

VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum- 590014, Karnataka.



LAB REPORT on **Machine Learning (23CS6PCMAL)**

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING



B.M.S. COLLEGE OF ENGINEERING
(Autonomous Institution under VTU)
BENGALURU - 560019
February 2025 – July 25

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 **Kusumanjali Lokesh (1BM22CS133)**, 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/kusumanjali133/ML-LAB>

LABORATORY PROGRAM – 1

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

OBSERVATION BOOK

LAB SESSION (B.T.Y)	
Date: 10/08/2023	
i) housing.csv	(Using df.read_csv)
(i) To load .csv file into the data frame	 → df = pd.read_csv('housing.csv')
(ii) To display information of all columns	 → print("Information about all columns: ") print(df.info())
(iii) To display statistical information of all numerical columns	 → print("In Statistical Information of numerical columns: ") print(df.describe())
(iv) To display the count of unique labels for "ocean_proximity" column	 → print("Count of unique labels for 'ocean_proximity': ") print(len(df['ocean_proximity'].value_counts()))
(v) To display which attributes (columns) in the dataset have missing values greater than zero.	 → print("In Attributes with missing values count greater than zero: ") print(df.isnull().sum().sum(df.isnull().sum().gt(0)))

OUTPUT:					
Data columns (total 10 columns):					
#	Name	Column Type	Non-null Count	Null Count	Dtype
0	longitude	float	20640	0	float
1	latitude	float	20640	0	float
2	housing_median_age	int64	20640	0	int64
3	total_bedrooms	int64	11	11	int64
4	total_rooms	int64	20640	0	int64
5	population	int64	20640	0	int64
6	households	int64	20640	0	int64
7	median_income	float	20640	0	float
8	median_house_value	int64	20640	0	int64
9	ocean_proximity	object	20640	0	object
Statistical Information of numerical columns:					
count	20640.0	20640.0	20445.0		
mean	-119.56	3563.0	2863.0		
std	2.00	0.13	1.58		
min	-124.35	0.04	1.0		
25%	-121.8	33.93	18.0		
50%	-118.49	34.06	29.0		
75%	-118.01	37.71	37.0		
max	-164.31	41.95	52.0		

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
```

M None

```
# 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_Z
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

```

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
1	False	False	False
2	False	False	False
3	False	False	False
4	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	1.641852	-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	Gender_M	Gender_f	\
0	-1.035084	1.810756	-1.085457	-0.369958	-1.124622	False	False
1	-0.678063	-0.158692	-0.457398	-0.342649	-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	-0.613180	-0.547121	-0.397267	-1.729472	True	False

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

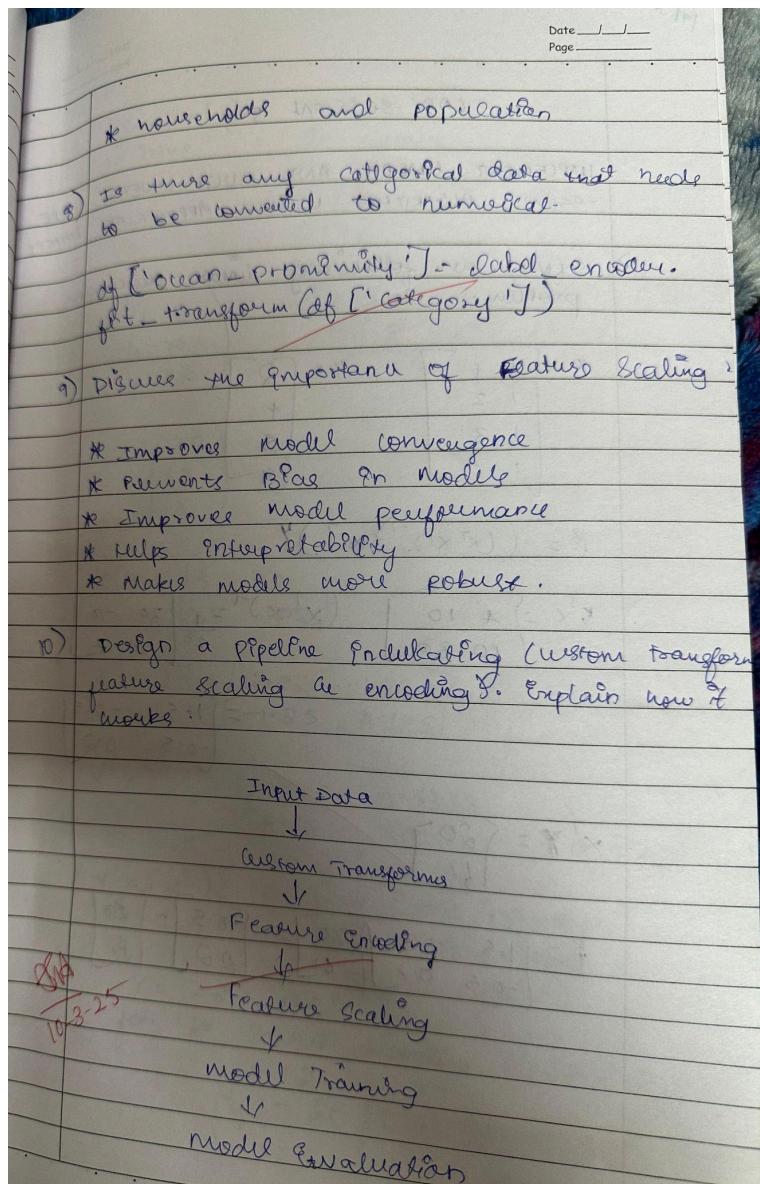
LABORATORY PROGRAM – 2

Demonstrate various data pre-processing techniques for a given dataset

OBSERVATION BOOK

LAB SESSION - 2	
DEMONSTRATE THE STEPS TO BUILD A MACHINE LEARNING MODEL THAT PREDICTS THE MEDIAN HOUSING PRICE USING THE CALIFORNIA HOME PRICE DATASET.	
1)	Download the dataset from https://raw.githubusercontent.com/dsrscientist/house-prices-advanced-regression-techniques/master/DATASETS/housing.csv Import pandas as pd <code>housing = pd.read_csv("housing.csv")</code> <code>housing.head()</code>
2)	Perform the descriptive & info steps: <code>housing.info()</code>
3)	Plot the histogram of each feature (Indicate what does histogram indicate on median_income and house_median_age) Import matplotlib.pyplot as plt <code>df.hist(figsize=(14,10))</code> <code>plt.tight_layout()</code> <code>plt.show()</code>
	median_income : The histogram of median income will likely show how income levels are distributed across the dataset. A sharp peak around certain income levels indicates common income ranges, and the spread indicates how varied

the income distribution over time house_median_age : The histogram of house median age will show how the ages of houses in the dataset are distributed. A peak around specific age groups might indicate a concentration of housing stock built in certain decades.	
4)	Demonstrate the process of creating a test set (write the difference b/w random and stratified test set).
	Random Sampling : * Randomly splits the dataset into training and test sets without considering the distribution of the target variable or other features. * Simple and easy to implement. * May lead to biased test sets, especially if the dataset is imbalanced.
	Stratified Sampling : * Preserves that the set has the same distribution of a specific feature as the entire dataset. * Reduces sampling bias and ensures that the test set is representative of the overall dataset. * Slightly more complex to implement.



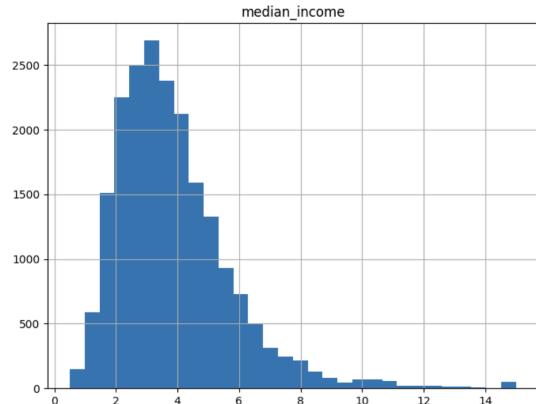
CODE WITH OUTPUT

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

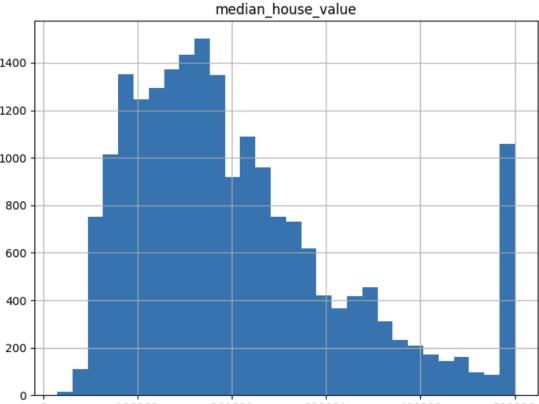
# Display descriptive statistics
df.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000

```
import matplotlib.pyplot as plt
df.hist(column="median_income", bins=30, figsize=(8,6))
plt.show()
```



```
import matplotlib.pyplot as plt
df.hist(column="median_house_value", bins=30, figsize=(8,6))
plt.show()
```



```
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])

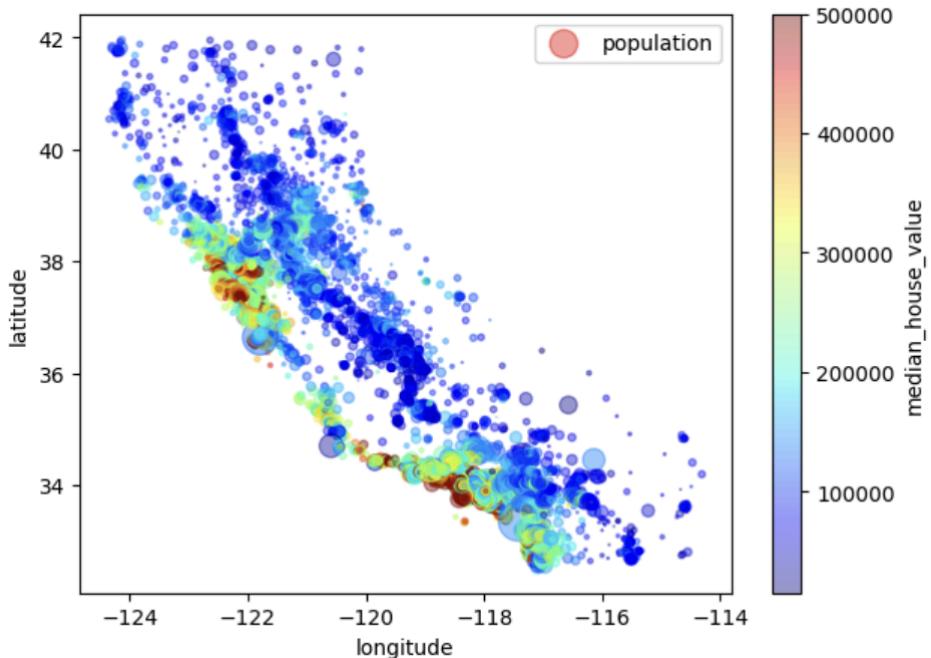
# Use StratifiedShuffleSplit to ensure the income distribution is preserved in both sets.
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing_selected, housing_selected['income_cat']):
    strat_train_set = housing_selected.loc[train_index]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

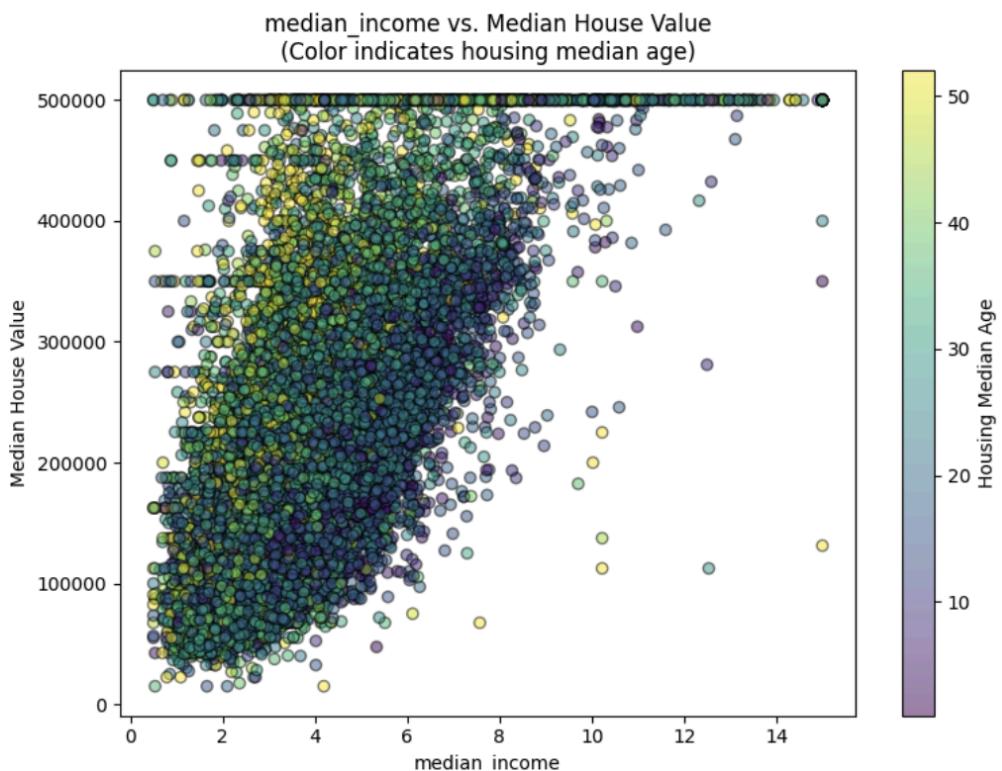


```

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()

```



```

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"]

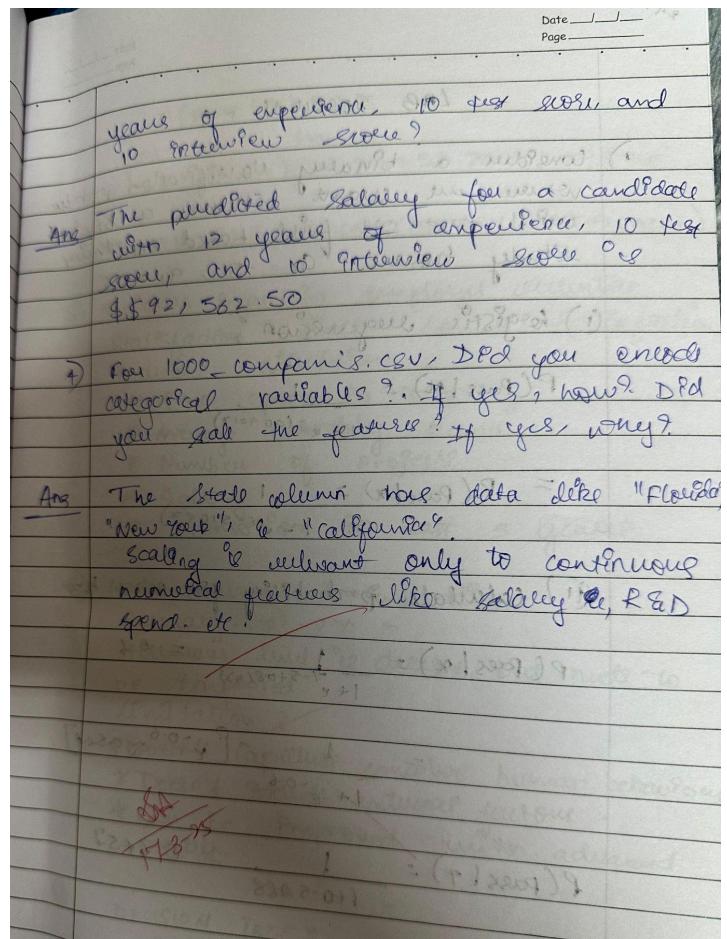
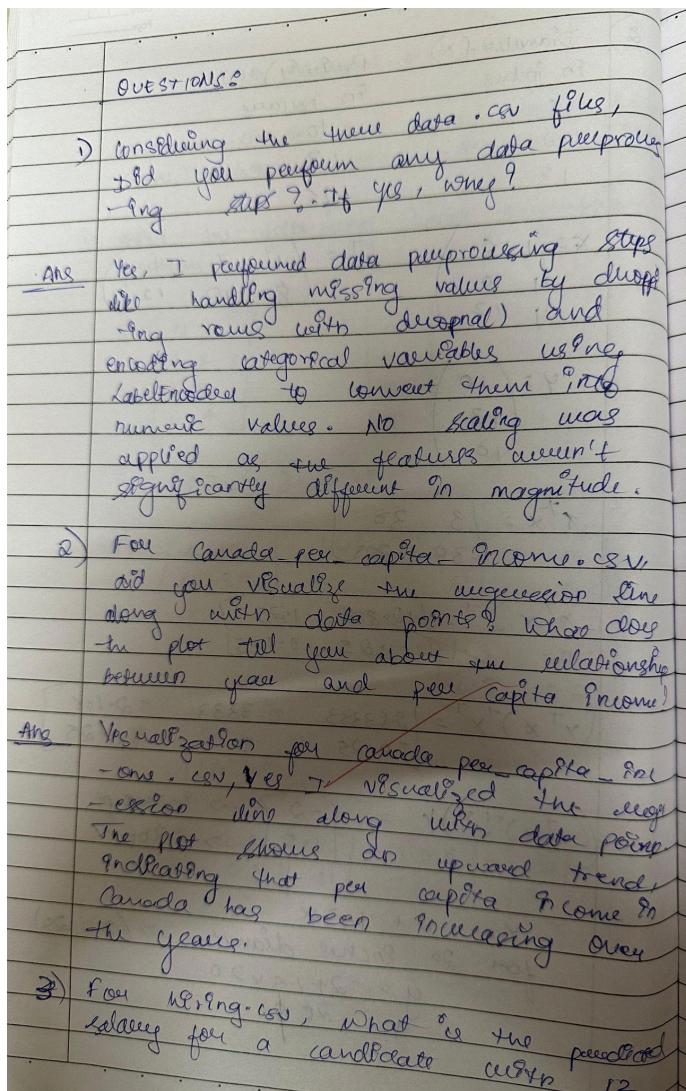
# Build numerical pipeline: impute missing values, add new attributes, then scale
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()),
])
# Build the full pipeline combining numerical and categorical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



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))

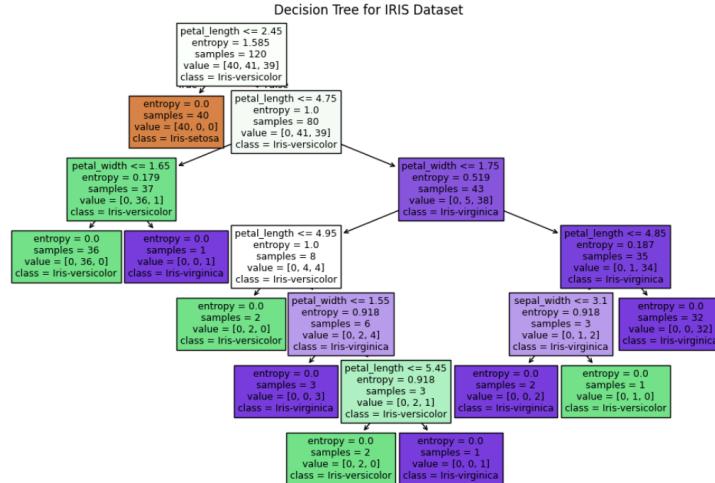
# Visualize the decision tree
plt.figure(figsize=(12, 8))
plot_tree(clf_iris, filled=True, feature_names=X.columns, class_names=clf_iris.classes_)
plt.title("Decision Tree for IRIS Dataset")
plt.show()
```

```

IRIS Dataset Decision Tree Classifier
Accuracy: 1.0
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

```



```

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()

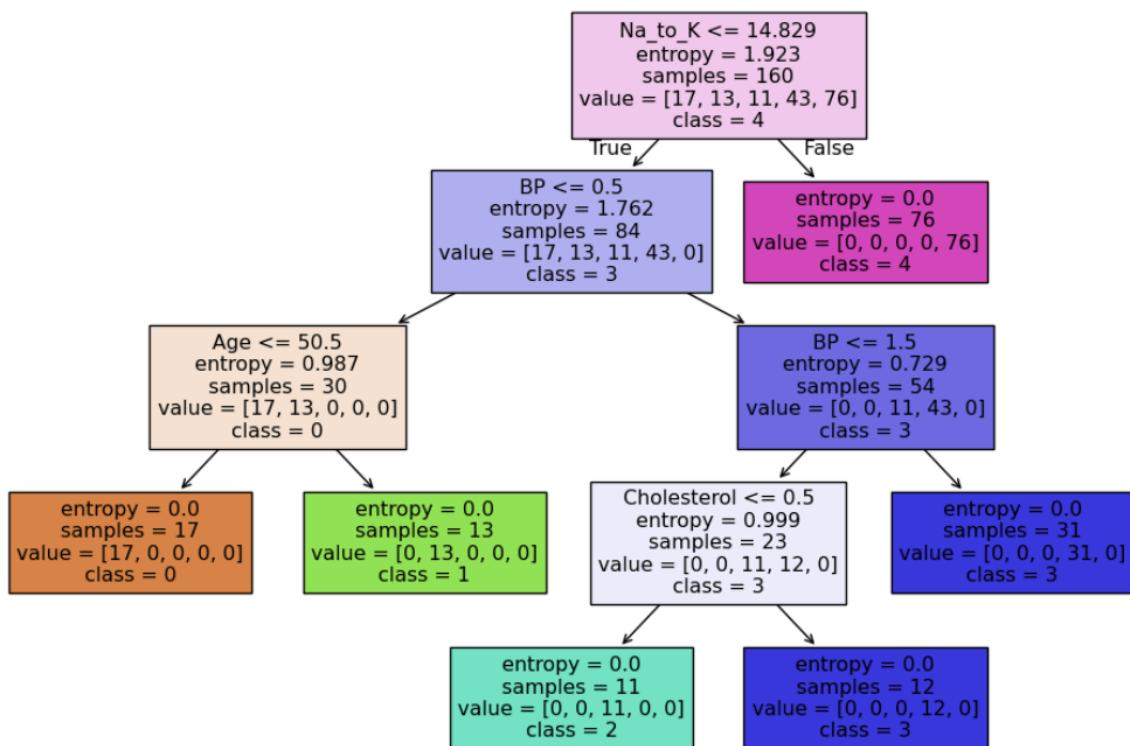
```

```

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 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

```

Decision Tree for Drug Dataset



LABORATORY PROGRAM – 4

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

OBSERVATION BOOK

LAB SESSION - 4

1) Consider a binary classification problem where we want whether a student will pass or fail based on three study hours $a_0 = -5$, $a_1 = 0.8$

(i) Logistic regression :

$$P(\text{Pass} | x) = \frac{1}{1 + e^{-(a_0 + a_1 x)}}$$

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

(ii) calculate probability for $x = 7$ hrs

$$P(\text{Pass} | x) = \frac{1}{1 + e^{-5+0.8(7)}} = 0.6$$

$$= \frac{1}{1 + e^{-0.6}} [e^{-0.6} \approx 0.548]$$

$$P(\text{Pass} | x) = \frac{1}{1 + 0.5488} \approx 0.6457$$

64.57% will pass.

(iii) Determine the prediction class using threshold of 0.5

$$P(\text{Pass} | x) > 0.5$$

Date / /
Page / /

$P(\text{Pass} | n) < 0.5$
for $n = 7$ hours
 $P(\text{Pass} | 7) \approx 0.6457 > 0.5 \rightarrow \text{Pass}$

LOGISTIC REGRESSION (BINARY CLASSIFICATION)

1) Variables impacting employee retention satisfaction level - hours Satisfaction, Income, Age, Attrition

- * Time spent in company
- * Average monthly hours
- * Number of projects
- * Salary
- * Promotions in last 5 years

2) Model Accuracy in evaluation

Accuracy - 75-77%
Accuracy limit is decent but needs to be improved.
Limitation ?

- * Doesn't capture complex human behaviour
- * Doesn't include external factors.
- * Can be improved with advanced models.

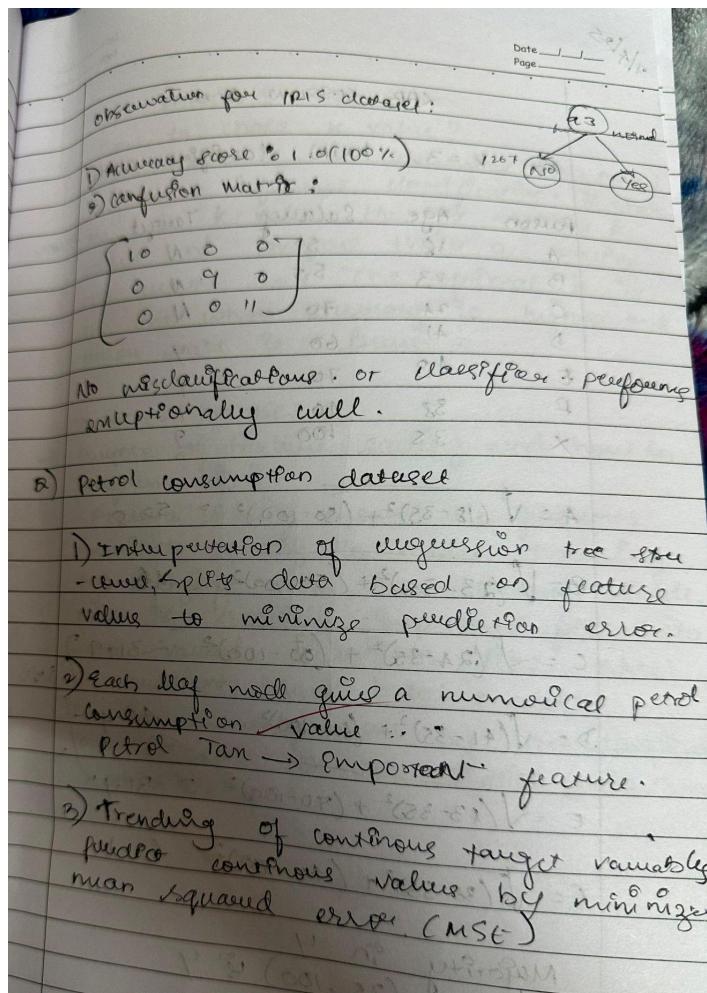
DECISION TREE:

$S = \lceil 1 + , 4 - \rceil$

$$P(\text{Yes}) = \frac{1}{5}, \quad P(\text{No}) = \frac{4}{5}$$

$$S = -P(\text{Yes}) \log_2 P(\text{Yes}) - P(\text{No}) \log_2 P(\text{No})$$

$$\begin{aligned}
 &= -\frac{1}{5} \log_2(1/5) + \frac{4}{5} \log_2(4/5) \\
 &\approx 0.4643 + 0.2555 \\
 &\approx 0.7218 \\
 \text{Gain}(S, A_2) &= \text{entropy}(S) - \frac{\sum I_S}{|S|} \text{ entropy} \\
 S_{\text{root}} &= [1+1, 3+] \\
 &= \frac{1}{2} \log_2(1/2) + \frac{3}{2} \log_2(3/4) = 0.811 \\
 S_{\text{root}} &= [0+1, 1-] = 0 \\
 G_{\text{root}} &= 0.7218 - \frac{(1+3)(0.811)}{(1+4)} - \frac{(1+0)(0)}{(1+4)} \\
 &= 0.7218 - 4(0.811) - 0 \\
 &= -0.073 \\
 \text{Gain}(S, A_3) &= \text{entropy}(S) - \sum I_S \text{ entropy} \\
 S_{\text{root}} &= [0+1, 1-] = 0 \\
 S_{\text{normal}} &= [1+1, 0-] = 0 \\
 G_{\text{root}} &= 0.7218 - 0 = 0 \\
 &= 0.7218 \\
 \text{Gain}(S, A_3) &> \text{Gain}(S, A_2) \\
 \text{Select } a_3 \rightarrow \text{splitting node.}
 \end{aligned}$$



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]])

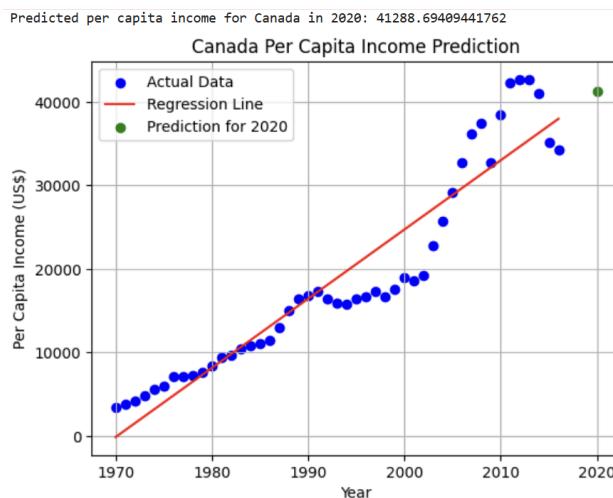
print("\nPredicted per capita income for Canada in 2020:", predicted_income[0])

# 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")
print(salary_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')

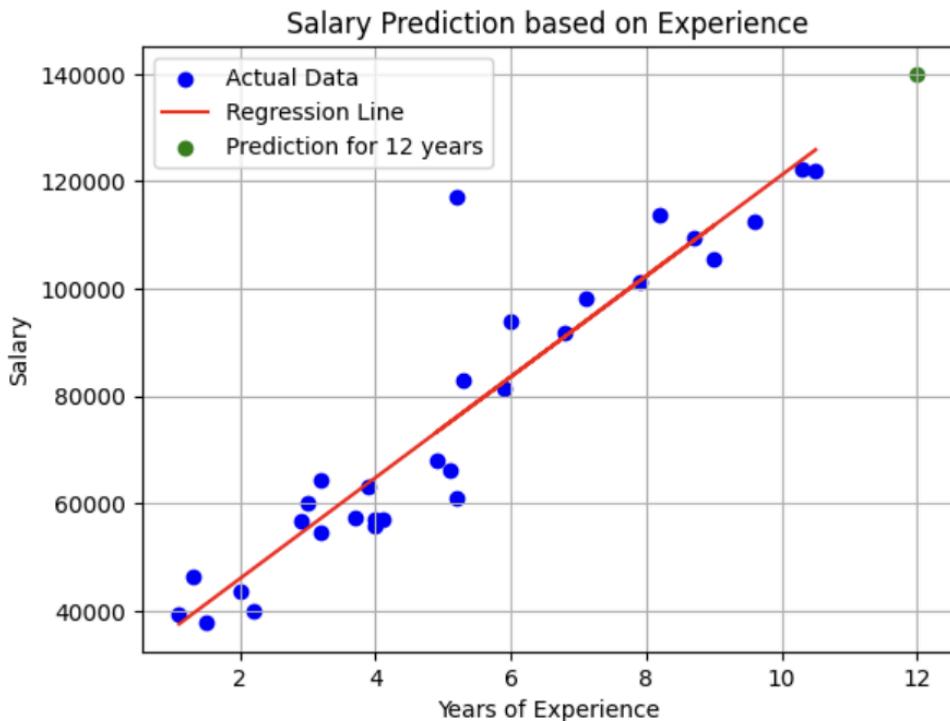
# Plot the prediction for 12 years of experience
plt.scatter(12, predicted_salary[0], color='green', label='Prediction for 12 years')

# 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



```

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")

# 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

LAB SESSION - 9

1) Consider a binary classification problem where we want whether a student will pass or fail based on three study hours $a_0 = -5$, $a_1 = 0.8$

(i) Logistic regression:

$$P(\text{Pass} | \mathbf{x}) = \frac{1}{1 + e^{-(a_0 + a_1 x)}}$$

$$= P(\text{Pass} | \mathbf{x}) = \frac{1}{1 + e^{(-5 + 0.8 \cdot 7)}}$$

(ii) calculate probability for $\mathbf{x} = 7$ hours

$$P(\text{Pass} | \mathbf{x}) = \frac{1}{1 + e^{-5 + 0.8(7)}} = 0.6$$

$$= \frac{1}{1 + e^{-0.6}} \quad [e^{-0.6} \approx 0.548]$$

$$P(\text{Pass} | \mathbf{x}) = \frac{1}{1 + 0.548} \approx 0.6457$$

64.57% will pass.

(iii) Determine the prediction class using threshold of 0.5

$$P(\text{Pass} | \mathbf{x}) > 0.5$$

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$P(\text{Pass} | \mathbf{x}) < 0.5$
for $\mathbf{x} = 7$ hours
 $P(\text{Pass} | \mathbf{x}) \approx 0.6457 > 0.5 \rightarrow \text{Pass}$

LOGISTIC REGRESSION (BINARY CLASSIFICATION)

1) Variables impacting employee retention satisfaction level - hours satisfied increased after promotion

- * Time spent in company
- * Average monthly hours
- * Number of projects
- * Salary
- * Promotion in last 5 years

2) Model Accuracy in evaluation

- Accuracy: 75-77%
- Accuracy level is decent but needs to be improved.
- Limitation:
- * Doesn't capture complex human behaviour
- * Doesn't include external factors.
- * Can be improved with advanced models.

DECISION TREE:

$S = [1+, 1-]$

$P(+|S) = \frac{1}{5}, P(-|S) = \frac{4}{5}$

$S = -P(+|S) \log_2 P(+|S) - P(-|S) \log_2 P(-|S)$

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))

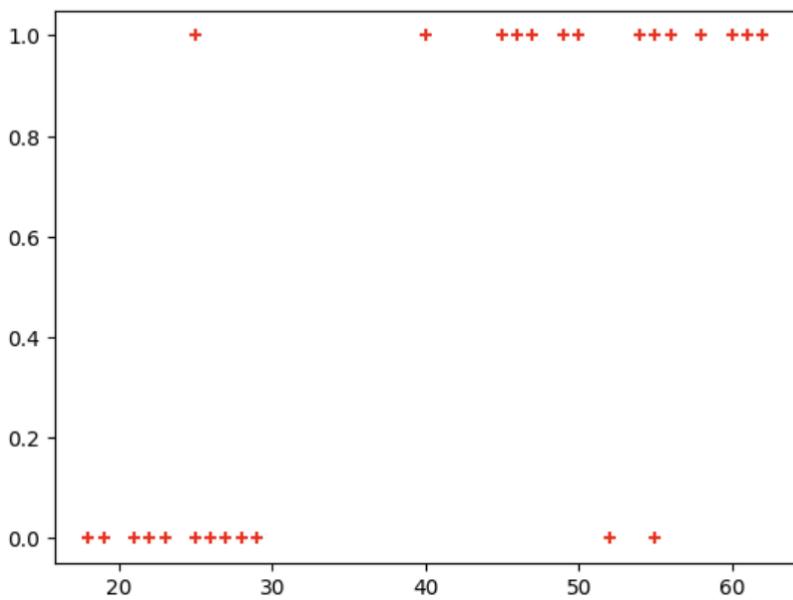
def prediction_function(age):
    z = 0.127 * age - 4.973 # 0.12740563 ~ 0.0127 and -4.97335111 ~ -4.97
    y = sigmoid(z)
    return y

age = 35
prediction_function(age)

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


```

'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)

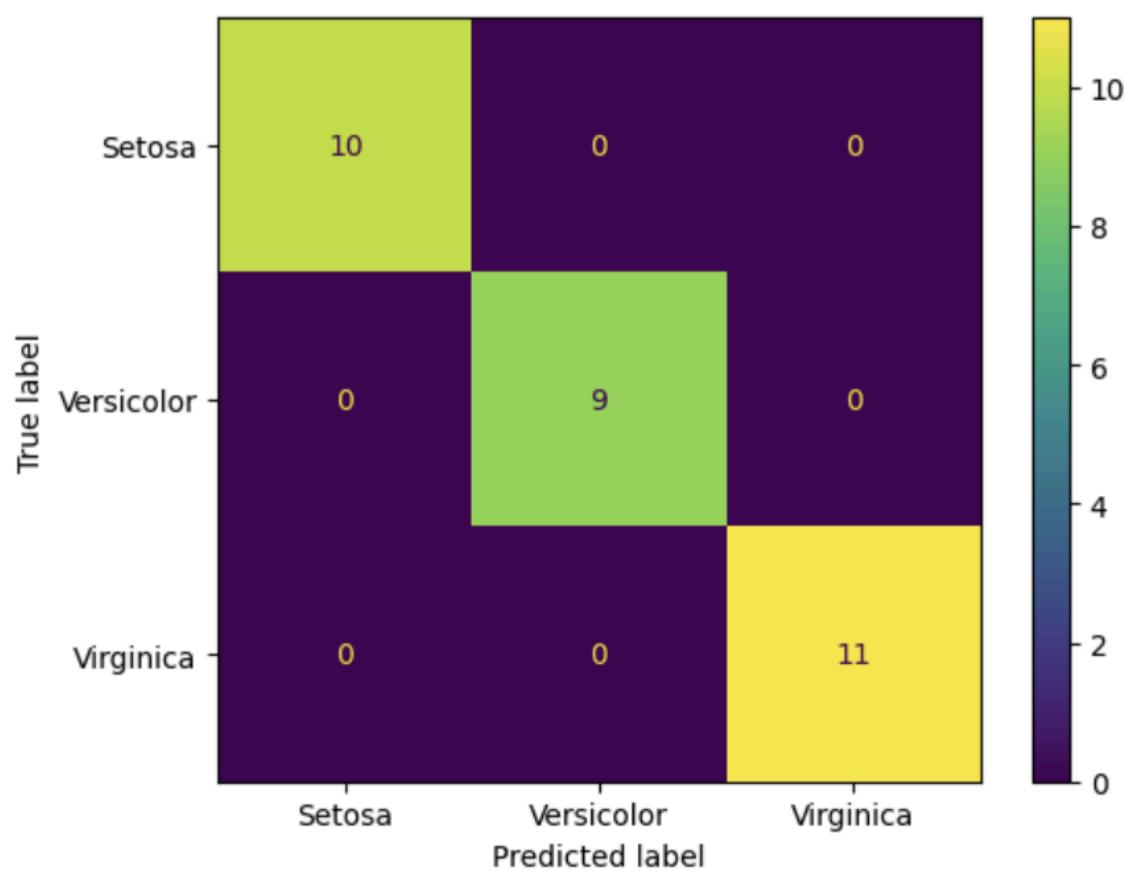
# Display the accuracy
print(f"Accuracy of the Multinomial Logistic Regression model on the test set: {accuracy:.2f}")

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 SESSION 6				
For k = 3, KNN classifier model				
Person	Age	Salary	Taught	distances
A	18	50	N	
B	23	55	N	
C	24	70	N	
D	41	60	Y	
E	43	70	Y	
F	38	40	Y	
X	35	100	Y	?

$A = \sqrt{(18-35)^2 + (50-100)^2} = 52.8$
 $B = \sqrt{(23-35)^2 + (55-100)^2} = 48.6$
 $C = \sqrt{(24-35)^2 + (70-100)^2} = 31.9$
 $D = \sqrt{(41-35)^2 + (60-100)^2} = 40.4$
 $E = \sqrt{(43-35)^2 + (70-100)^2} = 31.1$
 $F = \sqrt{(38-35)^2 + (40-100)^2} = 60.1$
 Majority in Y
 $\therefore (35, 100) \in Y$

IRIS DATASET :	
→ How to choose K value?	
The value of K determines how many neighbours influence classification. To choose the best K value, we test multiple K values and compare their accuracies and error rate. The optimal K is the one whose accuracy is highest and error rate is lowest.	
DIABETES DATASET :	
→ Purpose of Feature scaling and how to perform it?	
Feature scaling ensures all features contribute equally to model training by bringing them to a common scale. This is especially important for distance-based algorithms like KNN or gradient descent based models. It is commonly done by standardization (z-score) or Normalization (min-max scaling).	

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)

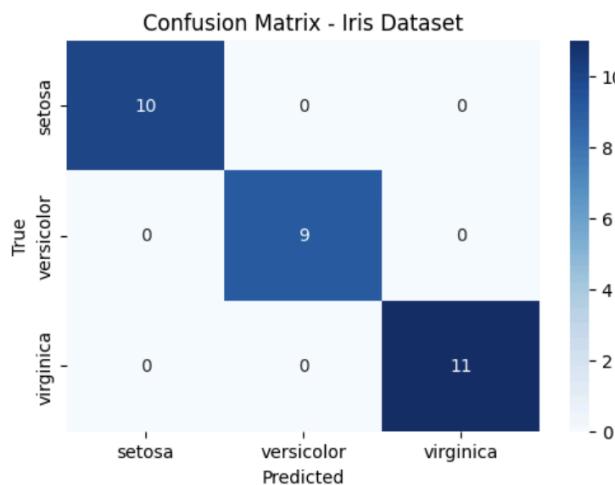
# Predict on test data
y_pred_iris = knn_iris.predict(X_test_iris)

# 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)
```

	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)

```

```

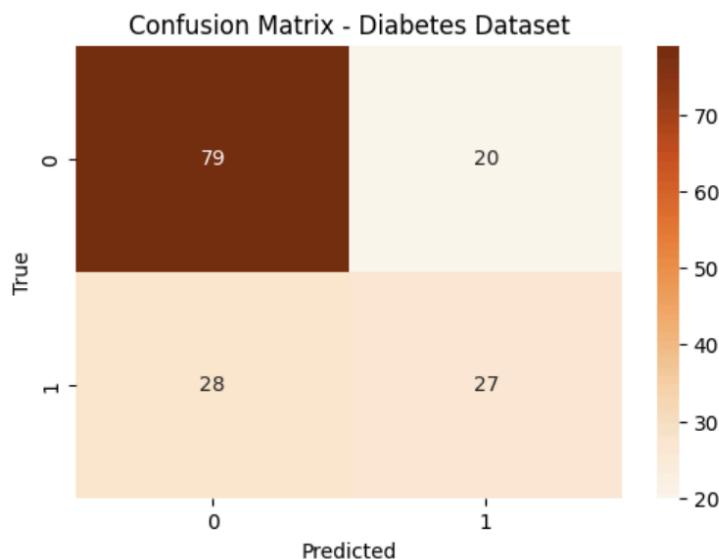
cr_diab = classification_report(y_test_diab, y_pred_diab)
print("\nDiabetes Dataset Classification Report:\n", cr_diab)

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)

```

```

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

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

Best k value: 6

```

```

# ----- 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)

```

```

# 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:

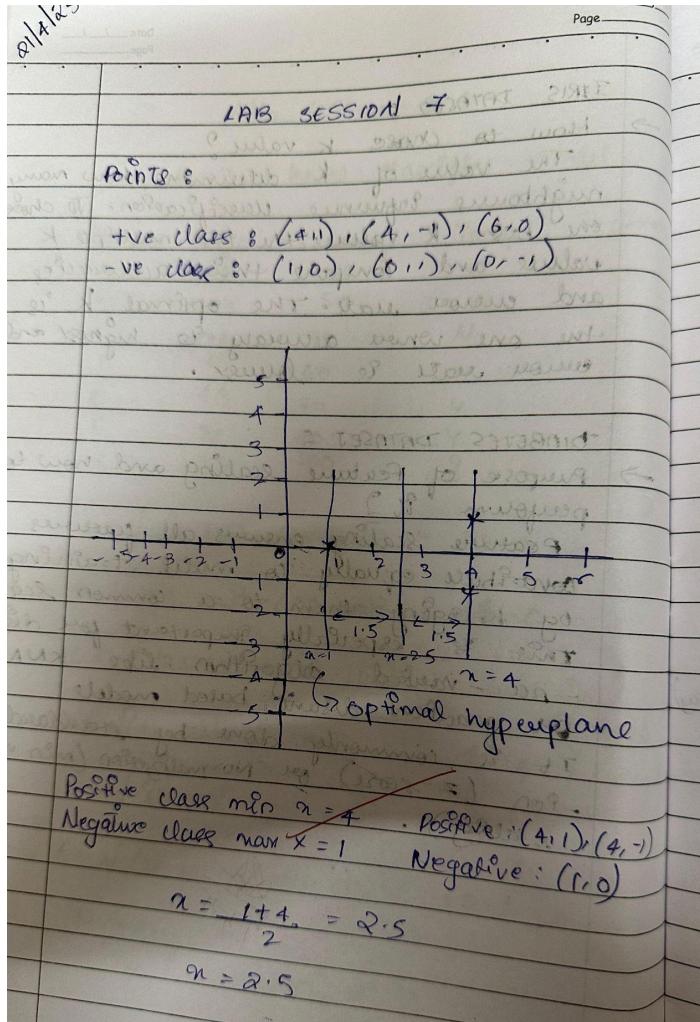
[[28 1]	
[3 29]]	

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



IRIS DATASET :

(a) Accuracy score of the classifier:
 Linear Kernel : 0.9733
 RBF Kernel : 0.9733

(b) Which Kernel gave better performance and why? :

Both the RBF and linear kernels performed equally well with an accuracy of 97.33%.

This similar performance is likely because the IRIS dataset is linearly separable for most parts. The linear kernel can already handle the classification well, and RBF does not provide a significant advantage in this case.

(c) LETTER-RECOGNITION DATASET :

(a) Confusion matrix interpretation:

The confusion matrix shows diagonal dominance, indicating that most letters are correctly classified. However, some letters are frequently confused, such as:

- C and G
- I and L
- M and N

These confusions typically occur due

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)

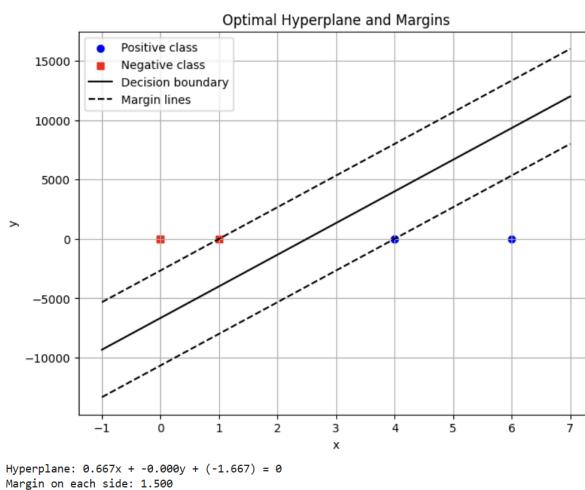
# Extract model parameters
w = clf.coef_[0]
b = clf.intercept_[0]

# 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)

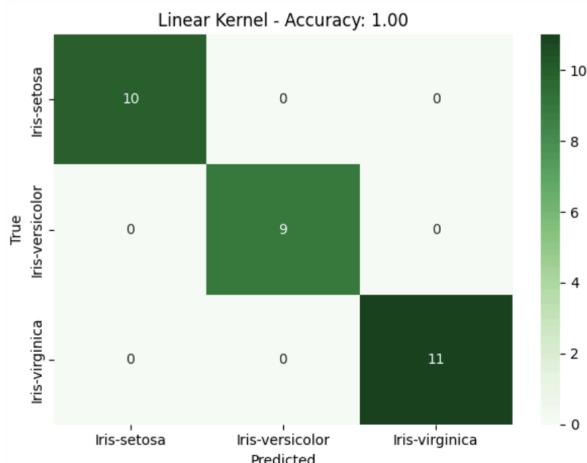
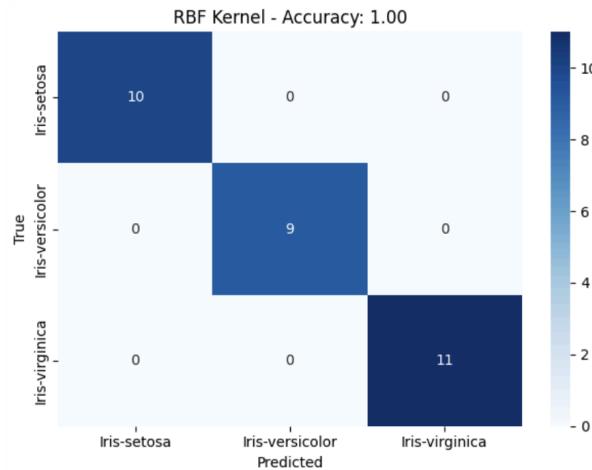
# Predictions
y_pred_rbf = svm_rbf.predict(X_test_iris)
y_pred_linear = svm_linear.predict(X_test_iris)

```

```

# 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

```

```

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()

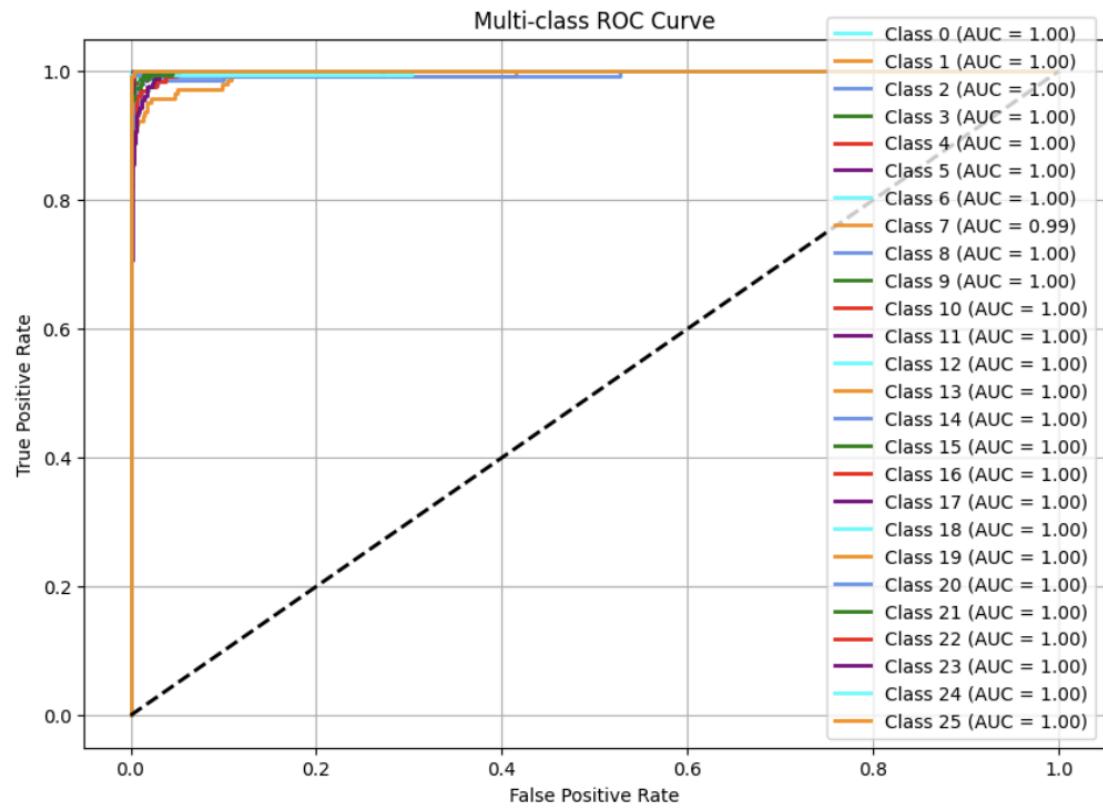
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# 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()

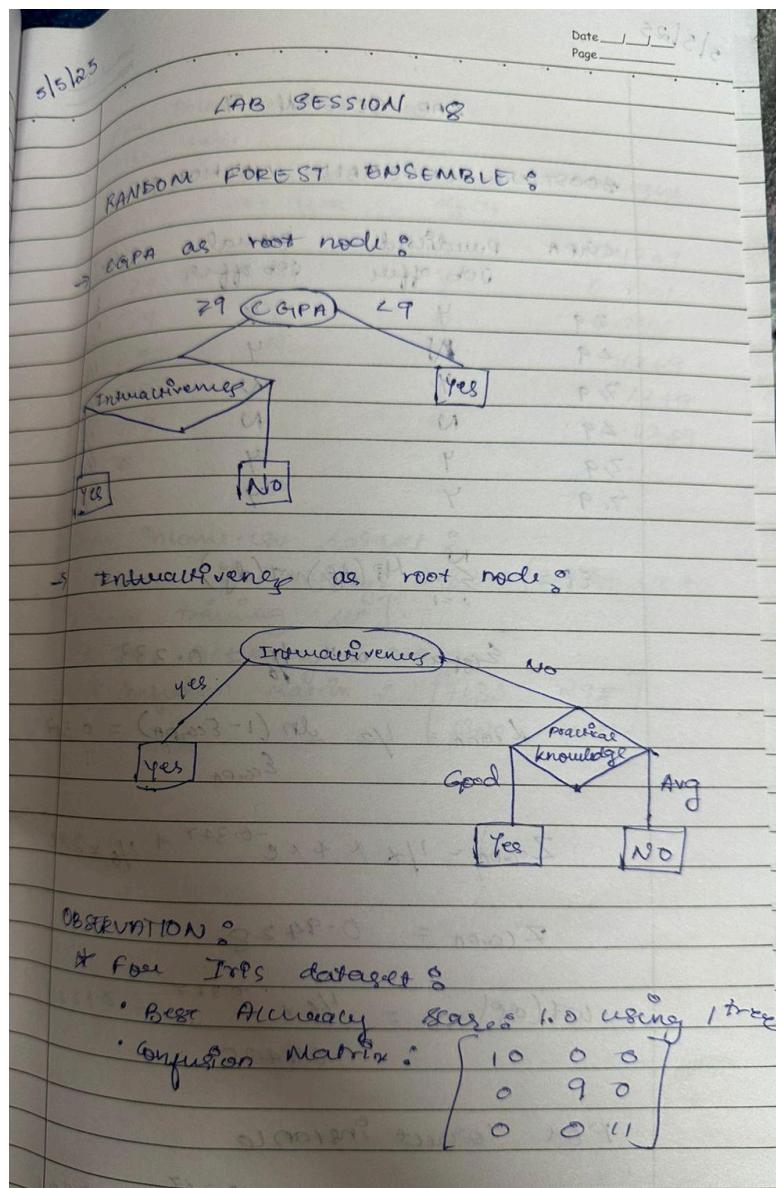
```



LABORATORY PROGRAM – 8

Implement Random forest ensemble method on a given dataset.

OBSERVATION BOOK



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:
```

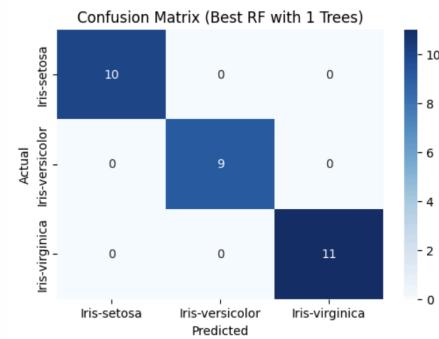
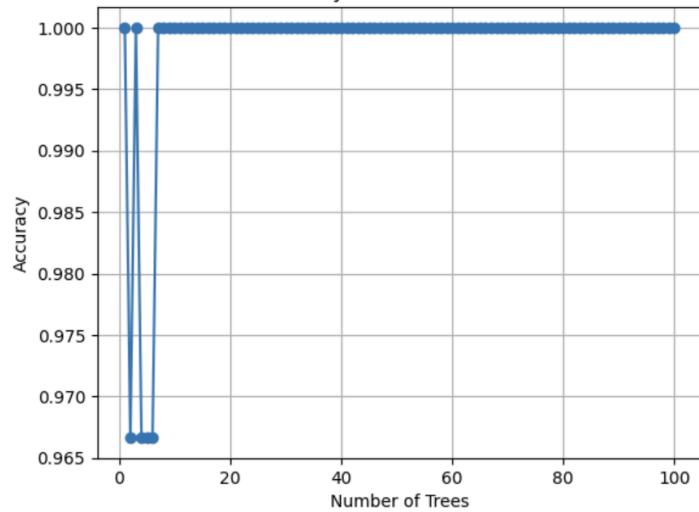
```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

```
Best Accuracy: 1.0 using 1 trees
```

```
Best Confusion Matrix:
```

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

Accuracy vs Number of Trees



LABORATORY PROGRAM – 9

Implement Boosting ensemble method on a given dataset.

OBSERVATION BOOK

SLN 51225

LAB SESSION 9

BOOSTING ENSEMBLE METHOD

CGPA	Predicted job offer	Actual job offer	Weight
7.9	Y	Y	1/16
2.9	N	Y	1/16
7.9	Y	N	1/16
2.9	N	N	1/16
7.9	Y	Y	1/16
7.9	Y	Y	1/16

$\epsilon_P = \sum_{j=1}^N w_j (d_j) \text{wt}(d_j)$

$E_{CGPA} = 2 \times \frac{1}{16} = 0.333$

$E_{CGPA} = \frac{1}{2} \ln(1 - E_{CGPA}) = 0.347$

$Z_{CGPA} = \frac{1}{16} \times 4 \times e^{-0.347} + \frac{1}{16} \times 2 \times 0.347$

$Z_{CGPA} = 0.9428$

$w_t(d_j)_{t+1} = \frac{1}{16} \times e^{-0.347} = 0.1249$

For 2nd instance

$w_t(d_j)_{t+1} = \frac{1}{16} \times e^{+0.347} = 0.2501$

Date _____
Page _____

For 2nd instance
The table is

CGPA	Predicted job offer	Actual job offer	Weight
7.9	Y	Y	0.1249
2.9	N	Y	0.2501
7.9	Y	N	0.2501
2.9	N	N	0.1249
7.9	Y	Y	0.1249
7.9	Y	Y	0.1249

i) For income.csv dataset

- * Best CV Accuracy: 0.8330 [5-fold CV on the training set].
- * Test Accuracy: 0.8344
- * Confusion matrix: $\begin{bmatrix} 7133 & 298 \\ 1320 & 1018 \end{bmatrix}$

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', preprocess),
    ('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}")

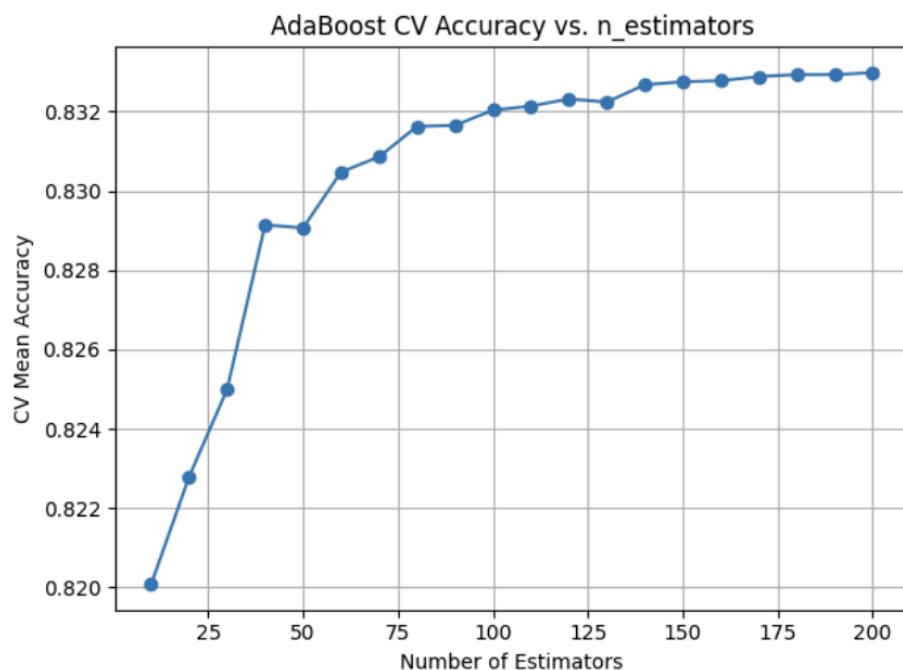
# Plot comparison of initial vs. best test accuracy
plt.figure()
plt.bar(['n=10', f'n={best_n}'], [initial_acc, best_test_acc])
plt.title('Test Accuracy: Initial vs. Optimized')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.tight_layout()
plt.show()

# 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()

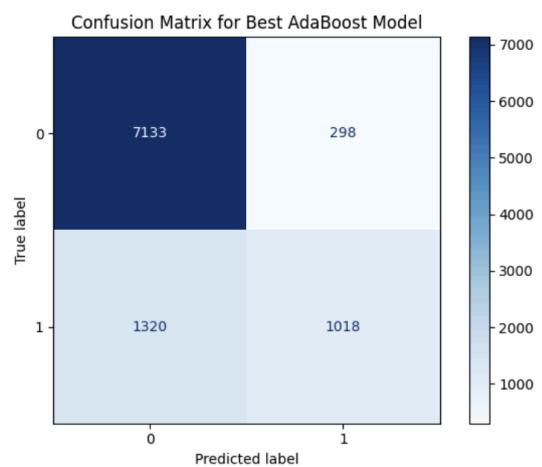
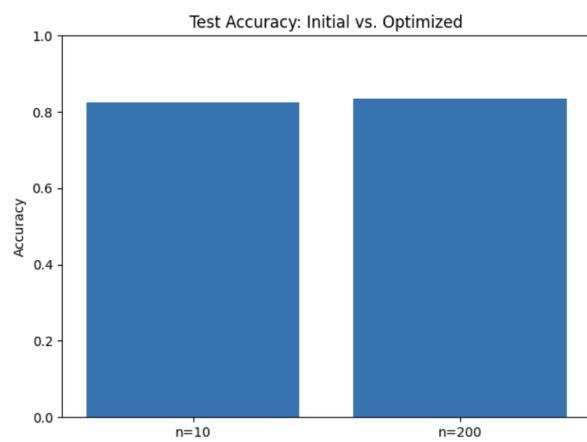
```

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



LABORATORY PROGRAM – 10

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

OBSERVATION BOOK

LAB SESSION 10 NOV 2018			
Record No.	Close to C ₁	Close to C ₂	Assign to cluster
R ₁ (1,1)	0	7.21	C ₁
R ₂ (1,3,2)	1.12	6.12	C ₁
R ₃ (3,1,4)	3.61	3.61	C ₁
R ₄ (5,7)	7.21	0.0	C ₂
R ₅ (3,5,6)	4.12	2.5	C ₂
R ₆ (4,5,5)	5.81	2.06	C ₂
R ₇ (3,3,4,5)	4.30	2.92	C ₂

The new centroids are:

$$C_1 = \frac{5.5 + 7.0}{2} = 6.25$$

$$C_2 = \frac{16.5 + 21.5}{2} = 19.0$$

$$C_1 = 1.83, 2.33 \quad C_2 = 4.12, 5.37$$

Iteration 2:

Record No.	Close to C ₁	Close to C ₂	Assign to cluster
R ₁	1.57	5.37	C ₁
R ₂	0.47	4.27	C ₁
R ₃	2.04	1.77	C ₁
R ₄	3.64	1.85	C ₂
R ₅	3.15	0.72	C ₂
R ₆	3.78	0.52	C ₂
R ₇	2.74	1.07	C ₂

1. New clusters
 $\{R_1, R_2\}$ & $\{R_3, R_4, R_5, R_6, R_7\}$

$$C_1 = 1.25, 1.5 \quad C_2 = 3.9, 5.1$$

For QPSO CSV

The elbow plot shows a sharp elbow at $k=3$, indicating that these clusters are the optimal choice for the petal lengths / width of iris dataset.

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.
    """
    pass
```

```

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')

```

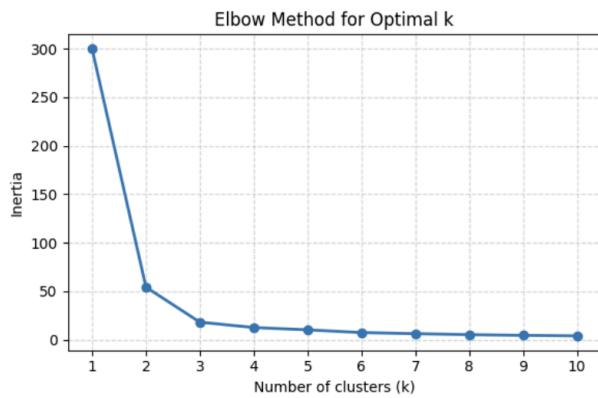
```

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()

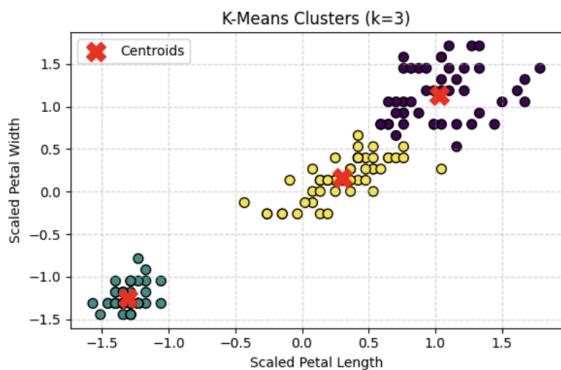
# 7) Confusion matrix vs. true species
plot_confusion(df, labels, optimal_k)

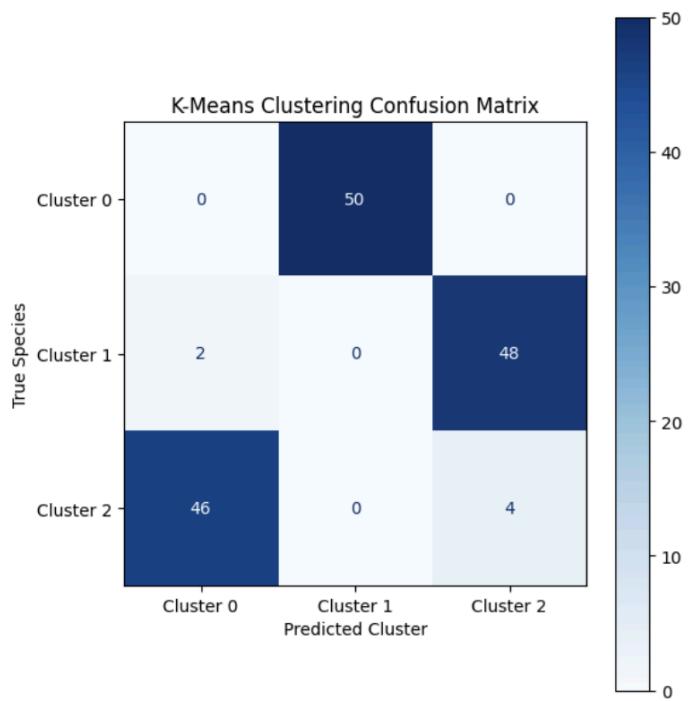
if __name__ == "__main__":
    main()

```



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





LABORATORY PROGRAM – 11

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

OBSERVATION BOOK

LAB SESSION 11	
DIMENSIONALITY REDUCTION USING PCA METHOD	
\Rightarrow Data Matrix \hat{x}	
$x_1 \quad 4 \quad 8 \quad 18 \quad -7$ $x_2 \quad 11 \quad 4 \quad 5 \quad 14$	
$\lambda_1 = 30.3849 \quad e_1 = [0.5574, 0.8303]$ $x_2 = 6.6181 \quad [-0.8803, -0.5574]$	
$\text{Mean of } x_1 = \frac{4 + 18 + 13 + 7}{4} = \frac{32}{4} = 8$ $\text{Mean of } x_2 = \frac{11 + 4 + 5 + 14}{4} = \frac{34}{4} = 8.5$	
$X_{\text{centered}} = X - \text{Mean} = \begin{bmatrix} -4 & 0 & 5 & -1 \\ 2.5 & 4.5 & 3.5 & 5.5 \end{bmatrix}$ Since x_1 is larger, e_1 is the first principal component.	
$e_1^T = [0.5574 \quad 0.8303]$ $\text{But } Z_1 = e_1^T - x_1^T$	
$Z_1(-4, 2.5) = 0.5574(-4) + (0.8303)(2.5)$ $= -4.36535$ $Z_2(0, -1) = 0.5574(0) + (-0.8303)(-1)$ $= 0.8303$ $Z_3(5, 3.5) = 0.5574(5) + (-0.8303)(3.5)$ $= 5.69305$	

$Z_4(-1, 5.5) = 0.5574(-1) + (-0.8303)(5.5)$ $= -5.12405$
$Z = \begin{bmatrix} -4.36535 \\ 0.8303 \\ 5.69305 \\ -5.12405 \end{bmatrix}$
\Rightarrow 1) For "heart.csv" \hat{x} <ul style="list-style-type: none"> Accuracy Before PCA \hat{x} Logistic Regression: 0.9016 SVM: 0.8525 Random Forest: 0.8361
<ul style="list-style-type: none"> Accuracy After PCA \hat{x} Logistic Regression: 0.8689 SVM: 0.8689 Random Forest: 0.8852

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}")
```

The screenshot shows a Jupyter Notebook cell with two sections of output. The first section, titled 'Accuracy Before PCA:', lists the accuracy for three models: Logistic Regression (0.9016), SVM (0.8525), and Random Forest (0.8361). The second section, titled 'Accuracy After PCA (n_components=5):', lists the accuracy for the same three models after applying PCA with 5 components: Logistic Regression (0.8689), SVM (0.8689), and Random Forest (0.8852). The code used to generate these results is visible at the top of the cell.

```
→ ┌ 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
```