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

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning (23CS6PCMAL)" carried out by **Prajwal P (1BM22CS200),** who is a bonafide student of **B.M.S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements in respect of an Machine Learning (23CS6PCMAL) work prescribed for the said degree.

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Github Link: https://github.com/PrajwalP-BmsCS/ML-LAB

Program 1

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

Screenshot:

Lab 0

To-Do-1

→ Method-1 :- Directly into DF

```
import Pandas as pd
data = {
    'Name' : ["A", "B", "C", "D"],
    'Age' : [25, 30, 35, 40],
    'City' : ["New York", "Los Angeles", "Chicago",
              "Houstan"],
    }
df1 = pd.DataFrame(data)
```

→ Method-2 :- Importing datasets from sklearn.datasets

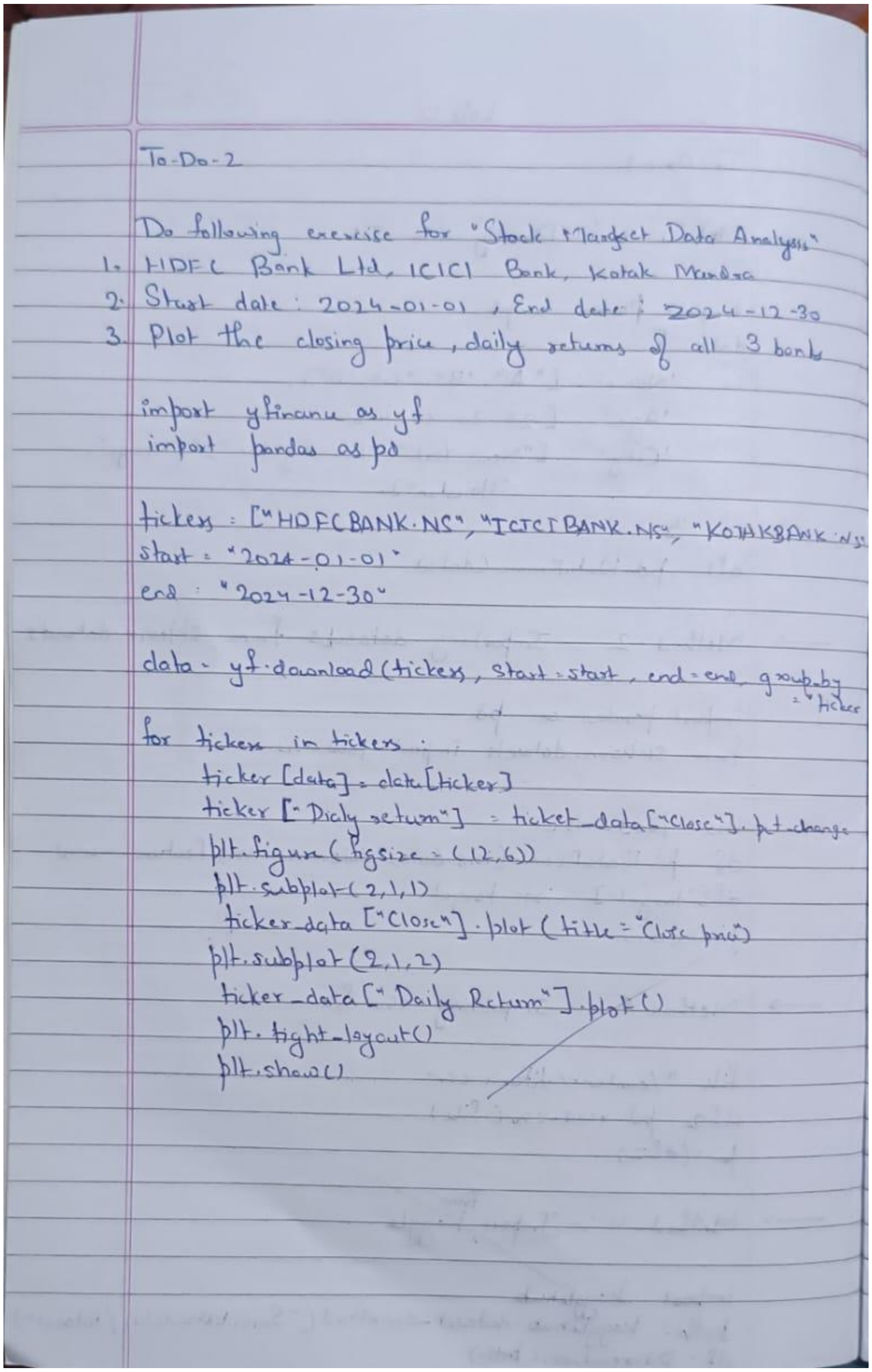
```
import pandas as pd
from sklearn.datasets import load_iris

iris = load_iris()
df = pd.DataFrame(iris.data, columns = iris.feature_names)
df["target"] = iris.target
print(df)
```

→ Method 3 :- Importing csv file

```
file = "/content/titanic.csv"
df2 = pd.read_csv(file)
print(df2)
```

→ Method 4 :- Import from Kaggle

```
import kagglehub
path = kagglehub.dataset_download("Samikshadalvi/dataset")
df = pd.read_csv(path)
```



To-Do-2

Do following exercise for "Stock Market Data Analysis"
1. HDFC Bank Ltd, ICICI Bank, Kotak Mandra
2. Start date : 2024-01-01 , End date : 2024-12-30
3. Plot the closing price, daily returns of all 3 banks

```
import yfinanu as yf
import pandas as pd

tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"
start = "2024-01-01"
end = "2024-12-30"

data = yf.download(tickers, start=start, end=end, group_by="ticker"

for tickers in tickers :
    ticker [data] = data[ticker]
    ticker ["Dialy return"] = ticker_data["Close"].pct_change
    plt.figure(figsize=(12,6))
    plt.subplot(2,1,1)
    ticker_data ["Close"].plot(title="Close price")
    plt.subplot(2,1,2)
    ticker_data["Daily Return"].plot()
    plt.tight_layout()
    plt.show()
```

Code:

import pandas as pd

data = {

'Name': ['Alice', 'Bob', 'Charlie', 'David'],

'Age': [25, 30, 35, 40],

'City': ['New York', 'Los Angeles', 'Chicago', 'Houston']

```
}
df = pd.DataFrame(data)
print("Sample data:")
print(df.head())

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

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

file_path = 'mobiles-dataset-2025.csv'
df = pd.read_csv(file_path, encoding='latin-1') # or 'cp1252' or other suitable encoding
print("Sample data:")
print(df.head())

import pandas as pd
data = {
    'USN': ['IS001','IS002','IS003','IS004','IS005'],
    'Name': ['Alice', 'Bob', 'Charlie', 'David','Eve'],
    'Marks': [25, 30, 35, 40,45]
}
df = pd.DataFrame(data)
print("Sample data:")
```

```
print(df.head())

file_path = 'sample_sales_data.csv'
df = pd.read_csv(file_path)
print("Sample data:")
print(df.head())
print("\n")

df = pd.read_csv("/content/dataset-of-diabetes .csv",encoding='latin-1')
print("Sample data:")
print(df.head())
print("\n")

df =pd.read_csv('sample_sales_data.csv')
print("Sample data:")
print(df.head())
df.to_csv('output.csv',index=False)
print("Data saved to output.csv")

sales_df =pd.read_csv('sample_sales_data.csv')
print("Sample data:")
print(sales_df.head())
sales_by_region =sales_df.groupby('Region')['Sales'].sum()
print("\nTotal sales by region:")
print(sales_by_region)
best_selling_products =sales_df.groupby('Product')['Quantity'].sum().sort_values(ascending=False)
print("\nBest-selling products by quantity:")
print(best_selling_products)
sales_by_region.to_csv('sales_by_region.csv')
best_selling_products.to_csv('best_selling_products.csv')
print("Data saved to sales_by_region.csv and best_selling_products.csv")
```

```
import yfinance as yf
import matplotlib.pyplot as plt
tickers = ["RELIANCE.NS", "TCS.NS", "INFY.NS"]
data = yf.download(tickers, start="2022-10-01", end="2023-10-01",
                   group_by='ticker')
print("First 5 rows of the dataset:")
print(data.head())
print("\nShape of the dataset:")
print(data.shape)
print("\nColumn names:")
print(data.columns)
print("\n")
reliance_data = data['RELIANCE.NS']
print("\nSummary statistics for Reliance Industries:")
print(reliance_data.describe())
reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
print("\n")
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
reliance_data['Close'].plot(title="Reliance Industries - Closing Price")
plt.subplot(2, 1, 2)
reliance_data['Daily Return'].plot(title="Reliance Industries - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
reliance_data.to_csv('reliance_stock_data.csv')

tickers = ["HDFCBANK.NS", "ICICI.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30",
                   group_by='ticker')
print("First 5 rows of the dataset:")
print(data.head())
print("\nShape of the dataset:")
```

```
print(data.shape)
print("\nColumn names:")
print(data.columns)
print("\n")
reliance_data = data['HDFCBANK.NS']
print("\nSummary statistics for Reliance Industries:")
print(reliance_data.describe())
reliance_data['Daily Return'] = reliance_data['Close'].pct_change()
print("\n")
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
reliance_data['Close'].plot(title="HDFC Industries - Closing Price")
plt.subplot(2, 1, 2)
reliance_data['Daily Return'].plot(title="HDFCIndustries - Daily Returns", color='red')
plt.tight_layout()
plt.show()
reliance_data.to_csv('hdfc_stock_data.csv')
print("\nhdfc stock data saved to 'hdfc_stock_data.csv'.")
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset.

Screenshot:

Date 03/03/25
Page

LAB 01 - DATA PREPROCESSING.

Write python codes considering filename as "housing.csv".

```
import pandas as pd.
#1. Load .csv file
df = pd. read_csv ("housing.csv")

#2. Display information of all columns.
df.info()

#3. Display statistical info. of all numerical columns
df. describe()

#4. Display count of unique labels for "Ocean Proximity"
df["Ocean Proximity"]. value_counts()

#5. To count attributes with missing values count>0
missing_values = df. isnull(). sum()
missing_values = missing_values[missing_values > 0]
print (missing_values)
```

3/3/25

Which columns in dataset had missing values? How did you handle them?

→ Diabetes dataset had no missing values.
→ Adult dataset had ? in columns 'workclass', 'occupation' and 'native country'
→ The ? were replaced by NaN to indicate missing
→ They were handled by Imputation

→ Missing Values in Adult Dataset after replacing '?'.

age	0
workclass	2757
fnlwgt	0
education	0
educational-num	0
marital-status	0
occupation	2765
relationchip	0
race	0
gender	0
native-country	542
income	0

→ These become zero after imputation (mean here)

Which categorical columns did you identify? How did you encode them?

→ Diabetes dataset has 'Gender' and 'class'
Adult dataset had almost all categorical columns.

Using Label Encoding, these categorical columns were encoded to numeric values, or One hot encoding

Diff b/w Min-Max Scaling and Standardization?

→ Min-Max scaling:

$$x_{std} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

$x \rightarrow$ dataset value
$\min(x) \rightarrow$ min of col.
$\max(x) \rightarrow$ max of col.

→ Standardization:

$$z = \frac{x - \mu}{\sigma}$$

$\mu \rightarrow$ mean
$\sigma \rightarrow$ std. deviation

Code:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.impute import SimpleImputer
```

```
try:
    diabetes_df = pd.read_csv('diabetes.csv')
    adult_df = pd.read_csv('adult.csv')
except FileNotFoundError:
    print("Error: Please upload 'diabetes.csv' and 'adult.csv' to your Google Colab environment.")
    exit()

diabetes_df.head(10)
adult_df.head(10)

diabetes_df.shape
adult_df.shape

#Handling Missing Values
diabetes_numeric_cols = diabetes_df.select_dtypes(include=[np.number]).columns
diabetes_categorical_cols = diabetes_df.select_dtypes(exclude=[np.number]).columns

adult_numeric_cols = adult_df.select_dtypes(include=[np.number]).columns
adult_categorical_cols = adult_df.select_dtypes(exclude=[np.number]).columns

diabetes_numeric_imputer = SimpleImputer(strategy='mean')
adult_numeric_imputer = SimpleImputer(strategy='mean')
diabetes_df[diabetes_numeric_cols] =
diabetes_numeric_imputer.fit_transform(diabetes_df[diabetes_numeric_cols])
adult_df[adult_numeric_cols] = adult_numeric_imputer.fit_transform(adult_df[adult_numeric_cols])

diabetes_categorical_imputer = SimpleImputer(strategy='most_frequent')
adult_categorical_imputer = SimpleImputer(strategy='most_frequent')
diabetes_df[diabetes_categorical_cols] =
diabetes_categorical_imputer.fit_transform(diabetes_df[diabetes_categorical_cols])
adult_df[adult_categorical_cols] =
```

```
adult_categorical_imputer.fit_transform(adult_df[adult_categorical_cols])

print("Missing values in Diabetes dataset after imputation:")
print(diabetes_df.isnull().sum())
print("Missing values in Adult Income dataset after imputation:")
print(adult_df.isnull().sum())

adult_df.replace("?", np.nan, inplace=True)
print("Missing values in Adult Income dataset after replacing '?':")
print(adult_df.isnull().sum())

from sklearn.impute import SimpleImputer

# Identify numeric and categorical columns
adult_numeric_cols = adult_df.select_dtypes(include=[np.number]).columns
adult_categorical_cols = adult_df.select_dtypes(exclude=[np.number]).columns

# Handle missing values in numeric columns using mean imputation
adult_numeric_imputer = SimpleImputer(strategy='mean')
adult_df[adult_numeric_cols] = adult_numeric_imputer.fit_transform(adult_df[adult_numeric_cols])

# Handle missing values in categorical columns using most frequent imputation
adult_categorical_imputer = SimpleImputer(strategy='most_frequent')
adult_df[adult_categorical_cols] =
adult_categorical_imputer.fit_transform(adult_df[adult_categorical_cols])
print("Missing values in Adult Income dataset after imputation:")
print(adult_df.isnull().sum())

from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

# Encode categorical columns in Diabetes dataset
```

```
for col in diabetes_categorical_cols:
    diabetes_df[col] = label_encoder.fit_transform(diabetes_df[col])

# Encode categorical columns in Adult Income dataset
for col in adult_categorical_cols:
    adult_df[col] = label_encoder.fit_transform(adult_df[col])
print("Encoded columns in Diabetes dataset:")
print(diabetes_df.head())
print("Encoded columns in Adult Income dataset:")
print(adult_df.head())

#Handling outliers
def remove_outliers(df):
    Q1 = df.quantile(0.25)
    Q3 = df.quantile(0.75)
    IQR = Q3 - Q1
    df_no_outliers = df[~((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).any(axis=1)]
    return df_no_outliers

diabetes_df_no_outliers = remove_outliers(diabetes_df)
adult_df_no_outliers = remove_outliers(adult_df)
print("Diabetes dataset shape after removing outliers:", diabetes_df_no_outliers.shape)
print("Adult Income dataset shape after removing outliers:", adult_df_no_outliers.shape)

#Min-max scaling
from sklearn.preprocessing import MinMaxScaler
min_max_scaler = MinMaxScaler()
diabetes_scaled_minmax = pd.DataFrame(min_max_scaler.fit_transform(diabetes_df_no_outliers),
columns=diabetes_df_no_outliers.columns)
adult_scaled_minmax = pd.DataFrame(min_max_scaler.fit_transform(adult_df_no_outliers),
columns=adult_df_no_outliers.columns)
print("Diabetes dataset after Min-Max scaling:")
```

```python
print(diabetes_scaled_minmax.head())
print("Adult Income dataset after Min-Max scaling:")
print(adult_scaled_minmax.head())

# Initialize Standard Scaler
from sklearn.preprocessing import StandardScaler
standard_scaler = StandardScaler()
diabetes_scaled_standard = pd.DataFrame(standard_scaler.fit_transform(diabetes_df_no_outliers),
columns=diabetes_df_no_outliers.columns)
adult_scaled_standard = pd.DataFrame(standard_scaler.fit_transform(adult_df_no_outliers),
columns=adult_df_no_outliers.columns)
print("Diabetes dataset after Standard scaling:")
print(diabetes_scaled_standard.head())
print("Adult Income dataset after Standard scaling:")
print(adult_scaled_standard.head())
```

Program 3

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

Screenshot:

Lab-04

→ Linear Regression

Algorithm

(a) Initialize b_0, b_1 to 0

(b) The line of best is represented as

$$y = b_0 + b_1 x + \varepsilon$$

(c) Let data points be $(x_1, y_1) \dots (x_n, y_n)$
Represent them in matrix form

$$Y = \begin{bmatrix} y_0 \\ y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \quad B = \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} \quad x = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

Where ε is the error

$Y = mx + c$ can be arranged as

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 + x_1 \\ 1 + x_2 \\ \vdots \\ 1 + x_n \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} + \varepsilon_1$$

Then b_0 and b_1 ~~and~~ can be determined by

$$B = ((X^T \cdot X)^{-1} \cdot X^T) Y$$

The b_0 and b_1 values can be used to plot the best fit line then using that we can predict future values

→ Multiple Linear Regression

In multiple Linear regression best fit line

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \cdots b_n x_n + \varepsilon$$

assume b_0, b_1 to be 0 initially

Let data points be $(x_{1i}, x_{2i} \cdots x_{ni}, y_i)\ \forall i \in \{0, m\}$ where $x_i\ \forall i \in \{0, m\}$ represents independent variables and y values are dependent variables

Represent datapoints in form of matrix

$$\begin{array}{ccccc} Y & & X & B & \\ \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} & = & \begin{bmatrix} 1 + x_{11} + x_{21} + \cdots x_{n1} \\ 1 + x_{12} + x_{22} + \cdots x_{n2} \\ \vdots \\ 1 + x_{1m} + x_{2m} + \cdots x_{nm} \end{bmatrix} & \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_n \end{bmatrix} & + \varepsilon \end{array}$$

B matrix can be found by

$$B = ((X^T \cdot X)^{-1} \cdot X^T) Y$$

the values $b_i\ \forall i \in \{0, n\}$ can be used to plot the best fit line which can be used to predict future values.

Code:

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

```
import matplotlib.pyplot as plt

df = pd.read_csv('housing_area_price.csv')
plt.xlabel('area')
plt.ylabel('price')
plt.scatter(df.area,df.price,color='red',marker='+')
new_df = df.drop('price',axis='columns')
new_df
price = df.price
reg = linear_model.LinearRegression()
reg.fit(new_df,price)

#(1) Predict price of a home with area = 3300 sqr ft
reg.predict([[3300]])
reg.coef_
reg.intercept_
3300*135.78767123 + 180616.43835616432

#(2) Predict price of a home with area = 5000 sqr ft
reg.predict([[5000]])

df = pd.read_csv('homeprices_Multiple_LR.csv')
df.bedrooms.median()
df.bedrooms = df.bedrooms.fillna(df.bedrooms.median())
reg = linear_model.LinearRegression()
reg.fit(df.drop('price',axis='columns'),df.price)
reg.coef_
reg.intercept_

#Find price of home with 3000 sqr ft area, 3 bedrooms, 40 year old
reg.predict([[3000, 3, 40]])
112.06244194*3000 + 23388.88007794*3 + -3231.71790863*40 + 221323.00186540384
```

```
df = pd.read_csv('canada_per_capita_income.csv')
print(df.head())
X = df[['year']]
y = df['per capita income (US$)']
reg = LinearRegression()
reg.fit(X, y)
predicted_income_2020 = reg.predict([[2020]])
print(f"Predicted per capita income for Canada in 2020: {predicted_income_2020[0]:.2f}")

plt.scatter(X, y, color='blue')
plt.plot(X, reg.predict(X), color='red')
plt.xlabel('Year')
plt.ylabel('Per Capita Income')
plt.title('Per Capita Income in Canada Over the Years')
plt.show()

df = pd.read_csv('salary.csv')
print(df.head())
print("Missing values in the dataset:")
print(df.isnull().sum())

df['YearsExperience'] = df['YearsExperience'].fillna(df['YearsExperience'].median())
print("\nMissing values after filling:")
print(df.isnull().sum())
X = df[['YearsExperience']]
y = df['Salary']
reg = LinearRegression()
reg.fit(X, y)
predicted_salary_12_years = reg.predict([[12]])
print(f"\nPredicted salary for an employee with 12 years of experience:
${predicted_salary_12_years[0]:,.2f}")
```

```
plt.scatter(X, y, color='blue')
plt.plot(X, reg.predict(X), color='red')
plt.xlabel('Years of Experience')
plt.ylabel('Salary')
plt.title('Salary vs. Years of Experience')
plt.show()

def convert_to_numeric(value):
    word_to_num = {
        'zero': 0, 'one': 1, 'two': 2, 'three': 3, 'four': 4, 'five': 5,
        'six': 6, 'seven': 7, 'eight': 8, 'nine': 9, 'ten': 10,
        'eleven': 11, 'twelve': 12, 'thirteen': 13, 'fourteen': 14,
        'fifteen': 15
    }
    return word_to_num.get(value.lower(), value) if isinstance(value, str) else value

df_hiring = pd.read_csv('hiring.csv')
print(df.head())
df_hiring['experience'] = df_hiring['experience'].apply(convert_to_numeric)

df_hiring['experience'].fillna(0, inplace=True)
df_hiring['test_score(out of 10)'].fillna(df_hiring['test_score(out of 10)'].median(), inplace=True)
df_hiring['interview_score(out of 10)'].fillna(df_hiring['interview_score(out of 10)'].median(),
inplace=True)
X_hiring = df_hiring[['experience', 'test_score(out of 10)', 'interview_score(out of 10)']]
y_hiring = df_hiring['salary($)']
reg_hiring = LinearRegression()
reg_hiring.fit(X_hiring, y_hiring)
candidates = np.array([[2, 9, 6], [12, 10, 10]])
predicted_salaries = reg_hiring.predict(candidates)
```

```
for i, candidate in enumerate(candidates):
    print(f"\nPredicted salary for candidate with {candidate[0]} yrs experience, {candidate[1]} test score,
{candidate[2]} interview score: {predicted_salaries[i]:.2f} USD")

plt.scatter(y_hiring, reg_hiring.predict(X_hiring), color='blue', label='Predicted vs Actual')
plt.xlabel("Actual Salary")
plt.ylabel("Predicted Salary")
plt.title("Actual vs Predicted Salary")
plt.legend()
plt.show()

df_companies = pd.read_csv('1000_Companies.csv')
print(df.head())
label_encoder = LabelEncoder()
df_companies['State'] = label_encoder.fit_transform(df_companies['State'])
X_companies = df_companies[['R&D Spend', 'Administration', 'Marketing Spend', 'State']]
y_companies = df_companies['Profit']
df_companies.fillna(df_companies.median(), inplace=True)
reg_companies = LinearRegression()
reg_companies.fit(X_companies, y_companies)

input_data = np.array([[91694.48, 515841.3, 11931.24, label_encoder.transform(['Florida'])[0]]])
predicted_profit = reg_companies.predict(input_data)
print(f"Predicted profit: {predicted_profit[0]:.2f} USD")

plt.scatter(y_companies, reg_companies.predict(X_companies), color='blue', label='Predicted vs
Actual')
plt.xlabel("Actual Profit")
plt.ylabel("Predicted Profit")
plt.title("Actual vs Predicted Profit")
plt.legend()
plt.show()
```

Program 4

Build Logistic Regression Model for a given dataset.

Screenshot:

Logistic Regression

Logistic regression operates on a sigmoid curve rather than a best fit line, we get a value $\in [0, 1]$ and then classify into +ve or -ve by comparing with median.

Let data points be $(x_i, y_i) \ \forall i \in \{0, n\}$

Find best fit line through previously mentioned methods as you do for linear regression

$$v = \frac{1}{1 + e^{-(mx+c)}} = \frac{1}{1 + e^{-(b_1 m + b_0)}}$$

would result in value v between 0, and 1, we could classify it into "no" (if its below 0.5) or "yes" (if its above 0.5)

Code:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv("HR_comma_sep.csv")
print(df.info())
numericCols = df.select_dtypes(include=['float64', 'int64']).columns
plt.figure(figsize=(10, 8))
sns.heatmap(df[numericCols].corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Matrix (Numeric Features)")
plt.show()

plt.figure(figsize=(8, 6))
sns.countplot(x='salary', hue='left', data=df)
plt.title("Impact of Salary on Employee Retention")
plt.xlabel("Salary Level")
plt.ylabel("Employee Count")
plt.show()

import pandas as pd
df = pd.read_csv("zoo-data.csv")
print(df.info())
print(df.head())
print(df.isnull().sum())
df.drop(columns=['animal_name'], inplace=True)
X = df.drop(columns=['class_type'])
y = df['class_type']

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
logreg = LogisticRegression(max_iter=200, multi_class='multinomial', solver='lbfgs')
logreg.fit(X_train, y_train)

from sklearn.metrics import accuracy_score
y_pred = logreg.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy:.2f}")

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=logreg.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix for Zoo Animal Classification")
plt.show()

y_pred = logreg.predict(X_test)
pred_classes = [class_mapping[pred] for pred in y_pred]
print("Predicted Classes:", pred_classes)

import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(x='class_type', data=df)
plt.title("Class Distribution of Animals in Zoo Dataset")
plt.xlabel("Class Type")
plt.ylabel("Count")
plt.show()
```

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred)
class_labels = [class_mapping[num] for num in logreg.classes_]
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_labels)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix with Class Names")
plt.show()
```

Program 5

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

Screenshot:

Lab-02

Implement ID3 Algorithm using decision tree method, Use appropriate dataset in building decision tree and apply this knowledge to classify a new example

→ ID3 Algorithm

→ • Input
- A set of training examples each with target class
- A set of features with possible values.

→ Initialize
- Start with entire dataset as root node.

→ Recursion
- Base case:
  - (i) If all instances in dataset belong same class, create leaf node with that class
  - (ii) If there are no features left to split on, create a leaf node with majority class
- Calculate Entropy:
  - (i) For the dataset at current node, calculate the entro

$$H(S) = -\sum_{i=1}^{n} p_i \log_2 p_i$$

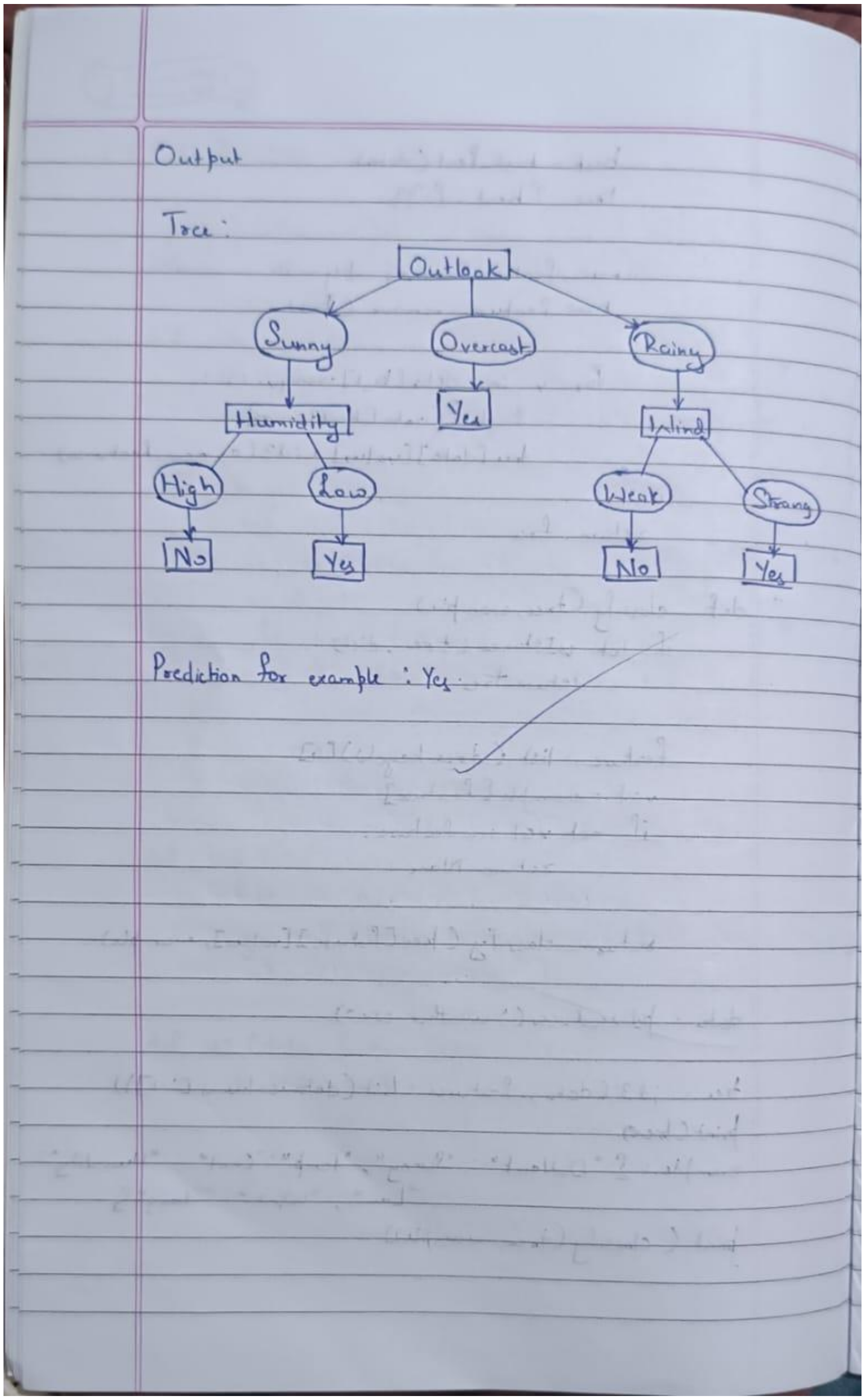
- Calculate Information Gain:
  - (i) $IG(S,A) = H(S) - \sum_{v \in val(A)} \frac{|S_v|}{|S|} H(S_v)$

    where S_v is subset of S where A takes value $\forall v$
  - (ii) Select feature with highest gain

(*) Split dataset :
Partition the dataset into subset based on features and for each subset apply ID3 as a new dataset

(*) Continue previous recursive steps until stopping condition is met (all instances are pure or no features left)

(*) Construct a decision tree to show the output



Code:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score, f1_score
from sklearn.preprocessing import LabelEncoder

def train_and_evaluate_iris():
    iris_df = pd.read_csv("iris.csv")
    X = iris_df.drop(columns=["species"])
    y = iris_df["species"]
    y_le = LabelEncoder()
    y = y_le.fit_transform(y)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    model = DecisionTreeClassifier(random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Evaluating the model
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, average='weighted')
    rec = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    cm = confusion_matrix(y_test, y_pred)

    print("IRIS Dataset Classification:")
    print(f"Accuracy Score: {acc:.4f}")
    print(f"Precision Score: {prec:.4f}")
    print(f"Recall Score: {rec:.4f}")
    print(f"F1 Score: {f1:.4f}")

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=y_le.classes_,
yticklabels=y_le.classes_)
    plt.xlabel("Predicted")
```

```python
    plt.ylabel("Actual")
    plt.title("Confusion Matrix: iris.csv")
    plt.show()

train_and_evaluate_iris()

def train_and_evaluate_drug():
    drug_df = pd.read_csv("drug.csv")
    categorical_features = ["Sex", "BP", "Cholesterol"]
    label_encoders = {}
    for col in categorical_features:
        le = LabelEncoder()
        drug_df[col] = le.fit_transform(drug_df[col])
        label_encoders[col] = le
    X = drug_df.drop(columns=["Drug"])
    y = drug_df["Drug"]
    y_le = LabelEncoder()
    y = y_le.fit_transform(y)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    model = DecisionTreeClassifier(random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, average='weighted')
    rec = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    cm = confusion_matrix(y_test, y_pred)

    print("Drug Dataset Classification:")
    print(f"Accuracy Score: {acc:.4f}")
```

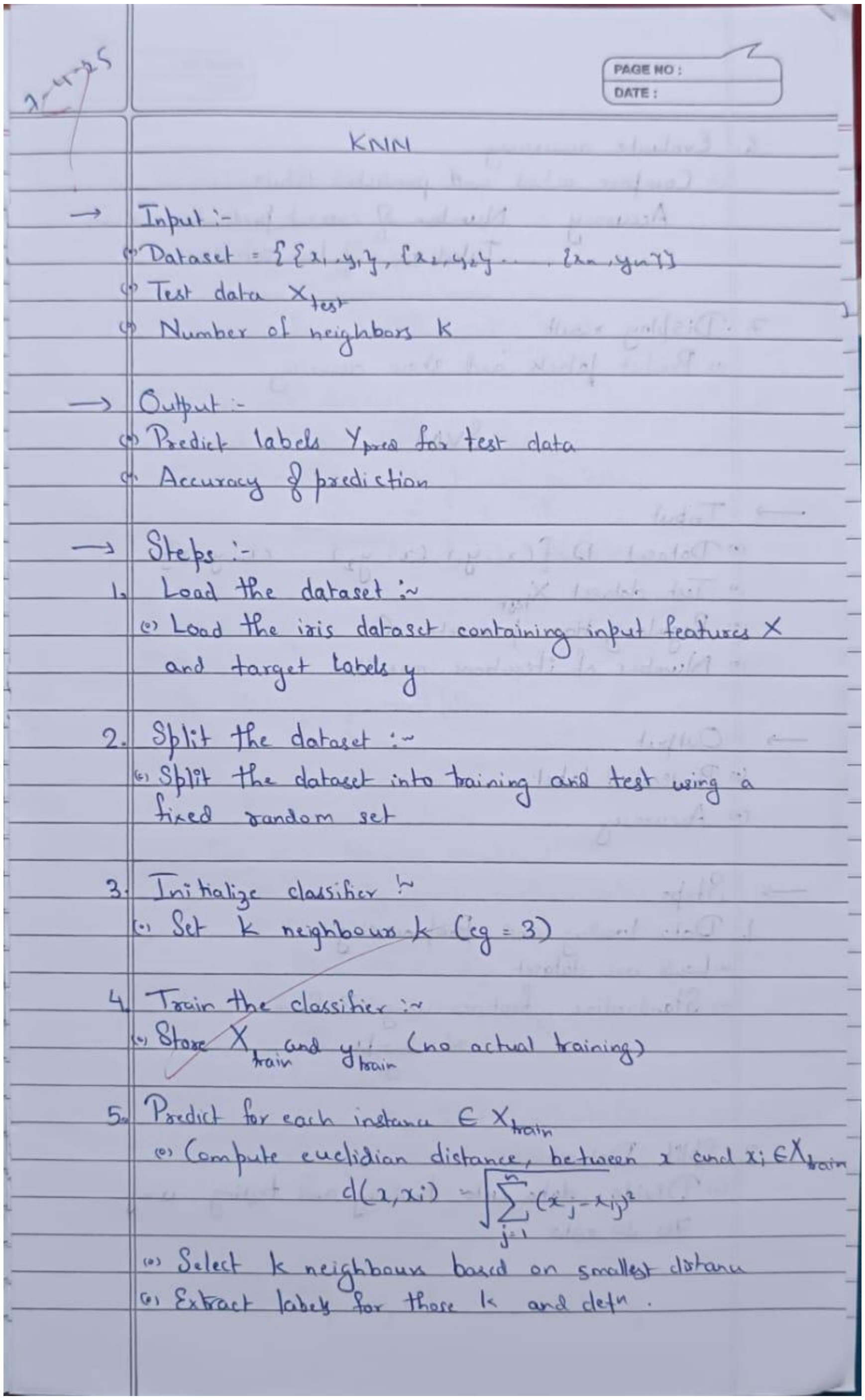
```
    print(f"Precision Score: {prec:.4f}")
    print(f"Recall Score: {rec:.4f}")
    print(f"F1 Score: {f1:.4f}")

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=y_le.classes_,
yticklabels=y_le.classes_)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title("Confusion Matrix: drug.csv")
    plt.show()

train_and_evaluate_drug()

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error

petrol_df = pd.read_csv("petrol_consumption.csv")
X = petrol_df.drop(columns=["Petrol_Consumption"])
y = petrol_df["Petrol_Consumption"]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
model = DecisionTreeRegressor(max_depth=5, random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

```
print("Petrol Consumption Regression:")
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error (RMSE):", np.sqrt(mean_squared_error(y_test, y_pred)))
```

Program 6

Build KNN Classification model for a given dataset.

Screenshot:



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KNN

→ Input :-
- Dataset = $\{\{x_1, y_1\}, \{x_2, y_2\} \dots \{x_n, y_n\}\}$
- Test data X_{test}
- Number of neighbors k

→ Output :-
- Predict labels Y_{pred} for test data
- Accuracy of prediction

→ Steps :-

1. Load the dataset :-
   - Load the iris dataset containing input features X and target labels y
2. Split the dataset :-
   - Split the dataset into training and test using a fixed random set
3. Initialize classifier :-
   - Set k neighbours k (eg = 3)
4. Train the classifier :-
   - Store X_{train} and y_{train} (no actual training)
5. Predict for each instance $\in X_{train}$
   - Compute euclidian distance, between x and $x_i \in X_{train}$

$$d(x, x_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2}$$

   - Select k neighbours based on smallest distance
   - Extract labels for those k and detn .

Code:

```
import pandas as pd
```

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

iris_df = pd.read_csv('iris.csv')
le = LabelEncoder()
iris_df['species'] = le.fit_transform(iris_df['species'])
X = iris_df.drop('species', axis=1)
y = iris_df['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

error_rates = []
accuracies = []
k_values = range(1, 10)
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred_k = knn.predict(X_test)
    error = 1 - accuracy_score(y_test, y_pred_k)
    error_rates.append(error)
    accuracies.append(accuracy_score(y_test, y_pred_k))

plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(k_values, accuracies, marker='o', color='blue')
plt.title("Accuracy vs K")
plt.xlabel("K Value")
plt.ylabel("Accuracy")
```

```
plt.subplot(1, 2, 2)
plt.plot(k_values, error_rates, marker='o', color='red')
plt.title("Error Rate vs K")
plt.xlabel("K Value")
plt.ylabel("Error Rate")
plt.tight_layout()
plt.show()
best_k = k_values[accuracies.index(max(accuracies))]
print(f"Best K: {best_k} with Accuracy: {max(accuracies):.2f}")

knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

# Evaluation
print("\n=== Final Evaluation on IRIS Dataset ===")
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred, labels=[0, 1, 2], target_names=le.classes_))

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=le.classes_, yticklabels=le.classes_)
plt.title("Confusion Matrix - IRIS")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

df = pd.read_csv('diabetes.csv')
X = df.drop('Outcome', axis=1)
```

```python
y = df['Outcome']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42, stratify=y
)
accuracy_scores = []
k_range = range(1, 21)

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

plt.figure(figsize=(8, 5))
plt.plot(k_range, accuracy_scores, marker='o', color='purple')
plt.title("Accuracy vs K (Diabetes Dataset)")
plt.xlabel("K Value")
plt.ylabel("Accuracy")
plt.xticks(k_range)
plt.grid()
plt.show()
best_k = k_range[accuracy_scores.index(max(accuracy_scores))]
print(f"Best K: {best_k} with Accuracy: {max(accuracy_scores):.2f}")

knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

print("=== Final Evaluation (Diabetes Dataset) ===")
```

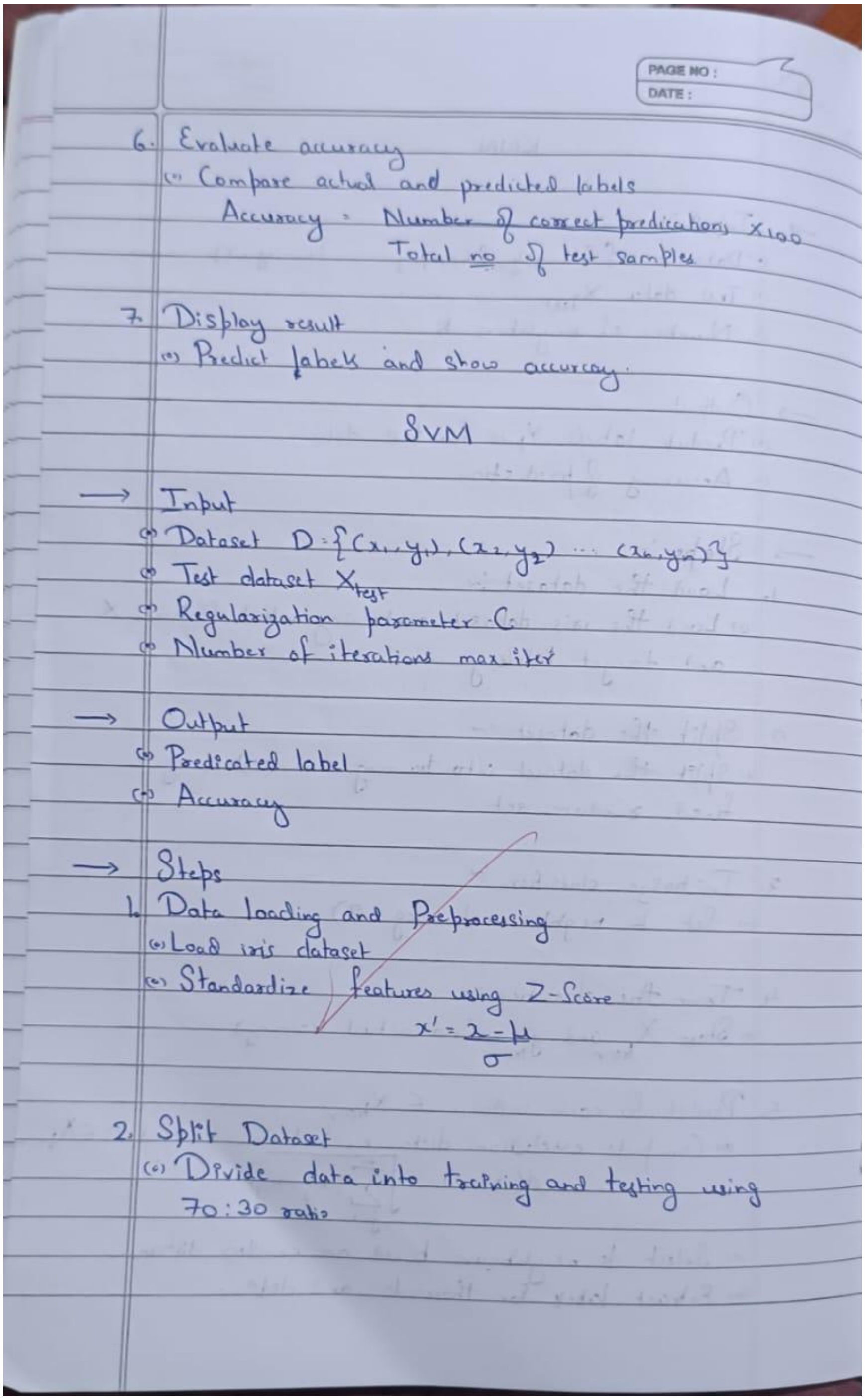
```
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Purples', xticklabels=['No Diabetes', 'Diabetes'],
yticklabels=['No Diabetes', 'Diabetes'])
plt.title("Confusion Matrix - Diabetes")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

heart_df = pd.read_csv('heart.csv')
X = heart_df.drop('target', axis=1)
y = heart_df['target']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42, stratify=y
)
accuracy_scores = []
k_range = range(1, 21)

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

plt.figure(figsize=(8, 5))
plt.plot(k_range, accuracy_scores, marker='o', color='red')
```

```
plt.title("Accuracy vs K (Heart Dataset)")
plt.xlabel("K Value")
plt.ylabel("Accuracy")
plt.xticks(k_range)
plt.grid()
plt.show()

best_k = k_range[accuracy_scores.index(max(accuracy_scores))]
print(f"Best K: {best_k} with Accuracy: {max(accuracy_scores):.2f}")

knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

print("=== Final Evaluation (Heart Dataset) ===")
print("\nAccuracy Score:", accuracy_score(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred, target_names=['No Disease', 'Disease']))
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Reds', xticklabels=['No Disease', 'Disease'],
yticklabels=['No Disease', 'Disease'])
plt.title("Confusion Matrix - Heart Disease")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Program 7

Build Support vector machine model for a given dataset.

Screenshot:



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6. Evaluate accuracy
   (i) Compare actual and predicted labels

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total no of test samples}} \times 100$$

7. Display result
   (i) Predict labels and show accuracy.

SVM

→ Input
- (i) Dataset $D = \{(x_1, y_1), (x_2, y_2) \cdots (x_n, y_n)\}$
- (ii) Test dataset X_{test}
- (iii) Regularization parameter C
- (iv) Number of iterations max_iter

→ Output
- (i) Predicated label
- (ii) Accuracy

→ Steps

1. Data loading and Preprocessing
   (i) Load iris dataset
   (ii) Standardize features using Z-Score

$$x' = \frac{x - \mu}{\sigma}$$

2. Split Dataset
   (i) Divide data into training and testing using 70:30 ratio

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3. Initialize the SVM
   - Set :-
     C : Regularization constant
     max_iter : max Iterations.
     kernal func : $K(x, x') = x \cdot x'$

4. One vs rest stratergy
   For each unique class $c \in$ classes
   - Convert multiclass into binary as below

$$y_{binary} = \begin{cases} 1 & \text{if } y = c \\ -1 & \text{otherwise} \end{cases}$$

5. SVM training
   Initialize :
   - $\alpha = \vec{0}$: Lagrange multiplier
   - $b = 0$: Bias term

   Repeat for max_iter times :
   - For each training example i :
     - Randomly choose another index $j \neq i$
     - Compute prediction error E_i, E_j
     - Store old α_i, α_j
     - Compute L, H for α_j
     - If L = H continue
     - Compute

$$\eta = 2K(x_i, x_j) - K(x_i, x_i) - K(x_j, x_j)$$

     if $\eta \geq 0$ skip update
     - ~~[illegible]~~ α_j using

$$\alpha_j = \alpha_j + y_i \frac{(E_i - E_j)}{\eta}$$

     - Clip $\alpha_j \in [L, H]$, update α_j

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(c) Compute new b_1, b_2 (intercepts)

(c) Update bias term b based on a_i, a_j in bounds

Check convergence

(c) Stop if $\|\alpha - \alpha_{prev}\| < 10^{-5}$

6 Predictions

For test sample x:

(c) Compute decision value:

$$f(x) = \sum_j \alpha_j y_j K(x, x_j) + b$$

(c) Store score

Assign label with max score.

7 Accuracy

Compare predicted labels and actual labels.

$$\text{Accuracy} = \frac{\text{correct predictions}}{\text{total prediction}} \times 100$$

Code:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.svm import SVC
```

```
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score, roc_curve
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import seaborn as sns

iris = pd.read_csv("iris.csv")
label_encoder = LabelEncoder()
iris['species'] = label_encoder.fit_transform(iris['species'])
class_names_iris = label_encoder.classes_
X_iris = iris.drop('species', axis=1)
y_iris = iris['species']
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)

scaler = StandardScaler()
X_train_iris = scaler.fit_transform(X_train_iris)
X_test_iris = scaler.transform(X_test_iris)
svm_linear = SVC(kernel='linear')
svm_linear.fit(X_train_iris, y_train_iris)
y_pred_linear = svm_linear.predict(X_test_iris)
acc_linear = accuracy_score(y_test_iris, y_pred_linear)
cm_linear = confusion_matrix(y_test_iris, y_pred_linear)

plt.figure(figsize=(6,4))
sns.heatmap(cm_linear, annot=True, fmt='d', cmap='Blues', xticklabels=class_names_iris,
yticklabels=class_names_iris)
plt.title(f'IRIS SVM Linear Kernel\nAccuracy: {acc_linear:.2f}')
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()
```

```
svm_rbf = SVC(kernel='rbf')
svm_rbf.fit(X_train_iris, y_train_iris)
y_pred_rbf = svm_rbf.predict(X_test_iris)
acc_rbf = accuracy_score(y_test_iris, y_pred_rbf)
cm_rbf = confusion_matrix(y_test_iris, y_pred_rbf)

plt.figure(figsize=(6,4))
sns.heatmap(cm_rbf, annot=True, fmt='d', cmap='Greens', xticklabels=class_names_iris,
yticklabels=class_names_iris)
plt.title(f'IRIS SVM RBF Kernel\nAccuracy: {acc_rbf:.2f}')
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.tight_layout()
plt.show()

letters = pd.read_csv("letter-recognition.csv")
X_letters = letters.drop('letter', axis=1)
y_letters = letters['letter']
label_encoder_letters = LabelEncoder()
y_letters_encoded = label_encoder_letters.fit_transform(y_letters)
class_names_letters = label_encoder_letters.classes_

X_train_letters, X_test_letters, y_train_letters, y_test_letters = train_test_split(
    X_letters, y_letters_encoded, test_size=0.2, random_state=42)

scaler_letters = StandardScaler()
X_train_letters = scaler_letters.fit_transform(X_train_letters)
X_test_letters = scaler_letters.transform(X_test_letters)
svm_letters = SVC(kernel='rbf', probability=True)
svm_letters.fit(X_train_letters, y_train_letters)

y_pred_letters = svm_letters.predict(X_test_letters)
```

```
acc_letters = accuracy_score(y_test_letters, y_pred_letters)
cm_letters = confusion_matrix(y_test_letters, y_pred_letters)

plt.figure(figsize=(14, 12))
sns.heatmap(cm_letters, annot=True, fmt='d', cmap='Purples',
            xticklabels=class_names_letters,
            yticklabels=class_names_letters,
            annot_kws={"size": 8},
            cbar=True)
plt.title(f'Letter Recognition - SVM RBF Kernel\nAccuracy: {acc_letters*100:.2f}%', fontsize=16)
plt.xlabel("Predicted Label", fontsize=14)
plt.ylabel("True Label", fontsize=14)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()

y_test_binarized = label_binarize(y_test_letters, classes=np.arange(len(class_names_letters)))
y_score = svm_letters.predict_proba(X_test_letters)
auc_score = roc_auc_score(y_test_binarized, y_score, average='macro')

fpr = dict()
tpr = dict()
for i in range(len(class_names_letters)):
    fpr[i], tpr[i], _ = roc_curve(y_test_binarized[:, i], y_score[:, i])

plt.figure(figsize=(8, 6))
for i in range(0, len(class_names_letters), 4): # Plot every 4th class
    plt.plot(fpr[i], tpr[i], lw=1.5, label=f'Class {class_names_letters[i]}')

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel("False Positive Rate")
```

```
plt.ylabel("True Positive Rate")
plt.title(f"Multi-Class ROC Curve (Macro AUC = {auc_score:.6f})")
plt.legend(loc="lower right", fontsize='small')
plt.grid()
plt.tight_layout()
plt.show()

print(f"Exact AUC Score = {auc_score}")
```

Program 8

Implement Random forest ensemble method on a given dataset.

Screenshot:

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Lab-06

→ Random forest

(a) Data Preparation

Given dataset D with N samples and M features, $D = \{(x_1, y_1), \ldots\}$ where x_i represents features and y_i represented the target variable for ith variable

(b) Bootstrap sampling

For each tree draw a bootstrap sample from D by sampling N instance with replacement.

Let $D^b_{bootstrap}$ be the bootstrap sample for bth tree

(c) Random Forest Subset Selection

For each split, randomly select a subset of m features from the M total, At each node the best feature to split on is chosen on some criterion

(d) Build Decision Tree

For each tree b, build a decision tree T^b using $D^b_{bootstrap}$ and the random feature F_{subset}. Recursively split the data at each node by selecting the feature and threshold that minimize chosen splitting criterion.

The tree continues to split until criterion is met.

(e) Calculate ~~Impurity~~

~~If~~ performing classification, at each node, compute the impurity measure for each possible split of the dataset

(f) Calculate MSE

Performing regression use the MSE as splitting criterion

- Recursive Splitting (Construct Trees)
  Recursely splitting the data at each node of the tree based on the feature the provides best split according to impurity
  The splitting continues until the tree reaches the stopping criteria

- Repeat for Multiple Trees
  Repeat steps 2 to 7 B times to construct the Random Forest
  The result in B decision tree each trained on diff bootstrap sample

- Make Predictions
  For classification tasks, make predictions by taking a majority vote from all trees.

- Evaluate model
  For classification evaluate accuracy following metric MSE, MAE, Accuracy.

Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix

iris_df = pd.read_csv("iris.csv")
X = iris_df.drop('species', axis=1)
y = iris_df['species']
le = LabelEncoder()
y_encoded = le.fit_transform(y)

X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.3, random_state=42)
rf_model = RandomForestClassifier(n_estimators=10, random_state=42)
rf_model.fit(X_train, y_train)
y_pred = rf_model.predict(X_test)
print("Random Forest Accuracy with 10 trees:", accuracy_score(y_test, y_pred))

scores = []
n_range = range(1, 101)
best_model = None
best_preds = None

for n in n_range:
    model = RandomForestClassifier(n_estimators=n, random_state=42)
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    acc = accuracy_score(y_test, preds)
    scores.append(acc)
    if acc == max(scores):
        best_model = model
        best_preds = preds
```

```python
best_score = max(scores)
best_n = n_range[scores.index(best_score)]
print(f"Best Random Forest Accuracy: {best_score:.4f} with {best_n} trees")

plt.figure(figsize=(10, 5))
plt.plot(n_range, scores, marker='o', linestyle='-', color='blue')
plt.title('Random Forest Accuracy vs Number of Trees (Iris Dataset)')
plt.xlabel('Number of Trees')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()

cm = confusion_matrix(y_test, best_preds)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=le.classes_, yticklabels=le.classes_)
plt.title(f"Confusion Matrix for Best Random Forest Model ({best_n} Trees)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Program 9

Implement Boosting ensemble method on a given dataset.

Screenshot:

Date ____
Page ____

→ Boosting ensemble

(1) Load the Dataset
Given the dataset $D = \{(x_i, y_i)\ldots\}$, where $y_i \in \{-1, +1\}$
for binary classification

(2) Initialize sample weights
$$w_i = \frac{1}{N}, \forall i = 1 \ldots N \cdot 4$$

(3) Choose Number of iteration T
Set the number of base learners, eg = 50

(4) For $t = 1$ to T, Train weak learner
Train a weak learner $h_t(x)$ (eg., decision stump) on weighted data

(5) Calculate Error of Weak Learner
Weighted classification error
$$\varepsilon_t = \sum_{i=1}^{N} w_i \cdot 1 (h_t(x_i) \neq y_i)$$

(6) Compute Learner Weight
Learner importance
$$\alpha_i = \frac{1}{2} \ln\left(\frac{1 - \varepsilon_i}{\varepsilon_i}\right)$$

(7) Update Sample Weights
Emphasize misclassified points
$$w_i \leftarrow w_i \cdot \exp(-\alpha_i y_i h_i(x))$$

(8) Normalize weights
Normalize so that $\sum w_i = 1$

(•) Final Strong Classifier

Combine weak learner

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_i h_i(x)\right)$$

(•) Evaluate Model

Use accuracy or other metrics on test data

$$\text{Accuracy} = \frac{\text{Correct predictions}}{N}$$

Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import AdaBoostClassifier
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix

income_df = pd.read_csv("income.csv")
X_income = income_df.drop('income_level', axis=1)
y_income = income_df['income_level']
X_train_i, X_test_i, y_train_i, y_test_i = train_test_split(X_income, y_income, test_size=0.3,
random_state=42)

ada_model = AdaBoostClassifier(n_estimators=10, random_state=42)
ada_model.fit(X_train_i, y_train_i)
y_pred_i = ada_model.predict(X_test_i)
print("AdaBoost Accuracy with 10 estimators:", accuracy_score(y_test_i, y_pred_i))

scores_ada = []
n_range_ada = range(1, 51)
best_model_ada = None
best_preds_ada = None

for n in n_range_ada:
    model = AdaBoostClassifier(n_estimators=n, random_state=42)
    model.fit(X_train_i, y_train_i)
    preds = model.predict(X_test_i)
    acc = accuracy_score(y_test_i, preds)
    scores_ada.append(acc)
    if acc == max(scores_ada):
        best_model_ada = model
        best_preds_ada = preds

best_score_ada = max(scores_ada)
```

```
best_n_ada = n_range_ada[scores_ada.index(best_score_ada)]
print(f"Best AdaBoost Accuracy: {best_score_ada:.4f} with {best_n_ada} estimators")

plt.figure(figsize=(10, 5))
plt.plot(n_range_ada, scores_ada, marker='o', linestyle='-', color='orange')
plt.title('AdaBoost Accuracy vs Number of Estimators (Income Dataset)')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()

cm_ada = confusion_matrix(y_test_i, best_preds_ada)
plt.figure(figsize=(6, 5))
sns.heatmap(cm_ada, annot=True, fmt='d', cmap='Oranges', xticklabels=[0, 1], yticklabels=[0, 1])
plt.title(f"Confusion Matrix for Best AdaBoost Model ({best_n_ada} Estimators)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

Program 10

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

Screenshot:

Date ______
Page ______

→ K-Means clustering

(•) Load the Dataset
Load the dataset from .csv file into pandas DataFrame

$$D = \{(x_1, x_2, \ldots x_m)\}, \; x_i \in \mathbb{R}^n$$

(•) Process the Dataset
Handle the missing values, normalize or standardize features and extract the features X for clustering
Normalization :- $x = \frac{x - \mu}{\sigma}$

(•) Choose k (No. of Clusters).
Select k. This is a hyperparameter that needs specified beforehand.

(•) Initialize Centroids :
Randomly select k points from data as initial centroids.

(•) Assign points to the nearest Cluster
For each point x assign it to cluster whose centroid is closet. The distance is typically calculated using Euclidian distance

$$d(x_i, C) = \sqrt{\sum_{m=1}^{M} (x_{im} - C_{jm})^2}$$

when x_{im} is the mth feature of x_i and C_{jm} is mth feature of Centroid j

Update Centroid

After assigning all points to clusters, calculate the new centroids by taking the mean of all points assigned to each cluster

$$C_j = \frac{1}{N_j} \cdot \sum_{x_i \in S_j} x_i$$

$S_j \rightarrow$ Set of all points in cluster j

$N_j \rightarrow$ No of points in cluster j

Check for convergence

If the centroids do not change significantly, stop the algo else go back to step 5

$$\| C_j^{new} - C_j^{old} \| < \varepsilon$$

$\varepsilon \rightarrow$ small threshold.

Repeat Steps 5 to 7

Continue till convergence is reached

Assign final cluster

Once convergence is reached the final cluster assignments and centroid are obtained. Each data point is assigned to cluster C_j based on proximity

Evaluate cluster

Use within-cluster variance or Silhouette Score

$$SSE = \sum_{i}^{N} \sum_{j}^{k} 1(x_i \in S_j) \cdot d(x_i \in C_j)^2$$

Code:

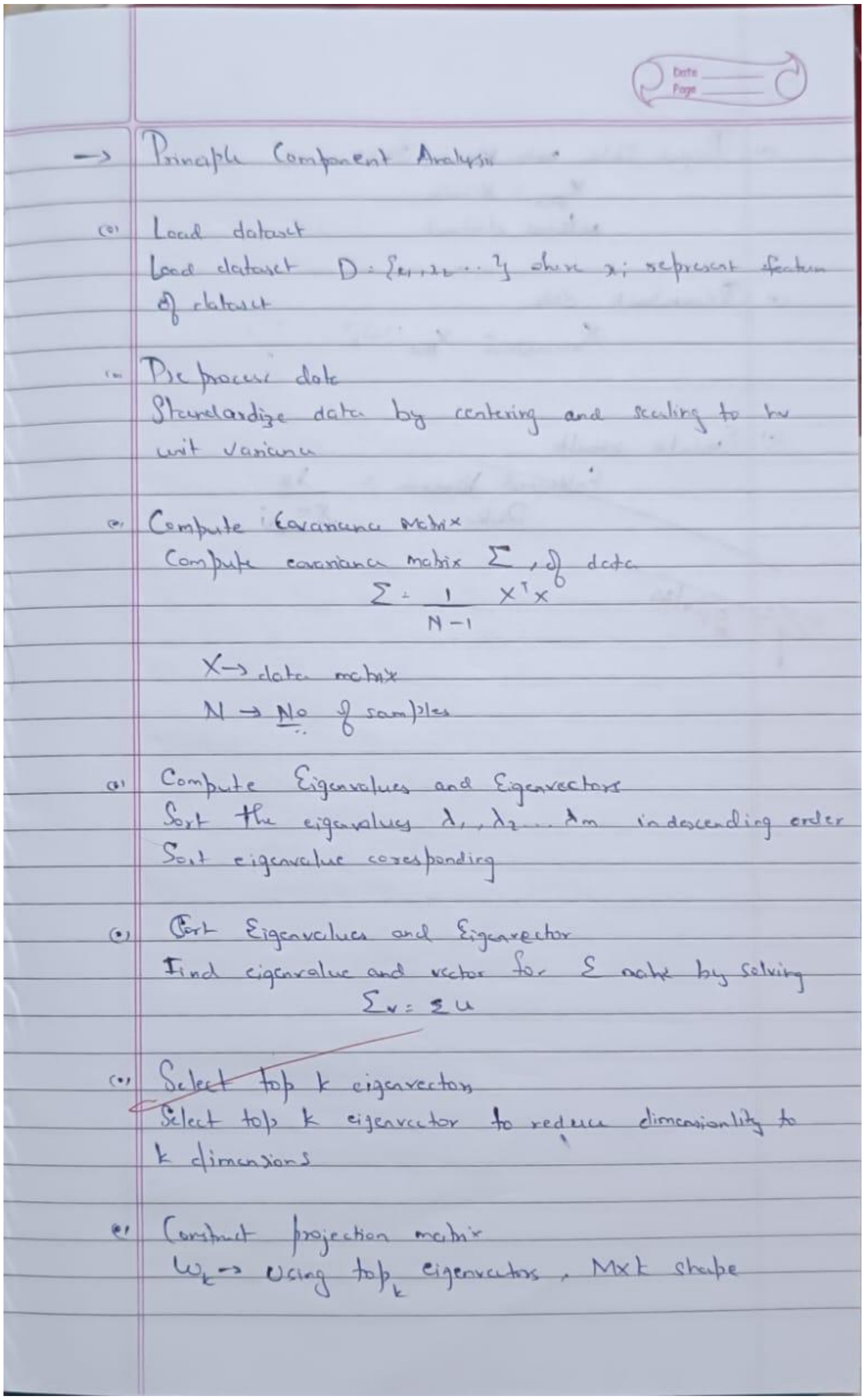
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from scipy import stats
```

```
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

df1=pd.read_csv("iris.csv")
df1.head()
df = df1.drop(['sepal_length','sepal_width','species'],axis=1)
scaler = StandardScaler()
scaled_df = scaler.fit_transform(df)
wcss = []
for i in range(1, 11):
kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
kmeans.fit(scaled_df)
wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

kmeans = KMeans(n_clusters=3, init='k-means++', max_iter=300, n_init=10, random_state=0)
pred_y = kmeans.fit_predict(scaled_df)
df['cluster'] = pred_y
plt.scatter(df['petal_length'], df['petal_width'], c=df['cluster'])
plt.title('Clusters of Iris Flowers')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.show()
```

Program 11

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

Screenshot:



→ Principle Component Analysis

(i) Load dataset
Load dataset $D = \{x_1, x_2 \ldots\}$ where x_i represent feature of dataset

(ii) Pre process data
Standardize data by centering and scaling to have unit variance

(iii) Compute Covariance Matrix
Compute covariance matrix Σ, of data

$$\Sigma = \frac{1}{N-1} X^T X$$

$X \rightarrow$ data matrix
$N \rightarrow$ No. of samples

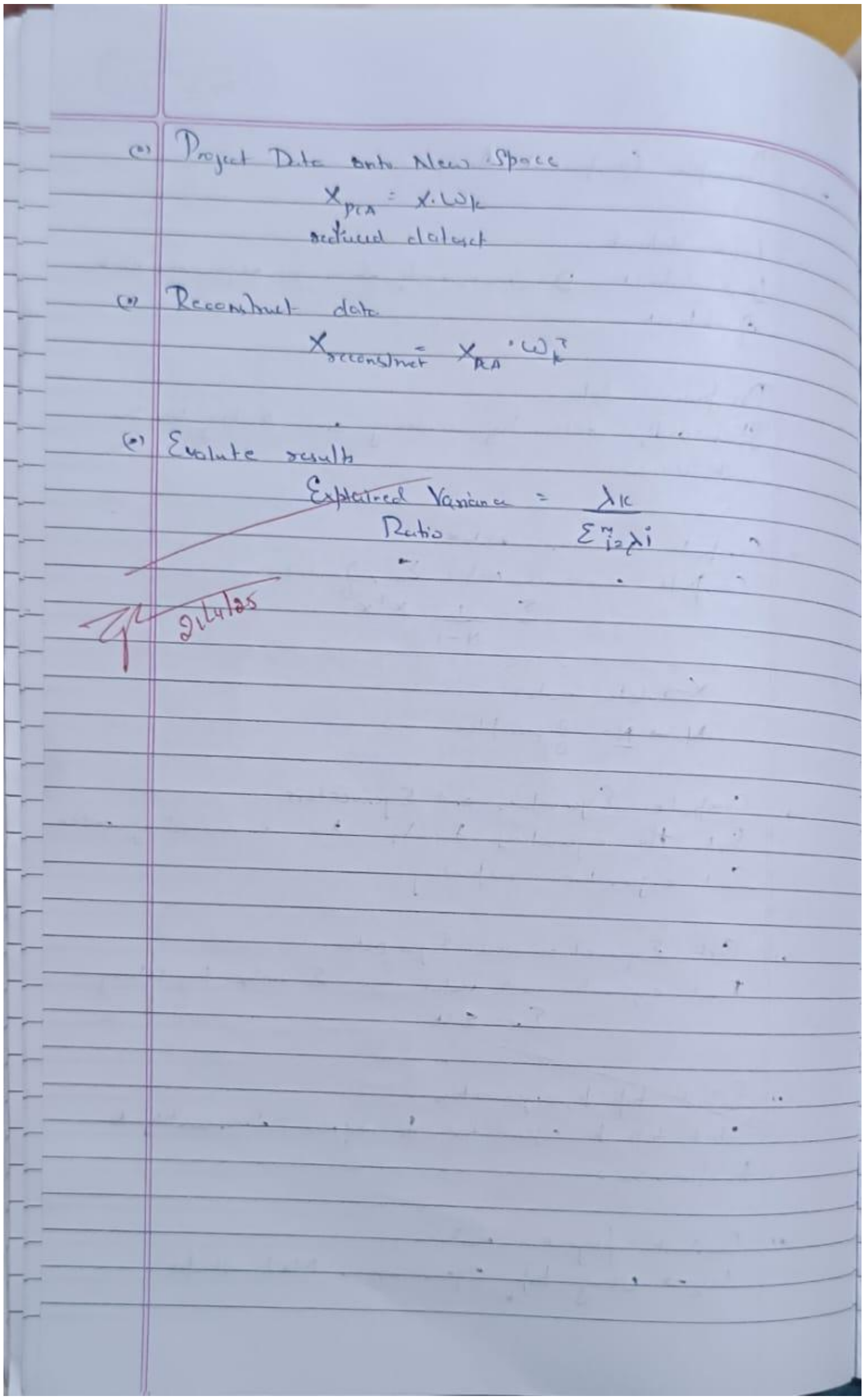
(iv) Compute Eigenvalues and Eigenvectors
Sort the eigenvalues $\lambda_1, \lambda_2 \ldots \lambda_m$ in descending order
Sort eigenvalue corresponding

(v) Sort Eigenvalues and Eigenvector
Find eigenvalue and vector for Σ matx by solving

$$\Sigma v = \varepsilon u$$

(vi) Select top k eigenvectors
Select top k eigenvector to reduce dimensionality to k dimensions

(vii) Construct projection matrix
$W_k \rightarrow$ Using top_k eigenvectors, $M \times k$ shape



(c) Project Data onto New Space

$$X_{PCA} = X \cdot W_k$$

reduced dataset

(d) Reconstruct data

$$X_{reconstruct} = X_{PCA} \cdot W_k^T$$

(e) Evaluate results

$$\text{Explained Variance Ratio} = \frac{\lambda_k}{\sum_{i=1}^{n} \lambda_i}$$

21/4/25

Code:

```
from google.colab import files
heart=files.upload()
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
from sklearn.model_selection import train_test_split
from scipy import stats
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA

df1=pd.read_csv("heart.csv")
df1.head()
text_cols = df1.select_dtypes(include=['object']).columns
label_encoder = LabelEncoder()
for col in text_cols:
df1[col] = label_encoder.fit_transform(df1[col])
print(df1.head())
X = df1.drop('HeartDisease', axis=1)
y = df1['HeartDisease']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Support Vector Machine
svm_model = SVC(kernel='linear', random_state=42)
svm_model.fit(X_train, y_train)
svm_predictions = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_predictions)
```

```
print(f"SVM Accuracy: {svm_accuracy}")

# Logistic Regression
lr_model = LogisticRegression(random_state=42)
lr_model.fit(X_train, y_train)
lr_predictions = lr_model.predict(X_test)
lr_accuracy = accuracy_score(y_test, lr_predictions)
print(f"Logistic Regression Accuracy: {lr_accuracy}")

# Random Forest
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
rf_predictions = rf_model.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_predictions)
print(f"Random Forest Accuracy: {rf_accuracy}")

models = {
"SVM": svm_accuracy,
"Logistic Regression": lr_accuracy,
"Random Forest": rf_accuracy}
best_model = max(models, key=models.get)
print(f"\nBest Model: {best_model} with accuracy {models[best_model]}")

pca = PCA(n_components=0.95)
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)
svm_model_pca = SVC(kernel='linear', random_state=42)
svm_model_pca.fit(X_train_pca, y_train)
svm_predictions_pca = svm_model_pca.predict(X_test_pca)
svm_accuracy_pca = accuracy_score(y_test, svm_predictions_pca)
print(f"SVM Accuracy (with PCA): {svm_accuracy_pca}")
```

```
lr_model_pca = LogisticRegression(random_state=42)
lr_model_pca.fit(X_train_pca, y_train)
lr_predictions_pca = lr_model_pca.predict(X_test_pca)
lr_accuracy_pca = accuracy_score(y_test, lr_predictions_pca)
print(f"Logistic Regression Accuracy (with PCA): {lr_accuracy_pca}")

rf_model_pca = RandomForestClassifier(random_state=42)
rf_model_pca.fit(X_train_pca, y_train)
rf_predictions_pca = rf_model_pca.predict(X_test_pca)
rf_accuracy_pca = accuracy_score(y_test, rf_predictions_pca)
print(f"Random Forest Accuracy (with PCA): {rf_accuracy_pca}")

models_pca = {
"SVM": svm_accuracy_pca,
"Logistic Regression": lr_accuracy_pca,
"Random Forest": rf_accuracy_pca}
best_model_pca = max(models_pca, key=models_pca.get)
print(f"\nBest Model (with PCA): {best_model_pca} with accuracy {models_pca[best_model_pca]}")
```