VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

Ankit Singh Bhatti (1BM22CS353)

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
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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 **Ankit Singh Bhatti (1BM22CS353),** 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: **Ms. Saritha A N** Assistant Professor Department of CSE, BMSCE	 **Dr. Kavitha Sooda** Professor & HOD Department of CSE, BMSCE

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Github Link: https://github.com/AnkitSB19/ML_LAB_1BM22CS353

Program 1

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

Screenshot

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LAB - 0

// Loading Datasets

1) import pandas as pd
from sklearn.datasets import load_diabetes
data = {
'USN' : ['1BM22CS353'],
'Name' : ['Alpha'],
'Marks' : [85]
}
df = pd.DataFrame(data)
print(df)

2) diabetes_data = load_diabetes()
df = pd.DataFrame(diabetes.data)
print(df)

3) df = pd.read_csv('sample_sales_data.csv')
print(df)

4) df = pd.read_csv('Dataset of Diabetes.csv')
print(df)

Code:

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

# Part 1: Student data
student_data = {
    'USN': ['1A18CS001', '1A18CS002', '1A18CS003', '1A18CS004', '1A18CS005'],
    'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Eve'],
    'Marks': [85, 78, 92, 88, 75]
}
student_df = pd.DataFrame(student_data)
print("Student Data:")
print(student_df)
print("\n" + "-"*50 + "\n")

# Part 2: Load diabetes dataset from sklearn
diabetes_data = load_diabetes()
diabetes_df = pd.DataFrame(diabetes_data.data, columns=diabetes_data.feature_names)
diabetes_df['target'] = diabetes_data.target
print("Scikit-learn Diabetes Dataset:")
print(diabetes_df.head())
print("\n" + "-"*50 + "\n")

# Part 3: Load sample sales data from CSV
```

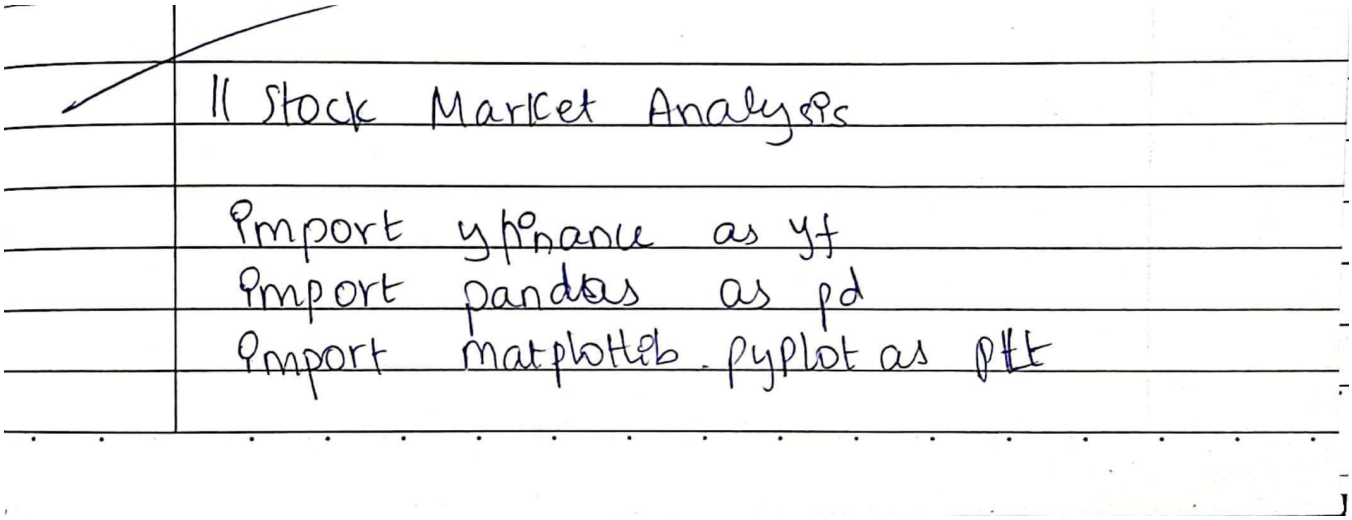
```
try:
    sales_df = pd.read_csv('sample_sales_data.csv')
    print("Sample Sales Data:")
    print(sales_df.head())
except FileNotFoundError:
    print("sample_sales_data.csv not found.")
print("\n" + "-"*50 + "\n")

# Part 4: Load diabetes dataset from external CSV
try:
    diabetes_csv_df = pd.read_csv('Dataset of Diabetes .csv')
    print("Diabetes Dataset from CSV:")
    print(diabetes_csv_df.head())
except FileNotFoundError:
    print("Dataset of Diabetes .csv not found.")
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshot:



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```
tickers = ['HDFCBANK.NS", "ICICI.NS", "KOTA
        -KBANK.NS"]

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

print("First 5 rows of the dataset :")
print(data.head())

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

plt.figure(figsize = (12,6))
plt.subplot(2,1,1)
hdfc_data['close'].plot(title = "HDFC
 Bank - closing Price")
plt.subplot(2,1,2)
hdfc_data['Daily Return'].plot(title" HDFC
  Bank - Daily Return", color = 'orange')

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

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// Loading Housing Data

import pandas as pd

i) Load .csv file into dataframe

```
df = pd.read_csv("housing.csv")
```

ii) Display information of all columns

```
df.info()
```

iii) Display statistical information

```
print(df.describe())
```

iv) Display counts of unique labels for "ocean proximity" column

```
print(df["Ocean Proximity"].value_coun
```

v) Display columns with missing values

```
missing_v = df.isnull().sum()
missing_c = missing_v[missing_v > 0]
print(missing_c)
```

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Code:

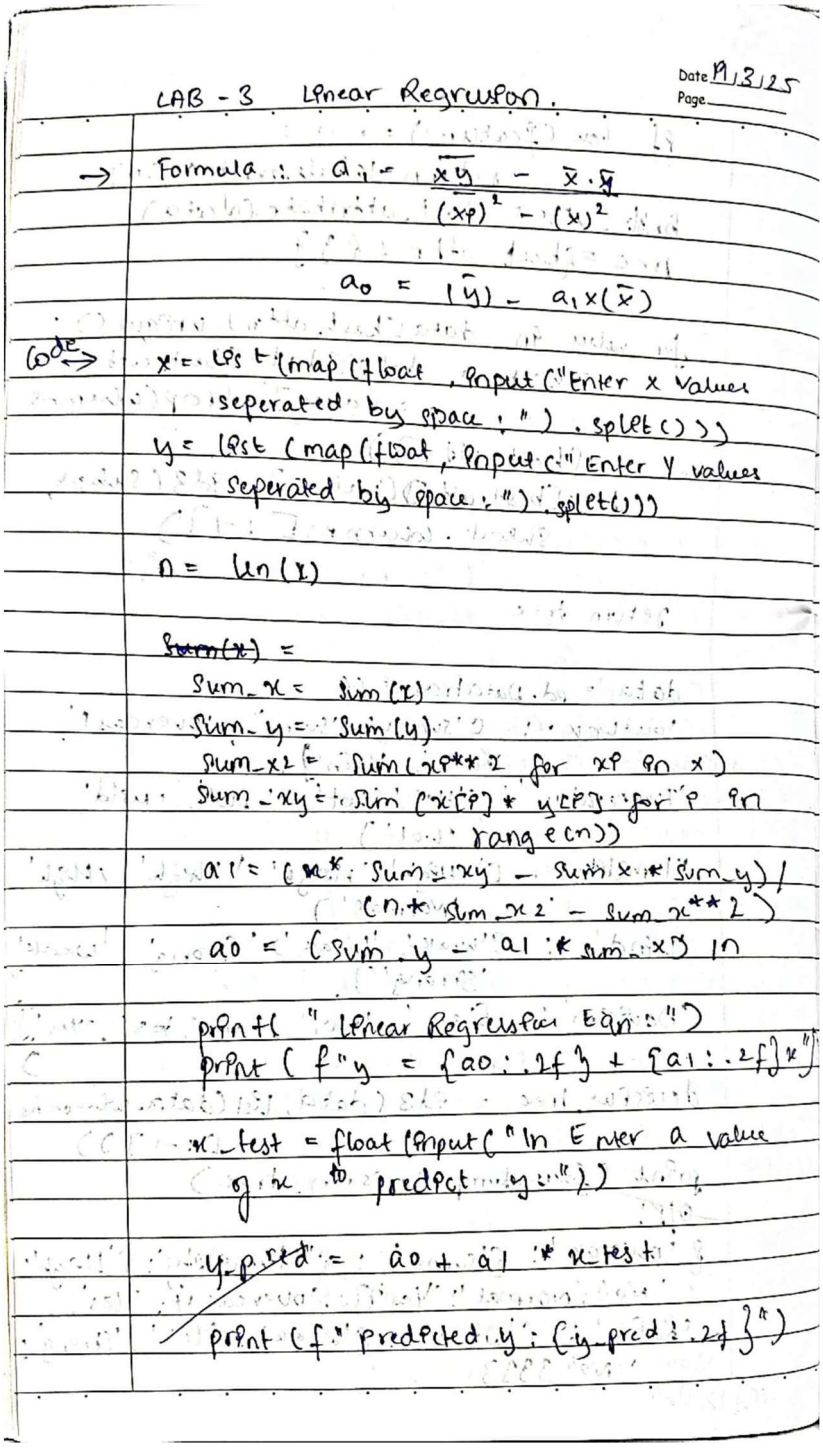
```
import yfinance as yf

import pandas as pd

import matplotlib.pyplot as plt


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


# Fetch historical data for the last 1 year

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


hdfc_data = data['HDFCBANK.NS']

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


ic_data = data['ICICIBANK.NS']

ic_data['Daily Return'] = ic_data['Close'].pct_change()


kb_data = data['KOTAKBANK.NS']

kb_data['Daily Return'] = kb_data['Close'].pct_change()


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

plt.subplot(2, 1, 1)

hdfc_data['Close'].plot(title="HDFC Bank - Closing Price")

plt.subplot(2, 1, 2)

hdfc_data['Daily Return'].plot(title="HDFC Bank - Daily Returns", color='orange')
```

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


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


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

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshot



LAB - 3 Linear Regression. Date 9/3/25 Page

→ Formula : $a_1 = \frac{\overline{xy} - \bar{x}\cdot\bar{y}}{(\overline{x^2}) - (\bar{x})^2}$

$a_0 = (\bar{y}) - a_1 \times (\bar{x})$

Code →

```
x = list(map(float, input("Enter x values seperated by space : ").split()))
y = list(map(float, input("Enter Y values seperated by space : ").split()))

n = len(x)

Sum(x) =
Sum_x = sum(x)
Sum_y = sum(y)
Sum_x2 = sum(xp**2 for xp in x)
Sum_xy = sum(x[p] * y[p] for p in range(n))

a1 = (n* Sum_xy - Sum_x * Sum_y) / (n* Sum_x2 - Sum_x**2)
a0 = (Sum_y - a1 * Sum_x) / n

print(" Linear Regression Eqn :")
print(f"y = {a0:.2f} + {a1:.2f}x")

x_test = float(input("In Enter a value of x to predict y :"))

y_pred = a0 + a1 * x_test

print(f" predicted y : {y_pred:.2f}")
```

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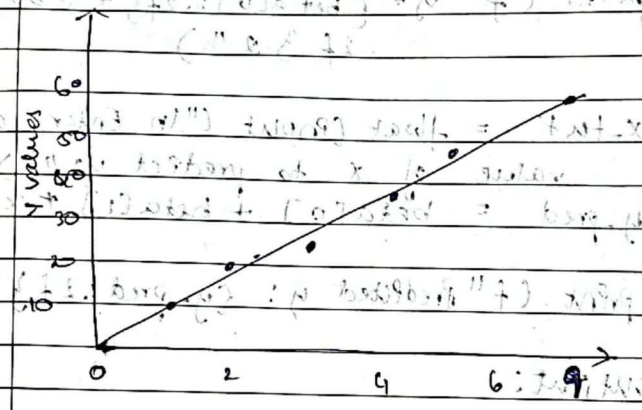
Output:

Enter x values seperated by space:
1 2 3 4 5
Enter y values seperated by space:
14 18 22 28 35

Linear Regression Equation:
$y = 6.40 + 5.60x$

Enter a value of x to predict y: 9
Predicted y: 56.60



→ MATRIX FORM:

Formula: $\beta = [(X^T \cdot X)^{-1} \cdot X^T] y$

Code →

```
import numpy as np

x = np.array(list(map(float, input("Enter x values seperated by space: ").split())))
```

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```
y = np.array(list(map(float, input("Enter
    Y values seperated by space : ").
    split())))

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

beta = np.linalg.inv(X.T @ X) @ X.T
                @ y

print("Linear Regression Equation (Matrix
            form) : ")
print(f" y = {beta[0]:.2f} + {beta[1]:.
            2f} x ")

x_test = float(input("In Enter a
    value of x to predict y: "))
y_pred = beta[0] + beta[1] * x_test

print(f"Predicted y: {y_pred:.2f}")
```

output:

```
Enter X values seperated by space : 1 2 3 4
Enter Y values seperated by space : 3 5 4 8

Linear Regression Equation (Matrix Form):
print(f" y = {beta[0]:.2f} +
        {beta[1]:.2f} x")

x_test = float(input(" Enter Value of
    x to predict y : ").)
y_pred = beta[0] + beta[1] * x_test
```

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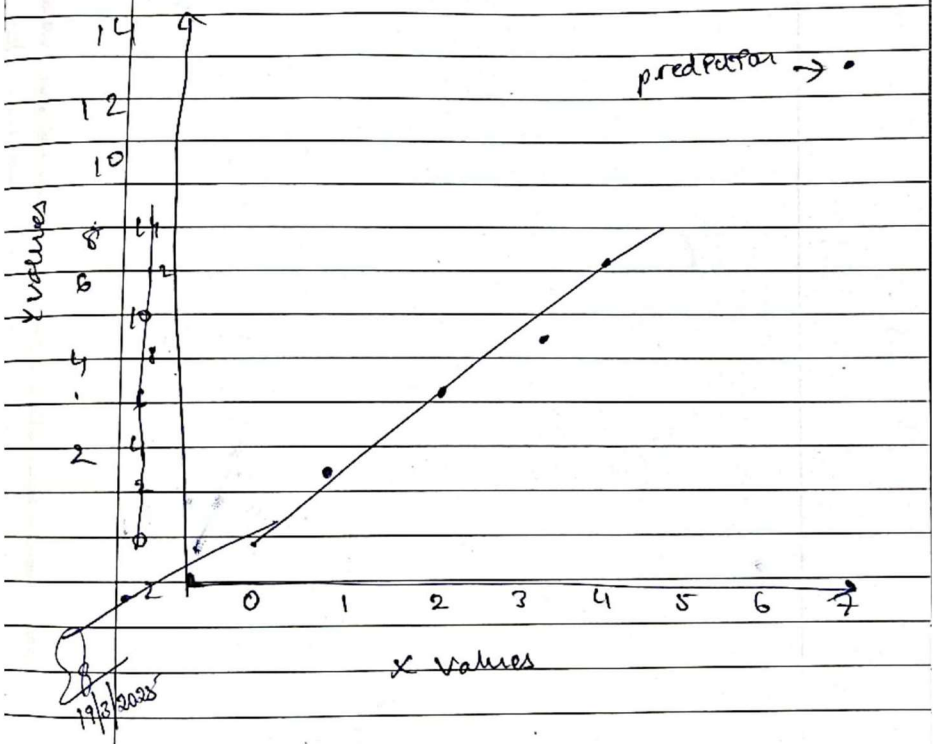
```
print(f" predicted y: {y_pred:.2f}")
```

Output:

```
Enter x values of seperated by space:
1 2 3 4
Enter y values seperated by space:
1 3 4 8

Linear Regression Equation:
y = -1.50 + 2.20 x

Enter a value of x to predict y: 7
predicted y: 13.90
```



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Code:

```
import matplotlib.pyplot as plt


x = list(map(float, input("Enter X values separated by space: ").split()))
y = list(map(float, input("Enter Y values separated by space: ").split()))
n = len(x)
sum_x = sum(x)
sum_y = sum(y)
sum_x2 = sum(xi**2 for xi in x)
sum_xy = sum(x[i] * y[i] for i in range(n))
a1 = (n * sum_xy - sum_x * sum_y) / (n * sum_x2 - sum_x**2)
a0 = (sum_y - a1 * sum_x) / n
print("\nLinear Regression Equation:")
print(f"y = {a0:.2f} + {a1:.2f}x")
x_test = float(input("\nEnter a value of x to predict y: "))
y_pred = a0 + a1 * x_test
print(f"Predicted y: {y_pred:.2f}")
plt.scatter(x, y, color='blue', label='Data Points')
x_line = [min(x) - 1, max(x) + 1]
y_line = [a0 + a1 * x_val for x_val in x_line]
plt.plot(x_line, y_line, color='red', label='Regression Line')
plt.scatter(x_test, y_pred, color='green', label=f'Prediction: ({x_test}, {y_pred:.2f})')
plt.xlabel('X values')
plt.ylabel('Y values')
```

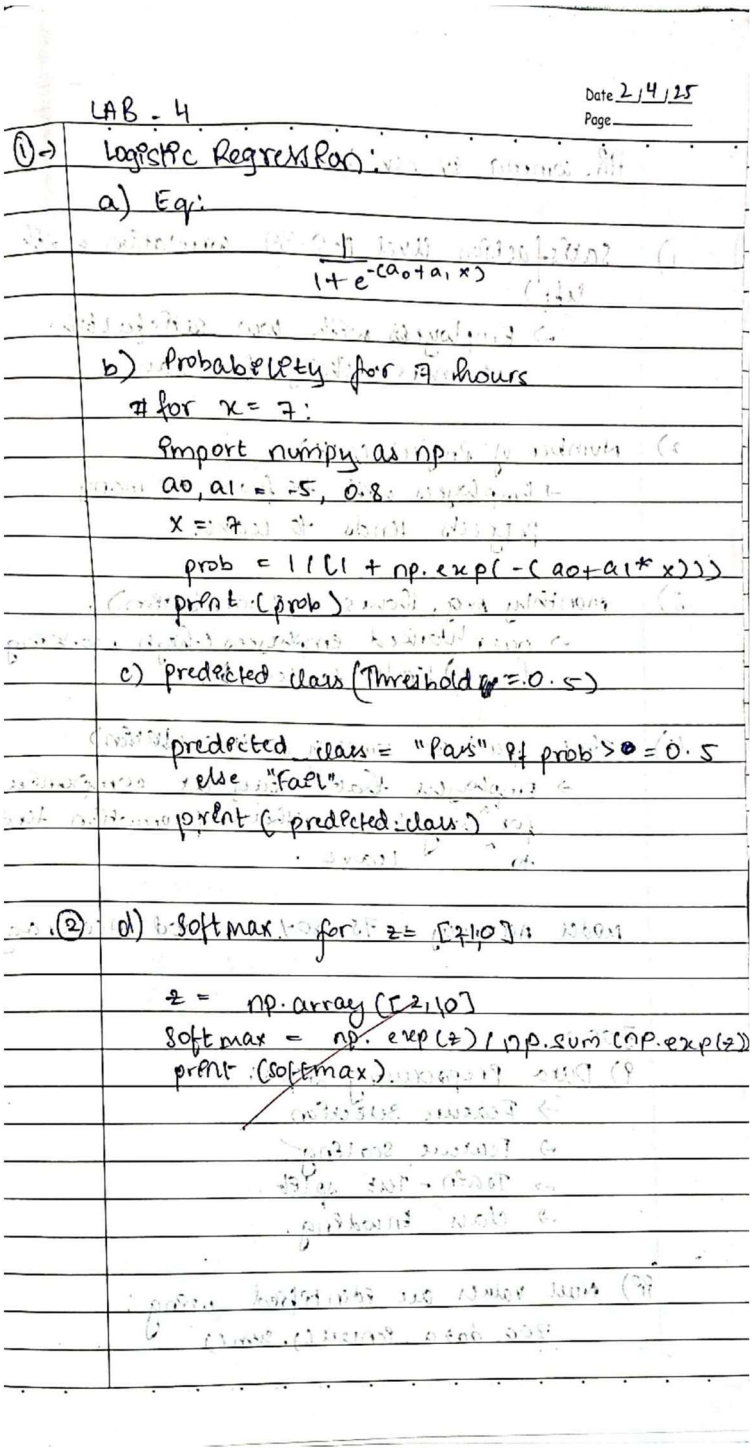
```
plt.title('Linear Regression Visualization')
plt.legend()
plt.grid(True)
plt.show()


import numpy as np
import matplotlib.pyplot as plt


x = np.array(list(map(float, input("Enter X values separated by space: ").split())))
y = np.array(list(map(float, input("Enter Y values separated by space: ").split())))
X = np.c_[np.ones(len(x)), x]
beta = np.linalg.inv(X.T @ X) @ X.T @ y
print("\nLinear Regression Equation (Matrix Form):")
print(f"y = {beta[0]:.2f} + {beta[1]:.2f}x")
x_test = float(input("\nEnter a value of x to predict y: "))
y_pred = beta[0] + beta[1] * x_test
print(f"Predicted y: {y_pred:.2f}")
plt.scatter(x, y, color='blue', label='Data Points')
x_line = np.linspace(min(x) - 1, max(x) + 1, 100)
y_line = beta[0] + beta[1] * x_line
plt.plot(x_line, y_line, color='red', label='Regression Line')
plt.scatter(x_test, y_pred, color='green', label=f'Prediction: ({x_test}, {y_pred:.2f})')
plt.xlabel('X values')
plt.ylabel('Y values')
```

```
plt.title('Linear Regression (Matrix Form)')

plt.legend()

plt.grid(True)

plt.show()
```

Program 4

Build Logistic Regression Model for a given dataset

Screenshot



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① Logistic Regression:

a) Eq:

$$\frac{1}{1+e^{-(a_0+a_1 x)}}$$

b) Probability for 7 hours

```
# for x = 7:
import numpy as np
a0, a1 = -5, 0.8
x = 7
prob = 1/(1 + np.exp(-(a0+a1*x)))
print(prob)
```

c) predicted class (Threshold = 0.5)

```
predicted_class = "Pass" if prob >= 0.5
else "Fail"
print(predicted_class)
```

② d) Softmax for z = [7,0]:

```
z = np.array([7,0])
Softmax = np.exp(z)/np.sum(np.exp(z))
print(Softmax)
```

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HR_comma_sv.csv

1) Satisfaction level (-0.39 correlation with left)
   → Employees with low satisfaction are more likely to leave.

2) Number of Projects (0.14):
   → Employees with too few or too many projects tends to leave.

3) Monthly avg. Hours (0.13 correlation):
   → overworked employees (high working hours) tends to leave.

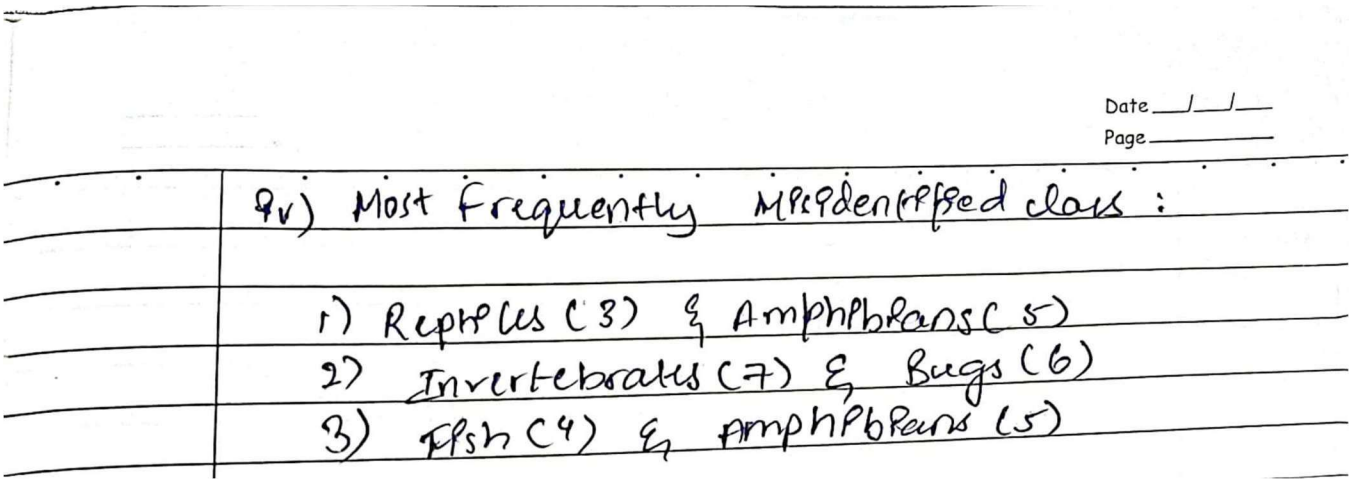
4) Time spent at company (0.14 correlation)
   → Employees that stay at companies for long time without promotion tend to leave.

Model Accuracy : 75-80% Good Accuracy

Zoo

P) Data Preprocessing steps:
   → Feature Selection
   → Feature Scaling
   → Train-Test split.
   → Class Encoding.

PP) Null values are identified using:
   Zoo_data.isnull().sum()



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 LabelEncoder

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# Load dataset

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


# Convert categorical variables to numerical

label_enc = LabelEncoder()

df["salary"] = label_enc.fit_transform(df["salary"])

df["Department"] = label_enc.fit_transform(df["Department"])
```

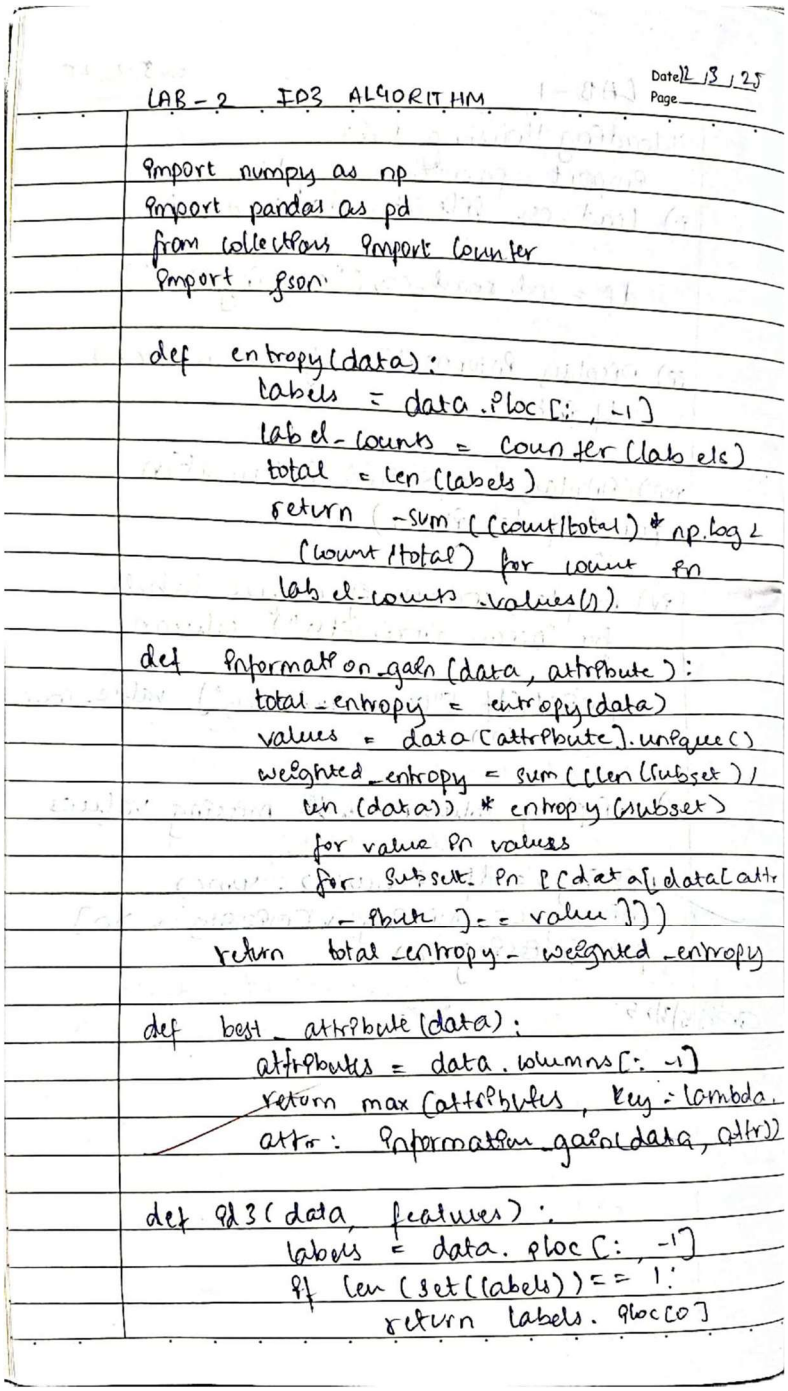
```
# Step 1: Exploratory Data Analysis (EDA)

correlation = df.corr()["left"].sort_values(ascending=False)

print("\nFeature Correlation with Employee Retention:\n", correlation)


# Step 2: Impact of Salary on Retention

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

sns.barplot(x="salary", y="left", data=df, ci=None)

plt.xlabel("Salary Level (Encoded)")

plt.ylabel("Retention Rate")

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

plt.show()


# Step 3: Correlation between Department and Retention

plt.figure(figsize=(8,4))

sns.barplot(x="Department", y="left", data=df, ci=None)

plt.xlabel("Department (Encoded)")

plt.ylabel("Retention Rate")

plt.title("Department vs Employee Retention")

plt.show()


# Step 4: Logistic Regression Model

features = ["satisfaction_level", "last_evaluation", "number_project", "average_montly_hours",
"time_spend_company", "salary"]

X = df[features]
```

```
y = df["left"]


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


model = LogisticRegression()

model.fit(X_train, y_train)


# Step 5: Model Accuracy

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)

print(f"\nModel Accuracy: {accuracy:.2f}")


# Display Confusion Matrix

conf_matrix = confusion_matrix(y_test, y_pred)

print("\nConfusion Matrix:\n", conf_matrix)


# Display Classification Report

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

Program 5

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

Screenshot



LAB - 2 ID3 ALGORITHM

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```
import numpy as np
import pandas as pd
from collections import Counter
import math, json

def entropy(data):
    labels = data.iloc[:, -1]
    label_counts = Counter(labels)
    total = len(labels)
    return -sum((count/total) * np.log2
    (count/total) for count in
    label_counts.values())

def information_gain(data, attribute):
    total_entropy = entropy(data)
    values = data[attribute].unique()
    weighted_entropy = sum((len(subset)/
    len(data)) * entropy(subset)
    for value in values
    for subset in [data[data[attr
    -ibute] == value]])
    return total_entropy - weighted_entropy

def best_attribute(data):
    attributes = data.columns[:-1]
    return max(attributes, key = lambda
    attr: information_gain(data, attr))

def id3(data, features):
    labels = data.iloc[:, -1]
    if len(set(labels)) == 1:
        return labels.iloc[0]
```

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```
if len(features) == 0:
    return labels.mode()[0]
best_attr = best_attribute(data)
tree = {best_attr : {}}

for value in data[best_attr].unique():
    subset = data[data[best_attr]
    == value].drop(columns
    =[best_attr])
    tree[best_attr][value] = id3(subset,
        subset.columns[ : -1])

return tree

data = pd.DataFrame.(d
'outlook' : ['sunny','sunny','overcast',
'rain','rain'],
'Temperature' : ['Hot','Hot','Hot','mild',
    'cool'],
'Humidity' : ['High','High','High','High',
    'Normal'],
'Wind' : ['weak','weak','Strong','weak'
    'Strong'],
'Decision' : ['no','no','yes','yes','yes']
    }
decision_tree = id3(data, list(data.columns
    [:-1]))
print (json.dump decision_tree)
op:
{'outlook': {'sunny' : {'Humidity': {'High':
    'No','Normal':'Yes'}},'overcast': 'Yes',
'Rain': {'Wind': {'weak':'Yes','Strong':
    'No'}}}}
```

4/12/3/25

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 LabelEncoder

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


# Load dataset

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


# Convert categorical variables to numerical

label_enc = LabelEncoder()

df["salary"] = label_enc.fit_transform(df["salary"])

df["Department"] = label_enc.fit_transform(df["Department"])


# Step 1: Exploratory Data Analysis (EDA)

correlation = df.corr()["left"].sort_values(ascending=False)

print("\nFeature Correlation with Employee Retention:\n", correlation)


# Step 2: Impact of Salary on Retention

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

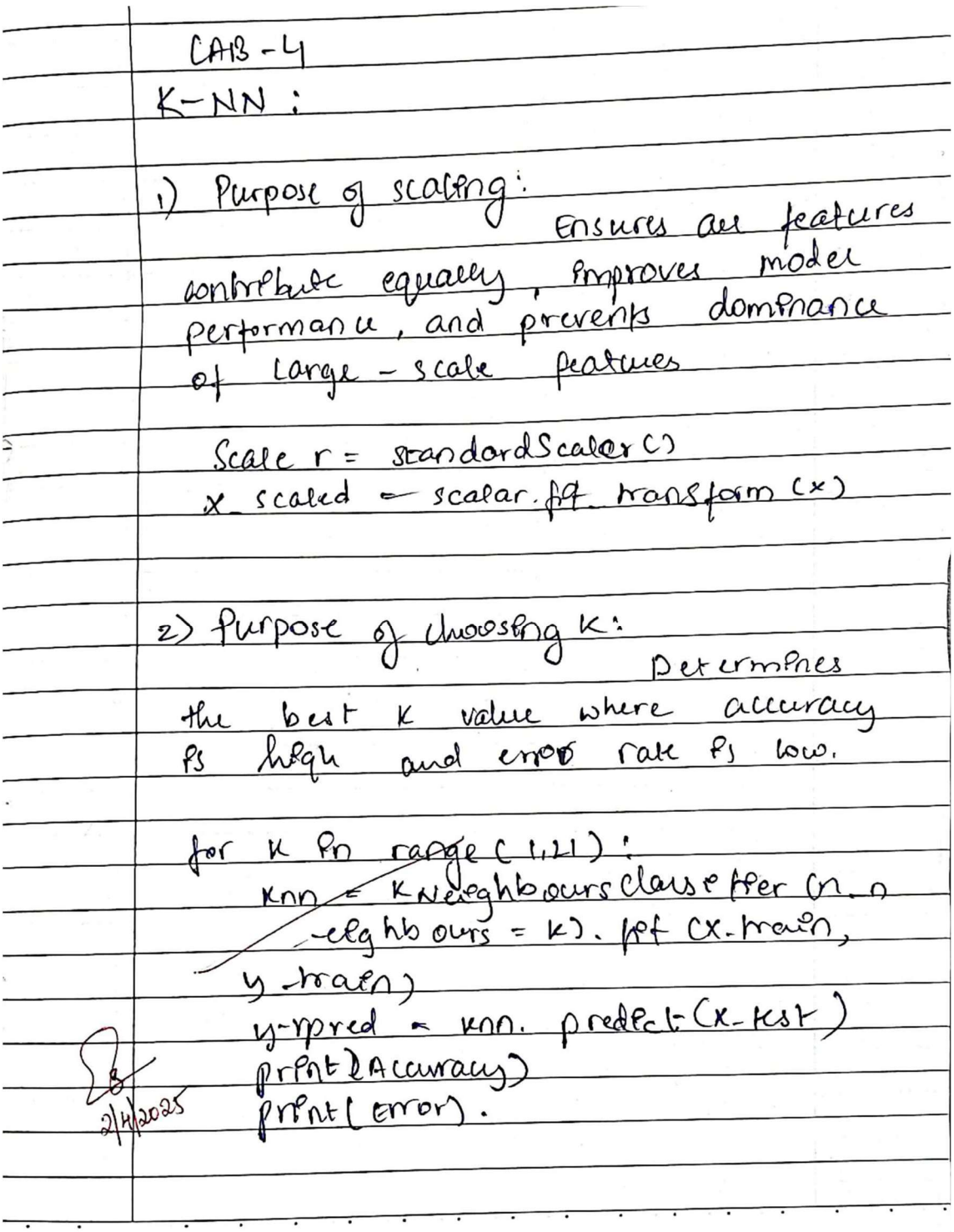
```
sns.barplot(x="salary", y="left", data=df, ci=None)

plt.xlabel("Salary Level (Encoded)")

plt.ylabel("Retention Rate")

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

plt.show()


# Step 3: Correlation between Department and Retention

plt.figure(figsize=(8,4))

sns.barplot(x="Department", y="left", data=df, ci=None)

plt.xlabel("Department (Encoded)")

plt.ylabel("Retention Rate")

plt.title("Department vs Employee Retention")

plt.show()


# Step 4: Logistic Regression Model

features = ["satisfaction_level", "last_evaluation", "number_project", "average_montly_hours",
"time_spend_company", "salary"]

X = df[features]

y = df["left"]


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


model = LogisticRegression()

model.fit(X_train, y_train)
```

```
# Step 5: Model Accuracy
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"\nModel Accuracy: {accuracy:.2f}")

# Display Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:\n", conf_matrix)

# Display Classification Report
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

Program 6

Build KNN Classification model for a given dataset

Screenshot



CAIB - 4

K-NN :

1) Purpose of scaling:

Ensures all features contribute equally, improves model performance, and prevents dominance of large-scale features

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

2) Purpose of choosing K:

Determines the best K value where accuracy is high and error rate is low.

```
for K in range(1,21):
    knn = KNeighboursClassifier(n_
    -eighbours = K).fit(X_train,
    y_train)
    y_pred = knn.predict(X_test)
    print(Accuracy)
    print(Error).
```

2/4/2025

Code:

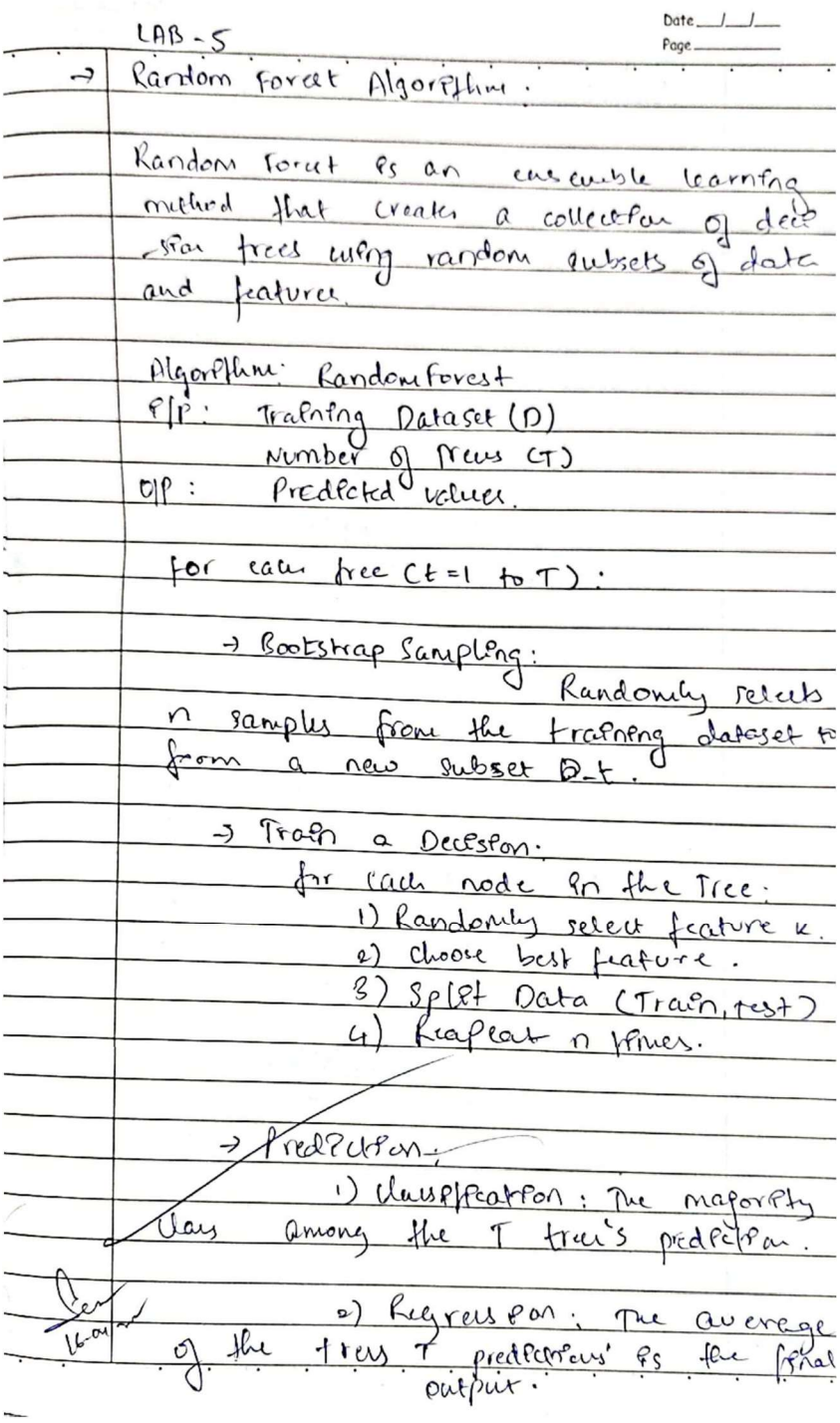
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score,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

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

# Automatically select the target column (assuming it's the last column)
target_column = df.columns[-1]

# Splitting features (X) and target variable (y)
X = df.iloc[:, :-1]  # All columns except last (features)
y = df.iloc[:, -1]  # Last column (target)

# Encode categorical target variable if necessary
if y.dtype == 'object':
    label_encoder = LabelEncoder()
    y = label_encoder.fit_transform(y)

# Convert categorical features to numerical if any
X = pd.get_dummies(X, drop_first=True)

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

# Standardize the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Determine optimal k (square root heuristic)
k = int(np.sqrt(len(y_train)))
if k % 2 == 0:
    k += 1

# Train the KNN classifier
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

# Make predictions
y_pred = knn.predict(X_test)
```

```
# Display accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy Score: {accuracy:.2f}")

# Display confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:\n", conf_matrix)

# Display classification report
class_report = classification_report(y_test, y_pred)
print("\nClassification Report:\n", class_report)

# Plot Confusion Matrix
plt.figure(figsize=(6,5))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=np.unique(y),
yticklabels=np.unique(y))
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.title("Confusion Matrix")
plt.show()
```

Program 7

Implement Random Forest ensemble method on a given dataset

Screenshot



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→ Random Forest Algorithm:

Random forest is an ensemble learning method that creates a collection of decision trees using random subsets of data and features.

Algorithm: RandomForest
I/P: Training Dataset (D)
Number of trees (T)
O/P: Predicted values.

for each tree (t=1 to T):

→ Bootstrap Sampling:
Randomly selects n samples from the training dataset to form a new subset D_t.

→ Train a Decision:
for each node in the tree:
1) Randomly select feature k.
2) Choose best feature.
3) Split Data (Train, test)
4) Repeat n times.

→ Prediction:
1) Classification: The majority class among the T tree's predictions.

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2) Regression: The average of the trees T predictions' is the final output.

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Implementation of Random Forest

observation:

Default accuracy (n_estimators = 10) :
1 ~ 0000

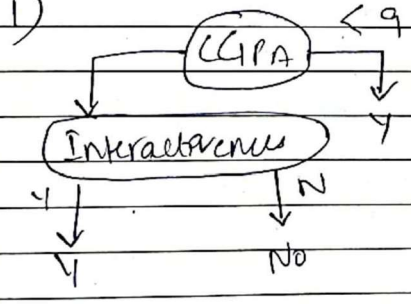
Best Accuracy : 1.000 with n_estimates = 1

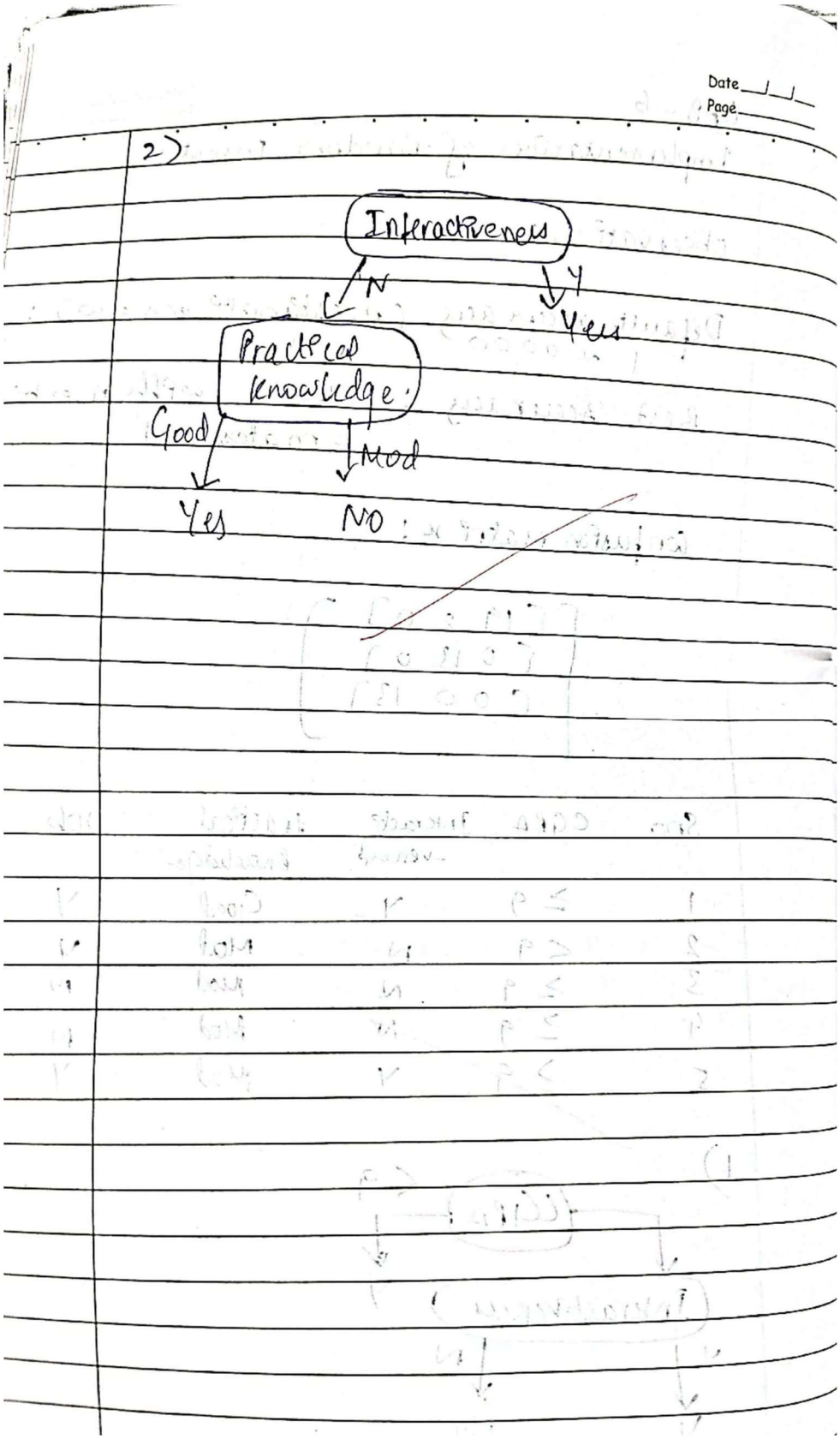
confusion matrix :

$$\begin{bmatrix} [19 & 0 & 0] \\ [0 & 13 & 0] \\ [0 & 0 & 13] \end{bmatrix}$$

Sno	CGPA	Interactiveness	Practical knowledge	JOB
1	≥ 9	Y	Good	Y
2	< 9	N	Mod	Y
3	≥ 9	N	Mod	N
4	≥ 9	N	Mod	N
5	≥ 9	Y	Mod	Y

1)

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2)
Interactiveness
N
Y
Yes
Practical knowledge.
Good
Mod
Yes
NO

Code:

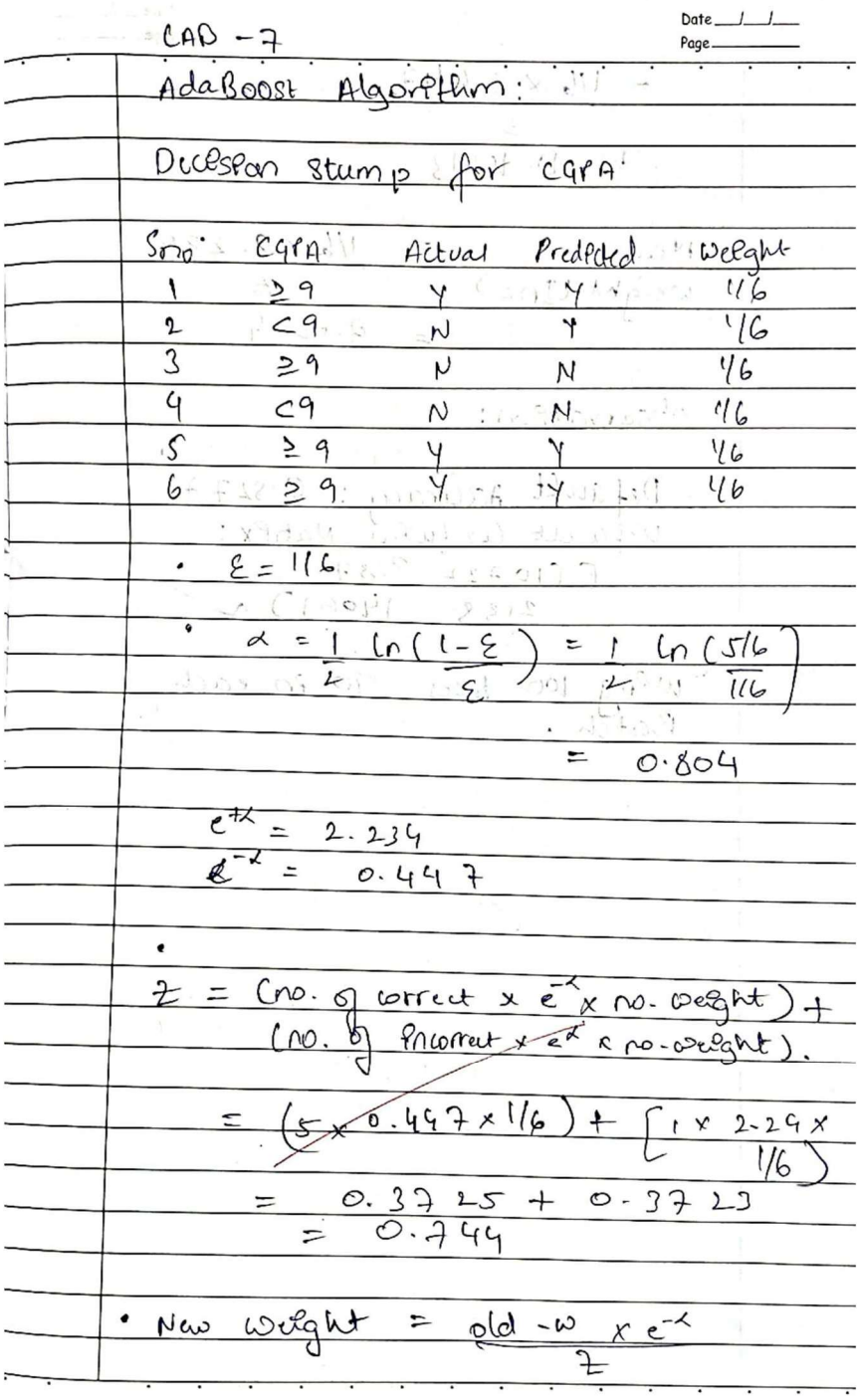
```
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

# Load dataset
df = pd.read_csv("iris.csv")

# Features and target
X = df.drop(columns=["species"])
y = df["species"]

# Split into train/test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# 1. Train 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)
default_score = accuracy_score(y_test, y_pred_default)

print(f"Accuracy with default (10 trees): {default_score:.4f}")
```

```
# 2. Fine-tune n_estimators
scores = []
tree_range = range(1, 51)

for n in tree_range:
    model = RandomForestClassifier(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)
    scores.append(acc)
# Plotting results
plt.figure(figsize=(10,5))
plt.plot(tree_range, scores, marker='o')
plt.title("Random Forest Accuracy vs Number of Trees")
plt.xlabel("Number of Trees (n_estimators)")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
# Best result
best_score = max(scores)
best_n = tree_range[scores.index(best_score)]

print(f"Best Accuracy = {best_score:.4f} with n_estimators = {best_n}")
```

Program 8

Implement Boosting ensemble method on a given dataset

Screenshot



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AdaBoost Algorithm:

Decision stump for CGPA

Sno	CGPA	Actual	Predicted	Weight
1	≥ 9	Y	Y	1/6
2	< 9	N	Y	1/6
3	≥ 9	N	N	1/6
4	< 9	N	N	1/6
5	≥ 9	Y	Y	1/6
6	≥ 9	Y	Y	1/6

- $\varepsilon = 1/6$
- $\alpha = \frac{1}{2} \ln\left(\frac{1-\varepsilon}{\varepsilon}\right) = \frac{1}{2} \ln\left(\frac{5/6}{1/6}\right)$

$= 0.804$

$e^{+\alpha} = 2.234$

$e^{-\alpha} = 0.447$

- $Z = (\text{no. of correct} \times e^{-\alpha} \times \text{no. weight}) + (\text{no. of incorrect} \times e^{\alpha} \times \text{no. weight})$.

$= (5 \times 0.447 \times 1/6) + [1 \times 2.24 \times 1/6)$

$= 0.3725 + 0.3723$

$= 0.744$

- New weight $= \frac{\text{old } -w \times e^{-\alpha}}{Z}$

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$= 1/6 \times 0.447$

$\approx$

± 0.10013

New weight (inc) $= 1/6 \times 2.234$

$\approx$

$= 0.5004$

observation:

Default Accuracy: 0.8277

Default confusion Matrix:

[[10722 387

2138 1406]] ✓

using 100 trees, 10 in each Batch.

Code:

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

# Load the dataset
data = pd.read_csv('income.csv')

# Explore the dataset
print(data.head())
print("\nDataset info:")
print(data.info())
print("\nClass distribution:")
print(data['income_level'].value_counts())

# Split into features and target
X = data.drop('income_level', axis=1)
y = data['income_level']

# Encode categorical features (one-hot encoding)
```

```
X = pd.get_dummies(X)


# Check for missing values
if X.isnull().sum().sum() > 0:
    print("Missing values found. Filling missing values with column mean.")
    X = X.fillna(X.mean())


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


# Define base estimator
base_estimator = DecisionTreeClassifier(max_depth=1)  # Stump tree for AdaBoost


# Initial AdaBoost model with 10 estimators
ada_model = AdaBoostClassifier(
    estimator=base_estimator,
    n_estimators=10,
    random_state=42
)


# Train the model
ada_model.fit(X_train, y_train)
```

```
# Make predictions
y_pred = ada_model.predict(X_test)

# Evaluate initial model
print("\nInitial Model with 10 estimators:")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# Fine-tune the number of trees
n_estimators_range = [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 150, 200]
train_scores = []
test_scores = []

for n in n_estimators_range:
    model = AdaBoostClassifier(
        estimator=base_estimator,
        n_estimators=n,
        random_state=42
    )
    model.fit(X_train, y_train)

    # Training accuracy
    train_pred = model.predict(X_train)
```

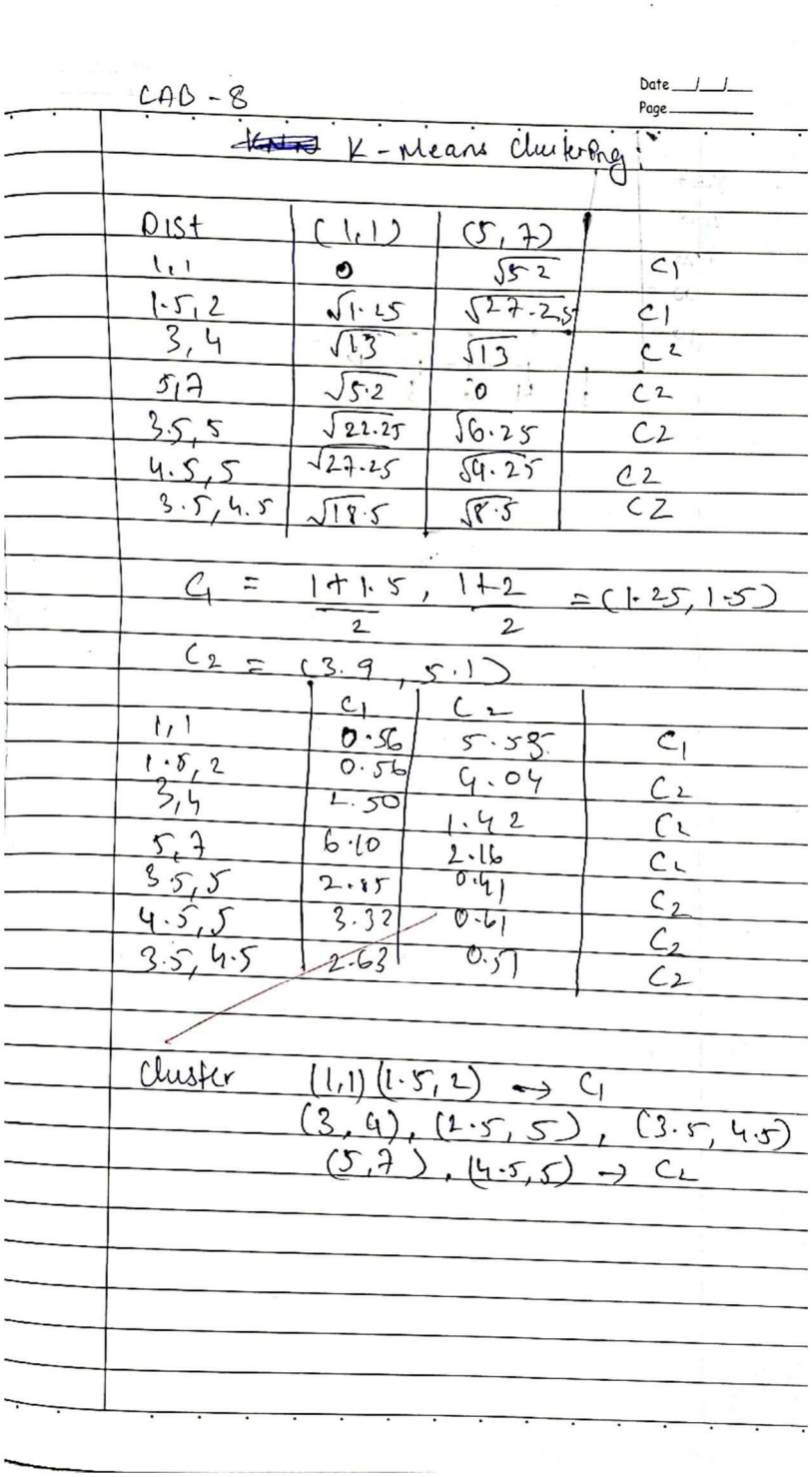
```
    train_acc = accuracy_score(y_train, train_pred)
    train_scores.append(train_acc)

    # Test accuracy
    test_pred = model.predict(X_test)
    test_acc = accuracy_score(y_test, test_pred)
    test_scores.append(test_acc)

    print(f"n_estimators: {n}, Train Accuracy: {train_acc:.4f}, Test Accuracy: {test_acc:.4f}")

# Find the best number of estimators
best_n = n_estimators_range[np.argmax(test_scores)]
best_score = max(test_scores)

print(f"\nBest performance: n_estimators={best_n} with test accuracy of {best_score:.4f}")

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(n_estimators_range, train_scores, label='Train Accuracy', marker='o')
plt.plot(n_estimators_range, test_scores, label='Test Accuracy', marker='o')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.title('AdaBoost Performance vs Number of Estimators')
plt.axvline(x=best_n, color='r', linestyle='--', label=f'Best n_estimators={best_n}')
```

```
plt.legend()
plt.grid()
plt.show()

# Train final model with best number of estimators
final_model = AdaBoostClassifier(
    estimator=base_estimator,
    n_estimators=best_n,
    random_state=42
)
final_model.fit(X_train, y_train)

# Evaluate final model
final_pred = final_model.predict(X_test)
print("\nFinal Model Performance:")
print("Accuracy:", accuracy_score(y_test, final_pred))
print("\nClassification Report:")
print(classification_report(y_test, final_pred))

print("\nFeature Importances:")
feature_importances = pd.Series(final_model.feature_importances_, index=X.columns)
print(feature_importances.sort_values(ascending=False))
```

Program 9

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

Screenshot



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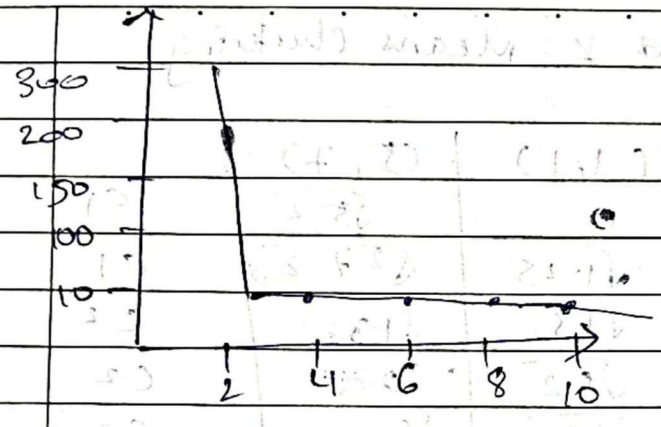


Code:

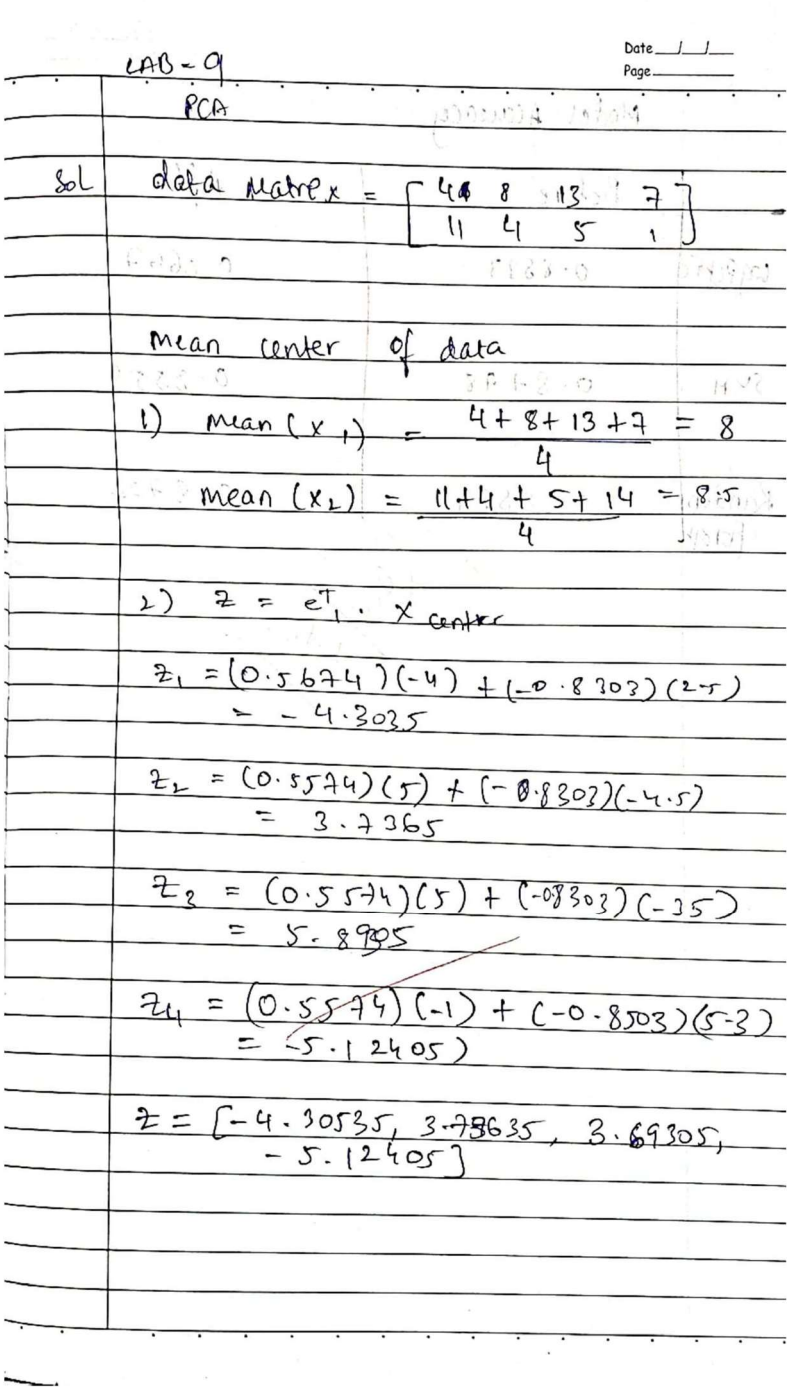
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

# Load your iris dataset
df = pd.read_csv("iris.csv")

# Use only Petal Length and Petal Width
X = df[["petal_length", "petal_width"]]

# Scale the features
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:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

# Plot Elbow Curve
```

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

# Final KMeans with optimal k (e.g., 3 from elbow)
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
df['Cluster'] = kmeans.fit_predict(X_scaled)

# Visualize Clusters
plt.figure(figsize=(8, 5))
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=df['Cluster'], cmap='viridis', s=50)
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
            color='red', marker='X', label='Centroids')
plt.xlabel("Petal Length (scaled)")
plt.ylabel("Petal Width (scaled)")
plt.title(f"K-Means Clustering (k={optimal_k}) on Iris Petal Features")
plt.legend()
plt.grid(True)
plt.show()
```

Program 10

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Screenshot



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Model Accuracy

	Before	After
Logistic	0.8833	0.8667
SVM	0.8778	0.8556
Random Forest	0.8889	0.8722

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Code:

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
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
from sklearn.pipeline import Pipeline

# Load dataset
data = pd.read_csv('heart.csv')

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

# Identify categorical and numerical columns
cat_cols = ['Sex', 'ChestPainType', 'RestingECG', 'ExerciseAngina', 'ST_Slope']
num_cols = [col for col in X.columns if col not in cat_cols]

# Label encode binary categorical columns with two categories (e.g. Sex, ExerciseAngina)
```

```
label_enc_cols = ['Sex', 'ExerciseAngina']
le = LabelEncoder()
for col in label_enc_cols:
    X[col] = le.fit_transform(X[col])

# For other categorical columns with more than two categories, apply OneHotEncoding
onehot_cols = list(set(cat_cols) - set(label_enc_cols))

# Preprocessing pipeline: OneHotEncoding + scaling numerical features
preprocessor = ColumnTransformer(
    transformers=[
        ('onehot', OneHotEncoder(drop='first'), onehot_cols),
        ('scaler', StandardScaler(), num_cols)
    ],
    remainder='passthrough'  # To keep label encoded columns as is
)

# Split data into train/test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y)

# Helper function to train and evaluate a model
def train_evaluate_model(model, X_train, X_test, y_train, y_test):
    pipeline = Pipeline(steps=[('preprocessor', preprocessor),
```

```
                    ('classifier', model)])
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    return acc, pipeline

# Train and evaluate SVM
svm = SVC(random_state=42)
svm_acc, svm_pipeline = train_evaluate_model(svm, X_train, X_test, y_train, y_test)

# Train and evaluate Logistic Regression
logreg = LogisticRegression(max_iter=1000, random_state=42)
logreg_acc, logreg_pipeline = train_evaluate_model(logreg, X_train, X_test, y_train, y_test)

# Train and evaluate Random Forest
rf = RandomForestClassifier(random_state=42)
rf_acc, rf_pipeline = train_evaluate_model(rf, X_train, X_test, y_train, y_test)

print(f"Accuracy Scores without PCA:\nSVM: {svm_acc:.4f}\nLogistic Regression:
{logreg_acc:.4f}\nRandom Forest: {rf_acc:.4f}")

# Now apply PCA for dimensionality reduction after preprocessing (scaling + encoding)
# We modify the pipeline to include PCA before classification

def train_evaluate_model_pca(model, X_train, X_test, y_train, y_test, n_components):
```

```
    pca = PCA(n_components=n_components, random_state=42)
    pipeline = Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('pca', pca),
        ('classifier', model)
    ])
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    return acc, pipeline

# Choose number of components to keep 95% variance or fixed number (e.g. 5)
# Here let's pick 5 components arbitrarily
n_components = 5

svm_pca_acc, _ = train_evaluate_model_pca(svm, X_train, X_test, y_train, y_test, n_components)
logreg_pca_acc, _ = train_evaluate_model_pca(logreg, X_train, X_test, y_train, y_test,
n_components)
rf_pca_acc, _ = train_evaluate_model_pca(rf, X_train, X_test, y_train, y_test, n_components)

print(f"\nAccuracy Scores with PCA (n_components={n_components}):")
print(f"SVM: {svm_pca_acc:.4f}")
print(f"Logistic Regression: {logreg_pca_acc:.4f}")
print(f"Random Forest: {rf_pca_acc:.4f}")
```