix
cm_display = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=unique_classes_in_test)
cm_display.plot(cmap='Blues', xticks_rotation=45)
plt.show()
```

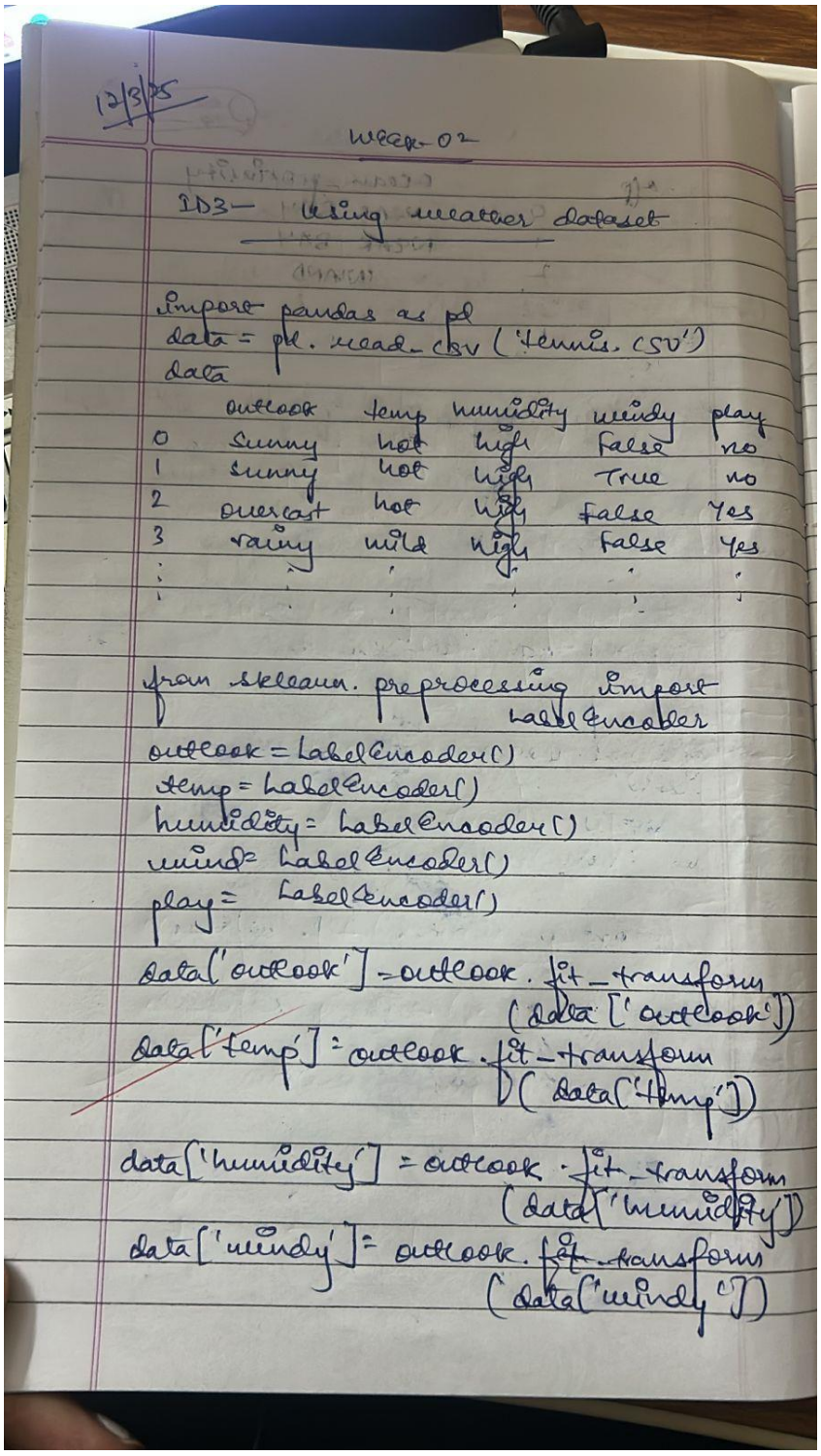
Accuracy of the Multinomial Logistic Regression model: 0.95

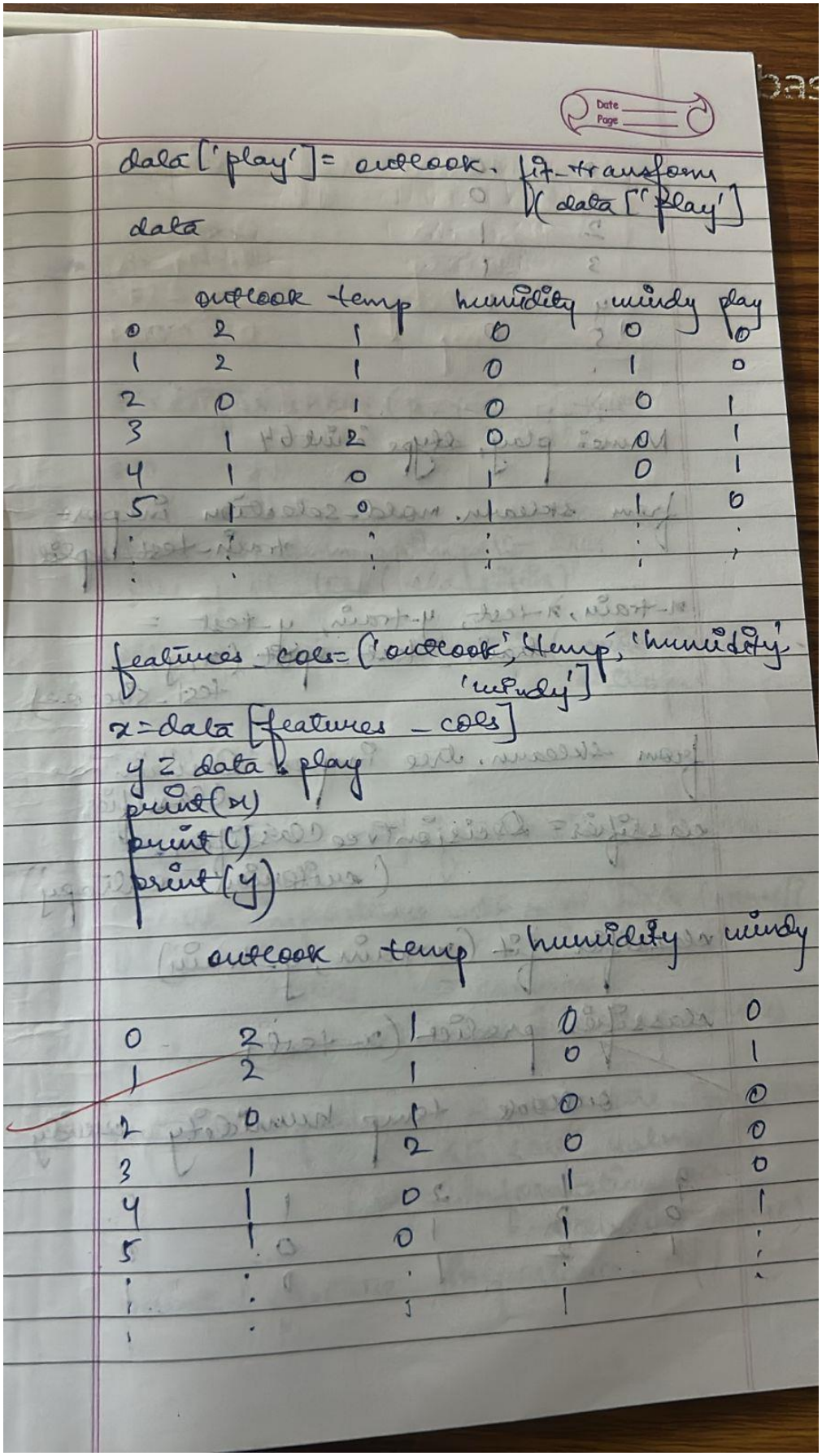


Program 5

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

Screenshot





data['play'] = outlook.fit_transform(data['play'])

data

	outlook	temp	humidity	windy	play
0	2	1	0	0	0
1	2	1	0	1	0
2	0	1	0	0	1
3	1	2	0	0	1
4	1	0	1	0	1
5	1	0	1	1	0
:	:	:	:	:	:

features_cols = ['outlook', 'temp', 'humidity', 'windy']

x = data[features_cols]

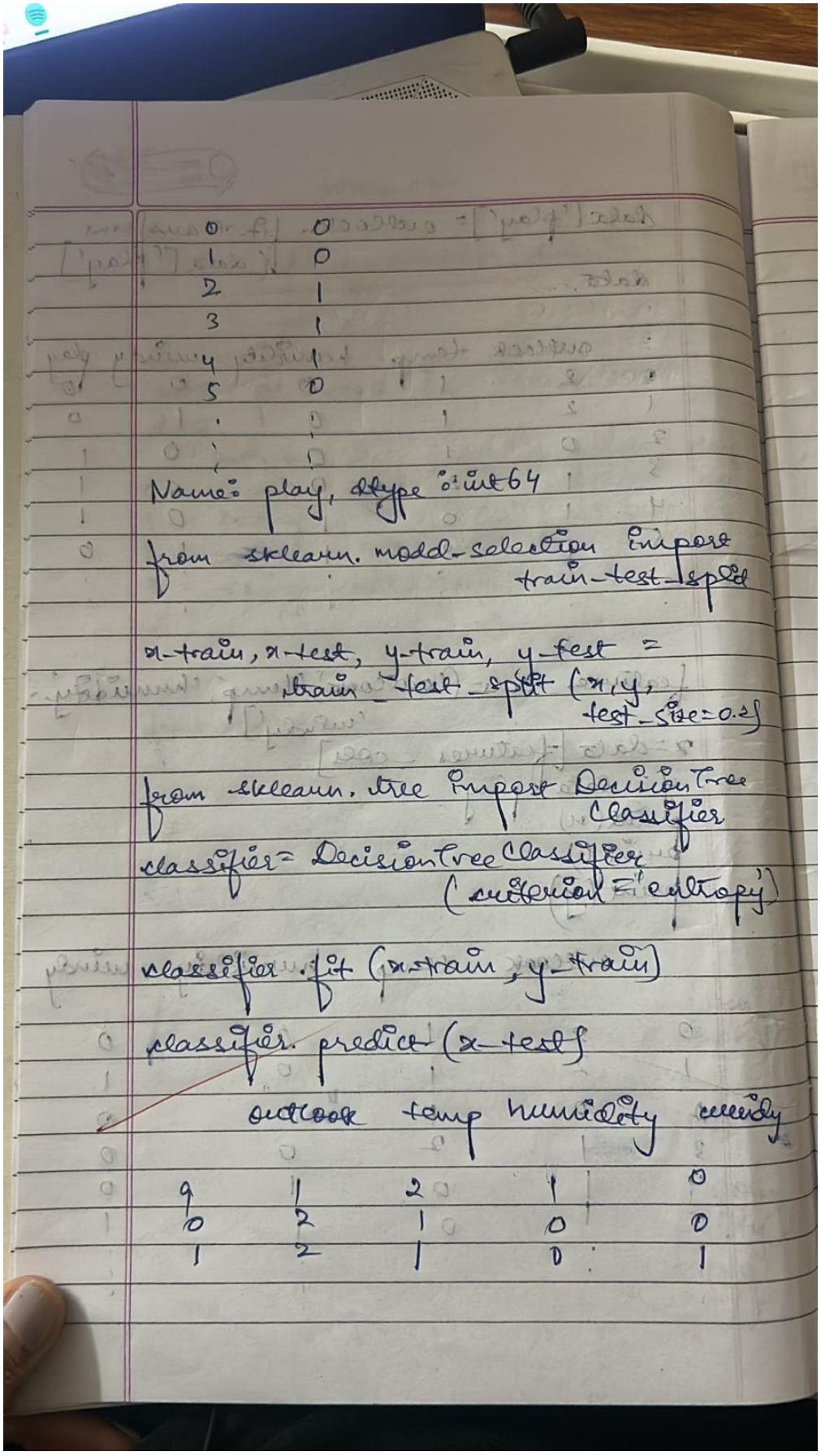
y = data.play

print(x)

print()

print(y)

	outlook	temp	humidity	windy
0	2	1	0	0
1	2	1	0	1
2	0	1	0	0
3	1	2	0	0
4	1	0	1	0
5	1	0	1	1
:	:	:	:	:



0	0
1	0
2	1
3	1
4	1
5	0
.	.
.	.

Name: play, dtype: int64

```
from sklearn.model_selection import
                        train_test_split

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

from sklearn.tree import DecisionTree
                         Classifier
classifier= DecisionTreeClassifier
                    (criterion='entropy')

classifier.fit(x_train, y_train)

classifier.predict(x_test)
```

outlook	temp	humidity	windy	
2	1	1	0	
0	2	1	0	0
1	2	1	0	1

y_test

	play
9	1
0	0
1	0

```
classifier.score(x_test, y_test)
```

1.0

```
from sklearn import tree
tree.plot_tree(classifier)
clf = DecisionTreeClassifier(criterion='entropy')
clf.fit(x,y)
importances = clf.feature_importances_
feature_Importance_df = pd.DataFrame({
        'Feature': x.columns,
        'Information Gain': Importances
})
feature_Importance_df = feature_Importance_df.sort_values(by='Information Gain', ascending=False)
print(feature_Importance_df)
```

	Feature	Information Gain
0	outlook	0.514558
3	windy	0.274205
2	humidity	0.211237
1	temp	0.000000

Code:

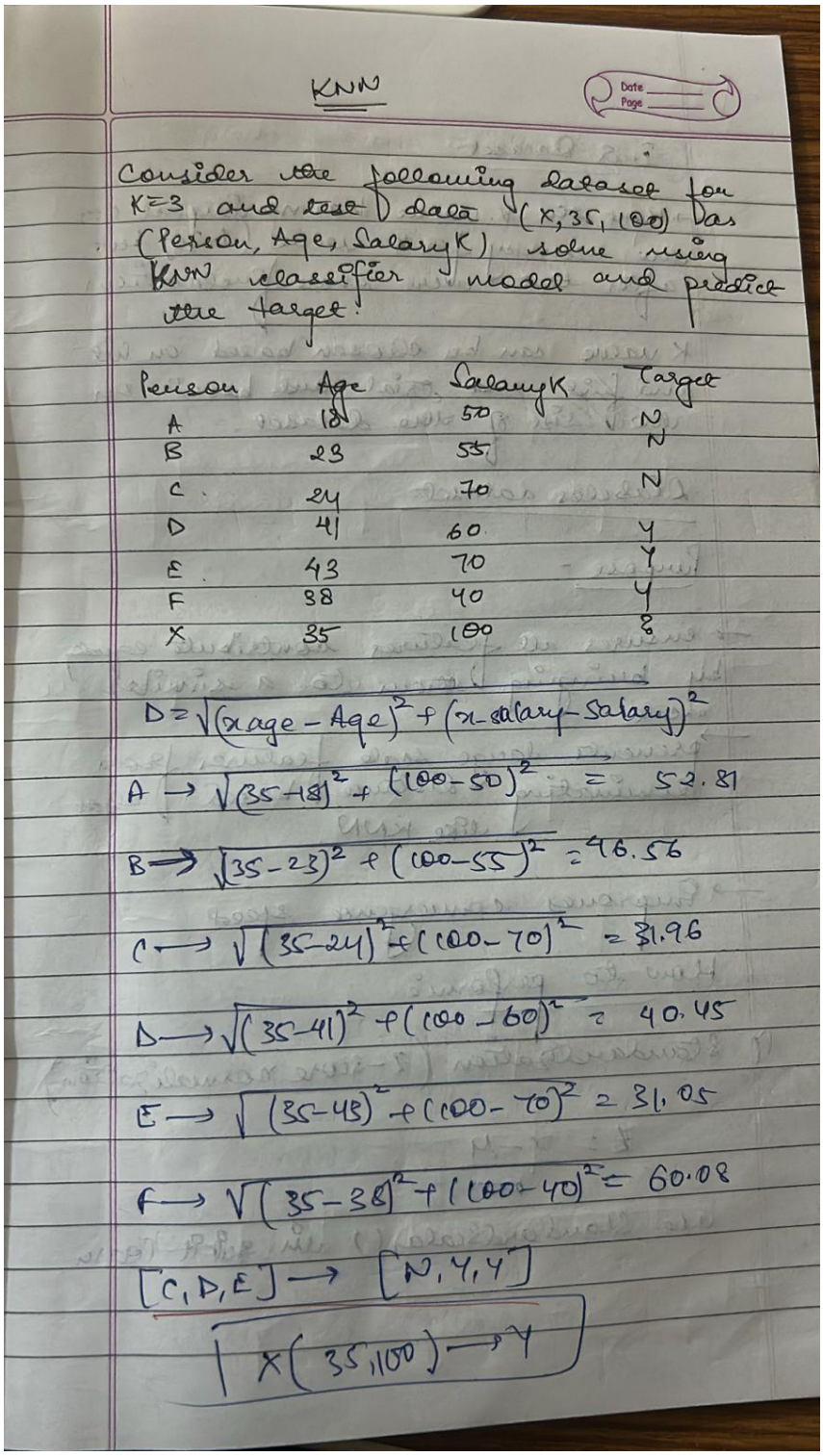
```
import numpy as np
import pandas as pd
from collections import Counter
class Node:
    def __init__(self, feature=None, value=None, label=None):
        self.feature = feature  # Attribute to split on
        self.value = value      # Value of the attribute
        self.label = label      # Label if it's a leaf node
        self.children = {}      # Dictionary of child nodes

def entropy(y):
    counts = np.bincount(y)
    probabilities = counts / len(y)
    return -np.sum([p * np.log2(p) for p in probabilities if p > 0])

def information_gain(X, y, feature):
    total_entropy = entropy(y)
    values, counts = np.unique(X[:, feature], return_counts=True)
    weighted_entropy = sum((counts[i] / sum(counts)) * entropy(y[X[:, feature] == v]) for i, v in
enumerate(values))
    return total_entropy - weighted_entropy

def best_feature_to_split(X, y):
    gains = [information_gain(X, y, i) for i in range(X.shape[1])]
    return np.argmax(gains)

def id3(X, y, features):
    if len(set(y)) == 1:
        return Node(label=y[0])
    if len(features) == 0:
        return Node(label=Counter(y).most_common(1)[0][0])
    best_feature = best_feature_to_split(X, y)
    node = Node(feature=features[best_feature])
    feature_values = np.unique(X[:, best_feature])
    for value in feature_values:
        sub_X = X[X[:, best_feature] == value]
        sub_y = y[X[:, best_feature] == value]
        if len(sub_y) == 0:
            node.children[value] = Node(label=Counter(y).most_common(1)[0][0])
        else:
            node.children[value] = id3(np.delete(sub_X, best_feature, axis=1), sub_y, features[:best_feature] +
features[best_feature+1:])
    return node
        if node.label is not None:
        print(f"{'  ' * depth}Leaf: {node.label}")
        return
    print(f"{'  ' * depth}Feature: {node.feature}")
```

```
    for value, child in node.children.items():
        print(f"{'  ' * depth}Value: {value}")
        print_tree(child, depth + 1)
# Example dataset
data = pd.DataFrame({
    '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'],
    'Wind': ['Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong',
'Weak', 'Strong'],
    'PlayTennis': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
})
X = data.iloc[:, :-1].apply(lambda col: pd.factorize(col)[0]).to_numpy()
y = pd.factorize(data['PlayTennis'])[0]
features = list(data.columns[:-1])
decision_tree = id3(X, y, features)
print_tree(decision_tree)

Feature: Outlook
Value: 0
  Feature: Humidity
  Value: 0
    Leaf: 0
  Value: 1
    Leaf: 1
Value: 1
  Leaf: 1
Value: 2
  Feature: Wind
  Value: 0
    Leaf: 1
  Value: 1
    Leaf: 0
```

Program 6

Build KNN Classification model for a given dataset

Screenshot



Iris Dataset

→ Here the K value has no impact on the accuracy for K value (1,26) but after that there some fluctuations

K value can be chosen based on hit and trial and based on the size of the dataset.

Diabetes dataset

Purpose -

→ ensures all features contribute equally by bringing them to a similar scale

→ prevents large scale features from dominating distance based algos like KNN.

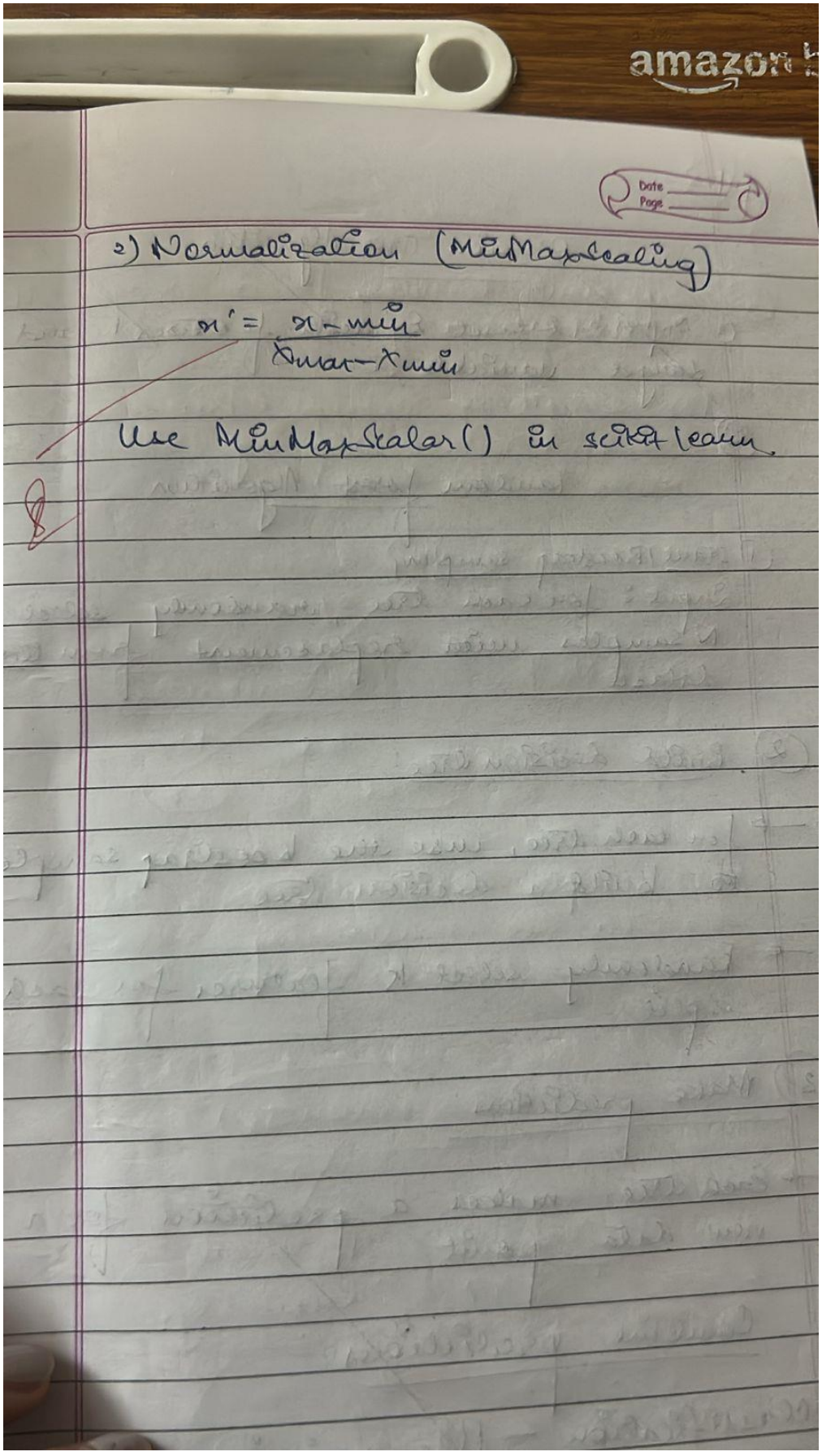
→ Improves convergence speed

How to perform:

1) Standardization (Z-score normalization)

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

use StandardScalar() in scikit-learn


amazon
Date
Page
2) Normalization (MinMaxScaling)
$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$
Use MinMaxScaler() in scikit learn.

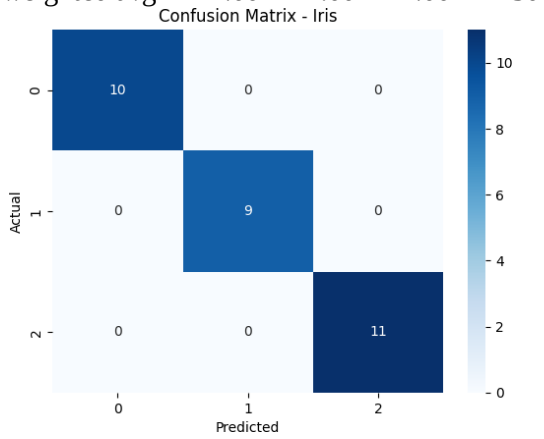
Code:

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

# Function to train and evaluate KNN model
def knn_classification(data_path, target_column, dataset_name, k=5):
    # Load dataset
    df = pd.read_csv(data_path)

    # Split features and target
    X = df.drop(columns=[target_column])
    y = df[target_column]

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

    # Feature scaling for better performance
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    # Train KNN model
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)

    # Make predictions
    y_pred = model.predict(X_test)

    # Evaluate model
    accuracy = accuracy_score(y_test, y_pred)
    print(f'Accuracy of KNN on {dataset_name} dataset: {accuracy:.4f}')
    print("Classification Report:")
    print(classification_report(y_test,  y_pred))

    # Confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix - {dataset_name}')
    plt.show()
```

 # Run KNN classification on both datasets
knn_classification('/content/iris (3).csv', 'species', 'Iris', k=5)
knn_classification('/content/diabetes.csv', 'Outcome', 'Diabetes', k=5)

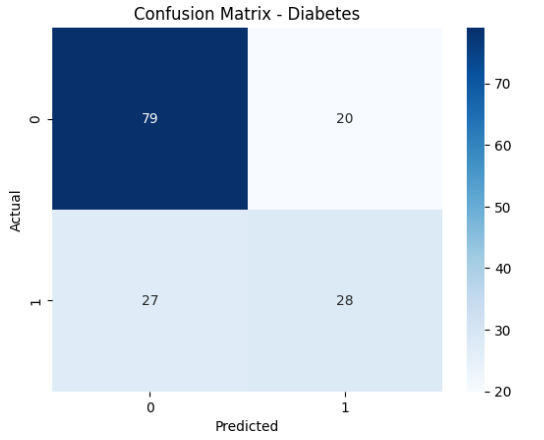
Accuracy of KNN on Iris dataset: 1.0000
Classification Report:

	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	10
versicolor	1.00	1.00	1.00	9
virginica	1.00	1.00	1.00	11
accuracy			1.00	30
macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30



Accuracy of KNN on Diabetes dataset: 0.6948
Classification Report:

	precision	recall	f1-score	support
0	0.75	0.80	0.77	99
1	0.58	0.51	0.54	55
accuracy			0.69	154
macro avg	0.66	0.65	0.66	154
weighted avg	0.69	0.69	0.69	154

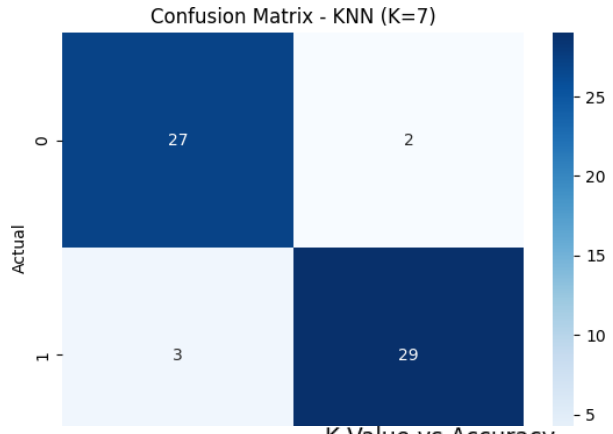


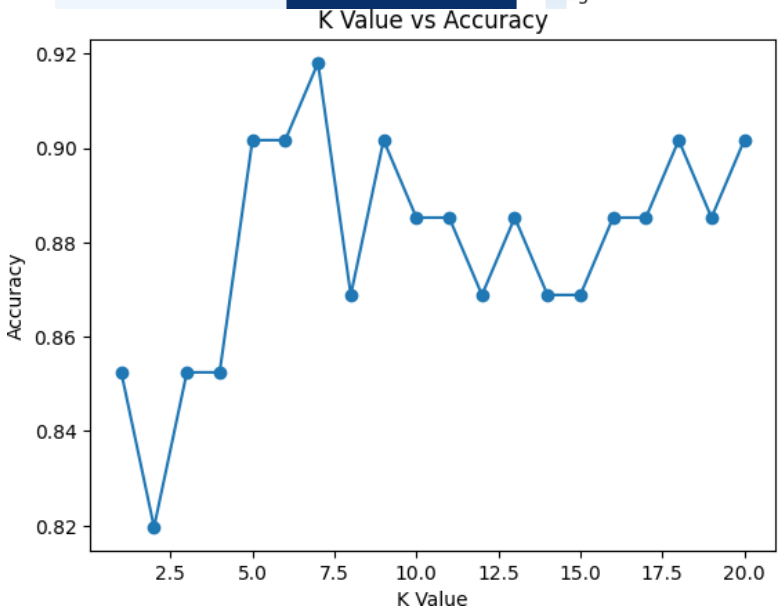
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,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

# Load dataset
df = pd.read_csv('/content/heart.csv')
# Define features and target
X = df.drop(columns=['target'])  # Assuming 'target' is the classification column
y = df['target']

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

# Feature scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Find the best K value
k_values = range(1, 21)
accuracy_scores = []
for k in k_values:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy_scores.append(accuracy_score(y_test, y_pred))

best_k = k_values[np.argmax(accuracy_scores)]
print(f'Best K value: {best_k}')

# Train model with best K
best_model = KNeighborsClassifier(n_neighbors=best_k)
best_model.fit(X_train, y_train)
y_pred = best_model.predict(X_test)

# Evaluate model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy with best K ({best_k}): {accuracy:.4f}')
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
```

```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix - KNN (K={best_k})')
plt.show()

# Plot K values vs. Accuracy
plt.plot(k_values, accuracy_scores, marker='o')
plt.xlabel('K Value')
plt.ylabel('Accuracy')
plt.title('K Value vs Accuracy')
plt.show()
```

Best K value: 7
Accuracy with best K (7): 0.9180
Classification Report:

	precision	recall	f1-score	support
0	0.90	0.93	0.92	29
1	0.94	0.91	0.92	32
accuracy			0.92	61
macro avg	0.92	0.92	0.92	61
weighted avg	0.92	0.92	0.92	61





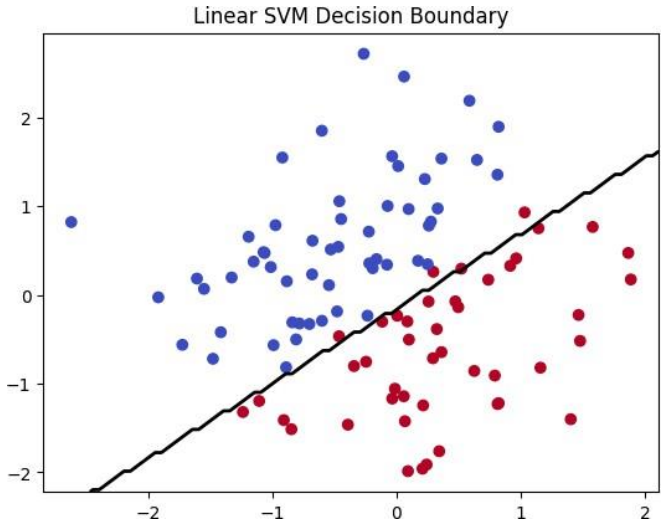
Program 7

Build Support vector machine model for a given dataset

Code:

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

# Define the Linear SVM class
class LinearSVM:
    def __init__(self, learning_rate=0.001, reg_strength=0.1, num_iterations=1000):
        self.learning_rate = learning_rate
        self.reg_strength = reg_strength
        self.num_iterations = num_iterations

    def fit(self, X, y):
        # Initialize weights and bias
        num_samples, num_features = X.shape
        self.W = np.zeros(num_features)  # Weights
        self.b = 0  # Bias

        # Gradient Descent
        for _ in range(self.num_iterations):
            # Compute the margin (decision function)
            margins = 1 - y * (np.dot(X, self.W) + self.b)
            # Compute gradient
            dw = -2 * np.dot(X.T, (y * (margins > 0))) / num_samples + 2 * self.reg_strength * self.W
            db = -2 * np.sum(y * (margins > 0)) / num_samples

            # Update weights and bias
            self.W -= self.learning_rate * dw
            self.b -= self.learning_rate * db

    def predict(self, X):
        # Make predictions
        return np.sign(np.dot(X, self.W) + self.b)

# Generate toy data (binary classification)
np.random.seed(42)
num_samples = 100
X = np.random.randn(num_samples, 2)
y = np.ones(num_samples)
y[X[:, 0] < X[:, 1]] = -1  # Assign different class based on condition

# Train the Linear SVM
svm = LinearSVM(learning_rate=0.001, reg_strength=0.1, num_iterations=1000)
svm.fit(X, y)
```

```
# Predict
y_pred = svm.predict(X)

# Visualize the decision boundary
plt.scatter(X[:, 0], X[:, 1], c=y, cmap='coolwarm')
ax = plt.gca()
xlim = ax.get_xlim()
ylim = ax.get_ylim()
xx, yy = np.meshgrid(np.linspace(xlim[0], xlim[1], 100), np.linspace(ylim[0], ylim[1], 100))
Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plt.contour(xx, yy, Z, levels=[0], linewidths=2, colors='black')
plt.title("Linear SVM Decision Boundary")
plt.show()

# Print accuracy (simple comparison)
accuracy = np.mean(y_pred == y)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

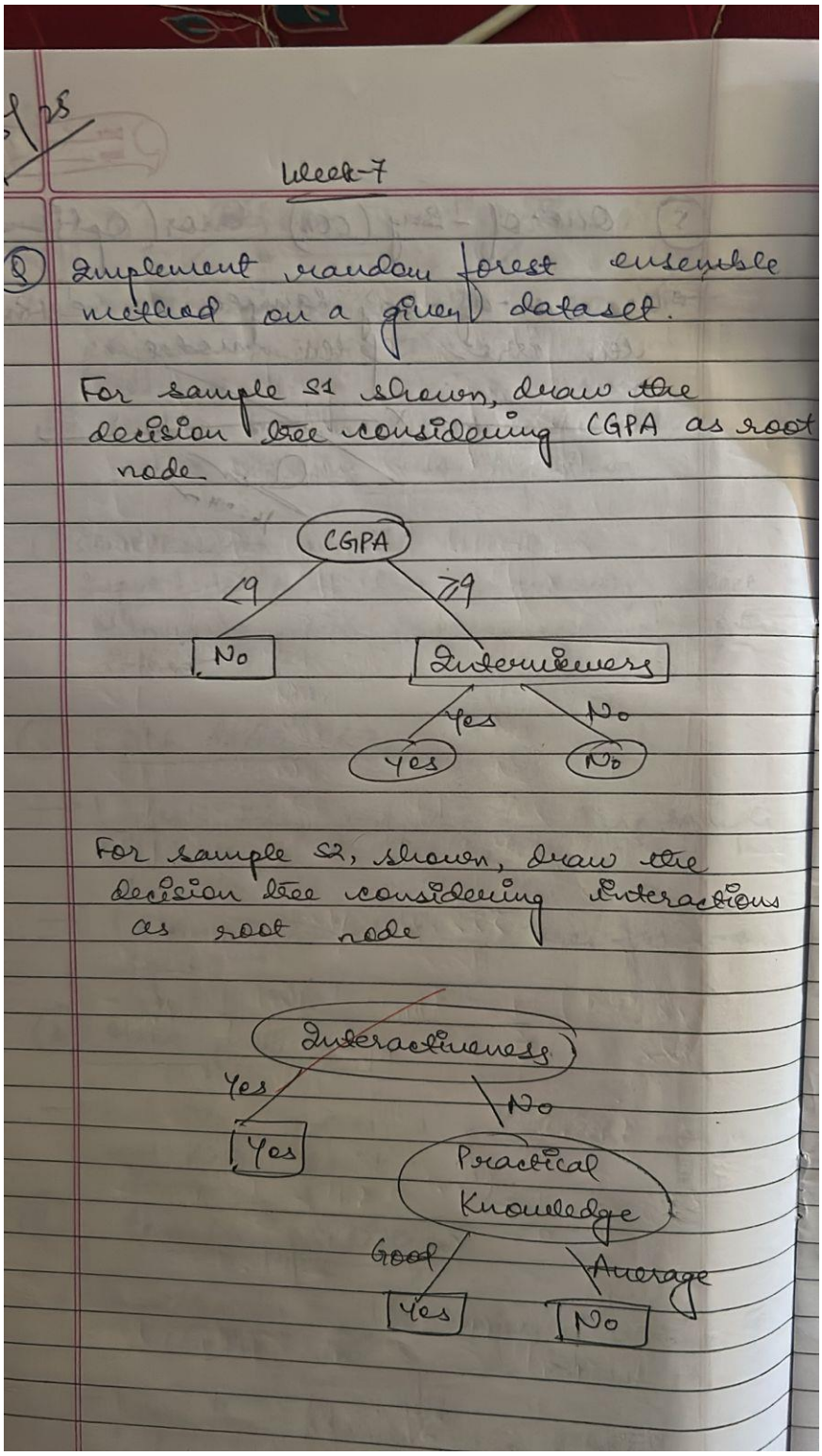


Accuracy: 96.00%

Program 8

Implement Random forest ensemble method on a given dataset

Screenshot



Write the answer for the following question -

(1) for "iris.csv" dataset -
what is the best accuracy score and confusion matrix of the classifier you observed and using how many trees?

⇒ Best accuracy score observed
⇒ 1.0

⇒ No. of trees (n-estimators)
: best_n

⇒ Confusion Matrix

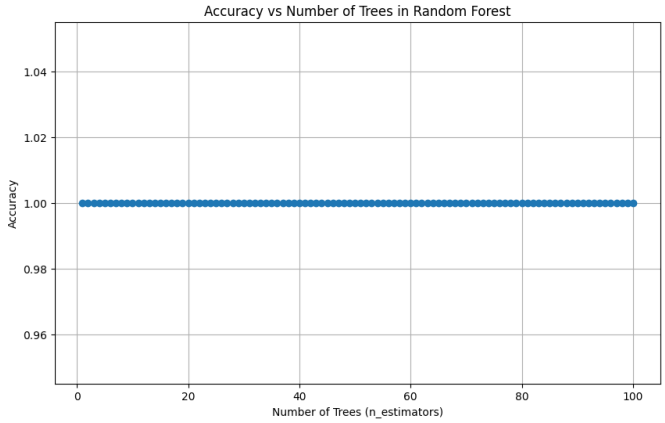
```
[[16  0  0]
 [ 0 14  0]
 [ 0  0 15]]
```

Code:

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

# Load the iris dataset from CSV
df = pd.read_csv("/content/iris (2).csv")

# Assuming last column is the label
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

# Split into training and test sets (70% train, 30% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# 1. Train RF Classifier with default n_estimators=10
rf_default = RandomForestClassifier(n_estimators=10, random_state=42)
rf_default.fit(X_train, y_train)
y_pred_default = rf_default.predict(X_test)
accuracy_default = accuracy_score(y_test, y_pred_default)

print(f"Default RF Accuracy (n_estimators=10): {accuracy_default:.4f}")

best_accuracy = 0
best_n = 0
accuracies = []

for n in range(1, 101):
    rf = RandomForestClassifier(n_estimators=n, random_state=42)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    accuracies.append(acc)

    if acc > best_accuracy:
        best_accuracy = acc
        best_n = n

print(f"Best RF Accuracy: {best_accuracy:.4f} with n_estimators = {best_n}")
# Plot accuracy vs. number of trees
plt.figure(figsize=(10, 6))
plt.plot(range(1, 101), accuracies, marker='o')
plt.title("Accuracy vs Number of Trees in Random Forest")
plt.xlabel("Number of Trees (n_estimators)")
```

```
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
```

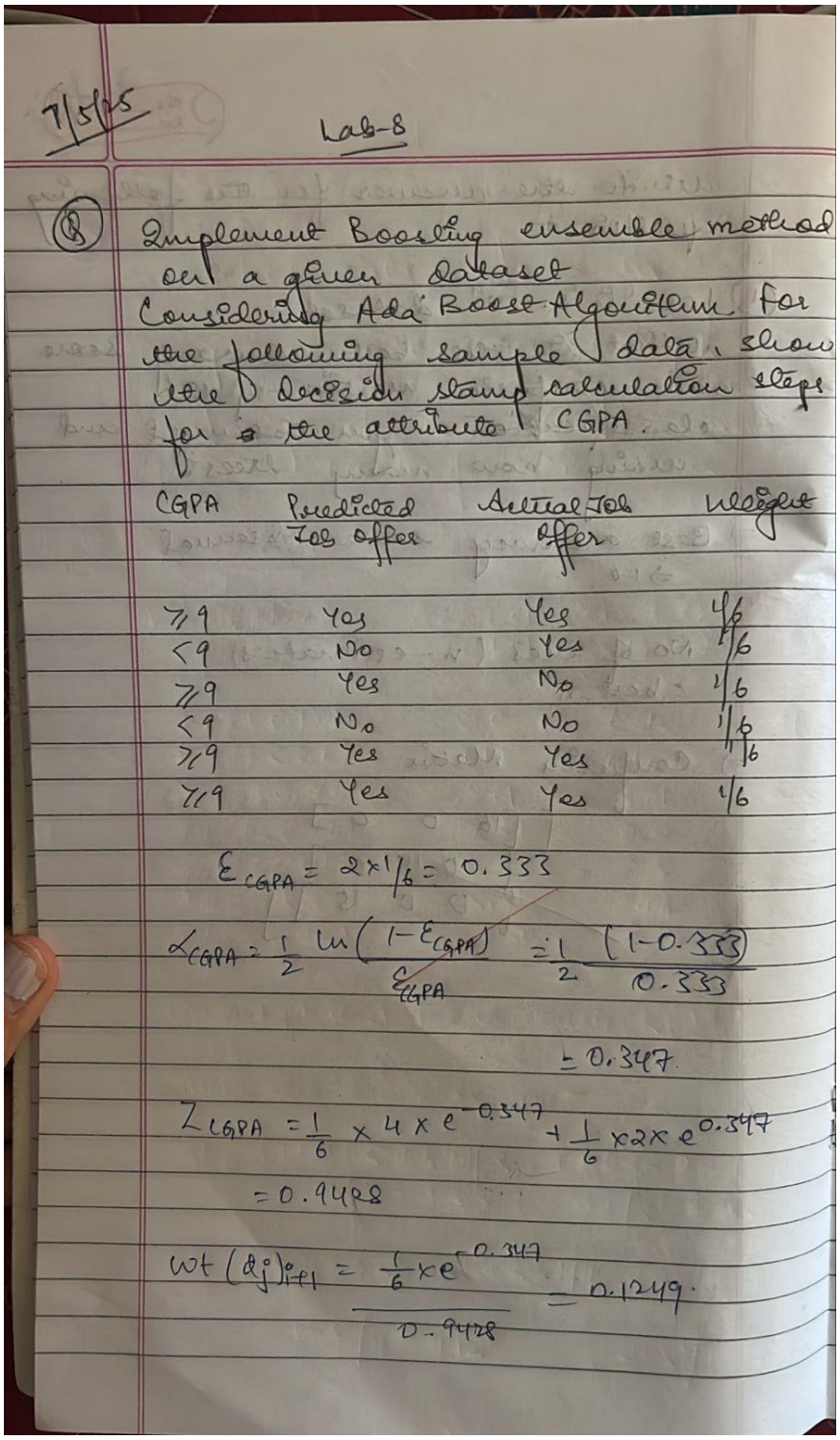
```
Default RF Accuracy (n_estimators=10): 1.0000
Best RF Accuracy: 1.0000 with n_estimators = 1
```



Program 9

Implement Boosting ensemble method on a given dataset

Screensho



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Lab-8

(8) Implement Boosting ensemble method on a given dataset
Considering Ada Boost Algorithm. For the following sample data, show the decision stump calculation steps for the attribute CGPA.

CGPA	Predicted Job offer	Actual Job offer	Weight
≥9	Yes	Yes	1/6
<9	No	Yes	1/6
≥9	Yes	No	1/6
<9	No	No	1/6
≥9	Yes	Yes	1/6
≥9	Yes	Yes	1/6

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

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

$= 0.347$

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

$= 0.9428$

$wt(\alpha_j)_{i+1} = \frac{\frac{1}{6} \times e^{-0.347}}{0.9428} = 0.1249$

$$wt(d_j)_{i+1} = \frac{\frac{1}{6} \times e^{0.347}}{0.9428} = 0.2501$$

CGPA	Predicted job offer	Actual job offer	Weight
≥9	Yes	Yes	0.1249
<9	No	Yes	0.1249
≥9	Yes	No	0.2501
<9	No	No	0.1249
≥9	Yes	Yes	0.1249
≥9	Yes	Yes	0.1249

Write the answer for the following question-

1) For "income.csv" dataset, what is the best accuracy score and confusion matrix of the classifier you observed and using how many trees?

⇒ Accuracy with 10 estimates : 0.8277

Confusion matrix (10 estimates):

```
[[10722   387]
 [ 2138  1408]]
```

Best accuracy: 0.831 with n-estimators = 72.

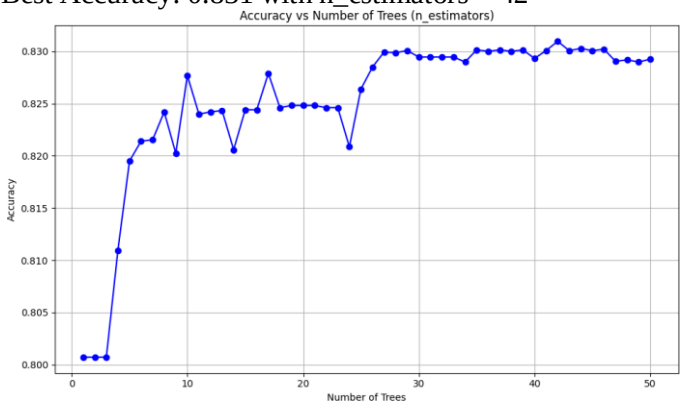
t

Code:

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

# Step 1: Load the dataset
df = pd.read_csv("/content/income.csv")

# Step 2: Split into features and target
X = df.drop(columns=['income_level'])
y = df['income_level']

# Step 3: Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Step 4: AdaBoost with 10 estimators
model_10 = AdaBoostClassifier(n_estimators=10, random_state=42)
model_10.fit(X_train, y_train)
y_pred_10 = model_10.predict(X_test)
accuracy_10 = accuracy_score(y_test, y_pred_10)
conf_matrix_10 = confusion_matrix(y_test, y_pred_10)

print("Accuracy with 10 estimators:", round(accuracy_10, 4))
print("Confusion Matrix (10 estimators):\n", conf_matrix_10)

# Step 5: Fine-tune number of trees (1 to 50)
best_accuracy = 0
best_n = 0
accuracies = []

for n in range(1, 51):
    model = AdaBoostClassifier(n_estimators=n, random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    accuracies.append(acc)

    if acc > best_accuracy:
        best_accuracy = acc
        best_n = n
```

```
print(f"\nBest Accuracy: {round(best_accuracy, 4)} with n_estimators = {best_n}")

# Step 6: Plot accuracy vs. number of estimators
plt.figure(figsize=(10,  6))
plt.plot(range(1, 51), accuracies, marker='o', linestyle='-', color='blue')
plt.title('Accuracy vs Number of Trees (n_estimators)')
plt.xlabel('Number of Trees')
plt.ylabel('Accuracy')
plt.grid(True)
plt.tight_layout()
plt.show()
```

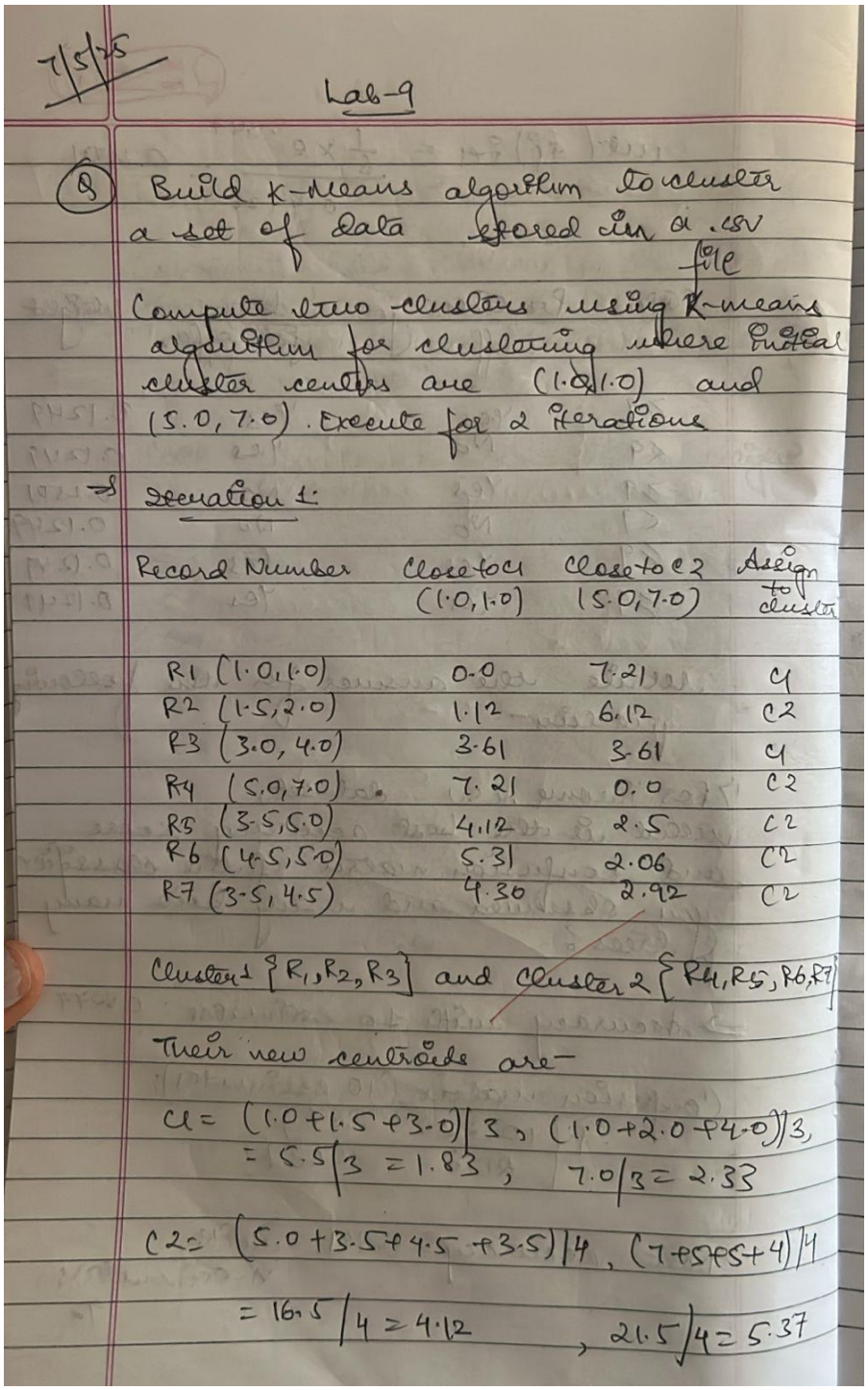
```
Accuracy with 10 estimators: 0.8277
Confusion Matrix (10 estimators):
[[10722   387]
 [ 2138  1406]]

Best Accuracy: 0.831 with n_estimators = 42
```



Program 10

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

Screenshot



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Lab-9

Q) Build k-Means algorithm to cluster a set of data stored in a .csv file

Compute two clusters using K-means algorithm for clustering where initial cluster centers are (1.0,1.0) and (5.0, 7.0). Execute for 2 iterations

→ Iteration 1:

Record Number	Close to C1 (1.0,1.0)	Close to C2 (5.0,7.0)	Assign to cluster
R1 (1.0,1.0)	0.0	7.21	C1
R2 (1.5,2.0)	1.12	6.12	C2
R3 (3.0, 4.0)	3.61	3.61	C1
R4 (5.0,7.0)	7.21	0.0	C2
R5 (3.5,5.0)	4.12	2.5	C2
R6 (4.5,5.0)	5.31	2.06	C2
R7 (3.5,4.5)	4.30	2.92	C2

Cluster 1 {R1, R2, R3} and Cluster 2 {R4, R5, R6, R7}

Their new centroids are-

C1 = (1.0+1.5+3.0)/3, (1.0+2.0+4.0)/3,
= 5.5/3 = 1.83, 7.0/3 = 2.33

C2 = (5.0+3.5+4.5+3.5)/4, (7+5+5+4)/4
= 16.5/4 = 4.12, 21.5/4 = 5.37

Iteration 2:

Record No.	Close to C1 (1.83, 2.33)	Close to C2 (4.12, 5.37)	Assign to cluster
R1 (1.0, 1.0)	1.57	5.64	C1
R2 (1.5, 2.0)	0.47	4.52	C1
R3 (3.0, 4.0)	2.12	1.63	C2
R4 (5.0, 7.0)	5.57	1.91	C2
R5 (3.5, 5.0)	3.16	0.72	C2
R6 (4.5, 5.0)	3.58	0.52	C2
R7 (3.5, 4.5)	2.63	1.05	C2

Cluster 1 {R1, R2} and Cluster 2 {R3, R4, R5, R6, R7}

Their new centroids are:

$C_1 = (1.0 + 1.5)/2 , (1.0 + 2.0)/2$

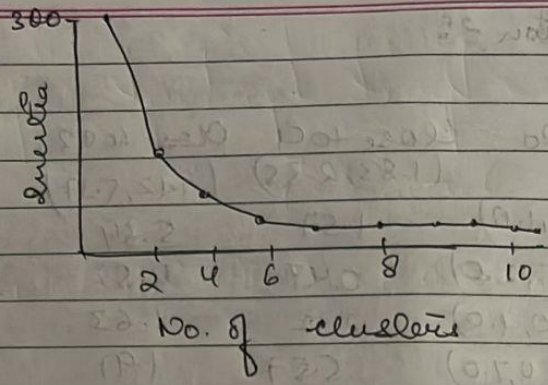
$= 2.50/2 = 1.25 , 3/2 = 1.5$

$C2 = (3 + 5 + 3.5 + 4.5 + 3.5)/5 > (4 + 7 + 5 + 5 + 4.5)/5$

$= 18.5/5 = 3.9 , 25.5/5 = 5.1$

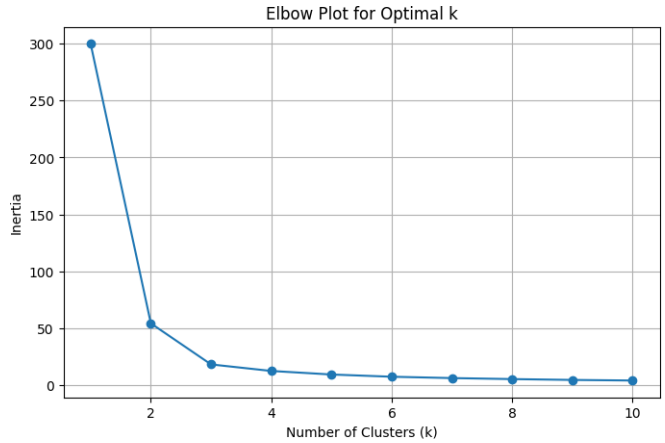
Q. Write the answers for the following questions:

(1) For "iris.csv" dataset,
Draw the elbow plot. What was the optimal k value obtained?


300
Inertia
2
4
6
8
10
No. of clusters

Code:

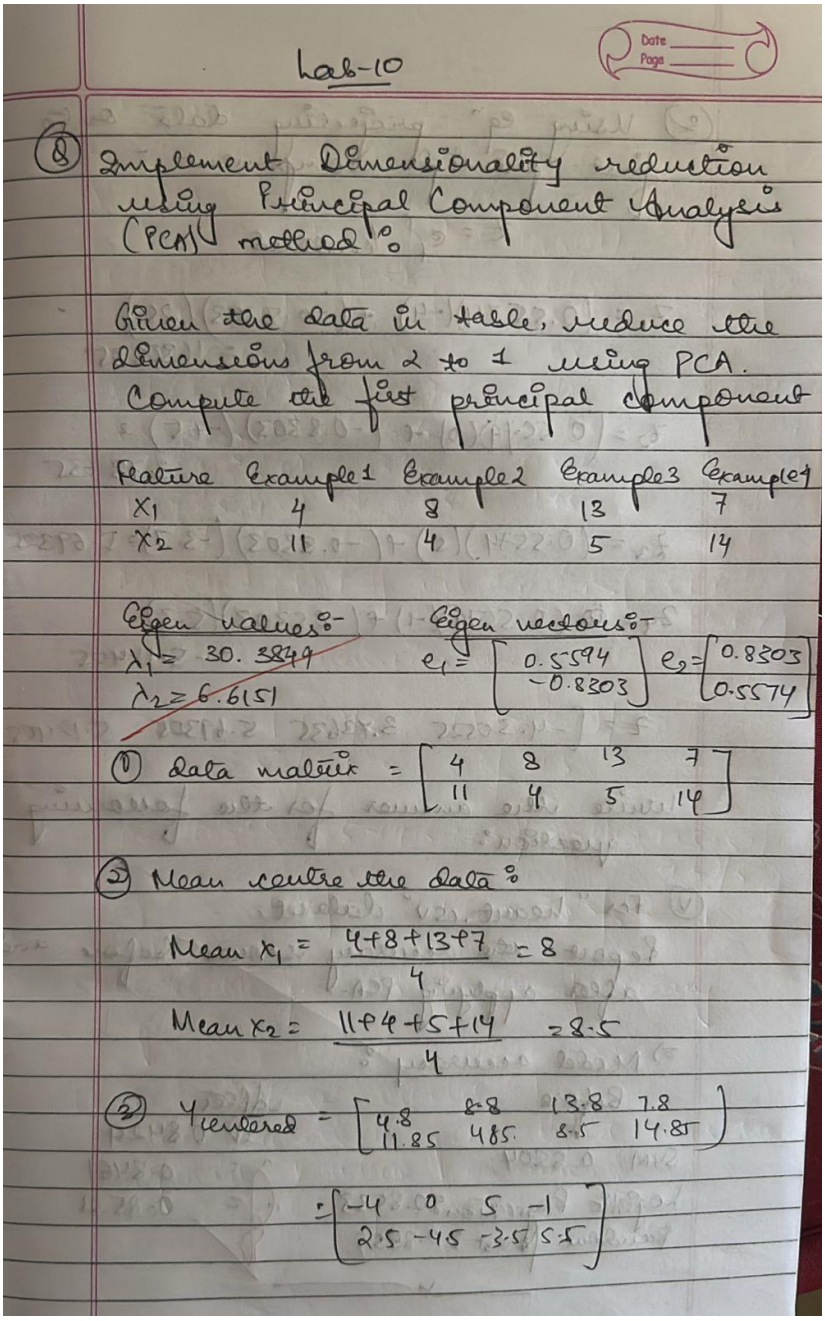
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Load the dataset
df = pd.read_csv("/content/iris (2).csv")

# Select only petal length and petal width
X = df[['petal_length', 'petal_width']]

# Optional: Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Elbow method to determine optimal k
inertia = []
k_range = range(1, 11)
for k in k_range:
    model = KMeans(n_clusters=k, random_state=42, n_init=10)
    model.fit(X_scaled)
    inertia.append(model.inertia_)

# Plot the elbow graph
plt.figure(figsize=(8, 5))
plt.plot(k_range, inertia, marker='o')
plt.title('Elbow Plot for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.grid(True)
plt.show()
```



Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Screenshot



Lab-10

(8) Implement Dimensionality reduction using Principal Component Analysis (PCA) method:

Given the data in table, reduce the dimensions from 2 to 1 using PCA. Compute the first principal component

Feature	Example1	Example2	Example3	Example4
X_1	4	8	13	7
X_2	11	4	5	14

Eigen values:-

$\lambda_1 = 30.3849$

$\lambda_2 = 6.6151$

Eigen vectors:-

$e_1 = \begin{bmatrix} 0.5594 \\ -0.8303 \end{bmatrix}$ $e_2 = \begin{bmatrix} 0.8303 \\ 0.5574 \end{bmatrix}$

(1) Data matrix $= \begin{bmatrix} 4 & 8 & 13 & 7 \\ 11 & 4 & 5 & 14 \end{bmatrix}$

(2) Mean centre the data:

Mean $x_1 = \frac{4+8+13+7}{4} = 8$

Mean $x_2 = \frac{11+4+5+14}{4} = 8.5$

(3) $Y_{centered} = \begin{bmatrix} 4-8 & 8-8 & 13-8 & 7-8 \\ 11-8.5 & 4-8.5 & 5-8.5 & 14-8.5 \end{bmatrix}$

$= \begin{bmatrix} -4 & 0 & 5 & -1 \\ 2.5 & -4.5 & -3.5 & 5.5 \end{bmatrix}$

(3) Using eq" projecting data onto first principle component;

$$Z = e_1^T \cdot X_{centered}$$

$$Z_1 = (0.5574)(-4) + (-0.8303)(25) = 4.30535$$

$$Z_2 = (0.5574)(0) + (-0.8303)(-4.5) = 3.73635$$

$$Z_3 = (0.5574)(5) + (-0.8303)(-3.7) = 5.69305$$

$$Z_4 = (0.5574)(-4) + (-0.8303)(5.3) = -5.12405$$

$$Z = [-4.30525 \quad 3.73635 \quad 5.69305 \quad 5.12405]$$

Write the answer for the following question:

(V) For "heart.csv" dataset, Report the accuracy scores before and after applying PCA-

→ Model accuracy:

	Before	After
SVM:	0.8804	= 0.8424
Logistic Regression:	0.8533	= 0.8461
Random forest:	0.8859	= 0.8533

Code:

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

# Load dataset
df = pd.read_csv("/content/heart (1).csv")  # Update to match your file path if needed

# Define features and target
X = df.drop('HeartDisease', axis=1)
y = df['HeartDisease']

# Identify categorical columns
categorical_cols = X.select_dtypes(include=['object']).columns.tolist()

# Encode categorical columns
for col in categorical_cols:
    if X[col].nunique() == 2:
        X[col] = LabelEncoder().fit_transform(X[col])
    else:
        X = pd.get_dummies(X, columns=[col])

# Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

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

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

# Train and evaluate models (without PCA)
```

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

# Apply PCA (reduce to 5 components)
pca = PCA(n_components=5)
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)

# Train and evaluate models (with PCA)
print("\n## Accuracy with PCA:")
for name, model in models.items():
    model.fit(X_train_pca, y_train_pca)
    y_pred_pca = model.predict(X_test_pca)
    print(f"{name}: {accuracy_score(y_test_pca, y_pred_pca):.4f}")
```

```
Accuracy without PCA:
SVM: 0.8804
Logistic Regression: 0.8533
Random Forest: 0.8859

## Accuracy with PCA:
SVM: 0.8424
Logistic Regression: 0.8641
Random Forest: 0.8533
```