VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

Dhanush T(1BM23CS406)

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 **Dhanush T(1BM23CS406),** 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.

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Github Link:
https://github.com/Dhanush200422/6thSem-ML-Lab.git

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)
```

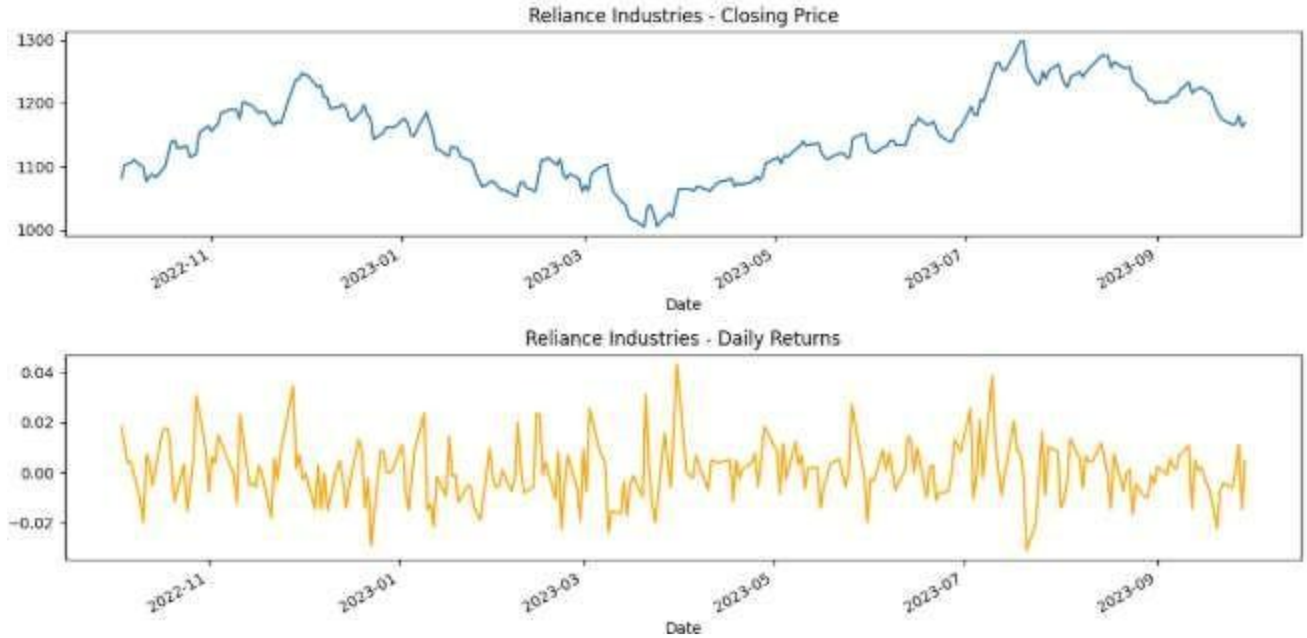
```
print("Sample data:")
print(df.head()) print("\n")
```

```
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()
```

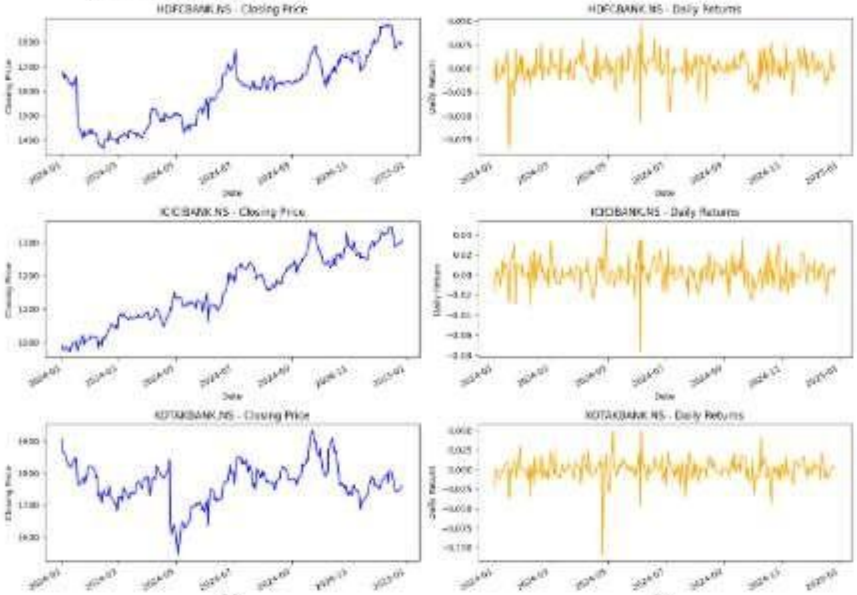
```
First 5 rows of the dataset:
Ticker      RELIANCE.NS                                                    \
Price              Open         High          Low        Close    Volume
Date
2022-10-03  1092.199963  1103.822945  1079.184026  1082.152588  11852723
2022-10-04  1095.077201  1104.302526  1091.583396  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'.")
```

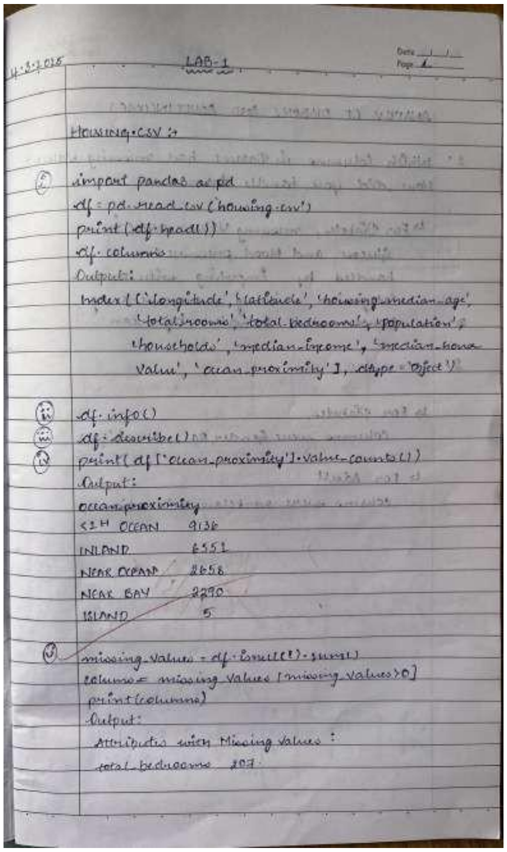
```
First 5 rows of the dataset:
Ticker      KOTAKBANK.NS                                                    \
Price               Open         High          Low        Close   Volume
Date
2024-01-01   1906.909954  1916.899886  1891.027338  1907.059814  1425902
2024-01-02   1905.911108  1905.911108  1858.063525  1863.008179  5128796
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  1669.206199  1675.223999   7119843
2024-01-02   1675.914685  1679.860799  1665.950651  1676.210571  14621046
2024-01-03   1679.071480  1681.735059  1646.466666  1650.363525  14194881
2024-01-04   1655.394910  1672.116528  1648.193203  1668.071777  13367828
2024-01-05   1664.421506  1681.932477  1645.628188  1659.538208  15944735

Ticker      ICICIBANK.NS
Price               Open        High         Low       Close    Volume
Date
2024-01-01    983.086778  996.273246  982.541485  990.860812   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  980.787295  973.519176  978.724365  22789148
2024-01-05    979.567084  989.779158  975.482928  985.218445  14875499

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'])
```

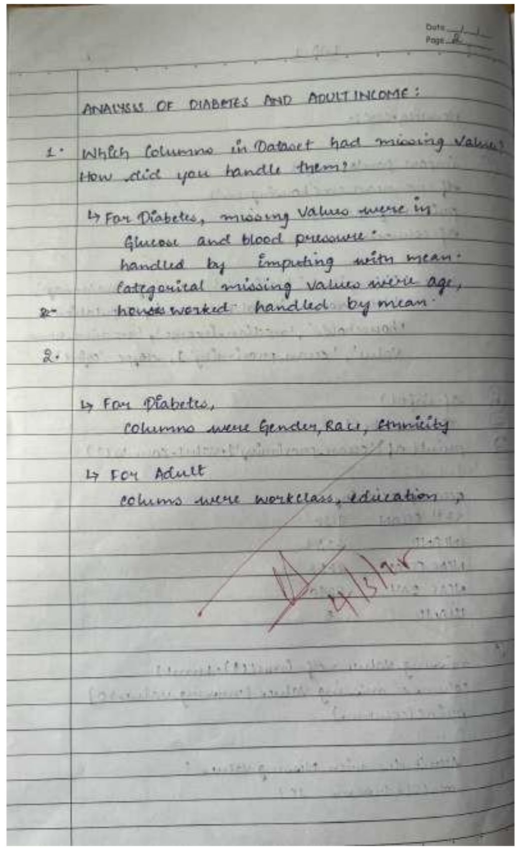



```
HDFCBANK.NS stock data saved to 'HDFCBANK.NS_stock_data.csv'.

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:





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)]
```

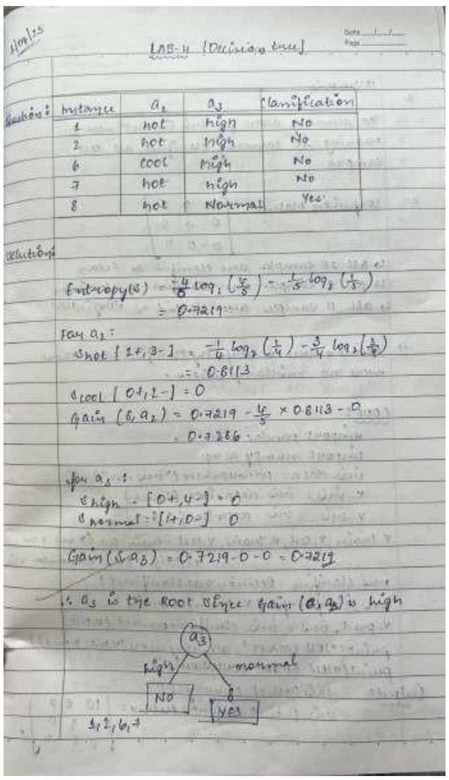
min_max_scaler = MinMaxScaler() df_minmax = pd.DataFrame(min_max_scaler.fit_transform(df), columns=df.columns) standard_scaler = StandardScaler() df_standard = pd.DataFrame(standard_scaler.fit_transform(df), columns=df.columns) print("\nProcessed Adult Income Dataset (Min-Max Scaled):") print(df_minmax.head()) print("\nProcessed Adult Income Dataset (Standard Scaled):") print(df_standard.head())

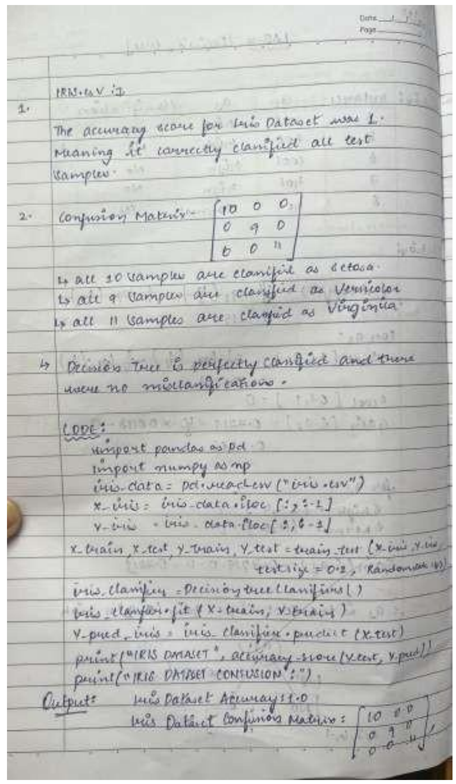
```
Processed Adult Income Dataset (Min-Max Scaled):
        age  workclass    fnlwgt  education  educational-num  marital-status  \
0  0.344262        0.0  0.188277   0.555556         0.363636        0.333333
1  0.114754        0.0  0.881156   1.000000         0.454545        0.666667
2  0.147541  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





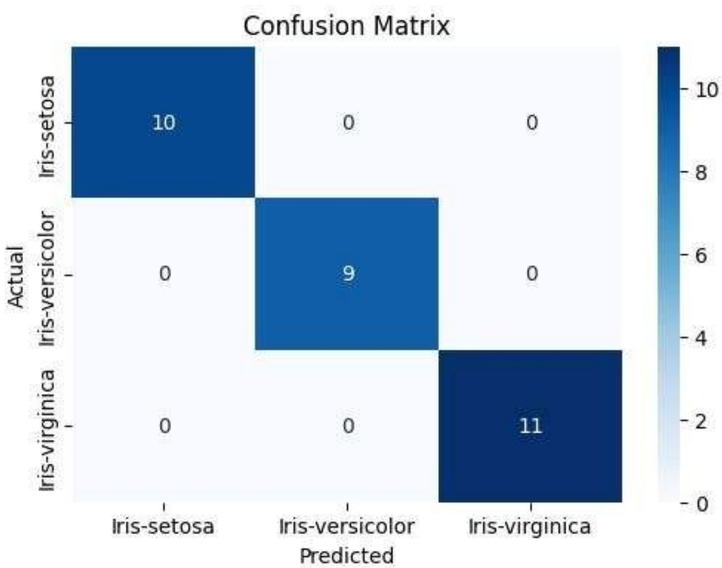
Code:

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
```

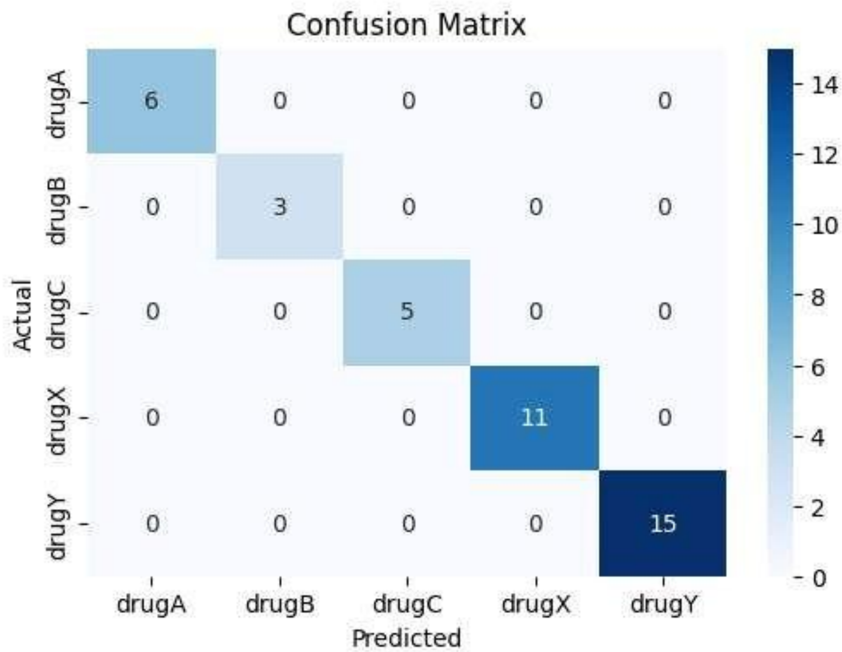


Drug.csv

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)

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()
```

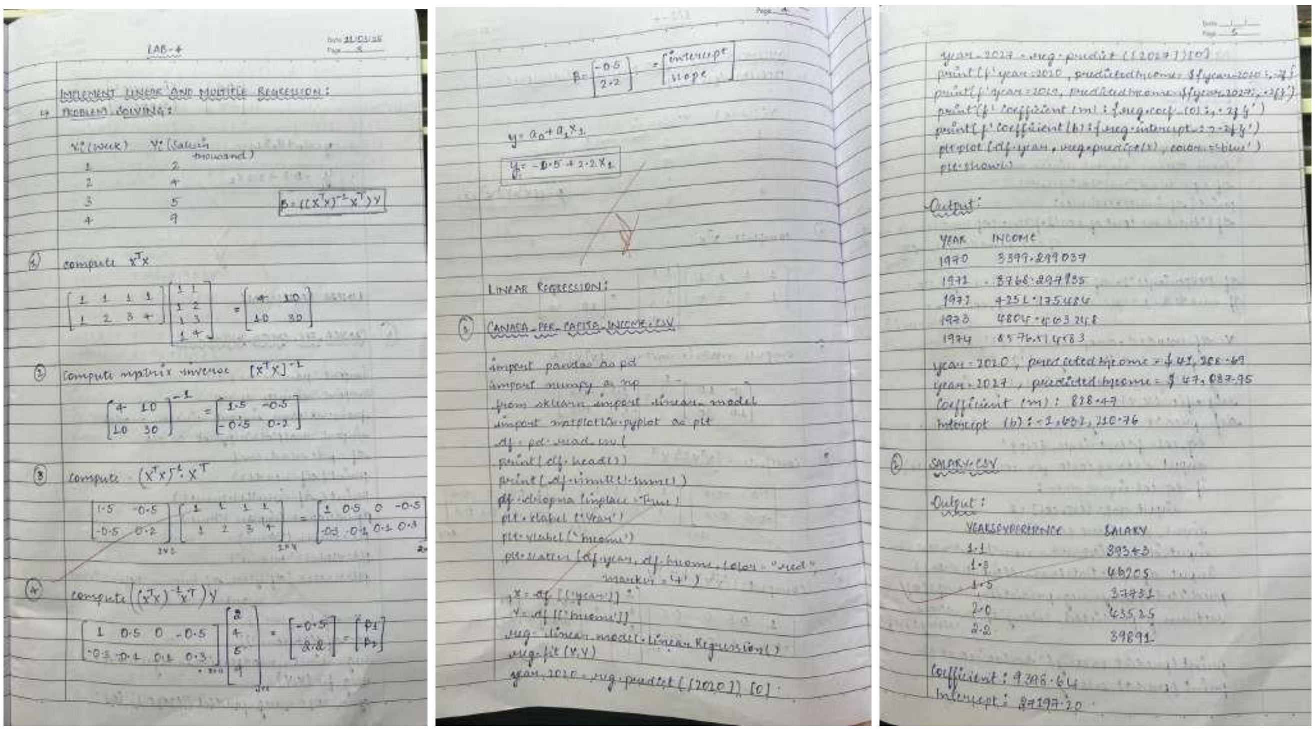
```
Regression Tree Evaluation Metrics:
Mean Absolute Error (MAE): 80.63
Mean Squared Error (MSE): 14718.40
Root Mean Squared Error (RMSE): 121.32
```

Program 4

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

Linear Regression:

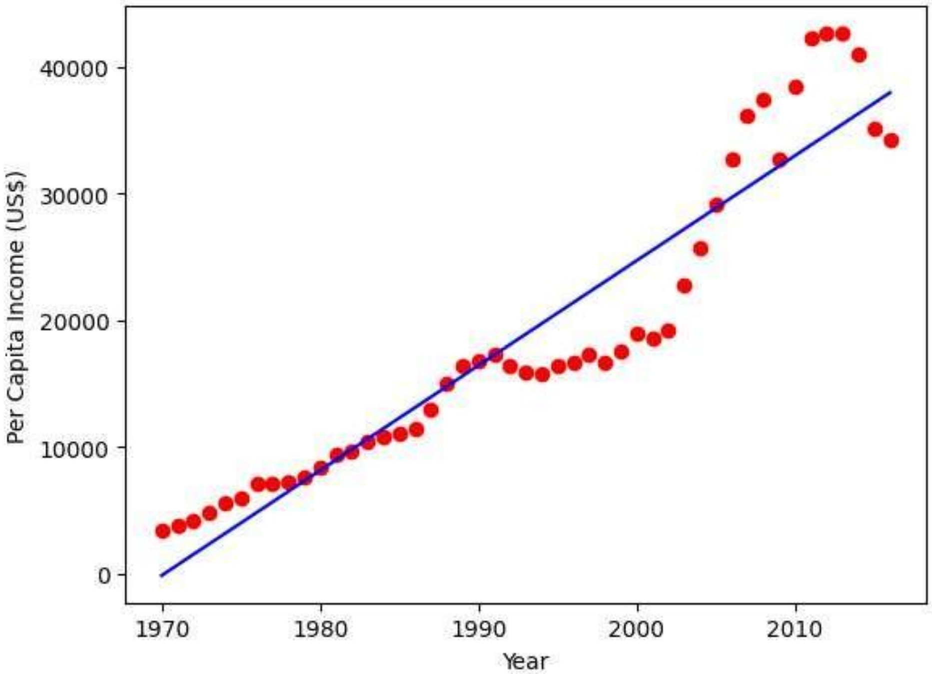
Screenshot:



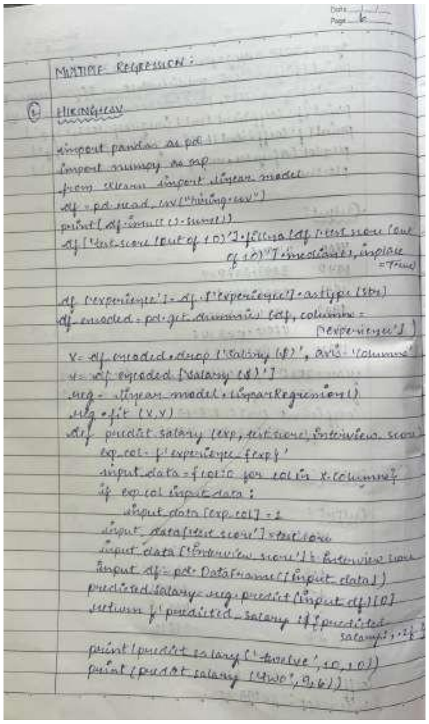
Code:

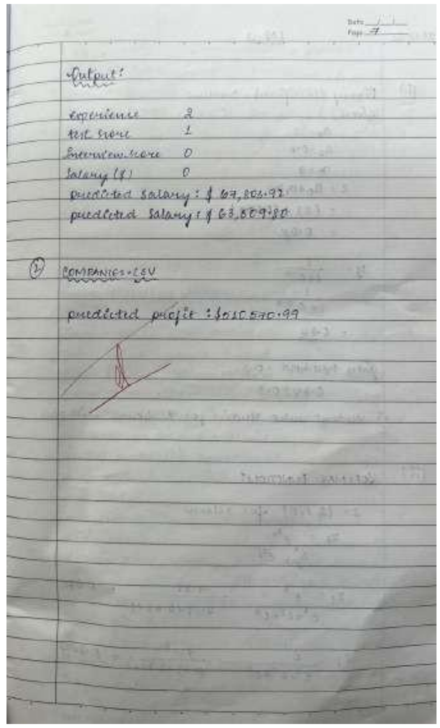
```
import pandas as pd import numpy as np from sklearn import linear_model
import matplotlib.pyplot as plt df =
pd.read_csv('canada_per_capita_income.csv') reg =
linear_model.LinearRegression() reg.fit(df[['year']], df['per capita income
(US$)']) print(f"Coefficient: {reg.coef_}") print(f"Intercept:
{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}")

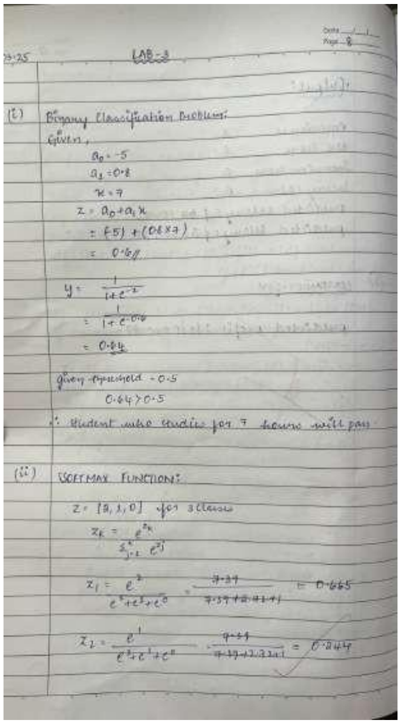
```
Original Data:
  experience  test_score(out of 10)  interview_score(out of 10)  salary($)
0        NaN                    8.0                           9      50000
1        NaN                    8.0                           6      45000
2       five                    6.0                           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,

a0 = -5

a1 = 0.8

x = 7

z = a0 + a1 x

= (-5) + (0.8 x 7)

= 0.6

y = 1 / (1 + e^-z)

= 1 / (1 + e^-0.6)

= 0.64

given threshold = 0.5

0.64 > 0.5

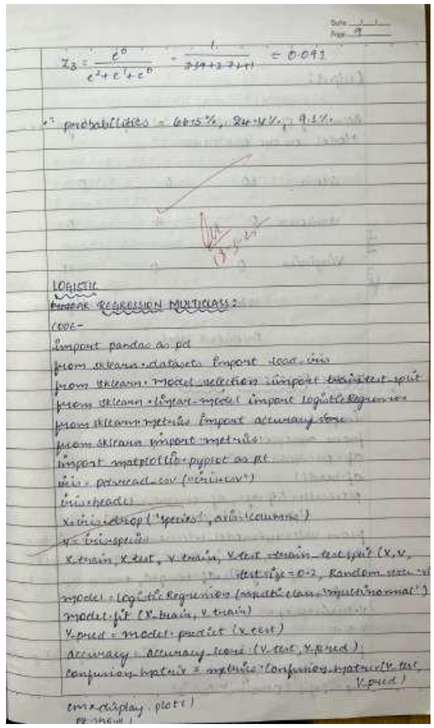
∴ student who studies for 7 hours will pass

(ii) SOFTMAX FUNCTION:

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

z1 = e^2 / (e^2 + e^1 + e^0) = 7.39 / (7.39 + 2.71 + 1) = 0.665

z2 = e^1 / (e^2 + e^1 + e^0) = 2.71 / (7.39 + 2.71 + 1) = 0.244

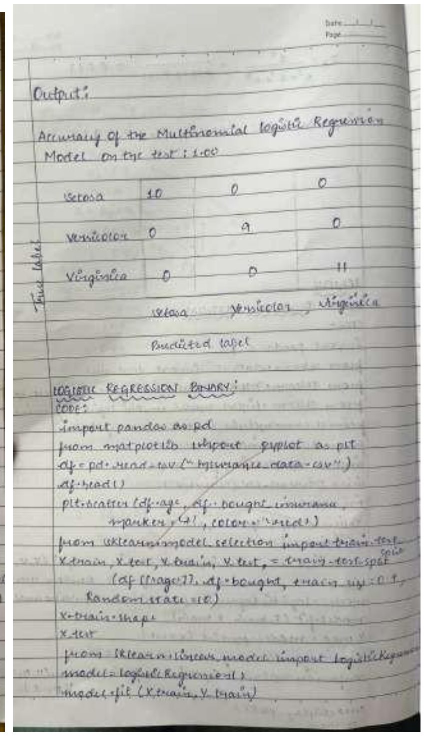

z3 = e^0 / (e^2 + e^1 + e^0) = 1 / (7.39 + 2.71 + 1) = 0.091

∴ 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=...)
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()
```


Output:

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

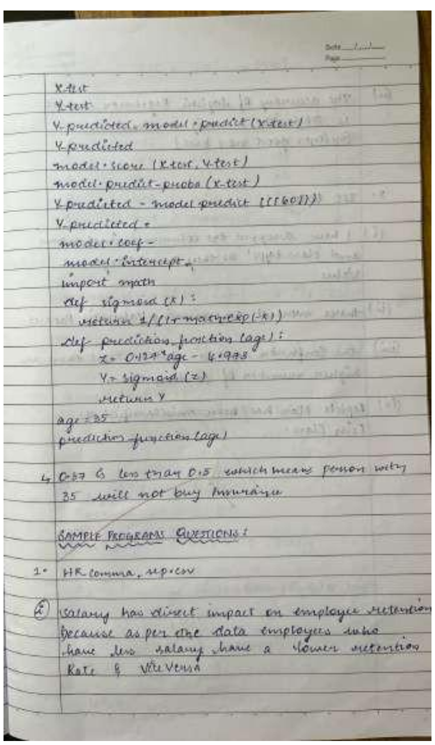
True label			
setosa	10	0	0
versicolor	0	9	0
virginica	0	0	11
	setosa	versicolor	virginica

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)
```

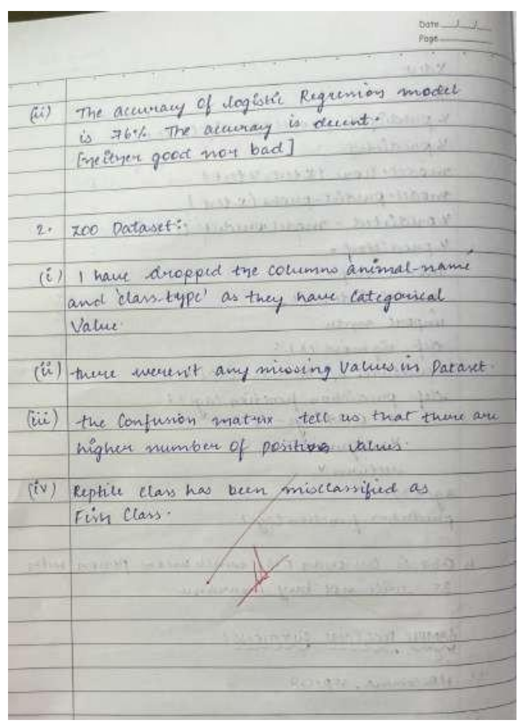

```
X_test
Y_test
Y_predicted = model.predict(X_test)
Y_predicted
model.score(X_test, Y_test)
model.predict_proba(X_test)
Y_predicted = model.predict([[60]])
Y_predicted
model.coef_
model.intercept_
import math
def sigmoid(x):
    return 1/(1+math.exp(-x))
def prediction_function(age):
    z = 0.127*age - 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 & vice versa


(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.

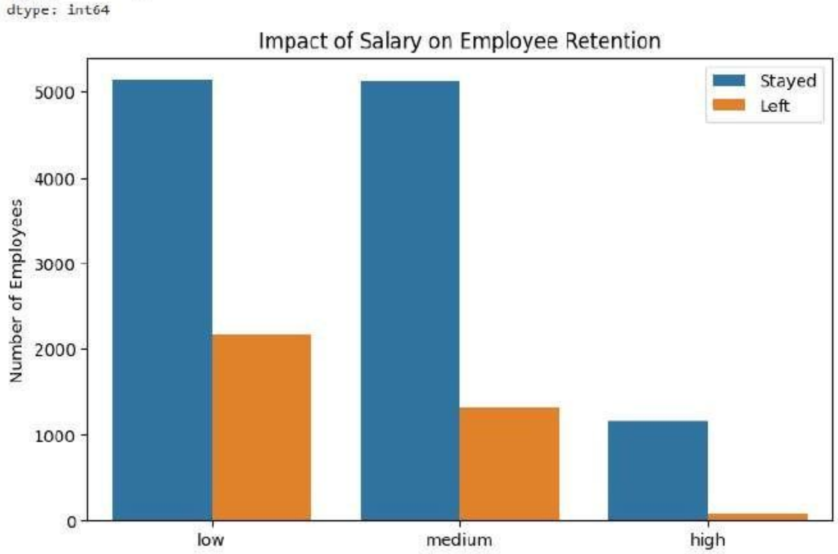
(iii) the confusion matrix tell us that there are higher number of positive values.

(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
```

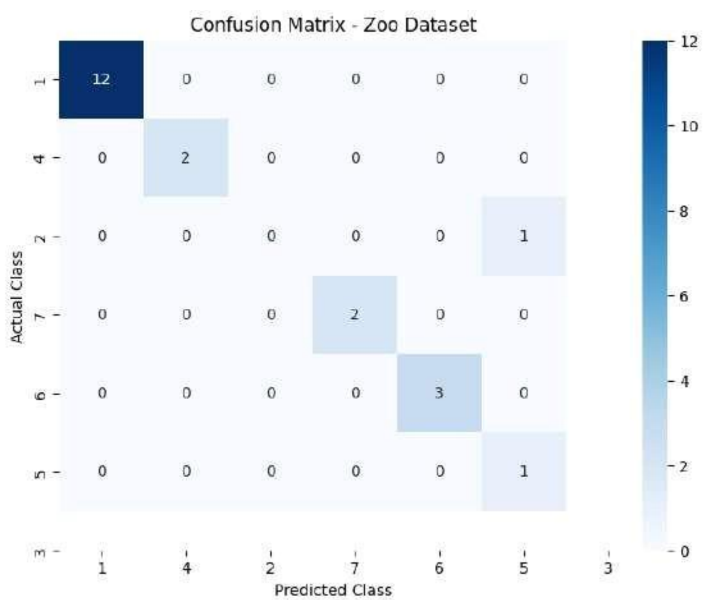


Multi Linear classification

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))
```

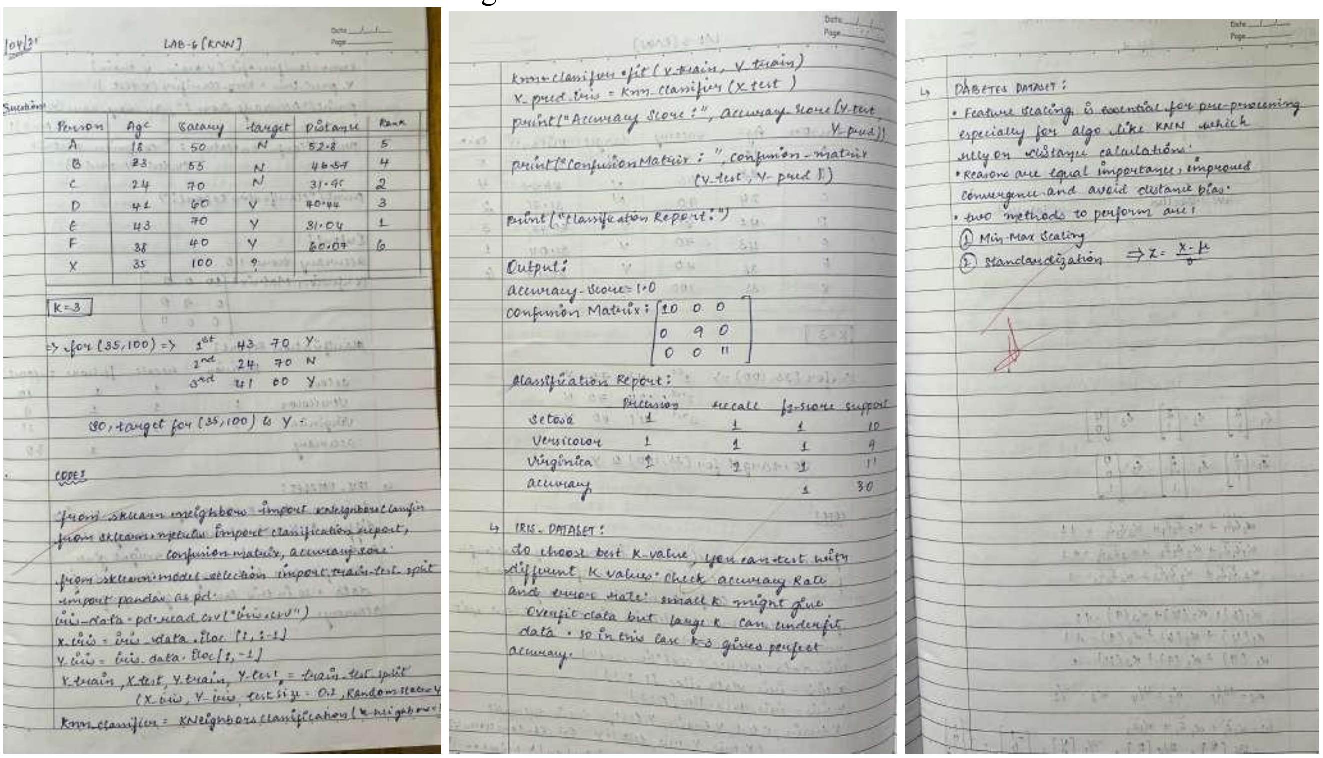
```
Zoo Data:
  animal_name  hair  feathers  eggs  milk  airborne  aquatic  predator  \
0    aardvark     1         0     0     1         0        0         1
1    antelope     1         0     0     1         0        0         0
2        bass     0         0     1     0         0        1         1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

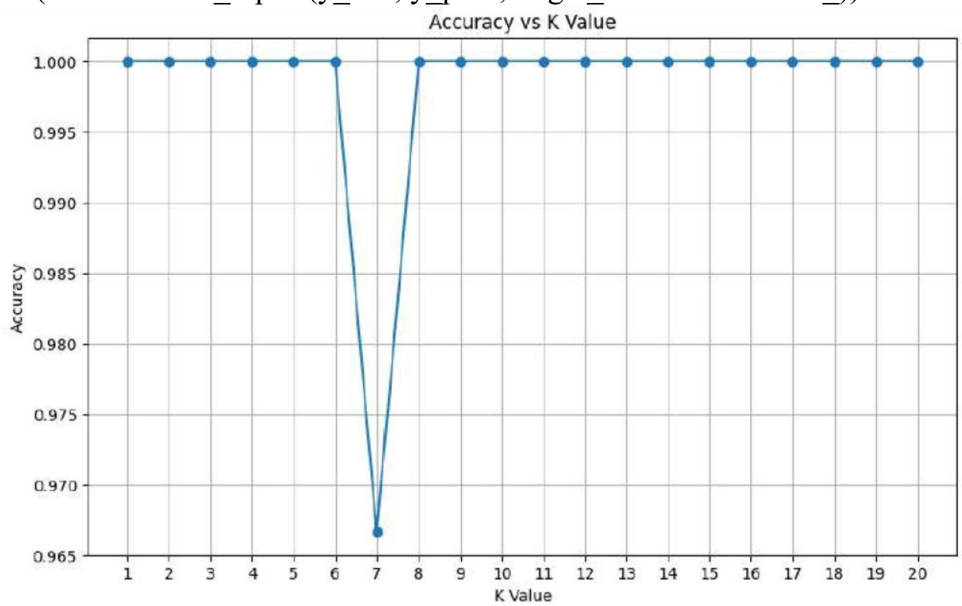
Build KNN Classification model for a given dataset. Screenshot:



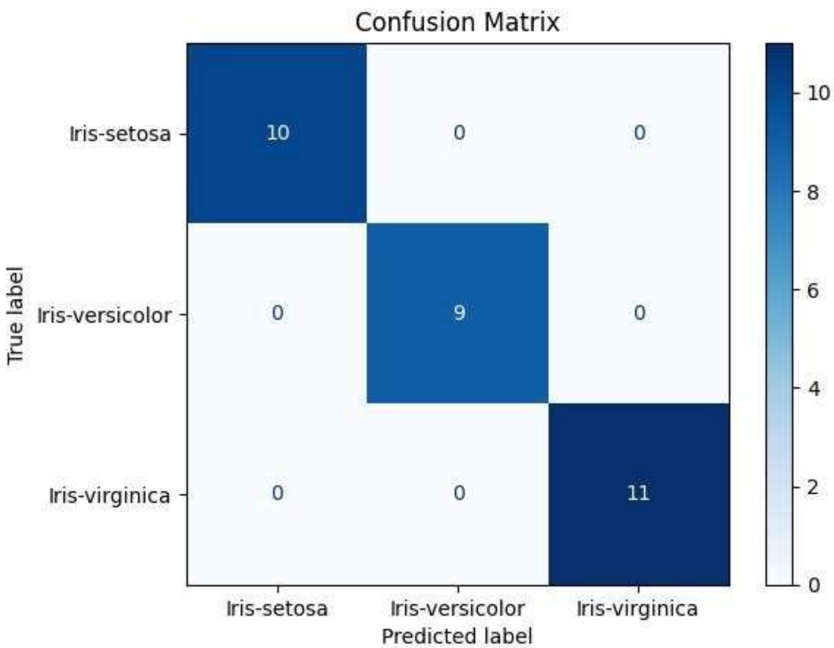
Code:

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]]
```

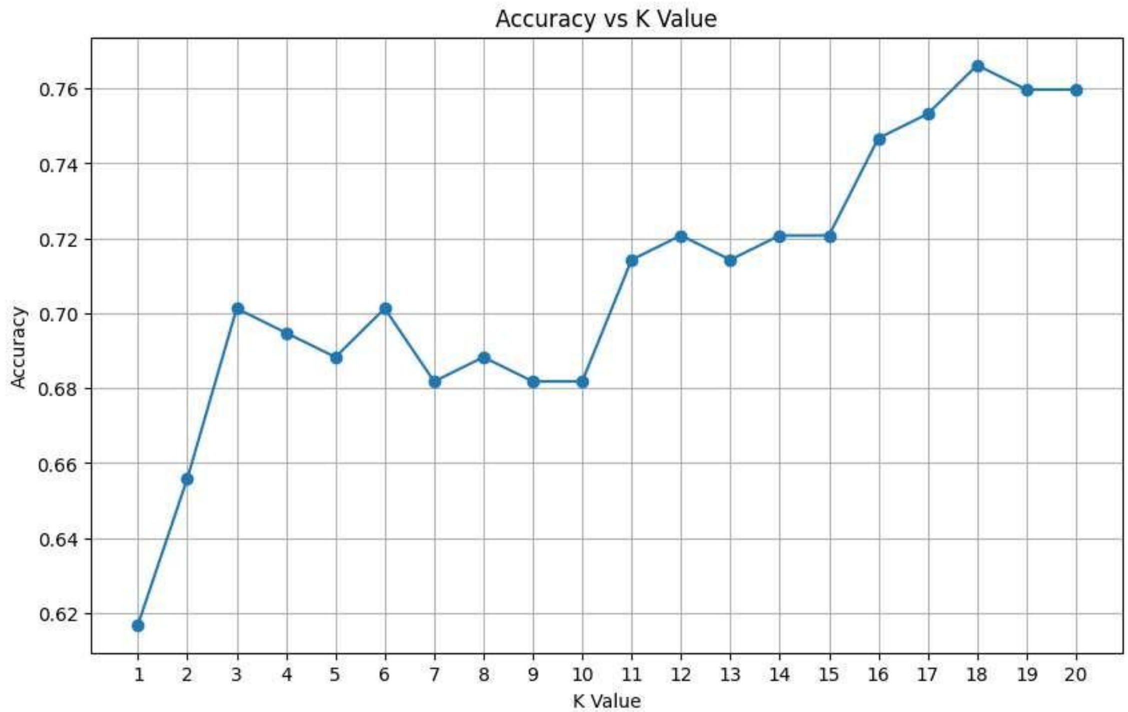



```
Classification Report:
                 precision    recall  f1-score   support

    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
```

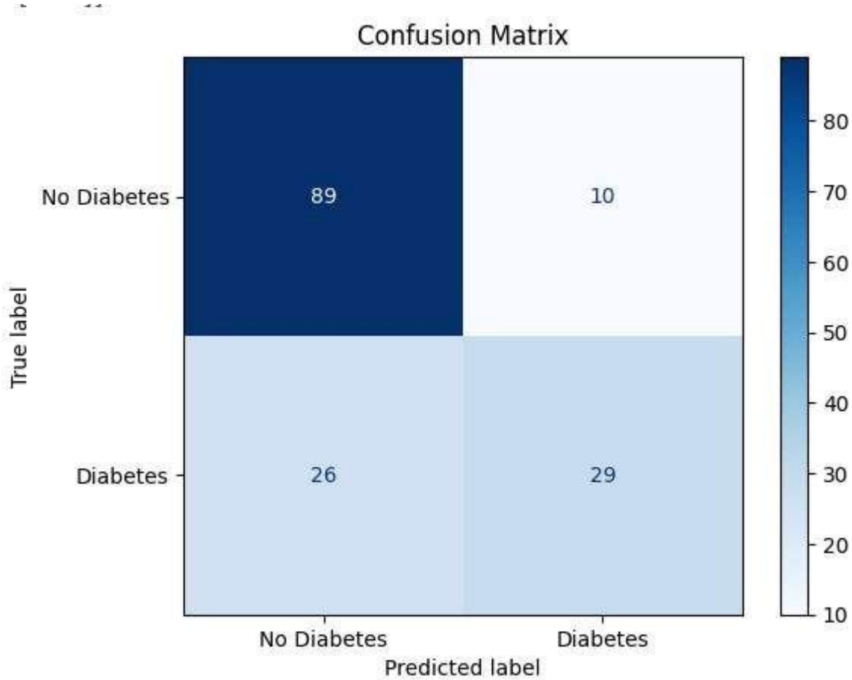
Diabetes.csv import pandas as pd import numpy as np import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split from sklearn.neighbors import KNeighborsClassifier from sklearn.preprocessing import StandardScaler from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay 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]}")

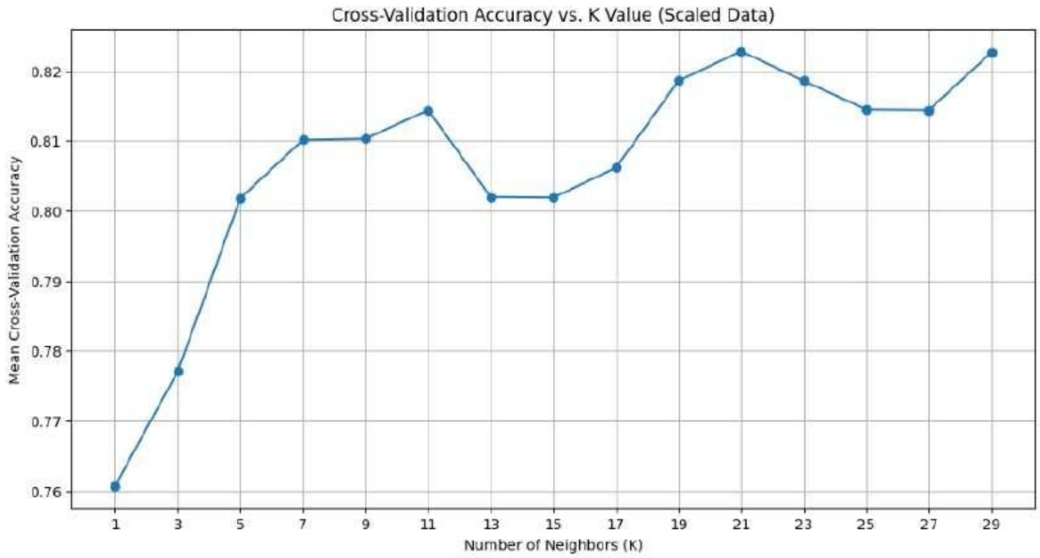



```
Optimal K value: 18

Accuracy: 0.7662

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

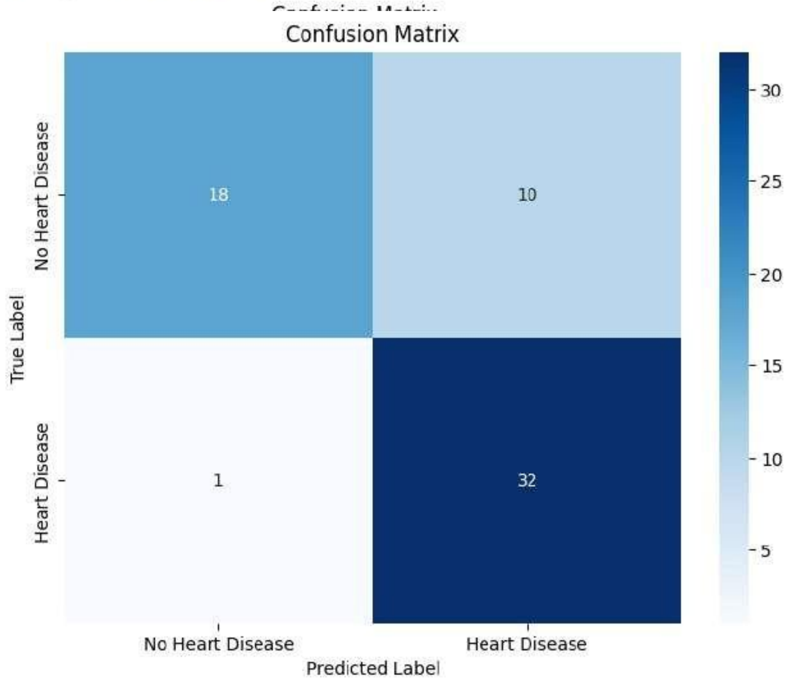



```
Model Evaluation:
- True Positives: 29
- True Negatives: 89
- False Positives: 10
- False Negatives: 26
```

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)
```



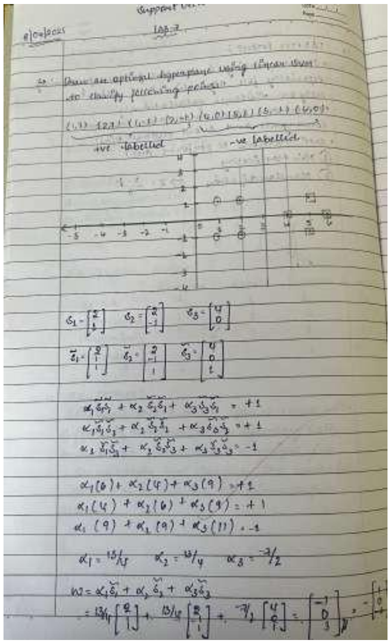

```
The optimal K value found through cross-validation is: 21

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

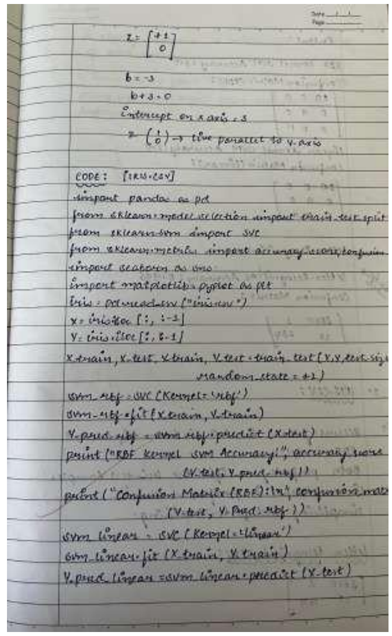



```
Classification Report on Test Data:
              precision    recall  f1-score   support

           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
```

<u>Program 7</u>

Build Support vector machine model for a given dataset Screenshot:





z = [+1, 0]

b = -3

b+3 = 0

Intercept on x axis = 3

= (1, 0) → line parallel to y-axis

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

import seaborn as sns

import matplotlib.pyplot as plt

iris = pd.read_csv("iris.csv")

x = iris.iloc[:, :-1]

y = iris.iloc[:, -1]

x_train, x_test, y_train, y_test = train_test(x, y, test_size

random_state = 42)

svm_rbf = SVC(kernel='rbf')

svm_rbf.fit(x_train, y_train)

y_pred_rbf = svm_rbf.predict(x_test)

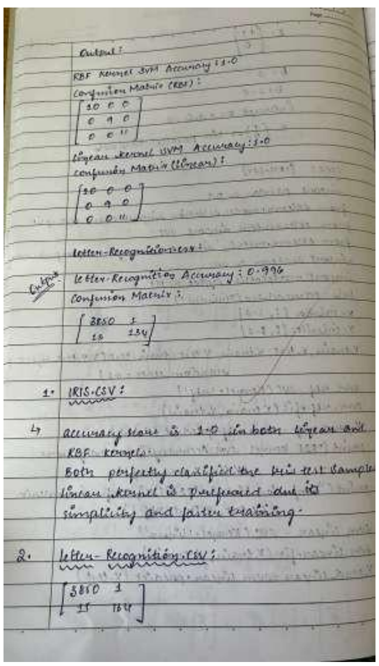
print("RBF kernel SVM Accuracy:", accuracy_score(y_test, y_pred_rbf))

print("Confusion Matrix (RBF):\n", confusion_mat(y_test, y_pred_rbf))

svm_linear = SVC(kernel='linear')

svm_linear.fit(x_train, y_train)

y_pred_linear = svm_linear.predict(x_test)



Output:

RBF Kernel SVM Accuracy: 1.0

Confusion Matrix (RBF):

[10 0 0; 0 9 0; 0 0 11]

Linear Kernel SVM Accuracy: 1.0

Confusion Matrix (Linear):

[10 0 0; 0 9 0; 0 0 11]

letter-Recognition.csv:

letter-Recognition Accuracy: 0.996

Confusion Matrix:

[3850 1; 15 134]

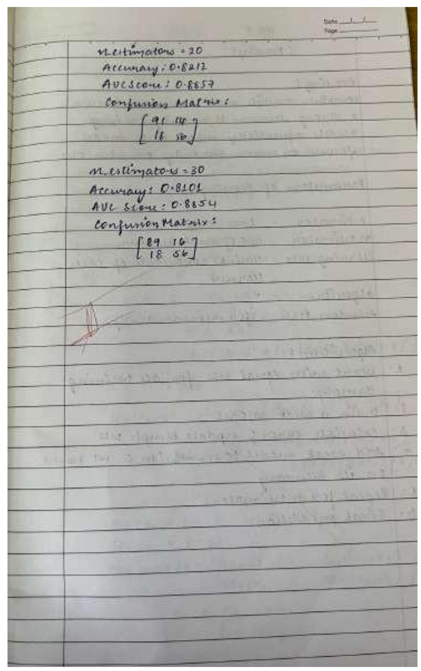
1. IRIS.CSV:

accuracy score is 1.0 in both linear and RBF kernels.

Both perfectly classified the iris test sample. linear kernel is preferred due to simplicity and faster training.

2. letter-Recognition.csv:

[3850 1; 15 134]



n_estimators = 20

Accuracy: 0.8212

AUC score: 0.8857

Confusion Matrix:

[91 14; 18 56]

n_estimators = 30

Accuracy: 0.8101

AUC score: 0.8854

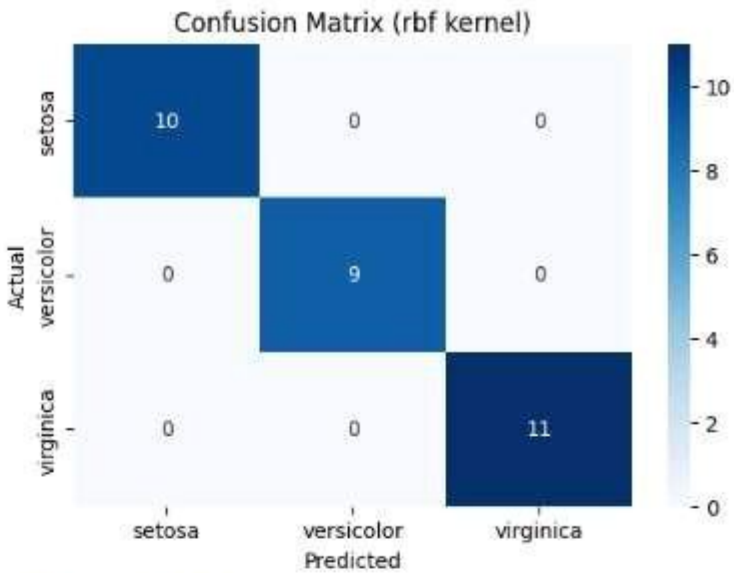
Confusion Matrix:

[89 16; 18 56]

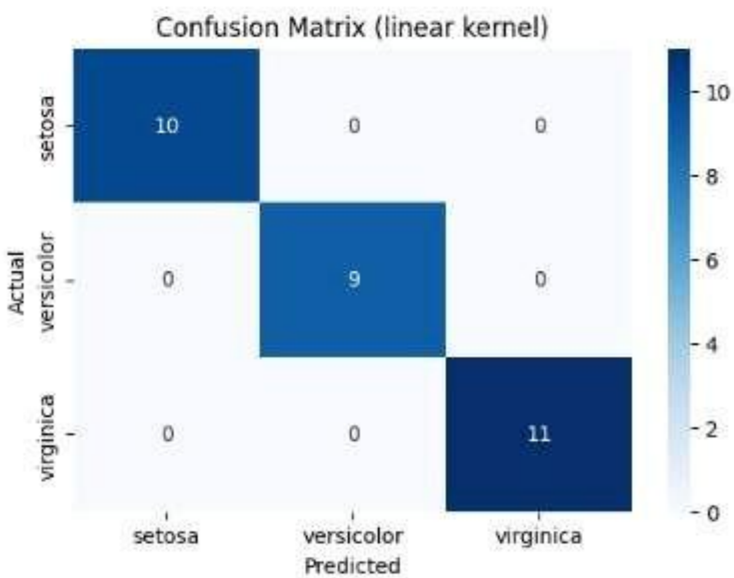
Code:

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')
```




```
Accuracy with rbf kernel: 1.0000
```



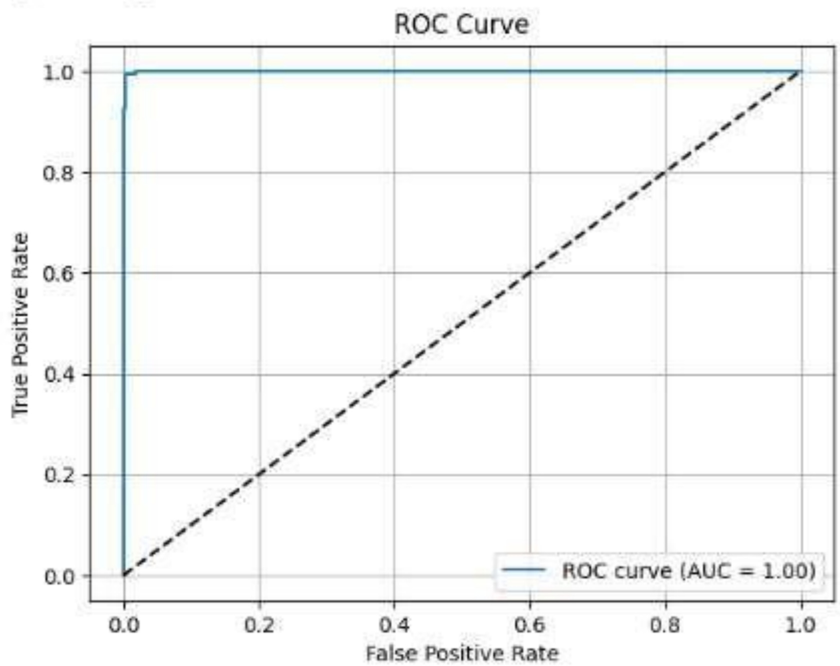

```
Accuracy with linear kernel: 1.0000
```

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]]
```

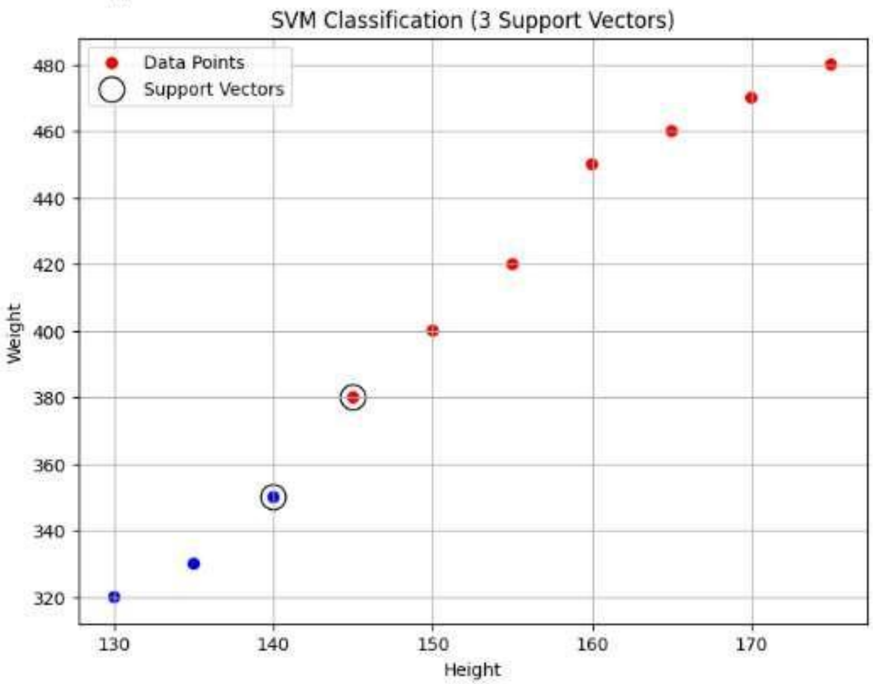


Horse Mule dataset

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 : 0.8833

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 :

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

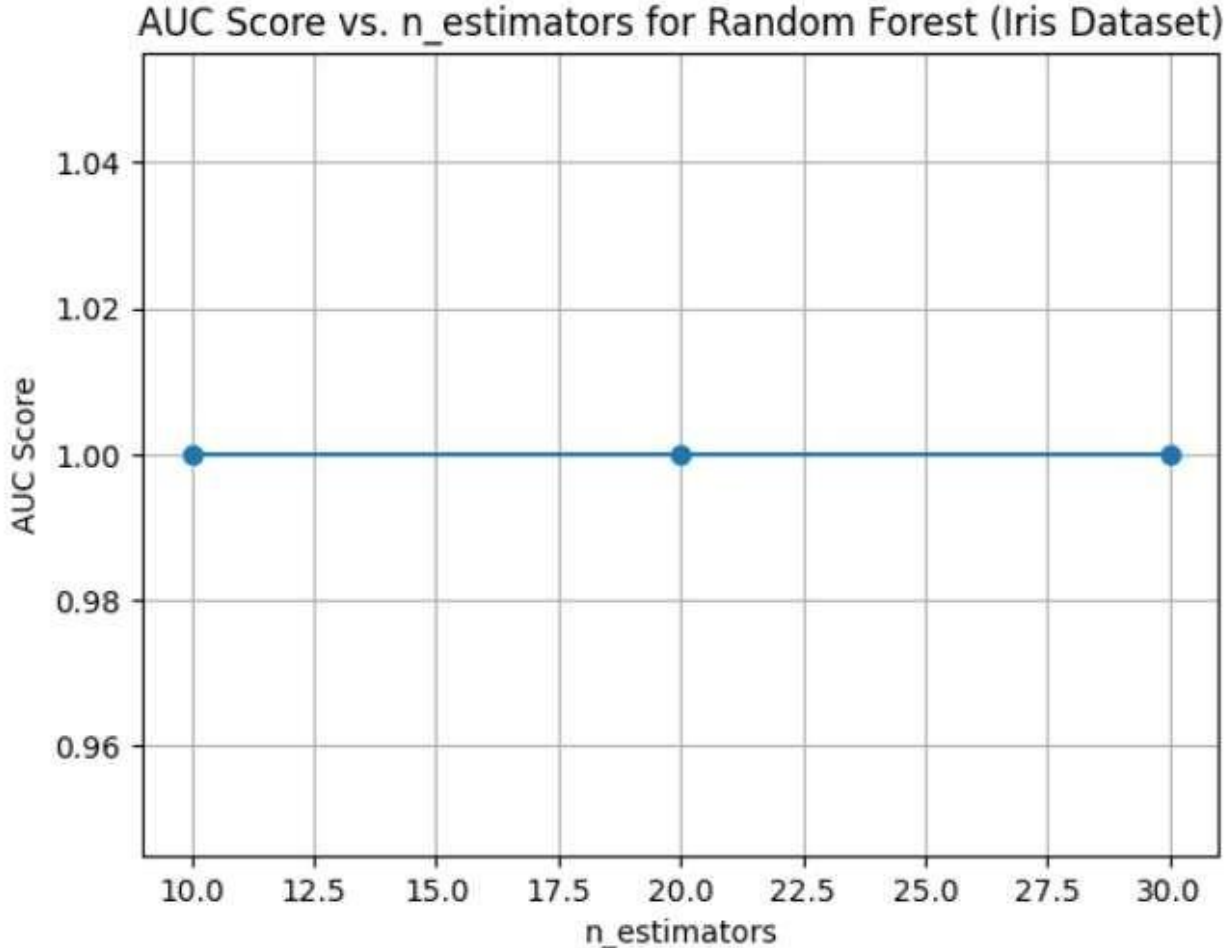
Code:

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
```



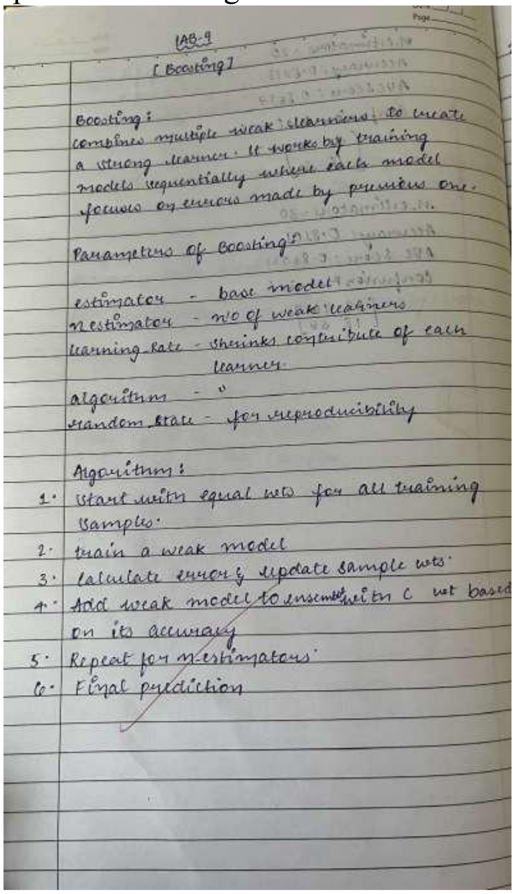
Train.csv import pandas as pd from sklearn.model_selection
import train_test_split from sklearn.ensemble import
RandomForestClassifier from sklearn.metrics import
accuracy_score, confusion_matrix from sklearn.preprocessing
import LabelEncoder
df = pd.read_csv("train.csv") df =
df.drop(columns=['PassengerId', '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

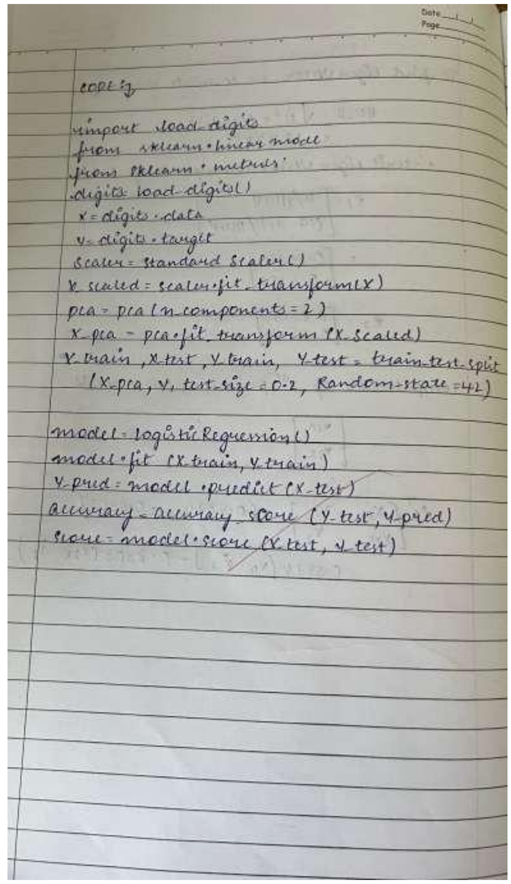
[Boosting]

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



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']

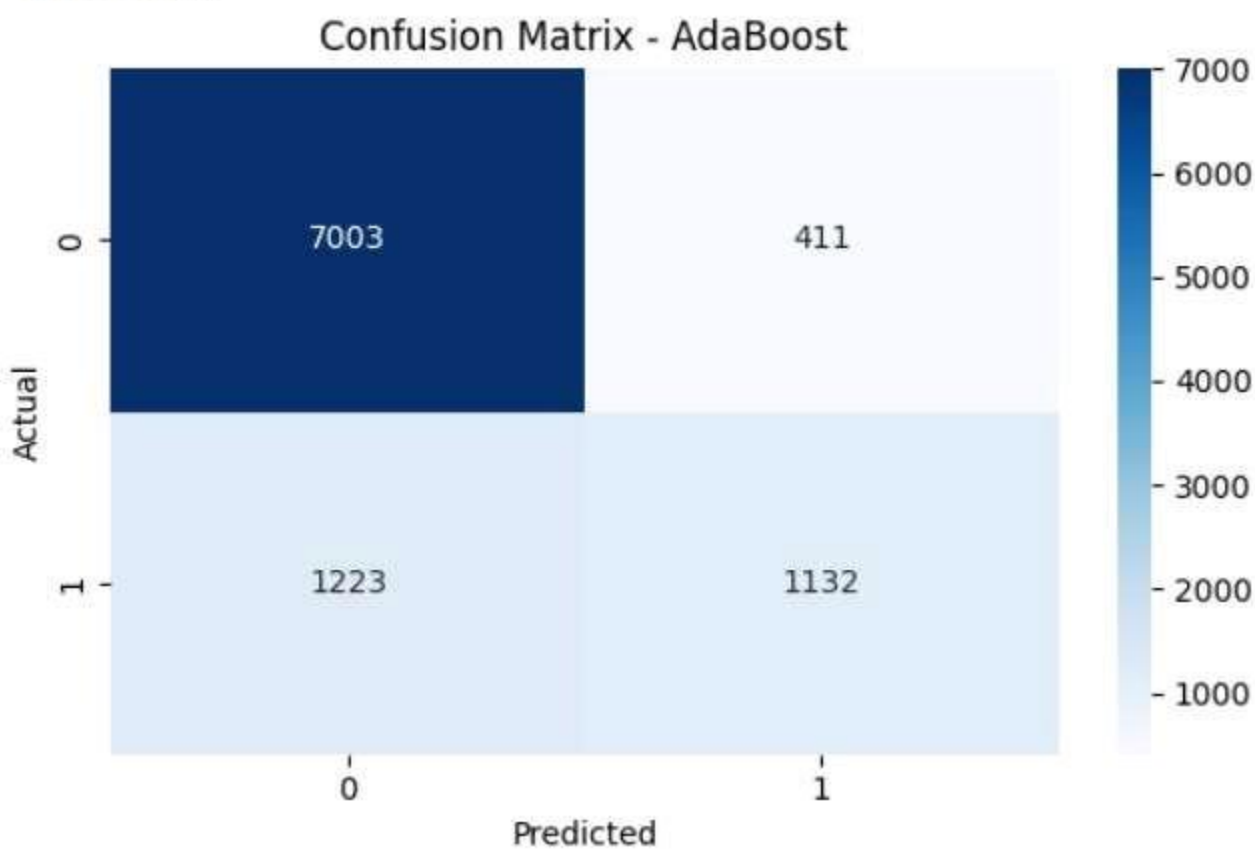
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

ada_boost = AdaBoostClassifier(n_estimators=50, random_state=42) ada_boost.fit(X_train,

y_train)

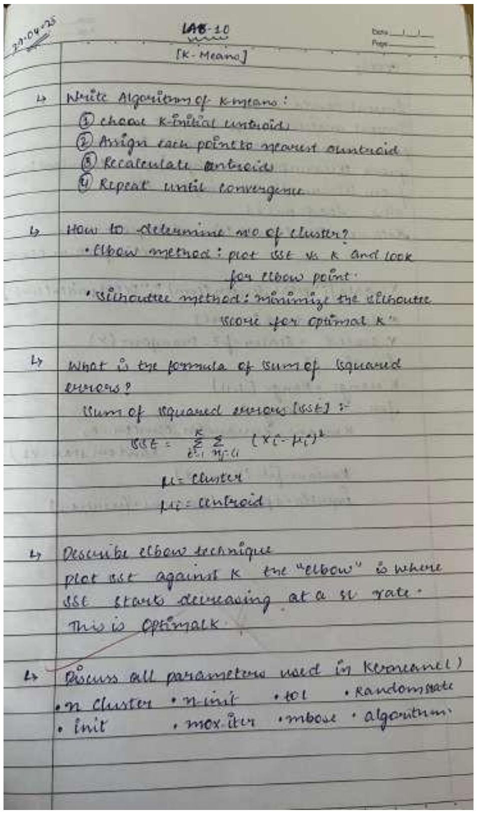
```
y_pred = ada_boost.predict(X_test) accuracy
= accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
conf_matrix = confusion_matrix(y_test, y_pred)
print(f"Confusion Matrix:\n{conf_matrix}") plt.figure(figsize=(6,
4))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=ada_boost.classes_,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

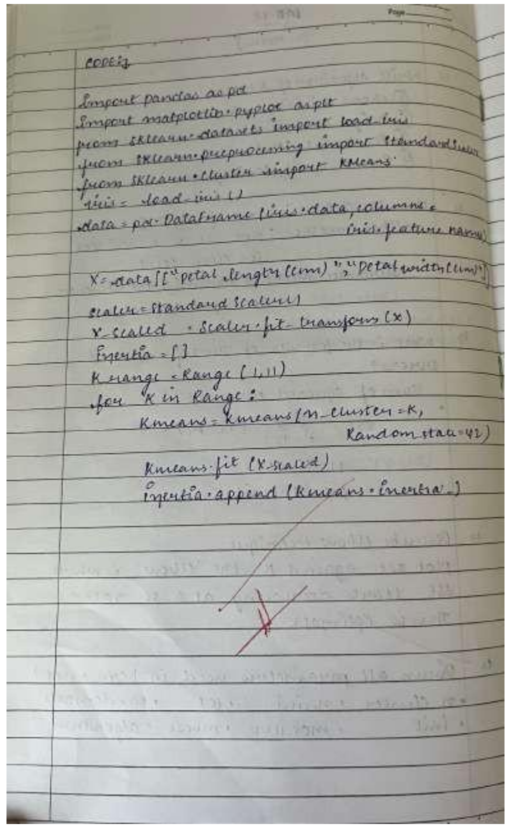
```
Accuracy: 0.8327362063670796
Confusion Matrix:
[[7003  411]
 [1223 1132]]
```



Program 10

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

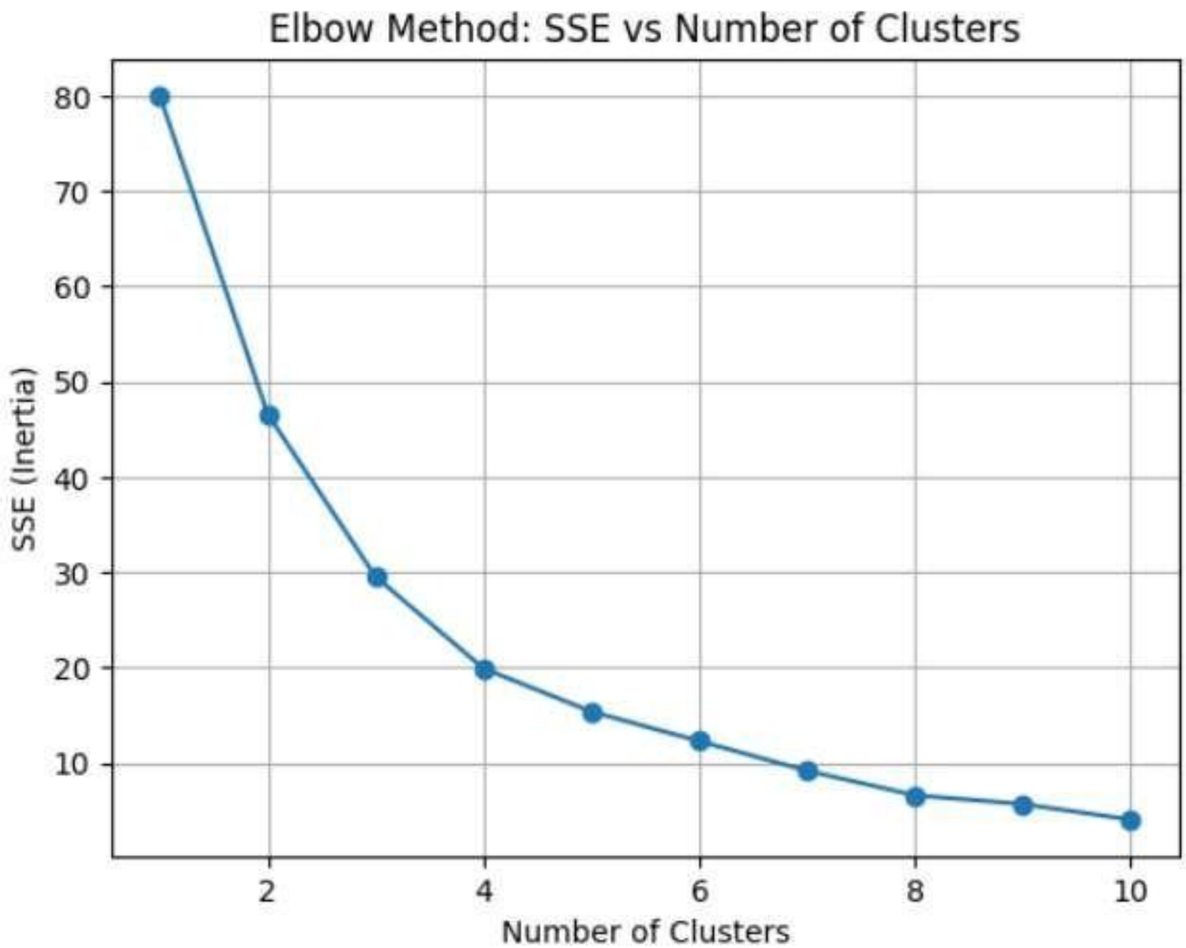




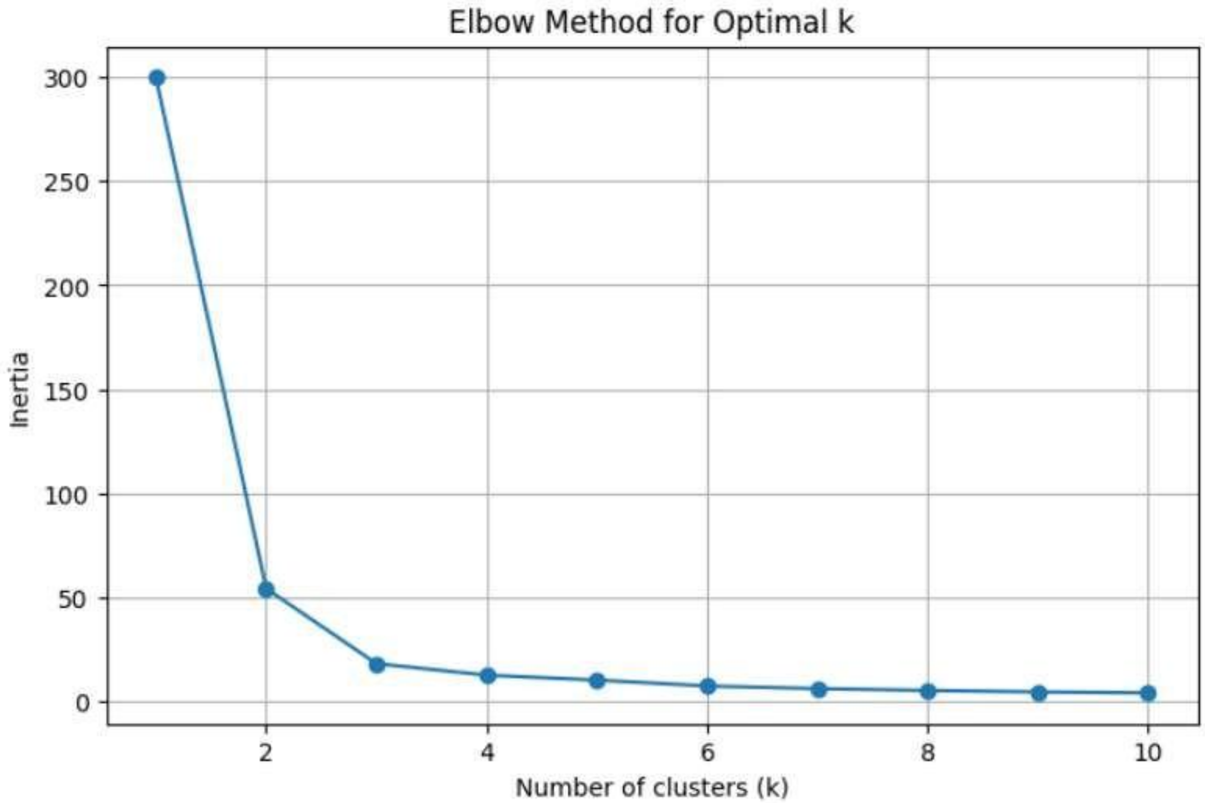
Code:

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))
```

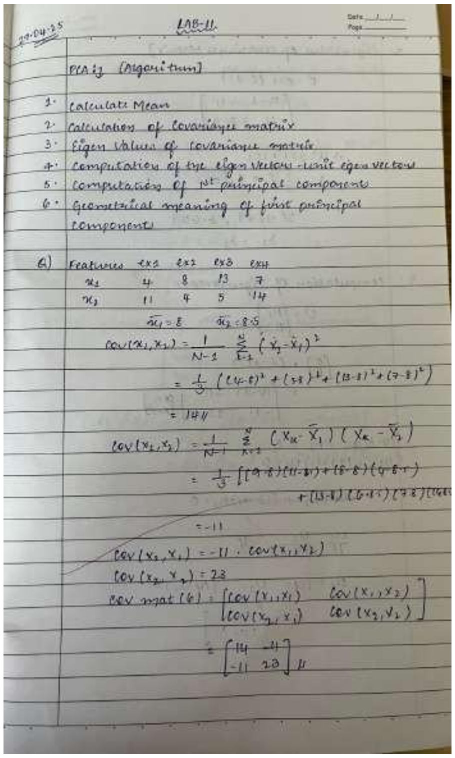


Iris.csv import pandas as pd import
matplotlib.pyplot as plt from sklearn.datasets
import load_iris from sklearn.preprocessing
import StandardScaler from sklearn.cluster
import KMeans
iris = load_iris() data = pd.DataFrame(iris.data,
columns=iris.feature_names)
X = data[["petal length (cm)", "petal width (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()


Elbow Method for Optimal k
300
250
200
150
100
50
0
Inertia
2
4
6
8
10
Number of clusters (k)

Program 11

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



29-04-25 LAB-11

PCA: (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

Features	ex1	ex2	ex3	ex4
x_1	4	8	13	7
x_2	11	4	5	14

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

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

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

$= 14$

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

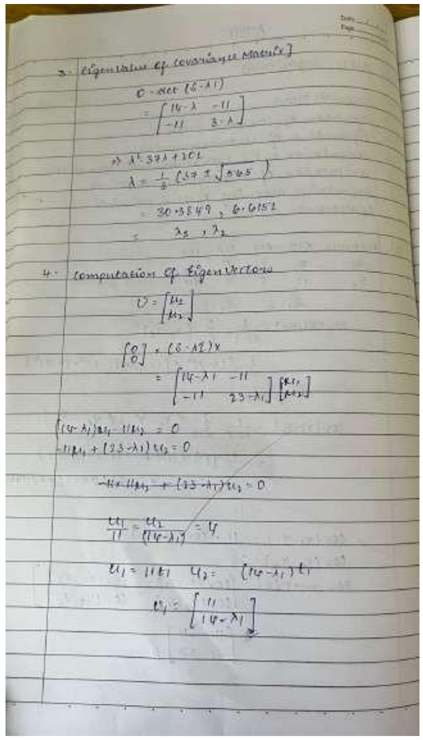
$= -11$

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

$cov(x_2, x_2) = 23$

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

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



3. Eigenvalue of covariance matrix

$0 = det(S - \lambda I)$

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

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

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

$= 30.3849, 6.6151$

$= \lambda_1, \lambda_2$

4. Computation of Eigen Vectors

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

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

$= \begin{bmatrix} 14-\lambda_1 & -11 \\ -11 & 23-\lambda_1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

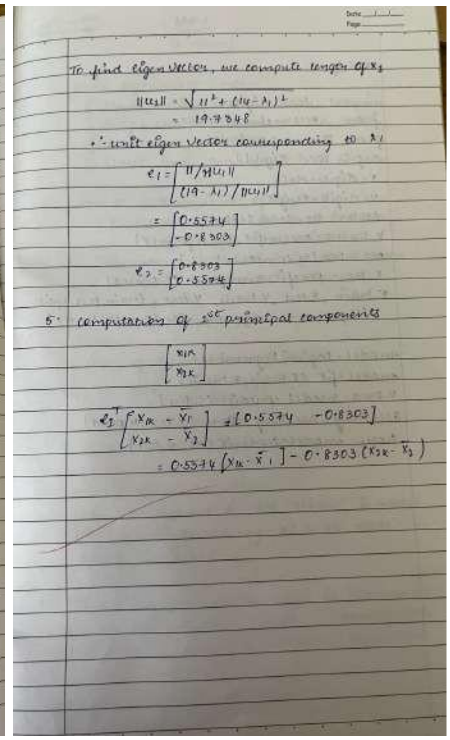
$(14-\lambda_1)u_1 - 11u_2 = 0$

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

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

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

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



To find eigen vector, we compute length of x_1

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

$= 19.7348$

$\therefore$ 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

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

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

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

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
```