VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

D V Vedith Varma (1BM22CS339)

in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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B.M.S. College of Engineering,
Bull Temple Road, Bangalore 560019
(Affiliated To Visvesvaraya Technological University, Belgaum)
Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning (23CS6PCMAL)" carried out by **D V Vedith Varma (1BM22CS339),** 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: Prof. Sarala D V Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

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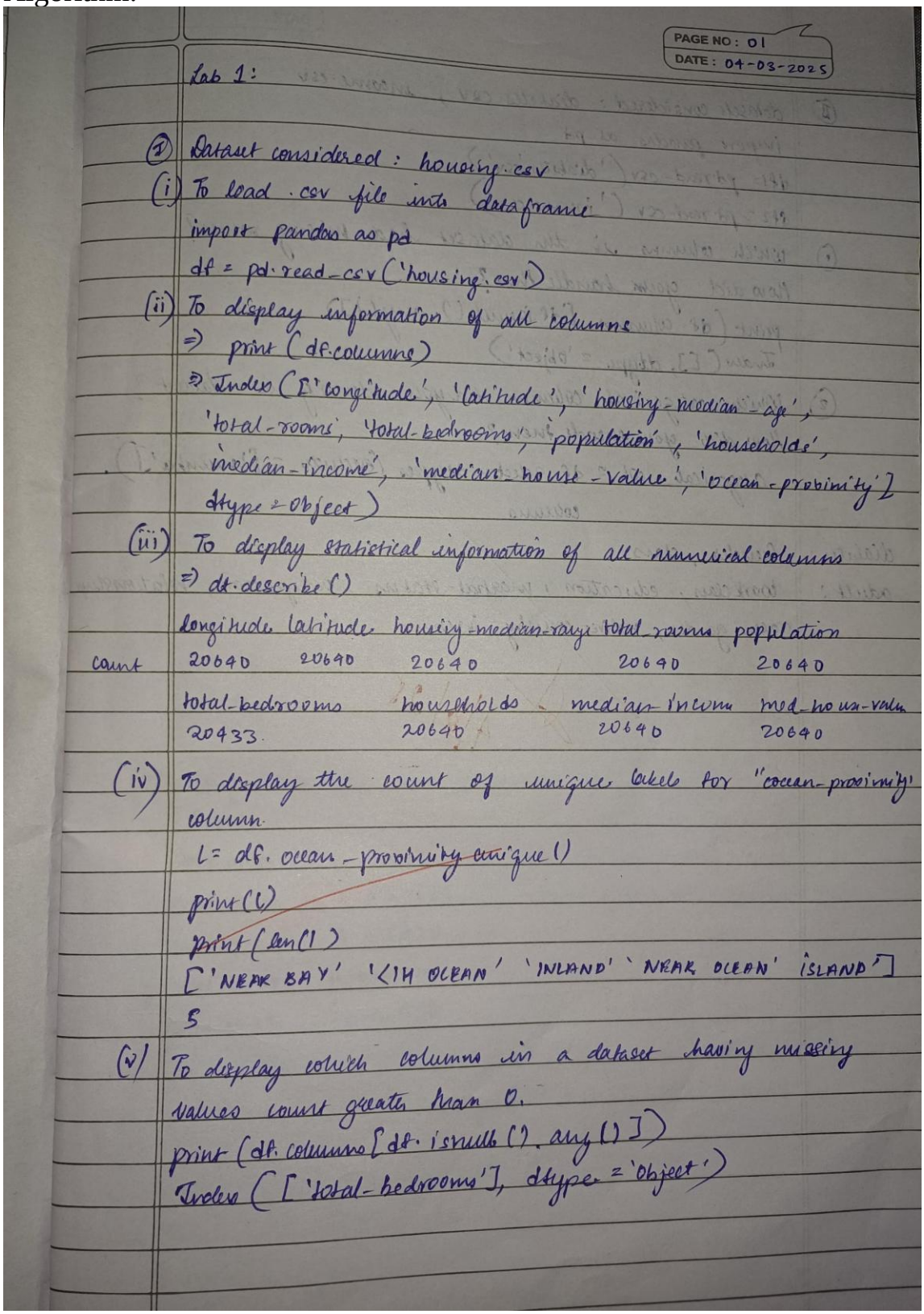
Github Link:
https://github.com/VedithVarma/ML_LAB_1BM22CS339

Program 1

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

Algorithm:



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Lab 1:

(i) Dataset considered : housing.csv

(ii) To load .csv file into dataframe

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

(iii) To display information of all columns

```
=> print(df.columns)
=> Index(['longitude', 'latitude', 'housing_median_age',
       'total_rooms', 'total_bedrooms', 'population', 'households',
       'median_income', 'median_house_value', 'ocean_proximity'],
      dtype='object')
```

(iv) To display statistical information of all numerical columns

```
=> df.describe()
```

	longitude	latitude	housing_median_age	total_rooms	population
count	20640	20640	20640	20640	20640

	total_bedrooms	households	median_income	med_house_val
	20433	20640	20640	20640

(v) To display the count of unique labels for "ocean_proximity" column.

```
l = df.ocean_proximity.unique()
print(l)
print(len(l))
['NEAR BAY' '<1H OCEAN' 'INLAND' 'NEAR OCEAN' 'ISLAND']
5
```

(vi) To display which columns in a dataset having missing values count greater than 0.

```
print(df.columns[df.isnull().any()])
Index(['total_bedrooms'], dtype='object')
```

DATE :

4. datasets considered : diabetes.csv , income.csv

```
import pandas as pd
df1 = pd.read_csv('diabetes.csv')
df2 = pd.read_csv('income.csv')
```

(1) Which columns in the dataset had missing values? How did you handle them?

```
print(df.columns[df.isnull().any()])
Index([], dtype='object')
```

(2) Which categorical columns did you identify in dataset? How did you encode them?

```
categorical_col = df.select_dtypes(exclude=['number']).columns
```

diabetes : Gender , class

adult : workclass , education , marital-status , occupation , relationship, race , gender , native-country , income

4/3/25

Code:

#1
import pandas as pd

In [32]:

#2
df= pd.read_csv('housing.csv')

In [33]:

#3
df.columns

Out[33]:
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
'total_bedrooms', 'population', 'households', 'median_income',
'median_house_value', 'ocean_proximity'],
dtype='object')
In [34]:

#4
df.describe()

Out[34]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000
25%	-121.80	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
	0000								
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	500001.000000

In [36]:

```
#5
l=df.ocean_proximity.unique()
print(l)
print(len(l))
```

```
['NEAR BAY' '<1H OCEAN' 'INLAND' 'NEAR OCEAN' 'ISLAND']
5
```

In [39]:

```
#6
df.isna().sum()
print(df.columns[df.isnull().any()])
```

```
Index(['total_bedrooms'], dtype='object')
```

In [42]:

```
df=pd.read_csv('/content/Dataset of Diabetes .csv')
print("Sample Data")
print(df.head())
print(df.isna().sum())
print(df.columns[df.isnull().any()])
categorical_cols = df.select_dtypes(exclude=['number']).columns
categorical_cols
```

```
Sample Data
   ID  No_Pation Gender  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL  \
0  502     17975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
1  735     34221      M   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6
```

```
2  420     47975     F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
3  680     87656     F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
4  504     34223     M   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4

    BMI CLASS
0  24.0     N
1  23.0     N
2  24.0     N
3  24.0     N
4  21.0     N
ID          0
No_Pation    0
Gender       0
AGE          0
Urea         0
Cr           0
HbA1c        0
Chol         0
TG           0
HDL          0
LDL          0
VLDL         0
BMI          0
CLASS        0
dtype: int64
Index([], dtype='object')
Out[42]:
Index(['Gender', 'CLASS'], dtype='object')
In [44]:

df=pd.read_csv('/content/adult.csv')
print("Sample Data")
print(df.head())
print(df.isna().sum())
print(df.columns[df.isnull().any()])
categorical_col = df.select_dtypes(exclude=['number']).columns
categorical_col

Sample Data
   age  workclass  fnlwgt     education  educational-num      marital-status  \
0   25    Private  226802          11th                7       Never-married
1   38    Private   89814       HS-grad                9  Married-civ-spouse
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-spouse
3   44    Private  160323  Some-college               10  Married-civ-spouse
4   18          ?  103497  Some-college               10       Never-married

         occupation relationship   race  gender  capital-gain  capital-loss  \
```

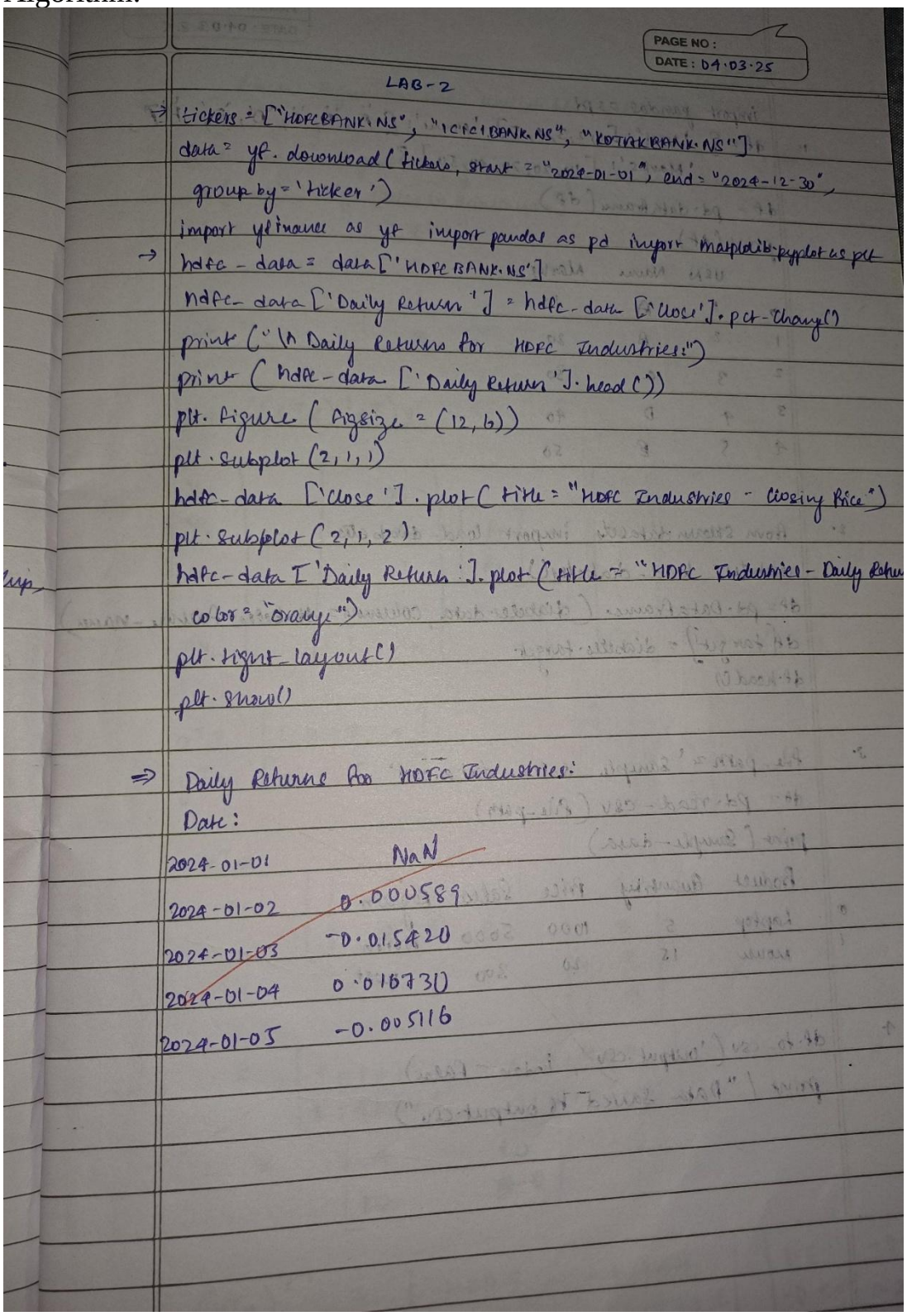
```
0  Machine-op-inspct    Own-child  Black    Male          0          0
1    Farming-fishing      Husband  White    Male          0          0
2    Protective-serv      Husband  White    Male          0          0
3  Machine-op-inspct      Husband  Black    Male       7688          0
4                  ?    Own-child  White  Female          0          0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
4              30  United-States  <=50K
age               0
workclass         0
fnlwgt            0
education         0
educational-num   0
marital-status    0
occupation        0
relationship      0
race              0
gender            0
capital-gain      0
capital-loss      0
hours-per-week    0
native-country    0
income            0
dtype: int64
Index([], dtype='object')
Out[44]:
Index(['workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'gender', 'native-country', 'income'],
      dtype='object')
In [ ]:
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Algorithm:



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LAB-2

```
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30",
group_by='ticker')
import yfinance as yf import pandas as pd import matplotlib.pyplot as plt
hdfc_data = data['HDFCBANK.NS']
hdfc_data['Daily Return'] = hdfc_data['Close'].pct_change()
print("\n Daily Returns for HDFC Industries:")
print(hdfc_data['Daily Return'].head())
plt.figure(figsize=(12,6))
plt.subplot(2,1,1)
hdfc_data['Close'].plot(title="HDFC Industries - Closing Price")
plt.subplot(2,1,2)
hdfc_data['Daily Return'].plot(title="HDFC Industries - Daily Retu
color="orange")
plt.tight_layout()
plt.show()
```

Daily Returns for HDFC Industries:

Date:

2024-01-01	NaN
2024-01-02	0.000589
2024-01-03	-0.015420
2024-01-04	0.016731
2024-01-05	-0.005116

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1.
```
import pandas as pd
df = { 'USN': [1,2,3,4,5], 'Name': ['A','B','C','D','E'],
       'Marks': [10,20,30,40,50] }
df = pd.DataFrame(df)
print(df)
```

	USN	Name	Marks
0	1	A	10
1	2	B	20
2	3	C	30
3	4	D	40
4	5	E	50

2.
```
from sklearn.datasets import load_diabetes
diabetes = load_diabetes()
df = pd.DataFrame(diabetes.data, columns = diabetes.feature_names)
df['target'] = diabetes.target
df.head()
```

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

	Product	Quantity	Price	Sales	Region
0	Laptop	5	1000	5000	North
1	Mouse	15	20	300	west

4.
```
df.to_csv('output.csv', index = False)
print("Data saved to output.csv")
```

Code:

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

```
      Name  Age         City
0    Alice   25     New York
1      Bob   30  Los Angeles
2  Charlie   35      Chicago
3    David   40      Houston
In [ ]:
```

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

```
     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                  5.1               3.5                1.4               0.2
1                  4.9               3.0                1.4               0.2
2                  4.7               3.2                1.3               0.2
3                  4.6               3.1                1.5               0.2
4                  5.0               3.6                1.4               0.2
..                 ...               ...                ...               ...
145                6.7               3.0                5.2               2.3
146                6.3               2.5                5.0               1.9
147                6.5               3.0                5.2               2.0
148                6.2               3.4                5.4               2.3
149                5.9               3.0                5.1               1.8

     target
0         0
1         0
2         0
3         0
4         0
..      ...
145       2
146       2
```

```
147      2
148      2
149      2

[150 rows x 5 columns]
In [ ]:

file_path='data.csv'
df=pd.read_csv(file_path)
print("Sample Data")
print(df.head())

Sample Data
   ID     Name  Age         City
0   1    Alice   25     New York
1   2      Bob   30  Los Angeles
2   3  Charlie   35      Chicago
3   4    David   40      Houston
4   5      Eva   28      Phoenix
In [20]:

df=pd.read_csv('mobiles.csv',encoding='unicode_escape')
print("Sample Data")
print(df.head())


Sample Data
  Company Name          Model Name Mobile Weight  RAM Front Camera  \
0        Apple      iPhone 16 128GB         174g  6GB        12MP
1        Apple      iPhone 16 256GB         174g  6GB        12MP
2        Apple      iPhone 16 512GB         174g  6GB        12MP
3        Apple  iPhone 16 Plus 128GB         203g  6GB        12MP
4        Apple  iPhone 16 Plus 256GB         203g  6GB        12MP

  Back Camera   Processor Battery Capacity Screen Size  \
0       48MP  A17 Bionic        3,600mAh  6.1 inches
1       48MP  A17 Bionic        3,600mAh  6.1 inches
2       48MP  A17 Bionic        3,600mAh  6.1 inches
3       48MP  A17 Bionic        4,200mAh  6.7 inches
4       48MP  A17 Bionic        4,200mAh  6.7 inches

  Launched Price (Pakistan) Launched Price (India) Launched Price (China)  \
0            PKR 224,999          INR 79,999          CNY 5,799
1            PKR 234,999          INR 84,999          CNY 6,099
2            PKR 244,999          INR 89,999          CNY 6,499
3            PKR 249,999          INR 89,999          CNY 6,199
4            PKR 259,999          INR 94,999          CNY 6,499
```

```
  Launched Price (USA) Launched Price (Dubai)  Launched Year
0             USD 799             AED 2,799           2024
1             USD 849             AED 2,999           2024
2             USD 899             AED 3,199           2024
3             USD 899             AED 3,199           2024
4             USD 949             AED 3,399           2024
In [21]:

#1
df={
    'USN':[1,2,3,4,5],
   'Name':['A','B','C','D','E'],
    'Marks':[10,20,30,40,50]
}

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

   USN Name  Marks
0    1    A     10
1    2    B     20
2    3    C     30
3    4    D     40
4    5    E     50
In [24]:

#2
from sklearn.datasets import load_diabetes
diabetes= load_diabetes()
df=pd.DataFrame(diabetes.data,columns=diabetes.feature_names)
df['target']=diabetes.target
df.head()
print(df)

          age       sex       bmi        bp        s1        s2        s3  \
0    0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1   -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2    0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
..        ...       ...       ...       ...       ...       ...       ...
437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
439  0.041708  0.050680 -0.015906  0.017293 -0.037344 -0.013840 -0.024993
440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
441 -0.045472 -0.044642 -0.073030 -0.081413  0.083740  0.027809  0.173816
```

```
         s4        s5        s6  target
0   -0.002592  0.019907 -0.017646   151.0
1   -0.039493 -0.068332 -0.092204    75.0
2   -0.002592  0.002861 -0.025930   141.0
3    0.034309  0.022688 -0.009362   206.0
4   -0.002592 -0.031988 -0.046641   135.0
..        ...       ...       ...     ...
437 -0.002592  0.031193  0.007207   178.0
438  0.034309 -0.018114  0.044485   104.0
439 -0.011080 -0.046883  0.015491   132.0
440  0.026560  0.044529 -0.025930   220.0
441 -0.039493 -0.004222  0.003064    57.0

[442 rows x 11 columns]
In [29]:

#3
file_path='sample_sales_data.csv'
df=pd.read_csv(file_path)
print("Sample Data")
print(df.head())

Sample Data
    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
In [30]:

#4
df=pd.read_csv('/content/Dataset of Diabetes .csv')
print("Sample Data")
print(df.head())


Sample Data
    ID  No_Pation Gender  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL  \
0  502      17975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
1  735      34221      M   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6
2  420      47975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
3  680      87656      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
4  504      34223      M   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4

    BMI CLASS
```

0 24.0   N
1 23.0   N
2 24.0   N
3 24.0   N
4 21.0   N
In [28]:

```
df.to_csv('output.csv', index=False)

print("Data saved to output.csv")
```

Data saved to output.csv
In [34]:

```
sales_df = pd.read_csv('sample_sales_data.csv')
sales_by_region = sales_df.groupby('Region')['Sales'].sum()
print("\nTotal sales by region:")
print(sales_by_region)
best_selling_products = sales_df.groupby('Product')['Quantity'].sum().sort_values(ascending=False)
print("\nBest-selling products by quantity:")
print(best_selling_products)
# Saving the sales by region data to a CSV file
sales_by_region.to_csv('sales_by_region.csv')
# Saving the best-selling products data to a CSV file
best_selling_products.to_csv('best_selling_products.csv')
print("\nAnalysis results saved to CSV files.")
```

Total sales by region:
Region
East   770
North   16400
South   3070
West   650
Name: Sales, dtype: int64

Best-selling products by quantity:
Product
Mouse   29
Laptop   17
Keyboard   16
Monitor   15
Name: Quantity, dtype: int64

Analysis results saved to CSV files.
In [35]:

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

In [36]:

```
# Step 2: Downloading Stock Market Data
# Define the ticker symbols for Indian companies
# Example: Reliance Industries (RELIANCE.NS), TCS (TCS.NS), Infosys (INFY.NS)
tickers = ["RELIANCE.NS", "TCS.NS", "INFY.NS"]

# Fetch historical data for the last 1 year
data = yf.download(tickers, start="2022-10-01", end="2023-10-01", group_by='ticker')

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

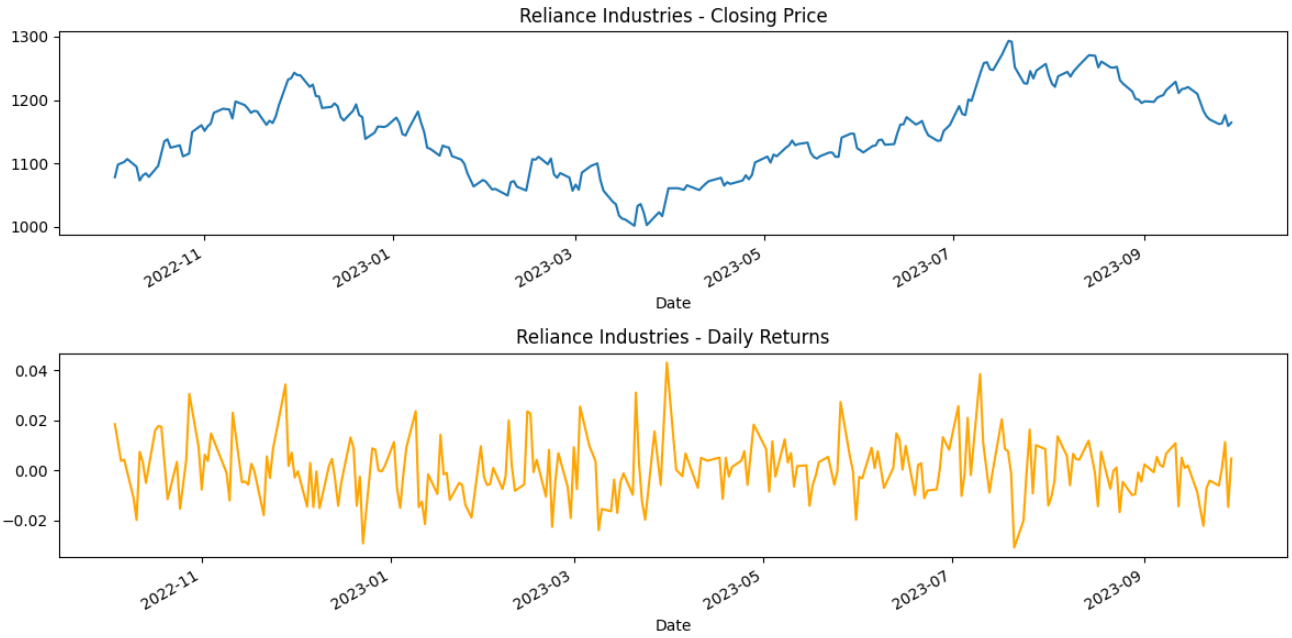
```
YF.download() has changed argument auto_adjust default to True
[**********100%**********]  3 of 3 completed
First 5 rows of the dataset:
Ticker      RELIANCE.NS                                         \
Price           Open        High         Low       Close    Volume
Date
2022-10-03  1088.493134  1100.076669  1075.521371  1078.479858  11852723
2022-10-04  1091.360592  1100.554607  1087.878645  1098.369873   8948850
2022-10-06  1105.561293  1115.119370  1100.622856  1102.420654  13352162
2022-10-07  1099.029980  1112.343173  1099.029980  1107.086182   7714340
2022-10-10  1094.637648  1100.372591  1086.900123  1095.001831   6329527

Ticker          TCS.NS                                          \
Price           Open        High         Low       Close   Volume
Date
2022-10-03  2799.043864  2823.062325  2779.417847  2789.651367  1763331
2022-10-04  2831.707536  2895.305232  2825.212304  2888.903320  2145875
2022-10-06  2907.454507  2919.603947  2890.118145  2898.996582  1790816
2022-10-07  2894.744206  2901.847047  2858.015696  2864.370605  1939879
2022-10-10  2813.062865  2922.407833  2808.390003  2914.510742  3064063

Ticker         INFY.NS
Price           Open        High         Low       Close   Volume
Date
2022-10-03  1337.743240  1337.743240  1313.110574  1320.453003  4943169
2022-10-04  1345.038201  1356.928245  1339.638009  1354.228149  6631341
2022-10-06  1369.007786  1383.029504  1368.155094  1378.624023  6180672
```

2022-10-07 1370.286676 1381.181893 1364.412779 1374.881592 3994466
2022-10-10 1351.338576 1387.956005 1351.338576 1385.729614 5274677
In [38]:

```
# Step 3: Basic Data Exploration
# Check the shape of the dataset
print("\nShape of the dataset:")
print(data.shape)

# Check column names
print("\nColumn names:")
print(data.columns)

# Summary statistics for a specific stock (e.g., Reliance)
reliance_data = data['RELIANCE.NS']
print("\nSummary statistics for Reliance Industries:")
print(reliance_data.describe())
```

```
Shape of the dataset:
(247, 15)

Column names:
MultiIndex([('RELIANCE.NS',   'Open'),
            ('RELIANCE.NS',   'High'),
            ('RELIANCE.NS',    'Low'),
            ('RELIANCE.NS',  'Close'),
            ('RELIANCE.NS', 'Volume'),
            (    'TCS.NS',   'Open'),
            (    'TCS.NS',   'High'),
            (    'TCS.NS',    'Low'),
            (    'TCS.NS',  'Close'),
            (    'TCS.NS', 'Volume'),
            (   'INFY.NS',   'Open'),
            (   'INFY.NS',   'High'),
            (   'INFY.NS',    'Low'),
            (   'INFY.NS',  'Close'),
            (   'INFY.NS', 'Volume')],
           names=['Ticker', 'Price'])

Summary statistics for Reliance Industries:
Price        Open         High          Low        Close        Volume
count   247.000000   247.000000   247.000000   247.000000  2.470000e+02
mean   1147.548565  1156.216094  1137.195377  1146.522438  1.316652e+07
std      65.890232    66.850140    65.752477    66.687266  6.754099e+06
min    1008.159038  1010.434788   992.228728  1001.900696  3.370033e+06
```

```
25%    1098.881943  1103.399363  1084.795104  1097.357178  8.717141e+06
50%    1147.435126  1155.036230  1138.787343  1147.253052  1.158959e+07
75%    1196.261444  1203.625226  1184.985050  1195.064575  1.530302e+07
max    1288.076823  1299.910771  1273.056848  1293.470337  5.708188e+07
In [39]:


# Calculate daily returns
reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
print("\nDaily returns for Reliance Industries:")
print(reliance_data['Daily Return'].head())

#

Daily returns for Reliance Industries:
Date
2022-10-03        NaN
2022-10-04    0.018443
2022-10-06    0.003688
2022-10-07    0.004232
2022-10-10   -0.010915
Name: Daily Return, dtype: float64
<ipython-input-39-2bd40fbe735c>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
In [40]:

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



In [41]:

```
# Step 4: Saving the Processed Data to a New CSV File
# Save the Reliance data to a CSV file
reliance_data.to_csv('reliance_stock_data.csv')
print("\nReliance stock data saved to 'reliance_stock_data.csv'.")
```

```
Reliance stock data saved to 'reliance_stock_data.csv'.
```

In [43]:

```
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30", group_by='ticker')
```

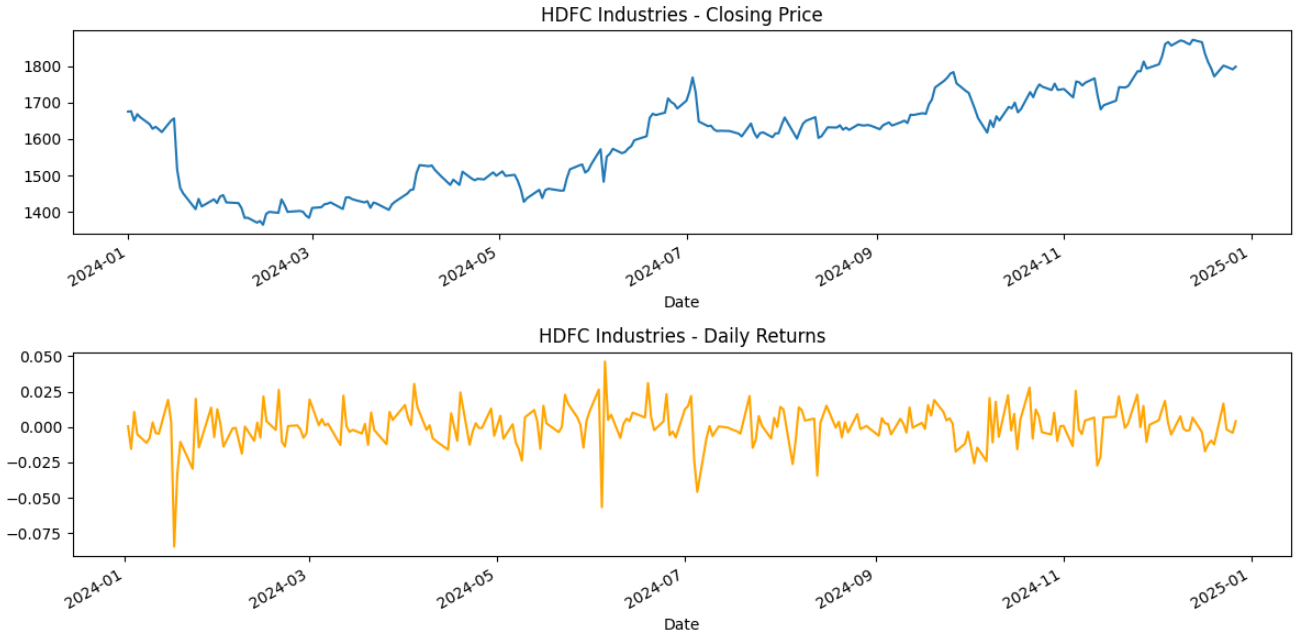
```
[**********100%**********]  3 of 3 completed
```

In [44]:

```
hdfc_data = data['HDFCBANK.NS']
hdfc_data['Daily Return'] = hdfc_data['Close'].pct_change()
print("\nDaily returns for HDFC Industries:")
print(hdfc_data['Daily Return'].head())
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
hdfc_data['Close'].plot(title="HDFC Industries - Closing Price")
plt.subplot(2, 1, 2)
hdfc_data['Daily Return'].plot(title="HDFC Industries - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
```

<ipython-input-44-f8f2798a87f5>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  hdfc_data['Daily Return'] = hdfc_data['Close'].pct_change()
Daily returns for HDFC Industries:
Date
2024-01-01   NaN
2024-01-02 0.000589
2024-01-03 -0.015420
2024-01-04 0.010730
2024-01-05 -0.005116
Name: Daily Return, dtype: float64



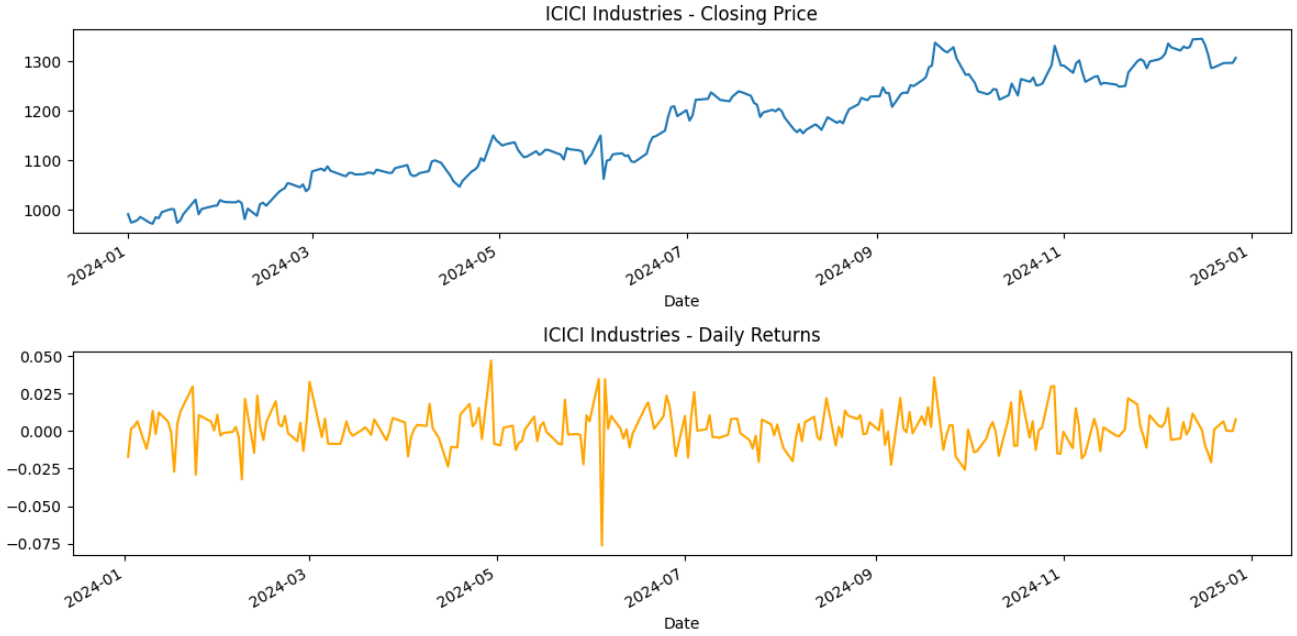
In [45]:

```
icici_data = data['ICICIBANK.NS']
icici_data['Daily Return'] = icici_data['Close'].pct_change()
print("\nDaily returns for ICICI Industries:")
print(icici_data['Daily Return'].head())
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
icici_data['Close'].plot(title="ICICI Industries - Closing Price")
plt.subplot(2, 1, 2)
icici_data['Daily Return'].plot(title="ICICI Industries - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
```

<ipython-input-45-6f81270ab07d>:2: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  icici_data['Daily Return'] = icici_data['Close'].pct_change()
Daily returns for ICICI Industries:
Date
2024-01-01   NaN
2024-01-02   -0.017160
2024-01-03   0.001833
2024-01-04   0.003150
2024-01-05   0.006635
Name: Daily Return, dtype: float64



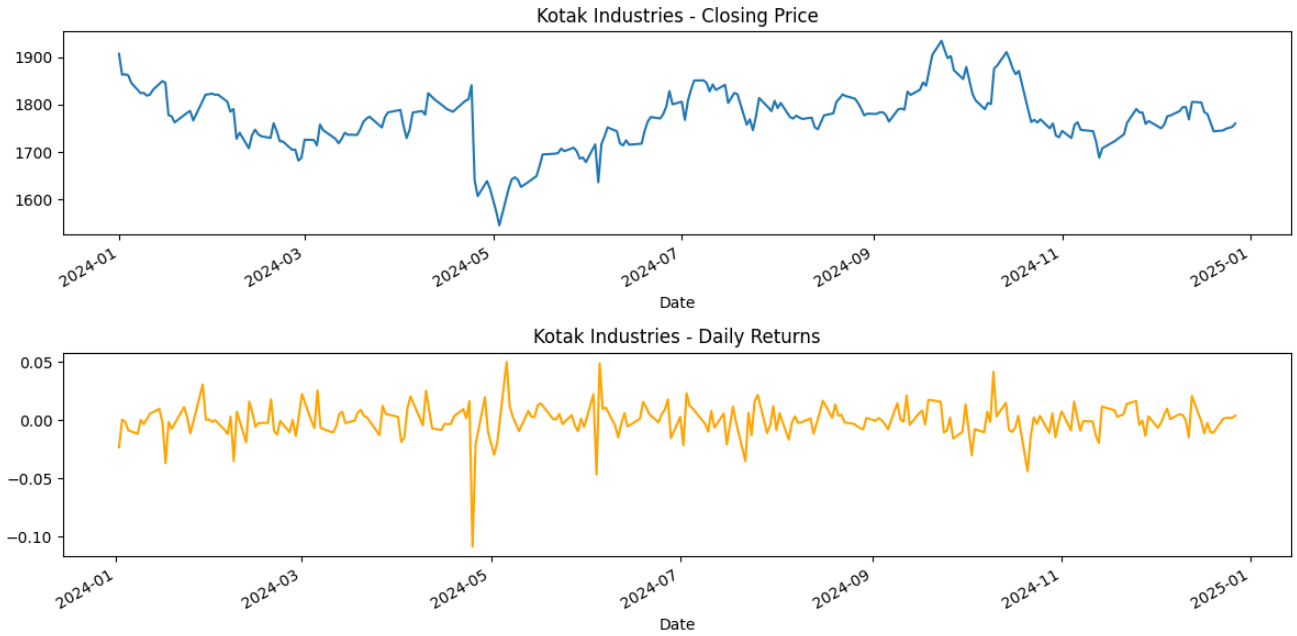
In [46]:

```
kotak_data = data['KOTAKBANK.NS']
kotak_data['Daily Return'] = kotak_data['Close'].pct_change()
print("\nDaily returns for Kotak Industries:")
print(kotak_data['Daily Return'].head())
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
kotak_data['Close'].plot(title="Kotak Industries - Closing Price")
plt.subplot(2, 1, 2)
kotak_data['Daily Return'].plot(title="Kotak Industries - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
```

<ipython-input-46-098de9be386a>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

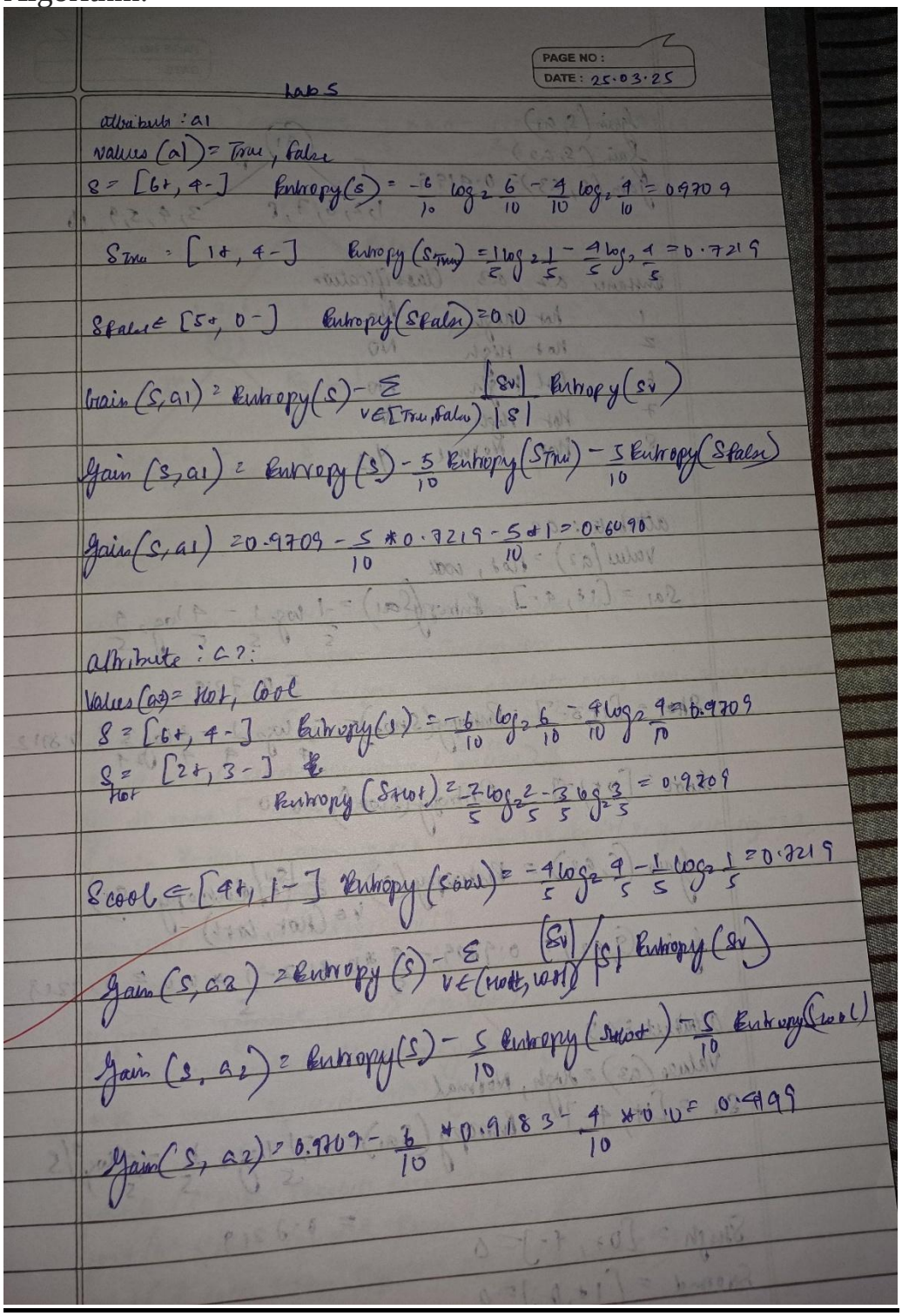
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  kotak_data['Daily Return'] = kotak_data['Close'].pct_change()
Daily returns for Kotak Industries:
Date
2024-01-01   NaN
2024-01-02   -0.023099
2024-01-03   0.000456
2024-01-04   -0.001233
2024-01-05   -0.008586
Name: Daily Return, dtype: float64



Program 3

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

Algorithm:



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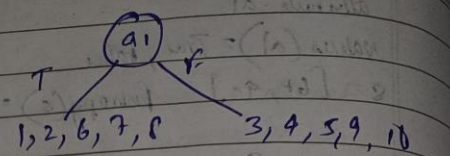
Gain (S, a1)
Gain (S, a2)
Gain (S, a3) = 0.4199



Instance	a2	a3	Classification
1	Not	High	No
2	Not	High	NO
6	Cool	High	No
7	Not	High	No
8	Not	Normal	Yes

attribute : a2
Values (a2) = Not, cool
S_{a1} = [1+, 4-] Entropy(S_{a1}) = $-\frac{1}{5}\log_2\frac{1}{5} - \frac{4}{5}\log_2\frac{4}{5}$

= 0.7219

S_{Not} = [1+, 3-] Entropy(S_{not}) = $-\frac{1}{4}\log_2\frac{1}{4} - \frac{3}{4}\log_2\frac{3}{4}$ = 0.8112

S_{cool} = [0+, 1-] Entropy(S_{cool}) = 0.0

Gain (S, a2) = Entropy(S) − $\sum_{v \in (Not, cool)} \frac{|S_v|}{|S|}$ Entropy(S_v)

Gain (S, a2) = 0.9709 − $\frac{4}{5}$ * 0.8112 − $\frac{1}{5}$ * 0.0 = 0.3219

Attribute : a3
Values (a3) = High, Normal
S_{a1} = [1+, 4-] Entropy(S_{a1}) = $-\frac{1}{5}\log_2\frac{1}{5} - \frac{4}{5}\log_2\frac{2}{5}$

= 0.7219

S_{High} = [0+, 4-] = 0
S_{Normal} = [1+, 0-] = 0

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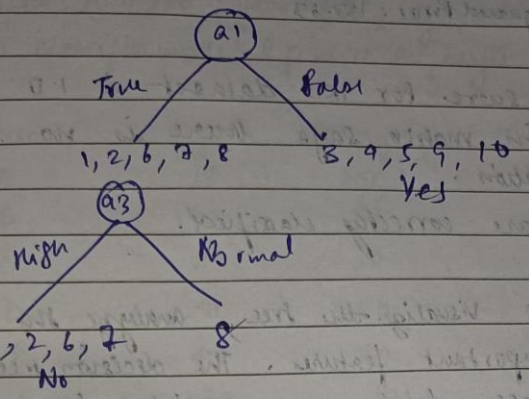
Gain (S, a2) = 0.9709 - $\frac{9}{5}$ * 0.0 - $\frac{1}{5}$ * 0.0 = 0.7219



Code:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
df = pd.read_csv('petrol_consumption.csv')
X = df.drop('Petrol_consumption', axis=1)
y = df[['Petrol_consumption']]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 random_state = 42)
regressor = DecisionTreeRegressor()
regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = mse**0.5
print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"Root Mean Squared Error: {rmse}")
```

Output:

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Mean Absolute Error : 96.2
Mean Squared Error : 10258.2
Root Mean Squared Error : 133.63

(1) The accuracy score for IRIS dataset is 1.0
The confusion matrix says there is no misclassification.
All classes are correctly classified.

(2) We need to visualize the tree, analyze the tree & identify important features. The decision tree classifies discrete class labels are predicted for each instance. The regression tree has continuous value for each instance. It aims to create split that minimize the variance of target variables.

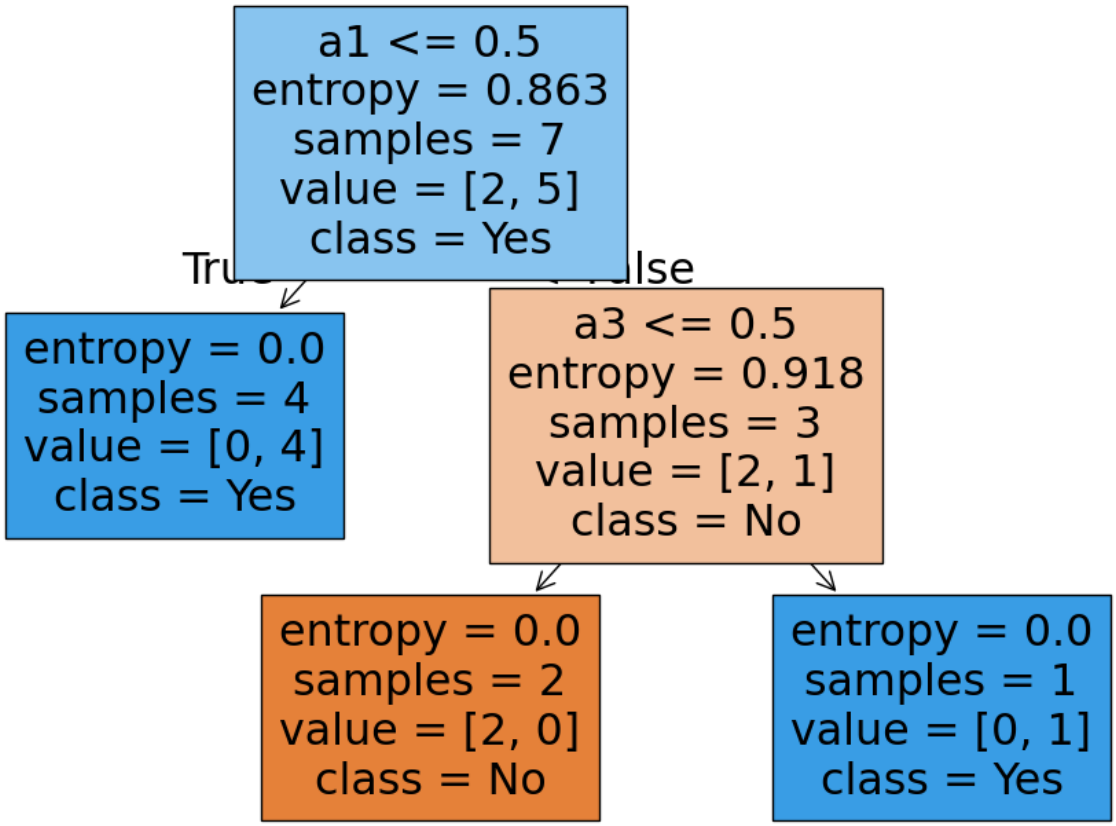
Code:

In [ ]:

```
# -*- coding: utf-8 -*-
"""Decision_Tree.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1RXDK8CR1doVCMHgkaXpJsNLAvzOIaXdd
"""

import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

# Create the dataset
data = {
    'a1': [True, True, False, False, False, True, True, True, False, False],
    'a2': ['Hot', 'Hot', 'Hot', 'Cool', 'Cool', 'Cool', 'Hot', 'Hot', 'Cool', 'Cool'],
    'a3': ['High', 'High', 'High', 'Normal', 'Normal', 'High', 'High', 'Normal', 'Normal', 'High'],
    'Classification': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'No', 'Yes', 'Yes', 'Yes']
}

data

# Convert to DataFrame
df = pd.DataFrame(data)

# Convert categorical data to numerical data
label_encoders = {}
for column in df.columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le

# Split the dataset into features and target
X = df.drop('Classification', axis=1)
y = df['Classification']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize the Decision Tree Classifier with entropy as the criterion
```

```
clf = DecisionTreeClassifier(criterion='entropy')

# Train the classifier
clf.fit(X_train, y_train)

# Make predictions
y_pred = clf.predict(X_test)

# Evaluate the classifier
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print(classification_report(y_test, y_pred, target_names=['No', 'Yes']))

# Optionally, visualize the decision tree
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

plt.figure(figsize=(12,8))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=['No', 'Yes'])
plt.show()
```

```
Accuracy: 1.00
              precision    recall  f1-score   support

          No       1.00      1.00      1.00         2
         Yes       1.00      1.00      1.00         1

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3
```

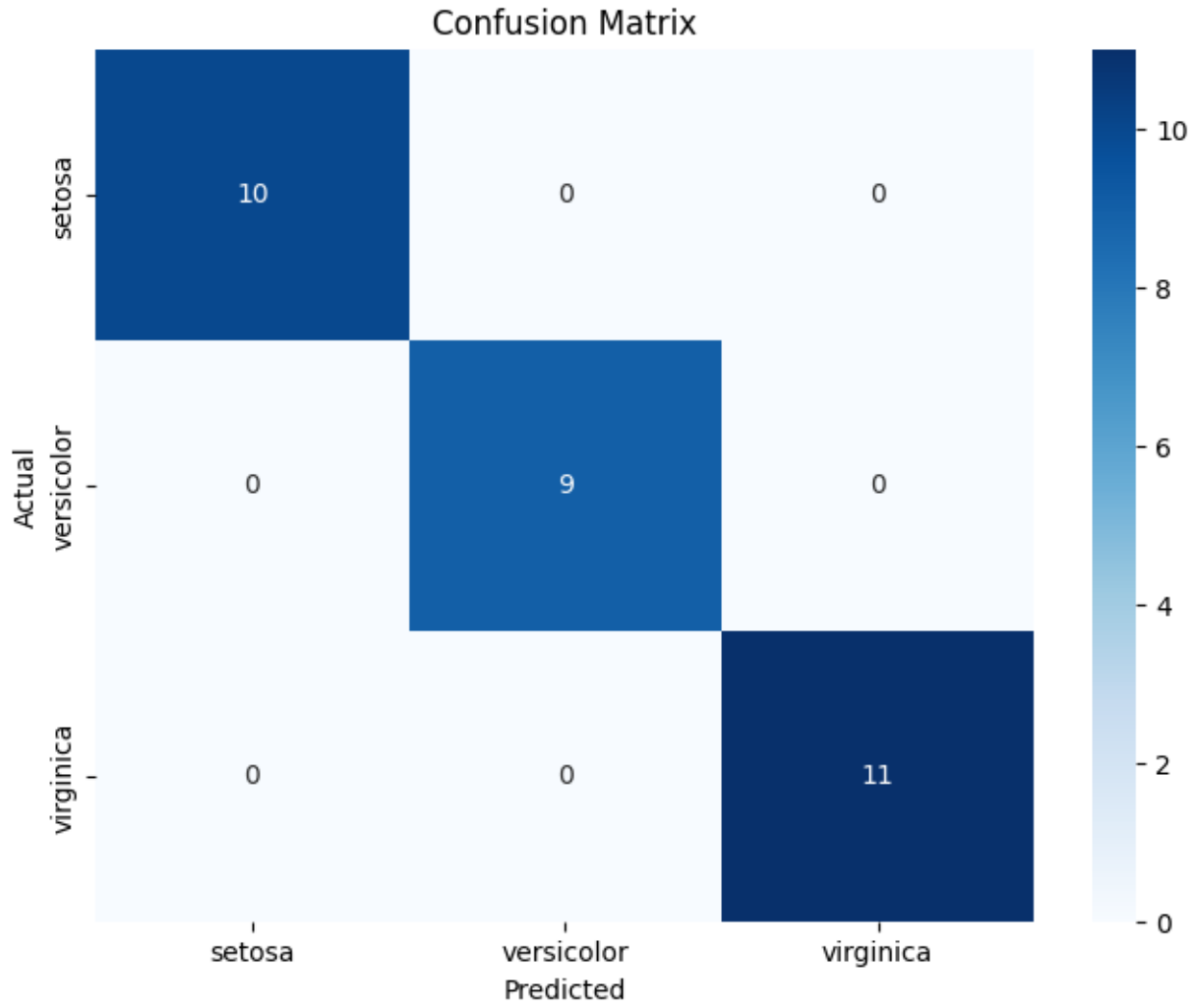


In [ ]:

```
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Load the iris dataset
iris = load_iris()
X = iris.data
y = iris.target

# 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)

# Initialize and train the DecisionTreeClassifier
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)

# Make predictions on the test set
y_pred = clf.predict(X_test)
```

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

# Create and display the confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

Accuracy: 1.0

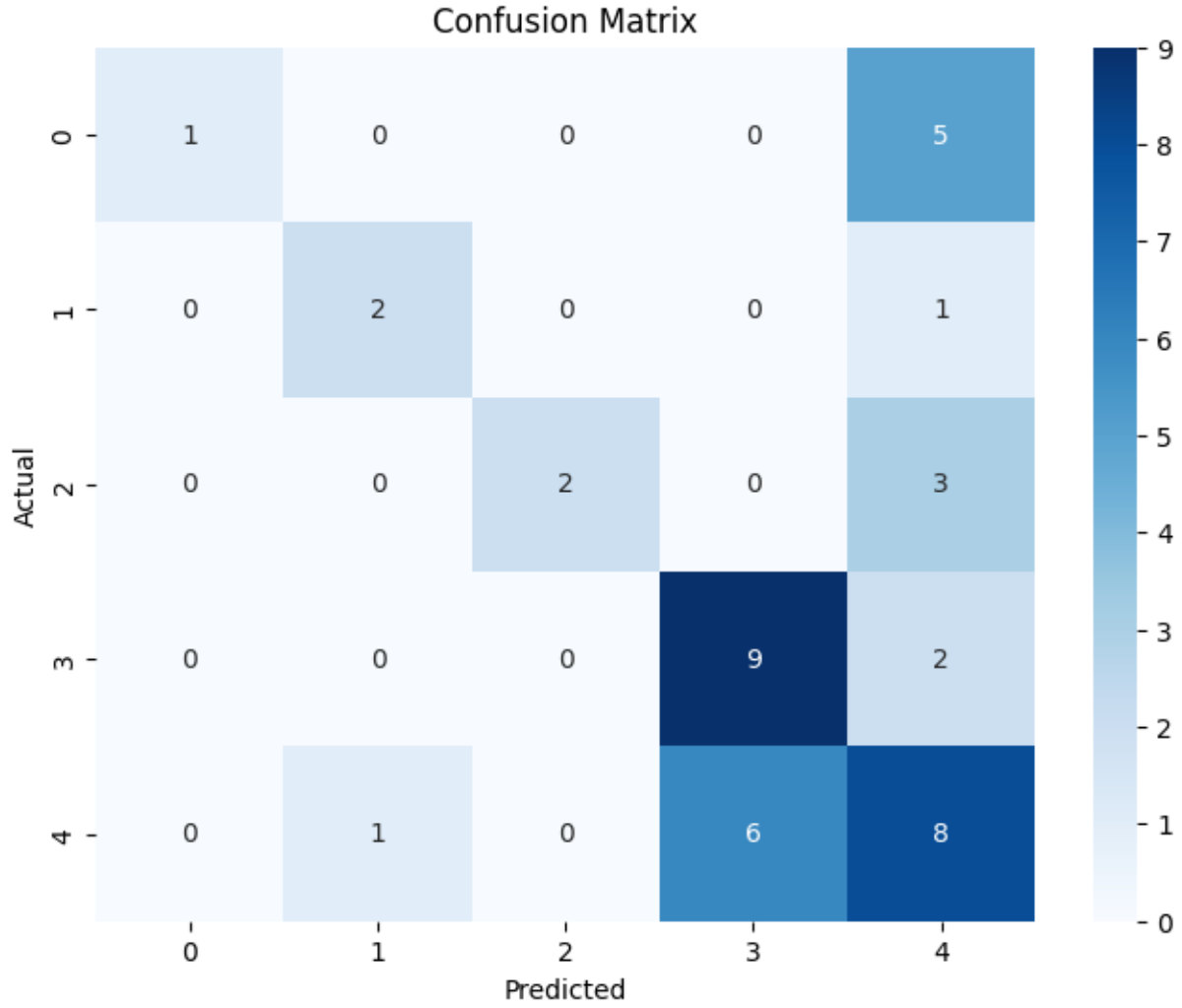


In [ ]:

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

try:
    df = pd.read_csv('drug.csv')
except FileNotFoundError:
    print("Error: 'drugdataset.csv' not found. Please upload the file or provide the correct path.")
    exit()

# Identify categorical columns (replace with your actual column names)
categorical_cols = ['Sex', 'BP', 'Cholesterol', 'Na_to_K']

# Use one-hot encoding for categorical features
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)


# Split data into features (X) and target (y)
X = df.drop('Drug', axis=1)  # Assuming 'Drug' is the target variable
y = df['Drug']

# Split data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the DecisionTreeClassifier
clf = DecisionTreeClassifier()

# Train the classifier
clf.fit(X_train, y_train)

# Make predictions on the test data
y_pred = clf.predict(X_test)

# Calculate the accuracy score
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

# Create and display the confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

Accuracy: 0.55



In [ ]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error

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

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

# Split data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the DecisionTreeRegressor
regressor = DecisionTreeRegressor()
```

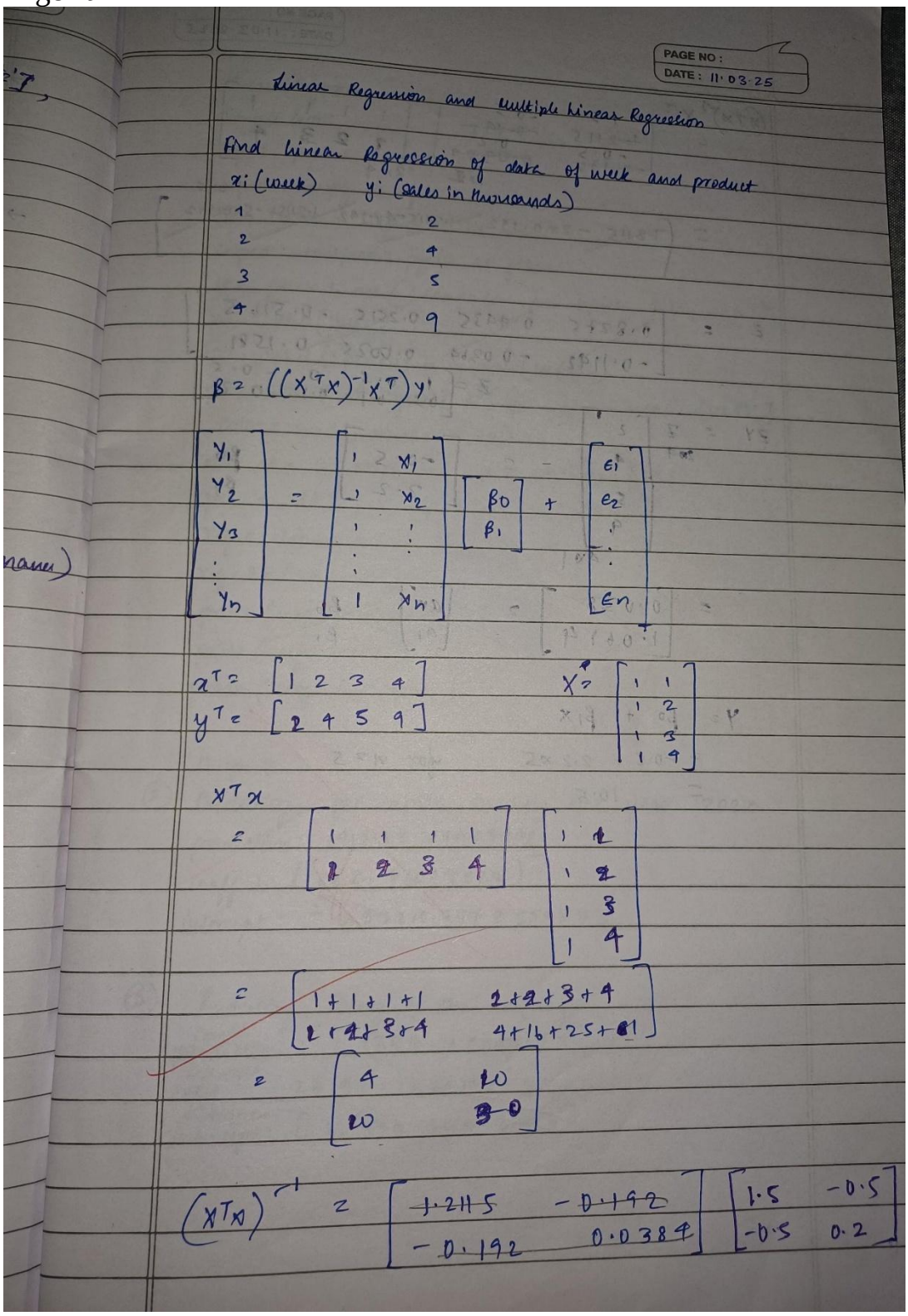
```
# Train the regressor
regressor.fit(X_train, y_train)

# Make predictions on the test data
y_pred = regressor.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = mse**0.5

print(f"Mean Absolute Error: {mae}")
print(f"Mean Squared Error: {mse}")
print(f"Root Mean Squared Error: {rmse}")
```

```
Mean Absolute Error: 96.2
Mean Squared Error: 17858.2
Root Mean Squared Error: 133.63457636405332
```

Program 4

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Algorithm



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$(X^TX)^{-1}X^T$

$$= \begin{bmatrix} 1.5 & -0.5 \\ 1.2115 & -0.192 \\ -0.5 & 0.2 \\ -0.192 & 0.0384 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 2 & 3 & 4 \end{bmatrix}$$

2×2 $\quad$ 2×4

$$= \begin{bmatrix} 1.2115 - 2\times 0.192 & 1.2115 - 4\times 0.192 & 1.2115 + -5\times 0.192 \end{bmatrix}$$

$$Z = \begin{bmatrix} 0.8275 & 0.4935 & 0.2515 & -0.5165 \\ -0.1192 & -0.0384 & 0.0025 & 0.1581 \end{bmatrix}$$

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

$$ZY = \underset{2\times 4}{Z} \begin{bmatrix} 2 \\ 4 \\ 5 \\ 9 \end{bmatrix}_{4\times 1} = \begin{bmatrix} -0.5 \\ 2.2 \end{bmatrix} \quad \begin{matrix} \beta_0 \\ \beta_1 \end{matrix}$$

$$= \begin{bmatrix} 0.038 \\ 1.0614 \end{bmatrix} = \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} \quad \begin{matrix} \beta_0 \\ \beta_1 \end{matrix}$$

$Y = \beta_0 + \beta_1 X$

$= -0.5 + 2.2 \times 5$ $\quad$ for $x = 5$

$= 10.5$

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Linear Regression

Sample code:

```
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt
df = pd.read_csv('cannada_per_capita_income.csv')
plt.xlabel('year')
plt.ylabel('per capita income (US($)')
plt.scatter(df['year'], df['per capita income (US $)'],
 color='red', marker='+')
new_df = df.drop('per capita income (US $)', axis='columns')
price = df['per capita income (US$)']
reg = linear_model.LinearRegression()
reg.fit(new_df, price)
print(reg.predict([[2020]]))
print(reg.coef_)
print(reg.intercept_)
```

Outputs

(I) Predicting per capita income for year 2020

prediction: [41288.69409442]

Coeff : [828.46507522]

intercept : -1632210.7578554575

(II) Predicting Salary of the employee

Coeff prediction: [9398.64060189]

intercept coff: 27197.2020175

Prediction intercept: [139980.88923969]

Multiple Linear Regression

```
import pandas as pd
import numpy as np
from sklearn import linear_model
df = pd.read_csv('1000_Companies.csv')
from sklearn.preprocessing import OrdinalEncoder
ord_enc = OrdinalEncoder()
df["State"] = ord_enc.fit_transform(df[["State"]])
reg = linear_model.LinearRegression()
reg.fit(df.drop('Profit', axis='columns'), df['Profit'])
print(reg.coef_)
print(reg.intercept)
print(reg.predict([[91894.48, 515841.3, 11931.29, 1.0]]))
```

Output

(3) Predicting salary

coff = [0.55389023 1.02672443 0.0805 46.623]

Intercept = -70214.49

predict = [511209.20332292]

(4) Predicting profit

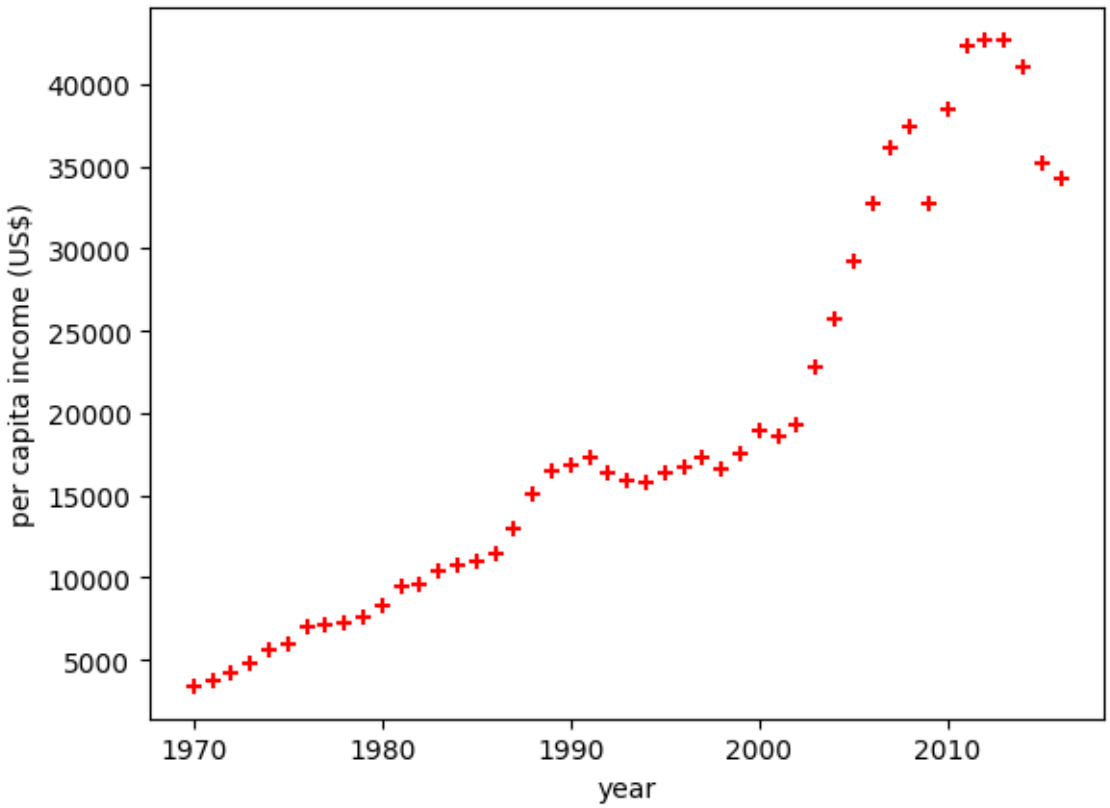
prediction : [45968.51077949]

prediction : [92412.47332889]

Code:

```
# -*- coding: utf-8 -*-
#1. LINEAR_LR
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt

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

# Commented out IPython magic to ensure Python compatibility.
# %matplotlib inline
plt.xlabel('year')
plt.ylabel('per capita income (US$)')
plt.scatter(df['year'],df['per capita income (US$)'],color='red',marker='+')

new_df = df.drop('per capita income (US$)',axis='columns')
new_df

price = df['per capita income (US$)']

# Create linear regression object
reg = linear_model.LinearRegression()
reg.fit(new_df,price)

print(reg.predict([[2020]]))

print(reg.coef_)

print(reg.intercept_)

"""Y = m * X + b (m is coefficient and b is intercept)"""
```

```
[41288.69409442]
[828.46507522]
-1632210.7578554575
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
Out[31]:
'Y = m * X + b (m is coefficient and b is intercept)'
```

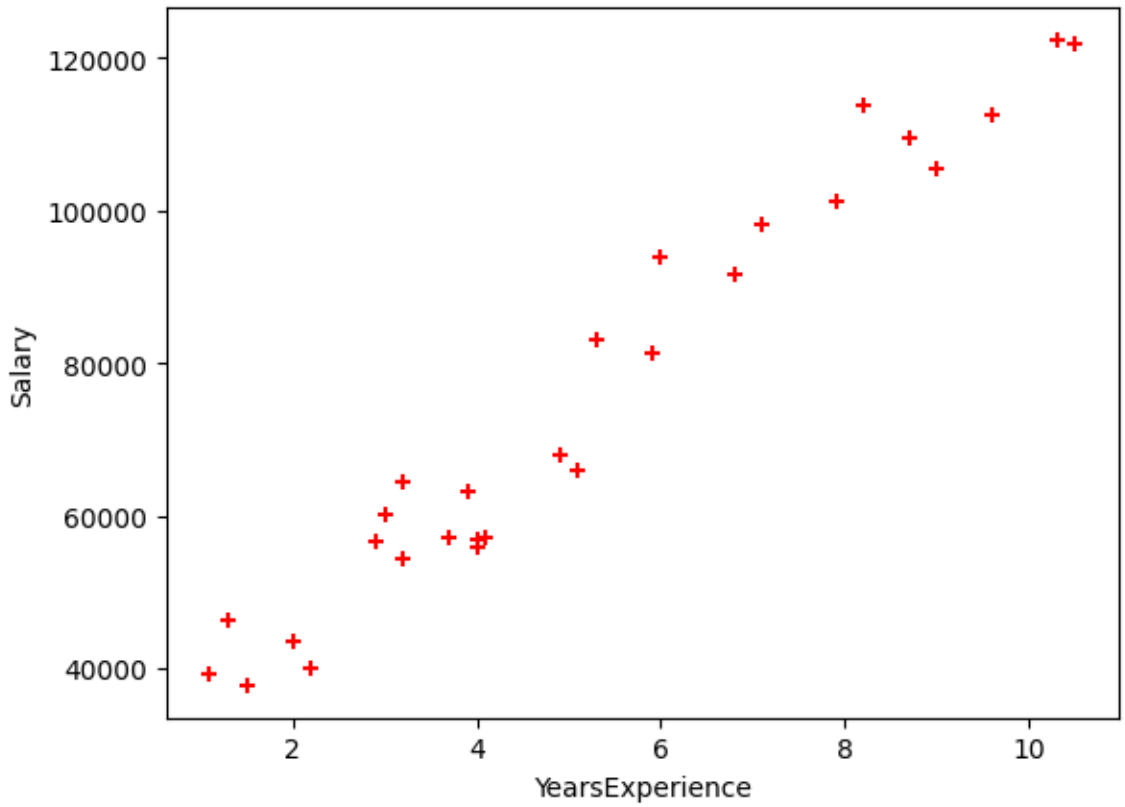


In [15]:

```
# -*- coding: utf-8 -*-
#2. LINEAR_LR
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt

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

# Commented out IPython magic to ensure Python compatibility.
# %matplotlib inline
plt.xlabel('YearsExperience')
plt.ylabel('Salary')
plt.scatter(df['YearsExperience'],df['Salary'],color='red',marker='+')

df['YearsExperience']=df['YearsExperience'].fillna(df['YearsExperience'].mean())
new_df = df.drop('Salary',axis='columns')
new_df

salary = df['Salary']

# Create linear regression object
```

```
reg = linear_model.LinearRegression()
reg.fit(new_df,salary)

reg.predict([[12]])

print(reg.coef_)

print(reg.intercept_)

"""Y = m * X + b (m is coefficient and b is intercept)"""


print(reg.predict([[12]]))
```

```
[9398.64060184]
27197.2020175696
[139980.88923969]
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```



In [17]:

```
!pip install word2number

Collecting word2number
  Downloading word2number-1.1.zip (9.7 kB)
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: word2number
  Building wheel for word2number (setup.py) ... done
  Created wheel for word2number: filename=word2number-1.1-py3-none-any.whl size=5568
sha256=88e1bcbd080599c701a9fbaf1d8af7e1c4b020a078bd8566ebf1efa7804baf89
  Stored in directory:
/root/.cache/pip/wheels/cd/ef/ae/073b491b14d25e2efafcffca9e16b2ee6d114ec5c643ba4f06
Successfully built word2number
Installing collected packages: word2number
Successfully installed word2number-1.1
In [20]:

#1 MULTIPLE_LR
# -*- coding: utf-8 -*-
from word2number import w2n
import pandas as pd
import numpy as np
from sklearn import linear_model

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

"""Data Preprocessing: Fill NA values with median value of a column"""


df.experience = df.experience.bfill()
# df.experience = df.experience.fillna("zero")
# df

df.experience = df.experience.apply(w2n.word_to_num)
# df
df['test_score(out of 10)'] = df['test_score(out of 10)'].fillna(df['test_score(out of 10)'].mean())
# df

reg = linear_model.LinearRegression()
reg.fit(df.drop('salary($)',axis='columns'),df['salary($)'])

reg.coef_

reg.intercept_

print(reg.predict([[2, 9, 6]]))
print(reg.predict([[12, 10, 10]]))
```

[45968.51077949]
[92712.4732389]
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
In [32]:

```
#2. MULTIPLE_LR
import pandas as pd
import numpy as np
from sklearn import linear_model

df = pd.read_csv('1000_Companies.csv')

from sklearn.preprocessing import OrdinalEncoder
ord_enc = OrdinalEncoder()
df["State"] = ord_enc.fit_transform(df[["State"]])

reg = linear_model.LinearRegression()
reg.fit(df.drop('Profit',axis='columns'),df['Profit'])

print(reg.coef_)

print(reg.intercept_)

print(reg.predict([[91694.48, 515841.3, 11931.24,1.0]]))
```

[0.55389023 1.02672443 0.08058525 46.62387015]
-70214.44175560221
[511209.20332292]
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
In [28]:

```
pd.get_dummies(df, columns=["State"]).head()
from sklearn.preprocessing import OrdinalEncoder
ord_enc = OrdinalEncoder()
df["State"] = ord_enc.fit_transform(df[["State"]])
df.head()
```

Out[28]:

	R&D Spend	Administration	Marketing Spend	State	Profit	state_code
0	165349.20	136897.80	471784.10	2.0	192261.83	2.0
1	162597.70	151377.59	443898.53	0.0	191792.06	0.0
2	153441.51	101145.55	407934.54	1.0	191050.39	1.0
3	144372.41	118671.85	383199.62	2.0	182901.99	2.0
4	142107.34	91391.77	366168.42	1.0	166187.94	1.0

In [3]:

```
# -*- coding: utf-8 -*-
"""Multiple_LR_HomePrice.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1fK78C8TPV44HdvT6lsMhaau2wMtKXquQ
"""

import pandas as pd
import numpy as np
from sklearn import linear_model

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

"""Data Preprocessing: Fill NA values with median value of a column"""

df.bedrooms.median()

df.bedrooms = df.bedrooms.fillna(df.bedrooms.median())
df

reg = linear_model.LinearRegression()
reg.fit(df.drop('price',axis='columns'),df.price)

reg.coef_

reg.intercept_

"""Find price of home with 3000 sqr ft area, 3 bedrooms, 40 year old"""

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

```
112.06244194*3000 + 23388.88007794*3 + -3231.71790863*40 + 221323.00186540384

/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not
have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
Out[3]:
498408.25157402386
In [4]:

# -*- coding: utf-8 -*-
"""Linear-Regression-Housing_Area_Price.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1CAlZml-P6V2V1RIrodgMfF8L3Ux4V9FT
"""

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

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

# Commented out IPython magic to ensure Python compatibility.
# %matplotlib inline
plt.xlabel('area')
plt.ylabel('price')
plt.scatter(df.area,df.price,color='red',marker='+')

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

price = df.price
price

# Create linear regression object
reg = linear_model.LinearRegression()
reg.fit(new_df,price)

"""(1) Predict price of a home with area = 3300 sqr ft"""

reg.predict([[3300]])

reg.coef_
```

reg.intercept_

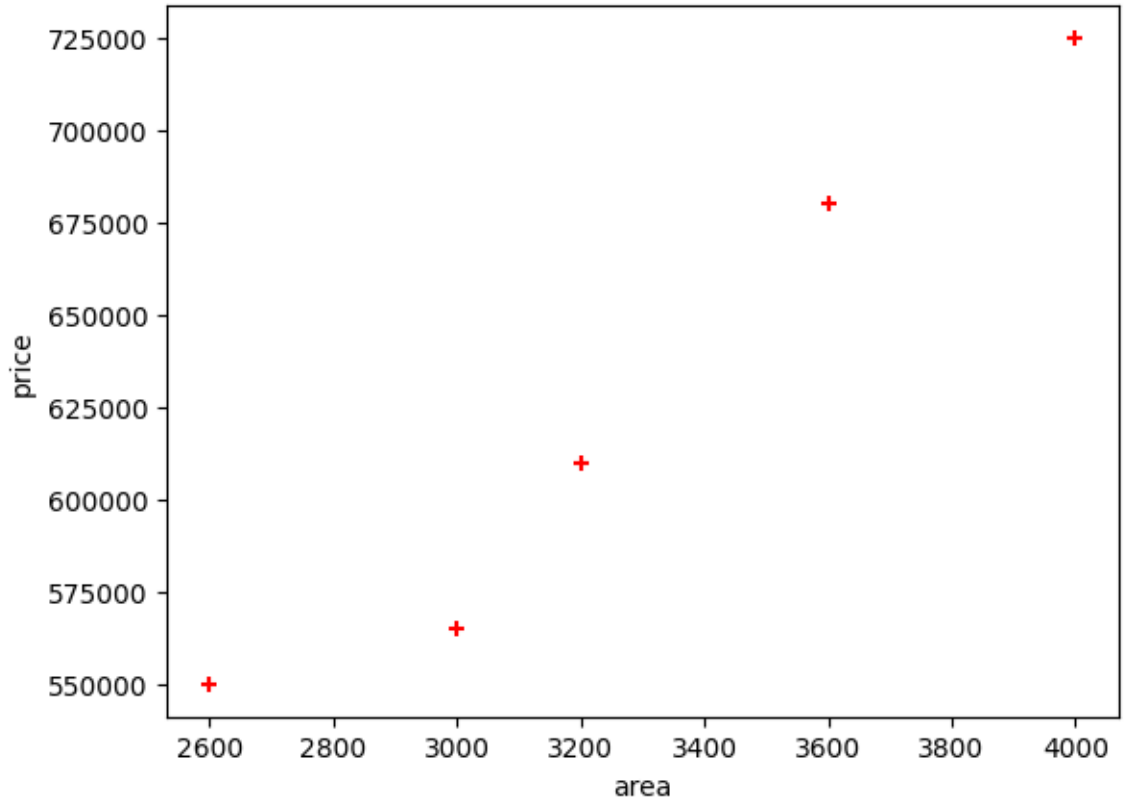
"""Y = m * X + b (m is coefficient and b is intercept)"""

3300*135.78767123 + 180616.43835616432

"""(1) Predict price of a home with area = 5000 sqr ft"""

reg.predict([[5000]])

/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
Out[4]:
array([859554.79452055])

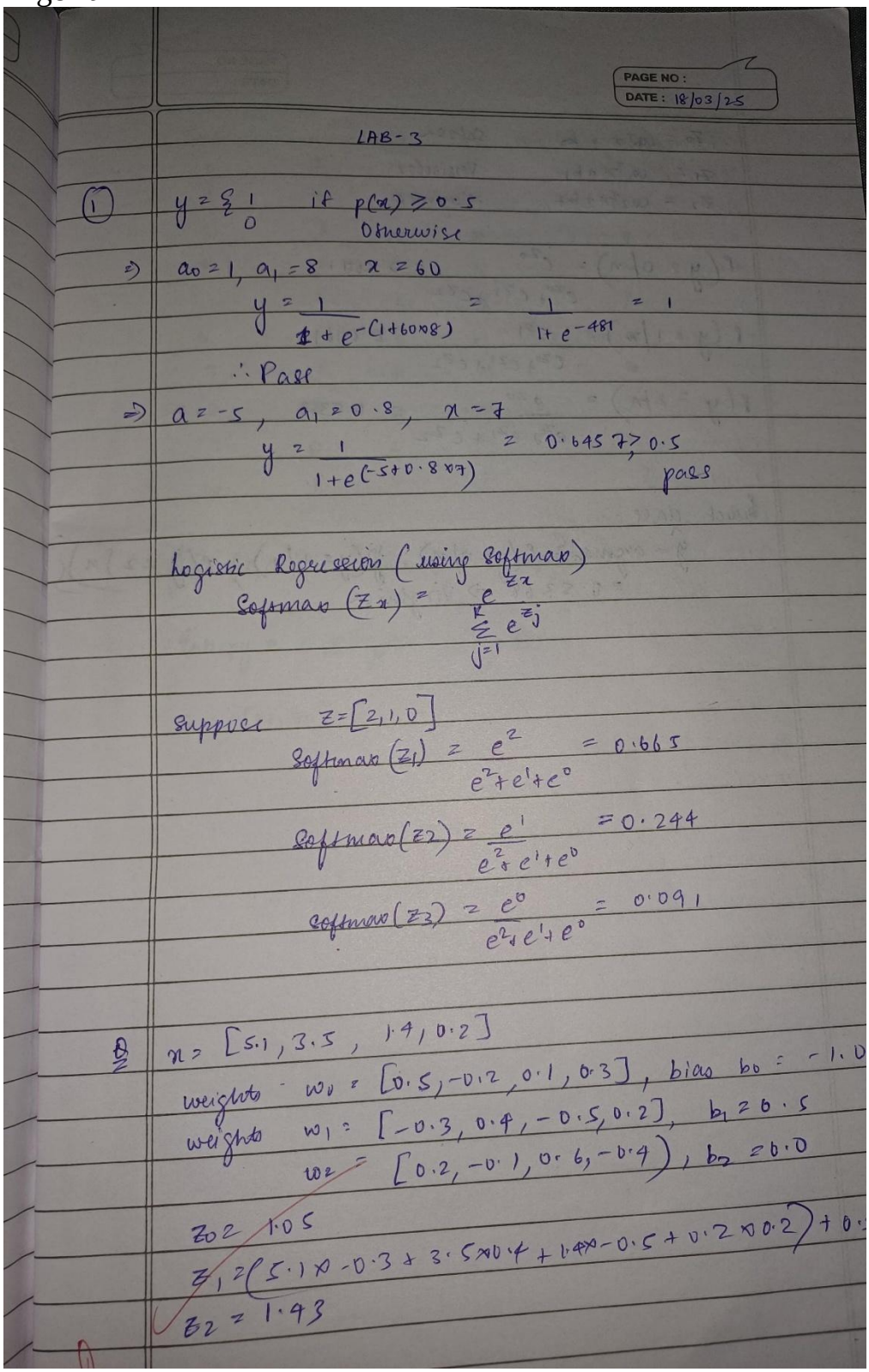


In [ ]:

Program 5

Build Logistic Regression Model for a given dataset

Algorithm



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$z_0 = w_0^T x + b_0$ Setosa

$z_1 = w_1^T x + b_1$ Versicolor

$z_2 = w_2^T x + b_2$ Virginica

$$P(y=0|x) = \frac{e^{z_0}}{e^{z_0} + e^{z_1} + e^{z_2}} = 0.3671$$

$$P(y=1|x) = \frac{e^{z_1}}{e^{z_0} + e^{z_1} + e^{z_2}} = 0.0961$$

$$P(y=2|x) = \frac{e^{z_0}}{e^{z_0} + e^{z_1} + e^{z_2}} = 0.5368$$

Predict class.

$\hat{y} = \text{argmax}\{P(y=0|x), P(y=1|x), P(y=2|x)\}$

$= 0.5368 \Rightarrow$ Virginica

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Logistic Regression - Binary

```
import pandas as pd
from matplotlib import pyplot as plt
df = pd.read_csv("insurance_data.csv")
df.head()
plt.scatter(df.age, df.bought_insurance, marker='+', color='red')
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df[['age']],
df.bought_insurance, train_size=0.9, random_state=10)
X_train.shape
X_test
from sklearn.linear_model import LogisticRegression
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([[60]])
y_predict
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 = 3
prediction_function(age)
```

PAGE NO :
DATE :

0.37 is less than 0.5 which means person with 35 will not buy the insurance

LogisticRegression - Multiclass

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import logisticRegression
from sklearn.metrics import accuracy_score
from sklearn import metrics
import matplotlib.pyplot as plt
iris = pd.read_csv("iris.csv")
iris.head()
X= iris.drop('species', axis = 'columns')
y = iris.species
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2,
random_state = 42)
model = logistic Regression(multi_class='multinomial')
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the Multinomial logistic Regression
model on the test set : {accuracy : .2f}")
confusion_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot = True, fmt = "d", cmap = "Blues",
cbar = False)
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Accuracy of logistic Regression = 100%

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HR-comma-sep.py

(i) Salary and work-satisfaction have a direct impact on employee retention because as per the dataset, employees who have low salary & low satisfaction level have low retention

(ii) The accuracy of the logistic regression model is 79.29%.

Zoo-data.csv

(i) The most frequently misclassified label is mammal according to the confusion matrix

(ii) accuracy of the model = 95.29%.

(iii) The confusion matrix tells that is mostly accurate

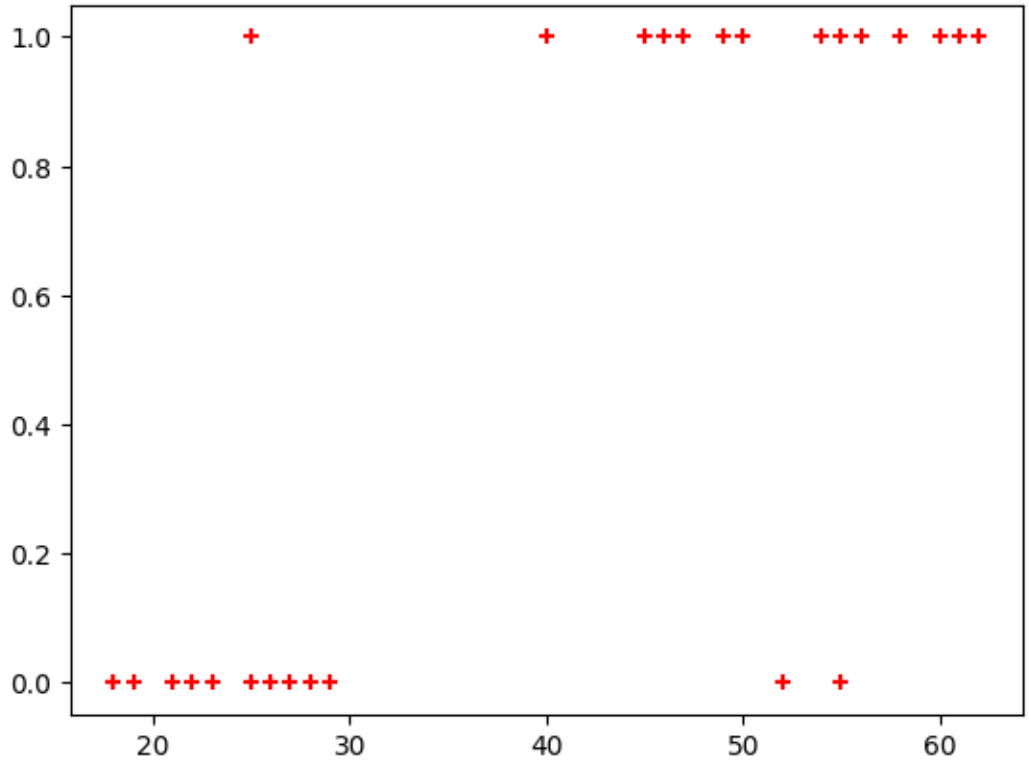
Code:

In [ ]:

```
# -*- coding: utf-8 -*-
"""LogisticRegression_Binary.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1M8PXdcmPsrQtqyVXpET3sgghAMr_MCg5
"""

# Commented out IPython magic to ensure Python compatibility.
import pandas as pd
from matplotlib import pyplot as plt
# %matplotlib inline
#"%matplotlib inline" will make your plot outputs appear and be stored within the notebook.

df = pd.read_csv("insurance_data.csv")
df.head()

plt.scatter(df.age,df.bought_insurance,marker='+',color='red')

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test =
train_test_split(df[['age']],df.bought_insurance,train_size=0.9,random_state=10)
X_train.shape

X_test

from sklearn.linear_model import LogisticRegression
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([[60]])
y_predicted

#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_

#Lets defined sigmoid function now and do the math with hand
import math
def sigmoid(x):
  return 1 / (1 + math.exp(-x))

def prediction_function(age):
   z = 0.127 * age - 4.973 # 0.12740563 ~ 0.0127 and -4.97335111 ~ -4.97
   y = sigmoid(z)
   return y

age = 35
prediction_function(age)

"""0.37 is less than 0.5 which means person with 35 will not buy the insurance"""
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not
have valid feature names, but LogisticRegression was fitted with feature names
  warnings.warn(
Out[ ]:
'0.37 is less than 0.5 which means person with 35 will not buy the insurance'
```

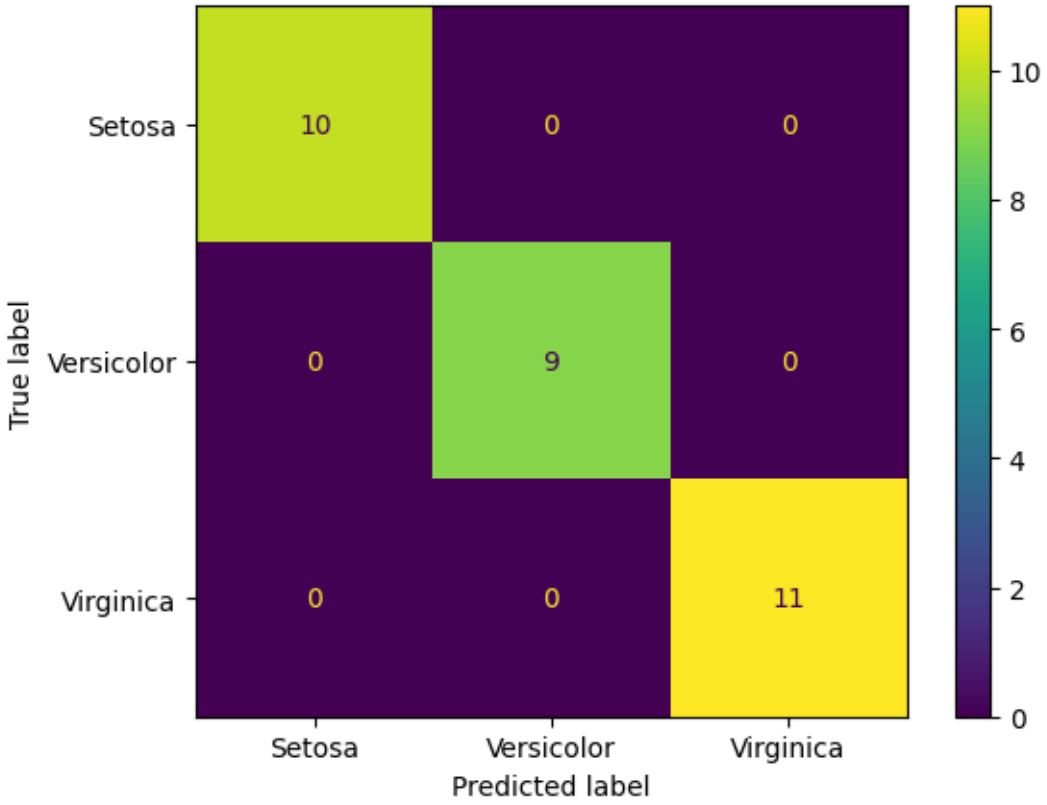


In [ ]:

```
# -*- coding: utf-8 -*-
"""LogisticRegression_Multiclass.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1anBybVXILenh0a_R4aM_ZemLrEqYWnJl
"""

# Import necessary libraries
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn import metrics
import matplotlib.pyplot as plt

# Load the Iris dataset
iris =  pd.read_csv("iris.csv")
iris.head()

X=iris.drop('species',axis='columns')# Features (sepal length, sepal width, petal length, petal width)
y = iris.species # Target labels (0: Setosa, 1: Versicolor, 2: Virginica)
```

```
# 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 Multinomial Logistic Regression model
# Use 'multinomial' for multi-class classification and 'lbfgs' solver
model = LogisticRegression(multi_class='multinomial')

# Train the model on the training data
model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = model.predict(X_test)

# Calculate the accuracy of the model on the test data
accuracy = accuracy_score(y_test, y_pred)

# Display the accuracy
print(f"Accuracy of the Multinomial Logistic Regression model on the test set: {accuracy:.2f}")

confusion_matrix = metrics.confusion_matrix(y_test, y_pred)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels
= ["Setosa", "Versicolor", "Virginica"])

cm_display.plot()
plt.show()
```

```
Accuracy of the Multinomial Logistic Regression model on the test set: 1.00
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:1247: FutureWarning:
'multi_class' was deprecated in version 1.5 and will be removed in 1.7. From then on, it will always
use 'multinomial'. Leave it to its default value to avoid this warning.
  warnings.warn(
```



In [ ]:

```
# Importing necessary libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix

# Load the dataset
df = pd.read_csv('HR_comma_sep.csv')

# 1. Exploratory Data Analysis (EDA)

# Check the first few rows of the dataset
print(df.head())

# Check for missing values
print(df.isnull().sum())

# Describe the dataset (summary statistics)
print(df.describe())

# Check the distribution of 'left' column (Employee Retention: 1 means left, 0 means stayed)
```

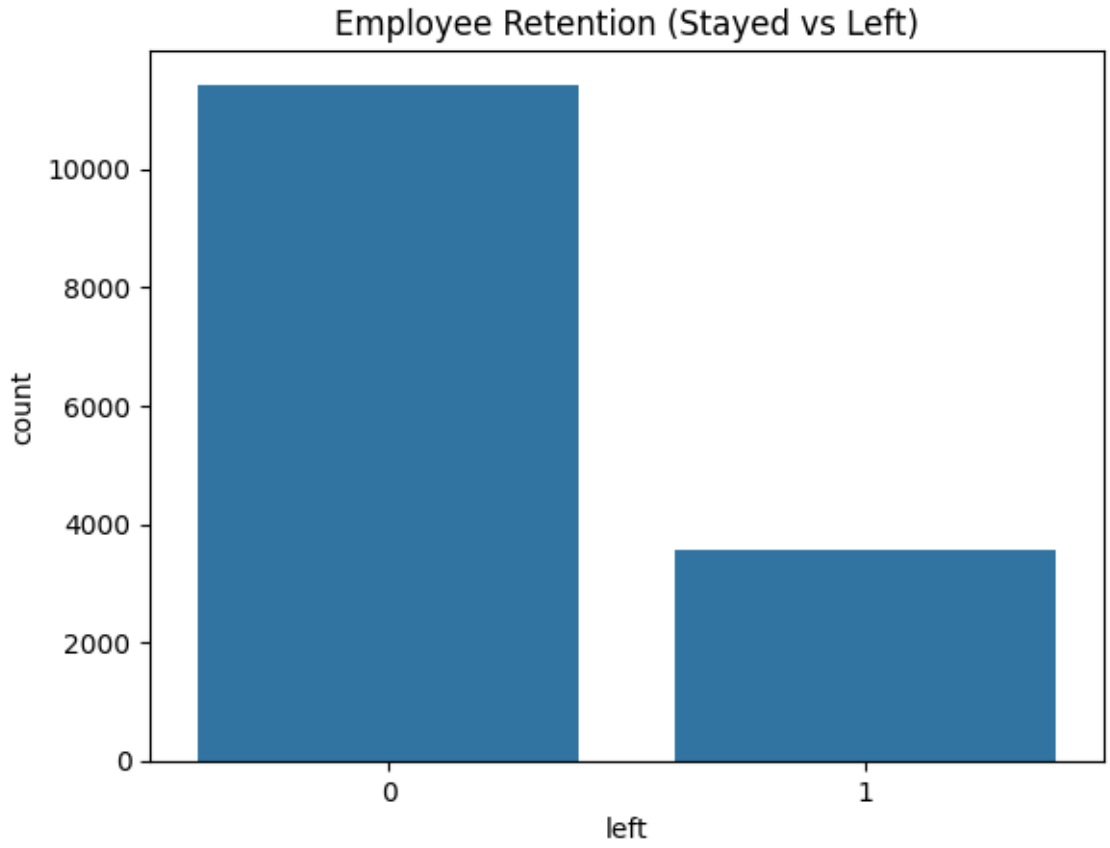
```
sns.countplot(x='left', data=df)
plt.title("Employee Retention (Stayed vs Left)")
plt.show()

# 2. Impact of Employee Salaries on Retention
# Plotting bar chart showing impact of employee salaries on retention
sns.countplot(x='salary', hue='left', data=df)
plt.title("Impact of Employee Salaries on Retention")
plt.show()

# 3. Correlation between Department and Employee Retention
# Plotting bar chart showing correlation between department and retention
sns.countplot(x='Department', hue='left', data=df)
plt.title("Correlation Between Department and Employee Retention")
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.show()

# 4. Build Logistic Regression Model

# Convert categorical columns to numeric using one-hot encoding
df_encoded = pd.get_dummies(df, drop_first=True)

# Split the dataset into features (X) and target (y)
X = df_encoded.drop('left', axis=1)  # Features (drop the 'left' column as it's the target)
y = df_encoded['left']  # Target: whether the employee left (1) or stayed (0)

# Split the data into training and testing sets (80% training, 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
logreg_model = LogisticRegression()

# Fit the model to the training data
logreg_model.fit(X_train, y_train)

# 5. Measure Model Accuracy

# Predict on the test set
y_pred = logreg_model.predict(X_test)

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

# Plot confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", cbar=False)
```

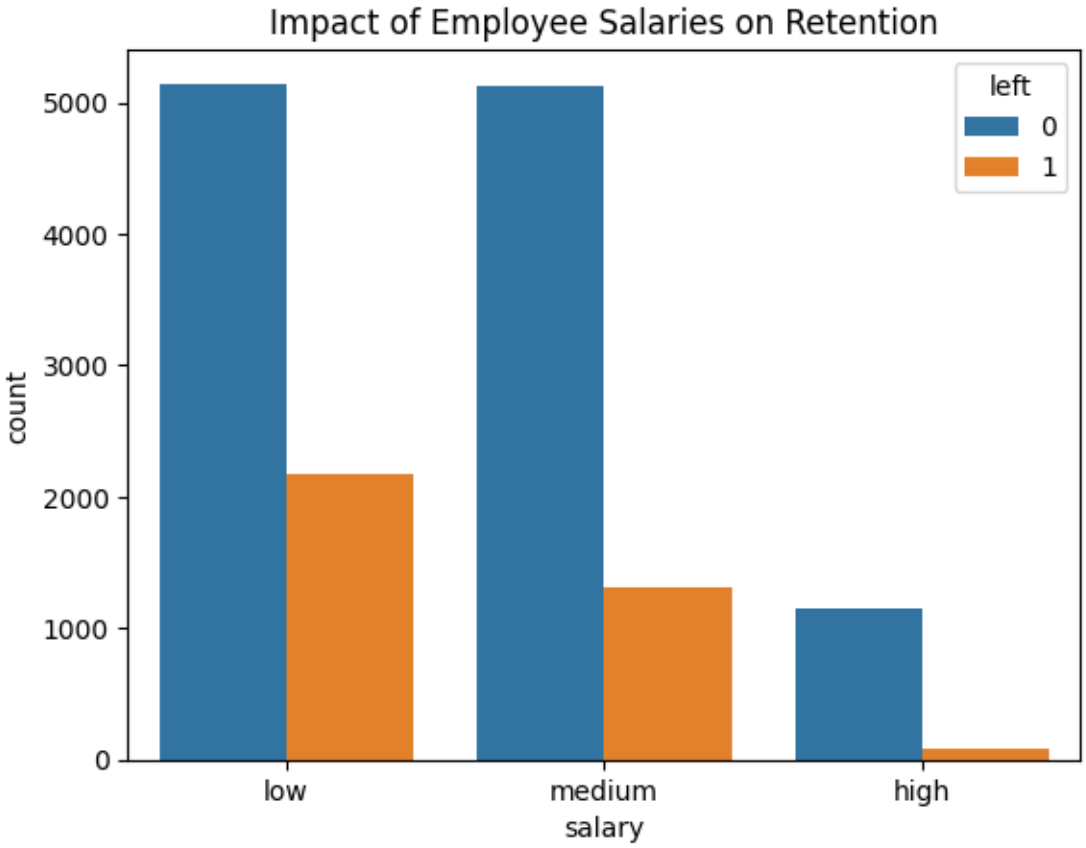
```
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

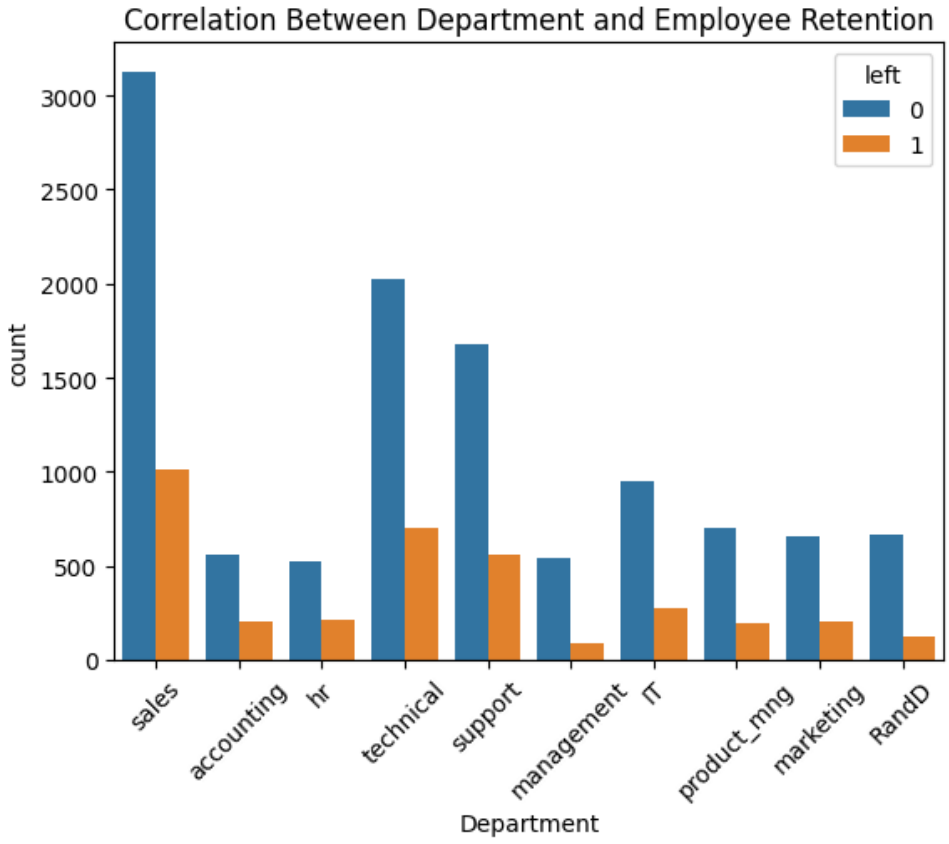
```
   satisfaction_level  last_evaluation  number_project  average_montly_hours  \
0                0.38             0.53               2                   157
1                0.80             0.86               5                   262
2                0.11             0.88               7                   272
3                0.72             0.87               5                   223
4                0.37             0.52               2                   159

   time_spend_company  Work_accident  left  promotion_last_5years Department  \
0                   3              0     1                      0      sales
1                   6              0     1                      0      sales
2                   4              0     1                      0      sales
3                   5              0     1                      0      sales
4                   3              0     1                      0      sales

   salary
0     low
1  medium
2  medium
3     low
4     low
satisfaction_level       0
last_evaluation          0
number_project           0
average_montly_hours     0
time_spend_company       0
Work_accident            0
left                     0
promotion_last_5years    0
Department               0
salary                   0
dtype: int64
       satisfaction_level  last_evaluation  number_project  \
count        14999.000000     14999.000000    14999.000000
mean             0.612834         0.716102        3.803054
std              0.248631         0.171169        1.232592
min              0.090000         0.360000        2.000000
25%              0.440000         0.560000        3.000000
50%              0.640000         0.720000        4.000000
75%              0.820000         0.870000        5.000000
max              1.000000         1.000000        7.000000
```

	average_montly_hours	time_spend_company	Work_accident	left	\
count	14999.000000	14999.000000	14999.000000	14999.000000	
mean	201.050337	3.498233	0.144610	0.238083	
std	49.943099	1.460136	0.351719	0.425924	
min	96.000000	2.000000	0.000000	0.000000	
25%	156.000000	3.000000	0.000000	0.000000	
50%	200.000000	3.000000	0.000000	0.000000	
75%	245.000000	4.000000	0.000000	0.000000	
max	310.000000	10.000000	1.000000	1.000000	

	promotion_last_5years
count	14999.000000
mean	0.021268
std	0.144281
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

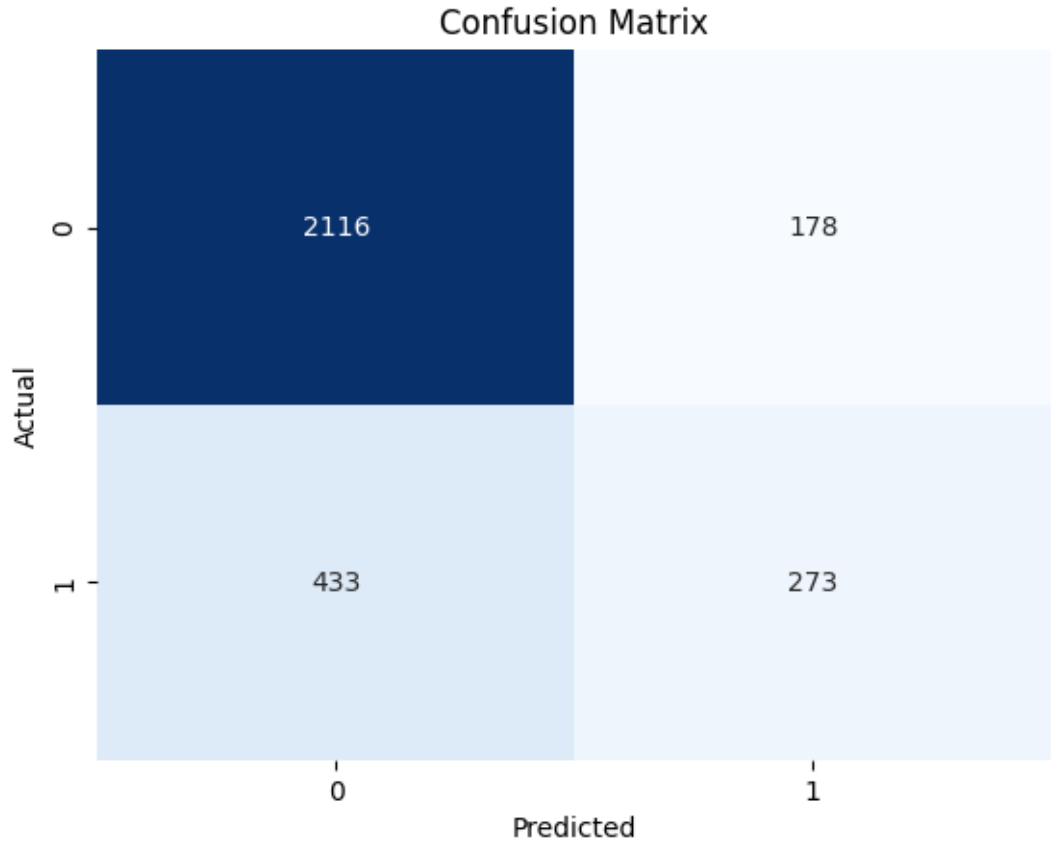



Impact of Employee Salaries on Retention
left
0
1
count
5000
4000
3000
2000
1000
0
low
medium
high
salary


Correlation Between Department and Employee Retention
left
0
1
count
3000
2500
2000
1500
1000
500
0
sales
accounting
hr
technical
support
management
IT
product_mng
marketing
RandD
Department

Accuracy of Logistic Regression Model: 79.63%
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(



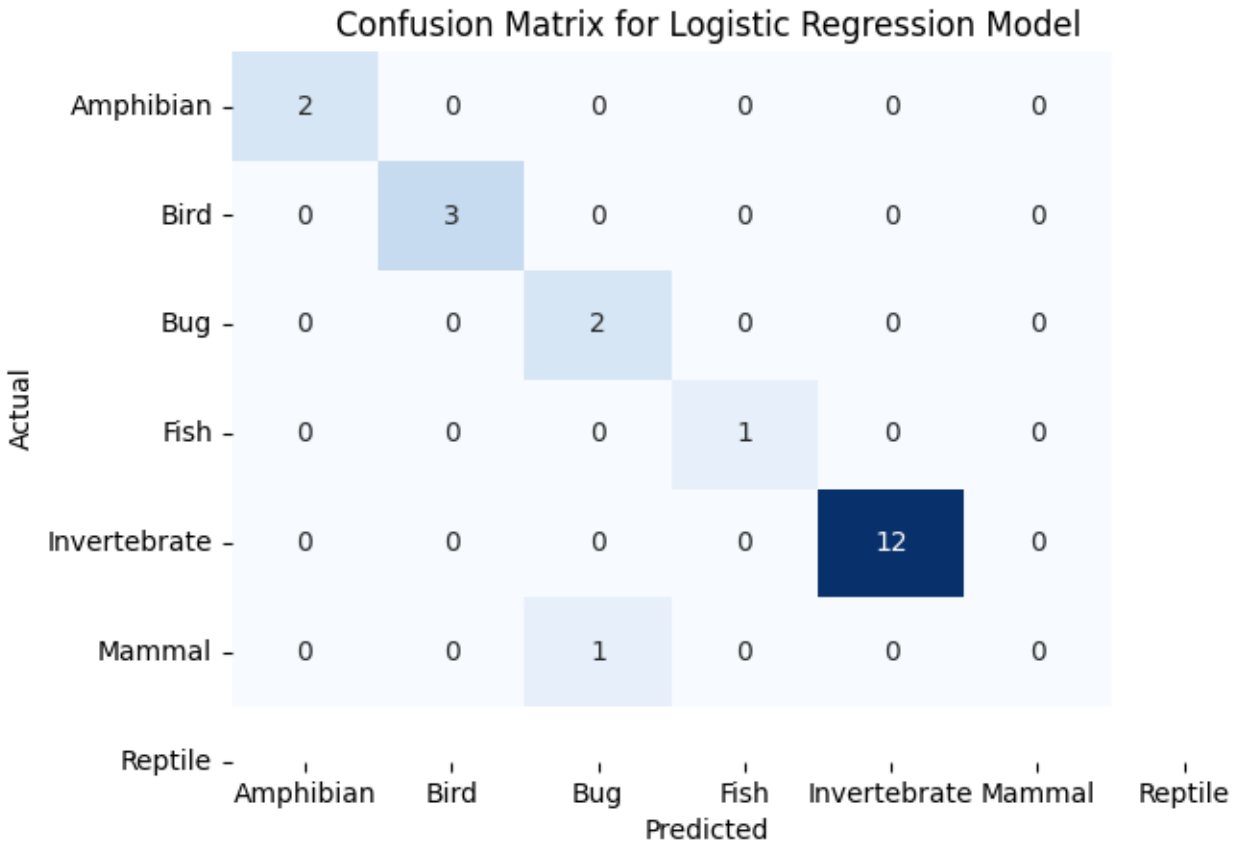
In [ ]:

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

# Load the datasets
zoo_data = pd.read_csv('zoo-data.csv')
class_type = pd.read_csv('zoo-class-type.csv')
```

```
# 1. Data Preprocessing: Merge datasets to get class_type
zoo_data = zoo_data.merge(class_type[['Class_Number', 'Class_Type']], how='left',
left_on='class_type', right_on='Class_Number')

# Drop the unnecessary 'Class_Number' column and keep 'Class_Type' as the target variable
zoo_data.drop(columns=['Class_Number'], inplace=True)

# Check for missing values
print(zoo_data.isnull().sum())

# Since we don't have missing values, we can proceed to encode categorical variables and model
building.

# 2. Feature Engineering: Encode categorical variables
# Here, we'll encode 'class_type' which is now 'Class_Type' into numeric labels using LabelEncoder
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

# Convert 'Class_Type' (target) into numerical labels
zoo_data['Class_Type'] = label_encoder.fit_transform(zoo_data['Class_Type'])

# 3. Split the data into features (X) and target (y)
X = zoo_data.drop(['animal_name', 'class_type', 'Class_Type'], axis=1)  # Features
y = zoo_data['Class_Type']  # Target

# 4. Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# 5. Build Logistic Regression Model
logreg_model = LogisticRegression(max_iter=1000, multi_class='ovr')  # Using 'ovr' for multiclass
classification
logreg_model.fit(X_train, y_train)

# 6. Predictions and Accuracy
y_pred = logreg_model.predict(X_test)

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

# 7. Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plotting Confusion Matrix
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", cbar=False,
xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
plt.title("Confusion Matrix for Logistic Regression Model")
```

```
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
animal_name    0
hair           0
feathers       0
eggs           0
milk           0
airborne       0
aquatic        0
predator       0
toothed        0
backbone       0
breathes       0
venomous       0
fins           0
legs           0
tail           0
domestic       0
catsize        0
class_type     0
Class_Type     0
dtype: int64
Accuracy of Logistic Regression Model: 95.24%
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:1256: FutureWarning:
'multi_class' was deprecated in version 1.5 and will be removed in 1.7. Use
OneVsRestClassifier(LogisticRegression(..)) instead. Leave it to its default value to avoid this
warning.
  warnings.warn(
```

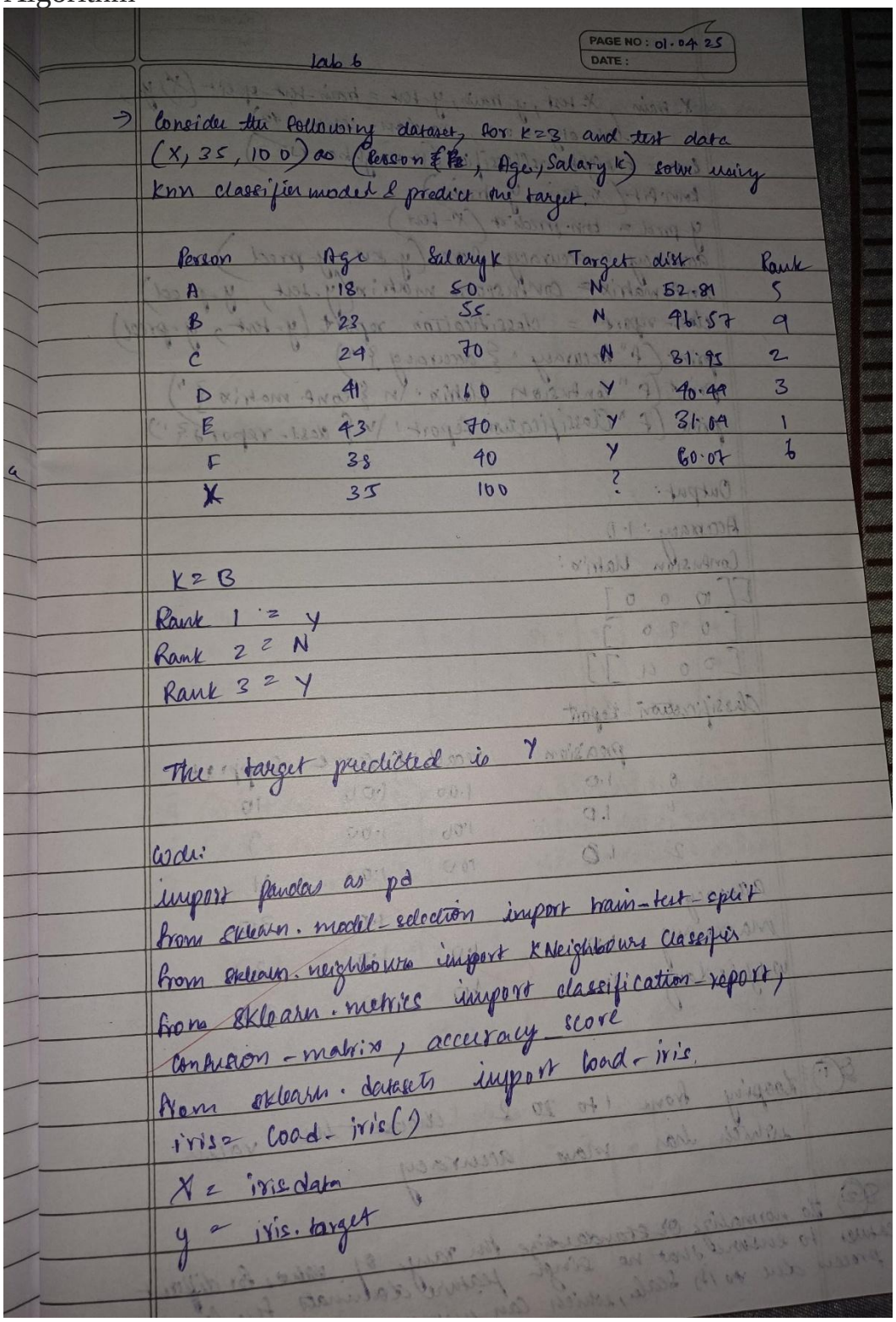

Confusion Matrix for Logistic Regression Model
Amphibian
Bird
Bug
Fish
Invertebrate
Mammal
Reptile
Actual
2 0 0 0 0 0
0 3 0 0 0 0
0 0 2 0 0 0
0 0 0 1 0 0
0 0 0 0 12 0
0 0 1 0 0 0
Amphibian
Bird
Bug
Fish
Invertebrate
Mammal
Reptile
Predicted

In [ ]:

Program 6

Build KNN Classification model for a given dataset.

Algorithm



lab 6

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→ Consider the following dataset for K=3 and test data (X, 35, 100) as (Person ₹, Age, Salary k) solve using knn classifier model & predict the target.

Person	Age	Salary k	Target	dist	Rank
A	18	50	N	52.81	5
B	23	55	N	46.57	9
C	24	70	N	31.95	2
D	41	60	Y	40.49	3
E	43	70	Y	31.04	1
F	38	40	Y	60.07	6
X	35	100	?		

K = 6

Rank 1 = Y
Rank 2 = N
Rank 3 = Y

The target predicted is Y

Code:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbours import KNeighboursClassifier
from sklearn.metrics import classification_report,
confusion_matrix, accuracy_score
from sklearn.datasets import load_iris
iris = load_iris()
X = iris.data
y = iris.target
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
    test_size = 0.2, random_state = 42)
knn = KNeighborsClassifier(n_neighbours=3)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
print(f"Accuracy: {accuracy}")
print(f"Confusion Matrix: \n{conf_matrix}")
print(f"Classification Report: \n{class_report}")
```

Output:

Accuracy: 1.0

Confusion Matrix:

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

Classification Report

	precision	recall	f1-score	support
0	1.0	1.00	1.00	10
1	1.0	1.00	1.00	9
2	1.0	1.00	1.00	11
accuracy			1.0	30
macro avg	1.0	1.0	1.0	30
weighted avg	1.0	1.0	1.0	30

(1) Looping from 1 to 20 & choose the value which has max accuracy

(2) To normalize or standardize the range of values for different features to ensure that no single feature dominates the learning process due to its scale, which can improve model performance

Code

IRIS DATASET
In [3]:

```
import pandas as pd

# Assuming the uploaded file is named 'iris.csv'
file_path = 'iris.csv'  # The path to your uploaded file

# Load the dataset into a pandas DataFrame
df = pd.read_csv(file_path)

# Display the first few rows to ensure the dataset loaded correctly
print(df.head())

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.preprocessing import LabelEncoder

# Assuming the dataset has columns: sepal_length, sepal_width, petal_length, petal_width, species
X = df[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']]  # Features
y = df['species']  # Target label

# Encode the target labels (species) if needed
le = LabelEncoder()
y = le.fit_transform(y)

# Split the data 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)

# Create and train the KNN model
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

# Make predictions on the test set
y_pred = knn.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

# Print results
print("Accuracy:", accuracy)
print("Confusion Matrix:\n", conf_matrix)
```

```
print("Classification Report:\n", class_report)
```

```
   sepal_length  sepal_width  petal_length  petal_width species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
3           4.6          3.1           1.5          0.2  setosa
4           5.0          3.6           1.4          0.2  setosa
Accuracy: 1.0
Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         9
           2       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
```

DIABETES PREDICTION

In [4]:

```
import pandas as pd
import numpy as np
```

In [5]:

```
data = pd.read_csv("diabetes.csv")
data.head()
```

Out[5]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [20]:

```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X = pd.DataFrame(sc_X.fit_transform(data_copy.drop(["Outcome"], axis
=1),),columns=['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin','BMI',
'DiabetesPedigreeFunction', 'Age'])
```

In [21]:

```
X.head()
```

Out[21]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	0.639947	0.865108	-0.033518	0.670643	-0.181541	0.166619	0.468492	1.425995
1	-0.844885	-1.206162	-0.529859	-0.012301	-0.181541	-0.852200	-0.365061	-0.190672
2	1.233880	2.015813	-0.695306	-0.012301	-0.181541	-1.332500	0.604397	-0.105584
3	-0.844885	-1.074652	-0.529859	-0.695245	-0.540642	-0.633881	-0.920763	-1.041549
4	-1.141852	0.503458	-2.680669	0.670643	0.316566	1.549303	5.484909	-0.020496

In [22]:

```
y =data_copy.Outcome
```

In [23]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1/3, random_state = 42, stratify=y)
```

In [24]:

```
from sklearn.neighbors import KNeighborsClassifier

train_scores = []
test_scores = []

for i in range(1,15):
    knn = KNeighborsClassifier(i)
    knn.fit(X_train, y_train)
    train_scores.append(knn.score(X_train, y_train))
    test_scores.append(knn.score(X_test, y_test))
```

In [25]:

```
max_test_score =max(test_scores)
```

In [26]:

```
test_score_index = [i for i, v in enumerate(test_scores) if v== max_test_score]

print('Max test score {} % and k = {}'.format(max_test_score*100,list(map(lambda x: x+1,
test_score_index))))
```

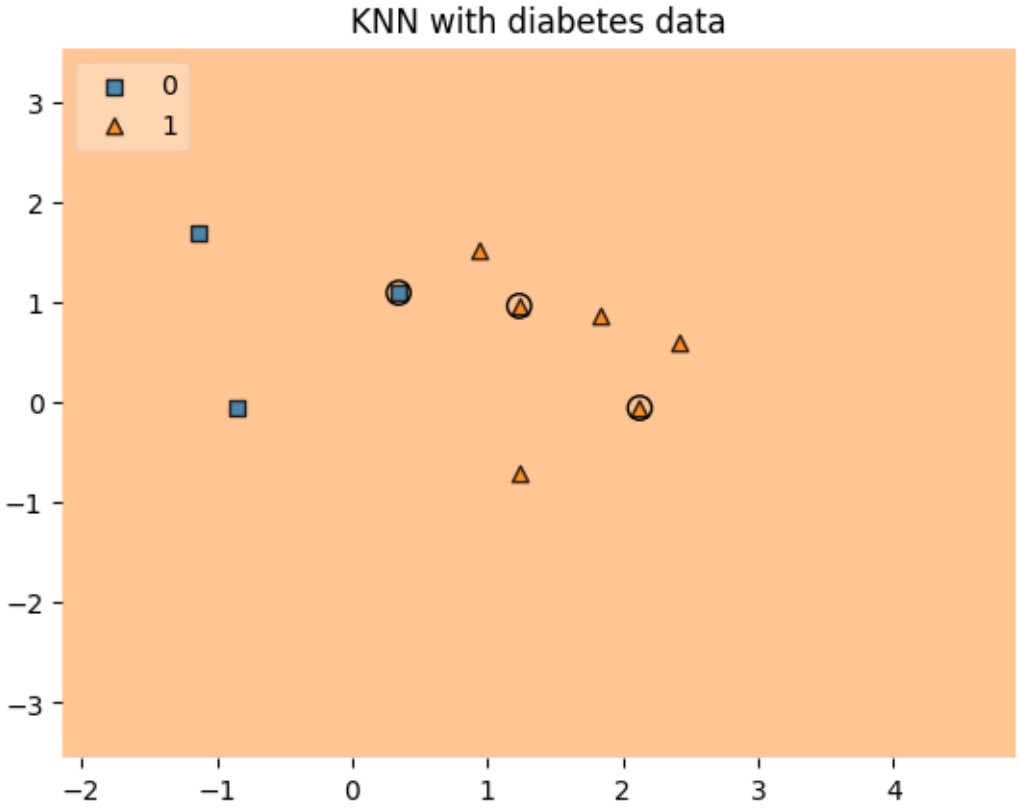
Max test score 76.5625 % and k = [11]
In [28]:

```
# K=11
#Setup a knn classifier with k neighbors
knn = KNeighborsClassifier(11)

knn.fit(X_train,y_train)
knn.score(X_test,y_test)
```

Out[28]:
0.765625
In [29]:

```
from mlxtend.plotting import plot_decision_regions
value = 20000
width  =20000

plot_decision_regions(X.values, y.values, clf = knn, legend =2,filler_feature_values={2: value, 3:
value, 4: value, 5: value, 6: value, 7: value},
                      filler_feature_ranges={2: width, 3: width, 4: width, 5: width, 6: width, 7: width},
                      X_highlight=X_test.values)
plt.title("KNN with diabetes data")
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not
have valid feature names, but KNeighborsClassifier was fitted with feature names
  warnings.warn(
```



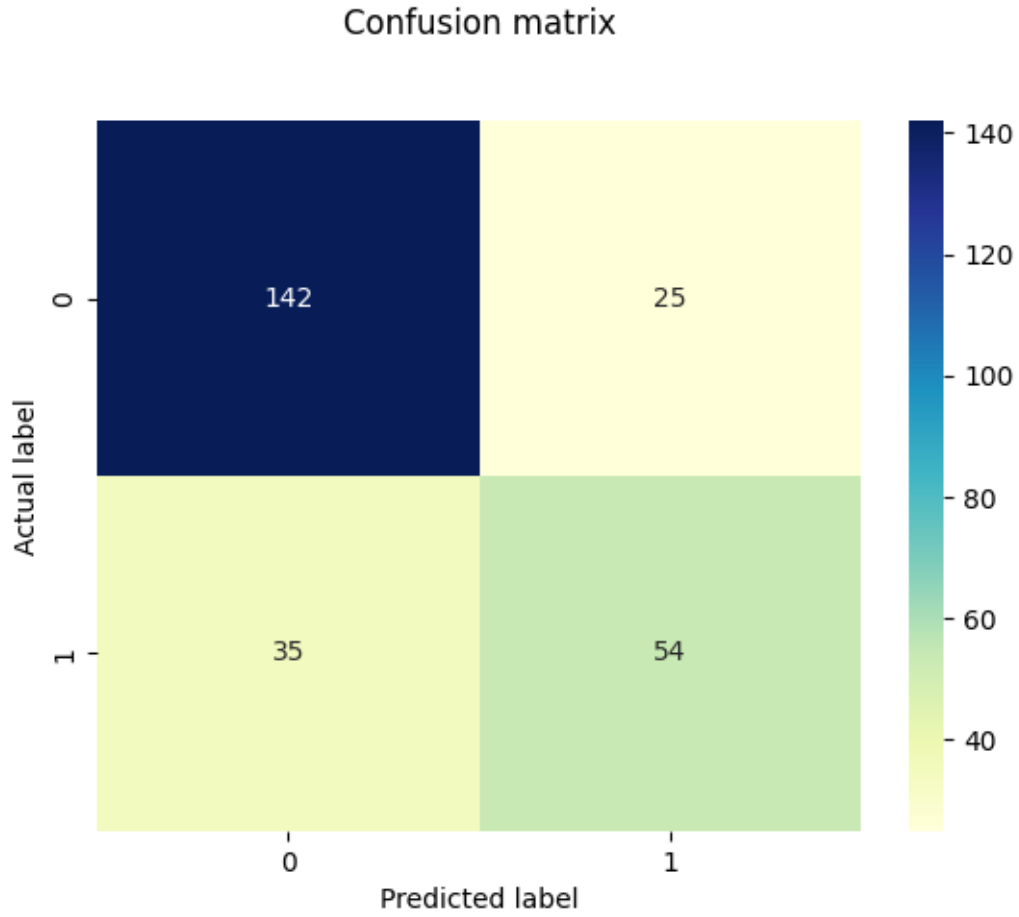
In [30]:

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, fbeta_score
y_pred = knn.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
```

In [31]:

```
p = sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[31]:
Text(0.5, 23.52222222222222, 'Predicted label')



In [32]:

```
def model_evaluation(y_test, y_pred, model_name):
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    f2 = fbeta_score(y_test, y_pred, beta = 2.0)

    results = pd.DataFrame([[model_name, acc, prec, rec, f1, f2]],
                           columns = ["Model", "Accuracy", "Precision", "Recall",
                                      "F1 SCore", "F2 Score"])
    results = results.sort_values(["Precision", "Recall", "F2 Score"], ascending = False)
    return results
```

model_evaluation(y_test, y_pred, "KNN")

Out[32]:

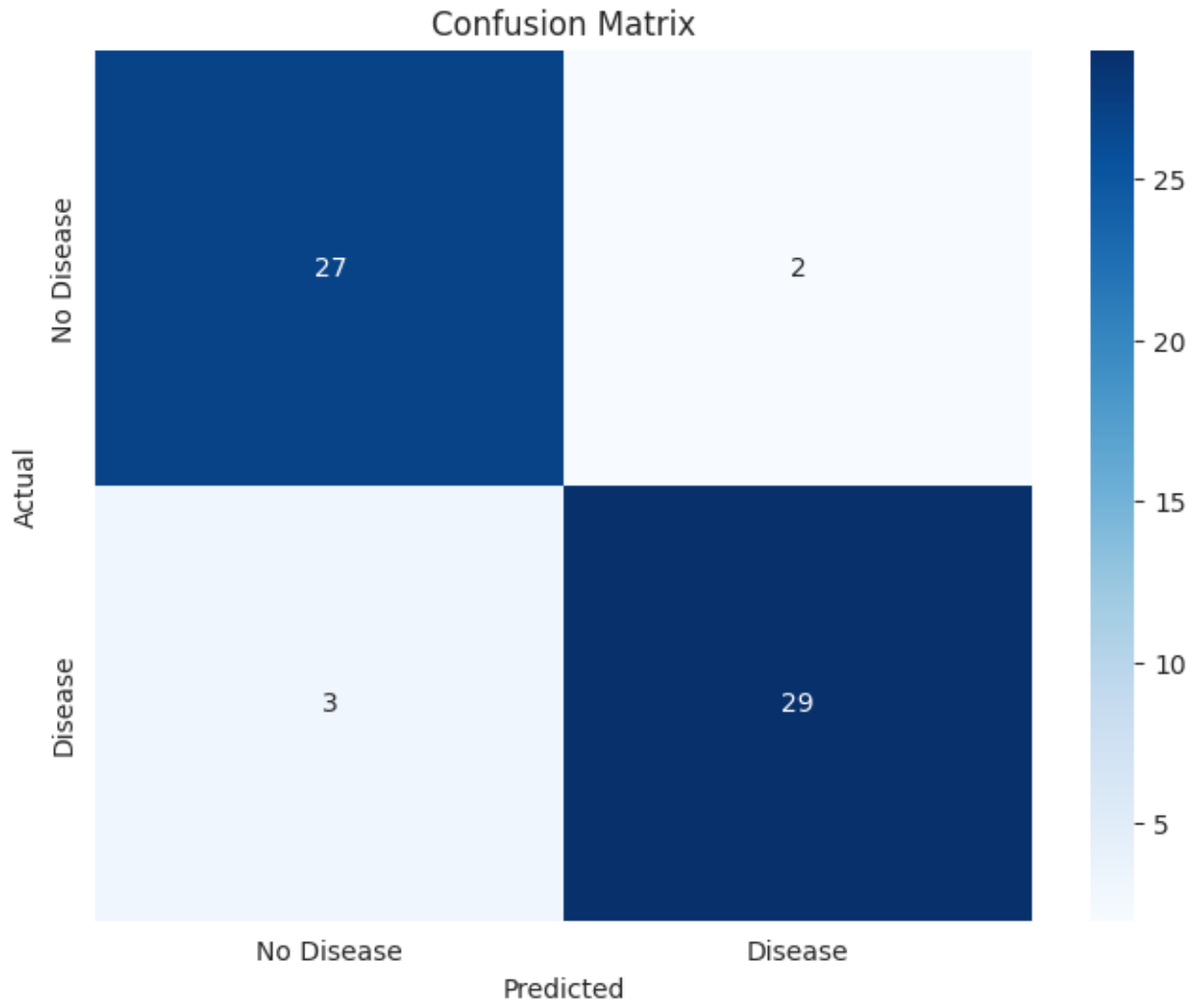
	Model	Accuracy	Precision	Recall	F1 SCore	F2 Score
0	KNN	0.765625	0.683544	0.606742	0.642857	0.62069

HEART DISEASE PREDICTION
In [62]:

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

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

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

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

# Find the best k value
best_k = 1
best_accuracy = 0
for k in range(1, 31):  # Test k values from 1 to 30
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_k = k

print(f"Best k: {best_k}")
```

```
# Train the KNN classifier with the best k value
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)

# Make predictions
y_pred = knn.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

# Display results
print(f"Accuracy: {accuracy}")
print(f"Confusion Matrix:\n{conf_matrix}")
print(f"Classification Report:\n{class_report}")

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['No Disease', 'Disease'],
            yticklabels=['No Disease', 'Disease'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Plot classification report (text-based, can't be plotted directly)
print("Classification Report:\n", class_report)
```

```
Best k: 7
Accuracy: 0.9180327868852459
Confusion Matrix:
[[27  2]
 [ 3 29]]
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
```



Classification Report:

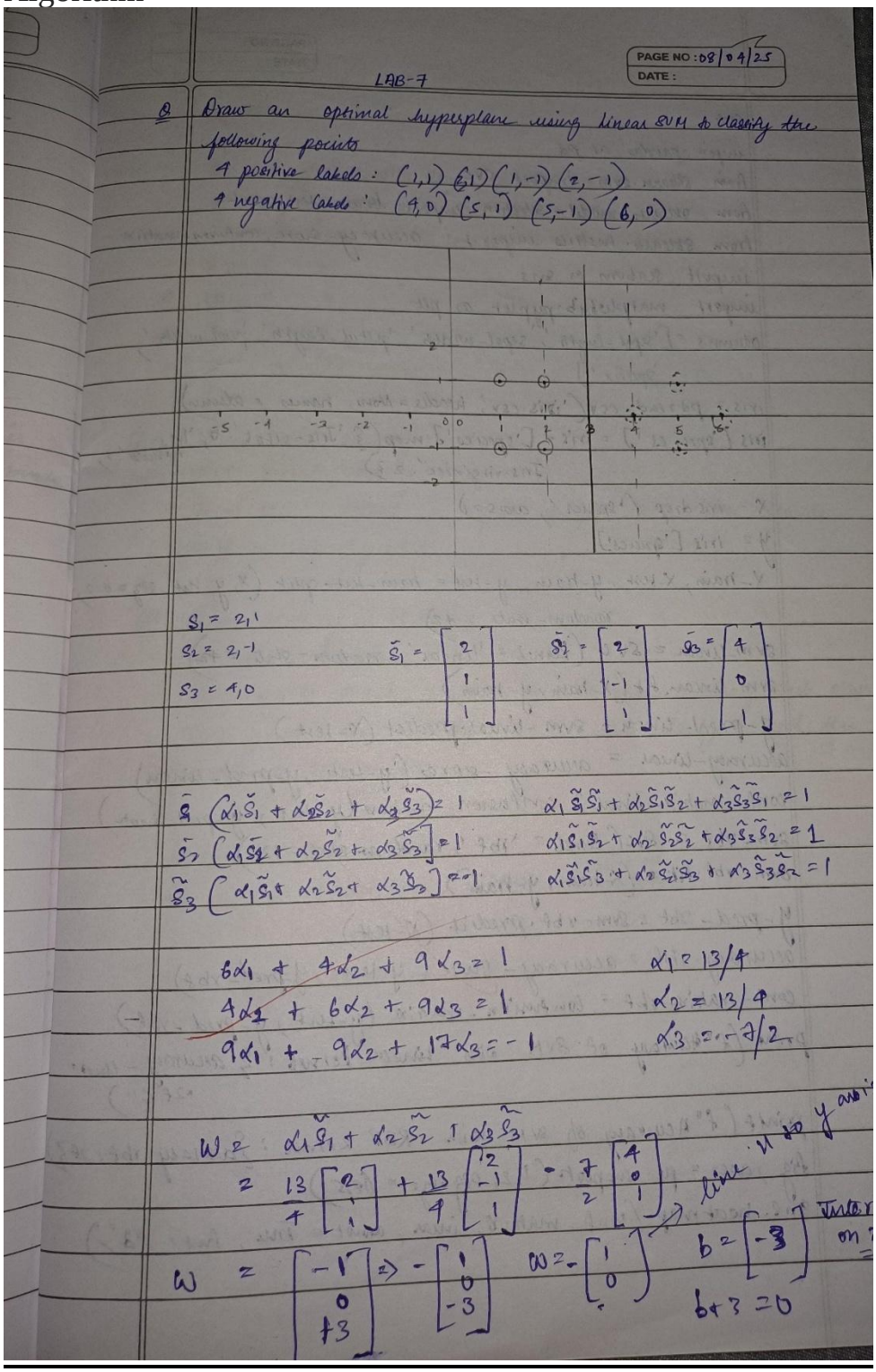
	precision	recall	f1-score	support
0	0.90	0.93	0.92	29
1	0.94	0.91	0.92	32
accuracy			0.92	61
macro avg	0.92	0.92	0.92	61
weighted avg	0.92	0.92	0.92	61

In [ ]:

Program 7

Build Support vector machine model for a given dataset

Algorithm



code

```
import pandas as pd
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width',
           'species']
iris = pd.read_csv('iris.csv', header = None, names = columns)
iris['species'] = iris['species'].map({'Iris-setosa': 0, 'Iris-versicolor': 1,
                                       'Iris-virginica': 2})
X = iris.drop('species', axis=1)
y = iris['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                   random_state = 42)
svm_linear = SVC(kernel = 'linear', random_state = 42)
svm_linear.fit(X_train, y_train)
y_pred_linear = svm_linear.predict(X_test)
accuracy_linear = accuracy_score(y_test, y_pred_linear)
conf_matrix_linear = confusion_matrix(y_test, y_pred_linear)
svm_rbf = SVC(kernel = 'rbf', random_state = 42)
svm_rbf.fit(X_train, y_train)
y_pred_rbf = svm_rbf.predict(X_test)
accuracy_rbf = accuracy_score(y_test, y_pred_rbf)
conf_matrix_rbf = confusion_matrix(y_test, y_pred_rbf)
print(f"Accuracy of SVM with Linear Kernel: {accuracy_linear:.2f}")
print(f"Accuracy of SVM with RBF Kernel: {accuracy_rbf:.2f}")
fig, axes = plt.subplots(1, 2, figsize = (12,5))
sns.heatmap(conf_matrix_linear, annot = True, fmt = "d",
```

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plt.show()

Output:

Accuracy of SVM with Linear Kernel : 1.00

Accuracy of SVM with RBF Kernel : 1.00

Confusion Matrix - Linear

	0	1	2
0	10	0	0
1	0	9	0
2	0	0	11

(1) Linear Kernel accuracy : 1.00

RBF Kernel accuracy : 1.00

Since the dataset is quite simple the both datasets performed equally well.

(2) Overall accuracy is 85.45%.

Common confusions:

C, Q, O, G or I, J, L, T show more confusion among each other. These pairs are visually similar, which likely leads the model to classify them.

Average AUC score : 0.987

Its a good performance across all letters in datasets

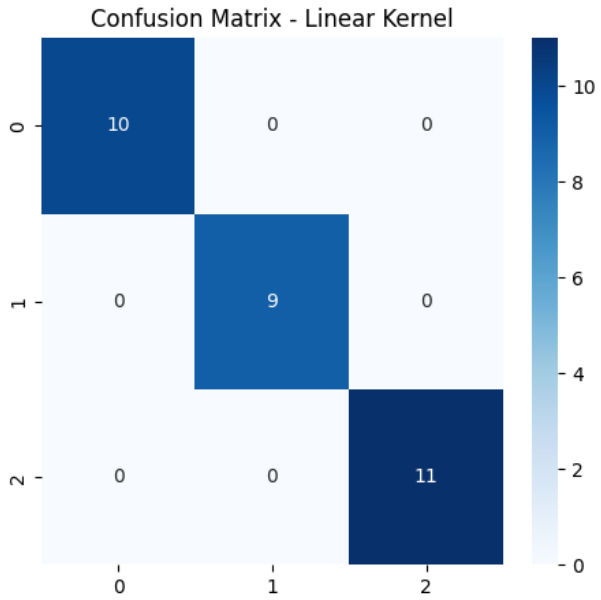
Code:

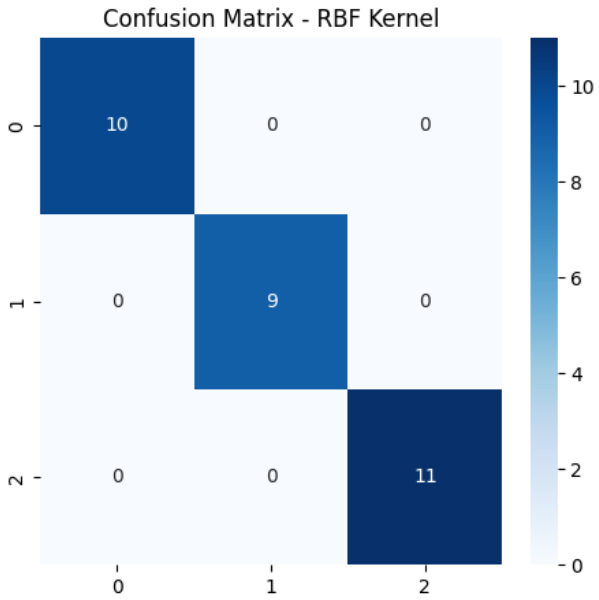
In [23]:

```
# Import necessary libraries
import pandas as pd
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# URL of the Iris dataset (adjust this URL if needed)
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"

# Column names as the dataset contains headers now
columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'species']

# Load the dataset from the URL into a pandas DataFrame
iris = pd.read_csv(url, header=None, names=columns)

# Map the species names to numeric values (for classification)
iris['species'] = iris['species'].map({'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2})

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

# Split data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train SVM with a linear kernel
svm_linear = SVC(kernel='linear', random_state=42)
svm_linear.fit(X_train, y_train)

# Predict and calculate accuracy for the linear kernel model
y_pred_linear = svm_linear.predict(X_test)
accuracy_linear = accuracy_score(y_test, y_pred_linear)
conf_matrix_linear = confusion_matrix(y_test, y_pred_linear)

# Initialize and train SVM with RBF kernel
```

```
svm_rbf = SVC(kernel='rbf', random_state=42)
svm_rbf.fit(X_train, y_train)

# Predict and calculate accuracy for the RBF kernel model
y_pred_rbf = svm_rbf.predict(X_test)
accuracy_rbf = accuracy_score(y_test, y_pred_rbf)
conf_matrix_rbf = confusion_matrix(y_test, y_pred_rbf)

# Display accuracy scores
print(f"Accuracy of SVM with Linear Kernel: {accuracy_linear:.2f}")
print(f"Accuracy of SVM with RBF Kernel: {accuracy_rbf:.2f}")

# Plot confusion matrices for both models
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Linear Kernel Confusion Matrix
sns.heatmap(conf_matrix_linear, annot=True, fmt="d", cmap="Blues",
xticklabels=iris['species'].unique(),
        yticklabels=iris['species'].unique(), ax=axes[0])
axes[0].set_title('Confusion Matrix - Linear Kernel')

# RBF Kernel Confusion Matrix
sns.heatmap(conf_matrix_rbf, annot=True, fmt="d", cmap="Blues",
xticklabels=iris['species'].unique(),
        yticklabels=iris['species'].unique(), ax=axes[1])
axes[1].set_title('Confusion Matrix - RBF Kernel')

plt.show()
```

```
Accuracy of SVM with Linear Kernel: 1.00
Accuracy of SVM with RBF Kernel: 1.00
```





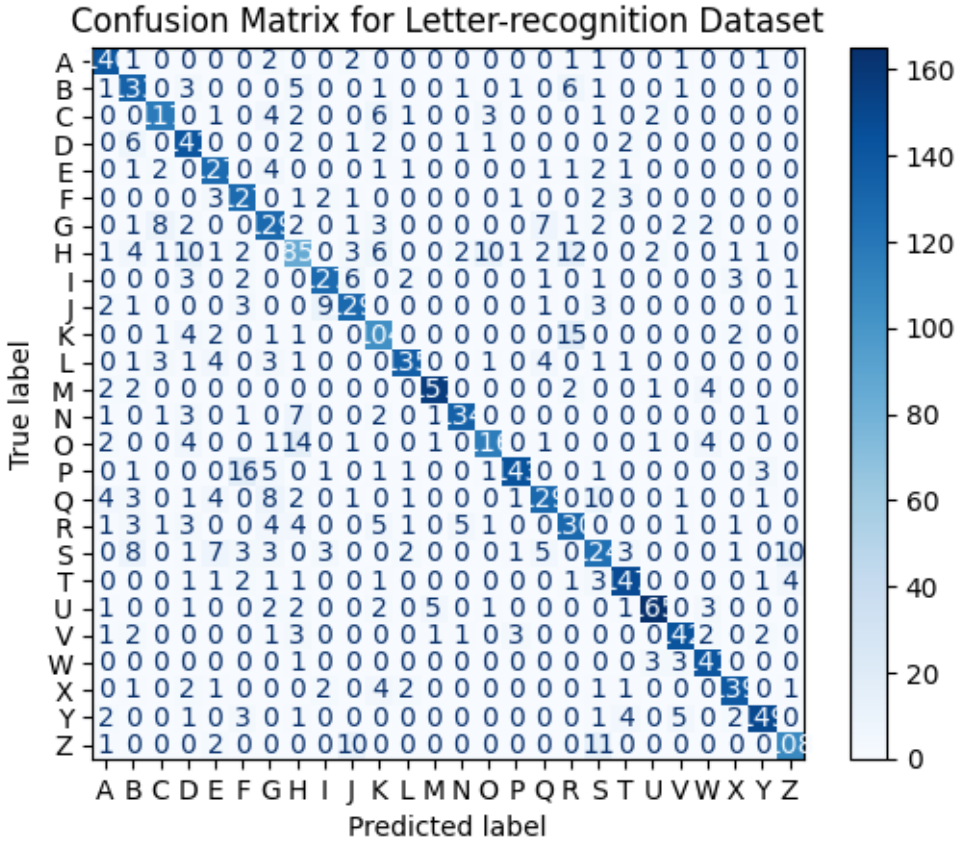
In [21]:

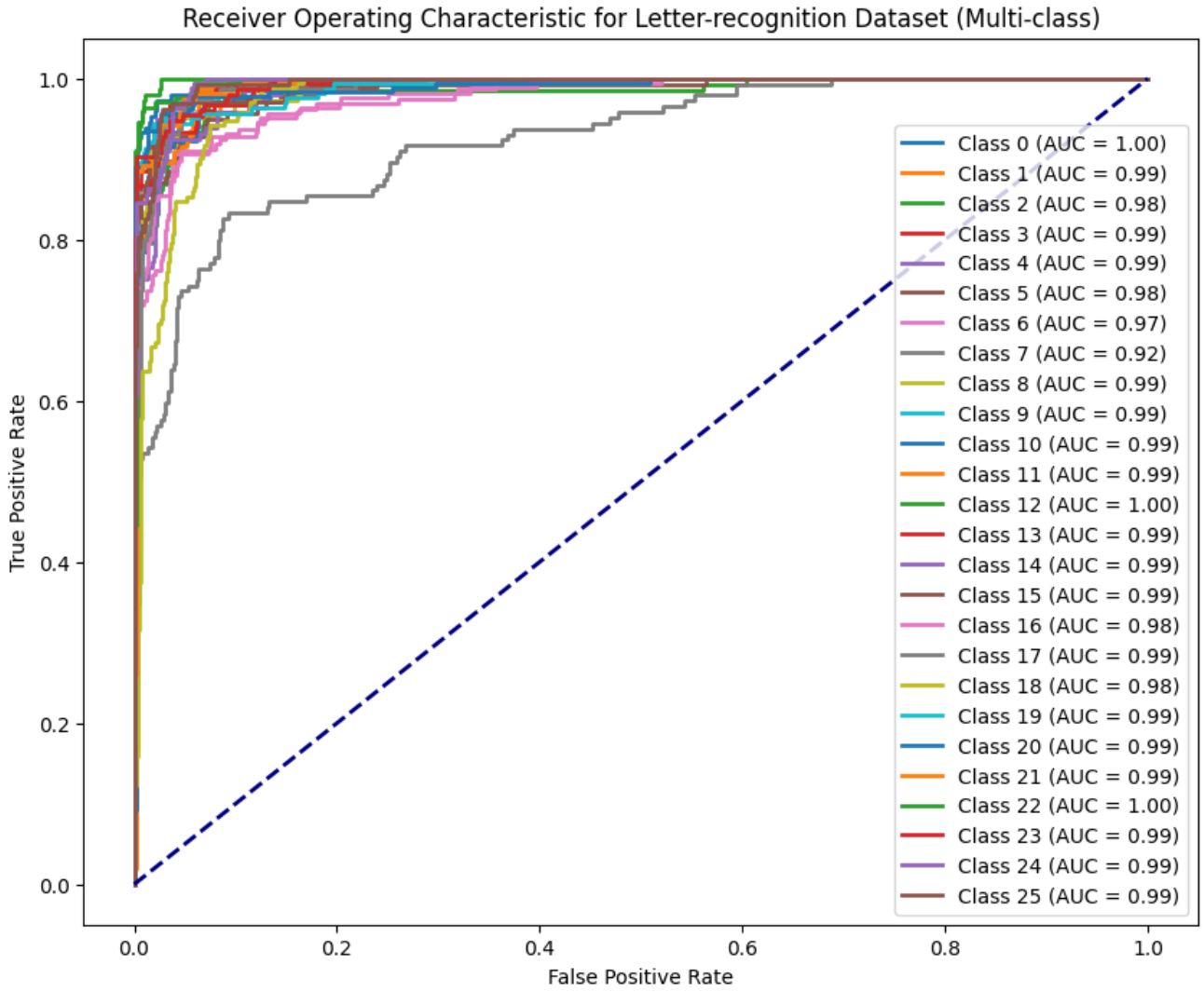
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, auc
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics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

# Load the Letter-recognition dataset
letter_data = pd.read_csv('letter-recognition.csv')

# Prepare the dataset
X_letter = letter_data.drop('letter', axis=1)
y_letter = letter_data['letter']

# Encode the letter labels to numerical values
le = LabelEncoder()
y_letter_encoded = le.fit_transform(y_letter)

# Split the data into training and testing sets (80% training, 20% testing)
X_train_letter, X_test_letter, y_train_letter, y_test_letter = train_test_split(X_letter,
y_letter_encoded, test_size=0.2, random_state=42)
```

```
# Train the SVM model with a linear kernel
svm_linear = SVC(kernel='linear')
svm_linear.fit(X_train_letter, y_train_letter)

# Make predictions
y_pred_letter = svm_linear.predict(X_test_letter)

# Calculate accuracy score
accuracy = accuracy_score(y_test_letter, y_pred_letter)
print(f"Accuracy Score with Linear Kernel: {accuracy:.4f}")

# Confusion Matrix
conf_matrix = confusion_matrix(y_test_letter, y_pred_letter)

# Plot Confusion Matrix (without printing the elements)
plt.figure(figsize=(10, 8))  # Make the plot larger
ConfusionMatrixDisplay(conf_matrix, display_labels=le.classes_).plot(cmap='Blues')
plt.title('Confusion Matrix for Letter-recognition Dataset')
plt.show()

# Binarize the labels for multi-class classification
y_test_letter_binarized = label_binarize(y_test_letter, classes=np.arange(26))  # 26 classes
y_pred_prob_letter = svm_linear.decision_function(X_test_letter)

# Compute ROC curve and AUC score for each class
fpr = {}
tpr = {}
roc_auc = {}
for i in range(26):  # 26 classes
    fpr[i], tpr[i], _ = roc_curve(y_test_letter_binarized[:, i], y_pred_prob_letter[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curve for each class
plt.figure(figsize=(10, 8))
for i in range(26):
    plt.plot(fpr[i], tpr[i], lw=2, label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic for Letter-recognition Dataset (Multi-class)')
```

```
plt.legend(loc="lower right")
plt.show()

# Display AUC scores for each class
for i in range(26):
    print(f"AUC score for Class {i}: {roc_auc[i]:.4f}")
```

Accuracy Score with Linear Kernel: 0.8545
<Figure size 1000x800 with 0 Axes>



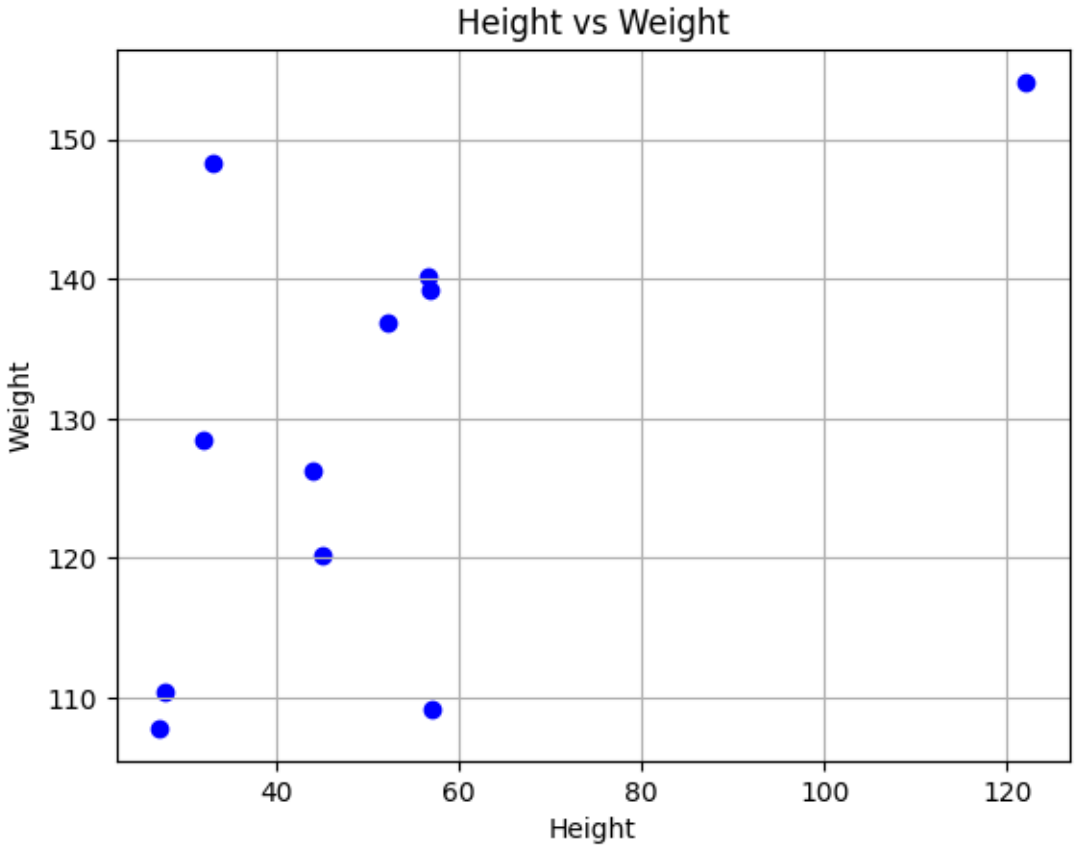


AUC score for Class 0: 0.9955
AUC score for Class 1: 0.9896
AUC score for Class 2: 0.9825
AUC score for Class 3: 0.9938
AUC score for Class 4: 0.9915
AUC score for Class 5: 0.9825
AUC score for Class 6: 0.9742
AUC score for Class 7: 0.9238
AUC score for Class 8: 0.9888
AUC score for Class 9: 0.9925
AUC score for Class 10: 0.9864
AUC score for Class 11: 0.9908
AUC score for Class 12: 0.9973
AUC score for Class 13: 0.9918
AUC score for Class 14: 0.9855
AUC score for Class 15: 0.9909

AUC score for Class 16: 0.9766
AUC score for Class 17: 0.9882
AUC score for Class 18: 0.9779
AUC score for Class 19: 0.9893
AUC score for Class 20: 0.9906
AUC score for Class 21: 0.9934
AUC score for Class 22: 0.9979
AUC score for Class 23: 0.9931
AUC score for Class 24: 0.9936
AUC score for Class 25: 0.9934
In [13]:

```
import pandas as pd

# Data
data = {
   "Height": [44, 52.1, 57.1, 33, 27.8, 27.2, 32, 45.1, 56.7, 56.9, 122.1],
   "Weight": [126.3, 136.9, 109.2, 148.3, 110.4, 107.8, 128.4, 120.2, 140.2, 139.2, 154.1]
}

# Create a DataFrame
df = pd.DataFrame(data)

# Save to CSV
df.to_csv('height_weight_data.csv', index=False)
import pandas as pd
import matplotlib.pyplot as plt

# Load the data from CSV
df = pd.read_csv('height_weight_data.csv')

# Plotting the data
plt.scatter(df['Height'], df['Weight'], color='blue', label='Data points')
plt.xlabel('Height')
plt.ylabel('Weight')
plt.title('Height vs Weight')
plt.grid(True)
plt.show()
from sklearn.svm import SVR
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

```
# Define features and target
X = df[['Height']]  # Feature: Height
y = df['Weight']  # Target: Weight

# 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)

# Create the model
svr = SVR(kernel='linear')

# Fit the model
svr.fit(X_train, y_train)

# Predict on the test set
y_pred = svr.predict(X_test)

# Calculate accuracy using Mean Squared Error (since it's regression)
mse = mean_squared_error(y_test, y_pred)
rmse = mse ** 0.5  # Root Mean Squared Error

# Print the support vectors and accuracy
print(f"Support Vectors: {svr.support_}")
print(f"Root Mean Squared Error: {rmse}")
```

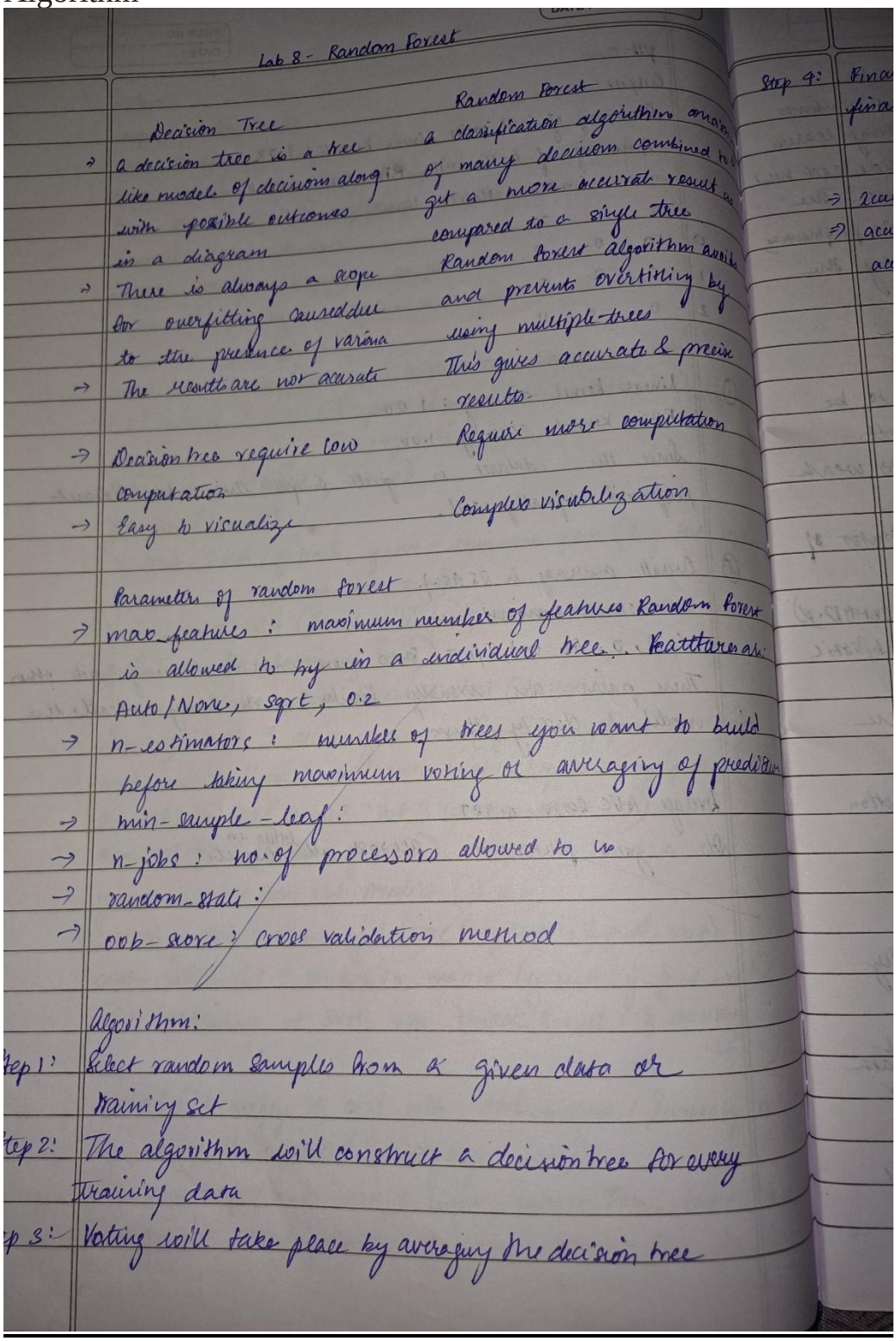


Support Vectors: [0 1 2 3 4 5 6 7]
Root Mean Squared Error: 11.680171349283054

Program 8

Implement Random forest ensemble method on a given dataset.

Algorithm



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Step 4: Finally, Select the most voted prediction result as the final prediction result.

⇒ accuracy with 10 n-estimators = 10 = 1.0

⇒ accuracy with 50 " = 50 = 1.0

accuracy with 100 " = 1.0

Code:

In [11]:

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

# Load the dataset
df = pd.read_csv('train.csv')

# Preprocess the dataset
# Convert categorical columns into numeric
# For simplicity, we'll drop columns that are not necessary for modeling (e.g., 'Name', 'Ticket', 'Cabin')
df = df.drop(columns=['Name', 'Ticket', 'Cabin'])

# Convert categorical features into numeric values (Sex, Embarked)
label_encoder = LabelEncoder()
df['Sex'] = label_encoder.fit_transform(df['Sex'])
df['Embarked'] = df['Embarked'].map({'S': 0, 'C': 1, 'Q': 2})  # 'S', 'C', 'Q' to numeric

# Handle missing values (impute with the median for simplicity)
df['Age'].fillna(df['Age'].median(), inplace=True)
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)  # Mode is used for Embarked

# Features and target variable
X = df.drop(columns=['Survived', 'PassengerId'])
y = df['Survived']

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

# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the model
rf_classifier.fit(X_train, y_train)

# Predict on the test set
y_pred = rf_classifier.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.4f}')
```

```
# Display confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print('Confusion Matrix:')
print(conf_matrix)
```

```
<ipython-input-11-ca7102c51cf1>:21: FutureWarning: A value is trying to be set on a copy of a
DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the
intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value},
inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the
original object.
```

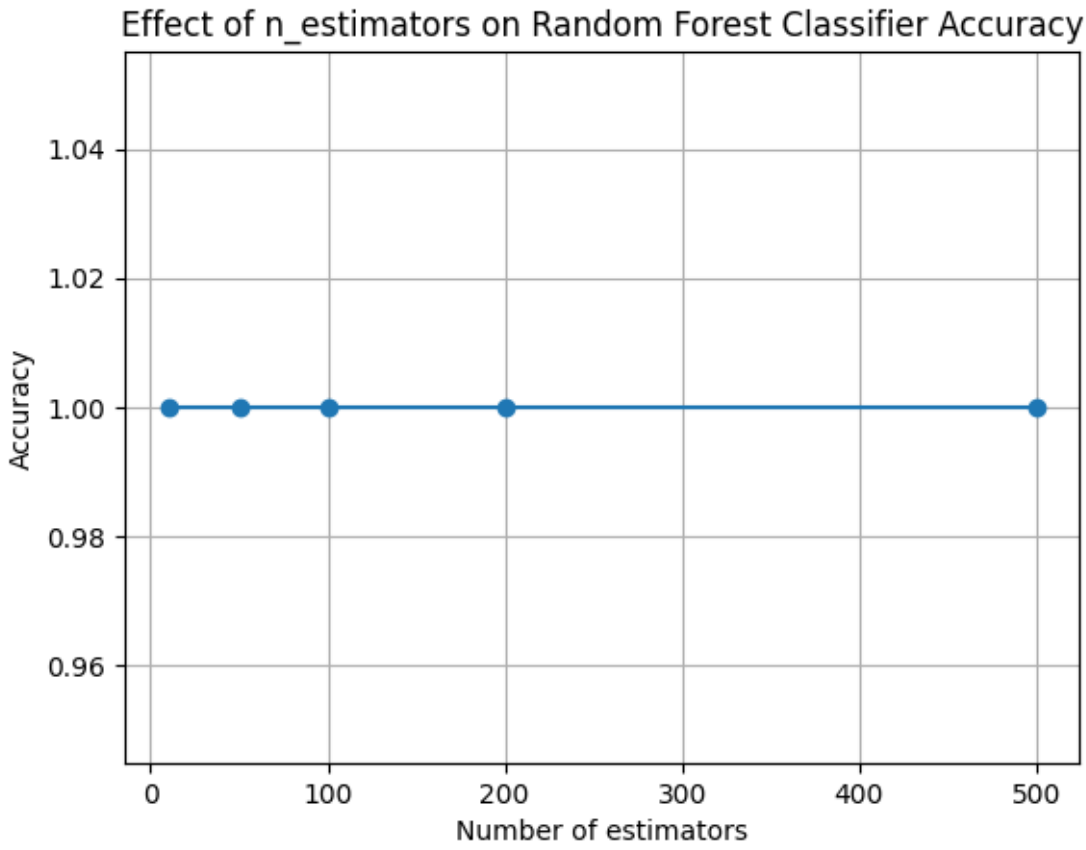
```
  df['Age'].fillna(df['Age'].median(), inplace=True)
<ipython-input-11-ca7102c51cf1>:22: FutureWarning: A value is trying to be set on a copy of a
DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the
intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value},
inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the
original object.
```

```
  df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)  # Mode is used for Embarked
Accuracy: 0.8212
Confusion Matrix:
[[91 14]
 [18 56]]
In [12]:
```

```
# Import necessary libraries
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
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
X = iris.data
y = iris.target
```

```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize RandomForestClassifier with default n_estimators=10
clf = RandomForestClassifier(n_estimators=10, random_state=42)

# Train the model
clf.fit(X_train, y_train)

# Predict on the test set
y_pred = clf.predict(X_test)

# Evaluate the performance
score_default = accuracy_score(y_test, y_pred)
print(f"Accuracy with n_estimators=10: {score_default}")

# Fine-tune the model by changing the value of n_estimators
n_estimators_values = [10, 50, 100, 200, 500]
scores = []

for n in n_estimators_values:
    clf = RandomForestClassifier(n_estimators=n, random_state=42)
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    score = accuracy_score(y_test, y_pred)
    scores.append(score)
    print(f"Accuracy with n_estimators={n}: {score}")

# Plot the results
plt.plot(n_estimators_values, scores, marker='o')
plt.xlabel('Number of estimators')
plt.ylabel('Accuracy')
plt.title('Effect of n_estimators on Random Forest Classifier Accuracy')
plt.grid(True)
plt.show()
```

```
Accuracy with n_estimators=10: 1.0
Accuracy with n_estimators=10: 1.0
Accuracy with n_estimators=50: 1.0
Accuracy with n_estimators=100: 1.0
Accuracy with n_estimators=200: 1.0
Accuracy with n_estimators=500: 1.0
```

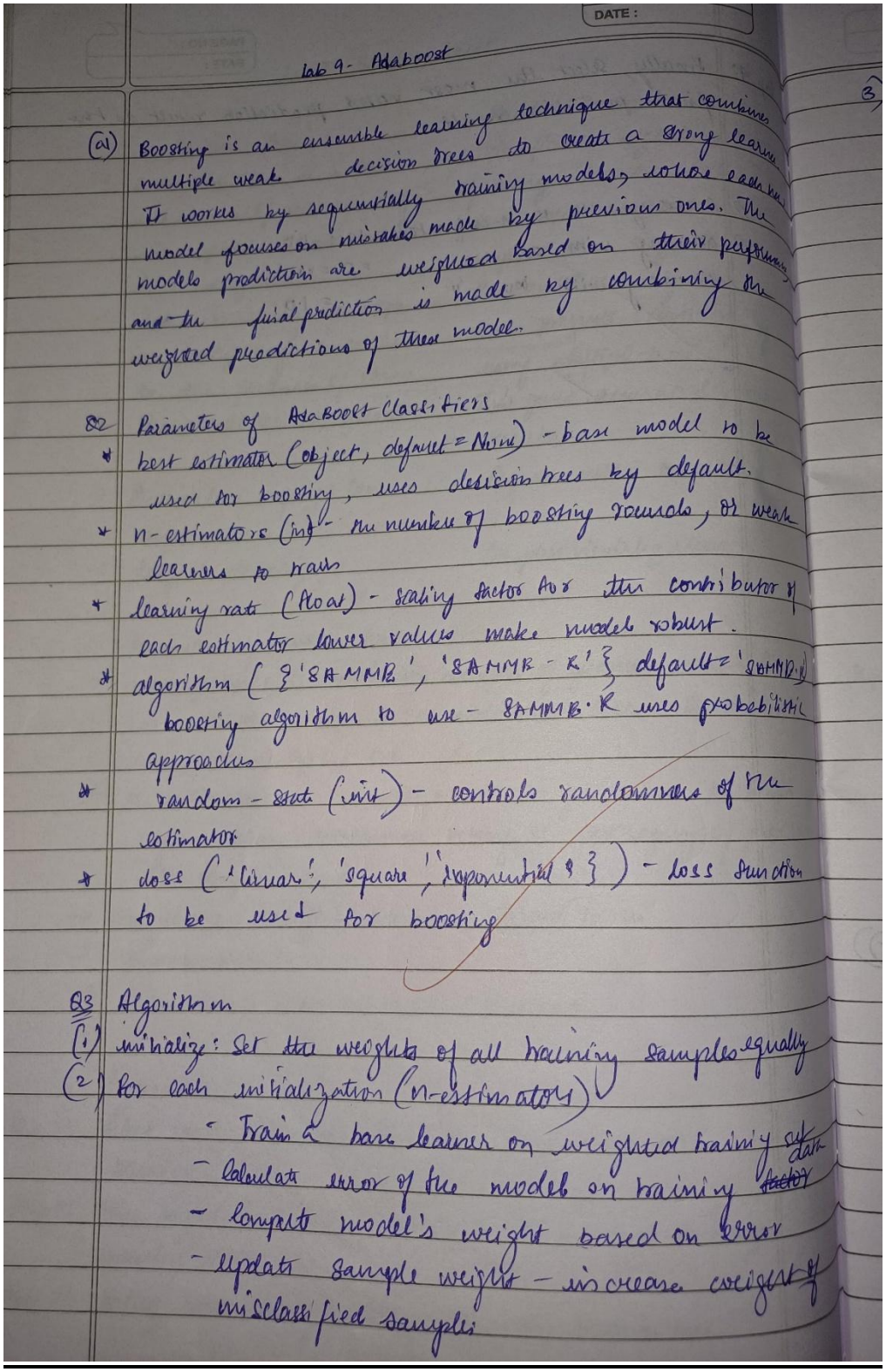

Effect of n_estimators on Random Forest Classifier Accuracy
Accuracy
1.04
1.02
1.00
0.98
0.96
0
100
200
300
400
500
Number of estimators

In [ ]:

Program 9

Implement Boosting ensemble method on a given dataset.

Algorithm



Lab 9 - AdaBoost

DATE :

(a) Boosting is an ensemble learning technique that combines multiple weak decision trees to create a strong learner. It works by sequentially training models, where each model focuses on mistakes made by previous ones. The models predictions are weighted based on their performance and the final prediction is made by combining the weighted predictions of these models.

Q2 Parameters of AdaBoost Classifiers

* best estimator (object, default = None) - base model to be used for boosting, uses decision trees by default.
* n-estimators (int) - no number of boosting rounds, or weak learners to train
* learning rate (float) - scaling factor for the contribution of each estimator lower values make model robust.
* algorithm ({'SAMME', 'SAMME.R'}, default='SAMME.R') boosting algorithm to use - SAMME.R uses probabilistic approaches
* random-state (int) - controls randomness of the estimator
* loss ('linear', 'square', 'exponential'}) - loss function to be used for boosting

Q3 Algorithm

(1) initialize: Set the weights of all training samples equally
(2) for each initialization (n-estimators)
- Train a base learner on weighted training set data
- Calculate error of the model on training data
- Compute model's weight based on error
- Update sample weight - increase weight of misclassified samples

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3) Combine : The final model is the weighted sum of the base learners, where learners with lower errors have higher weights

code:

```
data = pd.read_csv('income.csv')
X = data.drop(columns = ('income_level')
y = data['income_level']
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.
random_state = 42)
ada_model = AdaBoostClassifier(n_estimators = 50, learning_rate=1.
random_state = 42)
ada_model.fit(X_train, y_train)
y_pred = ada_model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
cont_matrix = confusion_matrix(y_test, y_pred)

print("Accuracy:", accuracy * 100)
print("Confusion Matrix:")
print(cont_matrix)
```

O/P

Accuracy = 83.28%

Confusion Matrix

[[1003 411]
 [1223 1132]]

Code

In [32]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.ensemble import  RandomForestClassifier
# Load the data (assume "income.csv" is already downloaded)
df = pd.read_csv('income.csv')

# Let's check the columns to see what we're dealing with
print(df.head())

# Preprocessing: Encode categorical data if necessary (in this case 'income_level' is categorical)
encoder = LabelEncoder()
df['income_level'] = encoder.fit_transform(df['income_level'])

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

# Split the data 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)
```

```
   age  fnlwgt  education_num  capital_gain  capital_loss  hours_per_week  \
0   39   77516             13          2174             0              40
1   50   83311             13             0             0              13
2   38  215646              9             0             0              40
3   53  234721              7             0             0              40
4   28  338409             13             0             0              40

   income_level
0             0
1             0
2             0
3             0
4             0
```

In [33]:

```
# Initialize the AdaBoost model with Random Forest as the base classifier
ada_boost = AdaBoostClassifier(RandomForestClassifier(n_estimators=10, max_depth=5,
random_state=42), n_estimators=50, learning_rate=1.0)

# Train the AdaBoost model
ada_boost.fit(X_train, y_train)

# Predictions
y_pred = ada_boost.predict(X_test)

# Evaluate accuracy and confusion matrix
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

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

```
Accuracy: 0.8368307912785341
Confusion Matrix:
[[7039  375]
 [1219 1136]]
```

In [34]:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Load the Iris dataset
iris = load_iris()
X = iris.data
y = iris.target

# 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)

base_classifier = RandomForestClassifier(n_estimators=10, max_depth=5, random_state=42)
```

```
# Initialize AdaBoost with Decision Tree as base classifier
ada_boost = AdaBoostClassifier(base_classifier, n_estimators=50)

# Train the model
ada_boost.fit(X_train, y_train)

# Evaluate accuracy on the test set
y_pred = ada_boost.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print(f"Accuracy of AdaBoost on Iris dataset: {accuracy}")
```

```
Accuracy of AdaBoost on Iris dataset: 1.0
```

In [35]:

```
# Varying n_estimators and measuring the accuracy
estimators = [10, 50, 100, 200, 500]
for n in estimators:
    ada_boost = AdaBoostClassifier(base_classifier, n_estimators=n)
    ada_boost.fit(X_train, y_train)
    y_pred = ada_boost.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy with n_estimators={n}: {accuracy}")
```

```
Accuracy with n_estimators=10: 1.0
Accuracy with n_estimators=50: 1.0
Accuracy with n_estimators=100: 1.0
Accuracy with n_estimators=200: 1.0
Accuracy with n_estimators=500: 1.0
```

In [36]:

```
# Varying n_estimators and learning_rate
learning_rates = [0.1, 0.5, 1.0, 1.5]
n_estimators_values = [50, 100, 200]

for lr in learning_rates:
    for n in n_estimators_values:
        ada_boost = AdaBoostClassifier(base_classifier,
                                       n_estimators=n, learning_rate=lr)
```

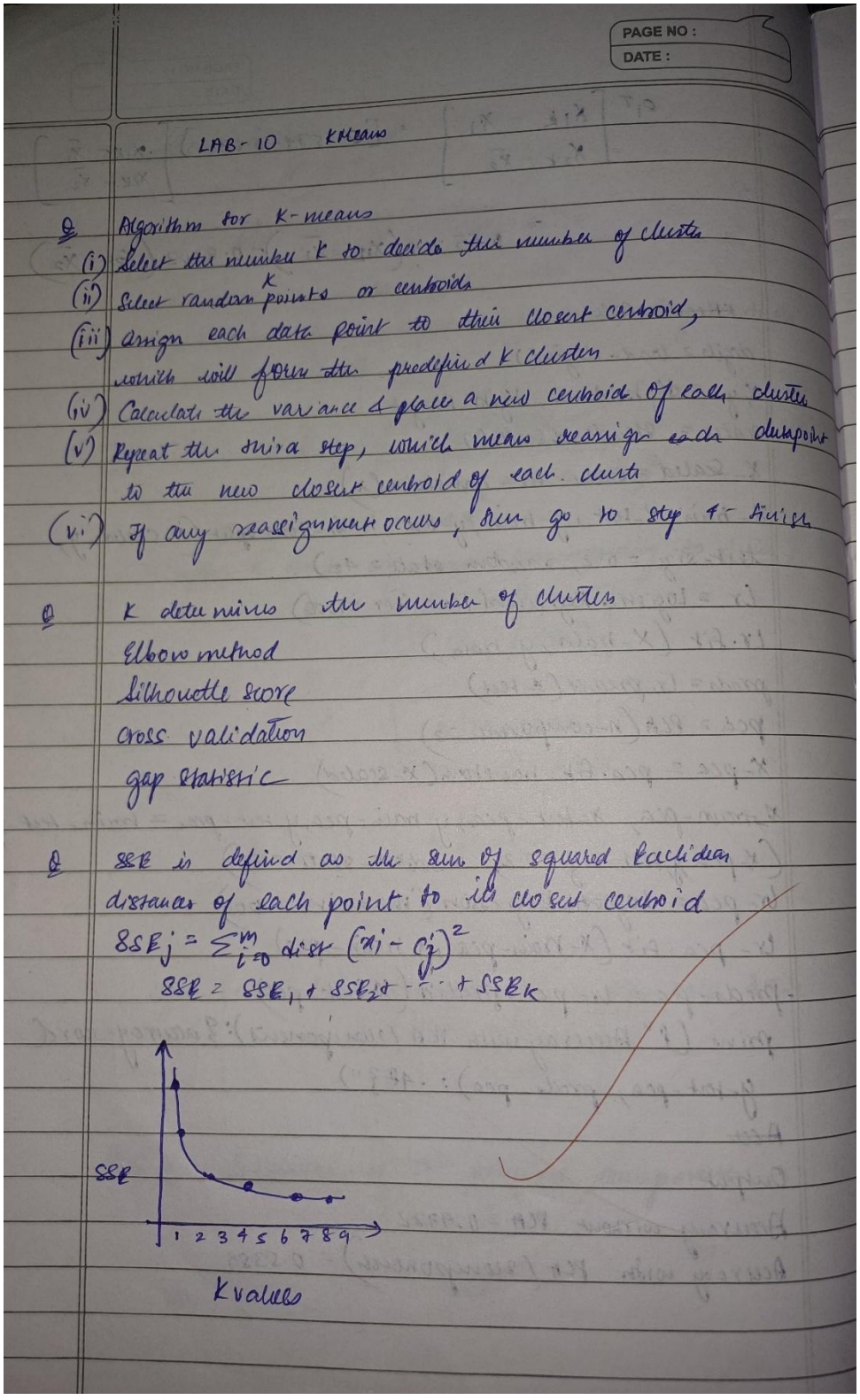
```
        ada_boost.fit(X_train, y_train)
        y_pred = ada_boost.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)
        print(f"Accuracy with n_estimators={n} and learning_rate={lr}: {accuracy}")
```
```
Accuracy with n_estimators=50 and learning_rate=0.1: 1.0
Accuracy with n_estimators=100 and learning_rate=0.1: 1.0
Accuracy with n_estimators=200 and learning_rate=0.1: 1.0
Accuracy with n_estimators=50 and learning_rate=0.5: 1.0
Accuracy with n_estimators=100 and learning_rate=0.5: 1.0
Accuracy with n_estimators=200 and learning_rate=0.5: 1.0
Accuracy with n_estimators=50 and learning_rate=1.0: 1.0
Accuracy with n_estimators=100 and learning_rate=1.0: 1.0
Accuracy with n_estimators=200 and learning_rate=1.0: 1.0
Accuracy with n_estimators=50 and learning_rate=1.5: 1.0
Accuracy with n_estimators=100 and learning_rate=1.5: 1.0
Accuracy with n_estimators=200 and learning_rate=1.5: 1.0
In [37]:
```
```
from sklearn.linear_model import LogisticRegression

# Using Logistic Regression as base estimator in AdaBoost
ada_boost_lr = AdaBoostClassifier(LogisticRegression(max_iter=1000), n_estimators=50)
ada_boost_lr.fit(X_train, y_train)
y_pred_lr = ada_boost_lr.predict(X_test)
accuracy_lr = accuracy_score(y_test, y_pred_lr)
print(f"Accuracy with Logistic Regression base estimator: {accuracy_lr}")
```
```
Accuracy with Logistic Regression base estimator: 0.9333333333333333
In [38]:
```
```
# Using Decision Tree as base estimator in AdaBoost
ada_boost_tree = AdaBoostClassifier(DecisionTreeClassifier(max_depth=1), n_estimators=50)
ada_boost_tree.fit(X_train, y_train)
y_pred_tree = ada_boost_tree.predict(X_test)
accuracy_tree = accuracy_score(y_test, y_pred_tree)
print(f"Accuracy with Decision Tree base estimator: {accuracy_tree}")
```
```
Accuracy with Decision Tree base estimator: 0.9333333333333333
In [ ]:
```

Program 10

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

Algorithm



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Q Elbow method is a technique used to determine the optimal number of clusters (k) in k-means clustering. It involves plotting the within-cluster-sum of squares (WCSS) against the number of clusters & identifying the "elbow" point, where the decrease in WCSS starts to level off. The elbow point suggests the optimal number of clusters.

Q → n_clusters : int, default = 8 : number of clusters to form as well as the number of centroids to generat
→ init : {k-means++, random} : chooses a method for initialization
→ n_init : number of times the k-means algorithm is run with different centroid speed
→ max_iter : max number of iterations of k-mean algorithm for a single run
→ tol : float : Relative tolerance with regards to Frobenius norm of the difference in the cluster centers of two consecutive iterations to declar convergence
→ verbose : verbosity mode
→ random_state
→ copy_x : bool
→ algorithm : {"lloyd", "elkan"}

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code:

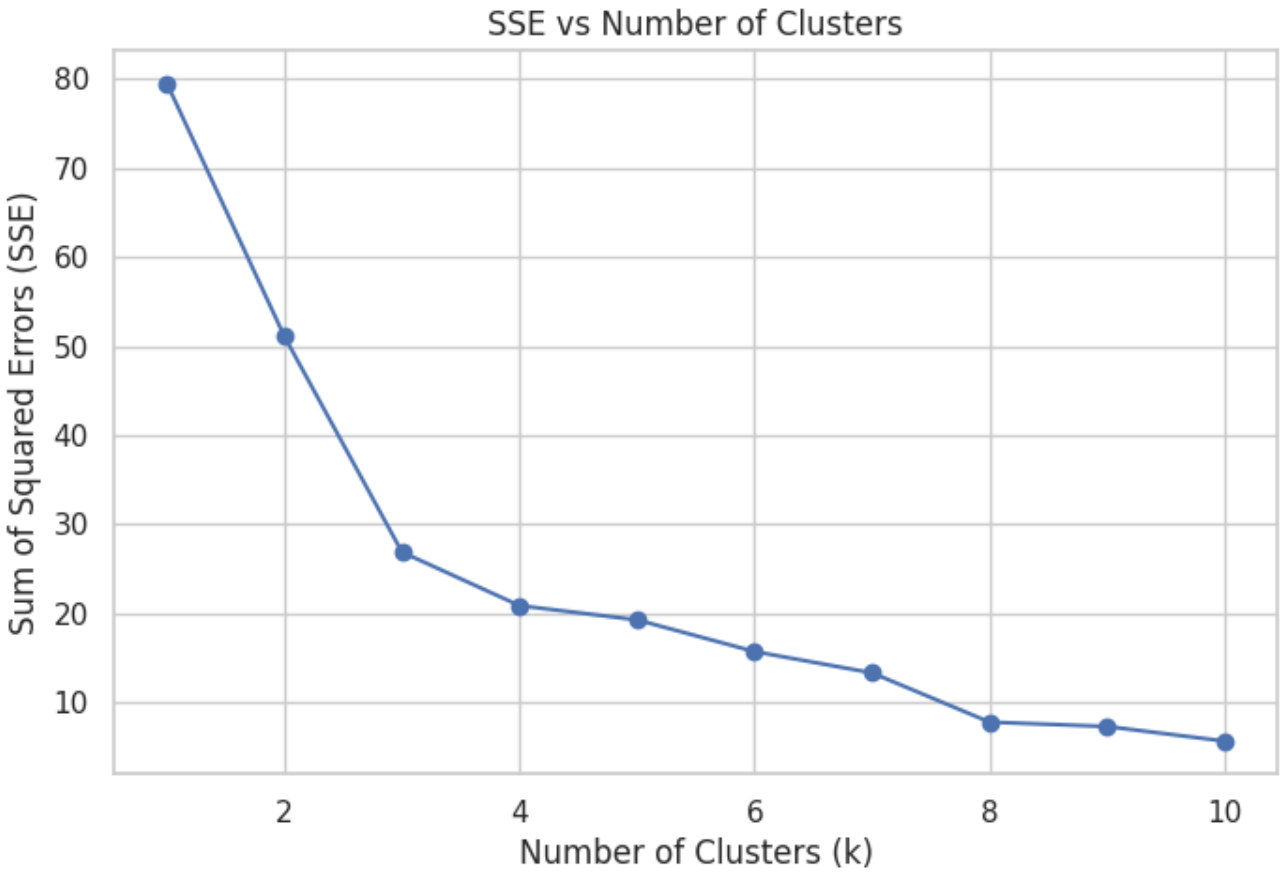
```
iris = load_iris()
iris_df = pd.DataFrame(iris.data, column = iris.feature_names)
iris_df = iris_df[['petal length (cm)', 'petal width (cm)']]
scaler = StandardScaler()
iris_scaled = scaler.fit_transform(iris_df)
sse = []
k_range = range(1,11)
for k in krange:
    km = KMeans(n_clusters = k, random_state = 42)
    km.fit(iris_scaled)
    sse.append(km.inertia_)
plt.figure(figsize = (8,5))
plt.plot(k_range, sse, marker = 'o')
plt.title("Elbow method: SSE V/s K")
plt.xlabel("K")
plt.ylabel("SSE")
plt.grid(True)
plt.show()
```

Code

In [13]:

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

# Step 1: Create synthetic income dataset
np.random.seed(42)
names = [f'Person_{i}' for i in range(1, 51)]
ages = np.random.randint(20, 60, size=50)
incomes = np.random.randint(20000, 120000, size=50)

income_df = pd.DataFrame({
    'Name': names,
    'Age': ages,
    'Income': incomes
})

# Save to CSV (optional)
income_df.to_csv("income.csv", index=False)

# Step 2: Load and preprocess
df = pd.read_csv("income.csv")

# Drop name (non-numeric)
df_numeric = df.drop('Name', axis=1)

# Step 3: Scaling
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df_numeric)

# Step 4: Train-test split
```

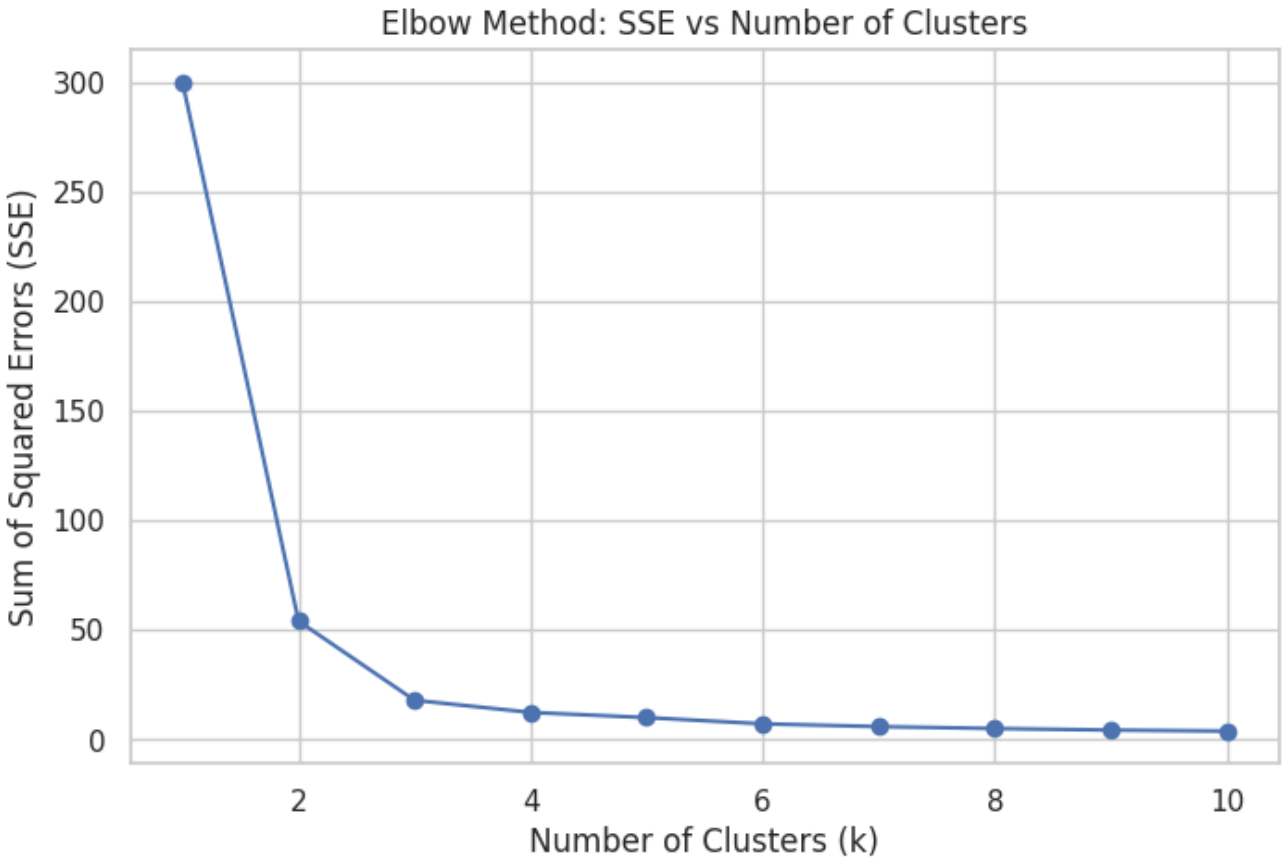
```
X_train, X_test = train_test_split(df_scaled, test_size=0.2, random_state=42)

# Step 5: SSE vs number of clusters (Elbow method)
sse = []
k_range = range(1, 11)
for k in k_range:
    km = KMeans(n_clusters=k, random_state=42)
    km.fit(X_train)
    sse.append(km.inertia_)

# Step 6: Plot SSE
plt.figure(figsize=(8, 5))
plt.plot(k_range, sse, marker='o')
plt.title('SSE vs Number of Clusters')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Sum of Squared Errors (SSE)')
plt.grid(True)
plt.show()

# Step 7: Fit KMeans with optimal k (e.g., 3)
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans.fit(X_train)

# Step 8: Predict clusters on test set
y_pred = kmeans.predict(X_test)

# Step 9: "Accuracy" – not meaningful in unsupervised, but just a check
print("Cluster labels for test data:", y_pred)
```

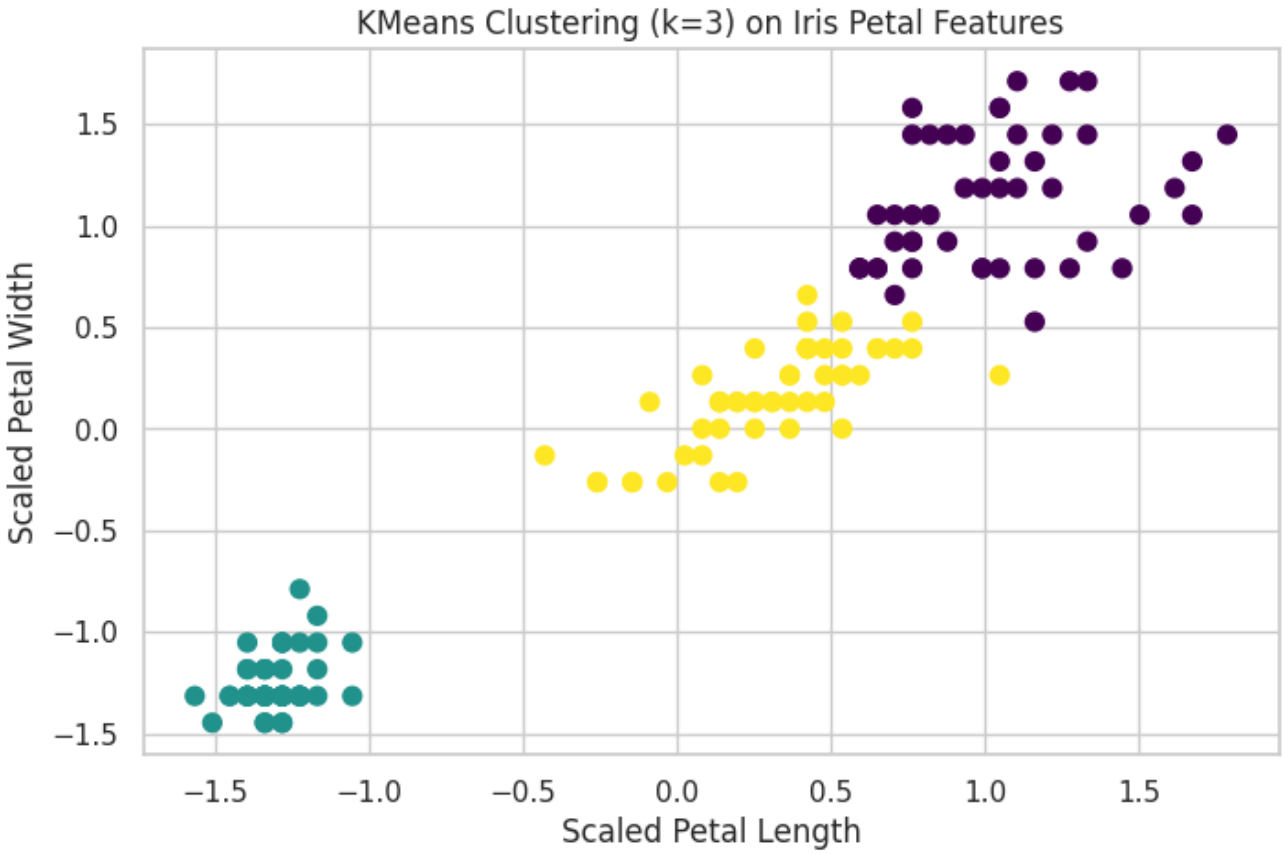


Cluster labels for test data: [2 1 1 1 2 0 2 2 1 0]
In [14]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_iris

# Step 1: Load iris dataset and use only petal length & width
iris = load_iris()
iris_df = pd.DataFrame(iris.data, columns=iris.feature_names)
iris_df = iris_df[['petal length (cm)', 'petal width (cm)']]  # drop other features

# Step 2: Scaling
scaler = StandardScaler()
iris_scaled = scaler.fit_transform(iris_df)

# Step 3: Elbow method to find optimal k
```

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

# Step 4: Plot SSE vs k
plt.figure(figsize=(8, 5))
plt.plot(k_range, sse, marker='o')
plt.title("Elbow Method: SSE vs Number of Clusters")
plt.xlabel("Number of Clusters (k)")
plt.ylabel("Sum of Squared Errors (SSE)")
plt.grid(True)
plt.show()

# Optional: Fit with optimal k = 3 and visualize clusters
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
labels = kmeans.fit_predict(iris_scaled)

plt.figure(figsize=(8, 5))
plt.scatter(iris_scaled[:, 0], iris_scaled[:, 1], c=labels, cmap='viridis', s=50)
plt.title("KMeans Clustering (k=3) on Iris Petal Features")
plt.xlabel("Scaled Petal Length")
plt.ylabel("Scaled Petal Width")
plt.grid(True)
plt.show()
```


Elbow Method: SSE vs Number of Clusters
Sum of Squared Errors (SSE)
300
250
200
150
100
50
0
2
4
6
8
10
Number of Clusters (k)

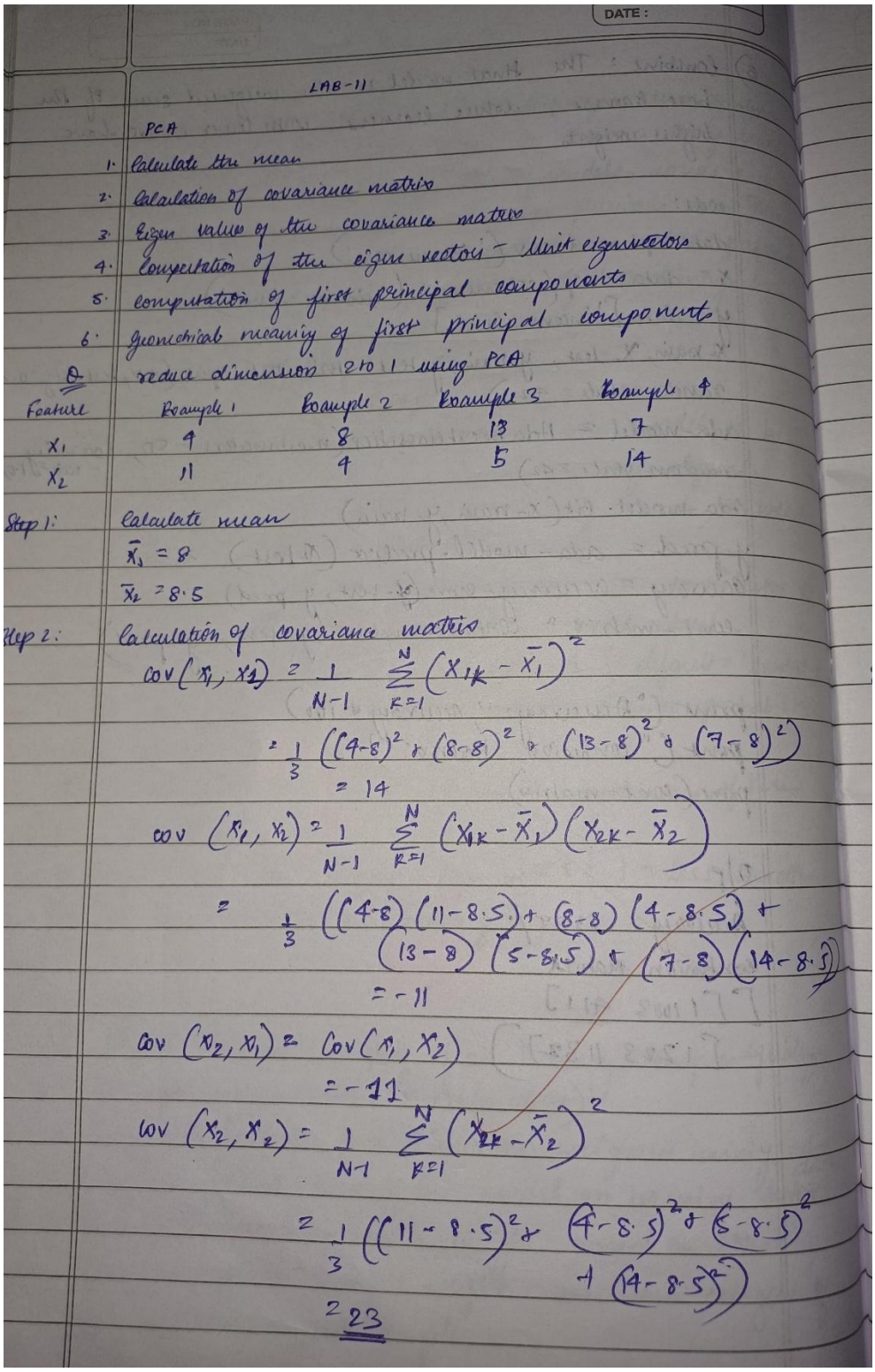

KMeans Clustering (k=3) on Iris Petal Features
Scaled Petal Width
Scaled Petal Length
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

In [ ]:

Program 11

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

Algorithm



LAB-11

PCA

1. Calculate the mean
2. Calculation of covariance matrix
3. Eigen value of the covariance matrix
4. Computation of the eigen vectors - Unit eigenvectors
5. Computation of first principal components
6. Geometrical meaning of first principal components

Q. reduce dimension 2 to 1 using PCA

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

Step 1: Calculate mean

$\bar{X}_1 = 8$

$\bar{X}_2 = 8.5$

Step 2: Calculation of covariance matrix

$$cov(X_1, X_1) = \frac{1}{N-1} \sum_{K=1}^{N} (X_{1K} - \bar{X}_1)^2$$

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

$$= 14$$

$$cov(X_1, X_2) = \frac{1}{N-1} \sum_{K=1}^{N} (X_{1K} - \bar{X}_1)(X_{2K} - \bar{X}_2)$$

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

$$= -11$$

$$cov(X_2, X_1) = cov(X_1, X_2)$$

$$= -11$$

$$cov(X_2, X_2) = \frac{1}{N-1} \sum_{K=1}^{N} (X_{2K} - \bar{X}_2)^2$$

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

$$= 23$$

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$$S = \begin{bmatrix} \text{cov}(X_1, X_1) & \text{cov}(X_1, X_2) \\ \text{cov}(X_2, X_1) & \text{cov}(X_2, X_2) \end{bmatrix}$$

Step 3: Eigen values of the covariance matrix

The characteristic equation of the covariance matrix is

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

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

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

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

solving characteristic equation we get

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

$$= 30.3849, 6.6151$$

$$= \lambda_1, \lambda_2 \text{ (say)}$$

Step 4: Computation of the eigen vector

largest eigen vector values = λ_1

$\lambda = \lambda_1$

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

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = (S - \lambda_1 I)X$$

$$= \begin{bmatrix} 14-\lambda_1 & -11 \\ -11 & 23-\lambda_1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$= \begin{bmatrix} (14-\lambda_1)u_1 - 11u_2 \\ -11u_1 + (23-\lambda_1)u_2 \end{bmatrix}$$

$$= (14-\lambda_1)u_1 - 11u_2 = 0$$

$$-11u_1 + (23-\lambda_1)u_2 = 0$$

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$$\frac{u_2}{11} = \frac{u_2}{14-\lambda_1} = 6$$

$$u_1 = 11t, \quad u_2 = (14-\lambda_1)t$$

where t is any real number

Taking $t=1$, we get an eigen vector corresponding to λ_1 as

$$v_1 = \begin{bmatrix} 11 \\ 14-\lambda_1 \end{bmatrix}$$

$$\|v_1\| = \sqrt{11^2 + (14-\lambda)^2}$$

$$= \sqrt{11^2 + (14-30.3849)^2}$$

$$= 19.7348$$

Therefore, a unit eigenvector corresponding to λ_1 is

$$e_1 = \begin{bmatrix} 11/\|v_1\| \\ (14-\lambda_1)/\|v_1\| \end{bmatrix}$$

$$= \begin{bmatrix} 11/19.7348 \\ (14-30.3849)/19.7348 \end{bmatrix}$$

$$= \begin{bmatrix} 0.5574 \\ -0.8303 \end{bmatrix}$$

eigen vector e_2 corresponding to eigen value $\lambda = \lambda_2$

$$e_2 = \begin{bmatrix} 0.8303 \\ 0.5574 \end{bmatrix}$$

Step 5: computation of 1st principal components

$$\begin{bmatrix} X_{1K} \\ X_{2K} \end{bmatrix}$$

Code

In [12]:

```
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score

# Load dataset
digits = load_digits()
X, y = digits.data, digits.target

# Scaling
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)

# Logistic Regression without PCA
lr = LogisticRegression(max_iter=1000)
lr.fit(X_train, y_train)
preds = lr.predict(X_test)
print(f"Accuracy without PCA: {accuracy_score(y_test, preds):.4f}")

# Apply PCA with 2 components
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Split PCA-reduced data
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)

# Logistic Regression with PCA-reduced data
lr_pca = LogisticRegression(max_iter=1000)
lr_pca.fit(X_train_pca, y_train_pca)
preds_pca = lr_pca.predict(X_test_pca)
print(f"Accuracy with PCA (2 components): {accuracy_score(y_test_pca, preds_pca):.4f}")
```

Accuracy without PCA: 0.9722
Accuracy with PCA (2 components): 0.5389
In [13]:

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

# Load dataset
heart_df = pd.read_csv("heart.csv")

# Print column names to verify
print("Column names in dataset:", heart_df.columns.tolist())

# Optional: rename columns if necessary (based on your dataset)
# Example only – skip this if your columns are already clean
heart_df.columns = [col.strip().lower() for col in heart_df.columns]

# Reprint cleaned column names
print("Cleaned column names:", heart_df.columns.tolist())

# Remove outliers using Z-score
z_scores = np.abs(zscore(heart_df.select_dtypes(include=[np.number])))
heart_df = heart_df[(z_scores < 3).all(axis=1)]

# Determine categorical columns that need encoding
categorical_cols = heart_df.select_dtypes(include=['object', 'category']).columns.tolist()

# Encode categorical columns using one-hot encoding
if categorical_cols:
    heart_df = pd.get_dummies(heart_df, columns=categorical_cols, drop_first=True)
```

```
# Split features and target
target_col = 'target' if 'target' in heart_df.columns else heart_df.columns[-1]
X = heart_df.drop(target_col, axis=1)
y = heart_df[target_col]

# Feature scaling
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)

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

print("\nModel Accuracy WITHOUT PCA:")
for name, model in models.items():
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    print(f"{name}: {accuracy_score(y_test, preds):.4f}")

# Apply PCA
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)

print("\nModel Accuracy WITH PCA:")
for name, model in models.items():
    model.fit(X_train_pca, y_train_pca)
    preds = model.predict(X_test_pca)
    print(f"{name}: {accuracy_score(y_test_pca, preds):.4f}")
```

```
Column names in dataset: ['Age', 'Sex', 'ChestPainType', 'RestingBP', 'Cholesterol', 'FastingBS',
'RestingECG', 'MaxHR', 'ExerciseAngina', 'Oldpeak', 'ST_Slope', 'HeartDisease']
```

Cleaned column names: ['age', 'sex', 'chestpaintype', 'restingbp', 'cholesterol', 'fastingbs', 'restingecg', 'maxhr', 'exerciseangina', 'oldpeak', 'st_slope', 'heartdisease']

Model Accuracy WITHOUT PCA:
Logistic Regression: 0.9444
SVM: 0.9333
Random Forest: 0.9222

Model Accuracy WITH PCA:
Logistic Regression: 0.8611
SVM: 0.8778
Random Forest: 0.8833
In [ ]: