VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT on

Machine Learning (23CS6PCMAL)

Submitted by

SHREE SUDHANVA K (1BM22CS262)

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 **SHREE SUDHANVA K (1BM22CS262),** 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.

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

Index

Github Link: https://github.com/Shree-sudhanva/ML-LAB

Program 1

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

Lab - 0

PAGE NO : 1
DATE :

To DO1:-

Method 1 :- Initialize values directly into Dataframe

Insert your known values, 5 rows of data with column heading as "USN, Name, Marks"

→ import pandas as pd
data = {
'USN' = ['1', '2', '3', '4', '5'],
'Name' = ['Arun', 'Soundarya', 'Neha', 'Suraj', 'Prajwal'],
'Marks' = [50, 80, 45, 99, 85]
}
df = pd.DataFrame(data)
print(df)

Method 2 : Importing datasets from sklearn.datasets.
Loading diabets datasets sklearn.datasets.load_diabetes

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

PAGE NO : 6
DATE :

Method 3 :- Importing dataset from a Specific .csv file [sample data sales data .csv)

→
```
file = 'sample sales data.csv'
df = pd.read_csv(file)
print(df)
```

Method 4 :- Downloading datasets from existing dataset repositories like kaggle, UCI Mendeley, KEEL etc

→
```
file = 'Dataset of Diabetes .csv'
df = pd.read_csv(file)
print(df)
```

TO DO :- Stock Market Data Analysis

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

tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(ticketers, start = "2024-01-01",
       end = "2024-12-30", groupby = 'tickers')
print("First 5 rows :")
print(data.head())

# calculate daily returns

hdfc = data["HDFCBANK.NS"]
```

Code:

```
import pandas as pd data={
   'USN':['1','2','3','4','5'],
   'Name':['Arun', 'Soudarya','neha', 'suraj', 'Prajju'],
   'marks':[50, 80, 45, 99, 87]
}
df=pd.DataFrame(data) print(df)

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


file_path='/sample_sales_data (1).csv'
df=pd.read_csv(file_path) print("Sample
data:")
print(df)


file='Dataset of Diabetes .csv'
df=pd.read_csv(file) print("Sample
data:")
print(df.head())

# Step 1: Import required libraries
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')

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

# Calculate daily returns
hdfc=data['HDFCBANK.NS'] hdfc['Daily Return']
= hdfc['Close'].pct_change() print("\nSummary
statistics for HDFC:") print(hdfc.describe())
```

```
icic=data['ICICIBANK.NS'] icic['Daily Return'] =
icic['Close'].pct_change() print("\nSummary
statistics for ICICI:") print(icic.describe())

kotak=data['KOTAKBANK.NS'] kotak['Daily
Return'] = kotak['Close'].pct_change()
print("\nSummary statistics for Kotak:")
print(kotak.describe())


# Plot the closing price and daily returns
plt.figure(figsize=(12,  6))  plt.subplot(2,
1,  1)  hdfc['Close'].plot(title="    Closing
Price")  icic['Close'].plot(title="    Closing
Price") kotak['Close'].plot(title=" Closing
Price") plt.subplot(2, 1, 2)
hdfc['Daily Return'].plot(title="Daily Returns" ) icic['Daily
Return'].plot(title=" Daily Returns") kotak['Daily
Return'].plot(title="Daily Returns") plt.tight_layout()
plt.show()
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Lab - 1

PAGE NO : 4
DATE :

To do 1 :- Housing.csv

1 # 1. To load .csv file into a DataFrame
df = pd.read_csv("housing.csv")

2 Display information of all columns
print("Information of all column:")
print(df.info())

3. Display statistical information of all numerical
print(df.describe())

4. To display the count of unique labels for "ocean proximity" column
print(df['ocean proximity'].value_counts())

5. To display which attributes (columns) in dataset have missing values count greater than zero.
missing_values = df.isnull().sum()
column_missing_val = missing_values[missing_values > 0]
print(column_missing_val)

~~Diata~~

Diabetes dataset :-

1. which columns in the dataset had missing value? How did you handle them?

PAGE NO : 5
DATE :

→ None of column had missing values but if had then numerical columns NAN can be replaced with median & categorial columns null can be replaced with mode

2. Which categorical columns did you identify in the dataset ? How did you encode them
→ The diabetes dataset had gender, & class as categorical column & adult dataset had workclass, education, marital - status, occupation relationship, race, gender, native - country & income as categorical column
using ordinal Encoder we can encode categ -ical columns

3. What is the difference between min - max scaling and standardization ? when would you one over the other?
→ Min - Max scaling, also called normalization Transforms data to fit within a specific range [usually 0 to 1] by scaling based on min - max values in dataset.
Standardization set scales to data by Subtracting mean and dividing.

e-03 ~ 0

Code:

```
#Handling Missing Values, Handling categorical data, Handling Outliers
import pandas as pd df=pd.read_csv('/content/Dataset of Diabetes .csv')
missing_values=df.isnull().sum() print(missing_values[missing_values >
0])

# Data Transformations: Min-max Scaler/Normalization , Standard Scaler
import pandas as pd import numpy as np
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder, StandardScaler
file_path = "Dataset of Diabetes .csv" df = pd.read_csv(file_path) df["Gender"] =
df["Gender"].str.upper()
ordinal_encoder = OrdinalEncoder(categories=[["M", "F"]])
df["Gender_Encoded"] = ordinal_encoder.fit_transform(df[["Gender"]])
onehot_encoder = OneHotEncoder(sparse_output=False, drop="first")
encoded_class = onehot_encoder.fit_transform(df[["CLASS"]])
encoded_class_df = pd.DataFrame(encoded_class,
columns=onehot_encoder.get_feature_names_out(["CLASS"])) df_encoded
= pd.concat([df, encoded_class_df], axis=1) df_encoded.drop(["Gender",
"CLASS"], axis=1, inplace=True)
num_cols = ["AGE", "Urea", "Cr", "HbA1c", "Chol", "TG", "HDL", "LDL", "VLDL", "BMI"] scaler
= StandardScaler()
df_encoded[num_cols] = scaler.fit_transform(df_encoded[num_cols]) print(df_encoded.head())
df_encoded.to_csv("cleaned_diabetes_dataset.csv", index=False)
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())
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

19/3/25

Lab - 3

PAGE NO: 9
DATE:

Logistic Regression

1. Consider a binary classification problem where we want to predict whether a student will pass or fail based on]

Linear Regression

1) Apply Linear regression technique to predict the 5th week sales:

```
import pandas as pd
import matplotlib.pyplot as plt
df = pd.DataFrame({'x': x, 'y': y})

xy = []
x2 = []
for i, j in zip(x, y):
    xy.append(i*j)
for i in x:
    x2.append(i**2)

x_mean = sum(x)/len(x)
y_mean = sum(y)/len(y)
xy_mean = sum(xy)/len(xy)
x2_mean = sum(x2)/len(x2)

a1 = (xy_mean - x_mean * y_mean)/(x2_mean - x2_mean**2)
a0 = y_mean - a1 * x_mean

print(f"a0 = {a0}, a1 = {a1}")
```

PAGE NO : 10
DATE :

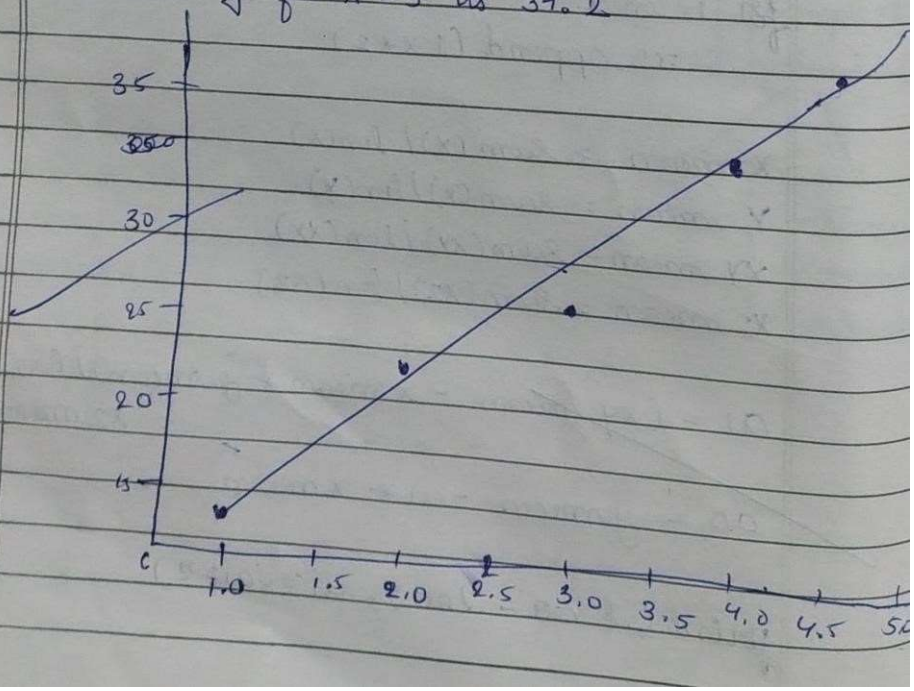
```
x_input = int(input("Enter the value of x:"))
y_pred = a0 + a1 * x_input
print(f"predicated y for x = {x_input} is : {y_pred}")
plt.scatter(x, y, color='blue', lable='Datapoint')
plt.plot(x,[a0 + a1* xi for xi in x], color='red',
        label = 'Regression line')
plt.xlabel('x')
plt.ylabel('y')
plt.title('Linear Regression')
plt.legend()
plt.grid(True)
plt.show()
```

Output :-

a0 = 6.1999 a1 = 5.6000

Enter the value of x : 5

Predicted y for x = 5 is 34.2



PAGE NO: 4
DATE:

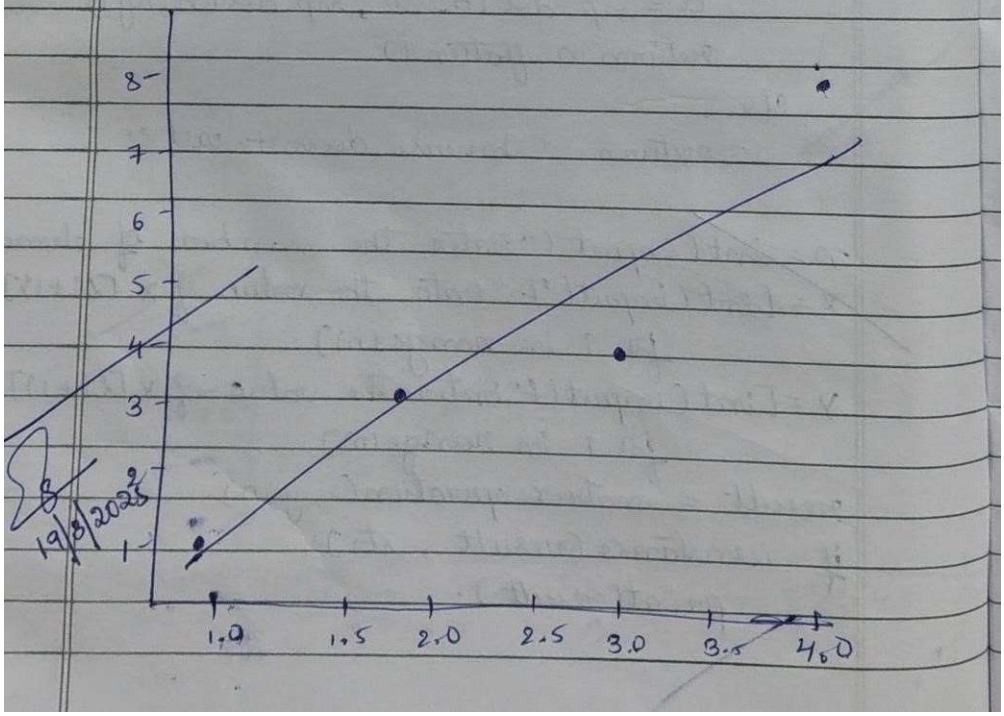
2) Find linear regression of data of week & product sales. use matrix approach for finding linear regression

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

def matrix (x, y, n):
    ax : np.ones ((n, 2))
    [ax:, 1] = x
    ay = np.array(y). reshape (-1, 1)

    xt = ax.T
    A = np. dot (xt, ax)
    detA = np. linalg: det (A)

    if detA != 0 :
        A_inv = np. linalg. inv(A)
        a = np. dot (A_inv , np. dot (xt, ay))
        return a. flatten ()
    else :
        return "Inverse doesn't exit"

n = int (input ("Enter the number of el
x = [int (input ("f "Enter the value of x [i-
        for i in range (n)]
y = [int (input (f"Enter the value of y [i+
        for i in range (n)]
result = matrix operation (x, y, n)
if isinstance (result , str):
    print(result ).
```

50

```
else :
    a0, a1 = result
    print (f"Slope (a1) = {a1:.2}, Intercept (a0) = {a0:.2}")

    plt.scatter (x, y, color = 'blue', lable = 'Data Points')
    plt.plot (x, a0+a1 * np.array (x), color = 'red',
              label = 'Regression line')
plt.xlabel ('x')
plt.ylabel ('y')
plt.title ('Linear regression')
plt.legend()
plt.grid (True)
plt.show()
```

Output :- Enter the number of element : 4
Enter the values of X : [1, 2, 3, 4]
Enter the values of Y : [1, 3, 4, 8]
Slope (a1) = 2.20 , Intercept (a0) = -1.5



19/8/2025

Code:

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

# Data
x = [1, 2, 3, 4, 5] y =
[12, 18, 22, 28, 35]
df = pd.DataFrame({'x': x, 'y': y})

# Calculate required values
xy = [] x2 = [] for
i, j in zip(x, y):
xy.append(i * j)
for i in x:
   x2.append(i ** 2)

x_mean = sum(x) / len(x) y_mean
= sum(y) / len(y) xy_mean =
sum(xy) / len(xy)
x2_mean = sum(x2) / len(x2)

# Calculate coefficients a0 and a1
a1 = (xy_mean - x_mean * y_mean) / (x2_mean - x_mean ** 2) a0
= y_mean - a1 * x_mean

# Output the coefficients
print(f"a0 = {a0}, a1 = {a1}")

# Predict y for a given x value x_input =
int(input("Enter the value of x: ")) y_pred =
a0 + a1 * x_input
print(f"Predicted y for x = {x_input} is: {y_pred}")

# Plotting
plt.scatter(x, y, color='blue', label='Data Points')  # Scatter plot for the data points
plt.plot(x, [a0 + a1 * xi for xi in x], color='red', label='Regression Line')  # Regression line
plt.xlabel('x') plt.ylabel('y') plt.title('Linear Regression') plt.legend() plt.grid(True)
plt.show()
```

Code:

```
import numpy as np
```

```
import matplotlib.pyplot as plt

def matrix_operations(x, y, n):
   ax = np.ones((n, 2))
   ax[:, 1] = x
   ay = np.array(y).reshape(-1, 1)

   xt = ax.T     A =
np.dot(xt, ax)
   det_A = np.linalg.det(A)

   if det_A != 0:
      A_inv = np.linalg.inv(A)        a =
np.dot(A_inv, np.dot(xt, ay))        return
a.flatten()  # Returns [a0, a1]     else:
      return "Inverse doesn't exist"

# Input
n = int(input("Enter the number of elements: ")) x =
[int(input(f"Enter the value of x[{i+1}]: ")) for i in range(n)]
y = [int(input(f"Enter the value of y[{i+1}]: ")) for i in range(n)]

# Perform matrix operation result
= matrix_operations(x, y, n) if
isinstance(result, str):
   print(result) else:
   a0, a1 = result
   print(f"Slope (a1) = {a1}, Intercept (a0) = {a0}")

   # Plotting
   plt.scatter(x, y, color='blue', label='Data Points')
   plt.plot(x, a0 + a1 * np.array(x), color='red', label='Regression Line')
plt.xlabel('x')     plt.ylabel('y')     plt.title('Linear Regression')
plt.legend()     plt.grid(True)     plt.show()
```

Program 4

Build Logistic Regression Model for a given dataset

02/04/25

Lab - 4

PAGE NO :
DATE :

Logistic regression

1) Consider a binary classification problem where we want to predict whether a student will pass or fail based on their study hours. the logistic regression model has been trained, & the learned parameters are $a_0 = -5$ (intercept) & $a_1 = 0.8$ [co-efficient for study hours]

(a) Write the logistic regression equation for this problem.

→ $P(y=1|x) = \frac{1}{1+e^{-(-5+0.8x)}}$

(b) Calculate the probability for 7 Hours of study

$x = 7$

$P(y=1|7) = \frac{1}{1+e^{-(-5+0.8(7))}}$

$P(y=1|7) = \frac{1}{1+e^{-(-5+5.6)}}$

$P(y=1|7) = \frac{1}{1+e^{-(0.6)}}$

$P(y=1|7) = \frac{1}{1+e^{-0.6}}$

$e^{-0.6} \approx 0.5488$

PAGE NO :
DATE :

$$P(y=1|7) = \frac{1}{1+0.5488} = \frac{1}{1.5488}$$

$$P(y=1|7) \approx 0.6457$$

hence, the probability that student who studies for 7 hours will pass is 0.6457 or 64.57%.

(c) Determine the predicted class [pass / fail] for this student based on threshhold of 0.5

→ if $P(y=1|7) \geq 0.5$ (or ~~$P(y=1|7)$~~) it predict class is pass

if $P(y=1|7) \leq 0.5$ it predict class is fail

so $P(y=1|7) \approx 0.6457$ is greater than 0.5

∴ Predicted class is "Pass"

(2) Consider $z = [2, 1, 0]$ for 3 classes. Apply softmax funtn to find probability values

$$P(y=i|z) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$ where $z_1 = 2$, $z_2 = 1$, $z_3 = 0$

$e^{z_1} = e^2 \approx 7.389$

$e^{z_2} = e^1 \approx 2.718$

$e^{z_3} = e^0 \approx 1$

$\sum_j e^{z_j} = e^2 + e^1 + e^0 \approx 7.389 + 2.718 + 1 = 11.107$

PAGE NO :
DATE :

$$P(y=1|z) = \frac{e^{z1}}{\sum_j e^{zj}} = \frac{7.389}{11.107} \approx 0.665$$

$$P(y=2|z) = \frac{e^{z2}}{\sum_j e^{zj}} = \frac{2.718}{11.107} \approx 0.245$$

$$P(y=3|z) = \frac{e^{z3}}{\sum_j e^{zj}} = \frac{1}{11.107} \approx 0.090$$

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

$P(y=1) \approx 0.665$

$P(y=2) \approx 0.245$

$P(y=3) \approx 0.090$

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.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
# Load dataset
file_path = "/content/zoo-data.csv" df
= pd.read_csv(file_path)
# Drop the animal_name column as it is not a feature
df = df.drop(columns=["animal_name"]) # Define
features and target X =
df.drop(columns=["class_type"]) y = df["class_type"]
# 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)
# Train multinomial logistic regression model
model = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=500)
model.fit(X_train, y_train) # Make predictions
y_pred = model.predict(X_test)
# Evaluate model
accuracy = accuracy_score(y_test, y_pred) print("Accuracy:",
accuracy)
print("Classification Report:\n", classification_report(y_test, y_pred))
# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
labels = np.unique(y) plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=labels, yticklabels=labels)
plt.xlabel('Predicted') plt.ylabel('Actual') plt.title('Confusion Matrix') plt.show() import pandas as pd
from matplotlib import pyplot as plt
import math
from sklearn.model_selection import train_test_split from
sklearn.linear_model import LogisticRegression

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

plt.scatter(df.satisfaction_level, df.left, marker='+', color='red')

# Splitting dataset into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(df[['satisfaction_level']], df.left, train_size=0.9,
random_state=10)
X_train.shape
X_test

# Training logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train) X_test
y_test
y_predicted = model.predict(X_test) y_predicted
model.score(X_test, y_test) model.predict_proba(X_test)
y_predicted = model.predict([[0.5]])

# model.coef_ indicates value of m in y=m*x + b equation model.coef_

# model.intercept_ indicates value of b in y=m*x + b equation
model.intercept_

# Define sigmoid function and do the math manually def
sigmoid(x):
   return 1 / (1 + math.exp(-x))

def prediction_function(satisfaction_level):
   z = model.coef_[0][0] * satisfaction_level + model.intercept_[0]
y = sigmoid(z)     return y satisfaction_level = 0.35
probability = prediction_function(satisfaction_level) print(f"Probability
of leaving: {probability:.2f}")

if probability >= 0.5:
   print("The employee will leave.") else:
   print("The employee will stay.")
```

Program 5

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

Lab - 09

PAGE NO : 6
DATE :

Implement ID3 [Iterative Dichotomiser 3] algorithm on Tennis weather database

```
import pandas as pd
data = pd.read_csv('tennis.csv')
data

from sklearn.preprocessing import
    LabelEncoder
Outlook = LabelEncoder()
temp = LabelEncoder()
humidy = LabelEncoder()
wind = LabelEncoder()
play = LabelEncoder()
data['outlook'] = outlook.fit_transform(data['outlook'])
data['temp'] = outlook.fit_transform(data['temp'])
data['humidy'] = outlook.fit_transform(data['humidy'])
data['wind'] = outlook.fit_transform(data['wind'])
data['play'] = outlook.fit_transform(data['play'])
data

features_cols = ['outlook', 'temp', 'humidity', 'windy']
x = data[features_cols]
Y = data.play
print(x)
print()
print(y)

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)
```

PAGE NO : 7
DATE :

```
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy')
classifier.fit(x_train, y_train)
classifier.predict(x_test)
x_test
y_test
classifier.score(x_test, y_test)

from sklearn import tree
tree.plot_tree(classifier)
clf = DecisionTreeClassifier(criterion = 'entropy')
clf.fit(X, Y)
importances = clf.features_importances_
features_importance_df = pd.DataFrame({
    'Feature' : X.columns,
    'Information Gain' : importances
})
feature_importance_df = feature_importance_df.sort_va
    -lues(by = 'Information Gain', Ascending = False)
print(features_importance_df)
```

output :-

	features	Information gain
0	outlook	0.369629
3	windy	0.274209
2	humidity	0.211237
1	temp	0.151929

Code: import pandas as pd
data=pd.read_csv('tennis.csv')
data
from sklearn.preprocessing import LabelEncoder
outlook=LabelEncoder() temp=LabelEncoder()
humidity=LabelEncoder() wind=LabelEncoder()
play=LabelEncoder()
data['outlook']=outlook.fit_transform(data['outlook'])
data['temp']=outlook.fit_transform(data['temp'])
data['humidity']=outlook.fit_transform(data['humidity'])
data['windy']=outlook.fit_transform(data['windy'])
data['play']=outlook.fit_transform(data['play']) data
features_cols=['outlook','temp','humidity','windy']
x=data[features_cols] y=data.play print(x) print()
print(y)
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 DecisionTreeClassifier
classifier=DecisionTreeClassifier(criterion='entropy')
classifier.fit(x_train,y_train)
classifier.predict(x_test)
x_test y_test
classifier.score(x_test,y_test) from
sklearn import tree
tree.plot_tree(classifier)
clf = DecisionTreeClassifier(criterion='entropy') *# Using entropy to calculate information gain*
clf.fit(x, y)
importances = clf.feature_importances_
 # Create a DataFrame to see the feature importances
feature_importance_df = pd.DataFrame({
   'Feature': x.columns,
   'Information Gain': importances
})
 # Sort by importance
feature_importance_df = feature_importance_df.sort_values(by='Information Gain', ascending=False)
print(feature_importance_df)

Program 6

Build KNN Classification model for a given dataset

2/4/25

Lab-06

PAGE NO :
DATE :

KNN classification

- Consider the following dataset for k=3 & test data (x, 35, 100) as (person, Age, Salary) solve using knn classifier model & predict the target

Person	Age (x)	Salary (y)	Target	distance
A	18	50	N	$\sqrt{(35-18)^2+(100-50)^2} = 52.8$
B	23	55	N	$\sqrt{(35-23)^2+(100-55)^2} = 46.6$
C	24	70	N	$\sqrt{(35-24)^2+(100-70)^2} = 31.9$
D	41	60	Y	$\sqrt{(35-41)^2+(100-60)^2} = 40.5$
E	43	70	Y	$\sqrt{(35-43)^2+(100-70)^2} = 31.1$
F	38	40	Y	$\sqrt{(35-38)^2+(100-40)^2} = 60.1$
X	35	100	?	

31.3 = N
31.9 = Y
40.5 = Y

1 N from C
2 Y from E & D

The majority is Y

The predicted target for X = (35, 100) is Y [pass]

- For this data set

Q) How to choose the k value ? Demonstrate using accuracy rate & error rate

Steps:
1) Split the data into training & testing sets
2) Train the model with various values of k
3) Evaluate accuracy & error rate for each k
4) Plot accuracy vs k & error rate vs k and select k with the highest accuracy & lowest error rate

accuracy = No. of correct predictions / Total prediction

Error rate = 1 - Accuracy

- For diabetes data set
What is the purpose of feature scaling?
How to perform it?

Purpose:- KNN uses ~~diabet~~ distance, so features with larger values dominates. Scaling ensure fairness

Perform:- Standardization (Z-score normalization):
Substract mean, divide by Standard deviation.

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 from
sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matri
# Load dataset
file_path = "/content/diabetes.csv" df
= pd.read_csv(file_path)
# Define features and target X =
df.drop(columns=["Outcome"]) y =
df["Outcome"]
# Split data into training (80%) and testing (20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Feature scaling (Standardization) scaler
= StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Initialize and train KNN classifier with k=5 k
= 5
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train) #
Make predictions y_pred =
knn.predict(X_test)
# Evaluate model
accuracy = accuracy_score(y_test, y_pred) print("Accuracy:",
accuracy)
print("Classification Report:\n", classification_report(y_test, y_pred))
conf_matrix = confusion_matrix(y_test, y_pred)
labels = ["Non-Diabetic", "Diabetic"] plt.figure(figsize=(8,
6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=labels, yticklabels=labels)
plt.xlabel('Predicted') plt.ylabel('Actual') plt.title('Confusion Matrix') plt.show() 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_repor 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()
```

Program 7

Build Support vector machine model for a given dataset

Lab - 06

PAGE NO :
DATE :

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

class SVM:
    def __init__(self, learning_rate = 0.001, lambd=
        , n_iters = 1000):
        self.lr = learning_rate
        self.lambda = lambd
        self.niters = niters
        self.w = None
        self.b = None

    def fit(self, X, y):
        y = np.where(y<=0, -1, 1)
        nsamples, nfeatures = X.shape
        self.w = np.zeros(n_features)
        self.b = 0

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

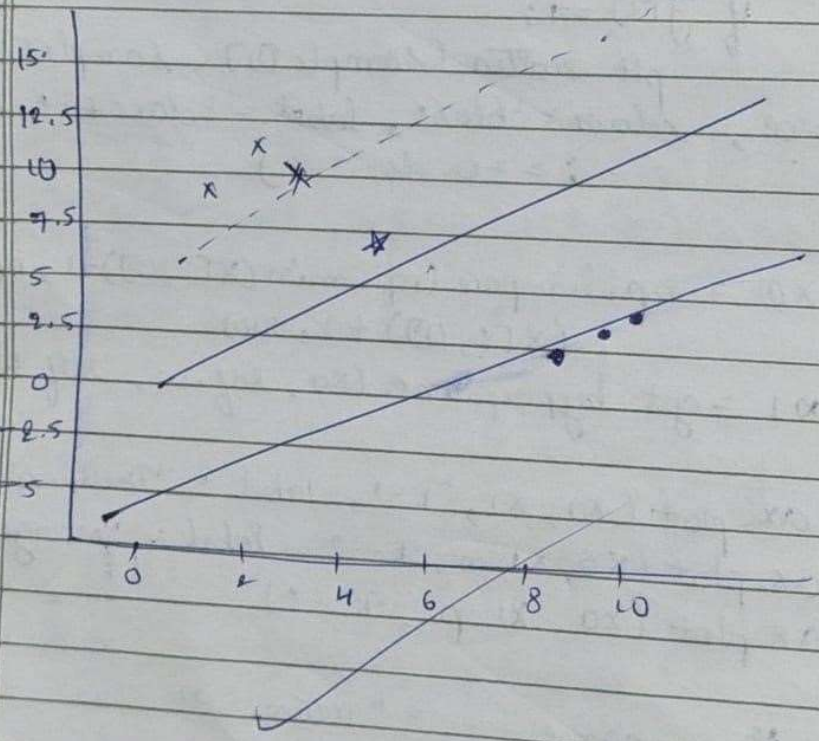
PAGE NO :
DATE :

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

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

    for i, sample in enumerate(X):
        if Y[i] == 1:
            plt.scatter(sample[0], sample[1], marker
='o', colour = 'blue', label = 'class +1' if
                i == 0 else "")

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

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

if __name__ = "__main__"
    X = np.array([[1, 7]
                  [2, 8]
                  [3, 8]
                  [8, 1]
                  [9, 2]
                  [10, 2]
```

PAGE NO:
DATE:

```
y = np.array([0, 0, 0, 1, 1, 1])

new_point = np.array([[5, 5]])

svm_visualize(x, y, new_point=new_point,
              prediction=prediction)

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

O/P



Code: import
numpy as np
import matplotlib.pyplot as plt

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

 def fit(self, X, y):
  y = np.where(y <= 0, -1, 1) *# Convert labels to -1 and 1*
n_samples, n_features = X.shape
  self.w = np.zeros(n_features)
self.b = 0 for _ in
range(self.n_iters): for idx,
x_i in enumerate(X):
    condition = y[idx] * (np.dot(x_i, self.w) + self.b) >= 1
if condition:
      self.w -= self.lr * (2 * self.lambda_param * self.w)
else:
      self.w -= self.lr * (2 * self.lambda_param * self.w - np.dot(x_i, y[idx]))
self.b += self.lr * y[idx] def predict(self, X):
  approx = np.dot(X, self.w) + self.b
return np.sign(approx)

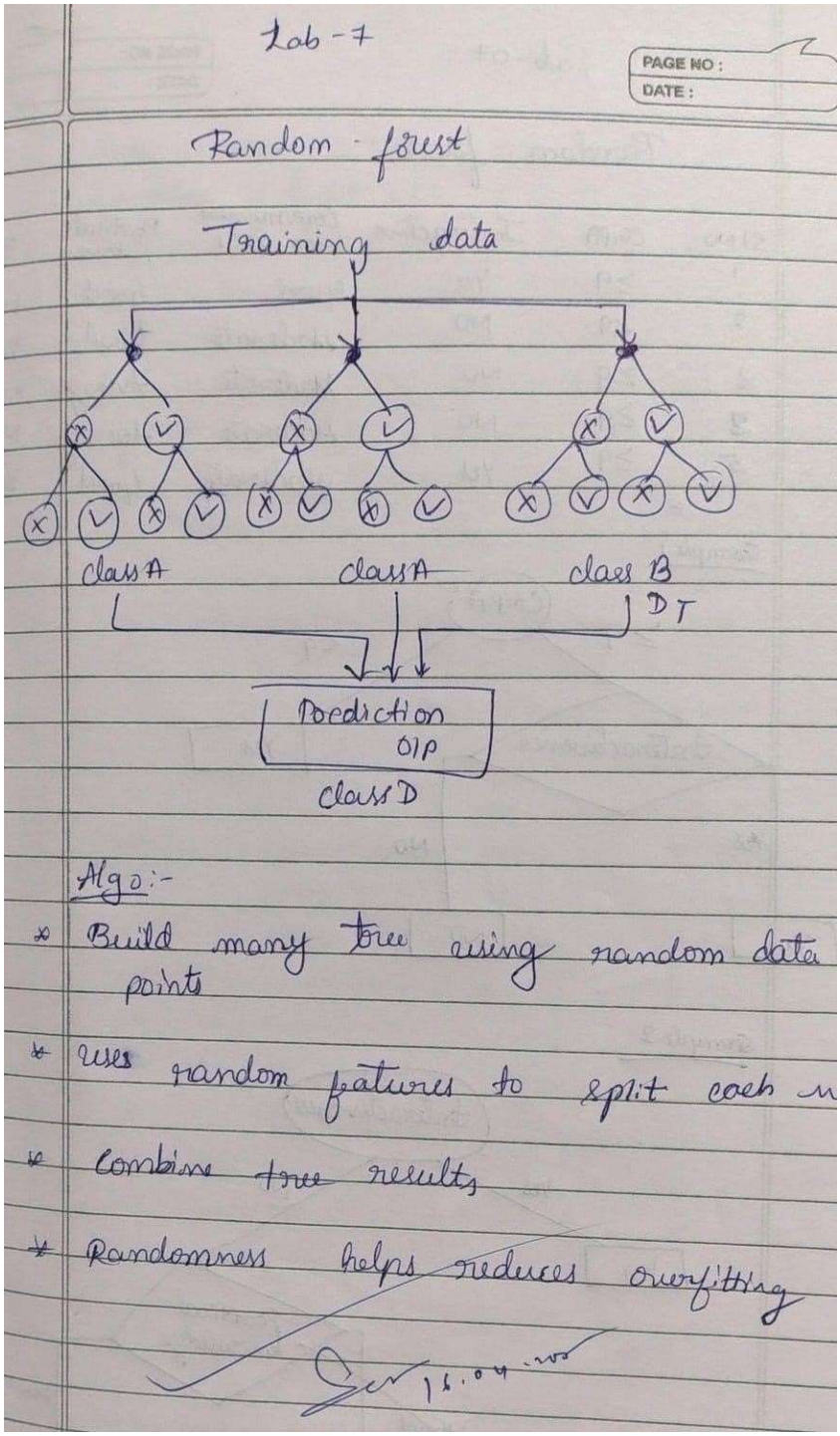
def visualize(self, X, y, new_point=None, prediction=None):
  def get_hyperplane(x, w, b, offset):
return (-w[0] * x + b + offset) / w[1]
  fig = plt.figure() ax =
fig.add_subplot(1, 1, 1) for i,
sample in enumerate(X): if
y[i] == 1:
    plt.scatter(sample[0], sample[1], marker='o', color='blue', label='Class +1' if i == 0 else "")
else:
    plt.scatter(sample[0], sample[1], marker='x', color='red', label='Class -1' if i == 0 else "")

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

```
        x1_p = get_hyperplane(x0, self.w, self.b, 1)
    ax.plot(x0, x1, 'k-', label='Decision Boundary')
    ax.plot(x0, x1_m, 'k--', label='Margins')
        ax.plot(x0, x1_p, 'k--')

        if new_point is not None:
            color = 'green' if prediction == 1 else 'orange'
    label = f'New Point: Class {"1" if prediction == 1 else "0"}'
            plt.scatter(new_point[0], new_point[1], c=color, s=100, edgecolors='black', label=label, marker='*')
    ax.legend()        plt.xlabel("Feature 1")        plt.ylabel("Feature 2")
        plt.title("SVM with New Point Prediction")
    plt.grid(True)
        plt.show()

if __name__ == "__main__":
    # Training data
    X = np.array([
        [1, 7],
        [2, 8],
        [3, 8],
        [8, 1],
        [9, 2],
        [10, 2]
    ])
    y = np.array([0, 0, 0, 1, 1, 1]) # 0 -> -1, 1 -> +1

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

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

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

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

Program 8

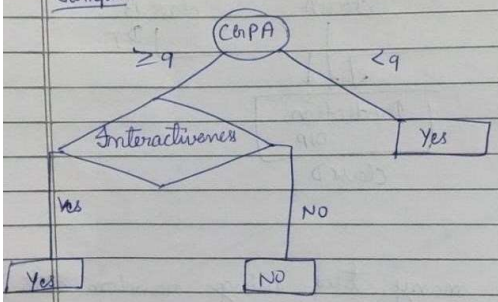
Implement Random forest ensemble method on a given dataset



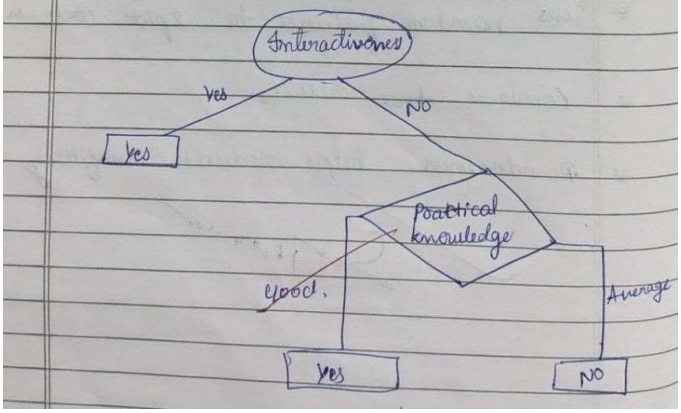
Random forest

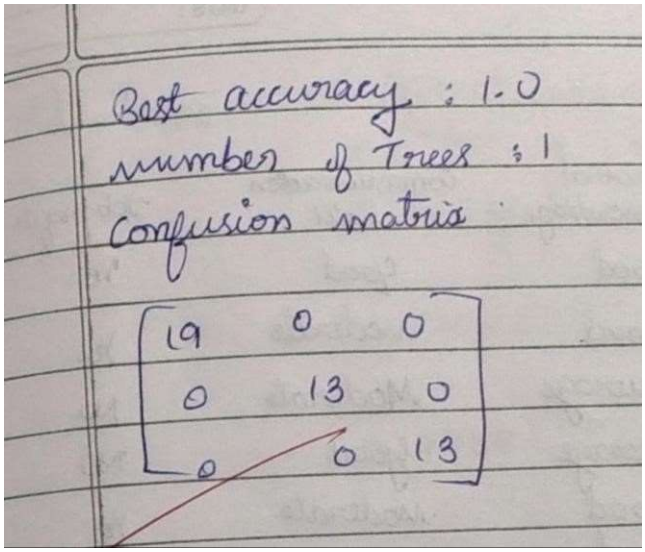
Sl No.	CGPA	Interactive	Communication Skill	Practical knowledge	Job offer
1	≥9	Yes	Good	Good	Yes
2	<9	NO	Moderate	Good	Yes
3	≥9	NO	Moderate	Average	NO
4	≥9	NO	Moderate	Average	NO
5	≥9	Yes	Moderate	Good	Yes

Sample 1



Sample 2





Code:

```
import pandas as pd
from sklearn.datasets import load_iris from
sklearn.model_selection import train_test_split from
sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix

# Load the iris dataset
iris = load_iris()

# Convert to DataFrame
df = pd.DataFrame(data=iris.data, columns=iris.feature_names) df['species']
= iris.target

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

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

best_score = 0 best_n
= 0
best_cm = None

# Try different numbers of trees for n in range(1, 101):     clf =
RandomForestClassifier(n_estimators=n, random_state=42)
clf.fit(X_train, y_train)     y_pred = clf.predict(X_test)     acc =
```

```
accuracy_score(y_test, y_pred)     if acc > best_score:
best_score = acc
      best_n = n
      best_cm = confusion_matrix(y_test, y_pred)

print(f"Best Accuracy: {best_score}")
print(f"Number of Trees: {best_n}")
print("Confusion Matrix:") print(best_cm)
```

Program 9

Implement Boosting ensemble method on a given dataset

Lab - 08

PAGE NO :
DATE :

AdaBoost

CGPA	Interacti -veness	Practical knowledge	Communication Skill	Job profile
>=9	Yes	Good	Good	Yes
<9	No	Good	moderate	Yes
>=9	No	Average	Moderate	No
<9	No	Average	Good	No
>=9	Yes	Good	moderate	Yes
>=9	Yes	Good	Moderate	Yes

~~2 wrong~~

CGPA	Predicted job offer	Job profile
>=9	Yes	Yes
<9	No	Yes
>=9	Yes	No
<9	No	No
>=9	Yes	Yes
>=9	Yes	Yes

2 wrong prediction
4 correct prediction

(i) $\varepsilon_{CGPA} = 2 \times \frac{1}{6} = 2/6 = 0.33$

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

$= \frac{1}{2} \ln \frac{(1-0.33)}{0.333}$

$= 0.347$

(iii) Z_{CGPA} = wt [correct instance] × [no. of correct classifier] $\times e^{-\alpha_{CGPA}}$ + wt [Incorrect do instance] × [no of Incorrect classifier] $\times e^{+\alpha_{CGPA}}$

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

$= 0.9428$ [normalize factor]

(iv) $wt(d_j)_{i+1} = \frac{wt(d_j)\ CGPA \text{ of correct instance} \times e^{-\alpha_{CGPA}}}{Z_{CGPA}}$

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

$= 0.1249$ [correct weight]

v) wt for incorrect instance

$= \frac{\frac{1}{6} \times e^{+0.347}}{0.9428}$

$= 0.2501$

CGPA	Initial weight	updated weight
>=9	1/6	0.1249
<9	1/6	0.2501
>=9	1/6	0.1249
<9	1/6	0.2501
>=9	1/6	0.1249
>=9	1/6	0.1249

Code:

```
import pandas as pd import
numpy as np
from sklearn.model_selection import train_test_split from
sklearn.ensemble import AdaBoostClassifier from
sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
# Load dataset
df = pd.read_csv("/content/income.csv")
# Define features and target X =
df.drop("income_level", axis=1) y =
df["income_level"]
# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 1: AdaBoost with 10 estimators
model = AdaBoostClassifier(n_estimators=10, random_state=42)
model.fit(X_train, y_train) y_pred = model.predict(X_test)
base_accuracy = accuracy_score(y_test, y_pred) conf_matrix =
confusion_matrix(y_test, y_pred) print(f"Accuracy with 10
estimators: {base_accuracy:.4f}") print("Confusion Matrix:\n",
conf_matrix) # Step 2: Fine-tuning n_estimators
estimator_range = range(10, 201, 10)
scores = [] for n in estimator_range:     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)     scores.append(acc)
   print(f"n_estimators={n}, Accuracy={acc:.4f}") # Plot
accuracy vs. number of estimators
plt.plot(estimator_range, scores, marker='o')
plt.title("Accuracy vs. Number of Estimators (AdaBoost)")
plt.xlabel("Number of Estimators") plt.ylabel("Accuracy")
plt.grid(True) plt.show()
# Best score and configuration best_n =
estimator_range[np.argmax(scores)]
best_score = max(scores)
print(f"Best accuracy: {best_score:.4f} achieved with {best_n} estimators.")
```

Program 10

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

PAGE NO :
DATE :

lab-09
k-means

cluster centers are (1.0, 1.0) & (5.0, 7.0)
execute two iteration

Record no	A	B
R_1	1.0	1.0
R_2	1.5	2.0
R_3	3.0	4.0
R_4	5.0	7.0
R_5	3.5	5.0
R_6	4.5	5.0
R_7	3.5	4.5

Distance $= \sqrt{(x_2-x_1)^2 + (y_2-y_1)^2}$

Iteration 1

Record	Point(A,B)	dist $C_1(1,1)$	Dist $C_2(5,7)$	Assign cluster
R1	(1,1)	0	7.21	C1
R2	(1.5,2.0)	1.12	6.10	C1
R3	(3,4)	3.61	4.24	C1
R4	(5,7)	7.21	0	C2
R5	(3.5,5)	4.72	2.50	C2
R6	(4.5,5)	5.32	2.24	C2
R7	(3.5,4.5)	4.30	2.92	C2

$C_1 = \left(\frac{1+1.5+3}{3}, \frac{1+2+4}{3}\right)$

$= \frac{5.5}{3}, \frac{7.0}{3}$

$= 1.83, 2.33$

$C_2 = \left(\frac{5+3.5+4.5+3.5}{4}, \frac{7+5+5+4.5}{4}\right)$

$= \left(\frac{16.5}{4}, \frac{21.5}{4}\right)$

$= 4.12, 5.37$

PAGE NO :
DATE :

Iteration 2

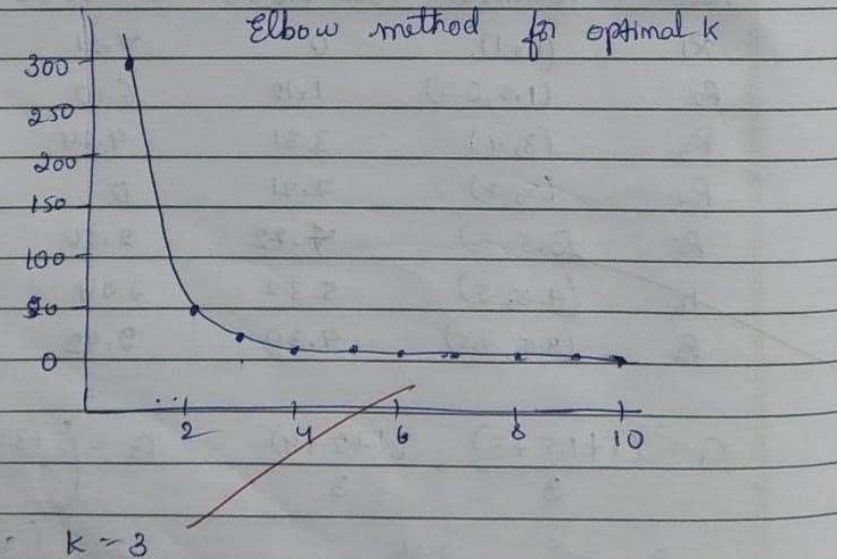
Record no	C_1 (1.83, 2.33)	C_2 (4.12, 5.37)	cluster
R_1 (1, 1)	1.57	5.37	C1
R_2 (1.5, 2)	0.47	4.27	C1
R_3 (3, 4)	2.04	1.77	C2
R_4 (5, 7)	5.64	1.85	C2
R_5 (3.5, 5)	3.14	0.72	C2
R_6 (4.5, 5)	3.78	0.53	C2
R_7 (3.5, 4.5)	2.74	1.04	C2

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

$C_1 = 1.25, 1.5$

$C_2 = \left(\frac{3+5+3.5+4.5+3.5}{5}, \frac{4+7+5+5+4.5}{5}\right)$

$C_2 = 3.9, 5.1$



Code:

```
import pandas as pd from sklearn.preprocessing
import StandardScaler from sklearn.cluster
import KMeans import matplotlib.pyplot as plt
df = pd.read_csv("/content/iris (6).csv")  # Replace with actual file path if needed
# Use only petal_length and petal_width
X = df[['petal_length', 'petal_width']]
scaler = StandardScaler() X_scaled =
scaler.fit_transform(X) # Elbow method
to find optimal k wcss = [] k_values =
range(1, 11) for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
kmeans.fit(X_scaled)     wcss.append(kmeans.inertia_)
plt.figure(figsize=(8, 5)) plt.plot(k_values, wcss, marker='o')
plt.title('Elbow Method for Optimal k') plt.xlabel('Number of
clusters (k)') plt.ylabel('WCSS') plt.grid(True) plt.tight_layout()
plt.show()
# Apply K-Means with optimal k = 3
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)
clusters = kmeans.fit_predict(X_scaled) #
Add cluster labels to original dataframe
df['cluster'] = clusters
plt.figure(figsize=(8, 5)) for cluster in
range(3):
    cluster_points = X_scaled[clusters == cluster]     plt.scatter(cluster_points[:,
0], cluster_points[:, 1], label=f'Cluster {cluster}')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
s=200, c='black', marker='X', label='Centroids') plt.title('K-Means Clustering
(k=3)') plt.xlabel('Petal Length (scaled)') plt.ylabel('Petal Width (scaled)')
plt.legend() plt.grid(True) plt.tight_layout()
plt.show()
```

Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Lab - 10

PAGE NO :
DATE :

PCA

Reduce dimension from 2 to 1

feature	Eg 1	Eg 2	Eg 3	Eg 4
x_1	4	8	13	7
x_2	11	4	5	11

Eigen values $\lambda_1 = 30.38$ $\lambda_2 = 6.61$

Eigen Vectors $e_1 = \begin{bmatrix} 0.5544 \\ -0.8303 \end{bmatrix}$ $e_2 = \begin{bmatrix} 0.8303 \\ 0.5574 \end{bmatrix}$

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

② mean center of data

$$\text{mean } 1 = \frac{4+8+13+7}{4} = 8$$

$$\text{mean } 2 = \frac{11+4+5+14}{4} = 6.3$$

$$x_{cluster} : \begin{bmatrix} 4-8 & 8-8 & 13-8 & 7-8 \\ 11-8 & 4-8.5 & 5-8.5 & 14-15 \end{bmatrix} = \begin{bmatrix} -4 & 0 & 5 & -1 \\ 2.5 & -4.5 & -3.5 & 5.5 \end{bmatrix}$$

③ using projecting data into first principale component $z = e_1^T \times \text{Centered}$

$$z_1 = (0.56 \times 4)(-4) + (0.8303)(2.5) = 4.305$$

$$z_2 = 3.7363$$

PAGE NO :
DATE :

$Z_3 = 5.6936$

$Z_4 = -5.124$

$\therefore Z[-4.305, 3.73, 5.69, -5.12]$

⇒ Model accuracy

	Before	After
logistic	0.8833	0.8667
Svm	0.8878	0.8556
Random forest	0.8989	0.8722

7/8/2025

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")  # Use
actual path if needed

# Label encode binary categorical columns le
= LabelEncoder()
df["Sex"] = le.fit_transform(df["Sex"])  # M/F -> 1/0
df["ExerciseAngina"] = le.fit_transform(df["ExerciseAngina"])  # Y/N -> 1/0

# One-hot encode categorical columns with >2 categories
df = pd.get_dummies(df, columns=["ChestPainType", "RestingECG", "ST_Slope"],
drop_first=True)

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

# 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)

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

```
# Train and evaluate models (before PCA)
print("=== Accuracy Before PCA ===") for
name, model in models.items():
model.fit(X_train, y_train)     acc =
accuracy_score(y_test,
model.predict(X_test))     print(f"{name}:
{acc:.4f}")

# Apply PCA to reduce dimensions to 2
pca = PCA(n_components=2) X_pca =
pca.fit_transform(X_scaled)

# Split again for PCA-transformed data
X_train_pca, X_test_pca, y_train, y_test = train_test_split(X_pca, y, test_size=0.2,
random_state=42)

# Train and evaluate models (after PCA) print("\n===
Accuracy After PCA (2 components) ===") for name,
model in models.items():     model.fit(X_train_pca,
y_train)     acc = accuracy_score(y_test,
model.predict(X_test_pca))     print(f"{name}: {acc:.4f}")
```