VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
(Autonomous Institution under VTU)
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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 **Arugunta Hamsika(1BM22CS054),** 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.

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/hamsika04/6thSem-ML-La

Program 1

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

Code:

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

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

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

```
Sample data:
   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

   target
0       0
1       0
2       0
3       0
4       0
```

```
from google.colab import files
uploaded = files.upload()
file_path = 'data.csv' # Ensure the file exists in the same directory
df = pd.read_csv(file_path)
```

```
print("Sample data:")
print(df.head())
print("\n")
```

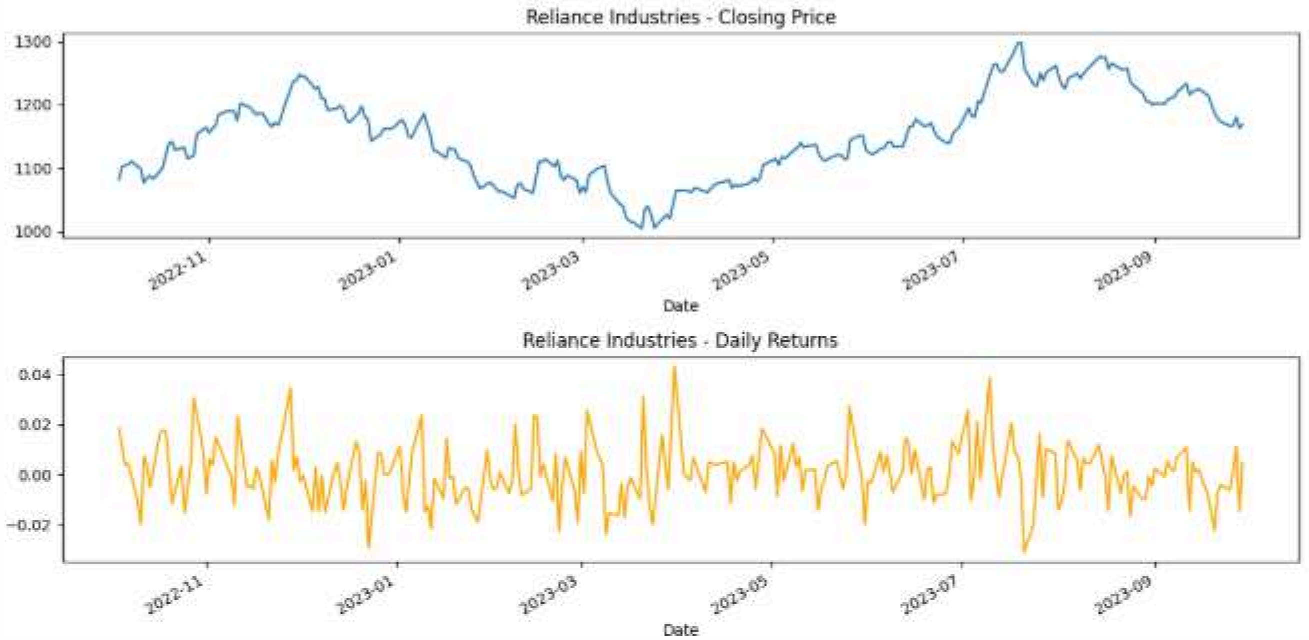
```
Saving data.csv to data.csv
Sample data:
   ID     Name  Age         City
0   1    Alice   25     New York
1   2      Bob   30  Los Angeles
2   3  Charlie   35      Chicago
3   4    David   40      Houston
4   5      Eva   28      Phoenix
```

```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
tickers = ["RELIANCE.NS", "TCS.NS", "INFY.NS"]
data = yf.download(tickers, start="2022-10-01", end="2023-10-01", group_by='ticker')
print("First 5 rows of the dataset:")
print(data.head())
print("\nShape of the dataset:")
print(data.shape)
print("\nColumn names:")
print(data.columns)
reliance_data = data['RELIANCE.NS']
print("\nSummary statistics for Reliance Industries:")
print(reliance_data.describe())
reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
```

```
First 5 rows of the dataset:
Ticker      RELIANCE.NS                                                    \
Price              Open         High          Low        Close    Volume
Date
2022-10-03  1092.199963  1103.822945  1079.184026  1082.152588  11852723
2022-10-04  1095.077201  1104.302526  1091.583396  1102.110352   8948850
2022-10-06  1109.326261  1118.916888  1104.371007  1106.174927  13352162
2022-10-07  1102.772687  1116.131217  1102.772687  1110.856323   7714340
2022-10-10  1098.365412  1104.119885  1090.601536  1098.730835   6329527

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

Ticker           TCS.NS
Price              Open         High          Low        Close   Volume
Date
2022-10-03  2799.044354  2823.062819  2779.418333  2789.651855  1763331
2022-10-04  2831.707297  2895.304988  2825.212065  2888.903076  2145875
2022-10-06  2907.454262  2919.603702  2890.117902  2898.996338  1790816
2022-10-07  2894.744206  2901.847047  2858.015696  2864.370605  1939879
2022-10-10  2813.062629  2922.407588  2808.389768  2914.510498  3064063

Shape of the dataset:
(247, 15)

Column names:
MultiIndex([('RELIANCE.NS',   'Open'),
            ('RELIANCE.NS',   'High'),
            ('RELIANCE.NS',    'Low'),
            ('RELIANCE.NS',  'Close'),
            ('RELIANCE.NS', 'Volume'),
            (    'INFY.NS',   'Open'),
            (    'INFY.NS',   'High'),
            (    'INFY.NS',    'Low'),
            (    'INFY.NS',  'Close'),
            (    'INFY.NS', 'Volume'),
            (     'TCS.NS',   'Open'),
            (     'TCS.NS',   'High'),
            (     'TCS.NS',    'Low'),
            (     'TCS.NS',  'Close'),
            (     'TCS.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   1151.456593  1160.153640  1141.068147  1150.426972  1.316652e+07
std      66.114624    67.077801    65.976400    66.914372  6.754099e+06
min    1011.592400  1013.875900   995.607838  1005.312744  3.370033e+06
25%    1102.624229  1107.157058  1088.489391  1101.094238  8.717141e+06
50%    1151.342807  1158.969749  1142.665512  1151.160156  1.158959e+07
75%    1200.335361  1207.724151  1189.020599  1199.134460  1.530302e+07
max    1292.463484  1304.337734  1277.392357  1297.875366  5.708188e+07
```

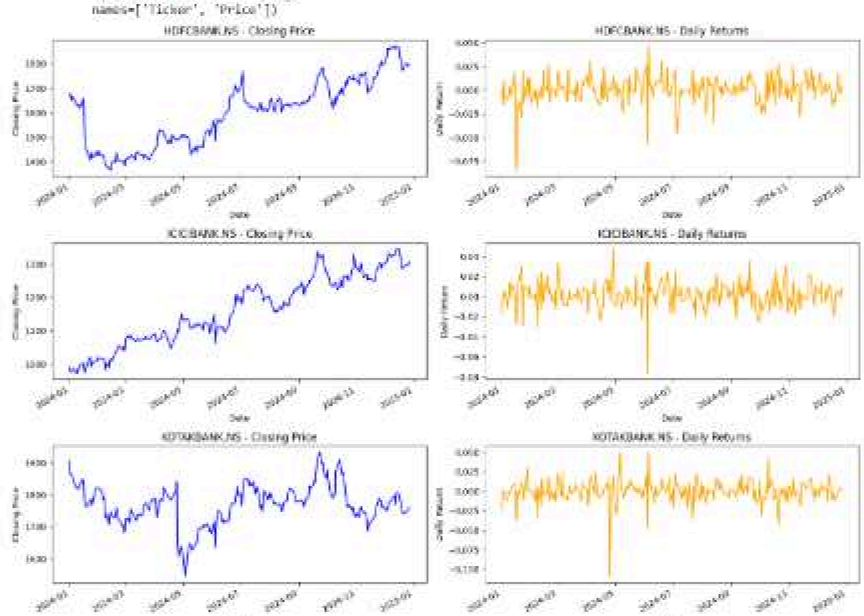
```
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
reliance_data['Close'].plot(title="Reliance Industries - Closing Price")
plt.subplot(2, 1, 2)
reliance_data['Daily Return'].plot(title="Reliance Industries - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
```

```
reliance_data.to_csv('reliance_stock_data.csv')
print("\nReliance stock data saved to 'reliance_stock_data.csv'.")
```




```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30", group_by='ticker')
print("First 5 rows of the dataset:")
print(data.head())
print("\nShape of the dataset:")
print(data.shape)
print("\nColumn names:")
print(data.columns)
plt.figure(figsize=(14, 10))
for i, ticker in enumerate(tickers):
    bank_data = data[ticker]
    bank_data['Daily Return'] = bank_data['Close'].pct_change()
    plt.subplot(3, 2, 2*i+1)
    bank_data['Close'].plot(title=f"{ticker} - Closing Price", color='blue')
    plt.ylabel('Closing Price')
    plt.subplot(3, 2, 2*i+2)
    bank_data['Daily Return'].plot(title=f"{ticker} - Daily Returns", color='orange')
    plt.ylabel('Daily Return')
plt.tight_layout()
plt.show()
for ticker in tickers:
    bank_data = data[ticker]
    bank_data.to_csv(f'{ticker}_stock_data.csv')
    print(f"\n{ticker} stock data saved to '{ticker}_stock_data.csv'.")
```

```
First 5 rows of the dataset:
Ticker      KOTAKBANK.NS                                                    \
Price               Open         High          Low        Close   Volume
Date
2024-01-01   1906.909954  1916.899886  1891.027338  1907.859814  1425982
2024-01-02   1905.911188  1905.911188  1858.063525  1863.008179  5120796
2024-01-03   1861.959234  1867.952665  1845.627158  1863.857178  3781515
2024-01-04   1869.451068  1869.451068  1858.513105  1861.550602  2865766
2024-01-05   1863.457575  1867.852782  1839.383085  1845.577148  7799341

Ticker       HDFCBANK.NS                                                     \
Price               Open         High          Low        Close    Volume
Date
2024-01-01   1683.017598  1686.125187  1669.286199  1675.223999   7119843
2024-01-02   1675.914685  1679.868799  1665.950651  1676.210571  14621046
2024-01-03   1679.071480  1681.735059  1646.466666  1650.363525  14194881
2024-01-04   1655.394910  1672.116528  1648.193283  1668.871777  13367828
2024-01-05   1664.421596  1681.932477  1645.628188  1659.538288  15944735

Ticker      ICICIBANK.NS
Price               Open        High         Low       Close    Volume
Date
2024-01-01    983.086778  996.273246  982.541485  998.869812   7683792
2024-01-02    988.490253  989.134738  971.883221  973.866150  16263825
2024-01-03    976.295294  979.567116  966.777197  975.650818  16826752
2024-01-04    977.980767  988.787295  973.519176  978.724365  22789140
2024-01-05    979.567884  989.779158  975.482928  985.218445  14875409

Shape of the dataset:
(244, 15)

Column names:
MultiIndex([('KOTAKBANK.NS',   'Open'),
            ('KOTAKBANK.NS',   'High'),
            ('KOTAKBANK.NS',    'Low'),
            ('KOTAKBANK.NS',  'Close'),
            ('KOTAKBANK.NS', 'Volume'),
            ( 'HDFCBANK.NS',   'Open'),
            ( 'HDFCBANK.NS',   'High'),
            ( 'HDFCBANK.NS',    'Low'),
            ( 'HDFCBANK.NS',  'Close'),
            ( 'HDFCBANK.NS', 'Volume'),
            ('ICICIBANK.NS',   'Open'),
            ('ICICIBANK.NS',   'High'),
            ('ICICIBANK.NS',    'Low'),
            ('ICICIBANK.NS',  'Close'),
            ('ICICIBANK.NS', 'Volume')],
           names=['Ticker', 'Price'])
```

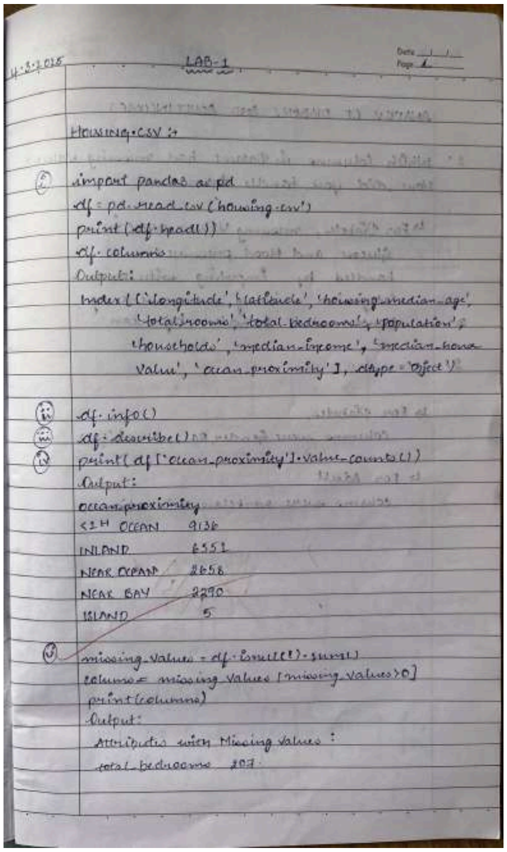



```
HDFCBANK.NS stock data saved to 'HDFCBANK.NS_stock_data.csv'.

ICICIBANK.NS stock data saved to 'ICICIBANK.NS_stock_data.csv'.

KOTAKBANK.NS stock data saved to 'KOTAKBANK.NS_stock_data.csv'.
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshot:



4-3-2025

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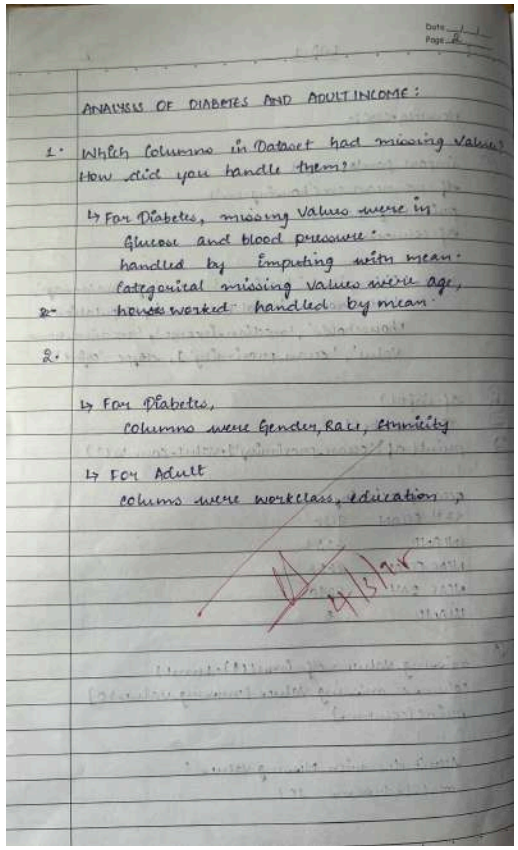
Page 1

HOUSING.CSV :-

(i) import pandas as pd
df = pd.read_csv('housing.csv')
print(df.head())
df.columns
Output:
Index(['longitude', 'latitude', 'housing_median_age',
'total_rooms', 'total_bedrooms', 'population',
'households', 'median_income', 'median_house_value', 'ocean_proximity'], dtype='object')

(ii) df.info()
(iii) df.describe()
(iv) print(df['ocean_proximity'].value_counts())
Output:
ocean_proximity
<1H OCEAN 9136
INLAND 6551
NEAR OCEAN 2658
NEAR BAY 2290
ISLAND 5

(v) missing_values = df.isnull().sum()
columns = missing_values[missing_values>0]
print(columns)
Output:
Attributes with Missing Values :
total_bedrooms 207



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ANALYSIS OF DIABETES AND ADULT INCOME :

1. Which columns in Dataset had missing values? How did you handle them?

↳ For Diabetes, missing values were in Glucose and blood pressure. handled by imputing with mean. Categorical missing values were age, hours worked handled by mean

2.

↳ For Diabetes, columns were Gender, Race, Ethnicity

↳ For Adult columns were workclass, education,

4/3/25

Code:

```
import pandas as pd
file_path = 'housing.csv'
df = pd.read_csv(file_path)
print("\nDataset Information:")
print(df.info())
print("\nStatistical Information of Numerical Columns:")
print(df.describe())
print("\nUnique Labels Count for 'Ocean Proximity' column:")
print(df['ocean_proximity'].value_counts())
print("\nAttributes with Missing Values:")
missing_values = df.isnull().sum()
columns_with_missing_values = missing_values[missing_values > 0]
print(columns_with_missing_values)
```

```
Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
None

Statistical Information of Numerical Columns:
          longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000

Unique Labels Count for 'Ocean Proximity' column:
ocean_proximity
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: count, dtype: int64

Attributes with Missing Values:
total_bedrooms    207
dtype: int64
```

```
import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler, StandardScaler
file_path = "diabetes.csv"
df = pd.read_csv(file_path)
df_numeric = df.select_dtypes(include=['number']).copy() # Select only numeric columns
imputer = SimpleImputer(strategy="mean")
df_numeric.iloc[:, :] = imputer.fit_transform(df_numeric)
df[df_numeric.columns] = df_numeric
Q1 = df_numeric.quantile(0.25) # Only compute quartiles on numeric data
Q3 = df_numeric.quantile(0.75) # Only compute quartiles on numeric data
IQR = Q3 - Q1
df = df[~((df_numeric < (Q1 - 1.5 * IQR)) | (df_numeric > (Q3 + 1.5 * IQR))).any(axis=1)]
min_max_scaler = MinMaxScaler()
df_minmax = pd.DataFrame(min_max_scaler.fit_transform(df_numeric),
columns=df_numeric.columns) # Only transform the numeric columns
standard_scaler = StandardScaler()
df_standard = pd.DataFrame(standard_scaler.fit_transform(df_numeric), columns=df_numeric.columns)
# Only transform the numeric columns
print("\nProcessed Diabetes Dataset (Min-Max Scaled):")
print(df_minmax.head())
```

```
print("\nProcessed Diabetes Dataset (Standard Scaled):")
print(df_standard.head())
```

```
Processed Diabetes Dataset (Min-Max Scaled):
         ID  No_Pation       AGE      Urea        Cr     HbA1c      Chol  \
0  0.627034   0.000237  0.508475  0.109375  0.050378  0.264901  0.407767
1  0.918648   0.000452  0.101695  0.104167  0.070529  0.264901  0.359223
2  0.524406   0.000634  0.508475  0.109375  0.050378  0.264901  0.407767
3  0.849812   0.001160  0.508475  0.109375  0.050378  0.264901  0.407767
4  0.629537   0.000452  0.220339  0.171875  0.050378  0.264901  0.475728

         TG       HDL       LDL      VLDL       BMI
0  0.044444  0.226804  0.114583  0.011461  0.173913
1  0.081481  0.092784  0.187500  0.014327  0.139130
2  0.044444  0.226804  0.114583  0.011461  0.173913
3  0.044444  0.226804  0.114583  0.011461  0.173913
4  0.051852  0.061856  0.177083  0.008596  0.069565

Processed Diabetes Dataset (Standard Scaled):
         ID  No_Pation       AGE      Urea        Cr     HbA1c      Chol  \
0  0.672140  -0.074747 -0.401144 -0.144781 -0.382672 -1.334983 -0.509436
1  1.641852  -0.069940 -3.130017 -0.212954 -0.115804 -1.334983 -0.893730
2  0.330868  -0.065869 -0.401144 -0.144781 -0.382672 -1.334983 -0.509436
3  1.412950  -0.054126 -0.401144 -0.144781 -0.382672 -1.334983 -0.509436
4  0.680463  -0.069939 -2.334096  0.673299 -0.382672 -1.334983  0.028576

         TG       HDL       LDL      VLDL       BMI
0 -1.035084  1.810756 -1.085457 -0.369958 -1.124622
1 -0.678063 -0.158692 -0.457398 -0.342649 -1.326239
2 -1.035084  1.810756 -1.085457 -0.369958 -1.124622
3 -1.035084  1.810756 -1.085457 -0.369958 -1.124622
4 -0.963680 -0.613180 -0.547121 -0.397267 -1.729472
```

```
import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder
file_path = "adult.csv"  # Update the path if needed
df = pd.read_csv(file_path)
df.replace("?", np.nan, inplace=True)
num_imputer = SimpleImputer(strategy="mean")
df[df.select_dtypes(include=['number']).columns] =
num_imputer.fit_transform(df.select_dtypes(include=['number']))
cat_imputer = SimpleImputer(strategy="most_frequent")
df[df.select_dtypes(include=['object']).columns] =
cat_imputer.fit_transform(df.select_dtypes(include=['object']))
label_encoders = {}
for col in df.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
```

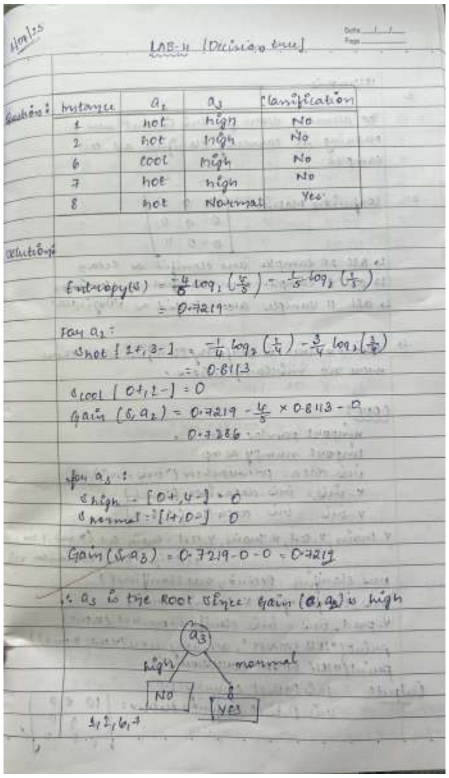
```
df = df[~((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).any(axis=1)]
min_max_scaler = MinMaxScaler()
df_minmax = pd.DataFrame(min_max_scaler.fit_transform(df), columns=df.columns)
standard_scaler = StandardScaler()
df_standard = pd.DataFrame(standard_scaler.fit_transform(df), columns=df.columns)
print("\nProcessed Adult Income Dataset (Min-Max Scaled):")
print(df_minmax.head())
print("\nProcessed Adult Income Dataset (Standard Scaled):")
print(df_standard.head())
```

```
Processed Adult Income Dataset (Min-Max Scaled):
        age  workclass    fnlwgt  education  educational-num  marital-status  \
0  0.344262        0.0  0.188277   0.555556         0.363636        0.333333
1  0.114754        0.0  0.881156   1.000000         0.454545        0.666667
2  0.147541        0.0  0.169156   0.555556         0.363636        0.666667
3  0.672131        0.0  0.708251   0.555556         0.363636        0.333333
4  0.131148        0.0  0.475807   0.333333         0.727273        0.333333

   occupation  relationship  race  gender  capital-gain  capital-loss  \
0    0.307692           0.0   0.0     1.0           0.0           0.0
1    0.538462           0.8   0.0     0.0           0.0           0.0
2    0.000000           0.2   0.0     0.0           0.0           0.0
3    0.692308           0.0   0.0     1.0           0.0           0.0
4    0.692308           0.0   0.0     1.0           0.0           0.0

   hours-per-week  native-country  income
0        0.894737             0.0     0.0
1        0.368421             0.0     0.0
2        0.315789             0.0     0.0
3        0.105263             0.0     0.0
4        0.368421             0.0     0.0

Processed Adult Income Dataset (Standard Scaled):
        age  workclass    fnlwgt  education  educational-num  marital-status  \
0  0.220179        0.0 -1.022983  -0.151256        -0.654083       -0.398228
1 -0.955630        0.0  2.234629   1.457372        -0.073261        0.828047
2 -0.787657        0.0 -1.112882  -0.151256        -0.654083        0.828047
3  1.899906        0.0  1.421707  -0.151256        -0.654083       -0.398228
4 -0.871644        0.0  0.328856  -0.955571         1.669207       -0.398228

   occupation  relationship  race    gender  capital-gain  capital-loss  \
0   -0.420679     -1.044582   0.0  0.770972           0.0           0.0
1    0.305840      1.629927   0.0 -1.297064           0.0           0.0
2   -1.389371     -0.375955   0.0 -1.297064           0.0           0.0
3    0.790186     -1.044582   0.0  0.770972           0.0           0.0
4    0.790186     -1.044582   0.0  0.770972           0.0           0.0

   hours-per-week  native-country  income
0        2.312838             0.0     0.0
1       -0.329781             0.0     0.0
2       -0.594043             0.0     0.0
3       -1.651090             0.0     0.0
4       -0.329781             0.0     0.0
```

Program 3

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

Screenshot:



LAB-4 [Decision tree]

Question:

Instance	a_1	a_3	Classification
1	hot	high	No
2	hot	high	No
6	cool	high	No
7	hot	high	No
8	hot	Normal	Yes

Solution:

$Entropy(S) = -\frac{4}{5}\log_2\left(\frac{4}{5}\right) - \frac{1}{5}\log_2\left(\frac{1}{5}\right) = 0.7219$

For a_2:

$S_{hot}[1+, 3-] = -\frac{1}{4}\log_2\left(\frac{1}{4}\right) - \frac{3}{4}\log_2\left(\frac{3}{4}\right) = 0.8113$

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

$Gain(S, a_2) = 0.7219 - \frac{4}{5} \times 0.8113 - 0 = 0.7286$

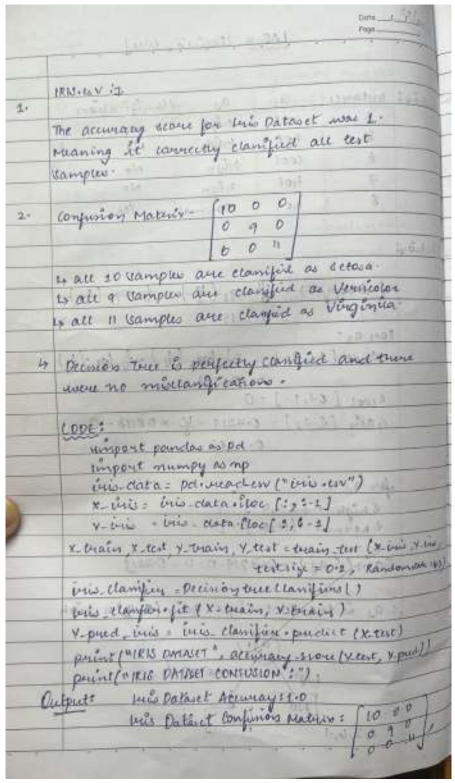
For a_3:

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

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

$Gain(S, a_3) = 0.7219 - 0 - 0 = 0.7219$

$\therefore a_3$ is the Root since Gain (S, a_3) is high



IRIS.csv :1

1. The accuracy score for Iris Dataset was 1. Meaning it correctly classified all test samples.

2. Confusion Matrix - $\begin{bmatrix} 10 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 11 \end{bmatrix}$

↳ all 10 samples are classified as Setosa

↳ all 9 samples are classified as Versicolor

↳ all 11 samples are classified as Virginica

↳ Decision Tree is perfectly classified and there were no misclassifications.

CODE:

```
import pandas as pd
import numpy as np
iris_data = pd.read_csv("iris.csv")
x_iris = iris_data.iloc[:, :-1]
y_iris = iris_data.iloc[:, -1]
x_train, x_test, y_train, y_test = train_test(x_iris, y_iris,
                                     testsize = 0.2, Randomstate(42))
iris_classifier = DecisionTreeClassifier()
iris_classifier.fit(X_train, y_train)
y_pred_iris = iris_classifier.predict(x_test)
print("IRIS DATASET", accuracy_score(y_test, y_pred))
print("IRIS DATASET CONFUSION :")
```

Output: Iris Dataset Accuracy: 1.0

Iris Dataset Confusion Matrix : $\begin{bmatrix} 10 & 0 & 0 \\ 0 & 9 & 0 \\ 0 & 0 & 11 \end{bmatrix}$

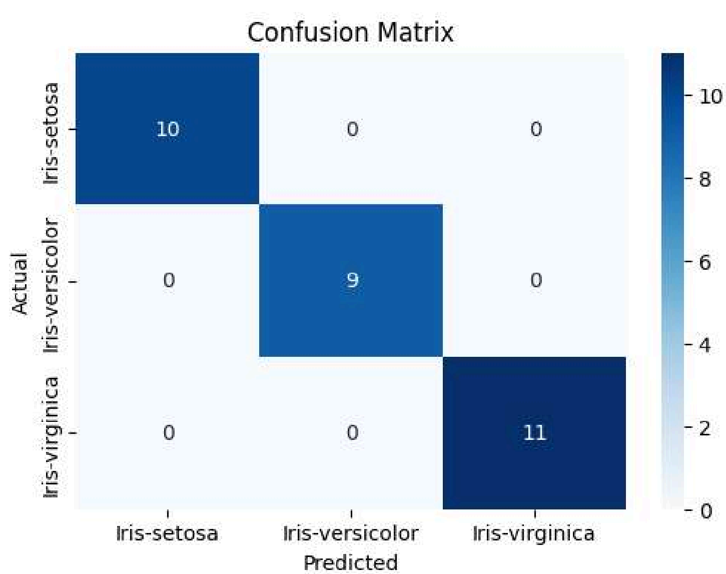
Code:

Iris.csv

```
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, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
df = pd.read_csv('iris.csv')
le = LabelEncoder()
df['species'] = le.fit_transform(df['species'])
X = df.drop('species', axis=1)
y = df['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
clf = DecisionTreeClassifier(criterion='entropy', random_state=42)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print(classification_report(y_test, y_pred, target_names=le.classes_))
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,4))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=le.classes_,
yticklabels=le.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
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)
plt.show()
```

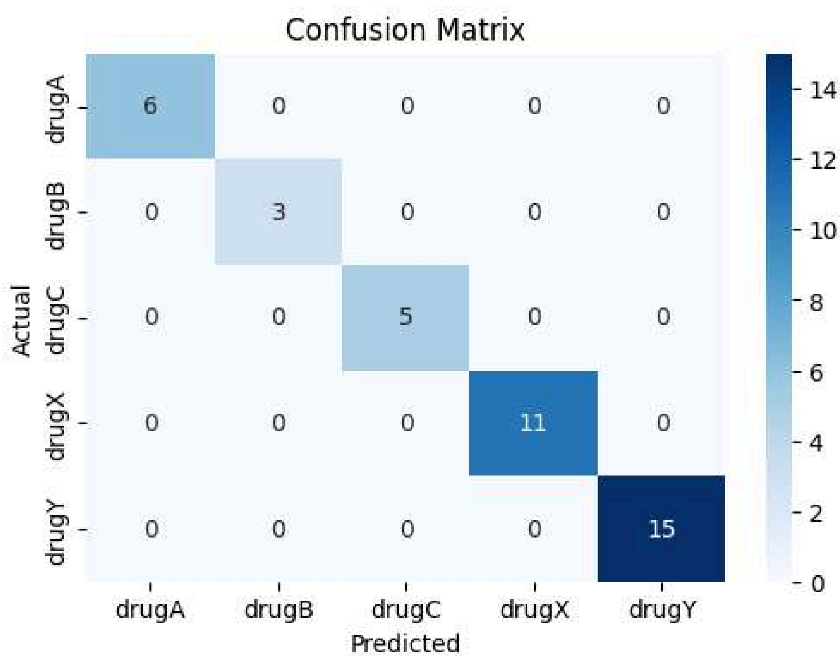
```
Accuracy: 1.00
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      1.00      1.00         9
 Iris-virginica       1.00      1.00      1.00        11

       accuracy                           1.00        30
      macro avg       1.00      1.00      1.00        30
   weighted avg       1.00      1.00      1.00        30
```



Drug.csv

```
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
df = pd.read_csv('drug.csv')
label_encoders = {}
for column in df.columns:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le
X = df.drop('Drug', axis=1)
y = df['Drug']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
clf = DecisionTreeClassifier(criterion='entropy')
clf.fit(X_train, y_train)
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))
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,4))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=le.classes_,
yticklabels=le.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
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)
plt.show()
```

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

           0       1.00      1.00      1.00         6
           1       1.00      1.00      1.00         3
           2       1.00      1.00      1.00         5
           3       1.00      1.00      1.00        11
           4       1.00      1.00      1.00        15

    accuracy                           1.00        40
   macro avg       1.00      1.00      1.00        40
weighted avg       1.00      1.00      1.00        40
```




```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.metrics import mean_absolute_error, mean_squared_error
import matplotlib.pyplot as plt
import math
data = pd.read_csv('petrol_consumption.csv')
X = data.drop('Petrol_Consumption', axis=1)
y = data['Petrol_Consumption']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
regressor = DecisionTreeRegressor(random_state=42, max_depth=3)  # Limiting depth for readability
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 = math.sqrt(mse)
```

```python
print("Regression Tree Evaluation Metrics:")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
plt.figure(figsize=(20,6))
plot_tree(
    regressor,
    feature_names=X.columns,
    filled=True,
    rounded=True,
    fontsize=10,
)
plt.title("Regression Tree for Petrol Consumption Prediction", fontsize=14)
plt.show()
```

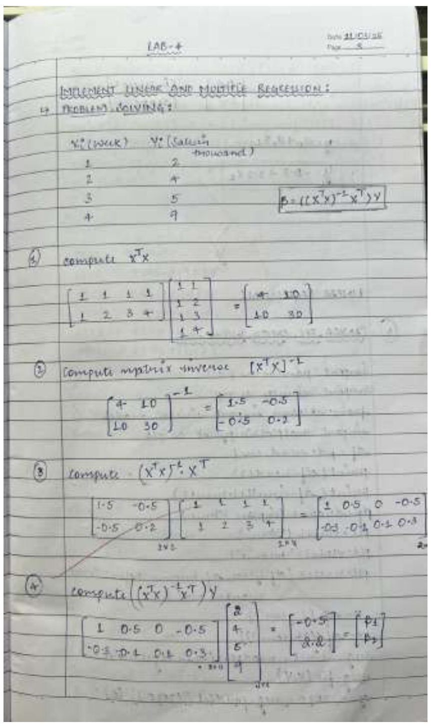
```
Regression Tree Evaluation Metrics:
Mean Absolute Error (MAE): 80.63
Mean Squared Error (MSE): 14718.40
Root Mean Squared Error (RMSE): 121.32
```

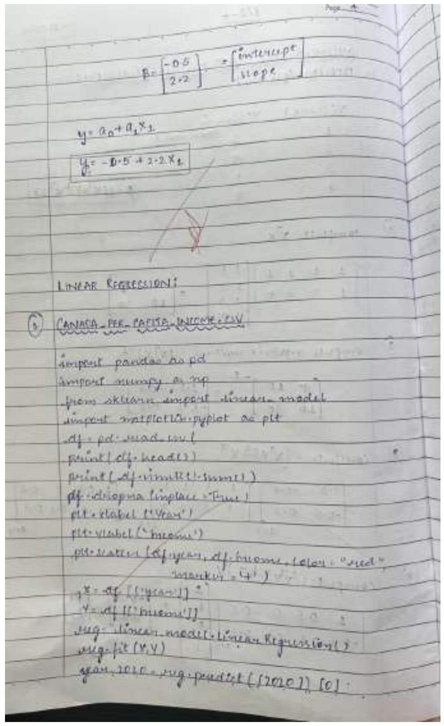
Program 4

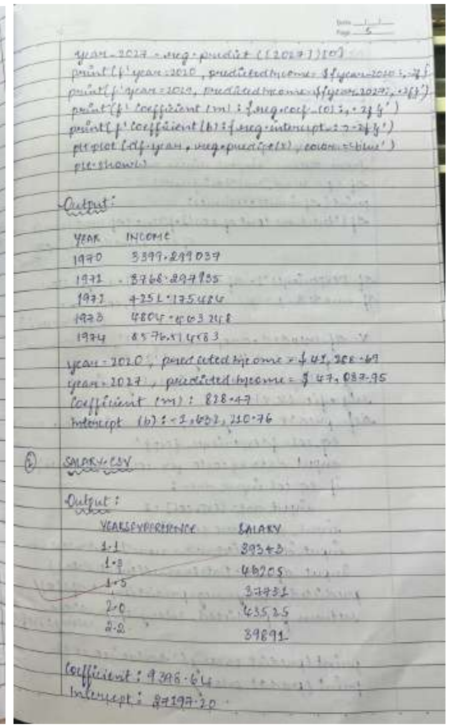
Implement Linear and Multi-Linear Regression algorithm using appropriate dataset.

Linear Regression:

Screenshot:



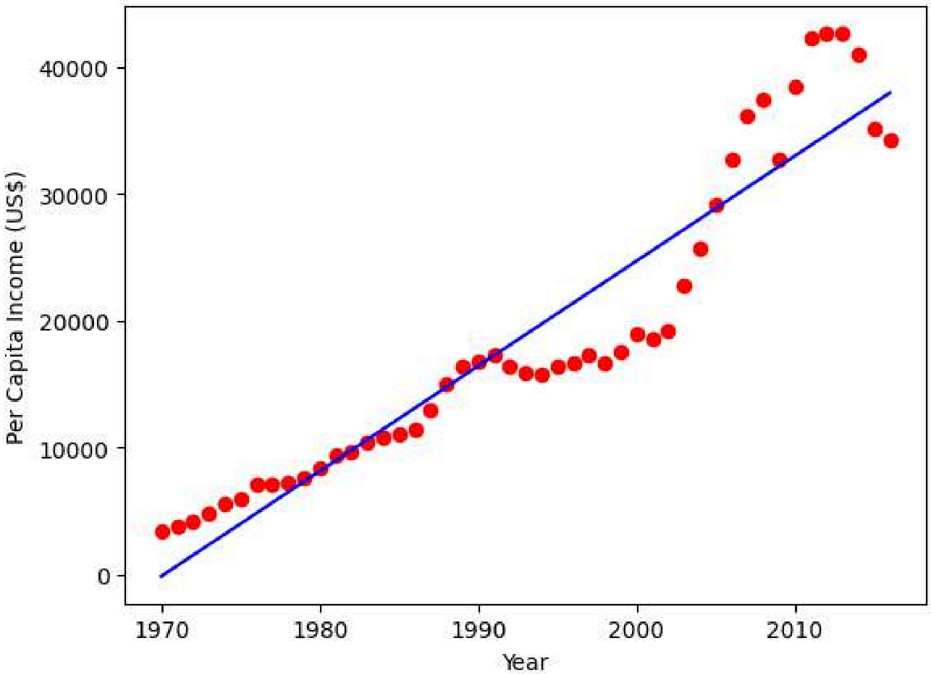




Code:

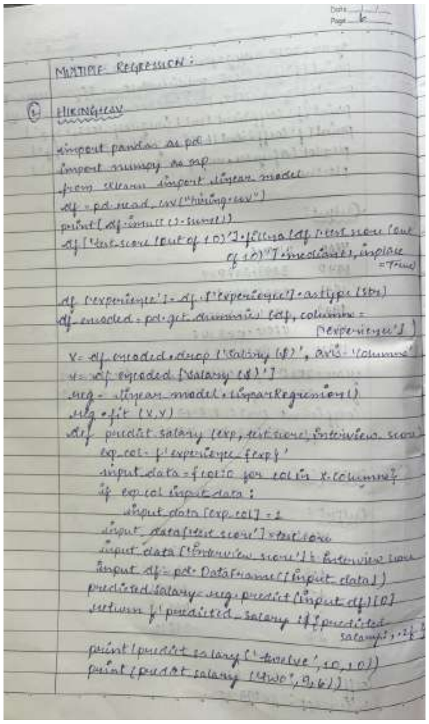
```
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt
df = pd.read_csv('canada_per_capita_income.csv')
reg = linear_model.LinearRegression()
reg.fit(df[['year']], df['per capita income (US$)'])
print(f"Coefficient: {reg.coef_}")
print(f"Intercept: {reg.intercept_}")
predicted_income = reg.predict([[2020]])
print(f"Predicted per capita income for 2020: ${predicted_income[0]:,.2f}")
plt.scatter(df['year'], df['per capita income (US$)'], color='red')
plt.plot(df['year'], reg.predict(df[['year']]), color='blue')
plt.xlabel('Year')
plt.ylabel('Per Capita Income (US$)')
plt.show()
print(results.head())
```

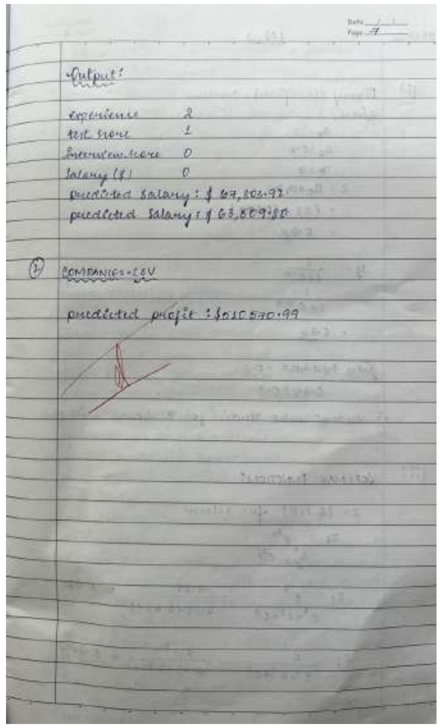
```
Coefficient: [828.46507522]
Intercept: -1632210.7578554575
Predicted per capita income for 2020: $41,288.69
```



Multiple Regression:

Screenshot:





Code:

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
df_hiring = pd.read_csv('hiring.csv')
print("Original Data:")
print(df_hiring.head())
df_hiring['experience'] = df_hiring['experience'].replace({
    'five': 5,
    'four': 4,
    'three': 3
})
df_hiring['experience'] = pd.to_numeric(df_hiring['experience'], errors='coerce')
df_hiring['test_score(out of 10)'] = pd.to_numeric(df_hiring['test_score(out of 10)'], errors='coerce')
df_hiring['interview_score(out of 10)'] = pd.to_numeric(df_hiring['interview_score(out of 10)'],
errors='coerce')
df_hiring['salary($)'] = pd.to_numeric(df_hiring['salary($)'], errors='coerce')
df_hiring['experience'] = df_hiring['experience'].fillna(df_hiring['experience'].median())
df_hiring['test_score(out of 10)'] = df_hiring['test_score(out of 10)'].fillna(df_hiring['test_score(out of
10)'].median())
df_hiring['interview_score(out of 10)'] = df_hiring['interview_score(out of
10)'].fillna(df_hiring['interview_score(out of 10)'].median())
df_hiring['salary($)'] = df_hiring['salary($)'].fillna(df_hiring['salary($)'].median())
X_hiring = df_hiring[['experience', 'test_score(out of 10)', 'interview_score(out of 10)']]
y_hiring = df_hiring['salary($)']
```

```
model_hiring = LinearRegression()
model_hiring.fit(X_hiring, y_hiring)
print(f"\nCoefficients: {model_hiring.coef_}")
print(f"Intercept: {model_hiring.intercept_}")
predictions_hiring = model_hiring.predict([[2, 9, 6], [12, 10, 10]])
print(f"\nPredicted salary for candidate 1 (2 years experience, 9 test score, 6 interview score): ${predictions_hiring[0]:,.2f}")
print(f"Predicted salary for candidate 2 (12 years experience, 10 test score, 10 interview score): ${predictions_hiring[1]:,.2f}")
```

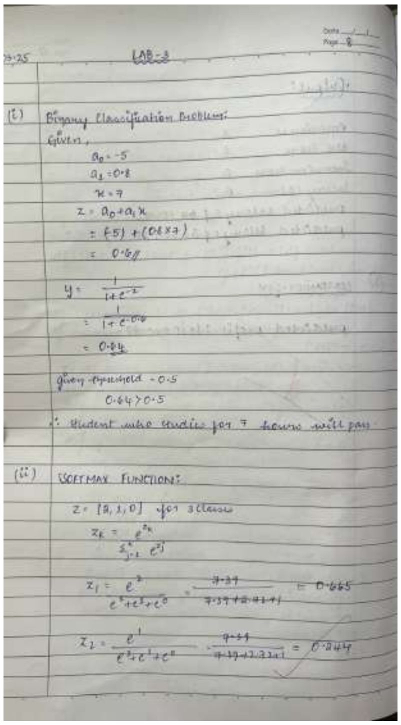
```
Original Data:
  experience  test_score(out of 10)  interview_score(out of 10)  salary($)
0        NaN                    8.0                           9      50000
1        NaN                    8.0                           6      45000
2       five                    6.0                           7      60000
3        two                   10.0                          10      65000
4      seven                    9.0                           6      70000

Coefficients: [-793.62416107   -5.03355705  139.26174497]
Intercept: 65117.44966442955

Predicted salary for candidate 1 (2 years experience, 9 test score, 6 interview score): $64,320.47
Predicted salary for candidate 2 (12 years experience, 10 test score, 10 interview score): $56,936.24
```

Program 5

Build Logistic Regression Model for a given dataset.

Binary Logical Regression:

Screenshot:



LAB-3

(i) Binary Classification Problem:

Given,

$a_0 = -5$

$a_1 = 0.8$

$x = 7$

$z = a_0 + a_1 x$

$= (-5) + (0.8 \times 7)$

$= 0.6$

$y = \frac{1}{1+e^{-z}}$

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

$= 0.64$

given threshold = 0.5

0.64 > 0.5

∴ Student who studies for 7 hours will pass

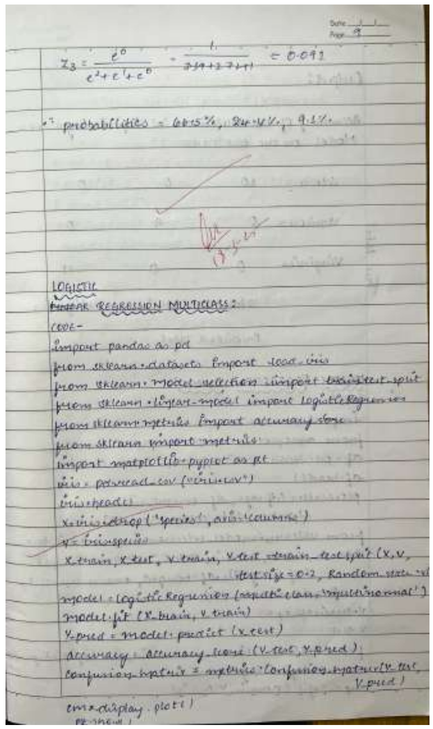
(ii) SOFTMAX FUNCTION:

z = [2, 1, 0] for 3 classes

$z_k = \frac{e^{z_k}}{\sum_{j=1}^{k} e^{z_j}}$

$z_1 = \frac{e^2}{e^2+e^1+e^0} = \frac{7.39}{7.39+2.71+1} = 0.665$

$z_2 = \frac{e^1}{e^2+e^1+e^0} = \frac{2.71}{7.39+2.71+1} = 0.244$



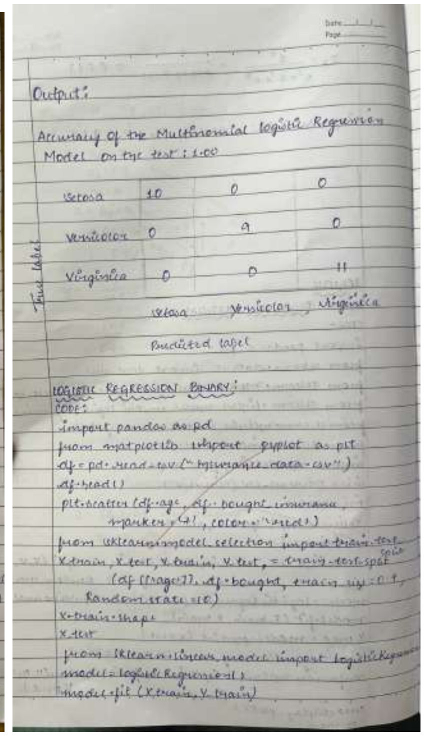
$z_3 = \frac{e^0}{e^2+e^1+e^0} = \frac{1}{7.39+2.71+1} = 0.091$

∴ probabilities = 66.5%, 24.4%, 9.1%

LOGISTIC REGRESSION MULTICLASS:

CODE-

```
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 = LogisticRegression(multi_class='multinomial')
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
confusion_matrix = metrics.confusion_matrix(y_test,
        y_pred)
cm.display.plot()
plt.show()
```



Output:

Accuracy of the Multinomial logistic Regression Model on the test : 1.00

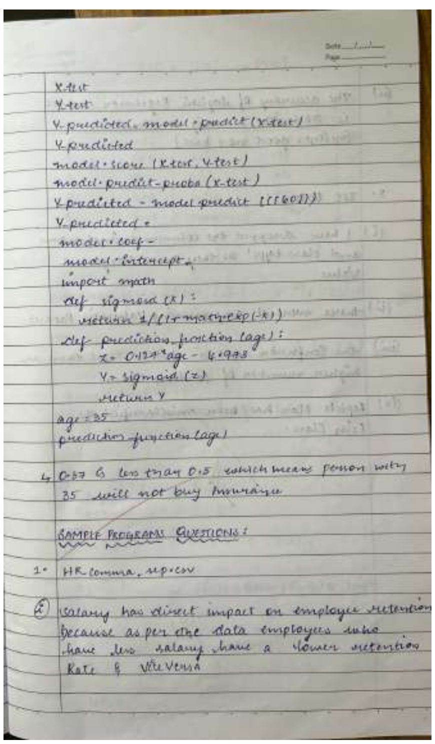
True label	Setosa	Versicolor	Virginica
Setosa	10	0	0
Versicolor	0	9	0
Virginica	0	0	11

Predicted label

LOGISTIC REGRESSION BINARY:

CODE:

```
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, 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)
```



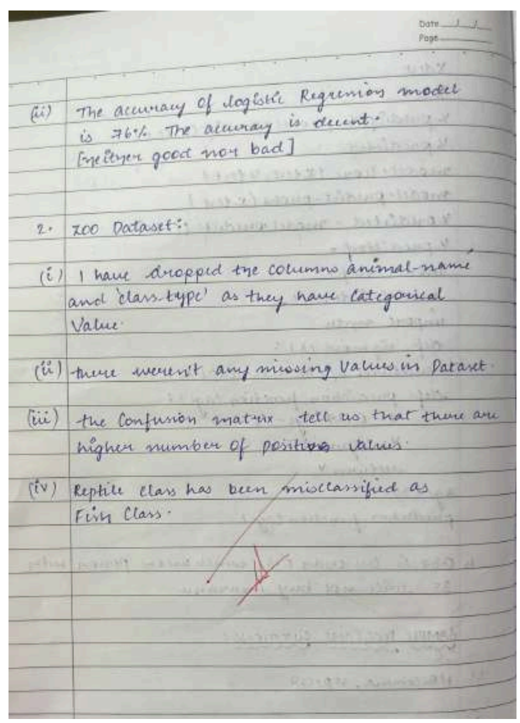
```
x_test
y_test
y_predicted = model.predict(x_test)
y_predicted
model.score(x_test, y_test)
model.predict_proba(x_test)
y_predicted = model.predict([[60]])
y_predicted
model.coef_
model.intercept_
import math
def sigmoid(x):
    return 1/(1+math.exp(-x))
def prediction_function(age):
    z = 0.127*age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

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

SAMPLE PROGRAMS QUESTIONS:

1. HR comma_sep.csv

(i) Salary has direct impact on employee retention because as per the data employees who have less salary have a lower retention Rate & viceversa



(ii) The accuracy of logistic Regression model is 76%. The accuracy is decent. [neither good nor bad]

2. Zoo Dataset:

(i) I have dropped the columns animal_name and 'class_type' as they have categorical value.

(ii) there weren't any missing values in Dataset

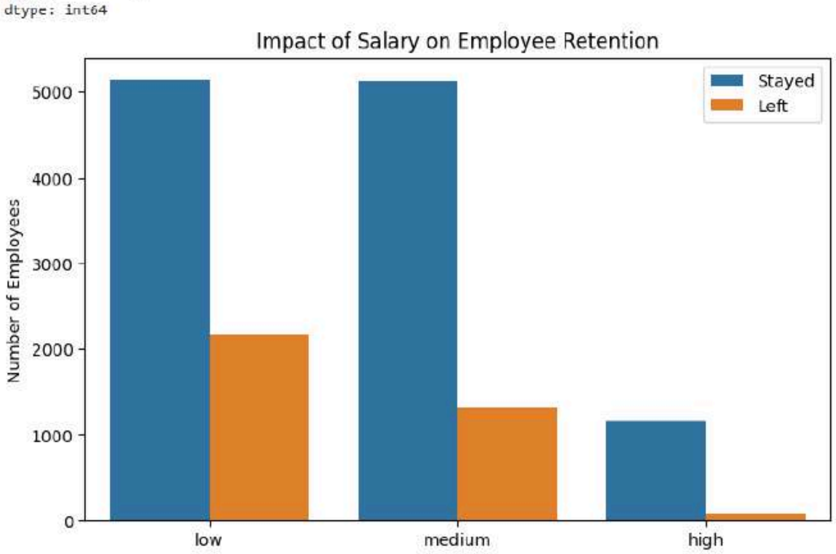
(iii) the Confusion matrix tell us that there are higher number of positive values.

(iv) Reptile class has been misclassified as Fish Class.

Code:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
hr_data = pd.read_csv("HR_comma_sep.csv")
print(hr_data.head())
print("\nMissing values:\n", hr_data.isnull().sum())
print("\nData Types:\n", hr_data.dtypes)
print("\nUnique values in categorical columns:\n",
hr_data.select_dtypes(include=['object']).nunique())
plt.figure(figsize=(8,5))
sns.countplot(x="salary", hue="left", data=hr_data)
plt.title("Impact of Salary on Employee Retention")
plt.xlabel("Salary Level")
plt.ylabel("Number of Employees")
plt.legend(["Stayed", "Left"])
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

Missing values:
 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

Data Types:
 satisfaction_level       float64
last_evaluation          float64
number_project             int64
average_montly_hours       int64
time_spend_company         int64
Work_accident              int64
left                       int64
promotion_last_5years      int64
Department                object
salary                    object
dtype: object

Unique values in categorical columns:
 Department    10
salary         3
dtype: int64
```

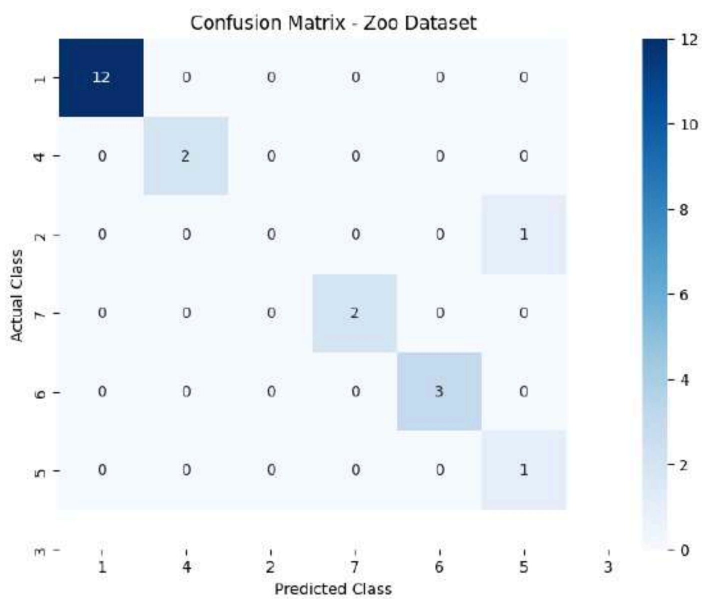


Multi Linear classification

Code:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
zoo_data = pd.read_csv("zoo-data.csv")
class_types = pd.read_csv("zoo-class-type.csv")
print("Zoo Data:\n", zoo_data.head())
print("\nClass Type Data:\n", class_types.head())
if "class_type" not in zoo_data.columns:
    print("\nError: 'class_type' column is missing in zoo-data.csv. Available columns: ",
zoo_data.columns)
else:
    X = zoo_data.drop(columns=["animal_name", "class_type"], errors="ignore")
    y = zoo_data["class_type"]
    print("\nUnique class types:", y.unique())
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)
    model = LogisticRegression(multi_class="multinomial", solver="lbfgs", max_iter=200)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"\nModel Accuracy: {accuracy:.4f}")
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(8,6))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=y.unique(), yticklabels=y.unique())
    plt.xlabel("Predicted Class")
    plt.ylabel("Actual Class")
    plt.title("Confusion Matrix - Zoo Dataset")
    plt.show()
    print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

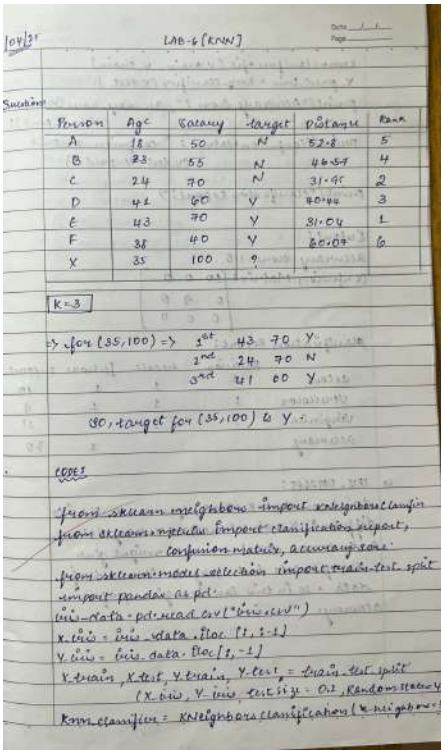
```
Zoo Data:
  animal_name  hair  feathers  eggs  milk  airborne  aquatic  predator  \
0    aardvark     1         0     0     1         0        0         1
1    antelope     1         0     0     1         0        0         0
2        bass     0         0     1     0         0        1         1
3        bear     1         0     0     1         0        0         1
4        boar     1         0     0     1         0        0         1

   toothed  backbone  breathes  venomous  fins  legs  tail  domestic  catsize  \
0        1         1         1         0     0     4     0         0        1
1        1         1         1         0     0     4     1         0        1
2        1         1         0         0     1     0     1         0        0
3        1         1         1         0     0     4     0         0        1
4        1         1         1         0     0     4     1         0        1

   class_type
0           1
1           1
2           4
3           1
4           1

Class Type Data:
   Class_Number  Number_Of_Animal_Species_In_Class Class_Type  \
0             1                                 41     Mammal
1             2                                 20       Bird
2             3                                  5    Reptile
3             4                                 13       Fish
4             5                                  4  Amphibian

                                      Animal_Names
0  aardvark, antelope, bear, boar, buffalo, calf,...
1  chicken, crow, dove, duck, flamingo, gull, haw...
2    pitviper, seasnake, slowworm, tortoise, tuatara
3  bass, carp, catfish, chub, dogfish, haddock, h...
4                           frog, frog, newt, toad

Unique class types: [1 4 2 7 6 5 3]

Model Accuracy: 0.9524
```




```
Classification Report:
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        12
           2       1.00      1.00      1.00         2
           3       0.00      0.00      0.00         1
           4       1.00      1.00      1.00         2
           6       1.00      1.00      1.00         3
           7       0.50      1.00      0.67         1

    accuracy                           0.95        21
   macro avg       0.75      0.83      0.78        21
weighted avg       0.93      0.95      0.94        21
```

Program 6

Build KNN Classification model for a given dataset.
Screenshot:



10/4/25 LAB-6 [KNN]

Person	Age	Salary	target	Distance	Rank
A	18	50	N	52.8	5
B	23	55	N	46.57	4
C	24	70	N	31.45	2
D	41	60	Y	40.44	3
E	43	70	Y	31.04	1
F	38	40	Y	60.07	6
X	35	100	?		

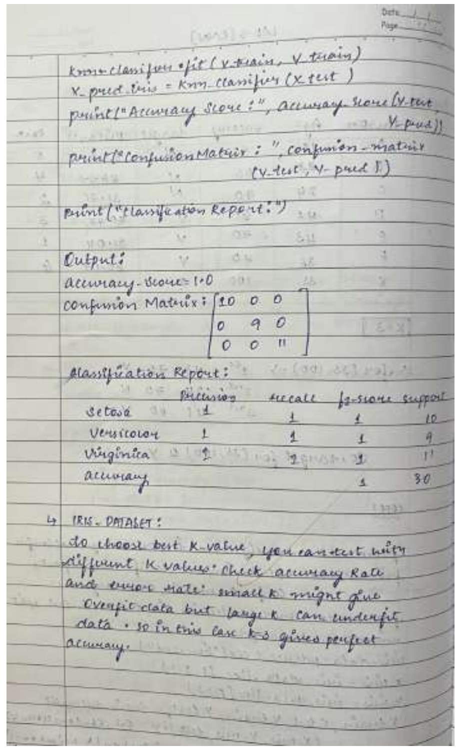
K=3

=> for (35,100) => 1st 43 70 Y
2nd 24 70 N
3rd 41 60 Y

So, target for (35,100) is Y.

CODE:

from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.model_selection import train_test_split
import pandas as pd
iris_data = pd.read_csv("iris.csv")
x_iris = iris_data.iloc[:, :-1]
y_iris = iris_data.iloc[:, -1]
x_train, x_test, y_train, y_test = train_test_split(x_iris, y_iris, test_size=0.2, random_state...
knn_classifier = KNeighborsClassifier(n_neighbors...



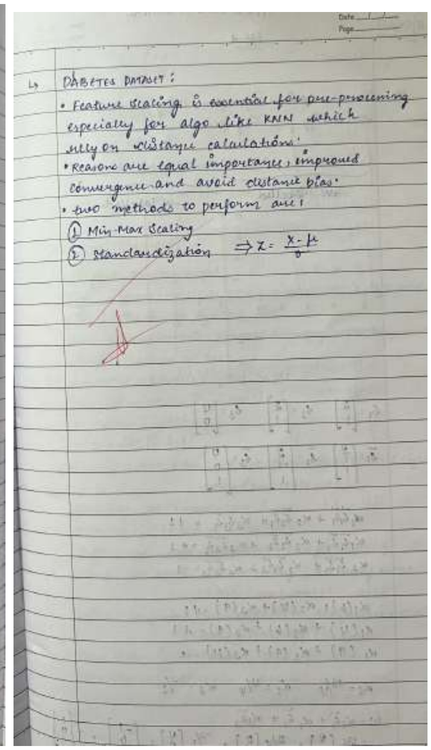
knn_classifier.fit(x_train, y_train)
y_pred_iris = knn_classifier(x_test)
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
print("Classification Report:")

Output:
Accuracy-Score = 1.0
Confusion Matrix: [10 0 0; 0 9 0; 0 0 11]

Classification Report:

	precision	recall	f1-score	support
Setosa	1	1	1	10
Versicolor	1	1	1	9
Virginica	1	1	1	11
accuracy			1	30

IRIS-DATASET:
To choose best K-value, you can test with different K values. Check accuracy rate and error rate. Small K might give overfit data but large K can underfit data. So in this case k=3 gives perfect accuracy.



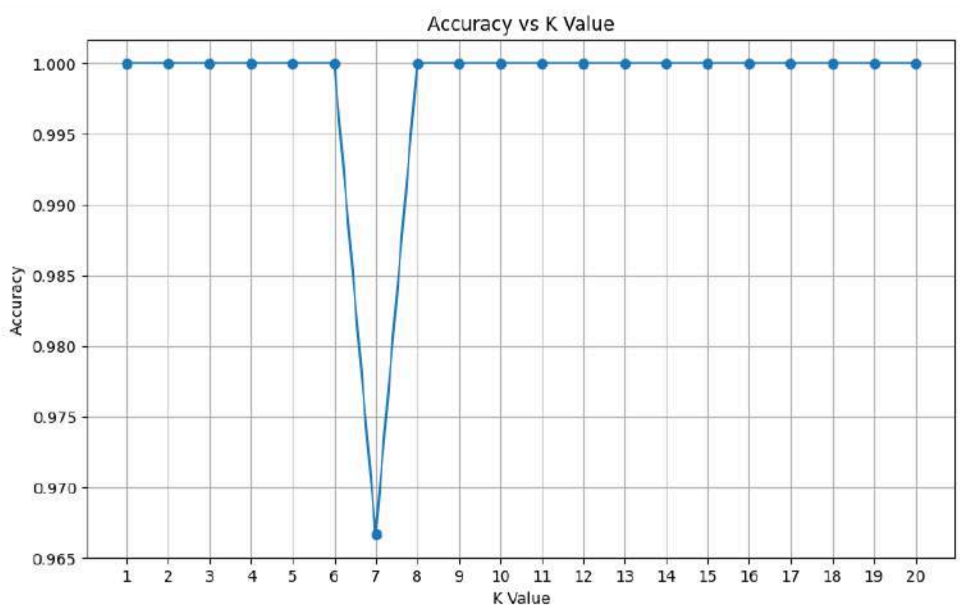
DIABETES DATASET:
• Feature scaling is essential for pre-processing especially for algo like KNN which rely on distance calculations.
• Reasons are equal importance, improved convergence and avoid distance bias.
• two methods to perform are:
1. Min-Max Scaling
2. Standardization $\Rightarrow z = \frac{x-\mu}{\sigma}$

Code:

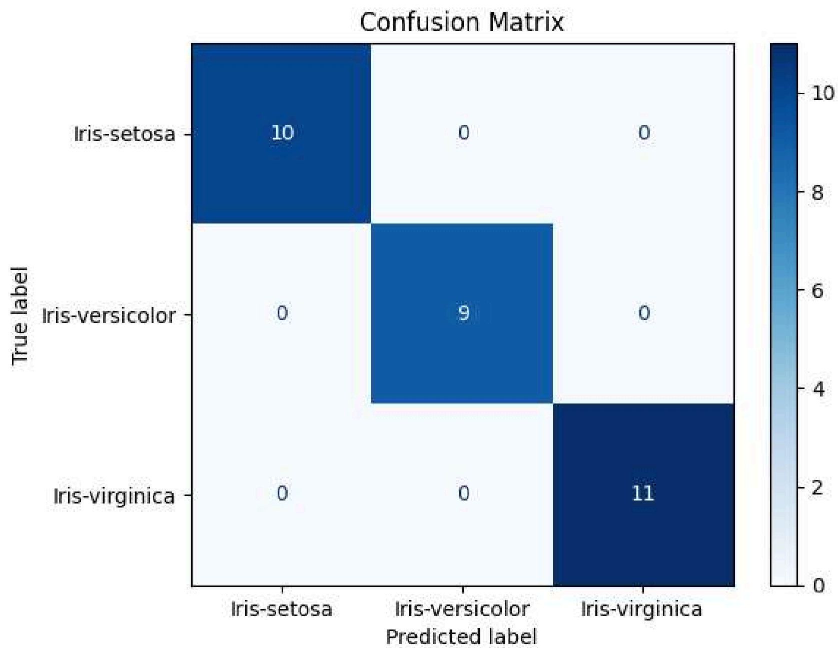
Iris.csv

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (accuracy_score, confusion_matrix, classification_report,
ConfusionMatrixDisplay)
from sklearn.preprocessing import LabelEncoder
data = pd.read_csv('iris.csv')
X = data.drop('species', axis=1)
y = data['species']
le = LabelEncoder()
y = le.fit_transform(y)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
accuracy = []
for k in range(1, 21):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    accuracy.append(accuracy_score(y_test, y_pred))
plt.figure(figsize=(10, 6))
```

```
plt.plot(range(1, 21), accuracy, marker='o')
plt.title('Accuracy vs K Value')
plt.xlabel('K Value')
plt.ylabel('Accuracy')
plt.xticks(range(1, 21))
plt.grid()
plt.show()
optimal_k = np.argmax(accuracy) + 1  # +1 because range starts at 1
print(f"\nOptimal K value: {optimal_k}")
knn = KNeighborsClassifier(n_neighbors=optimal_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy: {accuracy:.4f}")
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=le.classes_)
disp.plot(cmap='Blues')
plt.title('Confusion Matrix')
plt.show()
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=le.classes_))
```




```
Optimal K value: 1

Accuracy: 1.0000

Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

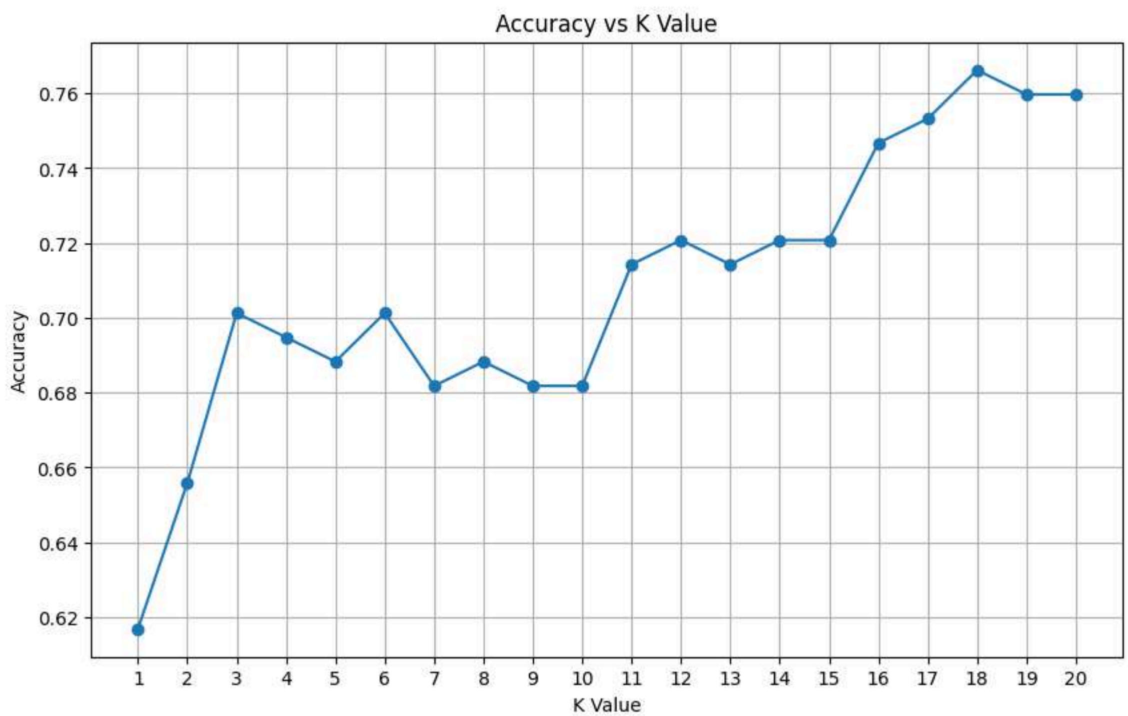



```
Classification Report:
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      1.00      1.00         9
 Iris-virginica       1.00      1.00      1.00        11

       accuracy                           1.00        30
      macro avg       1.00      1.00      1.00        30
   weighted avg       1.00      1.00      1.00        30
```

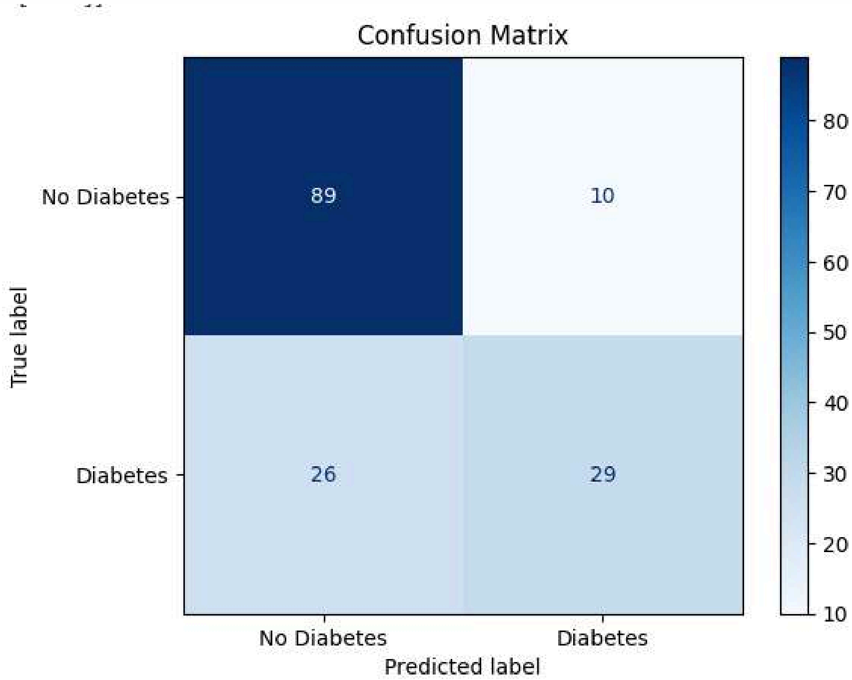
Diabetes.csv

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
data = pd.read_csv('diabetes.csv')
X = data.drop('Outcome', axis=1)
y = data['Outcome']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
k_values = range(1, 21)
accuracy_scores = []
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    accuracy_scores.append(accuracy_score(y_test, y_pred))
```

```
plt.figure(figsize=(10, 6))
plt.plot(k_values, accuracy_scores, marker='o')
plt.title('Accuracy vs K Value')
plt.xlabel('K Value')
plt.ylabel('Accuracy')
plt.xticks(k_values)
plt.grid()
plt.show()
optimal_k = k_values[np.argmax(accuracy_scores)]
print(f"Optimal K value: {optimal_k}")
knn = KNeighborsClassifier(n_neighbors=optimal_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy: {accuracy:.4f}")
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['No Diabetes', 'Diabetes'])
disp.plot(cmap='Blues')
plt.title('Confusion Matrix')
plt.show()
print("\nModel Evaluation:")
print(f"- True Positives: {cm[1,1]}")
print(f"- True Negatives: {cm[0,0]}")
print(f"- False Positives: {cm[0,1]}")
print(f"- False Negatives: {cm[1,0]}")
```




```
Optimal K value: 18

Accuracy: 0.7662

Confusion Matrix:
[[89 10]
 [26 29]]
```

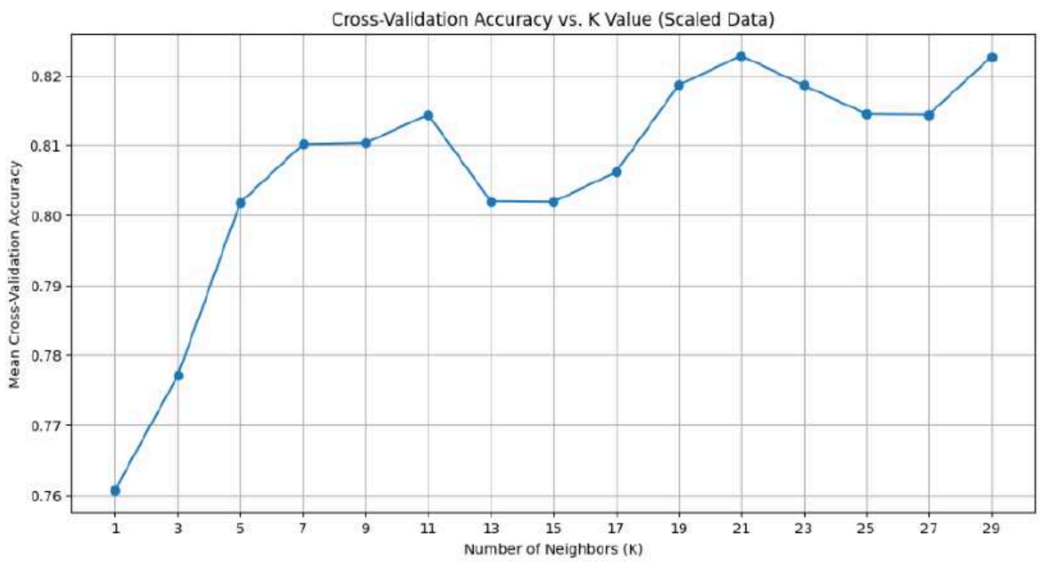



```
Model Evaluation:
- True Positives: 29
- True Negatives: 89
- False Positives: 10
- False Negatives: 26
```

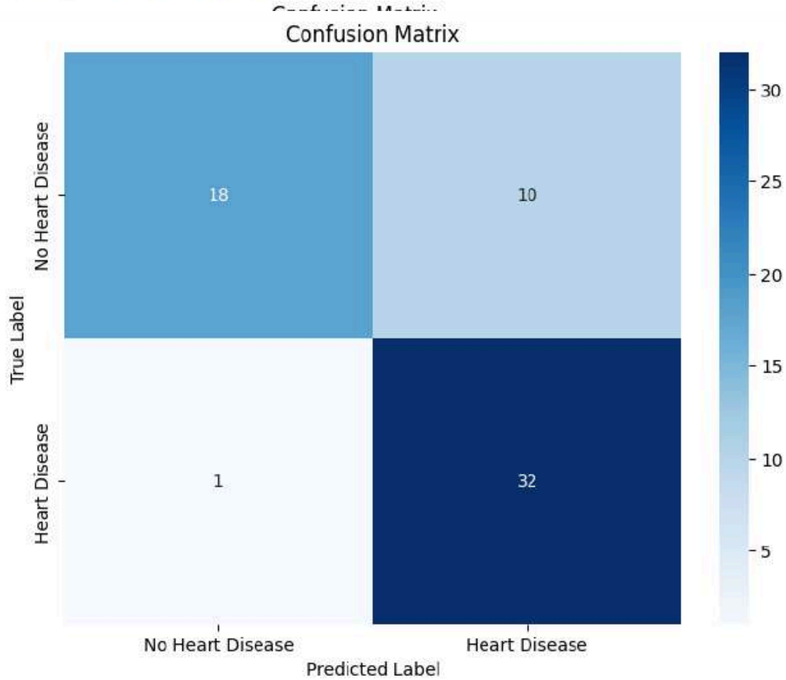
Heart.csv

```
import pandas as pd
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 StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import cross_val_score
try:
    df = pd.read_csv("heart.csv")
except FileNotFoundError:
    print("Error: 'heart.csv' not found. Please make sure the file is in the correct directory.")
    exit()
X = df.drop('target', axis=1)
y = df['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
k_values = list(range(1, 31, 2))  # Try odd k values from 1 to 30
cv_scores = []
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_train_scaled, y_train, cv=5, scoring='accuracy')
    cv_scores.append(scores.mean())
plt.figure(figsize=(12, 6))
plt.plot(k_values, cv_scores, marker='o')
plt.title('Cross-Validation Accuracy vs. K Value (Scaled Data)')
plt.xlabel('Number of Neighbors (K)')
plt.ylabel('Mean Cross-Validation Accuracy')
plt.xticks(k_values)
plt.grid(True)
plt.show()
best_k_index = cv_scores.index(max(cv_scores))
best_k = k_values[best_k_index]
print(f"\nThe optimal K value found through cross-validation is: {best_k}")
knn_classifier = KNeighborsClassifier(n_neighbors=best_k)
knn_classifier.fit(X_train_scaled, y_train)
y_pred = knn_classifier.predict(X_test_scaled)
accuracy = accuracy_score(y_test, y_pred)
confusion = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)
print(f"\nK-Nearest Neighbors Classifier with K = {best_k} (Scaled Data)")
print("Accuracy Score on Test Data:", accuracy)
plt.figure(figsize=(8, 6))
sns.heatmap(confusion, annot=True, fmt='d', cmap='Blues',
        xticklabels=['No Heart Disease', 'Heart Disease'], yticklabels=['No Heart Disease', 'Heart
```

```
Disease'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
print("\nClassification Report on Test Data:\n", report)
```



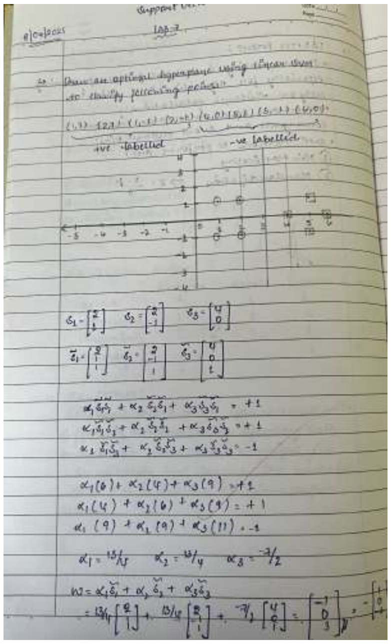

```
The optimal K value found through cross-validation is: 21

K-Nearest Neighbors Classifier with K = 21 (Scaled Data)
Accuracy Score on Test Data: 0.819672131147541
```

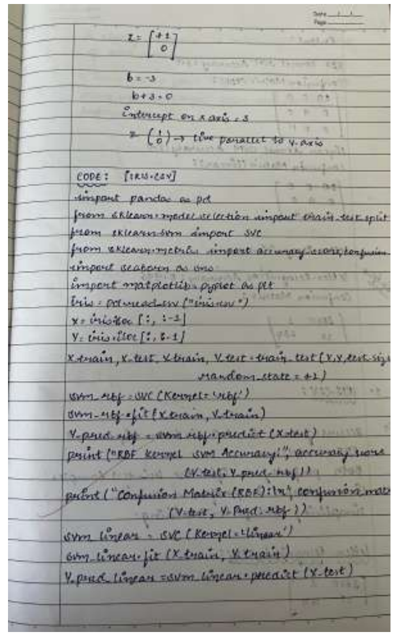


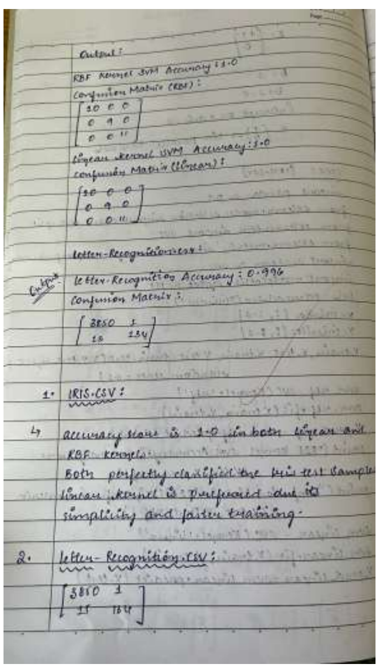

```
Classification Report on Test Data:
              precision    recall  f1-score   support

           0       0.95      0.64      0.77        28
           1       0.76      0.97      0.85        33

    accuracy                           0.82        61
   macro avg       0.85      0.81      0.81        61
weighted avg       0.85      0.82      0.81        61
```

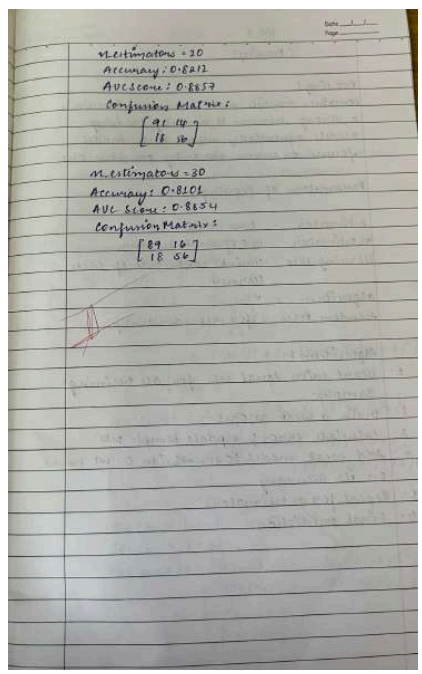
Program 7

Build Support vector machine model for a given dataset
Screenshot:







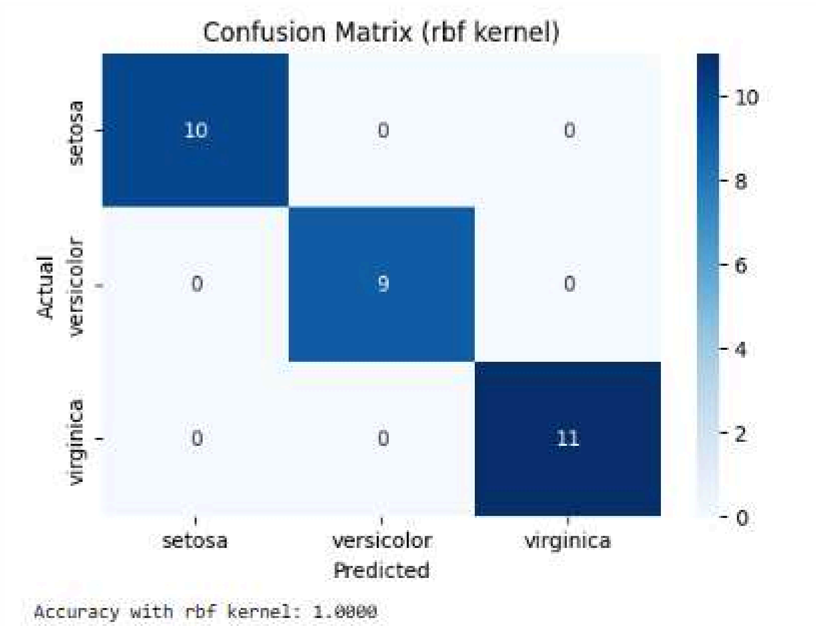


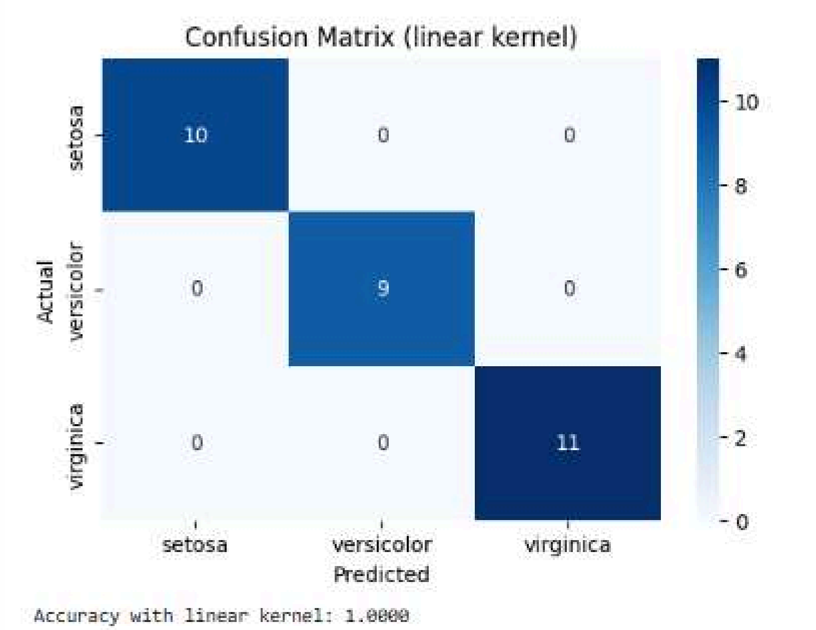
Code:

Iris.csv

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

```
iris_df = pd.read_csv('iris.csv')
X = iris_df.iloc[:, :-1]
y = iris_df.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
def evaluate_svm(kernel_type):
    svm_clf = SVC(kernel=kernel_type, random_state=42)
    svm_clf.fit(X_train, y_train)
    y_pred = svm_clf.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=svm_clf.classes_,
                yticklabels=svm_clf.classes_)
    plt.title(f'Confusion Matrix ({kernel_type} kernel)')
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.show()
    print(f"Accuracy with {kernel_type} kernel: {accuracy:.4f}")
    print("\n")
evaluate_svm('rbf')
evaluate_svm('linear')
```



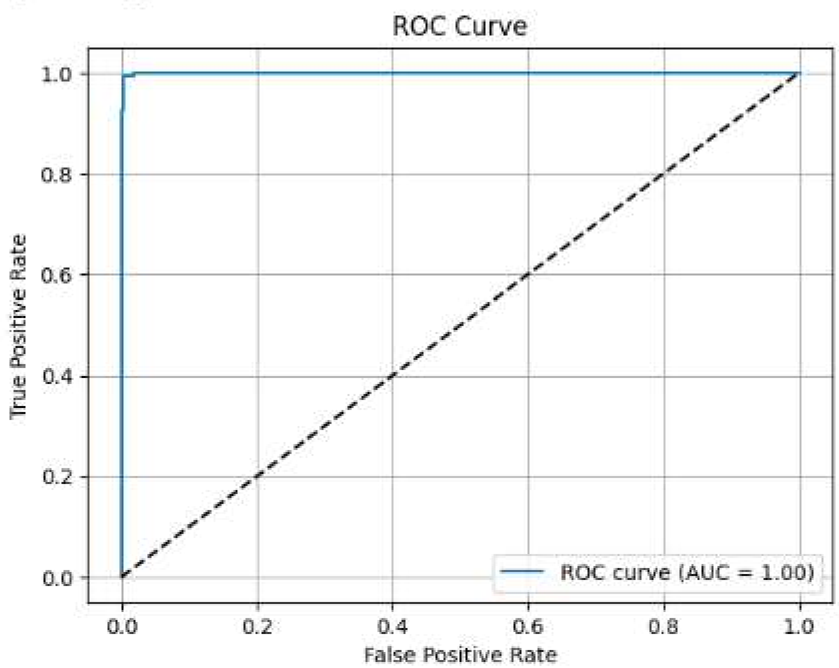


Letter Recognition

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score,
roc_curve
from sklearn.preprocessing import LabelBinarizer
import matplotlib.pyplot as plt
letters = pd.read_csv("letter-recognition.csv")
X = letters.iloc[:, 1:]
y = letters.iloc[:, 0]  # assuming first column is label
```

```
y_binary = (y == 'A').astype(int)  # modify based on actual dataset
X_train, X_test, y_train_bin, y_test_bin = train_test_split(X, y_binary,
test_size=0.2, random_state=42)
svm_model = SVC(kernel='rbf', probability=True)
svm_model.fit(X_train, y_train_bin)
y_pred = svm_model.predict(X_test)
y_prob = svm_model.predict_proba(X_test)[:, 1]
print("Letter Recognition Accuracy:", accuracy_score(y_test_bin, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test_bin, y_pred))
fpr, tpr, _ = roc_curve(y_test_bin, y_prob)
auc_score = roc_auc_score(y_test_bin, y_prob)
plt.figure()
plt.plot(fpr, tpr, label=f"ROC curve (AUC = {auc_score:.2f})")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```

```
Letter Recognition Accuracy: 0.996
Confusion Matrix:
 [[3850    1]
 [  15  134]]
```

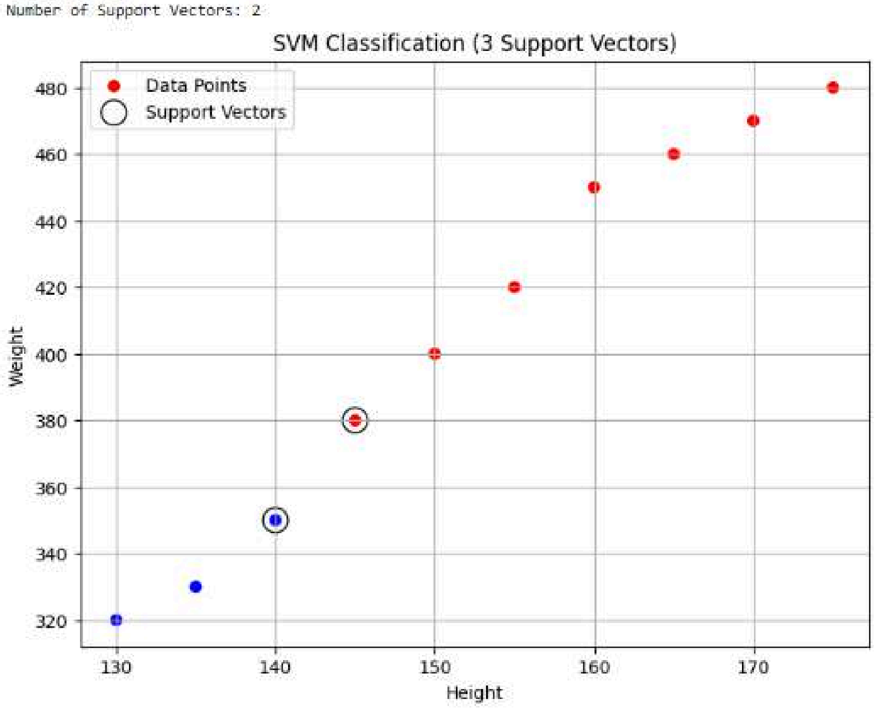


Horse Mule dataset

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.svm import SVC
from sklearn.preprocessing import LabelEncoder
```

```
df = pd.read_csv("horse_mule_data.csv")
# Encode 'Horse'=0, 'Mule'=1
df['Label'] = LabelEncoder().fit_transform(df['Label'])
X = df[['Height', 'Weight']]
y = df['Label']
model = SVC(kernel='linear', C=1000)  # High C -> fewer support vectors
model.fit(X, y)
support_vectors = model.support_vectors_
accuracy = model.score(X, y)
print("Accuracy:", accuracy)
print("Support Vectors:\n", support_vectors)
print("Number of Support Vectors:", len(support_vectors))
colors = ['red' if label == 0 else 'blue' for label in y]
plt.figure(figsize=(8,6))
plt.scatter(X['Height'], X['Weight'], c=colors, label='Data Points')
plt.scatter(support_vectors[:, 0], support_vectors[:, 1],
            s=200, facecolors='none', edgecolors='black', label='Support Vectors')
plt.xlabel("Height")
plt.ylabel("Weight")
plt.title("SVM Classification (3 Support Vectors)")
plt.legend()
plt.grid(True)
plt.show()
```

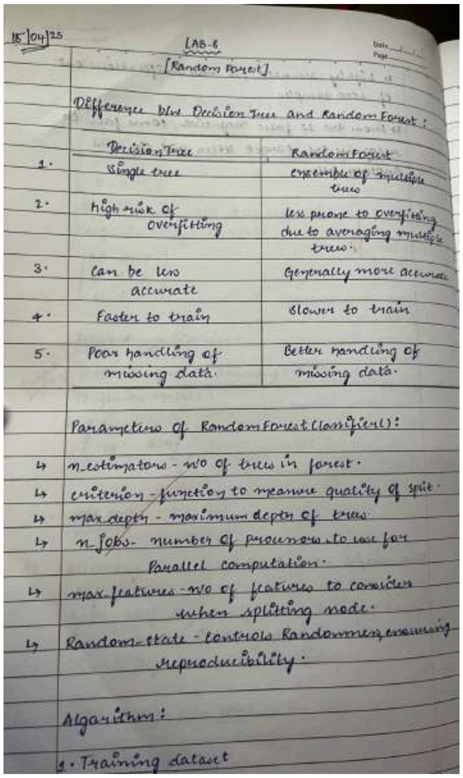
```
Accuracy: 1.0
Support Vectors:
 [[145. 380.]
 [140. 350.]]
Number of Support Vectors: 2
```



Program 8

Implement Random forest ensemble method on a given dataset.

Screenshot:



15/04/25

LAB-8

[Random Forest]

Difference b/w Decision Tree and Random Forest:

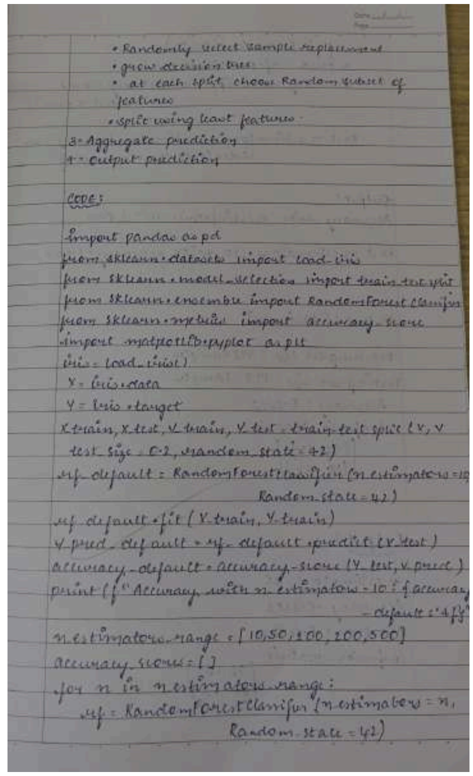
	Decision Tree	Random Forest
1.	single tree	ensemble of multiple trees
2.	high risk of overfitting	less prone to overfitting due to averaging multiple trees.
3.	can be less accurate	Generally more accurate
4.	Faster to train	slower to train
5.	Poor handling of missing data.	Better handling of missing data.

Parameters of RandomForestClassifier():

- n_estimators - n/o of trees in forest.
- criterion - function to measure quality of split.
- max depth - maximum depth of trees
- n_jobs - number of processors to use for parallel computation.
- max features - n/o of features to consider when splitting node.
- Random-state - controls Randomness, ensuring reproducibility.

Algorithm:

1. Training dataset

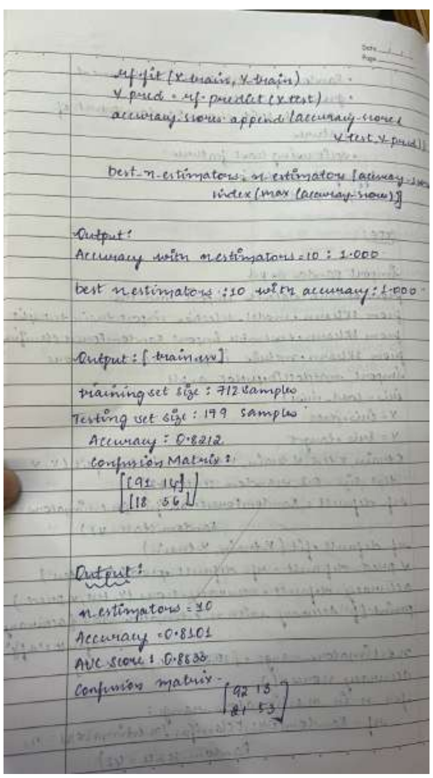


- Randomly select sample replacement
- grow decision tree
- at each split choose Random subset of features
- split using least features.

3. Aggregate prediction
4. Output prediction

CODE:

```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
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)
rf_default = RandomForestClassifier(n_estimators=10,
                     Random_state=42)
rf_default.fit(X_train, Y_train)
Y_pred_default = rf_default.predict(X_test)
accuracy_default = accuracy_score(Y_test, Y_pred)
print(f"Accuracy with n_estimators=10: {accuracy
                     _default:.4f}")
n_estimators_range = [10,50,100,200,500]
accuracy_scores = []
for n in n_estimators_range:
    rf = RandomForestClassifier(n_estimators = n,
                     Random_state = 42)
```



```
    rf.fit(X_train, Y_train)
    Y_pred = rf.predict(X_test)
    accuracy_scores.append(accuracy_score(
                     Y_test, Y_pred))

best_n_estimators = n_estimators[accuracy_scores.
                     index(max(accuracy_scores))]
```

Output:

Accuracy with n_estimators=10 : 1.000

best n_estimators : 10 with accuracy : 1.000

Output: [train.csv]

training set size : 712 samples

Testing set size : 179 samples

Accuracy : 0.8212

Confusion Matrix :

$$\begin{bmatrix} [91 & 14] \\ [18 & 56] \end{bmatrix}$$

Output:

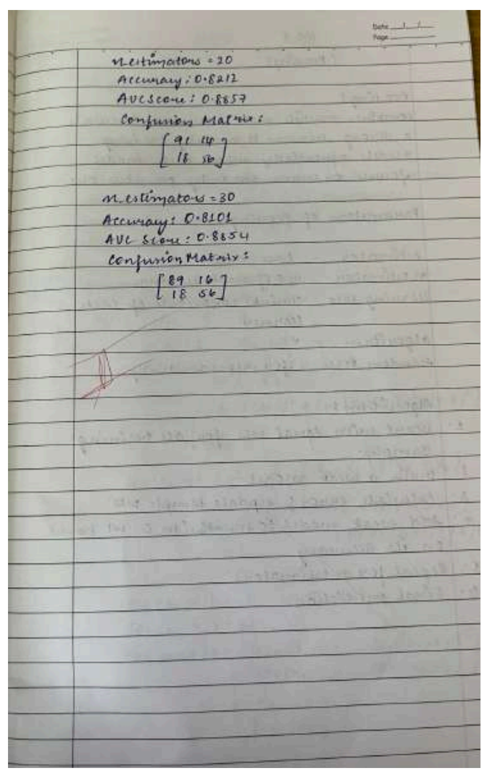
n_estimators = 10

Accuracy = 0.8101

AUC score : 0.8838

Confusion matrix -

$$\begin{bmatrix} 92 & 13 \\ 21 & 53 \end{bmatrix}$$



n_estimators = 20

Accuracy : 0.8212

AUC score : 0.8857

Confusion Matrix :

$$\begin{bmatrix} 91 & 14 \\ 18 & 56 \end{bmatrix}$$

n_estimators = 30

Accuracy : 0.8101

AUC score : 0.8854

Confusion Matrix :

$$\begin{bmatrix} 89 & 16 \\ 18 & 56 \end{bmatrix}$$

Code:

Iris.csv

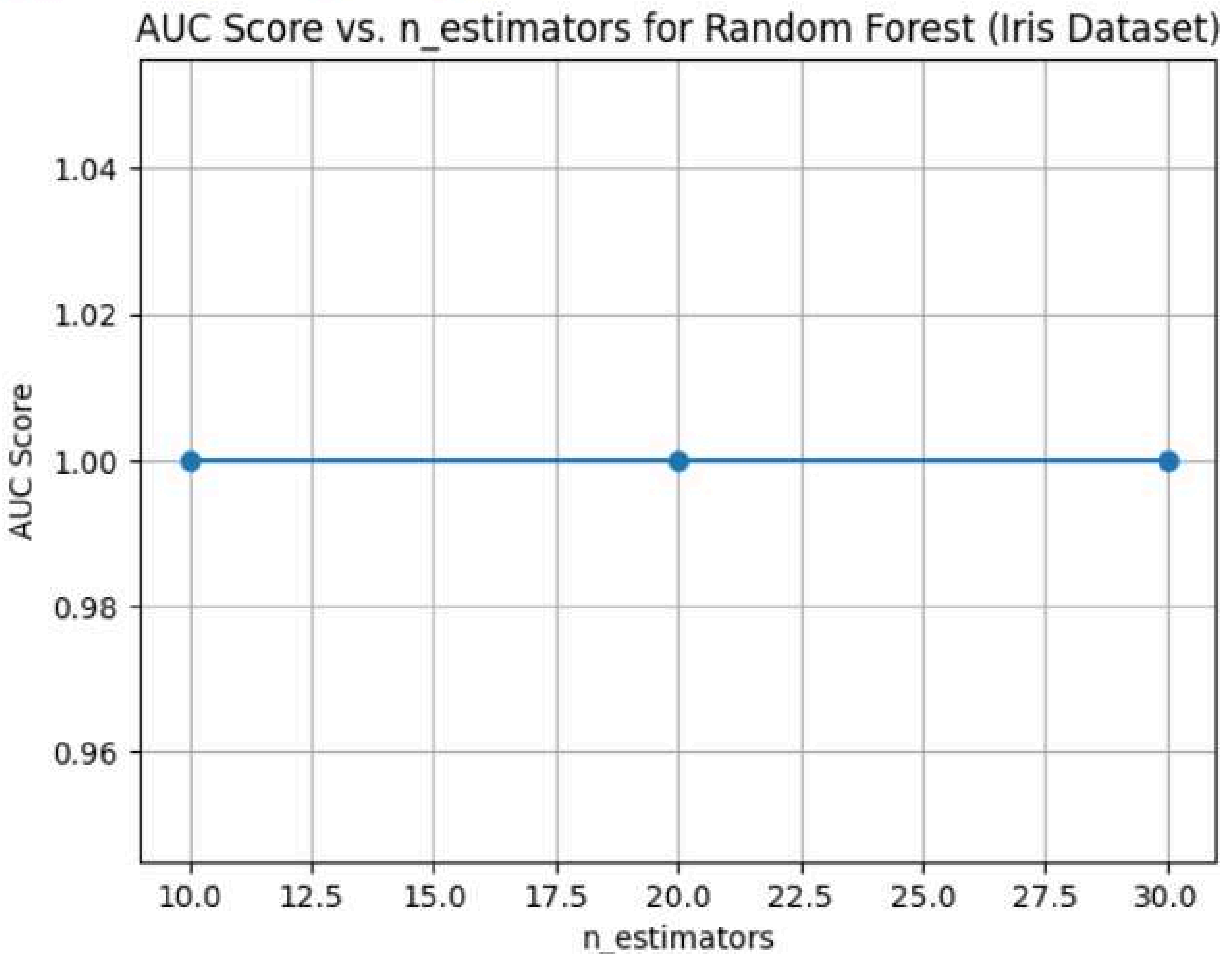
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
iris = pd.read_csv("iris.csv")
X = iris.iloc[:,:-1]
y = iris.iloc[:,-1]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
rf_classifier = RandomForestClassifier(random_state=42)
rf_classifier.fit(X_train, y_train)
y_pred = rf_classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy with default n_estimators (10): {accuracy:.4f}")
best_accuracy = 0
best_n_estimators = 0
for n_estimators in range(10, 201, 10):
    rf_classifier = RandomForestClassifier(n_estimators=n_estimators, random_state=42)
    rf_classifier.fit(X_train, y_train)
    y_pred = rf_classifier.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_n_estimators = n_estimators
print(f"Best accuracy: {best_accuracy:.4f} achieved with n_estimators = {best_n_estimators}")
```

```
Accuracy with default n_estimators (10): 1.0000
Best accuracy: 1.0000 achieved with n_estimators = 10
```

```
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_iris
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
iris = load_iris()
X, y = iris.data, iris.target
y = label_binarize(y, classes=[0, 1, 2])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
n_estimators_values = [10, 20, 30]
auc_scores = []
for n_estimators in n_estimators_values:
    rf_classifier = OneVsRestClassifier(RandomForestClassifier(n_estimators=n_estimators,
random_state=42))
    rf_classifier.fit(X_train, y_train)
    y_pred_proba = rf_classifier.predict_proba(X_test)
```

```
    auc_scores.append(roc_auc_score(y_test, y_pred_proba, average='weighted', multi_class='ovr'))
    print(f"AUC Score for n_estimators = {n_estimators}: {auc_scores[-1]}")
plt.plot(n_estimators_values, auc_scores, marker='o')
plt.xlabel('n_estimators')
plt.ylabel('AUC Score')
plt.title('AUC Score vs. n_estimators for Random Forest (Iris Dataset)')
plt.grid(True)
plt.show()
```

```
AUC Score for n_estimators = 10: 1.0
AUC Score for n_estimators = 20: 1.0
AUC Score for n_estimators = 30: 1.0
```



Train.csv

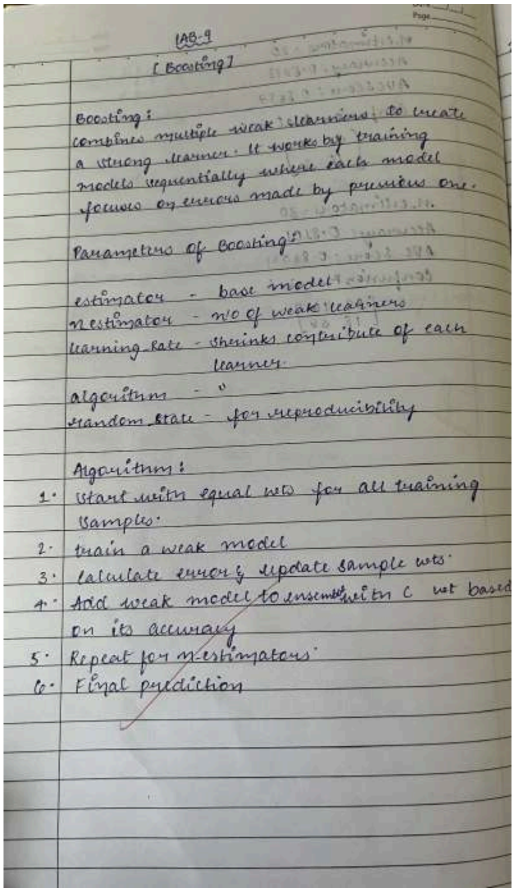
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.preprocessing import LabelEncoder
df = pd.read_csv("train.csv")
df = df.drop(columns=['PassengerId', 'Name', 'Ticket', 'Cabin'])
df['Age'].fillna(df['Age'].median(), inplace=True)
```

```
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
label_encoders = {}
for col in ['Sex', 'Embarked']:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
X = df.drop(columns=['Survived'])
y = df['Survived']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
print("Confusion Matrix:")
print(conf_matrix)
```

```
Accuracy: 0.8212
Confusion Matrix:
[[92 13]
 [19 55]]
```

Program 9

Implement Boosting ensemble method on a given dataset.
Screenshot:

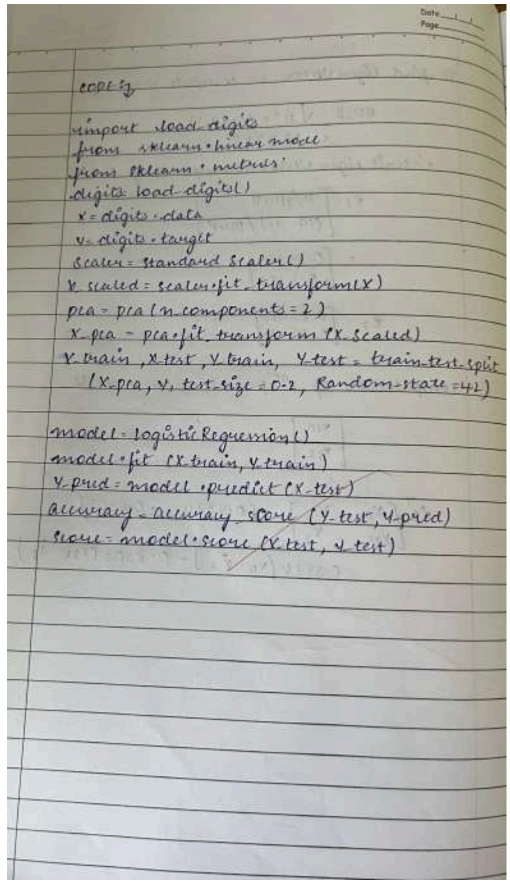

LAB-9
[Boosting]

Boosting:
combines multiple weak learners to create a strong learner. It works by training models sequentially where each model focuses on errors made by previous one.

Parameters of Boosting:

estimator - base model
n estimator - n/o of weak learners
learning_rate - shrinks contribute of each learner
algorithm - "
random_state - for reproducibility

Algorithm:
1. start with equal wts for all training samples.
2. train a weak model
3. calculate error & update sample wts.
4. Add weak model to ensemble with C wt based on its accuracy
5. Repeat for n-estimators.
6. Final prediction


Date / /
Page

code:

import load_digits
from sklearn.linear model
from sklearn.metrics
digits = load_digits()
x = digits.data
y = digits.target
Scaler = Standard Scaler()
x scaled = scaler.fit_transform(x)
pca = pca (n_components = 2)
x_pca = pca.fit_transform (x_scaled)
x_train, x_test, y_train, y_test = train_test_split (x_pca, y, test_size = 0.2, Random_state = 42)

model = logisticRegression()
model.fit (x_train, y_train)
y_pred = model.predict (x_test)
accuracy = accuracy_score (y_test, y_pred)
score = model.score (x_test, y_test)

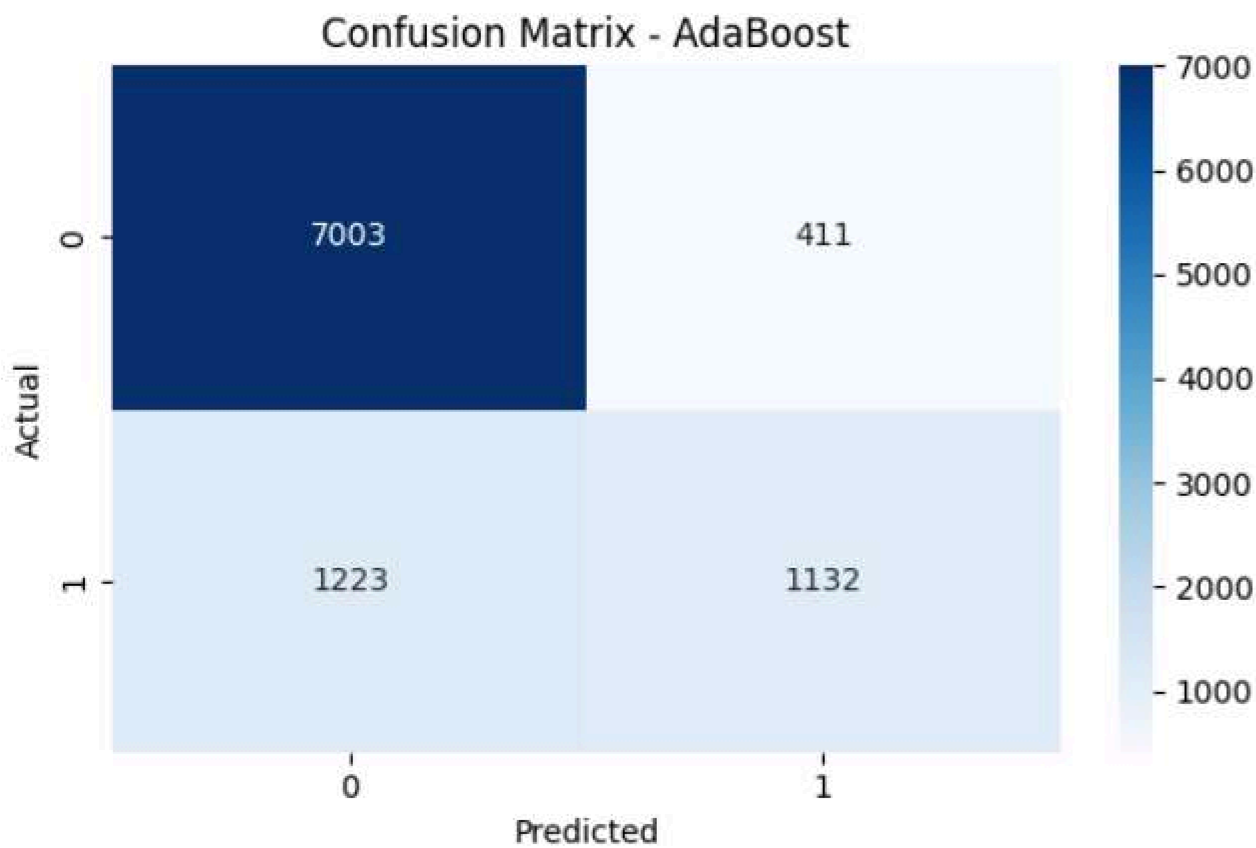
Code:

Income.csv

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
data = pd.read_csv('income.csv')
X = data.drop('income_level', axis=1)
y = data['income_level']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
ada_boost = AdaBoostClassifier(n_estimators=50, random_state=42)
ada_boost.fit(X_train, y_train)
```

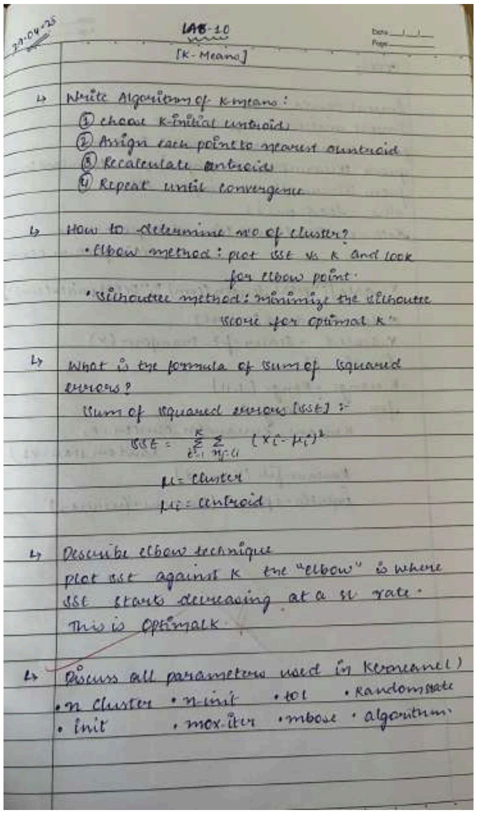
```
y_pred = ada_boost.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
conf_matrix = confusion_matrix(y_test, y_pred)
print(f"Confusion Matrix:\n{conf_matrix}")
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=ada_boost.classes_, yticklabels=ada_boost.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - AdaBoost')
plt.tight_layout()
plt.show()
```

```
Accuracy: 0.8327362063670796
Confusion Matrix:
[[7003  411]
 [1223 1132]]
```



Program 10

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



27-04-25

LAB-10

[K-Means]

Write Algorithm of K-means:
1. Choose K initial centroids
2. Assign each point to nearest centroid
3. Recalculate centroids
4. Repeat until convergence

How to determine no of cluster?
- Elbow method: plot SSE vs K and look for elbow point.
- Silhouette method: minimize the silhouette score for optimal K.

What is the formula of sum of squared errors?

Sum of squared errors [SSE]:

$$SSE = \sum_{i=1}^{K} \sum_{x_j \in C_i} (x_i - \mu_i)^2$$

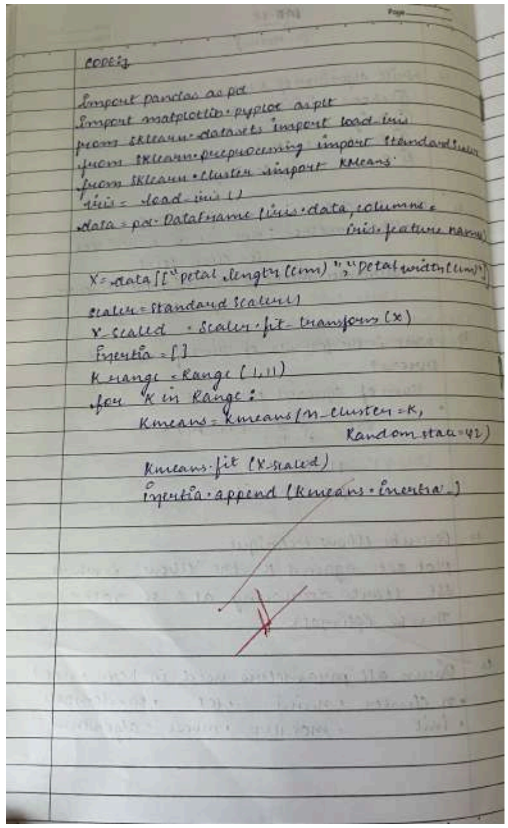
μ = cluster

μ_i = centroid

Describe elbow technique

plot SSE against K the "elbow" is where SSE starts decreasing at a sl rate. This is optimal K

Discuss all parameters used in Kmeans()
- n cluster
- n-init
- tol
- Random state
- init
- max-iter
- mbose
- algorithm



CODE:

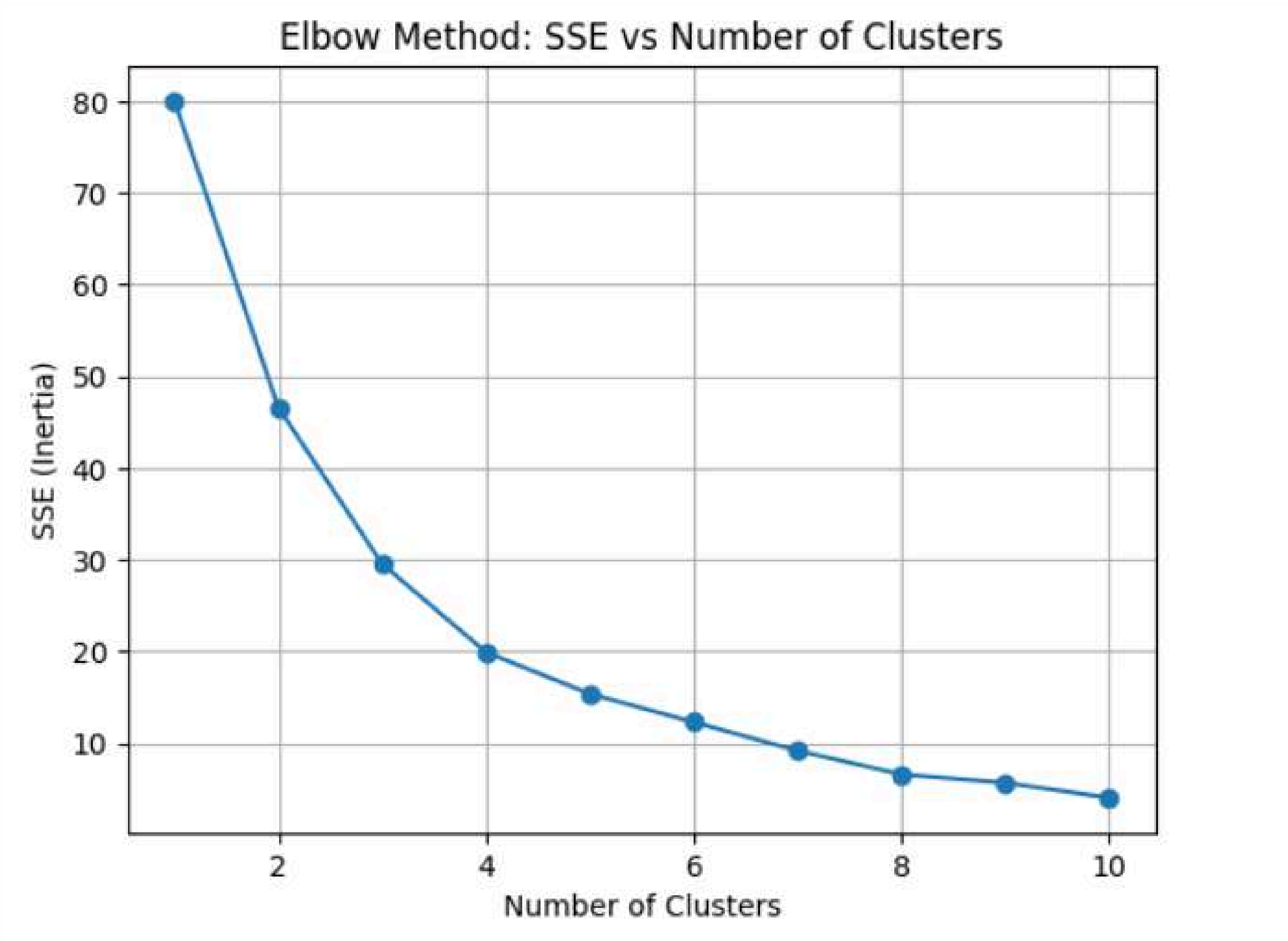
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
iris = load_iris()
data = pd.DataFrame(iris.data, columns=
                    iris.feature_names)

X = data[["petal length (cm)", "petal width (cm)"]]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
inertia = []
K_range = Range(1,11)
for K in Range:
    Kmeans = Kmeans(n_clusters=K,
                    Random_state=42)

    Kmeans.fit(X_scaled)
    inertia.append(Kmeans.inertia_)
```

Code:

Income.csv

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import adjusted_rand_score
import matplotlib.pyplot as plt
import random
np.random.seed(42)
names = [f"Person_{i}" for i in range(1, 51)]
ages = np.random.randint(20, 60, 50)
incomes = np.random.randint(20000, 100000, 50)
df = pd.DataFrame({
    'Name': names,
    'Age': ages,
    'Income': incomes
})
df.to_csv('income.csv', index=False)
print("‘income.csv' created successfully.")
```

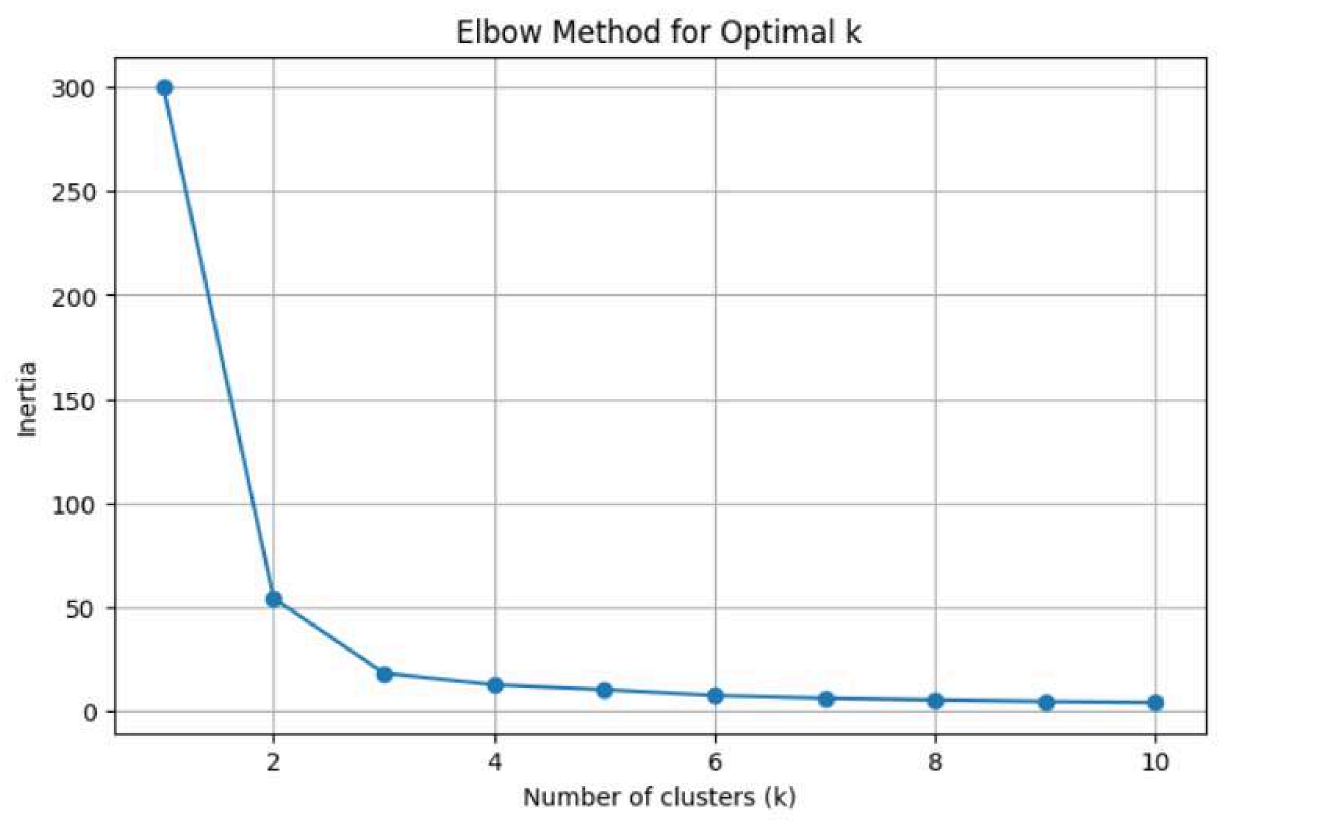
```
from google.colab import files
files.download('income.csv')
data = pd.read_csv('income.csv')
X = data[['Age', 'Income']]
X_train, X_test = train_test_split(X, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
sse = []
k_range = range(1, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_train_scaled)
    sse.append(kmeans.inertia_)
plt.plot(k_range, sse, marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('SSE (Inertia)')
plt.title('Elbow Method: SSE vs Number of Clusters')
plt.grid(True)
plt.show()
k = 3  # Change this based on the elbow plot
model = KMeans(n_clusters=k, random_state=42)
model.fit(X_train_scaled)
train_preds = model.predict(X_train_scaled)
test_preds = model.predict(X_test_scaled)
true_labels_train = [random.randint(0, k-1) for _ in range(len(train_preds))]
accuracy = adjusted_rand_score(true_labels_train, train_preds)
print("Adjusted Rand Index (proxy accuracy):", round(accuracy, 2))
```



Iris.csv

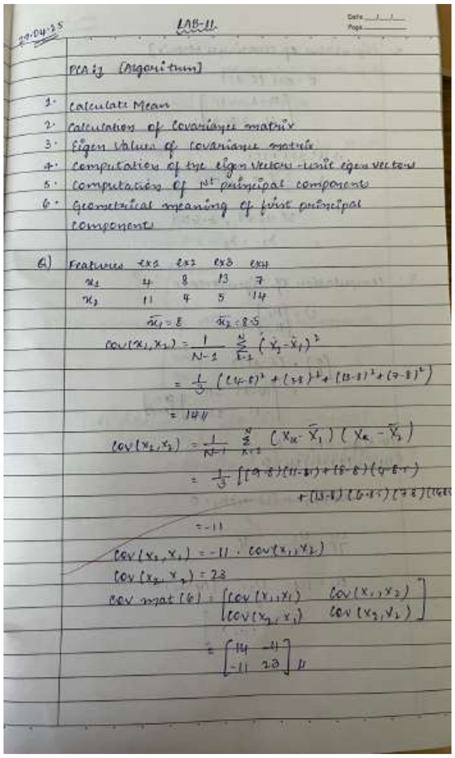
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
iris = load_iris()
data = pd.DataFrame(iris.data, columns=iris.feature_names)
X = data[["petal length (cm)", "petal width (cm)"]]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
inertia = []
K_range = range(1, 11)
for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)
plt.figure(figsize=(8, 5))
plt.plot(K_range, inertia, marker='o')
plt.title("Elbow Method for Optimal k")
plt.xlabel("Number of clusters (k)")
```

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



Program 11

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



29-04-25 LAB-11

PCA is (Algorithm)

1. Calculate Mean
2. Calculation of covariance matrix
3. Eigen values of covariance matrix
4. Computation of the eigen vectors, unit eigen vectors
5. Computation of 1st principal components
6. Geometrical meaning of first principal components

6) Features ex1 ex2 ex3 ex4

x_1 4 8 13 7

x_2 11 4 5 14

$\bar{x}_1 = 8$, $\bar{x}_2 = 8.5$

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

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

$= 14$

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

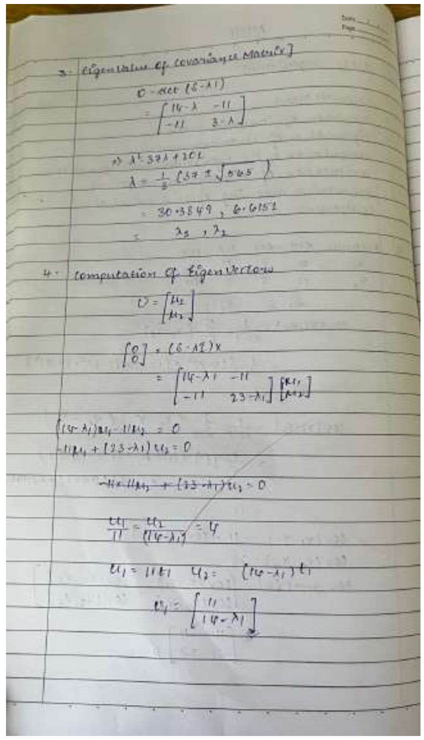
$= \frac{1}{3}\left[(4-8)(11-8.5)+(8-8)(4-8.5)+(13-8)(5-8.5)+(7-8)(14-8.5)\right]$

$= -11$

$cov(x_2,x_1) = -11 = cov(x_1,x_2)$

$cov(x_2,x_2) = 23$

$cov\ mat\ (S) = \begin{bmatrix} cov(x_1,x_1) & cov(x_1,x_2) \\ cov(x_2,x_1) & cov(x_2,x_2) \end{bmatrix} = \begin{bmatrix} 14 & -11 \\ -11 & 23 \end{bmatrix}$



3. Eigenvalue of covariance matrix

$0 = det(S - \lambda I) = \begin{vmatrix} 14-\lambda & -11 \\ -11 & 23-\lambda \end{vmatrix}$

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

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

$= 30.3849,\ 6.6151$

$= \lambda_1, \lambda_2$

4. Computation of Eigenvectors

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

$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = (S - \lambda I)U = \begin{bmatrix} 14-\lambda_1 & -11 \\ -11 & 23-\lambda_1 \end{bmatrix}\begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$

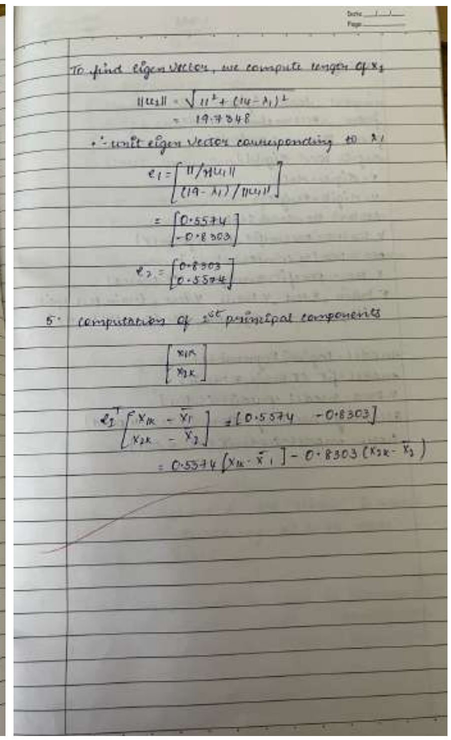
$(14-\lambda_1)u_1 - 11u_2 = 0$

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

$\frac{u_1}{11} = \frac{u_2}{(14-\lambda_1)} = t$

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

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



To find eigen vector, we compute length of x_1

$\|u_1\| = \sqrt{11^2 + (14-\lambda_1)^2}$

$= 19.7348$

∴ unit eigen vector corresponding to λ_1

$e_1 = \begin{bmatrix} 11/\|u_1\| \\ (14-\lambda_1)/\|u_1\| \end{bmatrix} = \begin{bmatrix} 0.5574 \\ -0.8303 \end{bmatrix}$

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

5. computation of 1st principal components

$\begin{bmatrix} x_{1k} \\ x_{2k} \end{bmatrix}$

$e_1^T \begin{bmatrix} x_{1k} - \bar{x}_1 \\ x_{2k} - \bar{x}_2 \end{bmatrix} = [0.5574\ \ -0.8303]$

$= 0.5574(x_{1k} - \bar{x}_1) - 0.8303(x_{2k} - \bar{x}_2)$

Code:

```
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
digits = load_digits()
X = digits.data
y = digits.target
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
X_train, X_test, y_train, y_test = train_test_split(
    X_pca, y, test_size=0.2, random_state=42
)
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
score = model.score(X_test, y_test)
print(" Model Score (accuracy using .score()):", round(score, 4))
```

```
print(" Accuracy using PCA with 2 components:", round(accuracy, 4))
```

```
Model Score (accuracy using .score()): 0.5389
Accuracy using PCA with 2 components: 0.5389
```

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder
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
df = pd.read_csv("/content/heart.csv")  # Adjust path if needed
z_scores = np.abs(zscore(df.select_dtypes(include=[np.number])))
df = df[(z_scores < 3).all(axis=1)]
df_encoded = df.copy()
for col in df_encoded.select_dtypes(include=["object"]).columns:
    if df_encoded[col].nunique() <= 2:
        le = LabelEncoder()
        df_encoded[col] = le.fit_transform(df_encoded[col])
    else:
        df_encoded = pd.get_dummies(df_encoded, columns=[col], drop_first=True)
X = df_encoded.drop("target", axis=1)  # Replace 'target' if it's named differently
y = df_encoded["target"]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(),
    "SVM": SVC()
}
print("Model Accuracies (without PCA):")
for name, model in models.items():
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    acc = accuracy_score(y_test, preds)
    print(f"{name}: {acc:.4f}")
pca = PCA(n_components=0.95)  # Retain 95% variance
X_pca = pca.fit_transform(X_scaled)
X_train_pca, X_test_pca, _, _ = train_test_split(X_pca, y, test_size=0.2, random_state=42)
print("\nModel Accuracies (with PCA):")
for name, model in models.items():
    model.fit(X_train_pca, y_train)
    preds = model.predict(X_test_pca)
```

```
acc = accuracy_score(y_test, preds)
print(f"{name}: {acc:.4f}")
```

```
Model Accuracies (without PCA):
Logistic Regression: 0.8103
Random Forest: 0.7759
SVM: 0.7931

Model Accuracies (with PCA):
Logistic Regression: 0.8276
Random Forest: 0.8103
SVM: 0.7586
```