Sl. No.	Experiment Description	Experiment Date	Submission Date	Remarks Signature
1.1	Fuel Consumption			
1.2	Used Car Price Prediction			
2	Housing Price Prediction			
3	Salary Prediction			
4	China GDP			
5	Cancer Prediction			
6	TeleCust			
7	Drug			
8	Diabetes - Naive Bayes			
9	Cancer			
10	Indian Diabetes			
11	XOR Neural Network			

1. Perform linear regression to predict
a) CO_2 Emission
b) The selling price of a used car.
Evaluate the quality of the models by computing relevant performance metrics, including the R^2 value. Generate and display a plot that compares the actual values to the predicted values (Actual vs Predicted) for both tasks.
Dataset : fuel_consumption_dataset.csv
Dataset : used_cars_dataset.csv

1.a)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_square_error

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

#Display first few rows
print(df.head())
```

No. 1.1

```
# Select relevant features and target variable
features = ['ENGINESIZE', 'CYLINDERS', 'FUELCONSUMPTI
           ON_COMB']
target = 'CO2EMISSIONS'

X = df[features]
y = df[target]

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

# Initialize and train the linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict CO2 emissions
y_pred = model.predict(X_test)

# Evaluate model performance
r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)

print(f"R² Score : {r2:.4f}")
```

Teacher's Signature .....

No.
1.1

```
print(f"Mean Squared Error: {mse:.4f}")

# Plot Actual vs Predicted values
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(),
          y_test.max()], color='red', linestyle='dashed')
plt.xlabel("Actual CO2 Emissions")
plt.ylabel("Predicted CO2 Emissions")
plt.title("Actual vs Predicted CO2 Emissions")
plt.show()
```

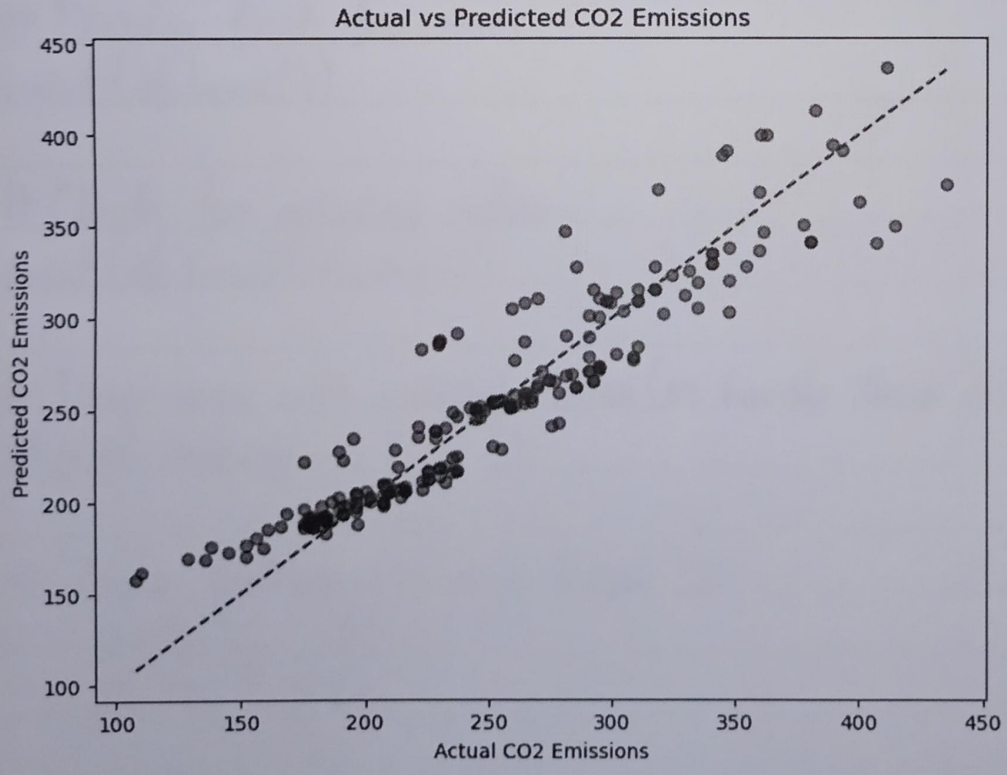
	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	\
0	2014	ACURA	ILX	COMPACT	2.0	4	
1	2014	ACURA	ILX	COMPACT	2.4	4	
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	

	TRANSMISSION	FUELTYPE	FUELCONSUMPTION_CITY	FUELCONSUMPTION_HWY	\
0	AS5	Z	9.9	6.7	
1	M6	Z	11.2	7.7	
2	AV7	Z	6.0	5.8	
3	AS6	Z	12.7	9.1	
4	AS6	Z	12.1	8.7	

	FUELCONSUMPTION_COMB	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	8.5	33	196
1	9.6	29	221
2	5.9	48	136
3	11.1	25	255
4	10.6	27	244

R^2 Score: 0.8760

Mean Squared Error: 512.8551



1. b)

```
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.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error

# Load dataset
df = pd.read_csv('used cars_dataset.csv')

# Display first few rows
print(df.head())

# Check for missing values
print(df.isnull().sum())

# Drop rows with missing values (or handle them differently)
df = df.dropna()

# Choose features (X) and target (y)
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

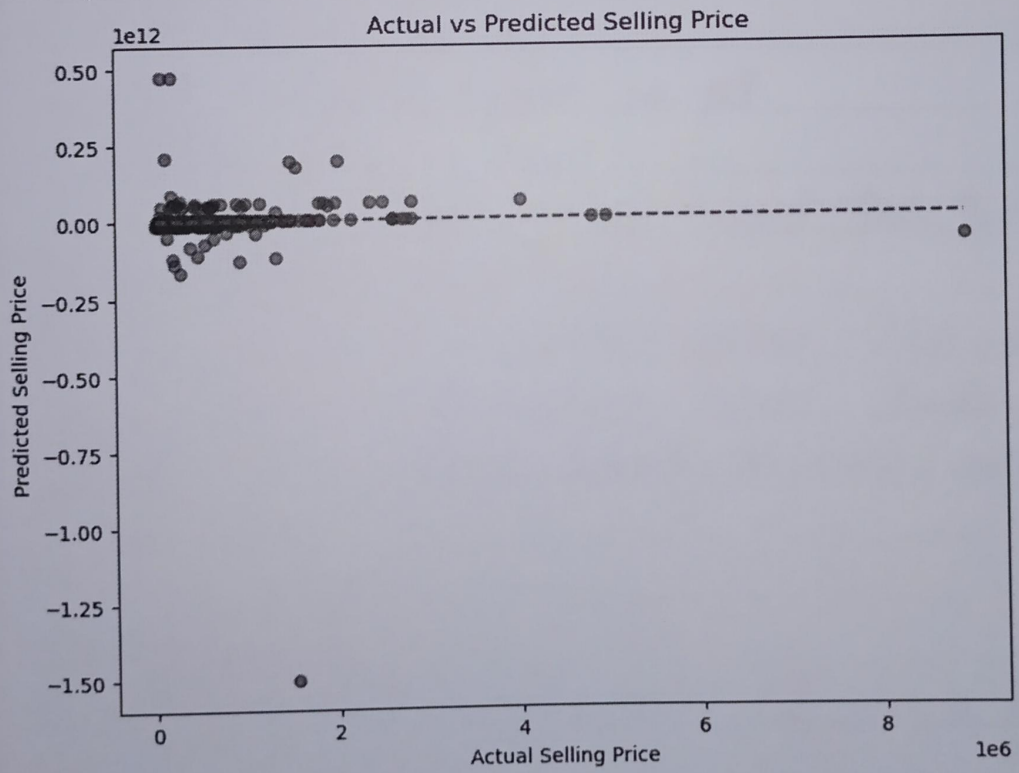
1.2

```
# Handle categorical data if present
X = pd.get_dummies(X, drop_first = True)

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

# Initialize and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict selling price
y_pred = model.predict(X_test)

# Evaluate model performance
r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)

print(f"R² Score: {r2:.4f}")
print(f"Mean Squared Error: {mse:.4f}")

# Plot Actual vs Predicted prices
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_pred, color='blue', alpha = 0.5)
```

Teacher's Signature .....

```
plt.plot([y_test.min(), y_test.max()], [y_test.min(),
          y_test.max()], color='red', linestyle='dashed')
plt.xlabel("Actual Selling Price")
plt.ylabel("Predicted Selling Price")
plt.title("Actual vs Predicted Selling Price")
plt.show()
```

```
                      name  year  km_driven    fuel seller_type transmission  \
0             Maruti 800 AC  2007      70000  Petrol  Individual       Manual
1  Maruti Wagon R LXI Minor  2007      50000  Petrol  Individual       Manual
2      Hyundai Verna 1.6 SX  2012     100000  Diesel  Individual       Manual
3    Datsun RediGO T Option  2017      46000  Petrol  Individual       Manual
4     Honda Amaze VX i-DTEC  2014     141000  Diesel  Individual       Manual

          owner  selling_price
0   First Owner          60000
1   First Owner         135000
2   First Owner         600000
3   First Owner         250000
4  Second Owner         450000
name             0
year             0
km_driven        0
fuel             0
seller_type      0
transmission     0
owner            0
selling_price    0
dtype: int64
R² Score: -11689013742.7553
Mean Squared Error: 35671396682280987525120.0000
```



Expt. No. 2

Page No. 7
Date. 16/3/2025

2) Perform linear regression with L1 (Lasso) and L2 (Ridge) regularization to predict the price of a House. Use hyper-parameter tuning for the best result. Evaluate the accuracy of the models by computing relevant performance metrics, including the R^2 value. Generate and display a plot that compares the actual values to the predicted values (Actual vs Predicted) for both tasks.

Dataset : housing_price_dataset.csv

```
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, GridSearchCV
from sklearn.linear_model import Ridge, Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_squared_error

# Load dataset
df = pd.read_csv('housing_price_dataset.csv')

# Display first few rows
```

```
print(df.head())

# Check for non-numeric columns
print(df.dtypes)

# Drop columns that are clearly non-numeric
df = df.drop(columns=['Address'], errors='ignore')

# Handle missing values (drop or impute)
df = df.dropna()

# Convert categorical variables into numerical using One-Hot Encoding
df = pd.get_dummies(df, drop_first=True)

# Ensure target variable is numeric
df.iloc[:,-1] = pd.to_numeric(df.iloc[:,-1], errors='coerce')

# Drop any remaining NaN values (if any exist after conversion)
df = df.dropna()

# Select features (X) and target variable (y)
X = df.iloc[:, :-1]
y = df.iloc[:,-1]
```

OXFORD

```
# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

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

# Hyperparameter tuning
param_grid = {'alpha': np.logspace(-3, 3, 7)}

# Lasso Regression (L1)
lasso = Lasso(max_iter = 10000)
lasso_grid = GridSearchCV(lasso, param_grid, scoring = 'r2',
                          cv = 5)
lasso_grid.fit(X_train, y_train)
best_lasso = lasso_grid.best_estimator_

# Ridge Regression (L2)
ridge = Ridge()
ridge_grid = GridSearchCV(ridge, param_grid, scoring = 'r2',
                          cv = 5)
ridge_grid.fit(X_train, y_train)
best_ridge = ridge_grid.best_estimator_
```

OXFORD

Expt. No. 2

```
# Predictions
y_pred_lasso = best_lasso.predict(X_test)
y_pred_ridge = best_ridge.predict(X_test)

# Performance Metrics
r2_lasso = r2_score(y_test, y_pred_lasso)
mse_lasso = mean_squared_error(y_test, y_pred_lasso)

r2_ridge = r2_score(y_test, y_pred_ridge)
mse_ridge = mean_squared_error(y_test, y_pred_ridge)

print(f"Lasso Regression - Best Alpha: {lasso_grid.best_params_
    ['alpha']}")
print(f"Lasso Regression - R² Score: {r2_lasso:.4f}, MSE:
    {mse_lasso:.4f}")

print(f"Ridge Regression - Best Alpha: {ridge_grid.best_params_
    ['alpha']}")
print(f"Ridge Regression - R² Score: {r2_ridge:.4f}, MSE:
    {mse_ridge:.4f}")

# Plot Actual vs Predicted Prices
plt.figure(figsize=(12,5))

plt.subplot(1,2,1)
```

OXFORD

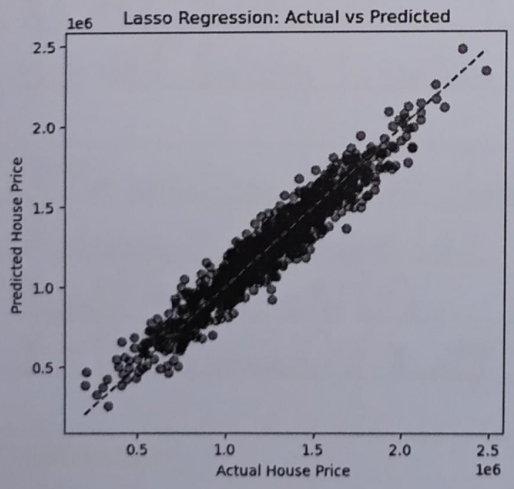
```
plt.scatter(y_test, y_pred_ridge, color='green', alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max
    ()], color='red', linestyle='dashed')
plt.xlabel("Actual House Price")
plt.ylabel("Predicted House Price")
plt.title("Ridge Regression: Actual vs Predicted")
plt.show()
```

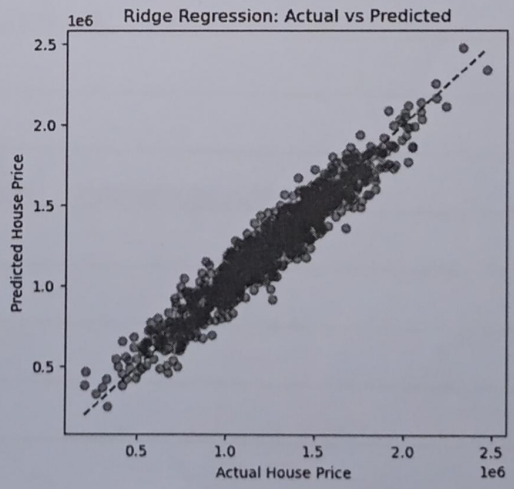
	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	\
0	79545.458574	5.682861	7.009188	
1	79248.642455	6.002900	6.730821	
2	61287.067179	5.865890	8.512727	
3	63345.240046	7.188236	5.586729	
4	59982.197226	5.040555	7.839388	

	Avg. Area Number of Bedrooms	Area Population	Price	\
0	4.09	23086.800503	1.059034e+06	
1	3.09	40173.072174	1.505891e+06	
2	5.13	36882.159400	1.058988e+06	
3	3.26	34310.242831	1.260617e+06	
4	4.23	26354.109472	6.309435e+05	

	Address
0	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	188 Johnson Views Suite 079\nLake Kathleen, CA...
2	9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3	USS Barnett\nFPO AP 44820
4	USNS Raymond\nFPO AE 09386

```
Avg. Area Income                float64
Avg. Area House Age             float64
Avg. Area Number of Rooms       float64
Avg. Area Number of Bedrooms    float64
Area Population                 float64
Price                           float64
Address                          object
dtype: object
Lasso Regression - Best Alpha: 0.1
Lasso Regression - R² Score: 0.9180, MSE: 10089007626.9052
Ridge Regression - Best Alpha: 1.0
Ridge Regression - R² Score: 0.9180, MSE: 10089005431.7701
```





DATE 17/3/25 | PAGE NO. 12 | EXPT. NO. 3

3) Perform linear regression with one feature using gradient descent (without using library function) to predict the salary of an employee based on the feature YearsExperience. Use hyper-parameter tuning for the best result. Plot the hypothesis function and the data points after each epoch. Evaluate the accuracy of the models by computing relevant performance metrics, including the R^2 value.
Dataset: salary_dataset.csv

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score

# Load dataset
df = pd.read_csv('salary_data.csv')

# Extract feature (YearsExperience) and target (Salary)
X = df['YearsExperience'].values
y = df['Salary'].values

# Normalize X for faster convergence
X_mean = np.mean(X)
X_std = np.std(X)
X = (X - X_mean) / X_std
```

LOKENATH®

DATE 17/3/25 | PAGE NO. 13 | EXPT. NO. 3

```
# Add bias term (X0 = 1)
X = np.c_[np.ones(X.shape[0]), X]

# Initialize parameters (theta0, theta1)
theta = np.zeros(2)

# Hyperparameters
learning_rate = 0.01
epochs = 100

# Number of training examples
m = len(y)

# Cost function history
cost_history = []

# Gradient Descent
for epoch in range(epochs):
    # Compute predictions
    y_pred = X.dot(theta)

    # Compute error
    error = y_pred - y

    # Compute gradients
    gradients = (1/m) * X.T.dot(error)
```

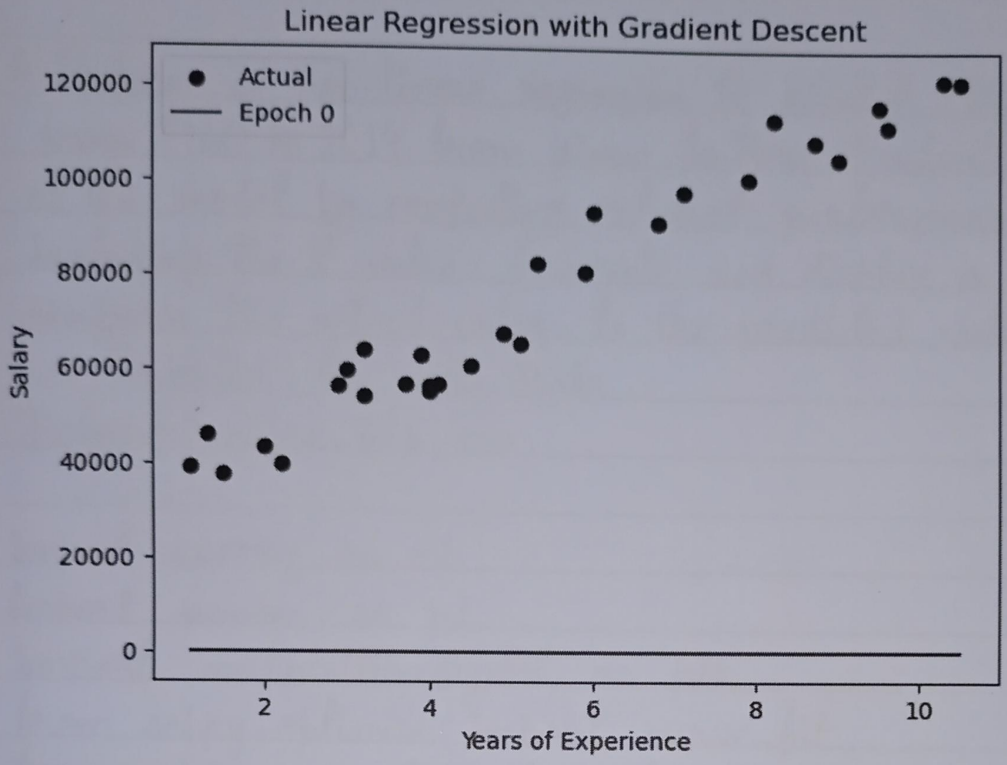
LOKENATH®

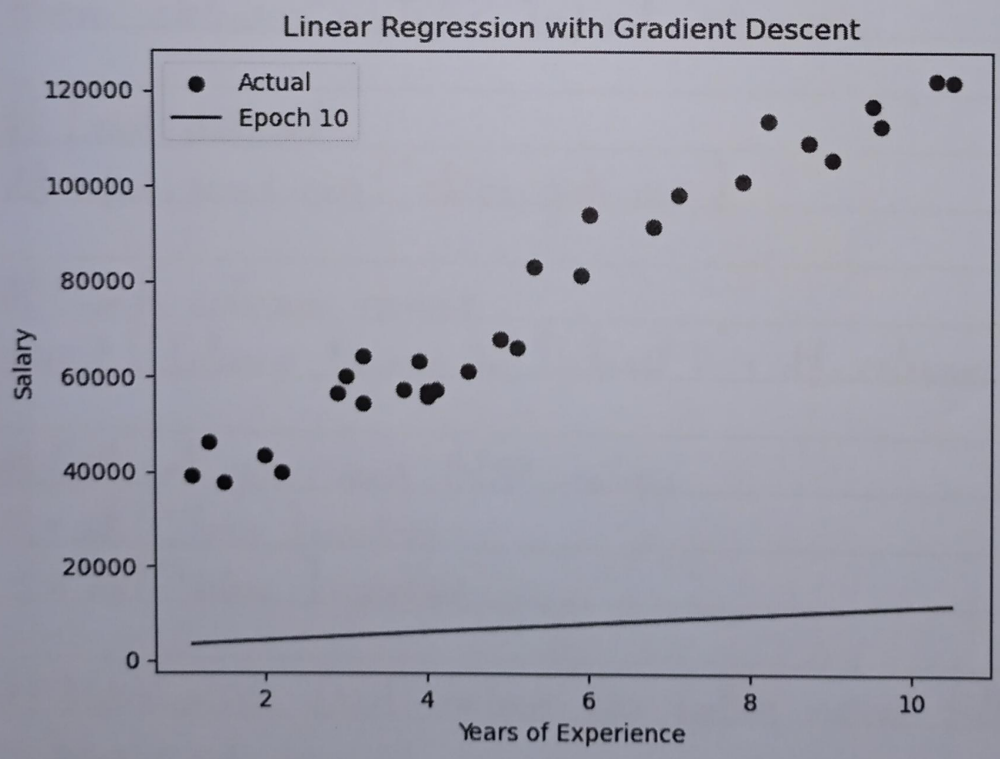
DATE 17/3/25 | PAGE NO. 14 | EXPT. NO. 3

```
#Update parameters
theta -= learning_rate * gradients

#Compute cost (Mean Squared Error)
cost = (1/(2*m)) * np.sum(error**2)
cost_history.append(cost)

#Plot regression line every 10 epochs
if epoch % 10 == 0:
    plt.scatter(df['YearsExperience'], y, color='blue',
                label='Actual')
    plt.plot(df['YearsExperience'], y_pred, color='red',
             label=f'Epoch {epoch}')
    plt.xlabel('Years of Experience')
    plt.ylabel('Salary')
    plt.title('Linear Regression with Gradient Descent')
    plt.legend()
    plt.show()

#Final model predictions
y_pred_final = X.dot(theta)

#Compute R^2 Score
r2 = r2_score(y, y_pred_final)

print(f"Final Parameters: Theta0 = {theta[0]:.4f}, Theta1 =
```

LOKENATH®

```
{theta[1]:.4f}")
print(f"Final R² Score: {r2:.4f}")

#Plot Cost Function Convergence
plt.plot(range(epochs), cost_history, color='green')
plt.xlabel('Epochs')
plt.ylabel('Cost')
plt.title('Cost Function Convergence')
plt.show()
```


Linear Regression with Gradient Descent
Actual
Epoch 0
120000
100000
80000
60000
40000
20000
0
Salary
2
4
6
8
10
Years of Experience


Linear Regression with Gradient Descent
Actual
Epoch 10
120000
100000
80000
60000
40000
20000
0
Salary
2
4
6
8
10
Years of Experience

DATE 17/3/25 | PAGE NO. 16 | EXPT. NO. 4

4) Perform a non-linear regression to predict China's GDP from 1960 to 2014 from given features. Evaluate the quality of the model by computing relevant performance metrics, including the R^2 value. Generate and display a plot that compares the actual values to the predicted values (Actual vs Predicted) for both tasks.
Dataset: china_gdp.csv

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit
from sklearn.metrics import r2_score

# Load dataset
df = pd.read_csv('china_gdp.csv')

#Check column names
print("Column Names in Dataset:", df.columns)

# Extract year and GDP values
X = df['Year'].values
y = df['Value'].values

# Normalize GDP values for better curve fitting
y_max = np.max(y)
```

LOKENATH®

DATE 18/3/25 | PAGE NO. 17 | EXPT. NO. 4

```
y = y / y_max

# Visualizing the dataset
plt.figure(figsize=(10,5))
plt.scatter(X, y, color='blue', label='Actual GDP
            (Normalized)')
plt.xlabel('Year')
plt.ylabel('GDP (Normalized)')
plt.title('China GDP Growth from 1960 to 2014')
plt.legend()
plt.show()

# Define Logistic Growth Function
def logistic_function(x, a, b, c):
    return c/(1+np.exp(-a*(x-b)))

# Provide initial parameter guesses to help curve_fit()
initial_guesses=[0.1, 2000, 1]

# Curve Fitting using scipy.optimize.curve_fit()
popt, _ = curve_fit(logistic_function, X, y, p0=initial_
                    guesses, maxfev=50000)

# Extract optimized parameters
a_opt, b_opt, c_opt = popt
```

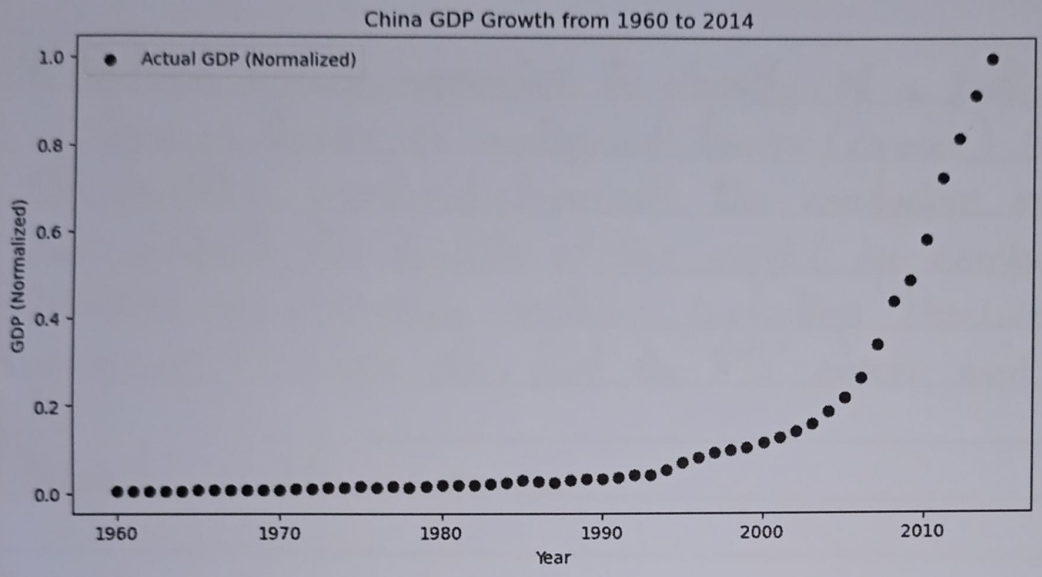
LOKENATH®

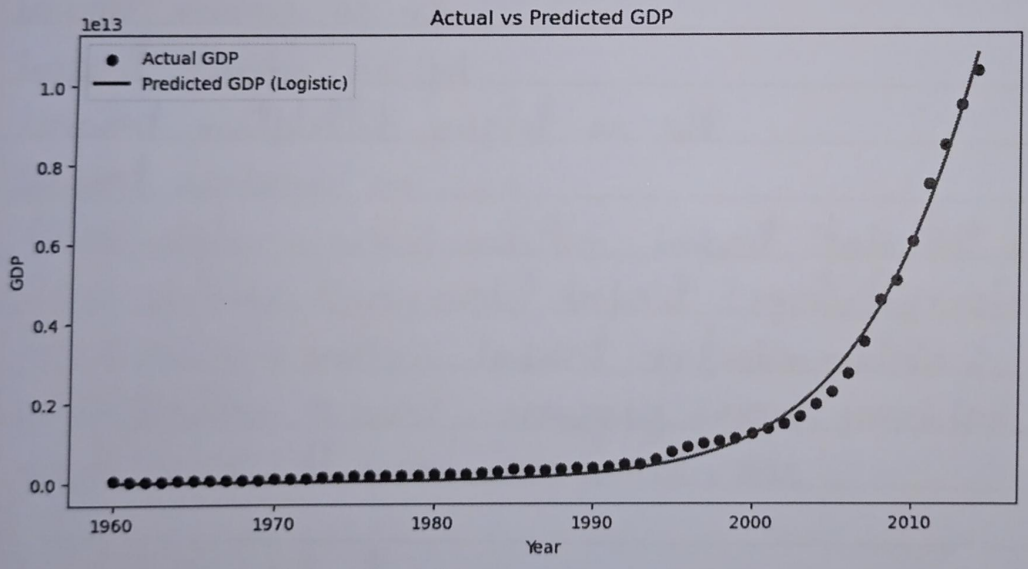
DATE 18/3/25 | PAGE NO. 18 | EXPT. NO. 4

```
# Generate predictions
y_pred = logistic_function(X, a_opt, b_opt, c_opt)

# Denormalize predictions
y_pred = y_pred * y_max

# Compute R^2 Score
r2 = r2_score(df['Value'], y_pred)

#Plot Actual vs Predicted GDP
plt.figure(figsize=(10,5))
plt.scatter(df['Year'], df['Value'], color='blue', label=
            'Actual GDP')
plt.plot(df['Year'], y_pred, color='red', linewidth=2,
         label='Predicted GDP (Logistic)')
plt.xlabel('Year')
plt.ylabel('GDP')
plt.title('Actual vs Predicted GDP')
plt.legend()
plt.show()

print(f"Optimized Parameters: a={a_opt:.4f}, b={b_opt=.4
      f}, c={c_opt:.4f}")
print(f"Final R^2 Score: {r2:.4f}")
```

LOKENATH®

```
Column Names in Dataset: Index(['Year', 'Value'], dtype='object')
```






```
Optimized Parameters: a=0.1752, b=2021.3700, c=4.8272
Final R² Score: 0.9938
```

DATE 18/3/25 | PAGE NO. 19 | EXPT. NO. 5

5) Perform logistic regression to classify if a patient has a benign tumor or malignant tumor (cancer) based on the features provided. Generate the confusion matrix and evaluate the quality of the model by computing relevant performance metrics including Precision, Recall, accuracy, F1-Score etc. Plot the ROC curve and calculate AUC.

Dataset : samples_cancer.csv

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix,
classification_report, accuracy_score, precision_score,
recall_score, f1_score, roc_curve, auc

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

# Display dataset info
print("Dataset Info:")
print(df.info())
```

DATE 18/3/25 | PAGE NO. 20 | EXPT. NO. 5

```
# Drop 'ID' column as it's not relevant for classification
df.drop(columns=['ID'], inplace=True)

# Convert 'BareNuc' column to numeric (if it contains '?' replace with NaN)
df['BareNuc'] = pd.to_numeric(df['BareNuc'], errors='coerce')

# Fill missing values with median of the column
df.fillna(df.median(), inplace=True)

# Define features and target variable
X = df.drop(columns=['Class'])
y = df['Class'].map({2:0, 4:1})

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

# Train Logistic Regression Model
model = LogisticRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)
```

LOKENATH®

DATE 18/3/25 | PAGE NO. 21 | EXPT. NO. 5

```
y_prob = model.predict_proba(X_test)[:,1]

#Compute Performance Metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

#Print Classification Report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

#Plot Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=["Benign","Malignant"],
            yticklabels=["Benign","Malignant"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()

#Plot ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)
```

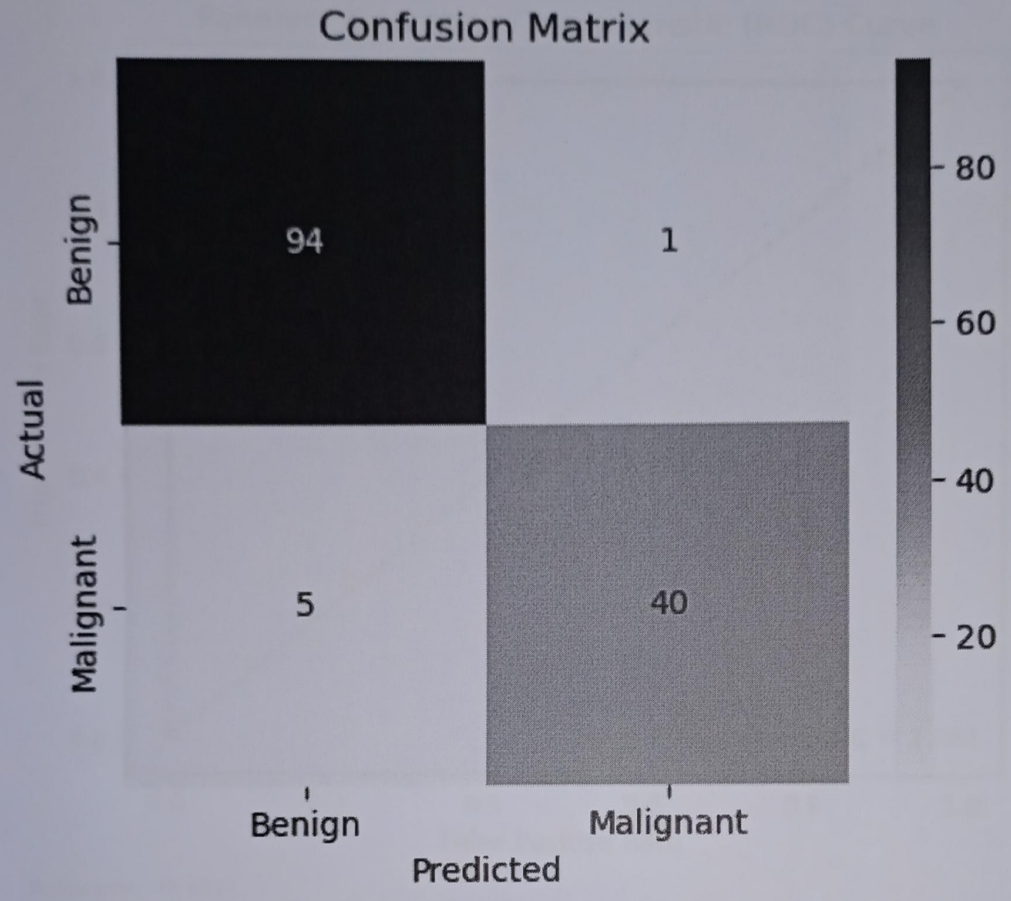
LOKENATH®

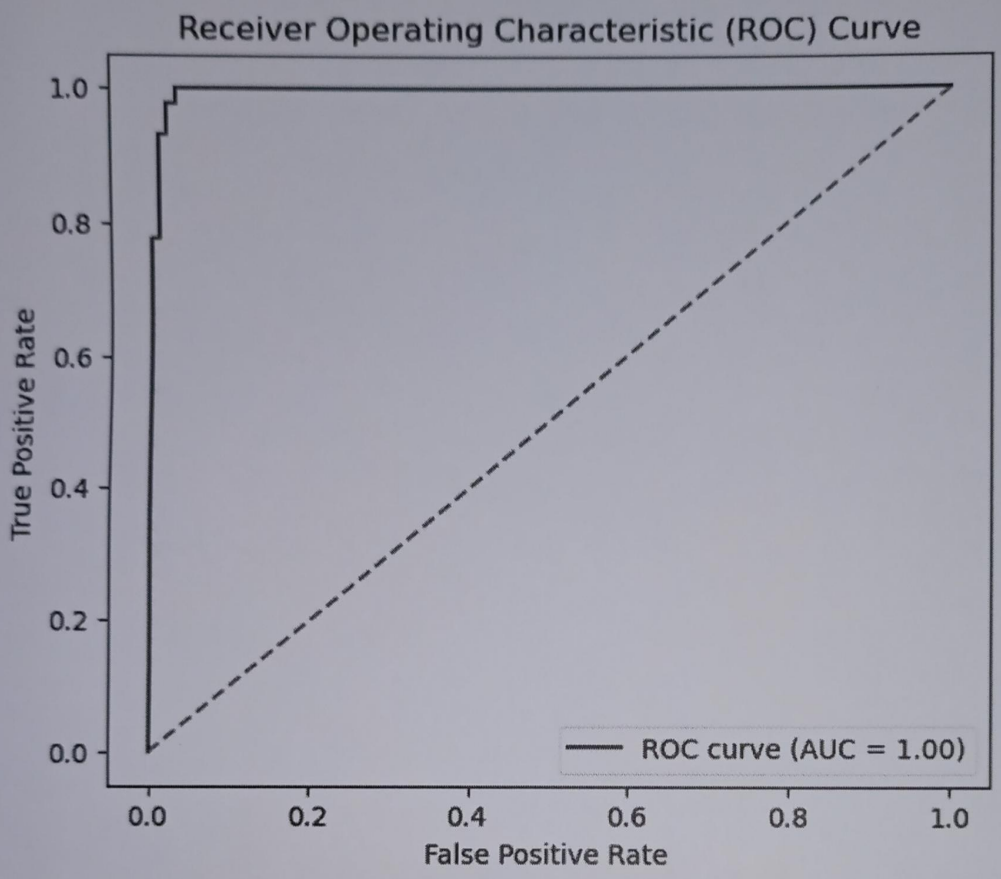
DATE 18/3/25 | PAGE NO. 22 | EXPT. NO. 5

```
plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, color='blue', label=f'ROC curve (AUC
        ={roc_auc:.2f})')
plt.plot([0,1],[0,1], color='gray', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()

# Print Evaluation Scores
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")
print(f"AUC Score: {roc_auc:.4f}")
```

LOKENATH®

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 699 entries, 0 to 698
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   ID           699 non-null    int64
 1   Clump        699 non-null    int64
 2   UnifSize     699 non-null    int64
 3   UnifShape    699 non-null    int64
 4   MargAdh      699 non-null    int64
 5   SingEpiSize  699 non-null    int64
 6   BareNuc      699 non-null    object
 7   BlandChrom   699 non-null    int64
 8   NormNucl     699 non-null    int64
 9   Mit          699 non-null    int64
 10  Class        699 non-null    int64
dtypes: int64(10), object(1)
memory usage: 60.2+ KB
None

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.99      0.97        95
           1       0.98      0.89      0.93        45

    accuracy                           0.96       140
   macro avg       0.96      0.94      0.95       140
weighted avg       0.96      0.96      0.96       140
```


Confusion Matrix
94
1
5
40
Benign
Malignant
Actual
Benign
Malignant
Predicted
80
60
40
20




```
Accuracy: 0.9571
Precision: 0.9756
Recall: 0.8889
F1 Score: 0.9302
AUC Score: 0.9967
```

DATE 12/4/2025 | PAGE NO. 1

Lab Assignment 2

EXPT. NO. 6

6) Using KNN algorithm, predict which category a customer belongs to on the basis of the data provided by a telecommunications firm. Find the accuracy of the KNN algorithm in predicting the category of a customer.
Dataset: teleCust.csv

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report

# Load the dataset
df = pd.read_csv("teleCust.csv")

# Display basic info
print(df.head())
print(df.info())

# Features and labels
X = df.drop("custcat", axis=1)
y = df["custcat"]

# Normalize the data
scaler = StandardScaler()
```

LOKENATH®

```
X_scaled = scaler.fit_transform(X)

# Split dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split
(X_scaled, y, test_size = 0.2, random_state = 42)

# Train KNN model
k = 4
knn = KNeighborsClassifier(n_neighbors = k)
knn.fit(X_train, y_train)

# Predict
y_pred = knn.predict(X_test)

# Evaluate
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of KNN (k={k}): {accuracy:.4f}")
print("\nClassification Report:\n", classification_report
(y_test, y_pred))
```

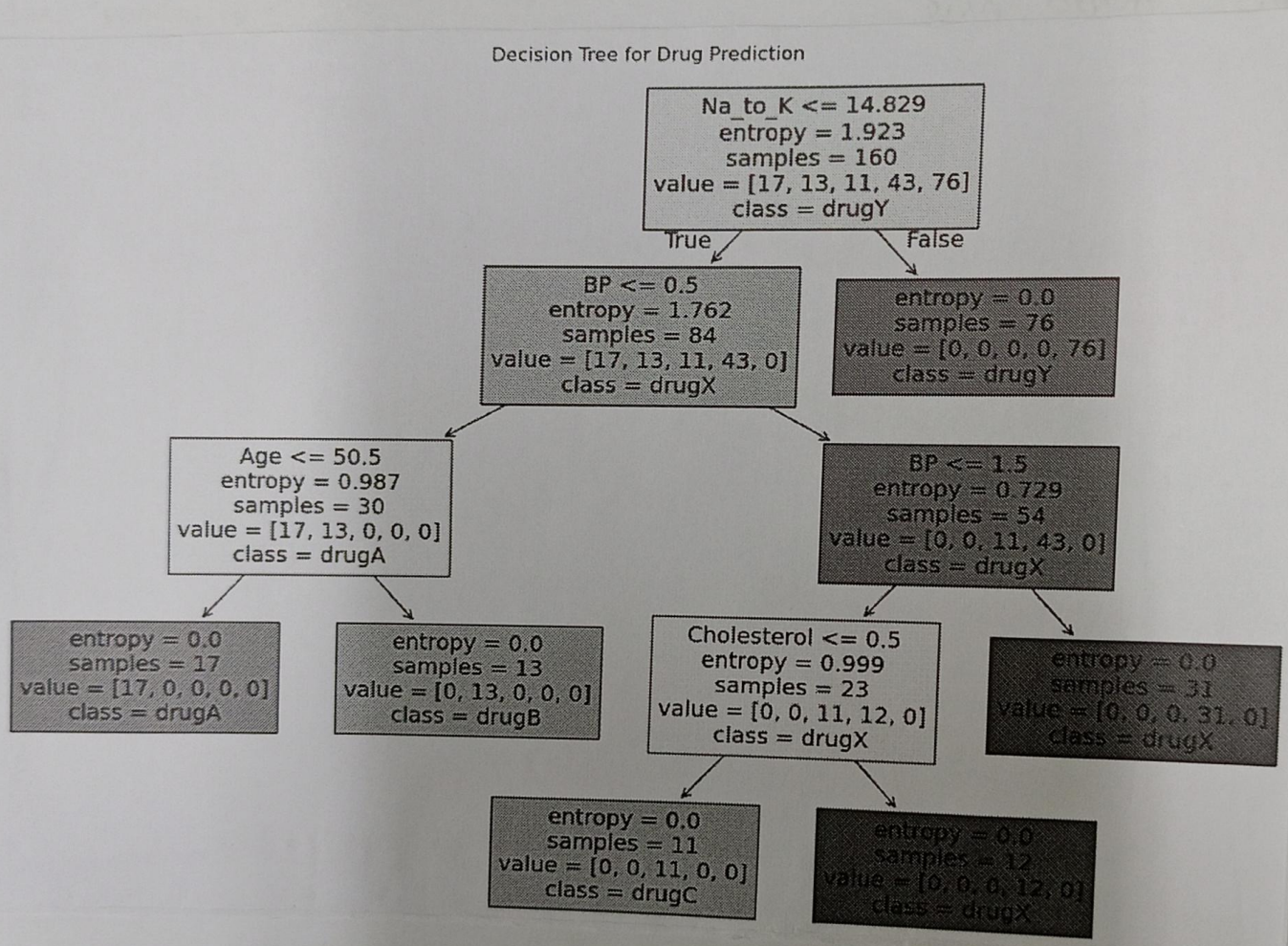
```
   region  tenure  age  marital  address  income  ed  employ  retire  gender  \
0       2      13   44        1        9    64.0   4       5     0.0       0
1       3      11   33        1        7   136.0   5       5     0.0       0
2       3      68   52        1       24   116.0   1      29     0.0       1
3       2      33   33        0       12    33.0   2       0     0.0       1
4       2      23   30        1        9    30.0   1       2     0.0       0

   reside  custcat
0       2        1
1       6        4
2       2        3
3       1        1
4       4        3
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 12 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   region   1000 non-null   int64
 1   tenure   1000 non-null   int64
 2   age      1000 non-null   int64
 3   marital  1000 non-null   int64
 4   address  1000 non-null   int64
 5   income   1000 non-null   float64
 6   ed       1000 non-null   int64
 7   employ   1000 non-null   int64
 8   retire   1000 non-null   float64
 9   gender   1000 non-null   int64
 10  reside   1000 non-null   int64
 11  custcat  1000 non-null   int64
dtypes: float64(2), int64(10)
memory usage: 93.9 KB
None
Accuracy of KNN (k=4): 0.3250
```

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

           1       0.37      0.48      0.42        60
           2       0.15      0.13      0.14        39
           3       0.32      0.31      0.31        55
           4       0.40      0.30      0.35        46

    accuracy                           0.33       200
   macro avg       0.31      0.31      0.30       200
weighted avg       0.32      0.33      0.32       200
```

7) Using Decision Tree algorithm, predict which drug among drug A, drug B, drug C, drug X and drug Y should be given to a patient. Find the accuracy of the decision tree in predicting the correct drug for the patient.
Dataset : drug.csv

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_
                                                report

from sklearn import tree
import matplotlib.pyplot as plt.

# Load the dataset
df = pd.read_csv("drug.csv")

# Display initial info
print(df.head())
print(df.info())

# Encode categorical variables
le_sex = LabelEncoder()
le_bp = LabelEncoder()
le_chol = LabelEncoder()
```

LOKENATH®


Decision Tree for Drug Prediction
Na_to_K <= 14.829
entropy = 1.923
samples = 160
value = [17, 13, 11, 43, 76]
class = drugY
True
False
BP <= 0.5
entropy = 1.762
samples = 84
value = [17, 13, 11, 43, 0]
class = drugX
entropy = 0.0
samples = 76
value = [0, 0, 0, 0, 76]
class = drugY
Age <= 50.5
entropy = 0.987
samples = 30
value = [17, 13, 0, 0, 0]
class = drugA
BP <= 1.5
entropy = 0.729
samples = 54
value = [0, 0, 11, 43, 0]
class = drugX
entropy = 0.0
samples = 17
value = [17, 0, 0, 0, 0]
class = drugA
entropy = 0.0
samples = 13
value = [0, 13, 0, 0, 0]
class = drugB
Cholesterol <= 0.5
entropy = 0.999
samples = 23
value = [0, 0, 11, 12, 0]
class = drugX
entropy = 0.0
samples = 31
value = [0, 0, 0, 31, 0]
class = drugX
entropy = 0.0
samples = 11
value = [0, 0, 11, 0, 0]
class = drugC
entropy = 0.0
samples = 12
value = [0, 0, 0, 12, 0]
class = drugX

```
df["Sex"] = le_sex.fit_transform(df["Sex"])
df["BP"] = le_bp.fit_transform(df["BP"])
df["Cholesterol"] = le_chol.fit_transform(df["Cholesterol"])

# Features and target
X = df[["Age", "Sex", "BP", "Cholesterol", "Na_to_K"]]
y = df["Drug"]

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

# Train the Decision Tree model
model = DecisionTreeClassifier(criterion = "entropy",
random_state = 42)

# Predict
y_pred = model.predict(X_test)

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of Decision Tree : {accuracy:.4f}")
print("\nClassification Report:\n", classification_report
(y_test, y_pred))
```

LOKENATH®

```
   Age Sex      BP Cholesterol  Na_to_K   Drug
0   23   F    HIGH        HIGH   25.355  drugY
1   47   M     LOW        HIGH   13.093  drugC
2   47   M     LOW        HIGH   10.114  drugC
3   28   F  NORMAL        HIGH    7.798  drugX
4   61   F     LOW        HIGH   18.043  drugY
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Age          200 non-null    int64
 1   Sex          200 non-null    object
 2   BP           200 non-null    object
 3   Cholesterol  200 non-null    object
 4   Na_to_K      200 non-null    float64
 5   Drug         200 non-null    object
dtypes: float64(1), int64(1), object(4)
memory usage: 9.5+ KB
None
Accuracy of Decision Tree: 1.0000

Classification Report:
              precision    recall  f1-score   support

       drugA       1.00      1.00      1.00         6
       drugB       1.00      1.00      1.00         3
       drugC       1.00      1.00      1.00         5
       drugX       1.00      1.00      1.00        11
       drugY       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
```

DATE 13/4/2025 | PAGE NO. 5 | EXPT. NO. 8

8) Using Naive Bayes algorithms, predict if a person is diabetic or not, based on the features provided. Find accuracy and F1-Scores of both algorithms.
Dataset : pima-indians-diabetes.data.csv

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn.metrics import accuracy_score, f1_score,
classification_report

#Column names as per UCI dataset description
columns = ["Pregnancies", "Glucose", "BloodPressure",
    "SkinThickness", "Insulin", "BMI", "DiabetesPedigreeFunction",
    "Age", "Outcome"]

#Load the data
df = pd.read_csv("pima-indians-diabetes.data.csv", header=None,
    names = columns)

#Check data
print(df.head())
print(df.info())

#Features and target
X = df.drop("Outcome", axis=1)
```

LOKENATH®

```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
None
Gaussian Naive Bayes
Accuracy: 0.7662
F1 Score: 0.6842
```

DATE 13/4/2025 | PAGE NO. 6 | EXPT. NO. 8

```
y = df["Outcome"]

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

# Gaussian Naive Bayes
gnb = GaussianNB()
gnb.fit(X_train, y_train)

# Predict
y_pred_gnb = gnb.predict(X_test)

# Evaluation
accuracy_gnb = accuracy_score(y_test, y_pred_gnb)
f1_gnb = f1_score(y_test, y_pred_gnb)

print("Gaussian Naive Bayes")
print(f"Accuracy: {accuracy_gnb:.4f}")
print(f"F1 Score: {f1_gnb:.4f}")
print(classification_report(y_test, y_pred_gnb))
```

	precision	recall	f1-score	support
0	0.83	0.80	0.81	99
1	0.66	0.71	0.68	55
accuracy			0.77	154
macro avg	0.75	0.75	0.75	154
weighted avg	0.77	0.77	0.77	154

Multinomial Naive Bayes
Accuracy: 0.6623
F1 Score: 0.5185

	precision	recall	f1-score	support
0	0.73	0.75	0.74	99
1	0.53	0.51	0.52	55
accuracy			0.66	154
macro avg	0.63	0.63	0.63	154
weighted avg	0.66	0.66	0.66	154

DATE 13/4/2025 | PAGE NO. 7 | EXPT. NO. 9

9) Using SVM algorithm, predict if a patient has a benign tumor or malignant tumor (cancer) based on the features provided. Use the following kernel for the SVM algorithm:
a) Linear b) Polynomial c) RBF d) Sigmoid
Find the following metrics for each of the SVM algorithms:
1) Accuracy 2) Recall 3) Precision 4) F1-Score
5) Jaccard Score 6) Error rates 7) Confusion Matrix
Compare all four SVM models using an ROC curve.
Dataset: samples_cancer.csv

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import (accuracy_score, recall_score,
precision_score, jaccard_score, confusion_matrix, roc_curve,
auc)
from sklearn.preprocessing import LabelEncoder,
StandardScaler
import seaborn as sns

#Load dataset
df = pd.read_csv("samples_cancer.csv")
```

LOKENATH®

DATE 13/4/2025 | PAGE NO. 8 | EXPT. NO. 9

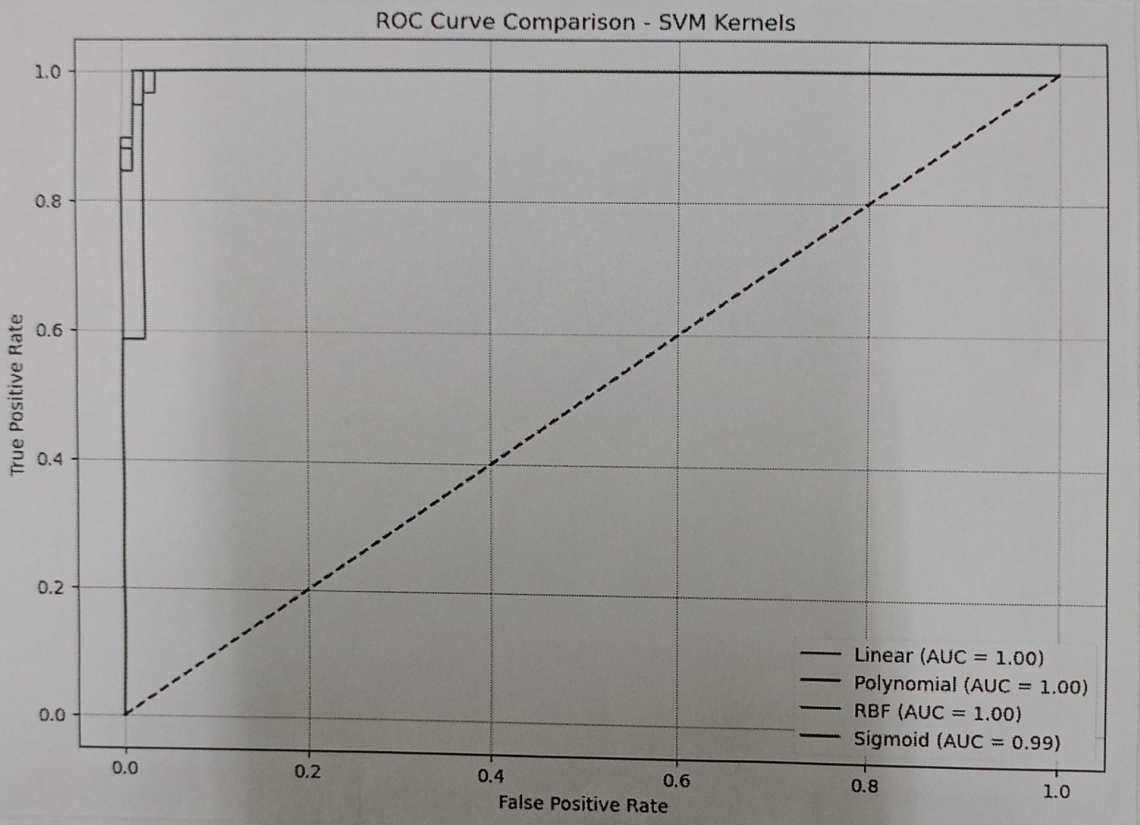
```
# Drop ID column
df = df.drop("ID", axis=1)

# Handle non-numeric 'BareNuc' if needed
df = df.replace('?', np.nan).dropna()
df["BareNuc"] = df["BareNuc"].astype(int)

# Features and labels
X = df.drop("Class", axis=1)
y = df["Class"].replace({2:0, 4:1})

# Normalize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

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

def evaluate_model(model, name, color):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_prob = model.decision_function(X_test)

    acc = accuracy_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
```

LOKENATH®

```
--- Linear Kernel ---
Accuracy:        0.9708
Recall:          0.9483
Precision:       0.9821
Jaccard Score:   0.9322
Error Rate:      0.0292
Confusion Matrix:
[[78  1]
 [ 3 55]]

--- Polynomial Kernel ---
Accuracy:        0.9124
Recall:          0.7931
Precision:       1.0000
Jaccard Score:   0.7931
Error Rate:      0.0876
Confusion Matrix:
[[79  0]
 [12 46]]

--- RBF Kernel ---
Accuracy:        0.9635
Recall:          0.9483
Precision:       0.9649
Jaccard Score:   0.9167
Error Rate:      0.0365
Confusion Matrix:
[[77  2]
 [ 3 55]]

--- Sigmoid Kernel ---
Accuracy:        0.9635
Recall:          0.9483
Precision:       0.9649
Jaccard Score:   0.9167
Error Rate:      0.0365
Confusion Matrix:
[[77  2]
 [ 3 55]]
```

```
prec = precision_score(y_test, y_pred)
jaccard = jaccard_score(y_test, y_pred)
err = 1 - acc
cm = confusion_matrix(y_test, y_pred)

#ROC curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

print(f"--- {name} Kernel ---")
print(f"Accuracy : {acc:.4f}")
print(f"Recall : {rec:.4f}")
print(f"Precision : {prec:.4f}")
print(f"Jaccard Score : {jaccard:.4f}")
print(f"Error Rate : {err:.4f}")
print(f"Confusion Matrix :\n{cm}\n")
plt.plot(fpr, tpr, label=f"{name} (AUC = {roc_auc:.2f})",
color = color)
return

plt.figure(figsize = (10, 7))

evaluate_model(SVC(kernel='linear', probability = True),
"Linear", "blue")
evaluate_model(SVC(kernel = 'poly', degree = 3, probability =
True), "Polynomial", "green")
```

LOKENATH®


ROC Curve Comparison - SVM Kernels
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Linear (AUC = 1.00)
Polynomial (AUC = 1.00)
RBF (AUC = 1.00)
Sigmoid (AUC = 0.99)

```
evaluate_model(SVC(kernel='rbf', probability=True),
"RBF", "red")
evaluate_model(SVC(kernel='sigmoid', probability=True),
"Sigmoid", "purple")

# Plot ROC Curve
plt.plot([0,1],[0,1],'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve Comparison - SVM Kernels")
plt.legend()
plt.grid(True)
plt.show()
```

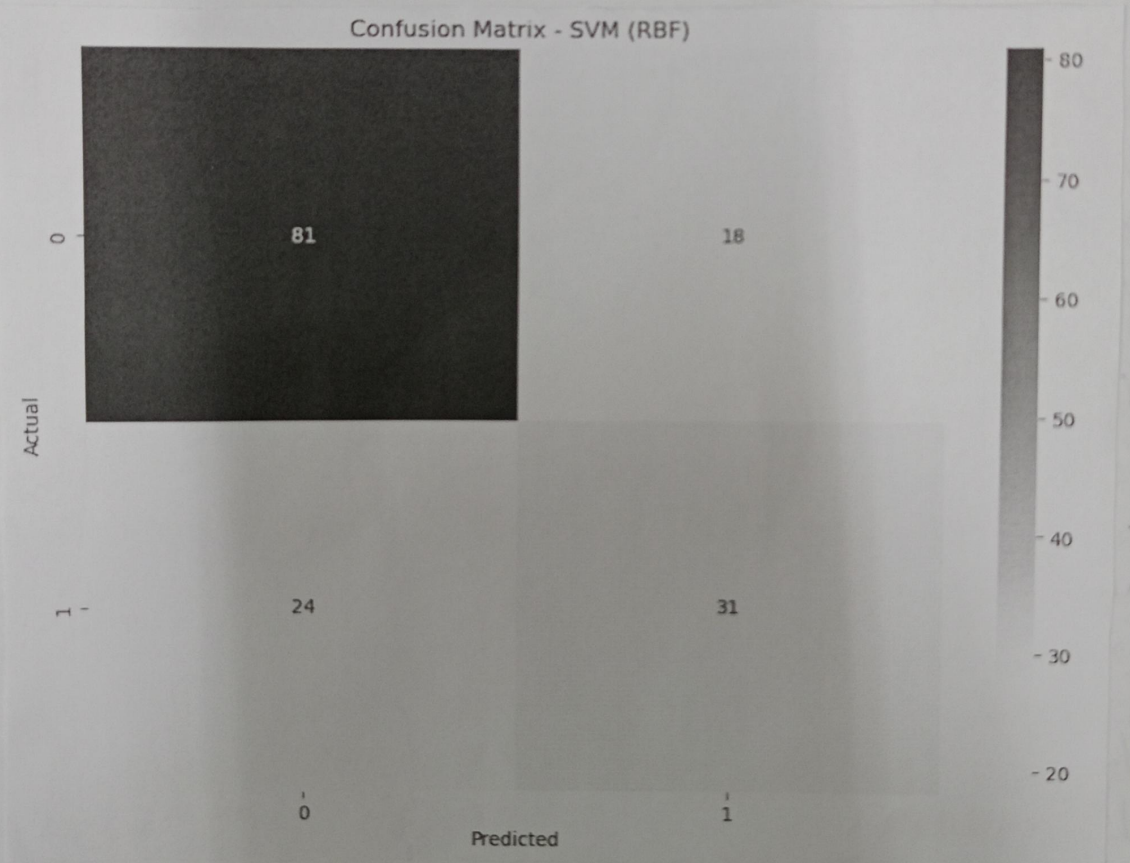
DATE 14/4/2025 | PAGE NO. 11 | EXPT. NO. 10

10) Applying SVM, Naive Bayes, Decision tree and KNN predict diabetes based on features set. Compare the four classification algorithms with performance metrics such as accuracy, recall, precision, F1-score. Also design the heat map confusion matrix for above algorithms and construct ROC curve for comparison.
Dataset: pima-indians-diabetes.data.csv

```
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.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_
score, recall_score, f1_score, confusion_matrix, roc_curve,
auc
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier

#Load dataset with column names
columns = ["Pregnancies", "Glucose", "BloodPressure",
    "SkinThickness", "Insulin", "BMI", "DiabetesPedigreeFunction",
    "Age", "Outcome"]
```

LOKENATH®

```
--- SVM (RBF) ---
Accuracy:  0.7273
Recall:    0.5636
Precision: 0.6327
F1 Score:  0.5962
Confusion Matrix:
[[81 18]
 [24 31]]
```

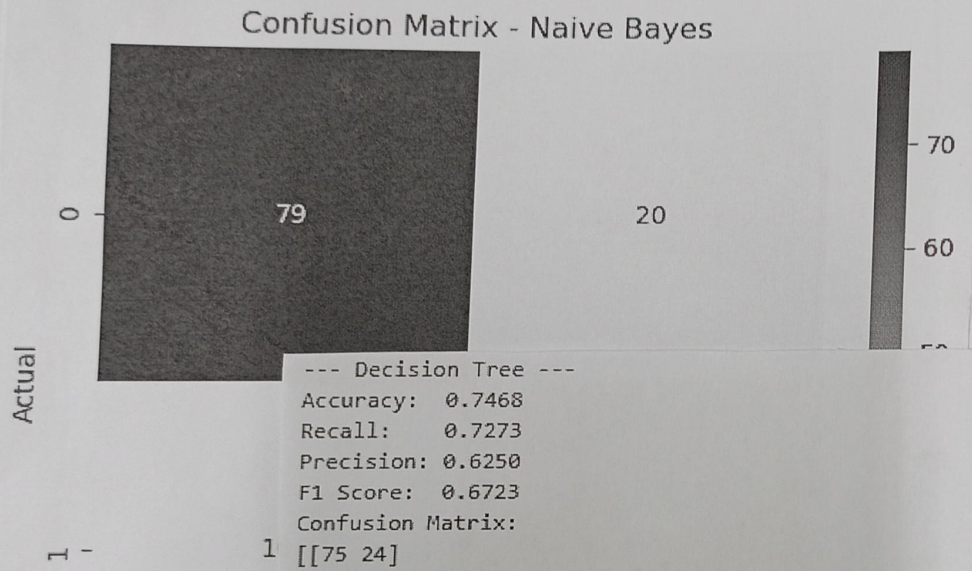


DATE 14/4/2025 | PAGE NO. 12 | EXPT. NO. 10

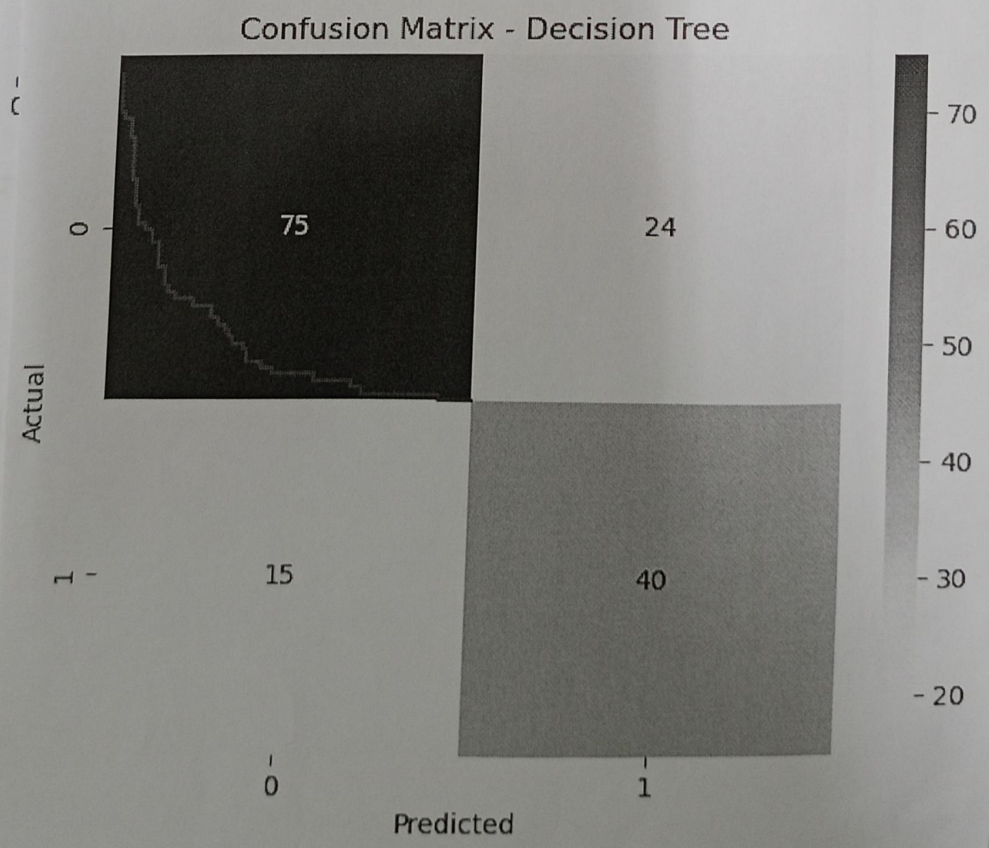
```
df = pd.read_csv("pima-indians-diabetes.data.csv", names = columns)

# Split features and target
X = df.drop("Outcome", axis = 1)
y = df["Outcome"]

# Normalize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

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

def evaluate_model(name, model, X_train, X_test, y_train, y_test, color):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    if hasattr(model, "predict_proba"):
        y_score = model.predict_proba(X_test)[:,1]
    else:
        y_score = model.decision_function(X_test)

    acc = accuracy_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
```

LOKENATH®

```
--- Naive Bayes ---
Accuracy:  0.7662
Recall:    0.7091
Precision: 0.6610
F1 Score:  0.6842
Confusion Matrix:
[[79 20]
 [16 39]]
```



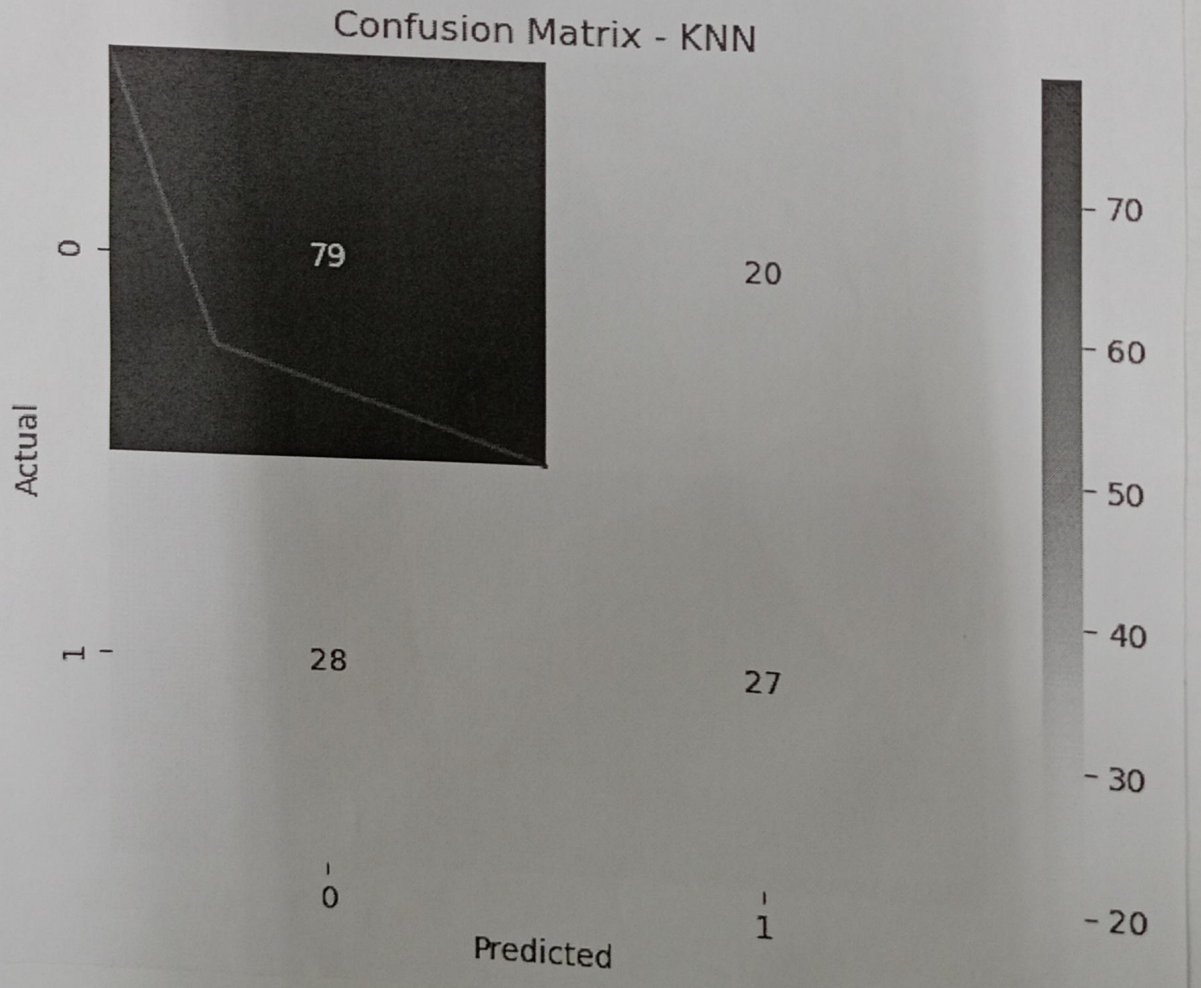

```
--- Decision Tree ---
Accuracy:  0.7468
Recall:    0.7273
Precision: 0.6250
F1 Score:  0.6723
Confusion Matrix:
[[75 24]
 [15 40]]
```

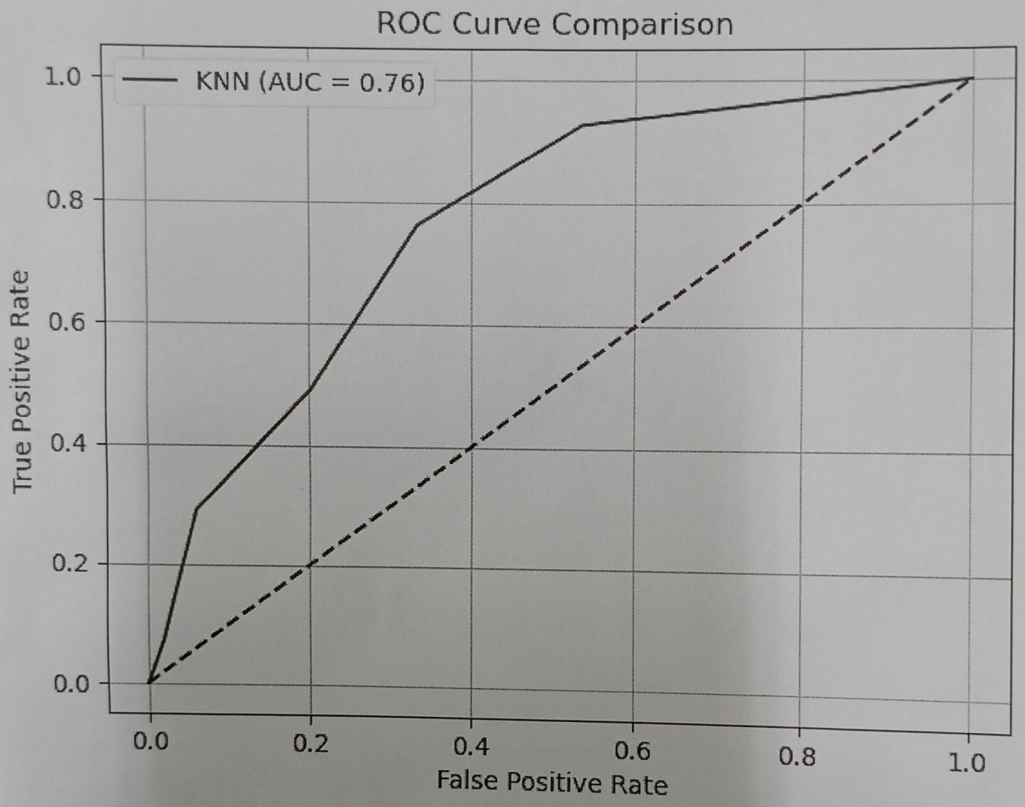


```
prec = precision_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)

print(f"--- {name} ---")
print(f"Accuracy: {acc:.4f}")
print(f"Recall: {rec:.4f}")
print(f"Precision: {prec:.4f}")
print(f"F1 Score: {f1:.4f}")
print(f"Confusion Matrix:\n{cm}\n")

#Plot Confusion Matrix Heatmap
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title(f"Confusion Matrix - {name}")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

#ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_score)
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, label=f"{name} (AUC = {roc_auc
:.2f})", color=color)

return {"model": name, "accuracy": acc,
"recall": rec, "precision": prec, "f1_score": f1}
```

LOKENATH®

```
--- KNN ---
Accuracy:  0.6883
Recall:    0.4909
Precision: 0.5745
F1 Score:  0.5294
Confusion Matrix:
[[79 20]
 [28 27]]
```





	model	accuracy	recall	precision	f1_score
0	SVM (RBF)	0.727273	0.563636	0.632653	0.596154
1	Naive Bayes	0.766234	0.709091	0.661017	0.684211
2	Decision Tree	0.746753	0.727273	0.625000	0.672269
3	KNN	0.688312	0.490909	0.574468	0.529412

DATE 14/4/2025 | PAGE NO. 15 | EXPT. NO. 11

11) Design and train a network of perceptrons that computes the functionality of XOR.

```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import SGD

#XOR Inputs and Outputs
X = np.array([[0,0],[0,1],[1,0],[1,1]])
y = np.array([[0],[1],[1],[0]])

#Define the model
model = Sequential()
model.add(Dense(2, input_dim=2, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid'))

#Compile the model
model.compile(optimizer=SGD(learning_rate=0.1),
loss='binary_crossentropy', metrics=['accuracy'])

#Train the model
model.fit(X, y, epochs=10000, verbose=0)

#Evaluate and predict
print("\nFinal predictions:")
```

LOKENATH®

```
Final predictions:
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 190ms/step
Input: [0 0], Predicted Output: 0.0515, Rounded: 0.0
Input: [0 1], Predicted Output: 0.9150, Rounded: 1.0
Input: [1 0], Predicted Output: 0.9150, Rounded: 1.0
Input: [1 1], Predicted Output: 0.0945, Rounded: 0.0
```

DATE	PAGE NO.	EXPT. NO.
14/4/2025	16	11

```
predictions = model.predict(X)
for i, x in enumerate(X):
    print(f"Input: {x}, Predicted Output: {predictions
    [i][0]:.4f}, Rounded: {np.round(predictions[i][0])
    }")
```