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AI23331 FUNDAMENTALS OF MACHINE LEARNING LAB

Laboratory Record Notebook

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EXPT NO: 1 **A python program to implement univariate regression**

DATE: 23.08.2024 **bivariate regression and multivariate regression.**

AIM:

To write a python program to implement univariate regression, bivariate regression and multivariate regression.

PROCEDURE:

Implementing univariate, bivariate, and multivariate regression using the Iris dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
import numpy as np import pandas as pd import seaborn as sns

import matplotlib.pyplot as plt from
```

```
sklearn.model_selection import train_test_split from

sklearn.linear_model import LinearRegression from

sklearn.metrics import mean_squared_error, r2_score
```

Step 2: Load the Iris Dataset

The Iris dataset can be loaded and display the first few rows of the dataset .

```
# Load the Iris dataset iris = sns.load_dataset('iris')



# Display the first few rows of the dataset print(iris.head())
```

OUTPUT :

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

Step 3: Data Preprocessing

Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```
# Check for missing values   print(iris.isnull().sum())

# Display the basic statistical details   print(iris.describe())
```

OUTPUT :

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.057333      3.758000     1.199333
std        0.828066     0.435866      1.765298     0.762238
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000
```

Step 4: Univariate Regression

Univariate regression involves predicting one variable based on a single predictor.

4.1 : Select the Features

Choose one feature (e.g., sepal_length) and one target variable (e.g., sepal_width).

```
        X_uni = iris[['sepal_length']]           y_uni =
iris['sepal_width']
```

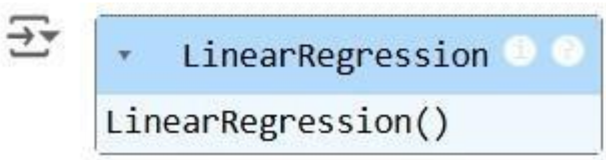
4.2 : Split the Data

Split the data into training and testing sets.
Fit the linear regression model on the training data.

```
X_uni_train, X_uni_test, y_uni_train, y_uni_test = train_test_split(X_uni,
y_uni, test_size=0.2, random_state=42)
```

4.3: Train the model

```
   uni_model = LinearRegression()
uni_model.fit(X_uni_train, y_uni_train)
```



4.4 : Make Predictions

Use the model to make predictions on the test data.

```
   y_uni_pred = uni_model.predict(X_uni_test)
```

4.5 : Evaluate the Model

Evaluate the model performance using metrics like Mean Squared Error (MSE) and R-squared.

```
   print(f'Univariate MSE: {mean_squared_error(y_uni_test, y_uni_pred)}')
print(f'Univariate R-squared: {r2_score(y_uni_test, y_uni_pred)}')
```

OUTPUT :

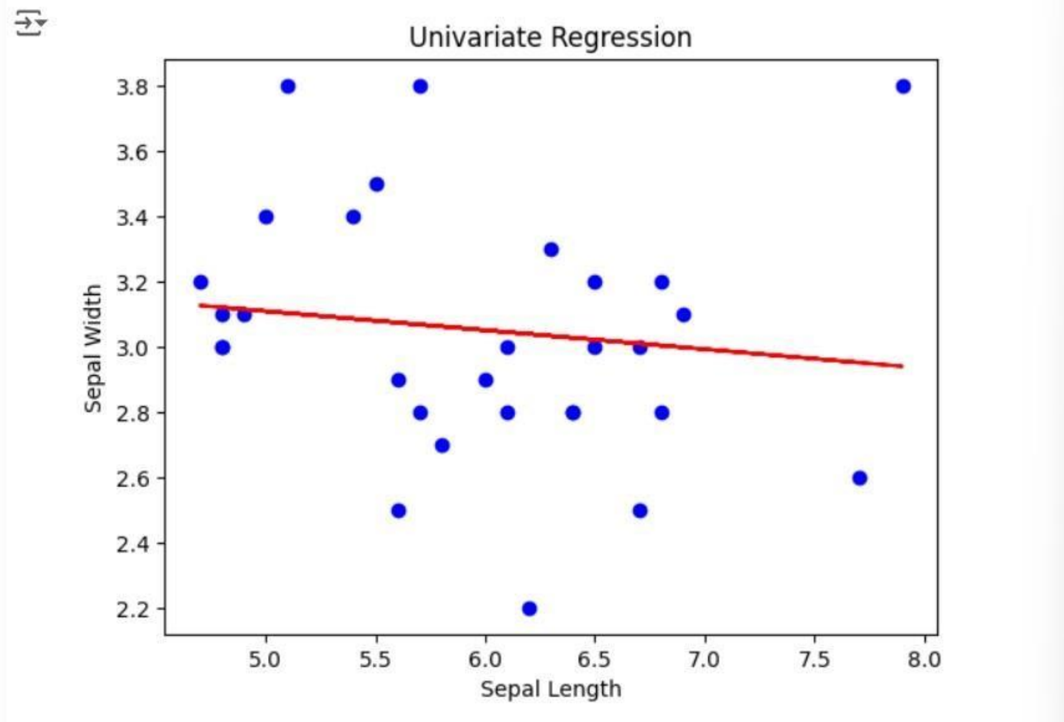
```
Univariate MSE: 0.13961895650579023
Univariate R-squared: 0.024098626473972984
```

4.6 : Visualize the Results

Visualize the relationship between the predictor and the target variable.

```
  plt.scatter(X_uni_test, y_uni_test, color='blue')
plt.plot(X_uni_test,  y_uni_pred,  color='red')
plt.xlabel('Sepal Length')    plt.ylabel('Sepal
Width')      plt.title('Univariate Regression')
plt.show()
```

OUTPUT :



Step 5 : Bivariate Regression

Bivariate regression involves predicting one variable based on two predictors.

5.1 : Select the Features

Choose two features (e.g., sepal_length, petal_length) and one target variable (e.g., sepal_width).

```
X_bi = iris[['sepal_length', 'petal_length']] y_bi

= iris['sepal_width']
```

5.2 : Split the Data

Split the data into training and testing sets.

```
X_bi_train, X_bi_test, y_bi_train, y_bi_test = train_test_split(X_bi,
y_bi, test_size=0.2, random_state=42)
```

5.3 : Train the Model

Fit the linear regression model on the training data.

```
bi_model = LinearRegression()

bi_model.fit(X_bi_train, y_bi_train)
```

OUTPUT :

```
LinearRegression
LinearRegression()
```

5.4 : Make Predictions

Use the model to make predictions on the test data.

```
y_bi_pred = bi_model.predict(X_bi_test)
```

5.5 : Evaluate the Model

Evaluate the model performance using metrics like MSE and R-squared.

```
print(f'Bivariate MSE: {mean_squared_error(y_bi_test, y_bi_pred)}')
print(f'Bivariate R-squared: {r2_score(y_bi_test, y_bi_pred)}')
```

OUTPUT :

```
Bivariate MSE: 0.08308605032913309
Bivariate R-squared: 0.4192494152204116
```

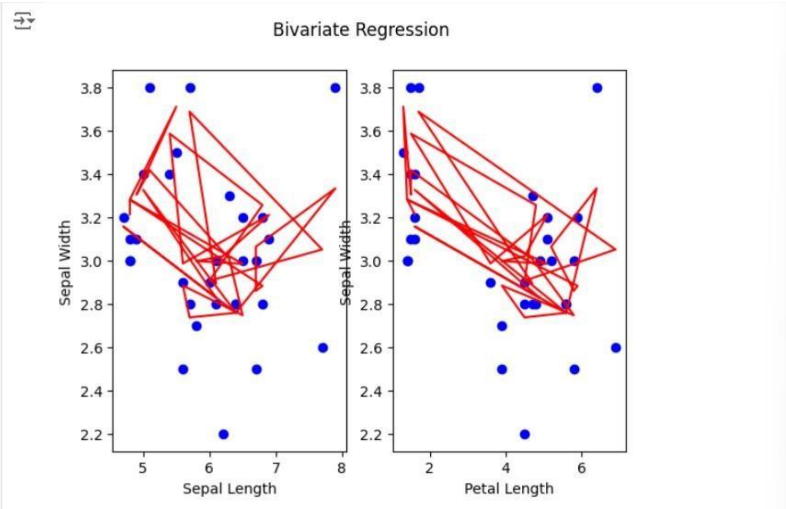
5.6 : Visualize the Results

Since visualizing in 3D is challenging, we can plot the relationships between the target and each predictor separately.

```
# Sepal Length vs Sepal Width plt.subplot(1, 2, 1)

plt.scatter(X_bi_test['sepal_length'], y_bi_test, color='blue')
```

```
plt.plot(X_bi_test['sepal_length'], y_bi_pred, color='red')

plt.xlabel('Sepal Length') plt.ylabel('Sepal Width') # Petal

Length vs Sepal Width plt.subplot(1, 2, 2)

plt.scatter(X_bi_test['petal_length'], y_bi_test, color='blue')

plt.plot(X_bi_test['petal_length'], y_bi_pred, color='red')

plt.xlabel('Petal Length') plt.ylabel('Sepal Width')

plt.suptitle('Bivariate Regression') plt.show()
```

OUTPUT :



Step 6: Multivariate Regression

Multivariate regression involves predicting one variable based on multiple predictors.

6.1 : Select the Features

Choose multiple features (e.g., sepal_length, petal_length, petal_width) and one target variable (e.g., sepal_width).

```
X_multi = iris[['sepal_length', 'petal_length', 'petal_width']] y_multi

= iris['sepal_width']
```

6.2 : Split the Data

Split the data into training and testing sets.

```
X_multi_train, X_multi_test, y_multi_train, y_multi_test =

train_test_split(X_multi, y_multi, test_size=0.2, random_state=42)
```

6.3 : Train the Model

Fit the linear regression model on the training data.

```
multi_model = LinearRegression()    multi_model.fit(X_multi_train, 
y_multi_train)
```

OUTPUT :

```
▾ LinearRegression
LinearRegression()
```

6.4 : Make Predictions

Use the model to make predictions on the test data.

```
y_multi_pred = multi_model.predict(X_multi_test)
```

6.5 : Evaluate the Model

Evaluate the model performance using metrics like MSE and R-squared.

```
print(f'Multivariate MSE: {mean_squared_error(y_multi_test, 
y_multi_pred)}')
print(f'Multivariate R-squared: {r2_score(y_multi_test, y_multi_pred)}')
```

OUTPUT :

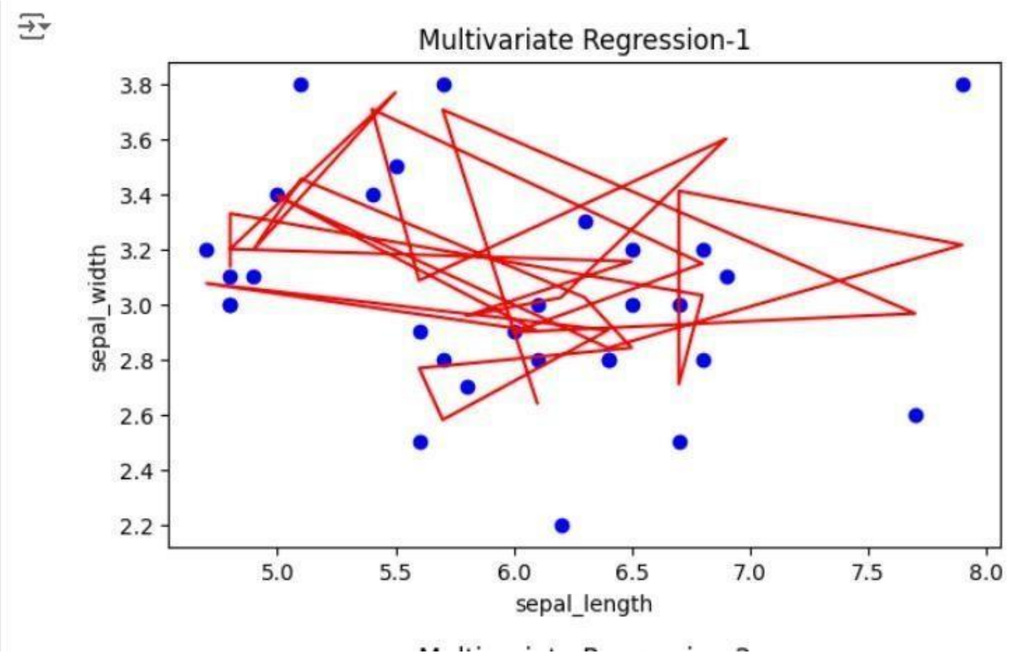
```
Multivariate MSE: 0.0868353771078583
Multivariate R-squared: 0.39304256448374897
```

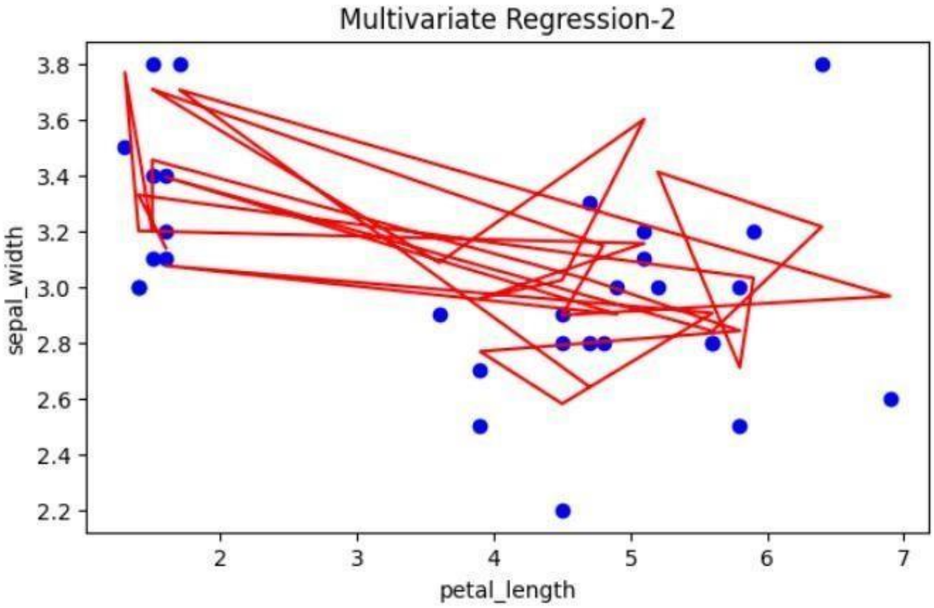
Step 7: Visualize the multivariate regression

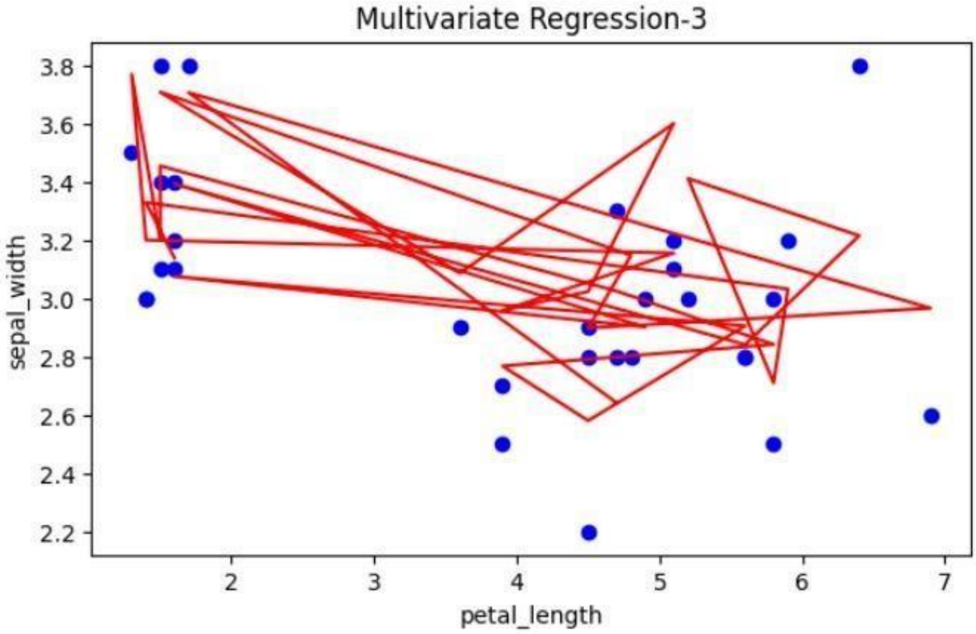
```
plt.figure(figsize=(15,4)) plt.subplot(1, 2, 1)

plt.scatter(X_multi_test['sepal_length'], y_multi_test, color='blue')

plt.plot(X_multi_test['sepal_length'], y_multi_pred, color='red')

plt.xlabel('sepal_length') plt.ylabel('sepal_width')

plt.title('Multivariate Regression-1') plt.show()

plt.figure(figsize=(15,4)) plt.subplot(1, 2, 1)

plt.scatter(X_multi_test['petal_length'], y_multi_test, color='blue')
```

```
plt.plot(X_multi_test['petal_length'], y_multi_pred, color='red')
plt.xlabel('petal_length') plt.ylabel('sepal_width')
plt.title('Multivariate Regression-2') plt.show()
plt.figure(figsize=(15,4)) plt.subplot(1, 2, 2 )
plt.scatter(X_multi_test['petal_length'], y_multi_test, color='blue')
plt.plot(X_multi_test['petal_length'], y_multi_pred, color='red')
plt.xlabel('petal_length') plt.ylabel('sepal_width')
plt.title('Multivariate Regression-3') plt.show()
```

OUTPUT :







Step 8: Interpret the Results

After implementing and evaluating the models, interpret the coefficients to understand the influence of each predictor on the target variable.

```
print('Univariate Coefficients:', uni_model.coef_)
print('Bivariate Coefficients:', bi_model.coef_)    print('Multivariate Coefficients:', multi_model.coef_)
```

OUTPUT :

```
Univariate Coefficients: [-0.05829418]
Bivariate Coefficients: [ 0.56420418 -0.33942806]
Multivariate Coefficients: [ 0.62934965 -0.63196673  0.6440201 ]
```

RESULT:

This step-by-step process will help us to implement univariate, bivariate, and multivariate regression models using the Iris dataset and analyse their performance.

EXPT NO : 2 **A python program to implement Simple linear**

DATE: 30.08.2024 **Regression using Least Square Method**

AIM:

To write a python program to implement Simple linear regression using Least Square Method.

PROCEDURE:

Implementing Simple linear regression using Least Square method using the headbrain dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
import pandas as pd import

matplotlib.pyplot as plt import numpy

as np
```

Step 2: Load the Iris Dataset The

HeadBrain dataset can be loaded.

```
data = pd.read_csv('/content/headbrain.csv')
```

Step 3: Data Preprocessing

Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```
x,y=np.array(list(data['Head Size(cm^3)'])),np.array(list(data['Brain

Weight(grams)'])) print(x[:5],y[:5])
```

OUTPUT :

```
[4512 3738 4261 3777 4177] [1530 1297 1335 1282 1590]
```

Step 4 :Compute the Least Squares Solution

Apply the least squares formula to find the regression coefficients.

```
def get_line(x,y):   x_m,y_m = np.mean(x), np.mean(y)

print(x_m,y_m)       x_d,y_d=x-x_m,y-y_m       m    =
```

```
np.sum(x_d*y_d)/np.sum(x_d**2)    c  =  y_m  -  (m*x_m)

print(m, c)  return lambda x : m*x+c lin=get_line(x,y)
```

OUTPUT :

```
3633.9915611814345 1282.873417721519
0.2634293394893993 325.5734210494428
```

Step 5 : Make Predictions

Use the model to make predictions based on the independent variable.

```
def get_error(line_fuc, x, y):

 y_m = np.mean(y)  y_pred = np.array([line_fuc(_) for _ in x])  ss_t =

np.sum((y-y_m)**2)  ss_r = np.sum((y-y_pred)**2)  return 1-(ss_r/ss_t)

get_error(lin, x, y)
```

```
from sklearn.linear_model import LinearRegression x

= x.reshape((len(x),1)) reg=LinearRegression()

reg=reg.fit(x, y) print(reg.score(x, y))
```

OUTPUT :

```
1.0
```

```
1.0
```

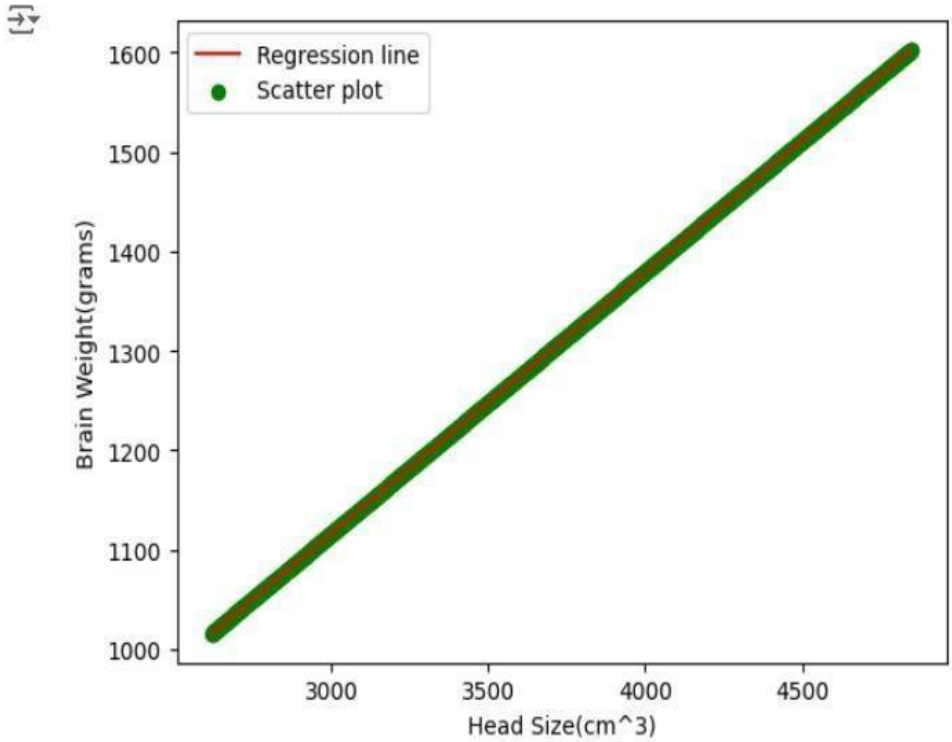
Step 6 :Visualize the Results

Plot the original data points and the fitted regression line.

```
x=np.linspace(np.min(x)-100,np.max(x)+100,1000)

y=np.array([lin(x)for x in x]) plt.plot(x, y,

color='red', label='Regression line') plt.scatter(x, y,

color='green', label='Scatter plot') plt.xlabel('Head

Size(cm^3)') plt.ylabel('Brain
```

```
Weight(grams)') plt.legend() plt.show()
```

OUTPUT :



RESULT:

This step-by-step process will help us to implement least square regression models using the HeadBrain dataset and analyse their performance.

EXPT NO : 3 **A python program to implement Logistic Model**

DATE: 06.09.2024

AIM:

To write a python program to implement a Logistic Model.

PROCEDURE:

Implementing Logistic method using the iris dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualisation, and model building.

```
# Step 1: Import Necessary Libraries import numpy as

np import pandas as pd import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
```

Step 2: Load the Iris Dataset The iris

dataset can be loaded.

```
# Step 2: Load the Dataset

# For this example, we'll use a built-in dataset from sklearn. You can replace

it with your dataset.  from sklearn.datasets import load_iris
```

```
# Load the iris dataset data

= load_iris() X = data.data

y = (data.target == 0).astype(int)  # For binary classification
(classifying Iris-setosa)
```

Step 3: Data Preprocessing

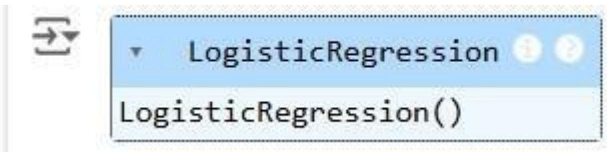
Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```
# Step 3: Prepare the Data

# Split the dataset 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)
```

Step 4 : Train a Model

```
# Step 4: Create and Train the Model model =

LogisticRegression() model.fit(X_train,

y_train)
```

OUTPUT :



Step 5 : Make Predictions

Use the model to make predictions based on the independent variable.

```
# Step 5: Make Predictions y_pred

= model.predict(X_test)
```

Step 6 : Evaluate the Model

Evaluate the model performance.

```
# Step 6: Evaluate the Model accuracy = accuracy_score(y_test,

y_pred) conf_matrix = confusion_matrix(y_test, y_pred)

class_report = classification_report(y_test, y_pred)

# Print evaluation metrics print(f"Accuracy:
{accuracy}") print("Confusion Matrix:")
print(conf_matrix) print("Classification
Report:") print(class_report)
```

OUTPUT :

```
Accuracy: 1.0
Confusion Matrix:
[[20  0]
 [ 0 10]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        20
           1       1.00      1.00      1.00        10

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

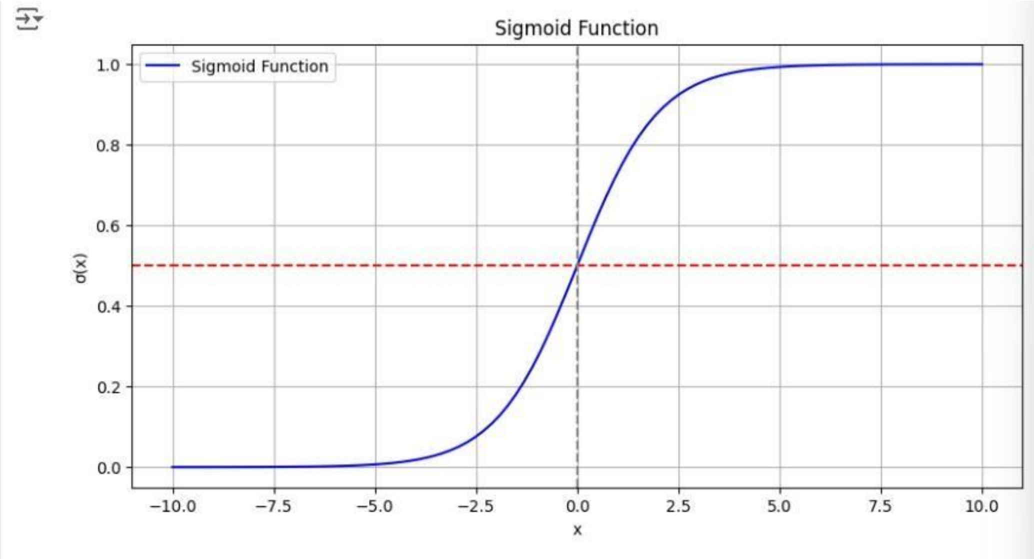
Step 7 :Visualize the Results

Plot the original data points and the fitted regression line.

```
# Step 7: Visualize Results (Optional)
x_values = np.linspace(-10, 10, 100) sigmoid_values

= 1 / (1 + np.exp(-x_values))



# Plot the sigmoid function plt.figure(figsize=(10,

5)) plt.plot(x_values, sigmoid_values, label='Sigmoid Function',

color='blue')
```

```
plt.title('Sigmoid Function') plt.xlabel('x')

plt.ylabel('σ(x)') plt.grid() plt.axhline(0.5,

color='red', linestyle='--')  # Line at y=0.5

plt.axvline(0, color='gray', linestyle='--')  #

Line at x=0 plt.legend() plt.show()
```

OUTPUT :



RESULT:

This step-by-step process will help us to implement Logistic models using the Iris dataset and analyse their performance.

EXPT NO : 4 **A python program to implement Single Layer**

DATE: 13.09.2024 **Perceptron**

AIM:

To write a python program to implement Single layer perceptron.

PROCEDURE:

Implementing Single layer perceptron method using the Keras dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
import numpy as np import pandas

as pd from tensorflow import

keras import matplotlib.pyplot

as plt
```

Step 2: Load the Keras Dataset The

Keras dataset can be loaded.

```
(X_train,y_train),(X_test,y_test)=keras.datasets.mnist.load_data()
```

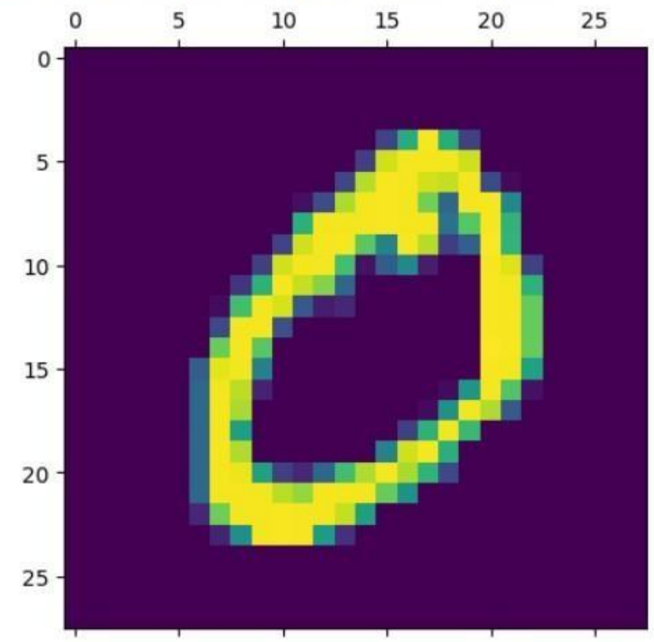
Step 3: Data Preprocessing

Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```
print(f"Training set:{X_train.shape}") print(f"Testing

set:{X_test.shape}")

 print(X_train[1].shape) plt.matshow(X_train[1])
```

OUTPUT :

```
Training set:(60000, 28, 28)
Testing set:(10000, 28, 28)
(28, 28)
<matplotlib.image.AxesImage at 0x7b83d00435e0>
```



Step 4 : Train a Model

```
#Normalizing the dataset x_train=X_train/255

x_test=X_test/255


#Flatting the dataset in order to compute for model building

x_train_flatten=x_train.reshape(len(x_train),28*28)

x_test_flatten=x_test.reshape(len(x_test),28*28) x_train_flatten.shape
```

Step 5 : Make Predictions

Use the model to make predictions based on the independent variable.

```
model=keras.Sequential([      keras.layers.Dense(10,input_shape=(784,),

activation='sigmoid')
```

```
]) model.compile(       optimizer='adam',

loss='sparse_categorical_crossentropy',       metrics=['accuracy'])

model.fit(x_train_flatten,y_train,epochs=5



          )
```

OUTPUT :

```
Epoch 1/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.8180 - loss: 0.7118
Epoch 2/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9148 - loss: 0.3101
Epoch 3/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 4s 956us/step - accuracy: 0.9238 - loss: 0.2769
Epoch 4/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 2s 940us/step - accuracy: 0.9250 - loss: 0.2744
Epoch 5/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 990us/step - accuracy: 0.9239 - loss: 0.2706
<keras.src.callbacks.history.History at 0x7b83d00c6a70>
```

Step 6 : Evaluate the Model Evaluate the

model performance.

```
model.evaluate(x_test_flatten,y_test)
```

OUTPUT :

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9138 - loss: 0.3021
[0.26686596870422363, 0.9257000088691711]
```

RESULT:

This step-by-step process will help us to implement Single Layer Perceptron models using the Keras dataset and analyse their performance.

EXPT NO : 5 A python program to implement Multi Layer

DATE: 20.09.2024 Perceptron With Backpropagation

AIM:

To write a python program to implement Multilayer perceptron with backpropagation .

PROCEDURE:

Implementing Multilayer perceptron with backpropagation using the Keras dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
# importing modules import tensorflow as tf

import numpy as np from tensorflow.keras.models

import Sequential from tensorflow.keras.layers

import Flatten from tensorflow.keras.layers
```

```
import Dense from tensorflow.keras.layers

import Activation import matplotlib.pyplot as

plt
```

Step 2: Load the Keras Dataset The

Keras dataset can be loaded.

```
   (x_train, y_train), (x_test, y_test) =
tf.keras.datasets.mnist.load_data()
```

OUTPUT :

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

Step 3: Data Preprocessing

Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```
# Cast the records into float values x_train

= x_train.astype('float32') x_test

= x_test.astype('float32')


# normalize image pixel values by dividing

# by 255 gray_scale = 255 x_train /=

gray_scale x_test /= gray_scale

print("Feature matrix:",

x_train.shape) print("Target matrix:",

x_test.shape) print("Feature matrix:",

y_train.shape) print("Target matrix:",

y_test.shape)
```

OUTPUT :

```
Feature matrix: (60000, 28, 28)
Target matrix: (10000, 28, 28)
Feature matrix: (60000,)
Target matrix: (10000,)
```

Step 4 : Train a Model

```
model = Sequential([

  # reshape 28 row * 28 column data to 28*28 rows

  Flatten(input_shape=(28, 28)),


  # dense layer 1

  Dense(256, activation='sigmoid'),
```

```
  # dense layer 2
  Dense(128, activation='sigmoid'),


  # output layer
  Dense(10, activation='sigmoid'),
])
```

OUTPUT:

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/reshaping/flatten.py:37: UserWarning:
  super().__init__(**kwargs)
```

Step 5 : Make Predictions

Use the model to make predictions based on the independent variable.

```
model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy',
metrics=['accuracy']) model.fit(x_train, y_train,
epochs=10,     batch_size=2000,
validation_split=0.2)
```

OUTPUT:

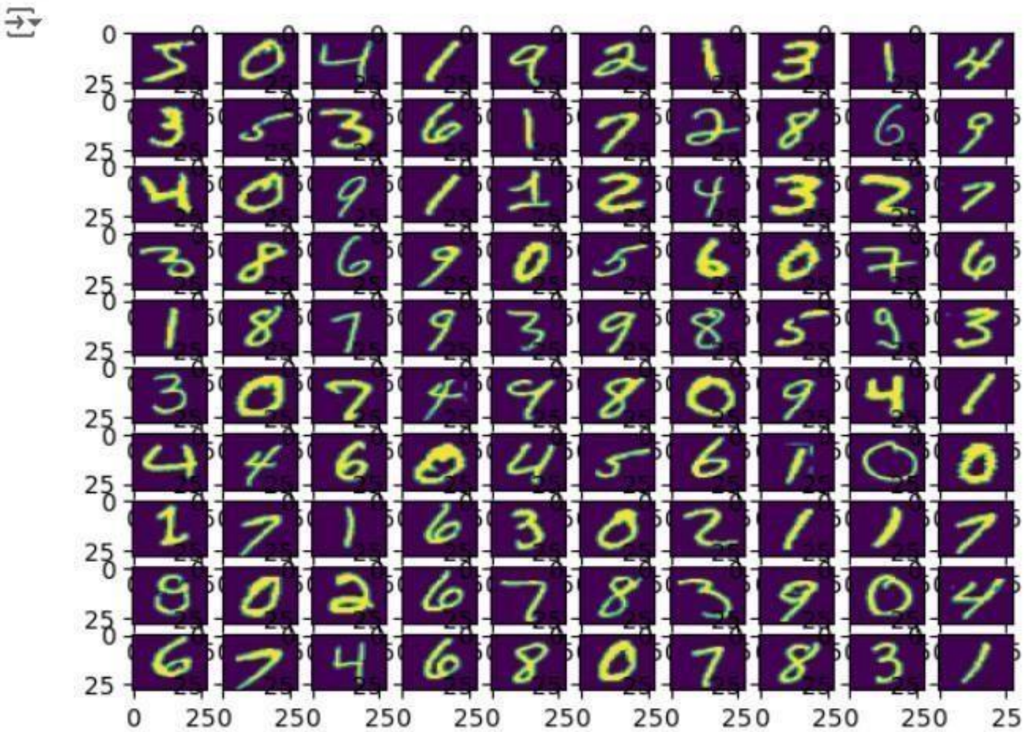
```
Epoch 1/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 5s 115ms/step - accuracy: 0.3546 - loss: 2.1596 - val_accuracy: 0.68
Epoch 2/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 4s 53ms/step - accuracy: 0.7116 - loss: 1.3743 - val_accuracy: 0.826
Epoch 3/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 1s 53ms/step - accuracy: 0.8221 - loss: 0.8221 - val_accuracy: 0.872
Epoch 4/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 3s 65ms/step - accuracy: 0.8720 - loss: 0.5676 - val_accuracy: 0.892
Epoch 5/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 99ms/step - accuracy: 0.8907 - loss: 0.4444 - val_accuracy: 0.902
Epoch 6/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 3s 102ms/step - accuracy: 0.8993 - loss: 0.3852 - val_accuracy: 0.91
Epoch 7/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 3s 104ms/step - accuracy: 0.9088 - loss: 0.3416 - val_accuracy: 0.91
Epoch 8/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 92ms/step - accuracy: 0.9119 - loss: 0.3188 - val_accuracy: 0.922
Epoch 9/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 92ms/step - accuracy: 0.9191 - loss: 0.2911 - val_accuracy: 0.926
Epoch 10/10
24/24 ━━━━━━━━━━━━━━━━━━━━ 3s 99ms/step - accuracy: 0.9245 - loss: 0.2704 - val_accuracy: 0.929
<keras.src.callbacks.history.History at 0x7d9ca1406a40>
```

Step 6 : Evaluate the Model Evaluate the model performance.

```
results = model.evaluate(x_test, y_test, verbose = 0)

print('test loss, test acc:', results) fig, ax =

plt.subplots(10, 10) k = 0 for i in range(10):    for j in

range(10):

    ax[i][j].imshow(x_train[k].reshape(28, 28),
aspect='auto')      k += 1 plt.show()
```

OUTPUT :

```
test loss, test acc: [0.2589016258716583, 0.9277999997138977]
```



RESULT:

This step-by-step process will help us to implement MultiLayer Perceptron with Backpropagation models using the Keras dataset and analyse their performance.

EXPT NO: 6 A python program to do face recognition using DATE: 27.09.2024

SVM Classifier

AIM:

To write a python program to implement face recognition using the SVM Classifier

PROCEDURE:

Implementing face recognition using the SVM Classifier using the cat and dog dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
import pandas as pd import imageio import os from

skimage.transform import resize from skimage.io

import imread import numpy as np import

matplotlib.pyplot as plt from sklearn import svm from

sklearn.model_selection import GridSearchCV from

sklearn.model_selection import train_test_split from

sklearn.metrics import accuracy_score from

sklearn.metrics import classification_report
```

Step 2: Load theDog and cat Dataset The dog

and cat dataset can be loaded.

```
Categories=['cats','dogs'] flat_data_arr=[] #input

array target_arr=[] #output array

datadir='/content/images'

#path which contains all the categories of images for

i in Categories:     print(f'loading... category :

{i}')    path=os.path.join(datadir,i)    for img in

os.listdir(path):

    img_array=imread(os.path.join(path,img))

img_resized=resize(img_array,(150,150,3))

flat_data_arr.append(img_resized.flatten())

target_arr.append(Categories.index(i))    print(f'loaded

category:{i} successfully') flat_data=np.array(flat_data_arr)

target=np.array(target_arr)

#dataframe
df=pd.DataFrame(flat_data) df['Target']=target
df.shape
```

OUTPUT :

```
(80, 67501)
```

Step 3: Separate input features and targets.

```
#input data x=df.iloc[:,:1]
#output data y=df.iloc[:,-
1]
```

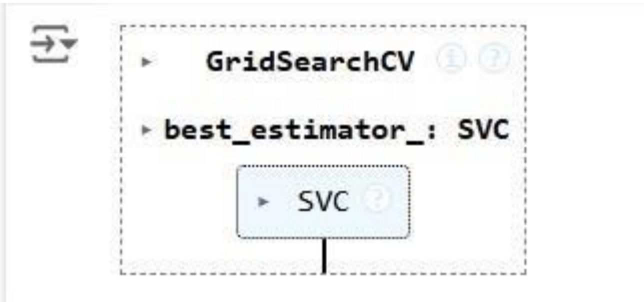
Step 4 : Separate the input features and target

```
# Splitting the data into training and testing sets
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,
random_state=77, stratify=y)
```

Step 5 : Build and train the model

```
# Defining the parameters grid for GridSearchCV
param_grid={'C':[0.1,1,10,100],       'gamma':[0.0001,0.001,0.1,1],
      'kernel':['rbf','poly']}

# Creating a support vector classifier svc=svm.SVC(probability=True)

# Creating a model using GridSearchCV with the parameters grid
model=GridSearchCV(svc,param_grid)

# Training the model using the training data model.fit(x_train,y_train)
```

OUTPUT :



Step 6 : Model evaluation

```
# Testing the model using the testing data y_pred =
model.predict(x_test)

# Calculating the accuracy of the model accuracy
= accuracy_score(y_pred, y_test)

# Print the accuracy of the model print(f"The model is
{accuracy*100}% accurate") print(classification_report(y_test,
y_pred, target_names=['cat', 'dog']))
```

OUTPUT :

The model is 62.5% accurate

	precision	recall	f1-score	support
cat	0.58	0.88	0.70	8
dog	0.75	0.38	0.50	8
accuracy			0.62	16
macro avg	0.67	0.62	0.60	16
weighted avg	0.67	0.62	0.60	16

Step 7 : Prediction

```
path='/content/cat.83.jpg'
img=imread(path) plt.imshow(img)
plt.show()
img_resize=resize(img,(150,150,3))
l=[img_resize.flatten()]
probability=model.predict_proba(l) for
ind,val in enumerate(Categories):
  print(f'{val} = {probability[0][ind]*100}%') print("The predicted
image is : "+Categories[model.predict(l)[0]])
```

OUTPUT :

cats = 52.70216647851706% dogs
= 47.29783352148294% The
predicted image is : cat

RESULT :

Thus the process helps us to implement the face recognition using SVM Classifier using python program.

EXPT NO: 7 **A python program to implement Decision tree**

DATE: 04.10.2024

AIM:

To write a python program to implement a Decision tree.

PROCEDURE:

Implementing the decision tree using the Iris dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

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

sklearn.model_selection import train_test_split from sklearn.tree import

DecisionTreeClassifier from sklearn import metrics import

matplotlib.pyplot as plt from sklearn.tree import plot_tree
```

Step 2: Load the Iris Dataset

The Iris dataset can be loaded and display the first few rows of the dataset .

```
# Load the Iris dataset iris
= datasets.load_iris() X =
iris.data # Features

y = iris.target # Target variable
```

Step 3 : Split the data set into training and testing sets

```
# Split the dataset 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)
```

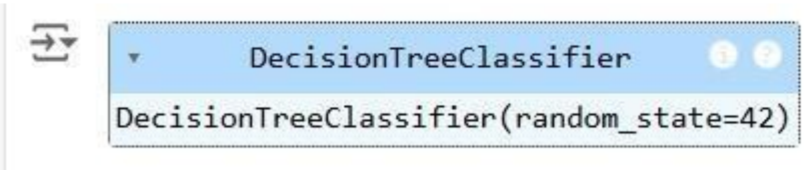
Step 4 : Create a decision tree classifier

```
# Create a Decision Tree classifier clf =

DecisionTreeClassifier(random_state=42)
```

Step 5 : Train the model : `# Train the model`

```
clf.fit(X_train, y_train)
```

OUTPUT :



Step 6 : Make the predictions and evaluate the model

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


# Evaluate the model accuracy = metrics.accuracy_score(y_test, y_pred)

confusion = metrics.confusion_matrix(y_test, y_pred)

classification_report = metrics.classification_report(y_test, y_pred)

 print(f"Accuracy:
{accuracy:.2f}") print("Confusion Matrix:")

print(confusion) print("Classification

Report:") print(classification_report)
```

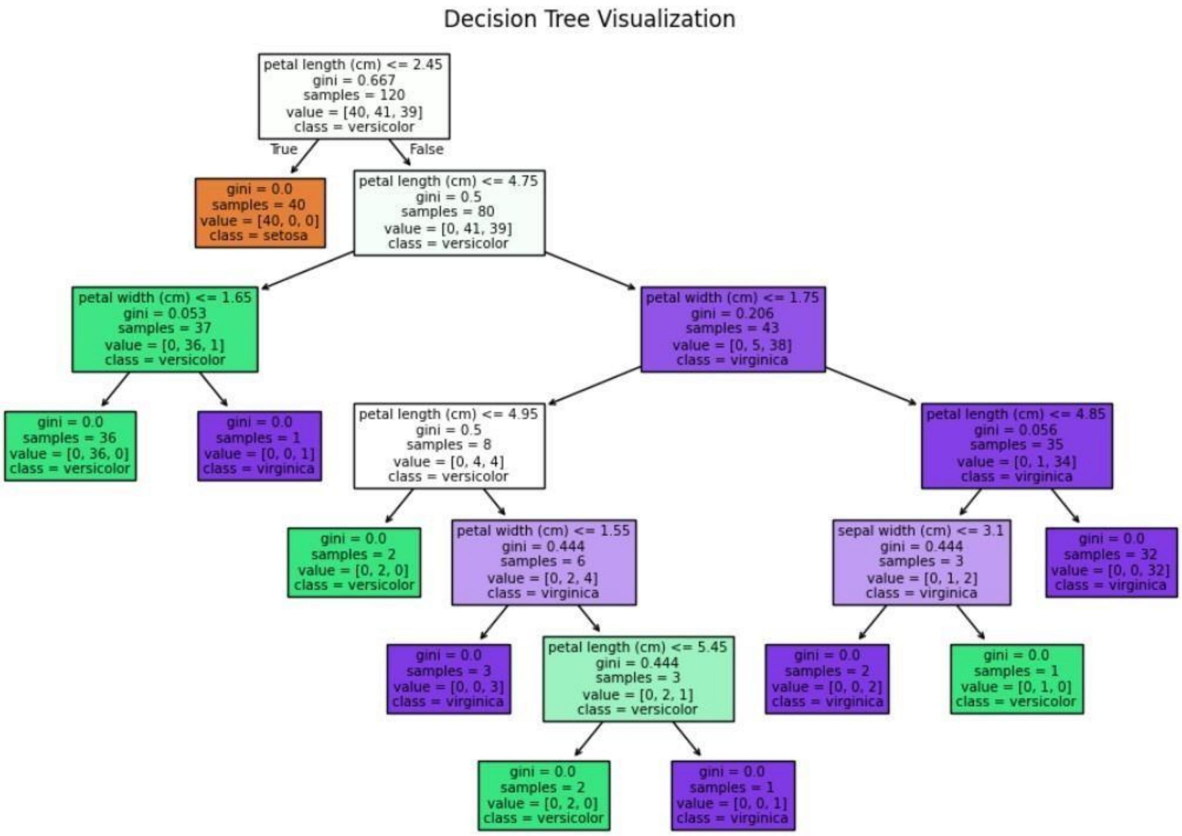
OUTPUT :

```
Accuracy: 1.00
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         9
           2       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

Step 7 : Visualize the decision tree

```
# Visualize the Decision Tree plt.figure(figsize=(12,8)) plot_tree(clf,

filled=True, feature_names=iris.feature_names, class_names=iris.target_names)

plt.title("Decision Tree

Visualization") plt.show()
```

OUTPUT :



Decision Tree Visualization
petal length (cm) <= 2.45
gini = 0.667
samples = 120
value = [40, 41, 39]
class = versicolor
True
False
gini = 0.0
samples = 40
value = [40, 0, 0]
class = setosa
petal length (cm) <= 4.75
gini = 0.5
samples = 80
value = [0, 41, 39]
class = versicolor
petal width (cm) <= 1.65
gini = 0.053
samples = 37
value = [0, 36, 1]
class = versicolor
petal width (cm) <= 1.75
gini = 0.206
samples = 43
value = [0, 5, 38]
class = virginica
gini = 0.0
samples = 36
value = [0, 36, 0]
class = versicolor
gini = 0.0
samples = 1
value = [0, 0, 1]
class = virginica
petal length (cm) <= 4.95
gini = 0.5
samples = 8
value = [0, 4, 4]
class = versicolor
petal length (cm) <= 4.85
gini = 0.056
samples = 35
value = [0, 1, 34]
class = virginica
gini = 0.0
samples = 2
value = [0, 2, 0]
class = versicolor
petal width (cm) <= 1.55
gini = 0.444
samples = 6
value = [0, 2, 4]
class = virginica
sepal width (cm) <= 3.1
gini = 0.444
samples = 3
value = [0, 1, 2]
class = virginica
gini = 0.0
samples = 32
value = [0, 0, 32]
class = virginica
gini = 0.0
samples = 3
value = [0, 0, 3]
class = virginica
petal length (cm) <= 5.45
gini = 0.444
samples = 3
value = [0, 2, 1]
class = versicolor
gini = 0.0
samples = 2
value = [0, 0, 2]
class = virginica
gini = 0.0
samples = 1
value = [0, 1, 0]
class = versicolor
gini = 0.0
samples = 2
value = [0, 2, 0]
class = versicolor
gini = 0.0
samples = 1
value = [0, 0, 1]
class = virginica

RESULT :

This process helps us to implement the decision tree using a python program.

EX.NO: 8 **A PYTHON PROGRAM TO IMPLEMENT ADA BOOSTING**

DATE : 18.10.2024

AIM:

To write a python program to implement ADA Boosting.

PROCEDURE:

Implementing ADA Boosting using the dataset involve the following steps:

Step 1: Import Necessary Libraries

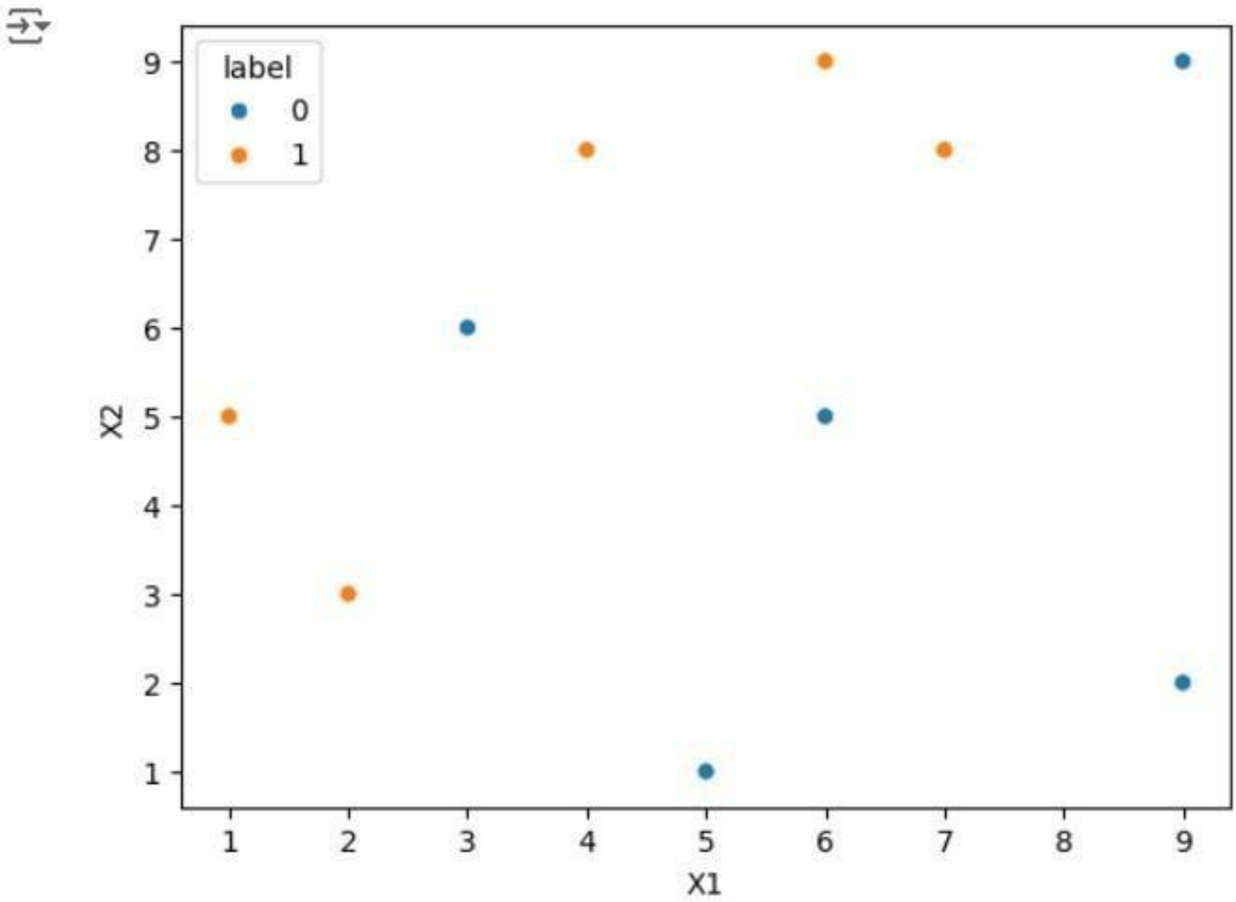
First, import the libraries that are essential for data manipulation, visualization, and model building.

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

sklearn.tree import DecisionTreeClassifier from

mlxtend.plotting import plot_decision_regions import

seaborn as sns from sklearn.metrics import

accuracy_score
```

Step 2 : Load and prepare data

```
df = pd.DataFrame() df['X1'] = [1, 2, 3, 4, 5, 6, 6, 7,

9, 9] df['X2'] = [5, 3, 6, 8, 1, 9, 5, 8, 9, 2] df['label']

= [1, 1, 0, 1, 0, 1, 0, 1, 0, 0]

sns.scatterplot(x=df['X1'], y=df['X2'], hue=df['label'])

 df['weights'] = 1 / df.shape[0]
x = df.iloc[:,
0:2].values

y = df.iloc[:, 2].values
```

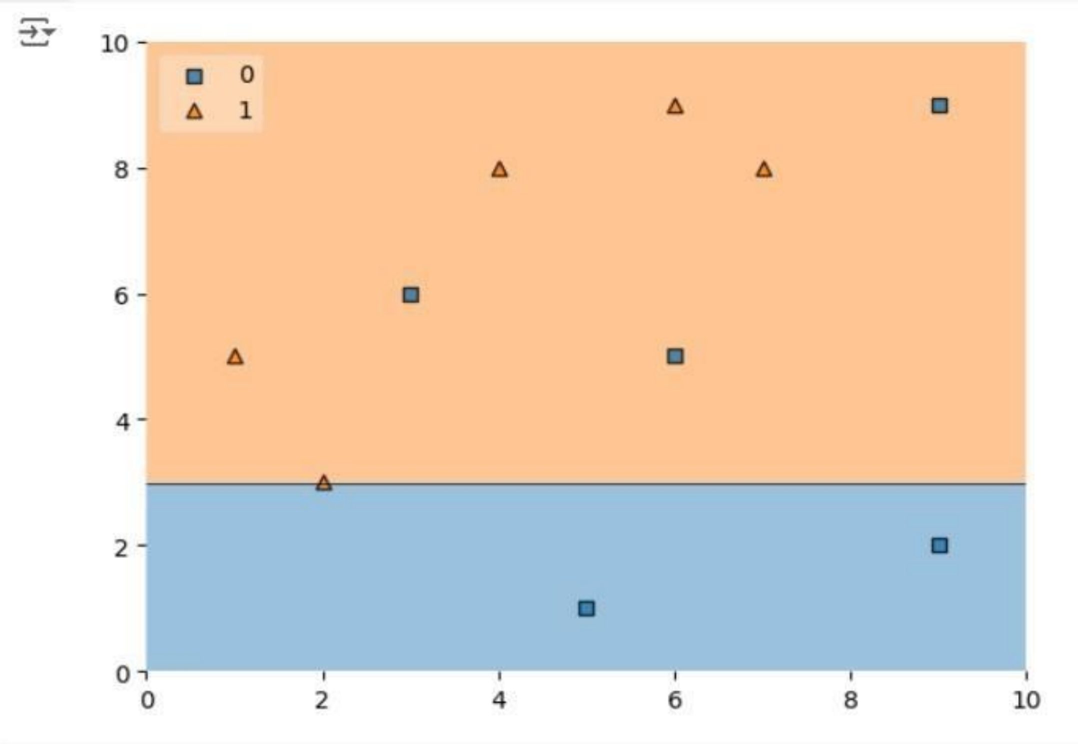
OUTPUT :



Step 3 : Train the 1st model

```
# Step 2: Train 1st Model dt1 =

DecisionTreeClassifier(max_depth=1) dt1.fit(x, y)

plot_decision_regions(x, y, clf=dt1, legend=2) df['y_pred'] =

dt1.predict(x)
```

OUTPUT :



Step 4 : Calculate model weight

```
# Step 4: Update Weights def

update_row_weights(row, alpha=0.423):     if

row['label'] == row['y_pred']:

        return row['weights'] * np.exp(-alpha)     else:

        return row['weights'] * np.exp(alpha)

df['updated_weights'] = df.apply(update_row_weights, axis=1)

df['normalized_weights'] = df['updated_weights'] /
df['updated_weights'].sum() df['cumsum_upper'] =
np.cumsum(df['normalized_weights']) df['cumsum_lower'] =
df['cumsum_upper'] - df['normalized_weights']
```

Step 5 : Create new dataset

```
# Step 5: Create New Dataset
def create_new_dataset(df):

    indices = []     for i in range(df.shape[0]):         a =

np.random.random()         for index, row in df.iterrows():

if row['cumsum_upper'] > a and a > row['cumsum_lower']:

                indices.append(index)     return

indices

 index_values = create_new_dataset(df) second_df
= df.iloc[index_values, [0, 1, 2, 3]]
```

Step 6 : Train 2nd model

```
# Step 6: Train 2nd Model dt2 =

DecisionTreeClassifier(max_depth=1) x =
```

```
second_df.iloc[:, 0:2].values y = second_df.iloc[:,

2].values dt2.fit(x, y)
```

OUTPUT :

```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=1)
```

Step 7 : Plot decision tree and calculate model weights for 2nd model

```
# Plot the decision tree for the second model
plot_decision_regions(x, y, clf=dt2, legend=2) second_df['y_pred']
= dt2.predict(x)
```

```
# Step 7: Calculate Model Weight for 2nd Model alpha2 =

calculate_model_weight(0.1) print(f"Alpha2: {alpha2}")
```

Step 8 : update weights for 2nd model

```
# Step 8: Update Weights for 2nd Model def

update_row_weights(row, alpha=1.09):     if

row['label'] == row['y_pred']:

        return row['weights'] * np.exp(-alpha)     else:

        return row['weights'] * np.exp(alpha)

second_df['updated_weights'] = second_df.apply(update_row_weights,

axis=1) second_df['nomalized_weights'] =

second_df['updated_weights'] / second_df['updated_weights'].sum()

second_df['cumsum_upper'] =

np.cumsum(second_df['nomalized_weights'])

second_df['cumsum_lower'] = second_df['cumsum_upper'] -
second_df['nomalized_weights']
```

Step 9 : Calculate alpha for 3rd model

```
# Step 9: Calculate Alpha for 3rd Model alpha3 =

calculate_model_weight(0.7) print(f"Alpha3: {alpha3}")




# Step 10: Accuracy Calculation y_true =

second_df['label'].values y_pred =

second_df['y_pred'].values


# Calculate accuracy for the AdaBoost model accuracy =
accuracy_score(y_true, y_pred) print(f"Accuracy of the
AdaBoost model: {accuracy:.4f}")
```

OUTPUT :

ALPHA 3: -0.4236489301936017

Accuracy of the Ada Boosting model : 0.80000

RESULT :

Thus the python program to implement Ada boosting has been executed successfully and the results have been verified.

EXPT NO: 9A **A python program to implement**

DATE: 25.10.2024 **KNN MODEL**

AIM:

To write a python program to implement KNN Model.

PROCEDURE:

Implementing KNN Model using the mall_customer dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
import numpy as np import matplotlib.pyplot as plt import pandas as

pd from sklearn.model_selection import train_test_split from

sklearn.preprocessing import StandardScaler from sklearn.neighbors

import KNeighborsClassifier from sklearn.metrics import

classification_report, confusion_matrix from sklearn.cluster import

KMeans
```

Step 2: Load the Dataset

The mall_customer dataset can be loaded and display the first few rows of the dataset.

```
# Load the dataset dataset =

pd.read_csv('/content/Mall_Customers.csv')



# Display the first few rows of the dataset
print(dataset.head())
```

```
# Display the dimensions of the dataset print(f"Dataset shape:

{dataset.shape}")



# Display descriptive statistics of the dataset

print(dataset.describe())
```

Step 3 : Separate the features (x) and target variable (y)

```
# Separate the features (X) and the target variable (y)

X = dataset.iloc[:, [3, 4]].values  # We use 'Annual Income' and
'Spending Score'



# Standardize the features scaler

= StandardScaler()

X_scaled = scaler.fit_transform(X)
```

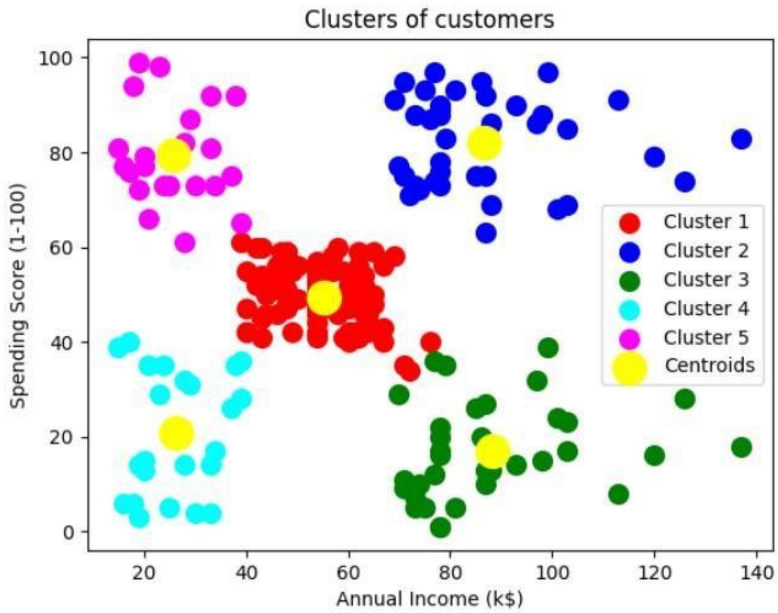
Step 4 : Visualizing the cluster of customer

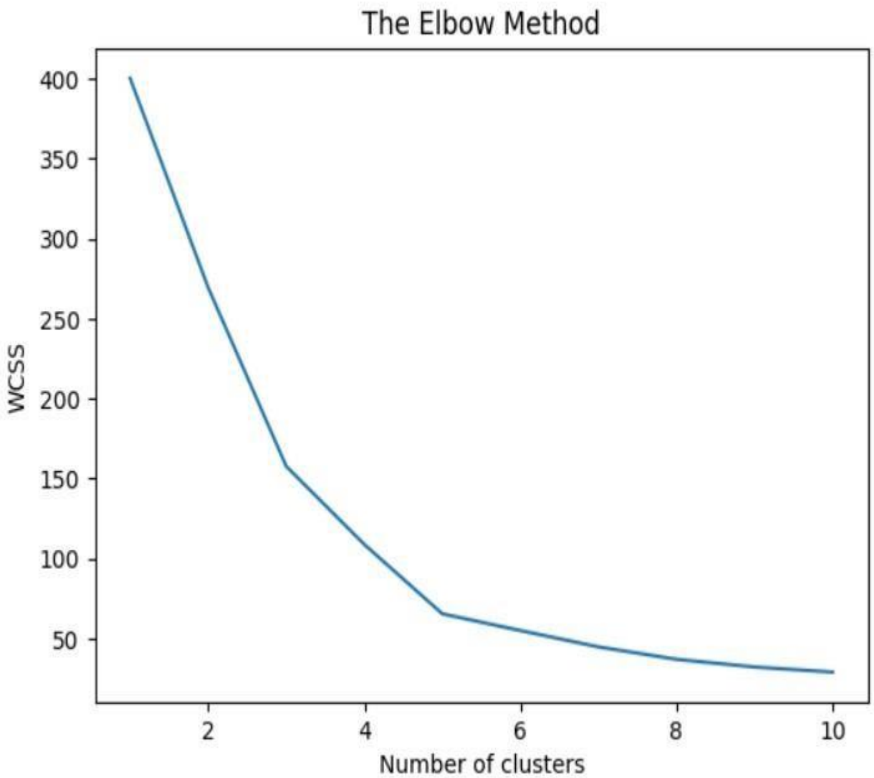
```
# Apply KMeans clustering using the Elbow Method to find the optimal

number of clusters wcss = []  # Within-cluster sum of squares 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(X_scaled)

wcss.append(kmeans.inertia_)



# Plot the Elbow Method graph plt.plot(range(1, 11),
wcss)
```

```
plt.title('The Elbow Method') plt.xlabel('Number

of clusters') plt.ylabel('WCSS') plt.show()


# From the plot, we can observe that the optimal number of clusters is 5
(elbow point)  kmeans = KMeans(n_clusters=5, init='k-means++',

max_iter=300, n_init=10, random_state=0) y_kmeans =

kmeans.fit_predict(X_scaled)


# Visualizing the clusters of customers

plt.scatter(X_scaled[y_kmeans == 0, 0], X_scaled[y_kmeans == 0, 1], s=100,
c='red', label='Cluster 1')

plt.scatter(X_scaled[y_kmeans == 1, 0], X_scaled[y_kmeans == 1, 1], s=100,
c='blue', label='Cluster 2')

plt.scatter(X_scaled[y_kmeans == 2, 0], X_scaled[y_kmeans == 2, 1], s=100,
c='green', label='Cluster 3')

plt.scatter(X_scaled[y_kmeans == 3, 0], X_scaled[y_kmeans == 3, 1], s=100,
c='cyan', label='Cluster 4')

plt.scatter(X_scaled[y_kmeans == 4, 0], X_scaled[y_kmeans == 4, 1], s=100,
c='magenta', label='Cluster 5')


# Plot the centroids

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
s=300, c='yellow', label='Centroids')

 plt.title('Clusters of customers')
plt.xlabel('Annual
Income (k$)')
```

```
plt.ylabel('Spending Score (1-100)') plt.legend()

plt.show()
```

OUTPUT :





RESULT :

Thus, the python program to implement KNN model has been successfully implemented and the results have been verified.

EXPT NO: 9B **A python program to implement**

DATE: 25.10.2024 **K-Means Model**

AIM:

To write a python program to implement the K-means Model.

PROCEDURE:

Implementing K - means Model using the mall_customer dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
import numpy as np import

pandas as pd from math

import sqrt
```

Step 2 : load the Dataset `data =`

```
pd.read_csv('/content/Mall_Customers.csv') data.head(5)
```

OUTPUT:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

Step 3 : Preprocess the data

```
req_data = data[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']]
req_data.head(5)
```

OUTPUT :

	Age	Annual Income (k$)	Spending Score (1-100)
0	19	15	39
1	21	15	81
2	20	16	6
3	23	16	77
4	31	17	40

Step 4 : Assign the data points to clusters

```
shuffle_index = np.random.permutation(req_data.shape[0])  # Shuffle the dataset
rows req_data = req_data.iloc[shuffle_index] req_data.head(5)
```

OUTPUT :

	Gender	Age	Annual Income (k$)	Spending Score (1-100)
14	Male	37	20	13
102	Male	67	62	59
89	Female	50	58	46
181	Female	32	97	86
183	Female	29	98	88

Step 5 : Update the clusters centers

```
train_size = int(req_data.shape[0]*0.7)  # Set 70% of the data for training
```

```
train_df = req_data.iloc[:train_size,:] test_df =
req_data.iloc[train_size:,:] train = train_df.values  #
Convert train data to numpy array test = test_df.values  #
Convert test data to numpy array y_true = test[:,-1]  # The
target values for the test set print('Train_Shape: ',
train_df.shape) print('Test_Shape: ', test_df.shape) from
math import sqrt  def euclidean_distance(x_test, x_train):
    distance = 0     for i in range(len(x_test)):  # Loop
through all features         distance +=
(x_test[i]x_train[i])**2     return sqrt(distance)   def
get_neighbors(x_test, x_train, num_neighbors):
    distances = []     data = []     for i in x_train:
distances.append(euclidean_distance(x_test, i))
data.append(i)     distances = np.array(distances)     data
= np.array(data)
    sort_indexes = distances.argsort()  # Sort distances in ascending
order     data = data[sort_indexes]  # Sort the data based on sorted
distances
```

```
    return data[:num_neighbors]  # Return the closest 'num_neighbors'
neighbors def prediction(x_test, x_train, num_neighbors):
    classes = []     neighbors = get_neighbors(x_test, x_train,
num_neighbors)      for i in neighbors:
        classes.append(i[-1])  # The target value is the last column
predicted = max(classes, key=classes.count)  # Return the most
frequent class (the majority vote)     return predicted   def
predict_classifier(x_test):
    classes = []      neighbors = get_neighbors(x_test, req_data.values,
5)  # Predict using the top 5 neighbors     for i in neighbors:
        classes.append(i[-1])      predicted = max(classes,
key=classes.count)  # Return the majority vote     print(predicted)
return predicted def accuracy(y_true, y_pred):
    num_correct = 0     for i in range(len(y_true)):
        if y_true[i] == y_pred[i]:  # Compare true values to predicted
values              num_correct += 1     accuracy = num_correct /
len(y_true)  # Calculate accuracy as the
```

```
ratio of correct predictions

return accuracy def accuracy(y_true,

y_pred):

    num_correct = 0      for i in

range(len(y_true)):          if

y_true[i] == y_pred[i]:

num_correct += 1      return num_correct

/ len(y_true) y_pred = [] for i in

test:

    y_pred.append(prediction(i, train, 5))  # Make predictions for each test
instance



# Calculate and print the accuracy acc = accuracy(y_true,
y_pred)
print(f"Accuracy: {acc * 1000:.2f}%")
```

OUTPUT :

```
Accuracy: 66.67%
```

RESULT:

Thus, the python program implementing the k-means model is successful.

EXPT NO: 10 A python program to implement Dimensionality DATE:

04.11.2024 Reduction -PCA.

AIM:

To write a python program to implement Dimensionality Reduction - PCA .

PROCEDURE:

ImplementingDimensionality reduction -pca using the Iris dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
# Importing necessary libraries from sklearn

import datasets import pandas as pd from

sklearn.preprocessing import StandardScaler from

sklearn.decomposition import PCA import seaborn as

sns import matplotlib.pyplot as plt
```

Step 2: Load the Iris Dataset

The Iris dataset can be loaded and display the first few rows of the dataset

```
# Load the Iris dataset iris = datasets.load_iris() df =

pd.DataFrame(iris['data'], columns=iris['feature_names'])

# Display the first few rows of the dataset df.head()
```

OUTPUT :

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

Step 3 : Standardize the data

```
# Standardize the features using StandardScaler scalar =

StandardScaler() scaled_data =
pd.DataFrame(scalar.fit_transform(df))  #

Scaling the data

# Display the scaled data (optional) scaled_data.head()
```

OUTPUT :

	0	1	2	3
0	-0.900681	1.019004	-1.340227	-1.315444
1	-1.143017	-0.131979	-1.340227	-1.315444
2	-1.385353	0.328414	-1.397064	-1.315444
3	-1.506521	0.098217	-1.283389	-1.315444
4	-1.021849	1.249201	-1.340227	-1.315444

Step 4 : Apply PCA

```
# Apply PCA to reduce the data to 3 components pca =

PCA(n_components=3) pca.fit(scaled_data)

# Fit PCA on scaled data
```

```
data_pca = pca.transform(scaled_data)  # Transform the data to principal
components
```

```
# Convert PCA data to a DataFrame for easier inspection data_pca =
pd.DataFrame(data_pca, columns=['PC1', 'PC2', 'PC3']) data_pca.head()
```

OUTPUT :

	PC1	PC2	PC3
0	-2.264703	0.480027	0.127706
1	-2.080961	-0.674134	0.234609
2	-2.364229	-0.341908	-0.044201
3	-2.299384	-0.597395	-0.091290
4	-2.389842	0.646835	-0.015738

Step 5 : Explained Variance Ratio

```
# Calculate the explained variance ratio for each principal component

explained_variance = pca.explained_variance_ratio_ print(f"Explained

Variance Ratio: {explained_variance}")

# This output shows how much variance each principal component explains.
```

OUTPUT :

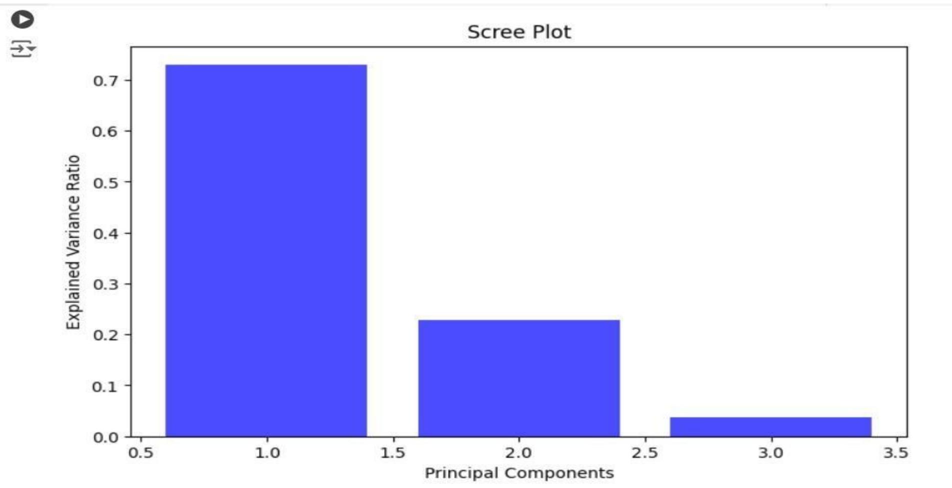
```
Explained Variance Ratio: [0.72962445 0.22850762 0.03668922]
```

Step 6 :Visualize the reduced data.

```
# Plotting the explained variance ratio as a scree plot

plt.figure(figsize=(8, 5))
```

```
plt.bar(range(1, len(explained_variance) + 1), explained_variance,

alpha=0.7, color='blue') plt.ylabel('Explained Variance Ratio')

plt.xlabel('Principal Components') plt.title('Scree Plot')

plt.show()
```

OUTPUT :



RESULT:

Thus, the Dimensionality Reduction has been implemented using PCA in python program Successfully.