VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

Rushil Magazine (1BM22CS225)

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

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B.M.S. College of Engineering

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

<u>CERTIFICATE</u>

This is to certify that the Lab work entitled “Machine Learning (23CS6PCMAL)” carried out by **Rushil Magazine (1BM22CS225),** who is bonafide student of **B.M.S. College of Engineering.** It is in partial fulfilment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Laboratory 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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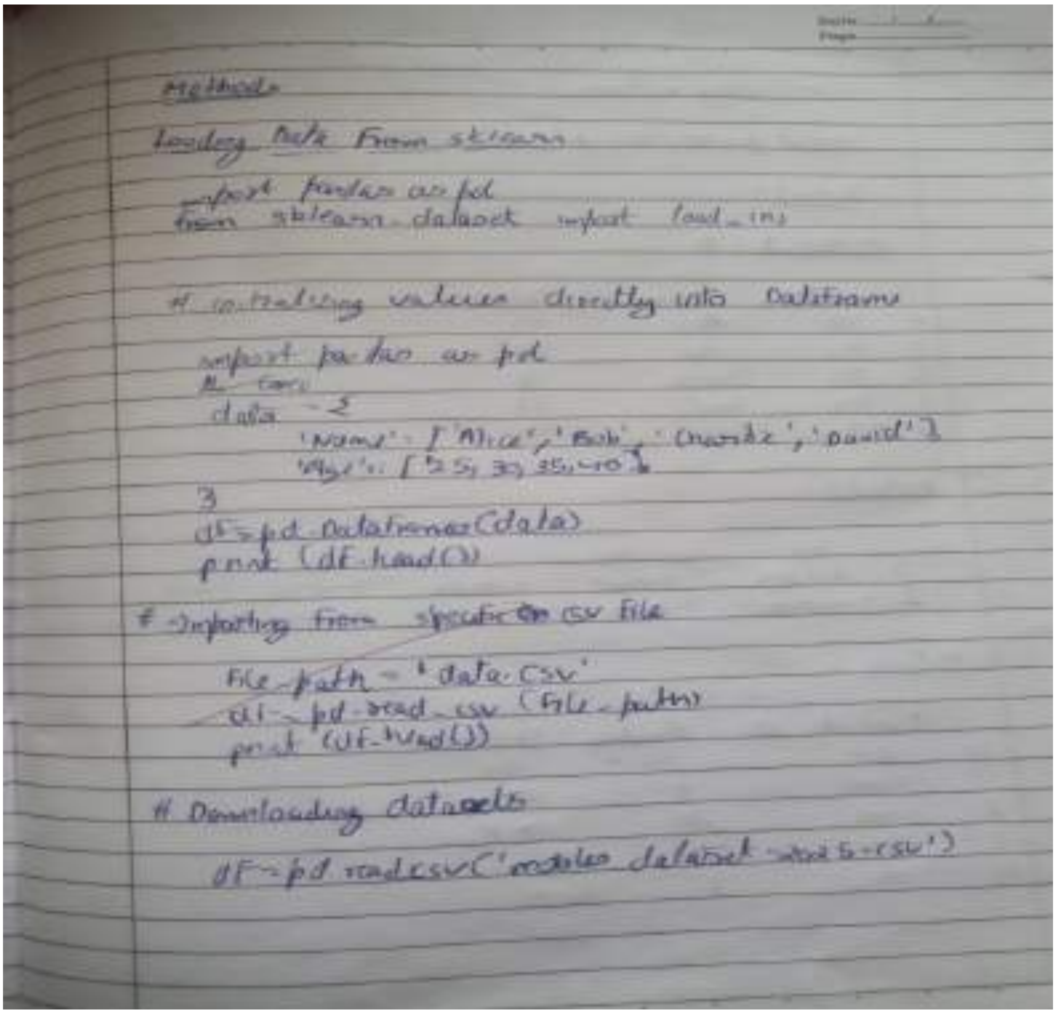
Github Link: https://github.com/bitpipi/ML-LAB-192

LABORATORY PROGRAM – 1

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

OBSERVATION BOOK



Method:

Loading Data From sklearn

import pandas as pd
from sklearn.dataset import load_iris

initializing values directly into Dataframe

import pandas as pd
# [illegible]
data = {
'Name': ['Alice', 'Bob', 'Charlie', 'David'],
'Age': [25, 30, 35, 40]
}
df = pd.DataFrame(data)
print (df.head())

Importing from specific csv File

File_path = 'data.csv'
df = pd.read_csv (File_path)
print (df.head())

Downloading datasets

df = pd.read_csv('[illegible] dataset [illegible].csv')

1) ~~with missing values~~

~~import pandas as pd~~

Output:

Method 1 : ~~df~~

	USN	Name	Marks
0	101	Alice	85
1	102	Bob	92
2	103	Charlie	78
3	104	David	88
4	105	Eve	95

Method 2

	age	sex	bmi	bp	s1	s2
0	0.038076	0.05068	0.061696	0.021872	-0.04423	-0.034821
1	-0.001882	-0.4864	-0.051474	-0.008449	0.019163	0.07442

Method 3

	Product ID	Quantity	UnitPrice
0	1001	10	25.5
1	1002	5	50.0
2	1003	20	10.75
3	1004	15	30.25
4	1005	8	60.0

Method 4

	Passenger ID	Survived	Pclass
0	1	0	3
1	2	1	1

10/10

3/3/24

CODE WITH OUTPUT

Diabetes Dataset

```
df=pd.read_csv('/content/Dataset of Diabetes .csv')
df.head()
```

	ID	No_Pation	Gender	AGE	Urea	Cr	HbA1c	Chol	TG	HDL	LDL	VLDL	BMI	CLASS
0	502	17975	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	N
1	735	34221	M	26	4.5	62	4.9	3.7	1.4	1.1	2.1	0.6	23.0	N
2	420	47975	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	N
3	680	87656	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	N
4	504	34223	M	33	7.1	46	4.9	4.9	1.0	0.8	2.0	0.4	21.0	N

```
df.shape
```

```
(1000, 14)
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   ID         1000 non-null   int64
 1   No_Pation  1000 non-null   int64
 2   Gender     1000 non-null   object
 3   AGE        1000 non-null   int64
 4   Urea       1000 non-null   float64
 5   Cr         1000 non-null   int64
 6   HbA1c      1000 non-null   float64
 7   Chol       1000 non-null   float64
 8   TG         1000 non-null   float64
 9   HDL        1000 non-null   float64
 10  LDL        1000 non-null   float64
 11  VLDL       1000 non-null   float64
 12  BMI        1000 non-null   float64
 13  CLASS      1000 non-null   object
dtypes: float64(8), int64(4), object(2)
memory usage: 109.5+ KB
None
```

M

```
# Summary statistics
print(df.describe())
```

```
                ID    No_Pation          AGE         Urea           Cr  \
count  1000.000000  1.000000e+03  1000.000000  1000.000000  1000.000000
mean    340.500000  2.705514e+05    53.528000     5.124743    68.943000
std     240.397673  3.380758e+06     8.799241     2.935165    59.984747
min       1.000000  1.230000e+02    20.000000     0.500000     6.000000
25%     125.750000  2.406375e+04    51.000000     3.700000    48.000000
50%     300.500000  3.439550e+04    55.000000     4.600000    60.000000
75%     550.250000  4.538425e+04    59.000000     5.700000    73.000000
max     800.000000  7.543566e+07    79.000000    38.900000   800.000000

             HbA1c         Chol           TG          HDL          LDL  \
count  1000.000000  1000.000000  1000.000000  1000.000000  1000.000000
mean      8.281160     4.862820     2.349610     1.204750     2.609790
std       2.534003     1.301738     1.401176     0.660414     1.115102
min       0.900000     0.000000     0.300000     0.200000     0.300000
25%       6.500000     4.000000     1.500000     0.900000     1.800000
50%       8.000000     4.800000     2.000000     1.100000     2.500000
75%      10.200000     5.600000     2.900000     1.300000     3.300000
max      16.000000    10.300000    13.800000     9.900000     9.900000

              VLDL          BMI
count  1000.000000  1000.000000
mean      1.854700    29.578020
std       3.663599     4.962388
min       0.100000    19.000000
25%       0.700000    26.000000
50%       0.900000    30.000000
75%       1.500000    33.000000
max      35.000000    47.750000
```

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

```
Series([], dtype: int64)
```

```
categorical_cols = df.select_dtypes(include=['object']).columns
print("Categorical columns identified:", categorical_cols)
if len(categorical_cols) > 0:
    df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
    print("\nDataFrame after one-hot encoding:")
    print(df.head())
else:
    print("\nNo categorical columns found in the dataset.")
```

```
Categorical columns identified: Index(['Gender', 'CLASS'], dtype='object')

DataFrame after one-hot encoding:
    ID  No_Pation  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL   BMI  \
0  502      17975   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
1  735      34221   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6  23.0
2  420      47975   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
3  680      87656   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
4  504      34223   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4  21.0

   Gender_M  Gender_f  CLASS_N  CLASS_P  CLASS_Y  CLASS_Y
0     False     False    False    False    False     False
1      True     False    False    False    False     False
2     False     False    False    False    False     False
3     False     False    False    False    False     False
4      True     False    False    False    False     False
```

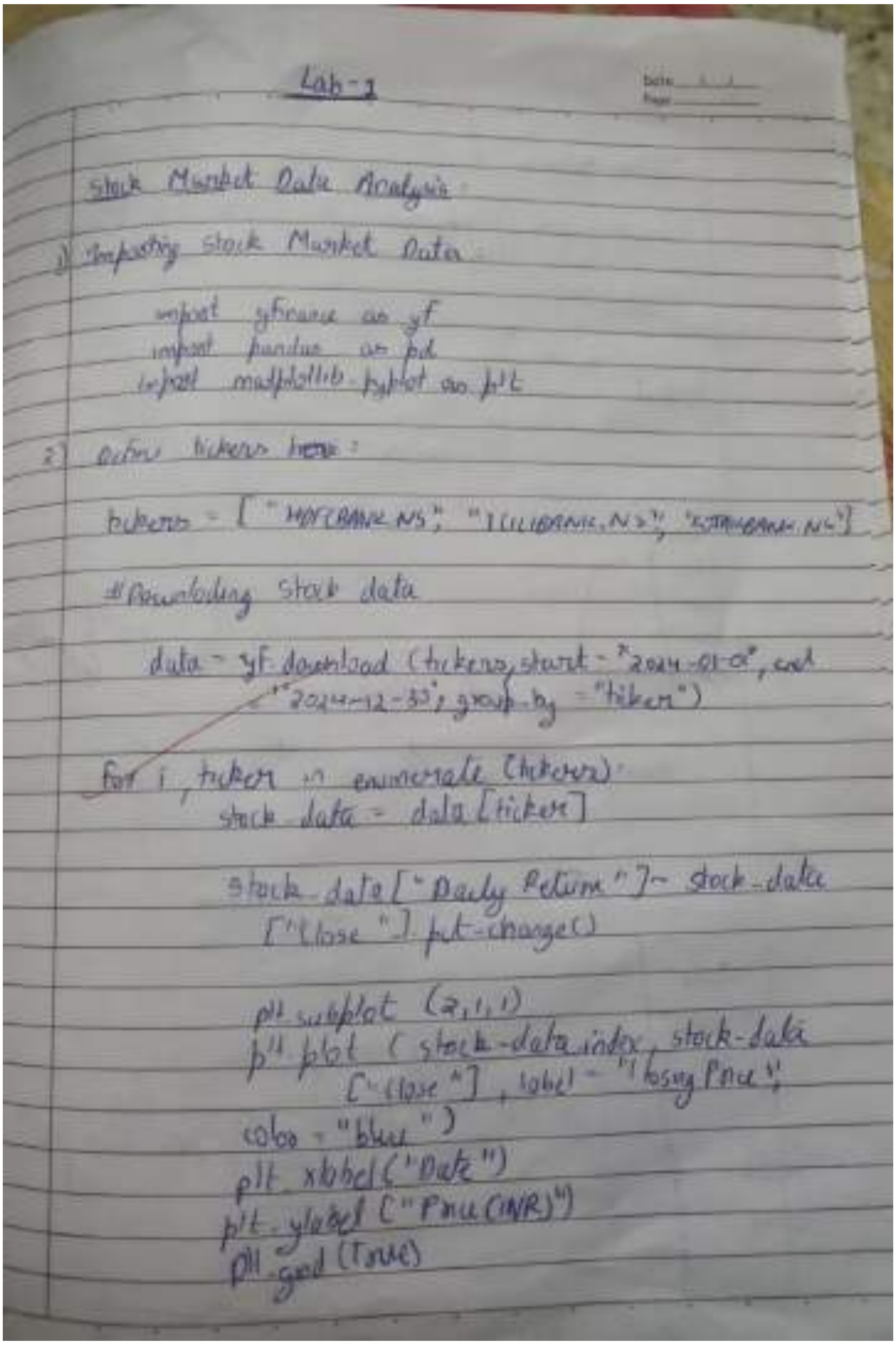
```python
from sklearn.preprocessing import MinMaxScaler, StandardScaler
import pandas as pd

numerical_cols = df.select_dtypes(include=['number']).columns

scaler = MinMaxScaler()
df_minmax = df.copy()  # Create a copy to avoid modifying the original
df_minmax[numerical_cols] = scaler.fit_transform(df[numerical_cols])

scaler = StandardScaler()
df_standard = df.copy()
df_standard[numerical_cols] = scaler.fit_transform(df[numerical_cols])
print("\nDataFrame after Min-Max Scaling:")
print(df_minmax.head())
print("\nDataFrame after Standardization:")
print(df_standard.head())
```

```
DataFrame after Min-Max Scaling:
         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  Gender_M  Gender_f  \
0  0.044444  0.226804  0.114583  0.011461  0.173913     False     False
1  0.081481  0.092784  0.187500  0.014327  0.139130      True     False
2  0.044444  0.226804  0.114583  0.011461  0.173913     False     False
3  0.044444  0.226804  0.114583  0.011461  0.173913     False     False
4  0.051852  0.061856  0.177083  0.008596  0.069565      True     False

   CLASS_N  CLASS_P  CLASS_Y  CLASS_Y
0    False    False    False    False
1    False    False    False    False
2    False    False    False    False
3    False    False    False    False
4    False    False    False    False

DataFrame after Standardization:
         ID  No_Pation       AGE      Urea        Cr     HbA1c      Chol  \
0  0.672140  -0.074747 -0.401144 -0.144781 -0.382672 -1.334983 -0.509436
1  1.641052  -0.069948 -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  1.412958  -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  Gender_M  Gender_f  \
0 -1.035084  1.810756 -1.085457 -0.369958 -1.124622     False     False
1 -0.678063 -0.158692 -0.457398 -0.342640 -1.326239      True     False
2 -1.035084  1.810756 -1.085457 -0.369958 -1.124622     False     False
3 -1.035084  1.810756 -1.085457 -0.369958 -1.124622     False     False
4 -0.963680 -0.613188 -0.547121 -0.397267 -1.729472      True     False

   CLASS_N  CLASS_P  CLASS_Y  CLASS_Y
0    False    False    False    False
1    False    False    False    False
2    False    False    False    False
3    False    False    False    False
4    False    False    False    False
```

LABORATORY PROGRAM – 2

Demonstrate various data pre-processing techniques for a given dataset

OBSERVATION BOOK



Lab-2

Stock Market Data Analysis

1) Importing Stock Market Data:

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

2) Define tickers here:

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

#Downloading stock data

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

for i, ticker in enumerate(tickers):
    stock_data = data[ticker]

    stock_data["Daily Return"] = stock_data
        ["Close"].pct_change()

    plt.subplot(2,1,1)
    plt.plot(stock_data.index, stock_data
        ["Close"], label="Closing Price",
    color="blue")
    plt.xlabel("Date")
    plt.ylabel("Price (INR)")
    plt.grid(True)
```

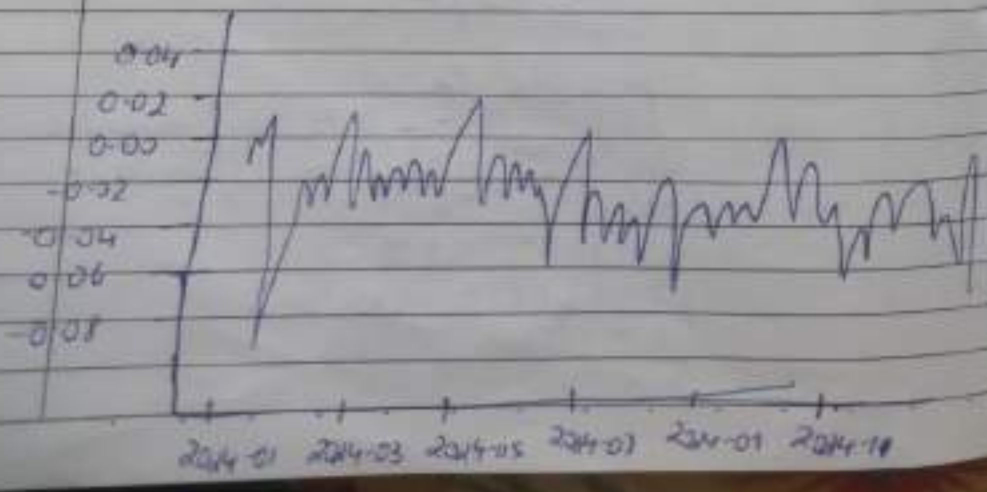
"Daily Returns Plot"

```
plt.plot(stock_data.index, stock_data["Daily Return"],
  label="Daily Return", color="orange")
```

Output:

HDFCBANK.NS - Closing Price

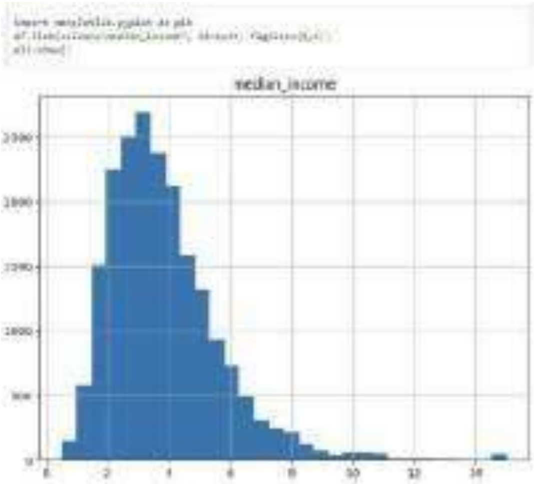
HDFCBANK.NS - Daily Returns

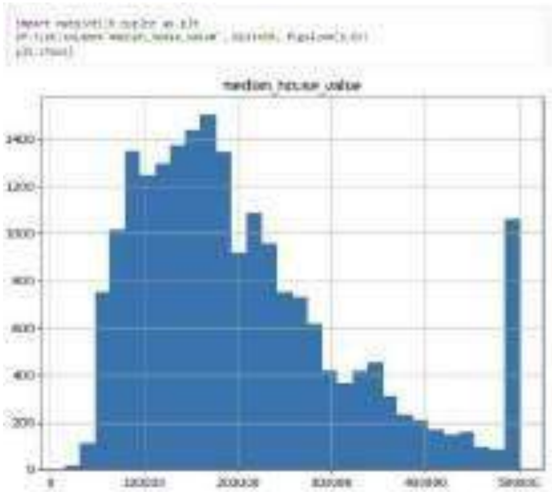


CODE WITH OUTPUT

```
# Load the dataset into a pandas DataFrame
df = pd.read_csv('housing.csv')

# Display descriptive statistics
df.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populatio
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.00000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.47674
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.46212
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.00000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.00000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.00000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.00000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.00000



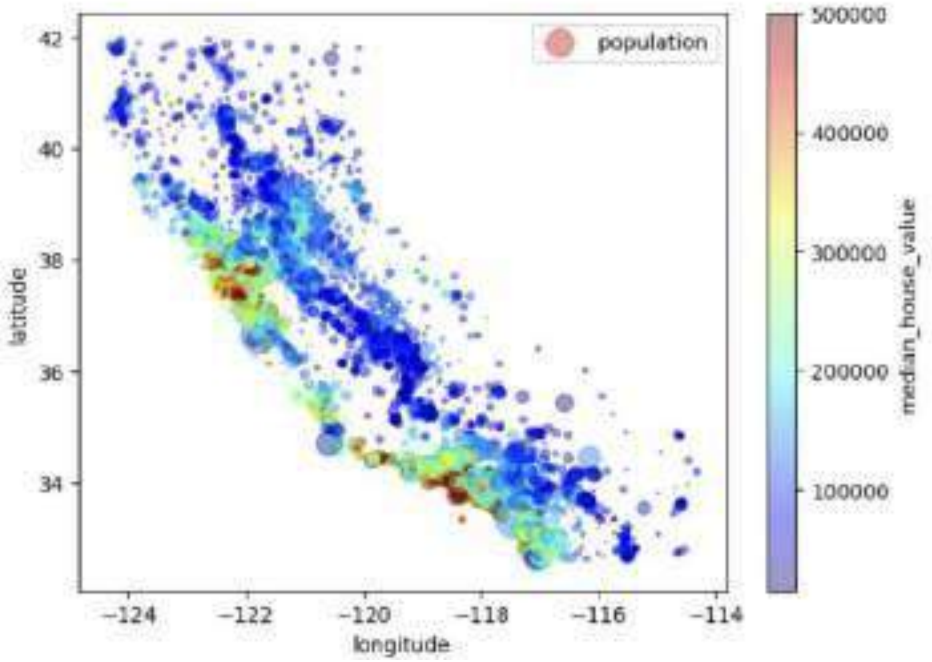



```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, StratifiedShuffleSplit

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

# For this demonstration, consider only 'median_income' and 'median_house_value'
housing_selected = housing[['median_income', 'median_house_value']].copy()

# Random split: This splits the data randomly without preserving any specific distribution.
train_set_random, test_set_random = train_test_split(housing_selected, test_size=0.2, random_state=42)

# For stratified sampling, first create an income category.
housing_selected['income_cat'] = pd.cut(housing_selected['median_income'],
                                        bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                                        labels=[1, 2, 3, 4, 5])

# Use StratifiedShuffleSplit to ensure the income distribution is preserved in both sets.
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing_selected, housing_selected['income_cat']):
    strat_train_set = housing_selected.loc[train_index]
    strat_test_set = housing_selected.loc[test_index]

# Remove the temporary income category attribute.
```

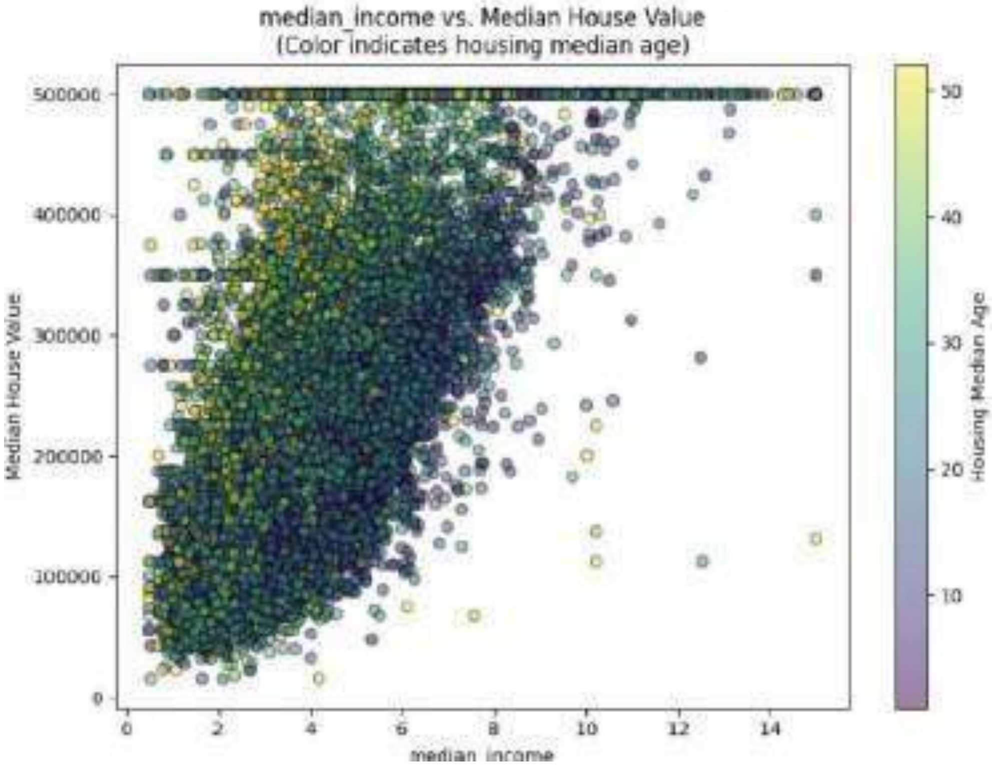
```
for dataset in (strat_train_set, strat_test_set):
    dataset.drop("income_cat", axis=1, inplace=True)
```

```
import matplotlib.pyplot as plt
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
             s=housing["population"]/100, label="population", figsize=(7,5),
             c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,)
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7e55a2076b10>
```



```python
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8,6))
# Differentiate by using 'housing_median_age' for the color
scatter = plt.scatter(housing_numeric[max_feature],
                      housing_numeric["median_house_value"],
                      alpha=0.5,
                      c=housing_numeric["housing_median_age"],
                      cmap='viridis',
                      edgecolor='k')
plt.xlabel(max_feature)
plt.ylabel("Median House Value")
plt.title(f"{max_feature} vs. Median House Value\n(Color indicates housing median age)")
# Add a colorbar to explain the color mapping
cbar = plt.colorbar(scatter)
cbar.set_label("Housing Median Age")
plt.tight_layout()
plt.show()
```



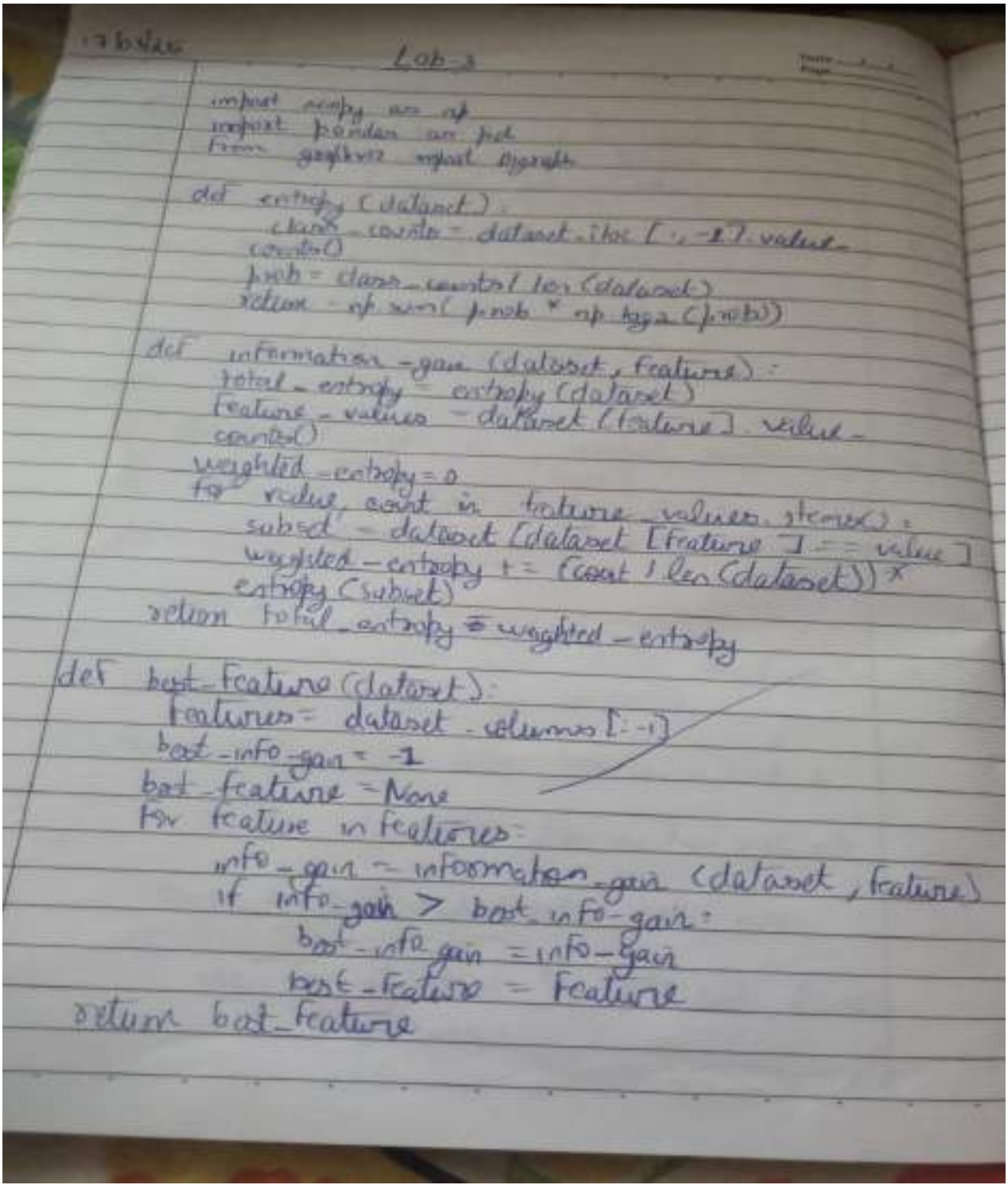

```python
from sklearn.preprocessing import OneHotEncoder

# Extract the categorical attribute
housing_cat = housing[["ocean_proximity"]]

# Perform one-hot encoding
encoder = OneHotEncoder()
housing_cat_1hot = encoder.fit_transform(housing_cat).toarray()

# Create a DataFrame for the encoded features
housing_cat_1hot_df = pd.DataFrame(housing_cat_1hot,
                           columns=encoder.get_feature_names_out(["ocean_proximity"]))
housing_cat_1hot_df.head()
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler

# Custom transformer to add engineered attributes
class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
```

```
    def __init__(self, add_bedrooms_per_room=True):
        self.add_bedrooms_per_room = add_bedrooms_per_room
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        # Assumes X is a NumPy array with the following columns:
        # total_rooms (index 3), total_bedrooms (index 2), population (index 4), households (index 5)
        rooms_per_household = X[:, 3] / X[:, 5]
        population_per_household = X[:, 4] / X[:, 5]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, 2] / X[:, 3]
            return np.c_[X, rooms_per_household, population_per_household, bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household, population_per_household]

# Identify numerical and categorical columns
num_attribs = housing.drop("ocean_proximity", axis=1).columns  # All numeric columns
cat_attribs = ["ocean_proximity"]

# Build numerical pipeline: impute missing values, add new attributes, then scale
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()),
])

# Build the full pipeline combining numerical and categorical processing
full_pipeline = ColumnTransformer([
    ("num", num_pipeline, num_attribs),
    ("cat", OneHotEncoder(), cat_attribs),
])

# Process the dataset using the pipeline
housing_prepared = full_pipeline.fit_transform(housing)
print("Shape of processed data:", housing_prepared.shape)
```

LABORATORY PROGRAM – 3

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

OBSERVATION BOOK



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Lab-3

import numpy as np
import pandas as pd
from graphviz import Digraph

def entropy (dataset):
    class_counts = dataset.iloc [:, -1].value_counts()
    prob = class_counts / len (dataset)
    return - np.sum(prob * np.log2 (prob))

def information_gain (dataset, feature):
    total_entropy = entropy (dataset)
    feature_values = dataset [feature] . value_counts()
    weighted_entropy = 0
    for value, count in feature_values.items():
        subset = dataset [dataset [feature] == value]
        weighted_entropy += (count / len (dataset)) * entropy (subset)
    return total_entropy - weighted_entropy

def best_feature (dataset):
    features = dataset . columns [: -1]
    best_info_gain = -1
    best_feature = None
    for feature in features:
        info_gain = information_gain (dataset, feature)
        if info_gain > best_info_gain:
            best_info_gain = info_gain
            best_feature = feature
    return best_feature

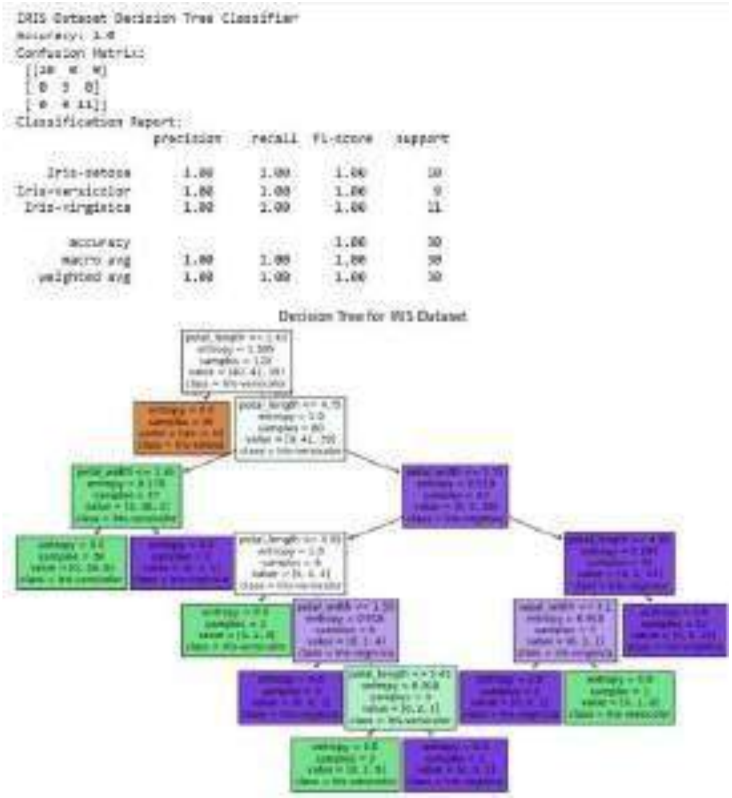
```
def id3 (dataset, max_depth = None, depth = 0):
    if len (dataset.iloc[:, -1].unique()) == 1:
        return dataset.iloc[0, -1]
    if len (dataset.columns) == 1:
        return dataset.iloc[:, -1].mode()[0]
    if max depth is not None and depth >= max_depth
        return dataset.iloc[:, -1].mode()[0]
    best = best_Feature (dataset)
    tree = {best: {}}
    for value in dataset[best].unique():
        subset = dataset[dataset[best] == value]
        tree[best][value] = id3(subset.drop(columns=
        [best]), max depth = max_depth, depth=depth +1)
    return tree

def create_tree_diagram (tree, dot=None, parent_name=
        "Root", parent_value=""):
    if dot is None:
        dot = Digraph(format="png", engine="dot")

    if isinstance (tree, dict):
        for feature, branches in tree.items():
            feature_name = f"{parent_name}_{feature}"
            dot.node(feature_name, feature)
            dot.edge(parent_name, feature_name, label=
            parent_value)

            for value, subtree in branches.items():
                value_name = f"{feature_name}_{value}"
                dot.node(value_name, f"{feature}_{value}"
                dot.node(value_name, f"{feature}_{value}"
                dot.edge(feature_name, value_name, label=st
                (value))
```

```
        create_tree_diagram(subtree, dot, value_name,
            str(value))

    else:
        dot.node(parent_name + "_class", f"Class:
            {tree}")
        dot.edge(parent_name, parent_name + "_class",
            label="Leaf")

    return dot

data = pd.read_csv("/content/weather.csv")
df = pd.DataFrame(data)
tree = id3(df, max_depth=3)
dot = create_tree_diagram(tree)
dot.render("decision_tree", view="True)
```

17.7

CODE WITH OUTPUT

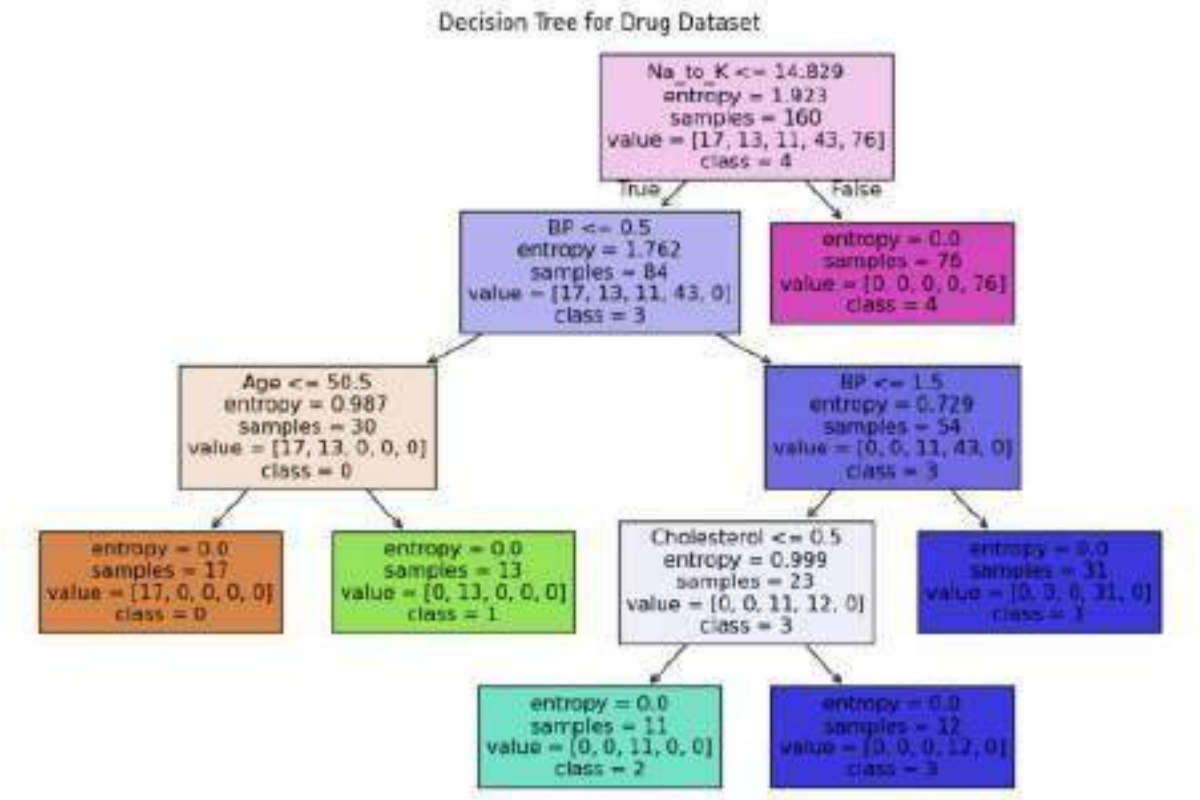
```
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Load the iris dataset (make sure iris.csv is in the working directory)
iris = pd.read_csv("iris.csv")
# Assuming the last column is the target (species) and the rest are features.
X = iris.iloc[:, :-1]
y = iris.iloc[:, -1]

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

# Initialize and train the Decision Tree classifier
clf_iris = DecisionTreeClassifier(criterion='entropy', random_state=42)
clf_iris.fit(X_train, y_train)

# Make predictions and evaluate the model
y_pred_iris = clf_iris.predict(X_test)
accuracy_iris = accuracy_score(y_test, y_pred_iris)
conf_matrix_iris = confusion_matrix(y_test, y_pred_iris)

print("IRIS Dataset Decision Tree Classifier")
print("Accuracy:", accuracy_iris)
print("Confusion Matrix:\n", conf_matrix_iris)
print("Classification Report:\n", classification_report(y_test, y_pred_iris))

# Visualize the decision tree
plt.figure(figsize=(12, 8))
plot_tree(clf_iris, filled=True, feature_names=X.columns, class_names=clf_iris.classes_)
plt.title("Decision Tree for IRIS Dataset")
plt.show()
```




```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Load the drug dataset (make sure drug.csv is in the working directory)
drug = pd.read_csv("drug.csv")

# Since the target column is 'Drug', drop it from the features
X_drug = drug.drop('Drug', axis=1)
y_drug = drug['Drug']

# If there are categorical features, perform necessary encoding
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
# Encode features that are categorical
for col in X_drug.select_dtypes(include='object').columns:
    X_drug[col] = le.fit_transform(X_drug[col])
# Also encode the target variable if necessary
y_drug = le.fit_transform(y_drug)

# Split the data (80% training, 20% testing)
X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_drug, y_drug, test_size=0.2, random_state=42)

# Initialize and train the Decision Tree classifier using entropy criterion
clf_drug = DecisionTreeClassifier(criterion='entropy', random_state=42)
clf_drug.fit(X_train_d, y_train_d)

# Make predictions and evaluate the model
y_pred_drug = clf_drug.predict(X_test_d)
accuracy_drug = accuracy_score(y_test_d, y_pred_drug)
conf_matrix_drug = confusion_matrix(y_test_d, y_pred_drug)

print("Drug Dataset Decision Tree Classifier")
print("Accuracy:", accuracy_drug)
```

```
print("Confusion Matrix:\n", conf_matrix_drug)
print("Classification Report:\n", classification_report(y_test_d, y_pred_drug))

# Visualize the decision tree
plt.figure(figsize=(12, 8))
plot_tree(clf_drug, filled=True, feature_names=X_drug.columns,
        class_names=[str(cls) for cls in clf_drug.classes_])
plt.title("Decision Tree for Drug Dataset")
plt.show()
```

```
Drug Dataset Decision Tree Classifier
Accuracy: 1.0
Confusion Matrix:
 [[ 6  0  0  0  0]
 [ 0  3  0  0  0]
 [ 0  0  5  0  0]
 [ 0  0  0 11  0]
 [ 0  0  0  0 15]]
Classification Report:
               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
```



LABORATORY PROGRAM – 4

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

OBSERVATION BOOK

Lab-4

```
def fit( x,y):
    n = len (x)
    if n != len(y):
        raise ValueError("The length of x and y
          must be the same")

    meax = sum(X)/n
    mean_y = sum(y)/n

    numerator = sum( (X[i] - mean_x)*(y[i] - mean_y)
    for i in range(n))
    denominator = sum((X[i] - mean_x)**2 for i in range(n))

    slope = numerator / denominator
    intercept = mean_y - (slope * mean_x)

    return slope, intercept

def predict (X, slope, intercept):
        return [slope * x + intercept for x in X]


if __name__ == "__main__":
    X = [1,2,3, 4, 5,6, 7, 8, 9,10]
    y = [2,3,5,7, 11,13, 17,19,23,29]
    slope, intercept = fit(X,y)
    predictions = predict( [11,12,13], slope, intercept )

    print ("Slope:", slope)
    print ("Intercept:", intercept)
    print ("Predictions for [11,12,13]:", predictions)
```

Output:

~~Intercept = -3.26~~

Slope : 2.9393939393934

Intercept: -3.2466666666675

Predictions For [11, 12, 13] = [29.0666666667, 32.0060606060061, 34.9454545454549]

Multiple Linear Regression

```
import numpy as np

def fit(X, y):
    n = len(X)
    if n != len(y):
        raise ValueError("The length of X and y must
            be the same")

    X_b = np.c_[np.ones((n, 1)), X]

    theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot
    (X_b.T).dot(y)
    return theta_best

def predict(X, theta):
    n = len(X)
    X_b = np.c_[np.ones((n, 1)), X]
    return X_b.dot(theta)
```

if _name_ == "_main_":

X = np.array ([[1,2],
[2,3],
[3,5],
[4,7],
[5,11],
[6,13],
[7,17],
[8,19],
[9,23],
[10,29]])

y = np.array([2,3,5,7,11,13,17,19,23,29])

theta = fit(X,y)

new_data = np.array([[11,31],[12,37],[13,41]])
predictions = predict(new_data, theta)

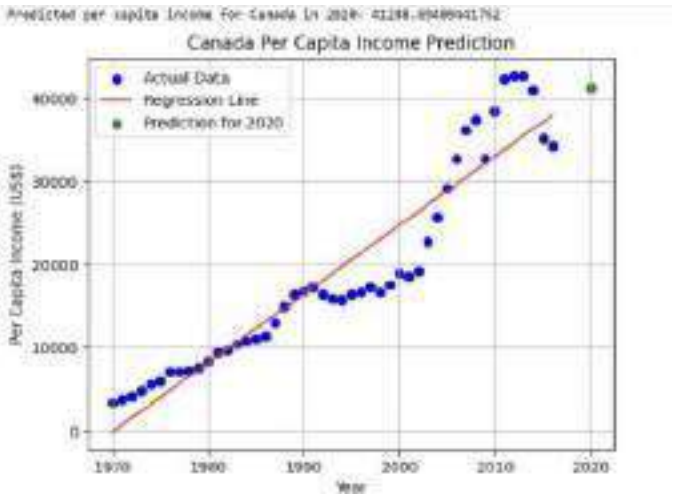
~~print~~ 6

Output:

coefficients (theta) = [-5.02708986e-13
8.70414858e-14 1.00000000e+00]
Predictions for new data points : [31. 37. 41.]

CODE WITH OUTPUT

```
import pandas as pd

from sklearn.linear_model import LinearRegression
# Load the data
income_data = pd.read_csv("canada_per_capita_income.csv")
# Assumed data columns: 'Year' and 'PerCapitaIncome'
print("Canada Income Data Head:")
print(income_data.head())
# Prepare feature and target
X_income = income_data[["year"]]      # Predictor variable: Year
y_income = income_data["per capita income (US$)"]
# Build and train the linear regression model
model_income = LinearRegression()
model_income.fit(X_income, y_income)

# Predict per capita income for the year 2020
predicted_income = model_income.predict([[2020]])

print("\nPredicted per capita income for Canada in 2020:", predicted_income[0])

# Plot the data points and the regression line
plt.scatter(X_income, y_income, color='blue', label='Actual Data')
plt.plot(X_income, model_income.predict(X_income), color='red', label='Regression Line')

# Plot the prediction for 2020
plt.scatter(2020, predicted_income[0], color='green', label='Prediction for 2020')

# Customize the plot
plt.xlabel('Year')
plt.ylabel('Per Capita Income (US$)')
plt.title('Canada Per Capita Income Prediction')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```




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

# Load the salary data
```

```
salary_data = pd.read_csv("salary.csv")
```

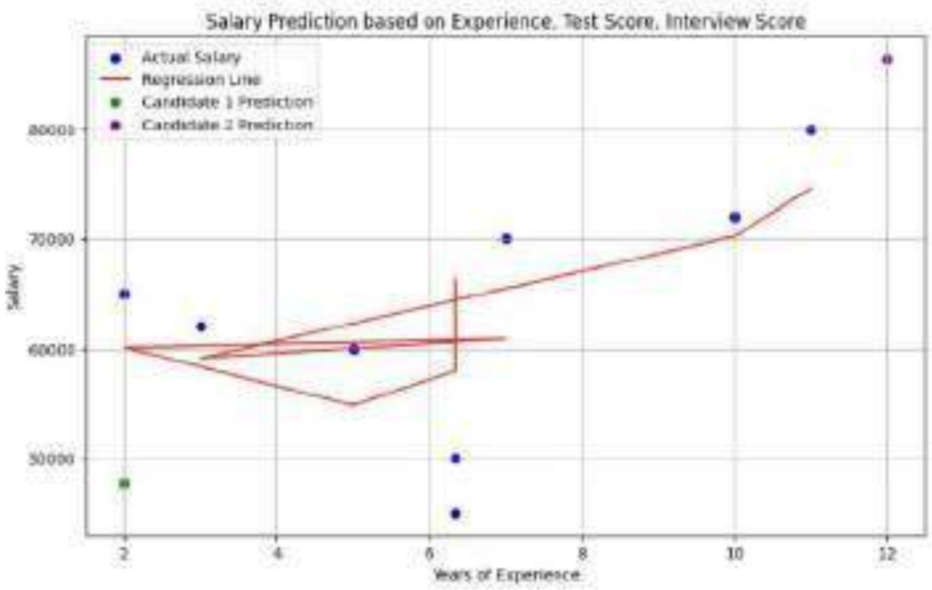
```python
print(income_data.head())

# Prepare feature and target
X_salary = salary_data[["YearsExperience"]]  # Predictor variable: Years of Experience
y_salary = salary_data["Salary"]


# Build and train the linear regression model
model_salary = LinearRegression()
model_salary.fit(X_salary, y_salary)

import matplotlib.pyplot as plt
# Plot the data points and the regression line
plt.scatter(X_salary, y_salary, color='blue', label='Actual Data')
plt.plot(X_salary, model_salary.predict(X_salary), color='red', label='Regression Line')

# Plot the prediction for 12 years of experience
plt.scatter(12, predicted_salary[0], color='green', label='Prediction for 12 years')

# Customize the plot
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.title('Salary Prediction based on Experience')
plt.legend()
plt.grid(True)

# Display the plot
plt.show()
```

```
Predicted salary for an employee with 12 years of experience: 139980.88923969213
```


```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression

# Read the CSV file (ensure the file is uploaded in your Colab environment)
df = pd.read_csv("hiring.csv")
```

```python
# Rename columns for convenience
df.columns = ['experience', 'test_score', 'interview_score', 'salary']

print("Original Data:")
print(df)
# Function to convert experience values to numeric
def convert_experience(x):
    try:
        return float(x)
    except:
        x_lower = str(x).strip().lower()
        return num_map.get(x_lower, np.nan)

# Convert the 'experience' column using the mapping
df['experience'] = df['experience'].apply(convert_experience)

# Convert 'test_score', 'interview_score', and 'salary' to numeric (coerce errors to NaN)
df['test_score'] = pd.to_numeric(df['test_score'], errors='coerce')
df['interview_score'] = pd.to_numeric(df['interview_score'], errors='coerce')
df['salary'] = pd.to_numeric(df['salary'], errors='coerce')

print("\nData After Conversion:")
print(df)

# Fill missing values in numeric columns using the column mean
df['experience'].fillna(df['experience'].mean(), inplace=True)
df['test_score'].fillna(df['test_score'].mean(), inplace=True)
df['interview_score'].fillna(df['interview_score'].mean(), inplace=True)

print("\nData After Filling Missing Values:")
print(df)

# Prepare the feature matrix X and target vector y
X = df[['experience', 'test_score', 'interview_score']]
y = df['salary']

# Build and train the Multiple Linear Regression model
model = LinearRegression()
model.fit(X, y)

# Predict salaries for the given candidate profiles
# Candidate 1: 2 years of experience, 9 test score, 6 interview score
candidate1 = np.array([[2, 9, 6]])
predicted_salary1 = model.predict(candidate1)

# Candidate 2: 12 years of experience, 10 test score, 10 interview score
candidate2 = np.array([[12, 10, 10]])
predicted_salary2 = model.predict(candidate2)


print("\nPredicted Salary for Candidate (2 yrs, 9 test, 6 interview): $", round(predicted_salary1[0], 2))
print("Predicted Salary for Candidate (12 yrs, 10 test, 10 interview): $", round(predicted_salary2[0], 2))
import matplotlib.pyplot as plt

# Create the plot
plt.figure(figsize=(10, 6))  # Adjust figure size for better visualization
plt.scatter(df['experience'], y, color='blue', label='Actual Salary') #Plot actual salary against years of experience

# Plot the regression line (this is an approximation since it's a multi-variable regression)
# You can visualize a single feature against the predicted salary
plt.plot(df['experience'], model.predict(X), color='red', label='Regression Line')

# Highlight predictions
plt.scatter(candidate1[0, 0], predicted_salary1, color='green', label='Candidate 1 Prediction')
plt.scatter(candidate2[0, 0], predicted_salary2, color='purple', label='Candidate 2 Prediction')

# Add labels and title
plt.xlabel("Years of Experience")
```

```
plt.ylabel("Salary")
plt.title("Salary Prediction based on Experience, Test Score, Interview Score")

# Add a legend
plt.legend()
plt.grid(True)
plt.show()
```



LABORATORY PROGRAM – 5

Build Logistic Regression Model for a given dataset

OBSERVATION BOOK

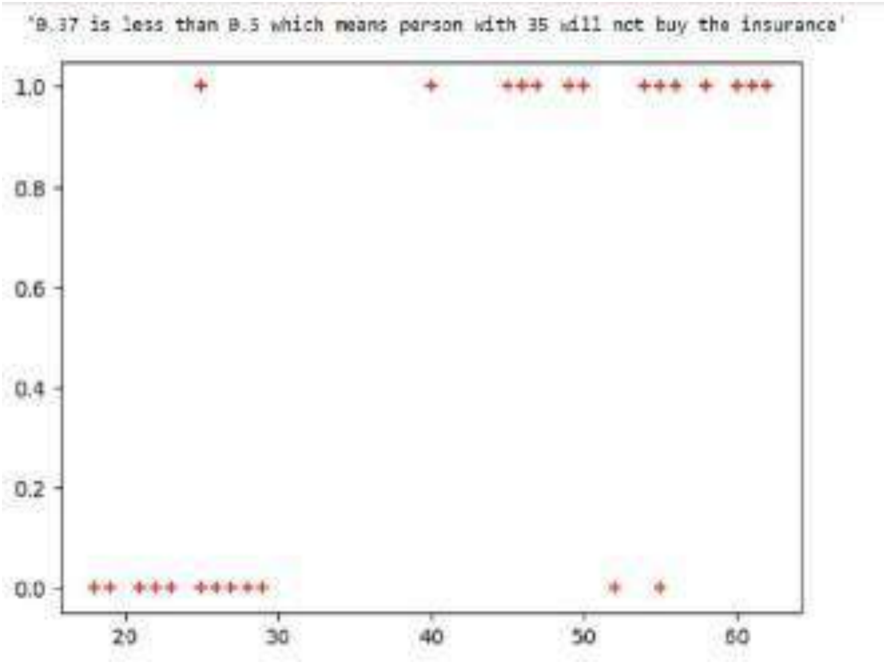
Date / /
Page

Logistic Regression:

```
import numpy as np

def sigmoid (z):
    return 1 / (1 + np.exp(-z))

def fit (X, y, learning_rate = 0.01, num_iterations = 1000):
    n_samples, n_features = X.shape
    weights = np.zeros(n_features)
    bias = 0.

    for _ in range (num_iterations):
        linear_model = np.dot (X, weights) + bias
        y_predicted = sigmoid (linear_model)

        dw = (1 / n_samples) * np.dot (X.T, (y_predicted - y))

        db = (1/n_samples) * np.sum(y_predicted - y)

        weights -= learning_rate * dw
        bias -= learning_rate * db

    return weights, bias

def predict (X, weights, bias):
    linear_model = np.dot (X, weights) + bias
    y_predicted = sigmoid (linear_model)
    y_predicted_class = [1 if i > 0.5 else 0 for i
        in y_predicted]
```

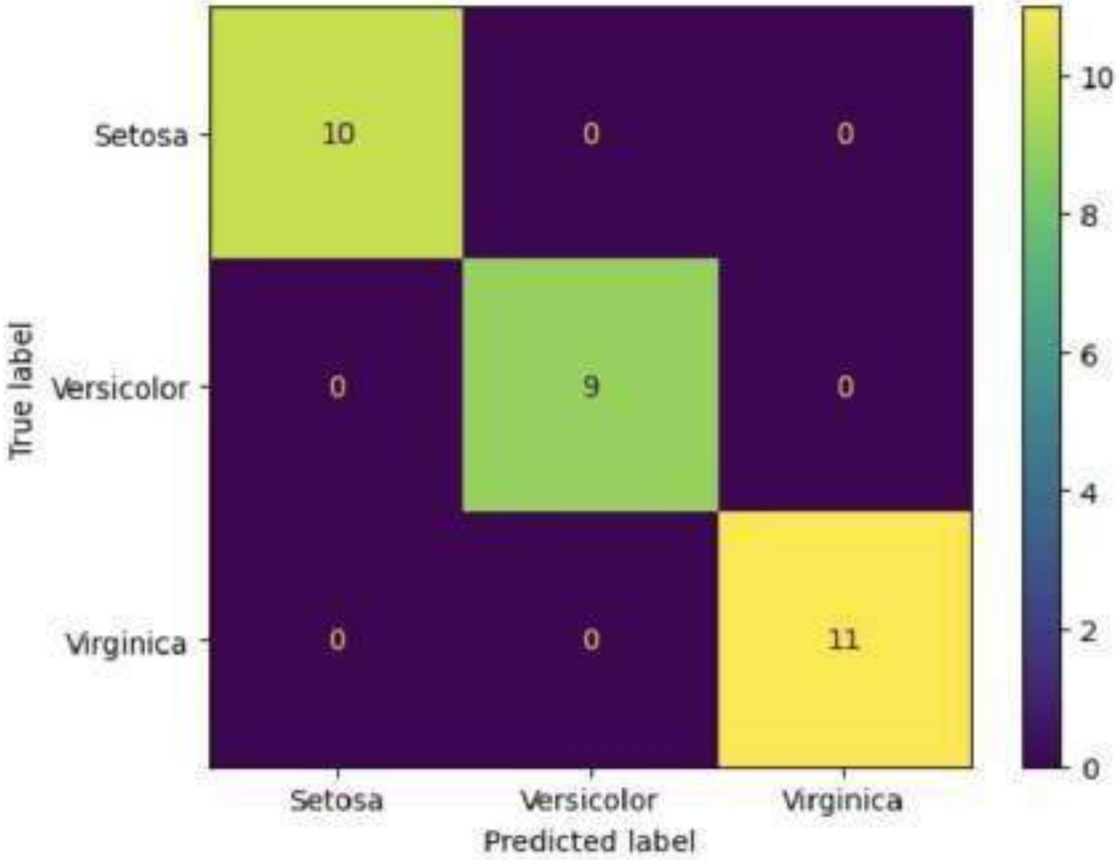
CODE WITH OUTPUT

```
import pandas as pd
from matplotlib import pyplot as plt
# %matplotlib inline
#"%matplotlib inline" will make your plot outputs appear and be stored within the notebook.

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

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

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

X_test

from sklearn.linear_model import LogisticRegression
model = LogisticRegression()

model.fit(X_train, y_train)

X_test

y_test

y_predicted = model.predict(X_test)
y_predicted

model.score(X_test,y_test)

model.predict_proba(X_test)

y_predicted = model.predict([[60]])
y_predicted

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

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

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

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

age = 35
prediction_function(age)

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




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

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

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

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

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

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

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

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

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

confusion_matrix = metrics.confusion_matrix(y_test, y_pred)

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

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

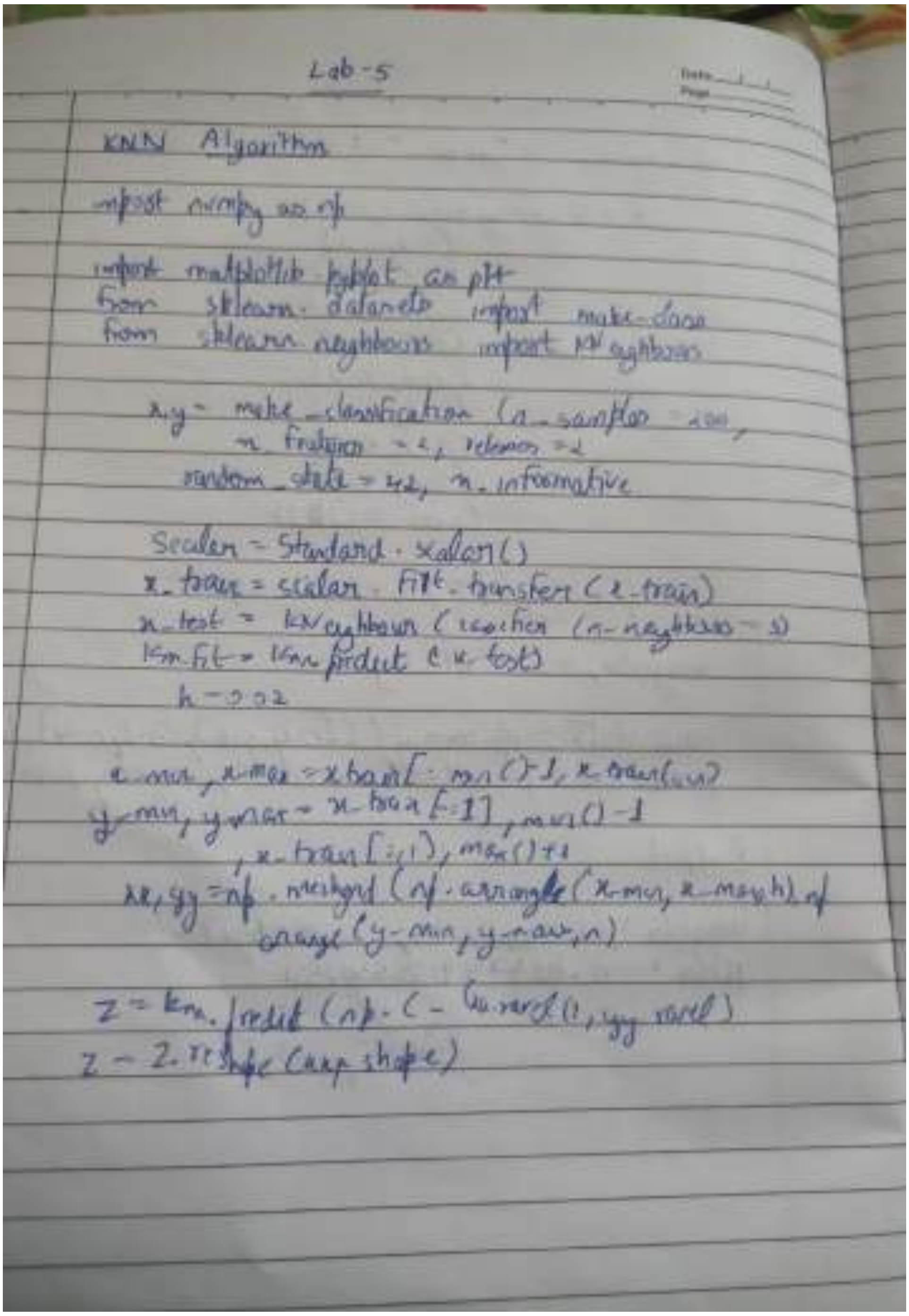
```
Accuracy of the Multinomial Logistic Regression model on the test set: 1.00
```



LABORATORY PROGRAM – 6

Build KNN Classification model for a given dataset.

OBSERVATION BOOK


Lab-5

KNN Algorithm

import numpy as np

import matplotlib.pyplot as plt
from sklearn.datasets import make_class
from sklearn.neighbors import KNeighbors

x,y = make_classification (n_samples = 200,
n_features = 2, redundant = 2
random_state = 42, n_informative

Scaler = Standard.scaler()
x_train = scalar.fit.transform (x_train)
x_test = KNeighbours (classifier (n_neighbours = 5)
knn.fit = knn.predict (x_test)
h = 0.02

x_min, x_max = x_train[:,0].min()-1, x_train[:,0].max()
y_min, y_max = x_train[:,1].min() -1
, x_train[:,1].max()+1
xx, yy = np.meshgrid (np.arange(x_min, x_max, h), np.
arange (y_min, y_max, h))

Z = knn.predict (np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape (xx.shape)

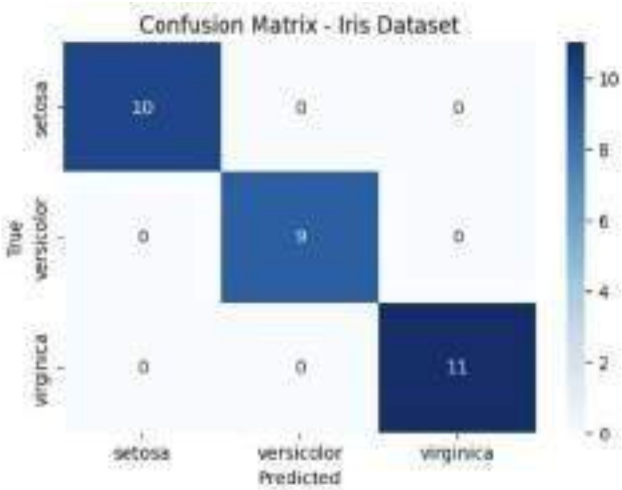
```
plt.figure (figsize = (10,6))

plt.contourf (xx, yy, z, alpha = 0.8))
plt.scatter (x test [:0], x-test [:1],
        c = y_test, edgecolor = 'k', marker
= 's', s= 100, label = 'Test Data', cmap =
     plt. cm. coolwarm)

plt.title ("KNearest Neighbour Pearson")
plt. xlabel ( Feature 1)
plt.ylabel ('Feature 2')
plt.legend()
plt. show()
```

CODE WITH OUTPUT

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# For model building and evaluation
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# -------------------- Part 1: IRIS Dataset -------------------- #
# Load the iris dataset (ensure iris.csv is in the same directory or provide correct path)
iris_df = pd.read_csv("iris.csv")

# Separate features and target
X_iris = iris_df.drop("species", axis=1)
y_iris = iris_df["species"]

# Split the data (80% training, 20% testing)
X_train_iris, X_test_iris, y_train_iris, y_test_iris = train_test_split(
    X_iris, y_iris, test_size=0.2, random_state=42
)

# Choose a value for k; here K=3 is used as an example.
knn_iris = KNeighborsClassifier(n_neighbors=3)

# Train the model on training data
knn_iris.fit(X_train_iris, y_train_iris)

# Predict on test data
y_pred_iris = knn_iris.predict(X_test_iris)

# Calculate accuracy score
acc_iris = accuracy_score(y_test_iris, y_pred_iris)
print("IRIS Dataset Accuracy Score:", acc_iris)
# Compute confusion matrix and classification report
cm_iris = confusion_matrix(y_test_iris, y_pred_iris)
print("\nIRIS Dataset Confusion Matrix:\n", cm_iris)
```

```
cr_iris = classification_report(y_test_iris, y_pred_iris)
print("\nIRIS Dataset Classification Report:\n", cr_iris)
```

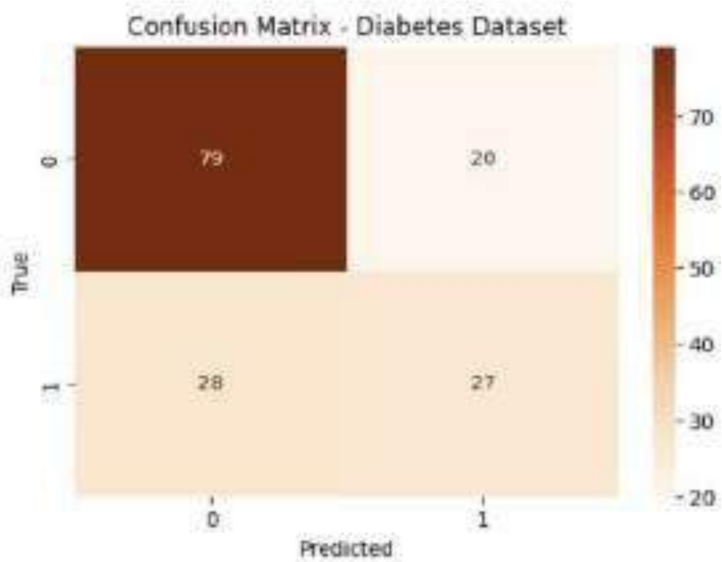
```
IRIS Dataset Classification Report:
               precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        10
  versicolor       1.00      1.00      1.00         9
   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
```




```
# ----------------- Part 2: Diabetes Dataset ------------------- #
# Load the diabetes dataset (ensure diabetes.csv is in the same directory or provide correct path)
diabetes_df = pd.read_csv("diabetes.csv")

# Separate features and target (Outcome column is assumed to be the target)
X_diabetes = diabetes_df.drop("Outcome", axis=1)
y_diabetes = diabetes_df["Outcome"]

# Perform feature scaling on the features
scaler = StandardScaler()
X_scaled_diabetes = scaler.fit_transform(X_diabetes)

# Split the scaled data (80% training, 20% testing)
X_train_diab, X_test_diab, y_train_diab, y_test_diab = train_test_split(
    X_scaled_diabetes, y_diabetes, test_size=0.2, random_state=42
)

# Choose a value for k; here K=5 is used as an example.
knn_diabetes = KNeighborsClassifier(n_neighbors=5)

# Train the model on training data
knn_diabetes.fit(X_train_diab, y_train_diab)

# Predict on test data
y_pred_diab = knn_diabetes.predict(X_test_diab)

# Calculate accuracy score
acc_diab = accuracy_score(y_test_diab, y_pred_diab)
print("Diabetes Dataset Accuracy Score:", acc_diab)

# Compute confusion matrix and classification report
cm_diab = confusion_matrix(y_test_diab, y_pred_diab)
print("\nDiabetes Dataset Confusion Matrix:\n", cm_diab)
```

```
cr_diab = classification_report(y_test_diab, y_pred_diab)
print("\nDiabetes Dataset Classification Report:\n", cr_diab)
```

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

           0       0.74      0.80      0.77        99
           1       0.57      0.49      0.53        55

    accuracy                           0.69       154
   macro avg       0.66      0.64      0.65       154
weighted avg       0.68      0.69      0.68       154
```




```
# ------------------- Load the Dataset ------------------- #
# Load heart.csv (make sure the file is in your working directory)
heart_df = pd.read_csv("heart.csv")

# Display the first few rows to check the data
heart_df.head()

# ------------------- Data Preparation ------------------- #
# Separate features and target
X_heart = heart_df.drop("target", axis=1)
y_heart = heart_df["target"]

# Perform feature scaling (important for distance-based algorithms like KNN)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_heart)

# Split data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_heart, test_size=0.2, random_state=42)
# ------------------- Finding the Best k ------------------- #
# We will try a range of k values (neighbors) and select the one with maximum accuracy.
k_range = range(1, 21)
accuracy_scores = []

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
```

```python
accuracy_scores.append(acc)
print(f"k = {k} --> Accuracy: {acc:.4f}")
```

```
k = 1 --> Accuracy: 0.8525
k = 2 --> Accuracy: 0.8197
k = 3 --> Accuracy: 0.8689
k = 4 --> Accuracy: 0.8852
k = 5 --> Accuracy: 0.9180
k = 6 --> Accuracy: 0.9344
k = 7 --> Accuracy: 0.9180
k = 8 --> Accuracy: 0.8525
k = 9 --> Accuracy: 0.8852
k = 10 --> Accuracy: 0.8852
k = 11 --> Accuracy: 0.8852
k = 12 --> Accuracy: 0.8689
k = 13 --> Accuracy: 0.8852
k = 14 --> Accuracy: 0.8689
k = 15 --> Accuracy: 0.9016
k = 16 --> Accuracy: 0.8852
k = 17 --> Accuracy: 0.8852
k = 18 --> Accuracy: 0.9016
k = 19 --> Accuracy: 0.8852
k = 20 --> Accuracy: 0.8852
```

```python
# Determine the best k value
best_k = k_range[np.argmax(accuracy_scores)]
print("\nBest k value:", best_k)
```

```
Best k value: 6
```

```python
# -------------------------- Train Final Model with Best k -------------------------- #
best_knn = KNeighborsClassifier(n_neighbors=best_k)
best_knn.fit(X_train, y_train)
y_pred_best = best_knn.predict(X_test)
```

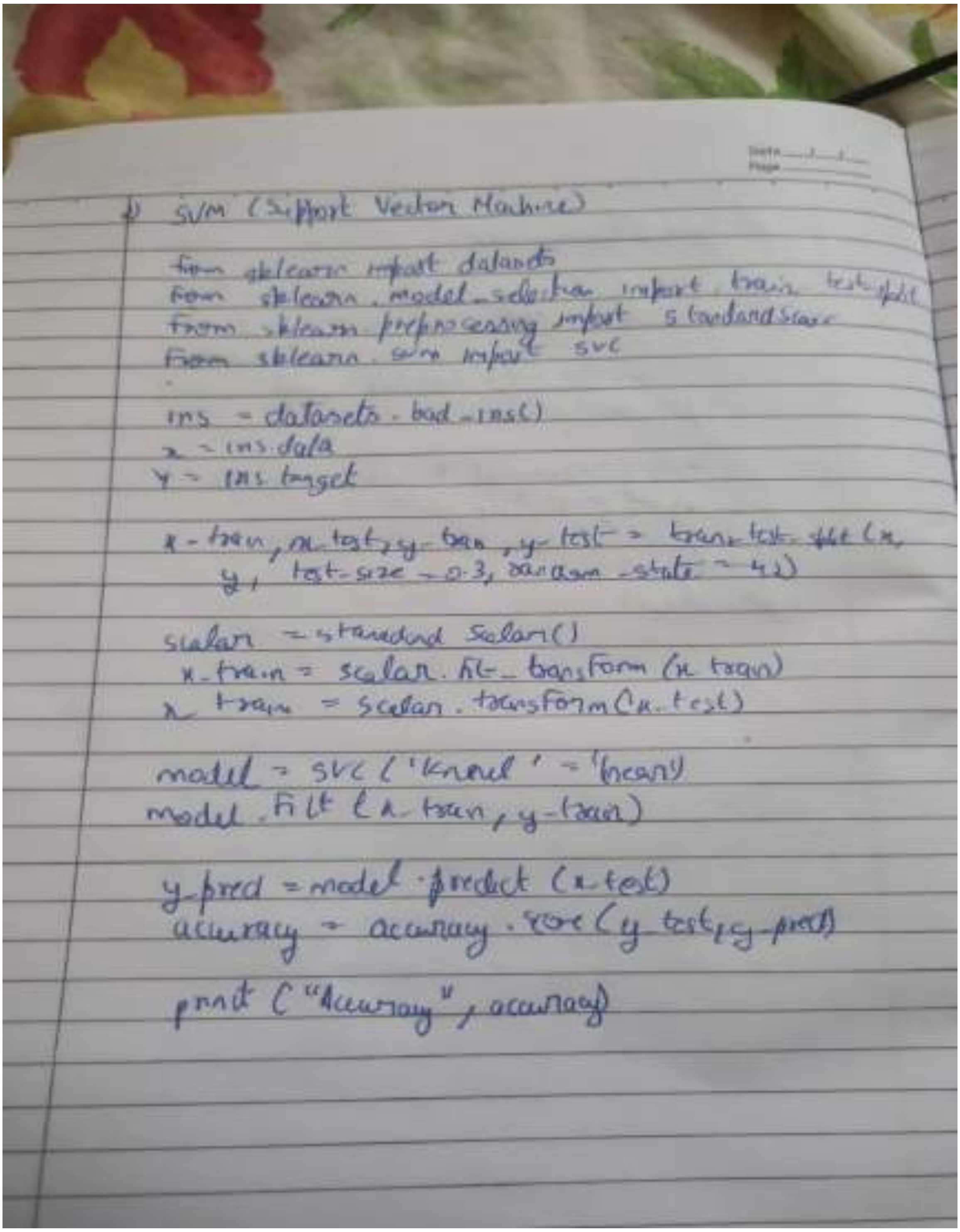
```python
# Compute final accuracy, confusion matrix and classification report
final_accuracy = accuracy_score(y_test, y_pred_best)
cm = confusion_matrix(y_test, y_pred_best)
cr_text = classification_report(y_test, y_pred_best)
print("\nFinal Accuracy Score:", final_accuracy)
print("\nConfusion Matrix:\n", cm)
print("\nClassification Report:\n", cr_text)
```

```
Final Accuracy Score: 0.9344262295081968

Confusion Matrix:
 [[28  1]
 [ 3 29]]

Classification Report:
               precision    recall  f1-score   support

           0       0.90      0.97      0.93        29
           1       0.97      0.91      0.94        32

    accuracy                           0.93        61
   macro avg       0.93      0.94      0.93        61
weighted avg       0.94      0.93      0.93        61
```

LABORATORY PROGRAM – 7

Build Support vector machine model for a given dataset

OBSERVATION BOOK

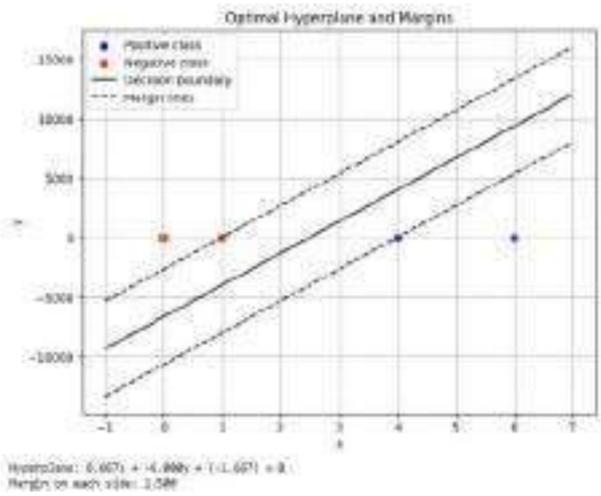


1) SVM (Support Vector Machine)

```
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC

iris = datasets.load_iris()
x = iris.data
y = iris.target

x_train, x_test, y_train, y_test = train_test_split(x,
    y, test_size = 0.3, random_state = 42)

scalar = StandardScalar()
x_train = scalar.fit_transform(x_train)
x_train = scalar.transform(x_test)

model = SVC('kernel' = 'linear')
model.fit(x_train, y_train)

y_pred = model.predict(x_test)
accuracy = accuracy.score(y_test, y_pred)

print("Accuracy", accuracy)
```

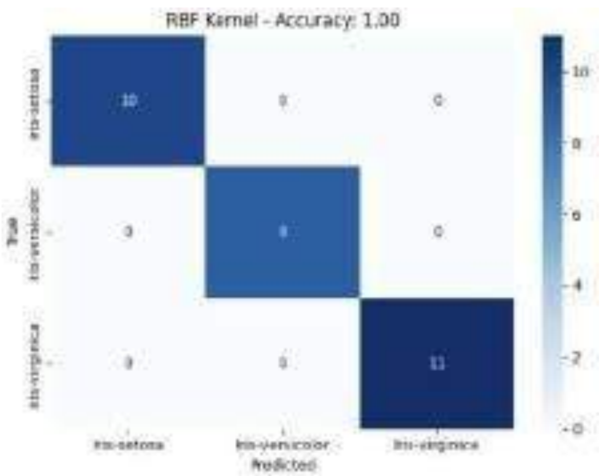
CODE WITH OUTPUT

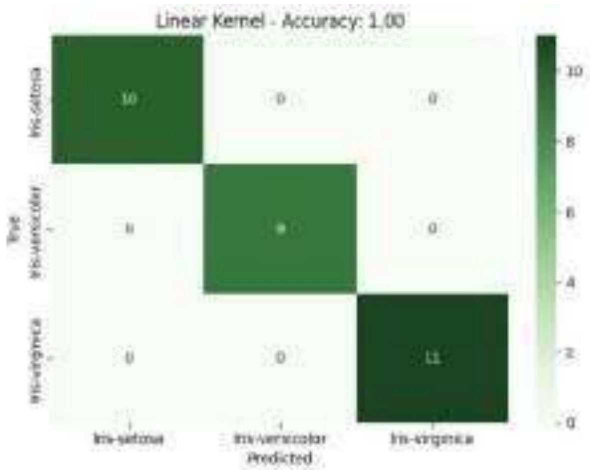
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.svm import SVC

# Data points
X = np.array([[4, 1], [4, -1], [6, 0], [1, 0], [0, 1], [0, -1]])
y = np.array([1, 1, 1, -1, -1, -1])

# Fit linear SVM with a very large C to approximate hard-margin
clf = SVC(kernel='linear', C=1e6)
clf.fit(X, y)

# Extract model parameters
w = clf.coef_[0]
b = clf.intercept_[0]

# Compute decision boundary and margins
xx = np.linspace(-1, 7, 500)
yy = -(w[0] * xx + b) / w[1]

# Margin offset: distance = 1/||w||
margin = 1 / np.linalg.norm(w)
yy_down = yy - np.sqrt(1 + (w[0] / w[1])**2) * margin
yy_up   = yy + np.sqrt(1 + (w[0] / w[1])**2) * margin

# Plotting
plt.figure(figsize=(8, 6))
plt.scatter(X[y == 1, 0], X[y == 1, 1], c='blue', marker='o', label='Positive class')
plt.scatter(X[y == -1, 0], X[y == -1, 1], c='red', marker='s', label='Negative class')
plt.plot(xx, yy, 'k-', label='Decision boundary')
plt.plot(xx, yy_down, 'k--', label='Margin lines')
plt.plot(xx, yy_up, 'k--')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.title('Optimal Hyperplane and Margins')
plt.grid(True)
plt.show()

# Print hyperplane equation
print(f"Hyperplane: {w[0]:.3f}x + {w[1]:.3f}y + ({b:.3f}) = 0")
print(f"Margin on each side: {margin:.3f}")
```




```
import pandas as pd

# Load both datasets
```

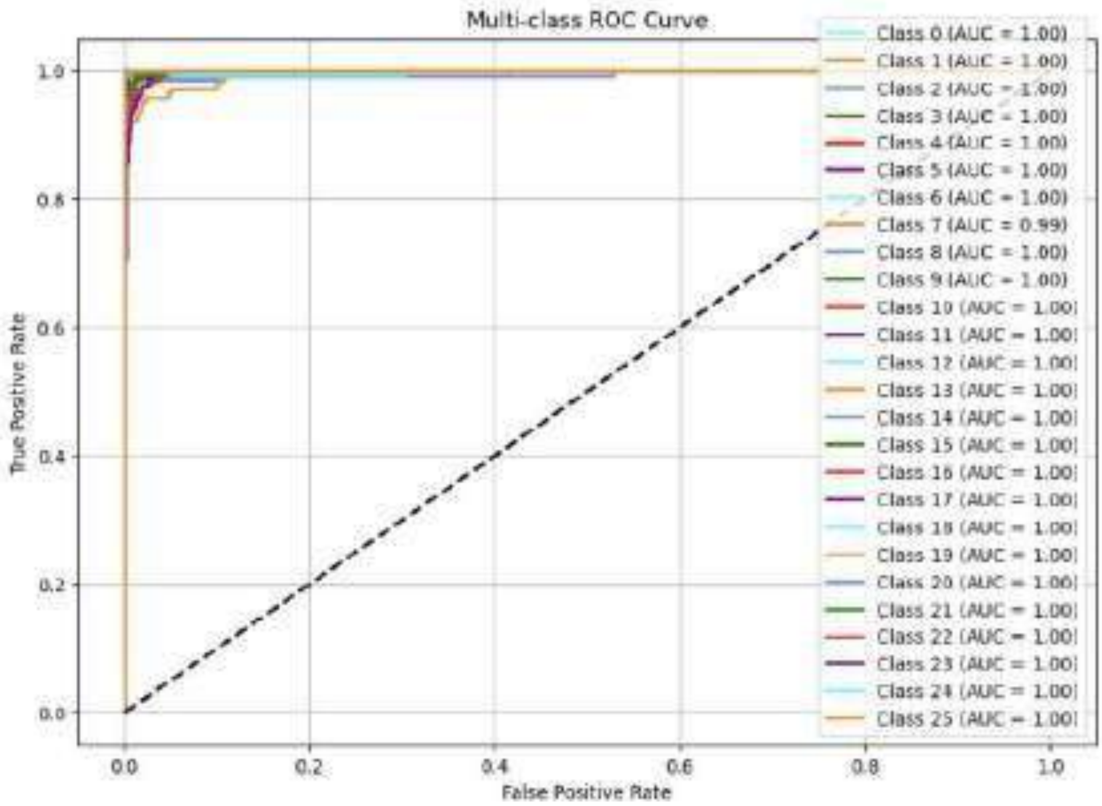
```
iris_df = pd.read_csv("/content/iris.csv")
# 1. IRIS DATASET - SVM with RBF and Linear Kernels
X_iris = iris_df.drop("species", axis=1)
y_iris = iris_df["species"]

# Encode labels
le_iris = LabelEncoder()
y_iris_encoded = le_iris.fit_transform(y_iris)

# Split dataset
X_train_iris, X_test_iris, y_train_iris, y_test_iris = train_test_split(X_iris, y_iris_encoded, test_size=0.2, random_state=42)

# Train models
svm_rbf = SVC(kernel='rbf')
svm_linear = SVC(kernel='linear')

svm_rbf.fit(X_train_iris, y_train_iris)
svm_linear.fit(X_train_iris, y_train_iris)

# Predictions
y_pred_rbf = svm_rbf.predict(X_test_iris)
y_pred_linear = svm_linear.predict(X_test_iris)

# Accuracy and Confusion Matrix
acc_rbf = accuracy_score(y_test_iris, y_pred_rbf)
acc_linear = accuracy_score(y_test_iris, y_pred_linear)
cm_rbf = confusion_matrix(y_test_iris, y_pred_rbf)
cm_linear = confusion_matrix(y_test_iris, y_pred_linear)
```






```
# Load dataset
letter_df = pd.read_csv("/content/letter-recognition.csv")  # Update path if needed
```

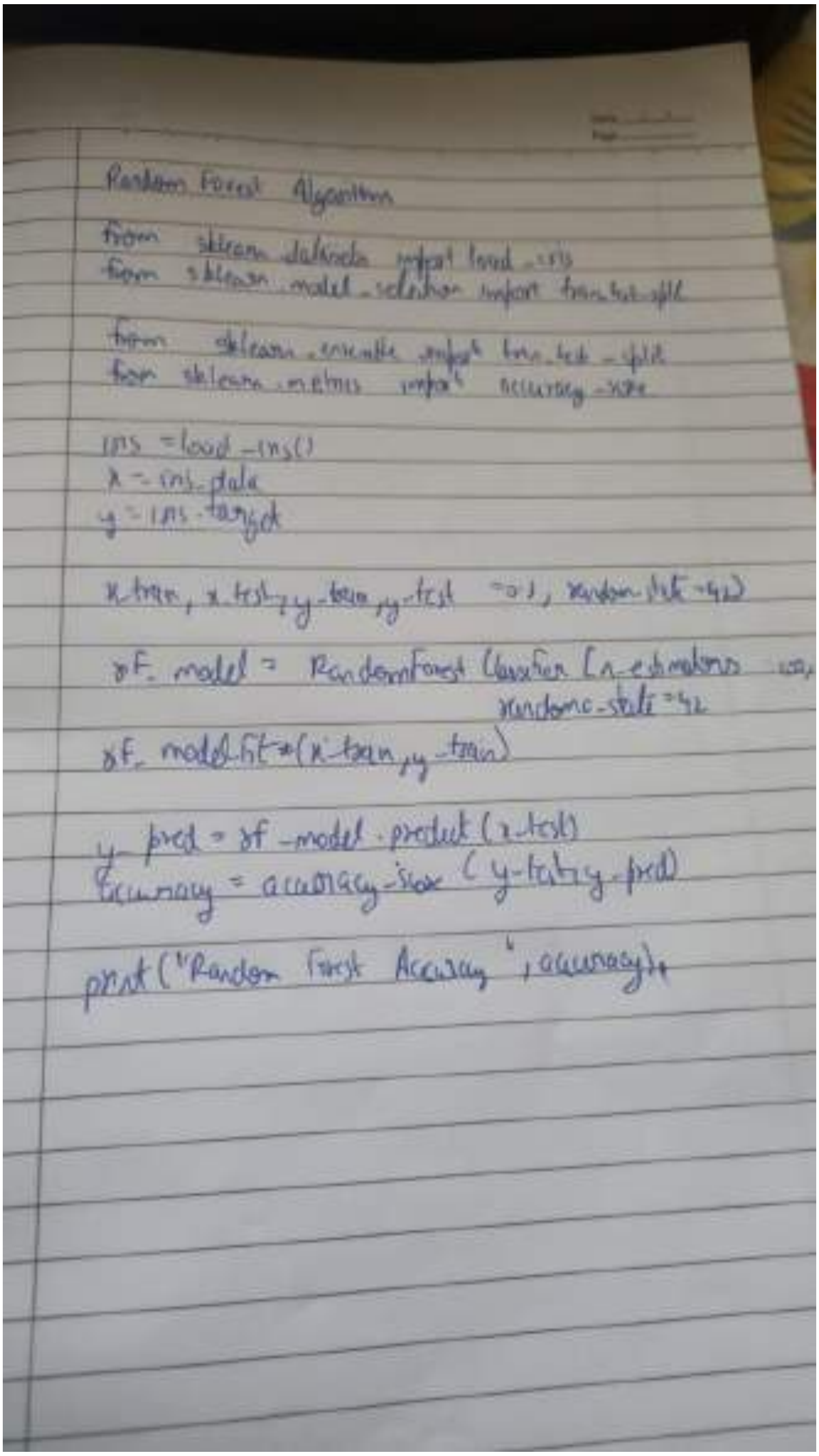
```python
letter_df['letter'] = LabelEncoder().fit_transform(letter_df['letter'])

# Split features and labels
X = letter_df.drop('letter', axis=1)
y = letter_df['letter']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

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

# Train SVM
svm = SVC(kernel='rbf', probability=True)
svm.fit(X_train, y_train)
y_pred = svm.predict(X_test)
y_prob = svm.predict_proba(X_test)

# Accuracy and Confusion Matrix
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

# ROC and AUC (one-vs-rest)
y_test_bin = label_binarize(y_test, classes=np.unique(y))
n_classes = y_test_bin.shape[1]

fpr = dict()
tpr = dict()
roc_auc = dict()

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC Curve
plt.figure(figsize=(10, 7))
colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'green', 'red', 'purple'])

for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f'Class {i} (AUC = {roc_auc[i]:0.2f})')

plt.plot([0, 1], [0, 1], 'k--', lw=2)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Multi-class ROC Curve")
plt.legend(loc="lower right")
plt.grid()
plt.show()
```


Multi-class ROC Curve
Class 0 (AUC = 1.00)
Class 1 (AUC = 1.00)
Class 2 (AUC = 1.00)
Class 3 (AUC = 1.00)
Class 4 (AUC = 1.00)
Class 5 (AUC = 1.00)
Class 6 (AUC = 1.00)
Class 7 (AUC = 0.99)
Class 8 (AUC = 1.00)
Class 9 (AUC = 1.00)
Class 10 (AUC = 1.00)
Class 11 (AUC = 1.00)
Class 12 (AUC = 1.00)
Class 13 (AUC = 1.00)
Class 14 (AUC = 1.00)
Class 15 (AUC = 1.00)
Class 16 (AUC = 1.00)
Class 17 (AUC = 1.00)
Class 18 (AUC = 1.00)
Class 19 (AUC = 1.00)
Class 20 (AUC = 1.00)
Class 21 (AUC = 1.00)
Class 22 (AUC = 1.00)
Class 23 (AUC = 1.00)
Class 24 (AUC = 1.00)
Class 25 (AUC = 1.00)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

LABORATORY PROGRAM – 8

Implement Random forest ensemble method on a given dataset.

OBSERVATION BOOK

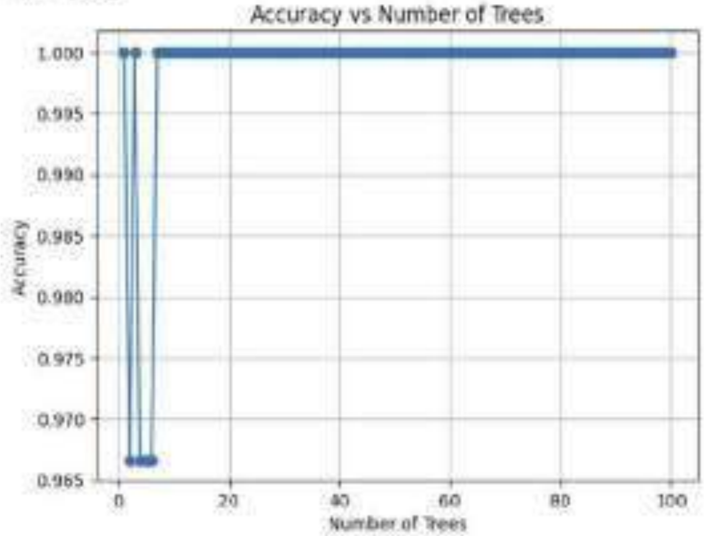


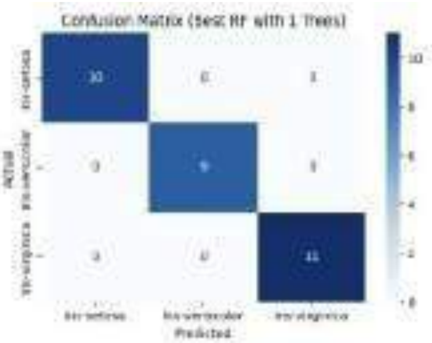
```
Random Forest Algorithm

from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split

from sklearn.ensemble import train_test_split
from sklearn.metrics import accuracy_score

iris = load_iris()
x = iris.data
y = iris.target

x_train, x_test, y_train, y_test  =0.2, random_state=42)

rf_model = RandomForestClassifier(n_estimators=100,
                                   random_state=42

rf_model.fit(x_train, y_train)

y_pred = rf_model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)

print("Random Forest Accuracy", accuracy)
```

CODE WITH OUTPUT

```
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
import matplotlib.pyplot as plt

# Load the dataset
df = pd.read_csv("iris.csv")  # Adjust filename if needed

# Prepare data
X = df.drop(columns=["species"])  # Assuming 'species' is the target column
y = df["species"]

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

# Default Random Forest with 10 trees
rf_default = RandomForestClassifier(n_estimators=10, random_state=42)
rf_default.fit(X_train, y_train)
y_pred_default = rf_default.predict(X_test)
acc_default = accuracy_score(y_test, y_pred_default)
conf_matrix_default = confusion_matrix(y_test, y_pred_default)

print(f"Default RF (10 trees) Accuracy: {acc_default}")
print("Confusion Matrix:\n", conf_matrix_default)

# Try different numbers of trees to find the best
best_acc = 0
best_n = 10
acc_list = []

for n in range(1, 101):
    rf = RandomForestClassifier(n_estimators=n, random_state=42)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    acc_list.append((n, acc))
    if acc > best_acc:
        best_acc = acc
        best_n = n
        best_conf_matrix = confusion_matrix(y_test, y_pred)

print(f"\nBest Accuracy: {best_acc} using {best_n} trees")
print("Best Confusion Matrix:\n", best_conf_matrix)
# Plot accuracy vs number of trees
x_vals, y_vals = zip(*acc_list)
plt.plot(x_vals, y_vals, marker='o')
plt.title("Accuracy vs Number of Trees")
plt.xlabel("Number of Trees")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
```

```
Default RF (10 trees) Accuracy: 1.0
Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]

Best Accuracy: 1.0 using 1 trees
Best Confusion Matrix:
 [[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```





LABORATORY PROGRAM – 9

Implement Boosting ensemble method on a given dataset.

OBSERVATION BOOK

AdaBoost Algorithm

```
import numpy as np

x = np.array [ [0,0], [0,1], [1,0], [1,1] ]
y = np.array ( [-1, 1, 1, -1] )
n_estimators = 5

n_samples = x.shape[0]
w = np.ones (n_samples) / n_sample

classification = []
alphas = []

def decision_stamp [x, feature, threshold, polarity):

        return 1 if polarity * x[feature]
        < polarity * threshold else -1

for estimator in range (n_estimators)

        min_error = float ('inf')
        best_stump = None

        for feature in range (x.shape[1]):
            threshold = np.unique ( x [:, feature ]

for polarity in [1, -1]:
        prediction = np.array ( [decision stamp (
        x, features, threshold, polarity)
```

```
for x a)
error = np.sum (w*(predictions != y))

if error < min error:
    min error = error
    best_stump = (features , threshold, polarity,
                  predictions)
epsilon = 1e-6
alpha = 0.5* np.log ([1 - min_error + epsilon) /
              min_error + epsilon)

w = w* np.exp(-alpha * y * best_stump [3])
w = w / np.sum (w)

classifiers.append(best_stump)
alphas.append (alpha)
```

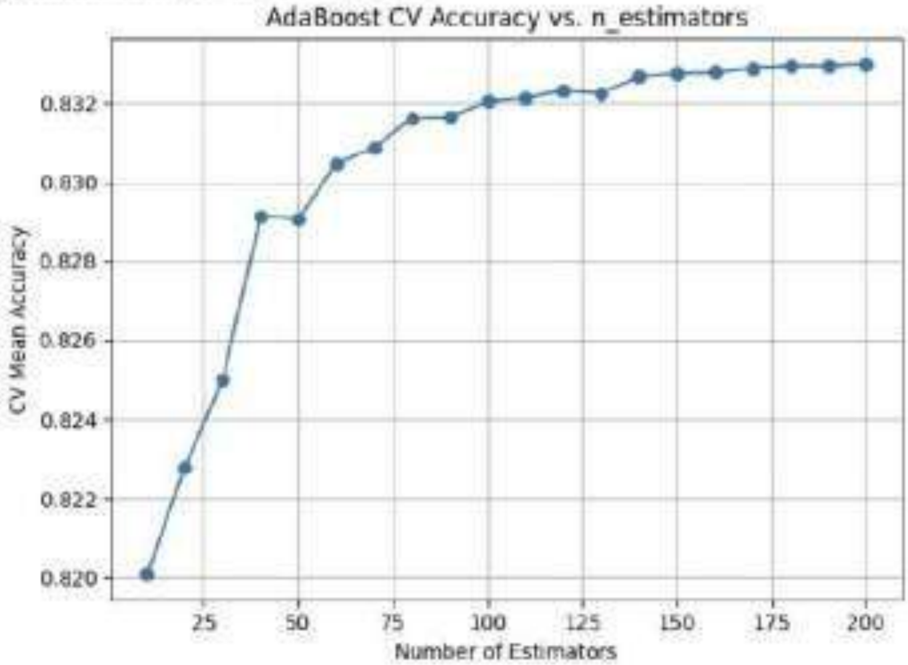
CODE WITH OUTPUT

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay

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

# Display basic info
print("First five rows:")
print(data.head())
print(f"\nDataset shape: {data.shape}")

# Define features and target
target_column = 'income_level'
y = data[target_column]
X = data.drop(columns=[target_column])

# Identify categorical vs numerical columns
categorical_cols = X.select_dtypes(include=['object', 'category']).columns.tolist()
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
print(f"\nNumerical columns: {numerical_cols}")
print(f"Categorical columns: {categorical_cols}")

# Preprocessor: scale numericals, one-hot encode categoricals
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
    ]
)

# Initial AdaBoost model with 10 estimators
pipeline = Pipeline([
    ('preprocess', preprocessor),
    ('clf', AdaBoostClassifier(n_estimators=10, random_state=42))
])

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

# Train and evaluate initial model
pipeline.fit(X_train, y_train)
y_pred = pipeline.predict(X_test)
initial_acc = accuracy_score(y_test, y_pred)
print(f"Initial test accuracy (n_estimators=10): {initial_acc:.4f}")

# Hyperparameter tuning: find best n_estimators
tree_counts = list(range(10, 201, 10))  # 10,20,...,200
cv_scores = []
for n in tree_counts:
    model = Pipeline([
        ('preprocess', preprocessor),
        ('clf', AdaBoostClassifier(n_estimators=n, random_state=42))
    ])
    scores = cross_val_score(
        model, X_train, y_train, cv=5, scoring='accuracy', n_jobs=-1
    )
    mean_score = scores.mean()
```

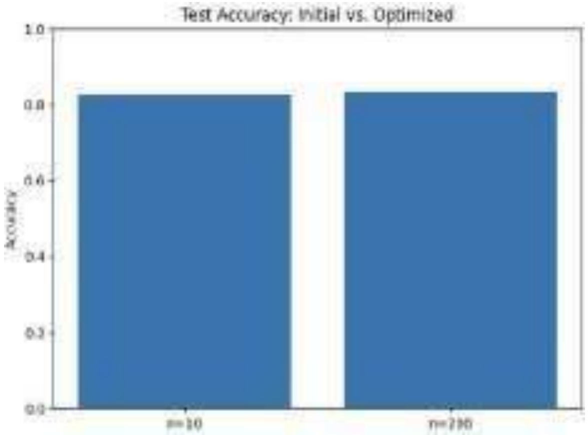
```
    cv_scores.append(mean_score)
    print(f"n_estimators={n}: CV mean accuracy={mean_score:.4f}")

# Plot CV accuracy vs. number of estimators
plt.figure()
plt.plot(tree_counts, cv_scores, marker='o')
plt.title('AdaBoost CV Accuracy vs. n_estimators')
plt.xlabel('Number of Estimators')
plt.ylabel('CV Mean Accuracy')
plt.grid(True)
plt.tight_layout()
plt.show()

# Determine optimal number of trees
best_score = max(cv_scores)
best_n = tree_counts[cv_scores.index(best_score)]
print(f"\nBest CV accuracy={best_score:.4f} with n_estimators={best_n}")

# Retrain and evaluate best model
best_model = Pipeline([
    ('preprocess', preprocessor),
    ('clf', AdaBoostClassifier(n_estimators=best_n, random_state=42))
])
best_model.fit(X_train, y_train)
y_best = best_model.predict(X_test)
best_test_acc = accuracy_score(y_test, y_best)
print(f"Test accuracy with best n_estimators ({best_n}): {best_test_acc:.4f}")

# Plot comparison of initial vs. best test accuracy
plt.figure()
plt.bar(['n=10', f'n={best_n}'], [initial_acc, best_test_acc])
plt.title('Test Accuracy: Initial vs. Optimized')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.tight_layout()
plt.show()

# Plot confusion matrix for best model
cm = confusion_matrix(y_test, y_best)
labels = best_model.named_steps['clf'].classes_
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
plt.figure()
disp.plot(cmap=plt.cm.Blues)
plt.title('Confusion Matrix for Best AdaBoost Model')
plt.tight_layout()
plt.show()
```

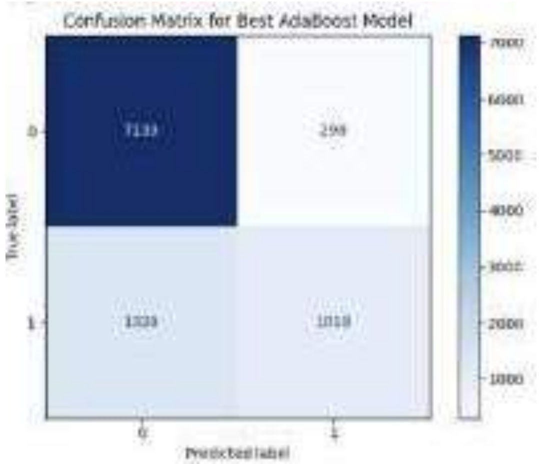
```
Dataset shape: (48842, 7)
```

```
Numerical columns: ['age', 'fnlwgt', 'education_num', 'capital_gain', 'capital_loss', 'hours_per_week']
Categorical columns: []
Initial test accuracy (n_estimators=10): 0.8257
n_estimators=10: CV mean accuracy=0.8201
n_estimators=20: CV mean accuracy=0.8228
n_estimators=30: CV mean accuracy=0.8250
n_estimators=40: CV mean accuracy=0.8291
n_estimators=50: CV mean accuracy=0.8291
n_estimators=60: CV mean accuracy=0.8305
n_estimators=70: CV mean accuracy=0.8309
n_estimators=80: CV mean accuracy=0.8316
n_estimators=90: CV mean accuracy=0.8316
n_estimators=100: CV mean accuracy=0.8320
n_estimators=110: CV mean accuracy=0.8321
n_estimators=120: CV mean accuracy=0.8323
n_estimators=130: CV mean accuracy=0.8322
n_estimators=140: CV mean accuracy=0.8327
n_estimators=150: CV mean accuracy=0.8327
n_estimators=160: CV mean accuracy=0.8328
n_estimators=170: CV mean accuracy=0.8329
n_estimators=180: CV mean accuracy=0.8329
n_estimators=190: CV mean accuracy=0.8329
n_estimators=200: CV mean accuracy=0.8330
```




```
Best CV accuracy=0.8330 with n_estimators=200
Test accuracy with best n_estimators (200): 0.8344
```

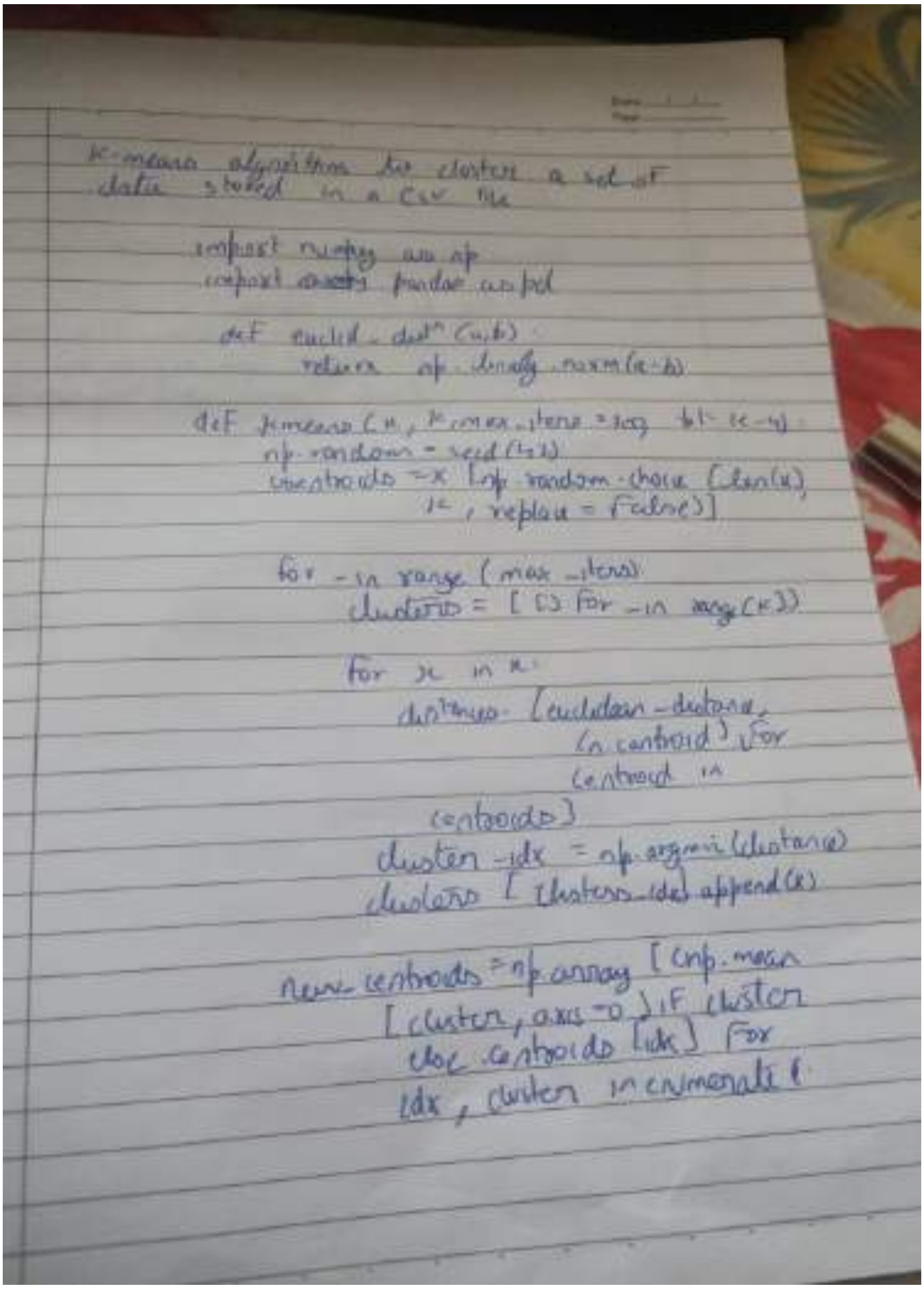

Test Accuracy: Initial vs. Optimized
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
n=10
n=200


Confusion Matrix for Best AdaBoost Model
True label
Predicted label
0
1
0
1
298
7000
6000
5000
4000
3000
2000
1000

LABORATORY PROGRAM – 10

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

OBSERVATION BOOK



K-means algorithm to cluster a set of data stored in a csv file

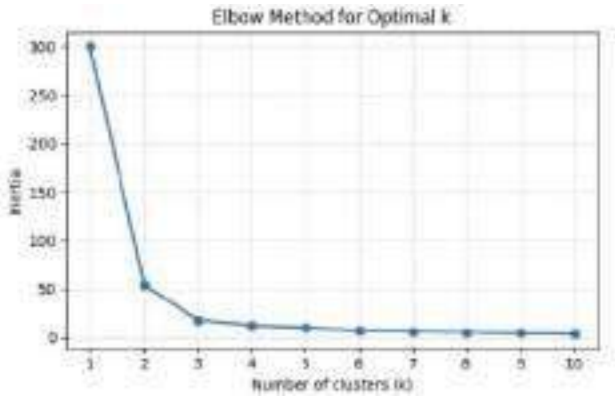
```
import numpy as np
import pandas as pd

def euclid_distn (a,b):
    return np.linalg.norm(a-b)

def kmeans(x, k, max_iters=100):
    np.random.seed(42)
    centroids = x[np.random.choice(len(x), k, replace=False)]

    for _ in range(max_iters):
        clusters = [[] for _ in range(k)]

        for x in x:
            distances = [euclidean_distance(x, centroid) for centroid in centroids]
            cluster_idx = np.argmin(distances)
            clusters[cluster_idx].append(x)

        new_centroids = np.array([np.mean(cluster, axis=0) if cluster else centroids[idx] for idx, cluster in enumerate(
```

CODE WITH OUTPUT

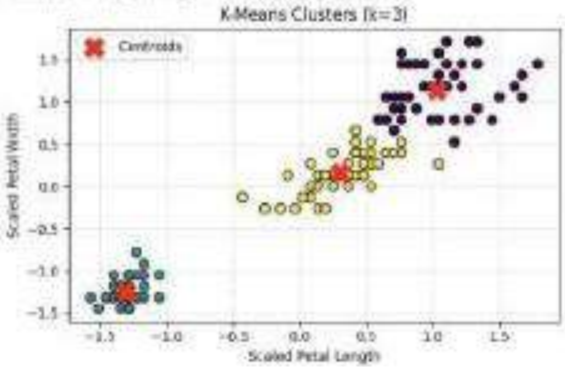
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

def load_data(csv_path='iris.csv'):
    """
    Try loading from csv_path; if not found, load via sklearn.
    Expects columns: sepal_length, sepal_width, petal_length, petal_width, species.
    Returns DataFrame with a 'species' column.
    """
    try:
        df = pd.read_csv(csv_path)
        # Fixed typo here: use c.strip().replace, not ace()
        df.columns = [c.strip().replace(' ', '_') for c in df.columns]
    except FileNotFoundError:
        iris = load_iris()
        df = pd.DataFrame(
            data=np.c_[iris['data'], iris['target']],
            columns=iris['feature_names'] + ['target']
        )
        df.columns = [c.strip().replace(' (cm)', '').replace(' ', '_')
                      for c in df.columns]
        df['species'] = df['target'].map(lambda x: iris['target_names'][int(x)])
    return df

def preprocess(df):
    """
    Select only petal_length & petal_width, then standard-scale.
    Returns scaled numpy array.
    """
    X = df[['petal_length', 'petal_width']].values
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    return X_scaled, scaler

def plot_elbow(X_scaled, max_k=10):
    """
    Compute KMeans inertia for k=1..max_k and plot the elbow curve.
    Returns list of inertias.
    """
    inertias = []
    ks = range(1, max_k + 1)
    for k in ks:
        km = KMeans(n_clusters=k, random_state=42)
        km.fit(X_scaled)
        inertias.append(km.inertia_)
    plt.figure(figsize=(6, 4))
    plt.plot(ks, inertias, 'o-', linewidth=2)
    plt.xlabel('Number of clusters (k)')
    plt.ylabel('Inertia')
    plt.title('Elbow Method for Optimal k')
    plt.xticks(ks)
    plt.grid(True, linestyle='--', alpha=0.5)
    plt.tight_layout()
    plt.show()
    return inertias

def run_kmeans(X_scaled, k):
    """
    Fit KMeans with k clusters, return labels and fitted model.
    """
```

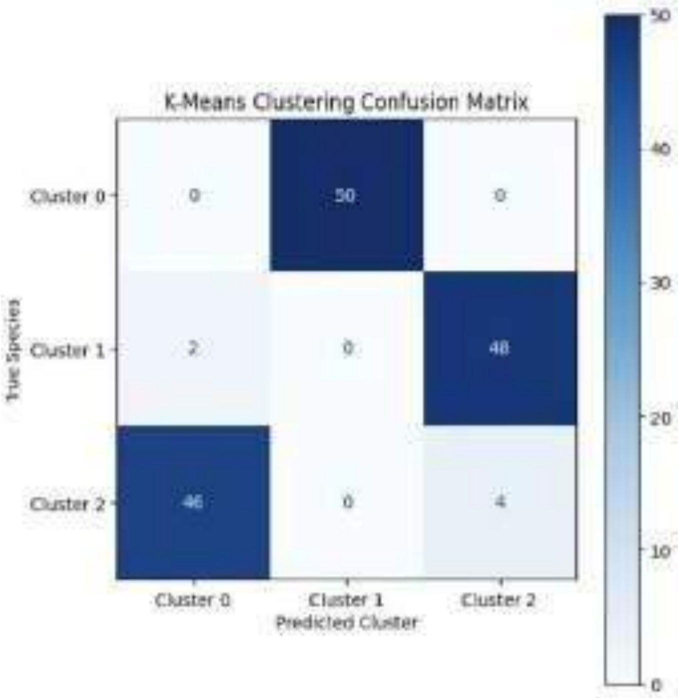
```
    km = KMeans(n_clusters=k, random_state=42)
    labels = km.fit_predict(X_scaled)
    return km, labels

def plot_confusion(df, labels, k):
    """
    Builds and displays a confusion matrix comparing true species vs. cluster.
    """
    species_names = df['species'].unique()
    species_to_num = {name: idx for idx, name in enumerate(species_names)}
    true_nums = df['species'].map(species_to_num)

    cm = confusion_matrix(true_nums, labels)
    disp = ConfusionMatrixDisplay(
        confusion_matrix=cm,
        display_labels=[f"Cluster {i}" for i in range(k)]
    )
    fig, ax = plt.subplots(figsize=(6, 6))
    disp.plot(ax=ax, cmap='Blues', colorbar=True)
    ax.set_xlabel('Predicted Cluster')
    ax.set_ylabel('True Species')
    plt.title('K-Means Clustering Confusion Matrix')
    plt.tight_layout()
    plt.show()

    cm_df = pd.DataFrame(
        cm,
        index=[f"True: {name}" for name in species_names],
        columns=[f"Cluster {i}" for i in range(k)]
    )
    print("\nConfusion Matrix (counts):")
    print(cm_df)

def main():
    # 1) Load data
    df = load_data('iris.csv')
    if 'species' not in df.columns:
        print("Error: 'species' column not found.")
        return

    # 2) Preprocess
    X_scaled, scaler = preprocess(df)

    # 3) Elbow plot to decide k
    print("Generating elbow plot to find optimal k...")
    inertias = plot_elbow(X_scaled, max_k=10)

    # 4) From the elbow you'll typically see a bend at k=3
    optimal_k = 3
    print(f"Choosing k = {optimal_k} (you can adjust this based on the plot).")

    # 5) Run K-Means and assign clusters
    km_model, labels = run_kmeans(X_scaled, optimal_k)
    df['cluster'] = labels

    # 6) Visualize clusters in feature space
    plt.figure(figsize=(6, 4))
    plt.scatter(
        X_scaled[:, 0], X_scaled[:, 1],
        c=labels, cmap='viridis', edgecolor='k', s=50
    )
    centroids = km_model.cluster_centers_
    plt.scatter(
        centroids[:, 0], centroids[:, 1],
        marker='X', c='red', s=200, label='Centroids'
    )
    plt.xlabel('Scaled Petal Length')
```

```python
    plt.ylabel('Scaled Petal Width')
    plt.title(f'K-Means Clusters (k={optimal_k})')
    plt.legend()
    plt.grid(True, linestyle='--', alpha=0.5)
    plt.tight_layout()
    plt.show()

    # 7) Confusion matrix vs. true species
    plot_confusion(df, labels, optimal_k)

if _name_ == "_main_":
    main()
```



Choosing k = 3 (you can adjust this based on the plot).




K-Means Clustering Confusion Matrix
True Species
Cluster 0
Cluster 1
Cluster 2
0
50
0
2
0
48
46
0
4
Cluster 0
Cluster 1
Cluster 2
Predicted Cluster
50
40
30
20
10
0

LABORATORY PROGRAM – 11

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

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4. Principal Component Modelling (PCM)

1. Standardize the data

• Input: A dataset $X \in R^{n \times d}$, with n samples & d variables (features)

• Standardize each variable

$$X_s = \frac{X - \mu}{\sigma}$$

2. Compute the PCA model

• Compute the covariance matrix

$$\Sigma = \frac{1}{n-1} X_s^T X_s$$

• Perform eigenvalue decomposition or use SVD.

$$\Sigma = V \Lambda V^T$$

3. Select number of Principal Components k

→ choose top k components such that high proportion of total variance is captured.

4. Project data into Principal Components Space

• Scores matrix: $T = X_s \cdot V_k$

• Reconstruction of data: $\hat{X}_s = T \cdot V_k^T$

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5. Compute Monitoring Statistics:

→ Hotelling's T^2 Statistic

• $T_i^2 = t_i^T \Lambda_k^{-1} t_i$

→ Squared Prediction Error (SPE) or Q - Statistic

- $SPE_i = \|x_{si} - \hat{x}_{si}\|^2$

6. Set control limit

7. Prediction / Monitoring

• Standardize using training data mean & std.
• Project onto the model
• Compute T^2 & SPE
• Compare to control limits.
  • If both within limits → "Normal"
  • If outside limits → "Faulty / Anomaly / Outlier"

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CODE WITH OUTPUT

```
import pandas as pd

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

# Step 3: Split Features and Target
X = df.drop("target", axis=1)
y = df["target"]

# Step 4: Preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

categorical_features = ["cp", "thal", "slope"]
numerical_features = [col for col in X.columns if col not in categorical_features]

preprocessor = ColumnTransformer(transformers=[
    ("num", StandardScaler(), numerical_features),
    ("cat", OneHotEncoder(), categorical_features)
])

# Step 5: Train/Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 6: Models
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

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

# Step 7: Train and Evaluate Models (Before PCA)
print("Accuracy Before PCA:")
results = {}
for name, model in models.items():
    pipeline = Pipeline(steps=[
        ("preprocessor", preprocessor),
        ("classifier", model)
    ])
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    results[name] = acc
    print(f"{name}: {acc:.4f}")

from sklearn.decomposition import PCA

print("\nAccuracy After PCA (n_components=5):")
pca_results = {}

for name, model in models.items():
    pipeline_pca = Pipeline(steps=[
        ("preprocessor", preprocessor),
        ("pca", PCA(n_components=5)),
        ("classifier", model)
    ])
    pipeline_pca.fit(X_train, y_train)
    y_pred_pca = pipeline_pca.predict(X_test)
    acc_pca = accuracy_score(y_test, y_pred_pca)
```

```
pca_results[name] = acc_pca
print(f"{name}: {acc_pca:.4f}")
```

```
📋 Accuracy Before PCA:
Logistic Regression: 0.9016
SVM: 0.8525
Random Forest: 0.8361

📉 Accuracy After PCA (n_components=5):
Logistic Regression: 0.8689
SVM: 0.8689
Random Forest: 0.8852
```