RAJALAKSHMIENGINEERING COLLEGE

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RAJALAKSHMI
ENGINEERING COLLEGE
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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

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



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

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

```python
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 .

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.

```python
# 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

```
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)
```

linear regression model on the training data.

4.3: Train the model

```
uni_model = LinearRegression()

uni_model.fit(X_uni_train, y_uni_train)
```

```
LinearRegression
LinearRegression()
```

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 :

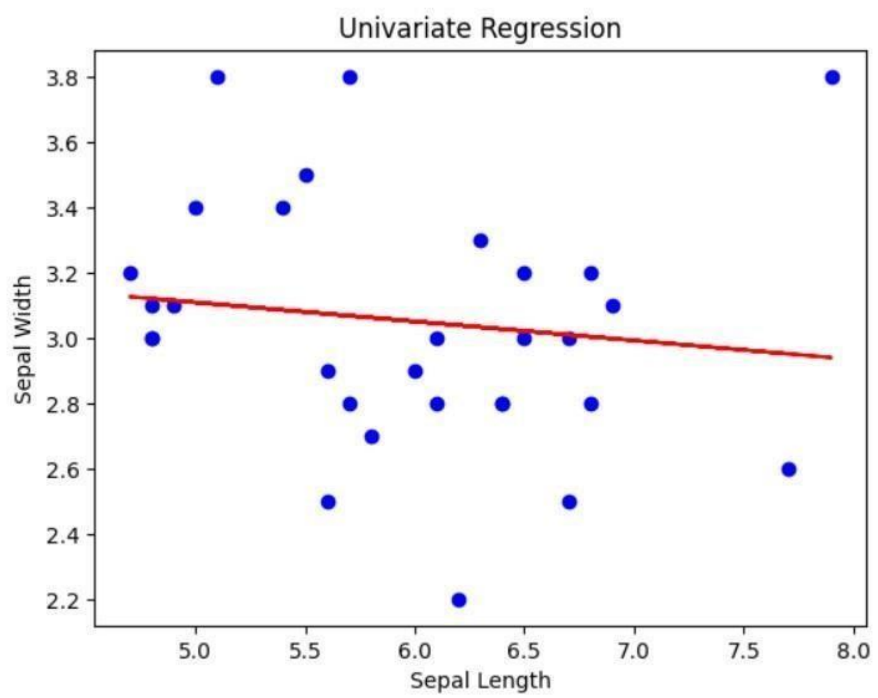
```
Univariate MSE: 0.13961895650579023
Univariate R-squared: 0.024098626473972984
```

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.

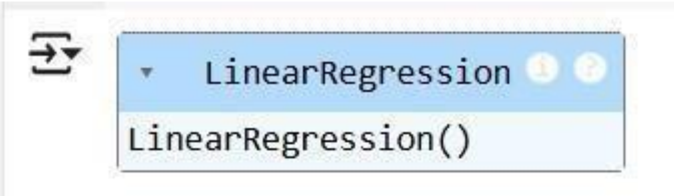
```
X_bi_train, X_bi_test, y_bi_train, y_bi_test = train_test_split(X_bi,
y_bi,

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 :



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 :

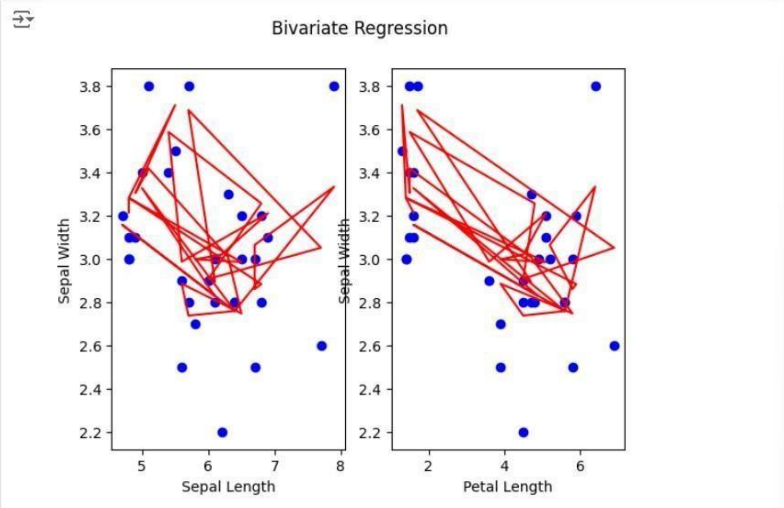
```
Bivariate MSE: 0.08308605032913309
Bivariate R-squared: 0.4192494152204116
```

5.6: Visualize the Results

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

```python
# 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
```

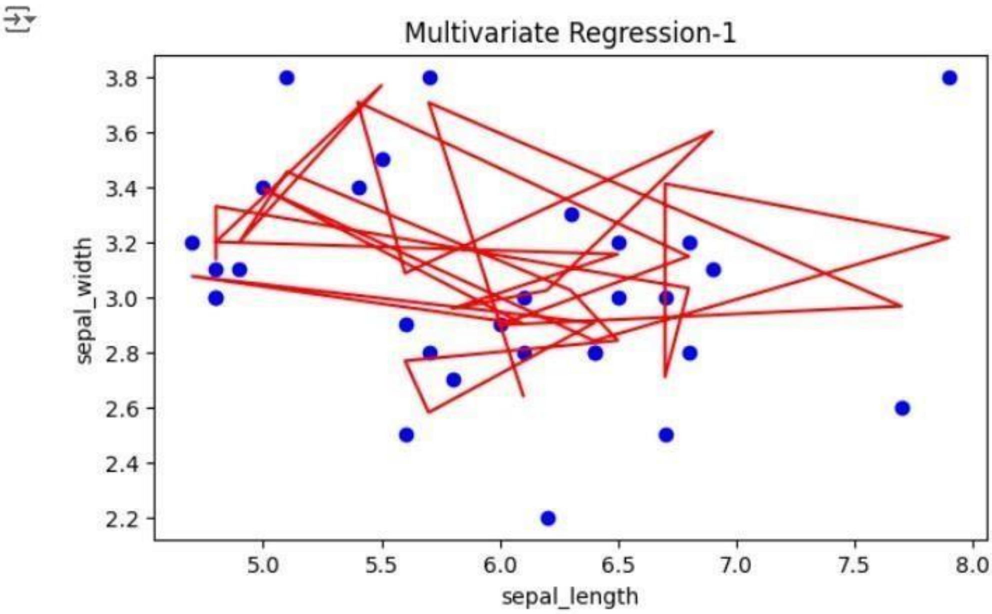
Step 7: Visualize the multivariate regression

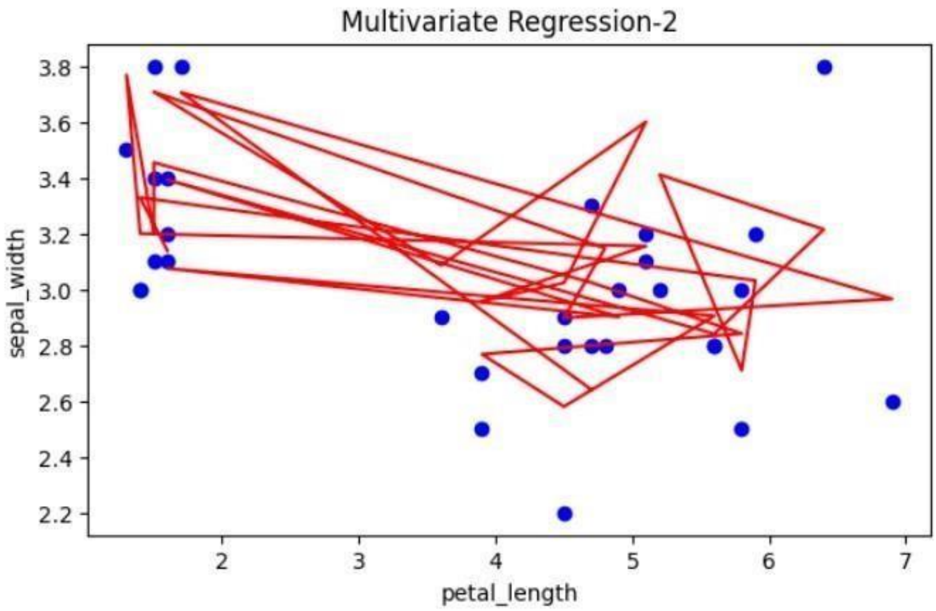
```
plt.figure(figsize=(15,4))

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')
```

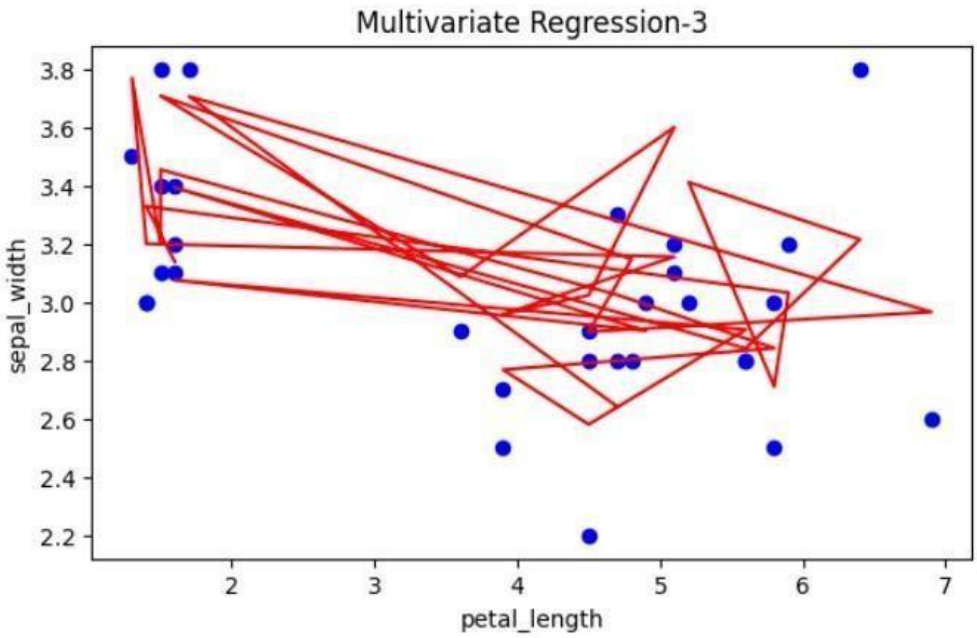
```
plt.xlabel('sepal_length')

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
```

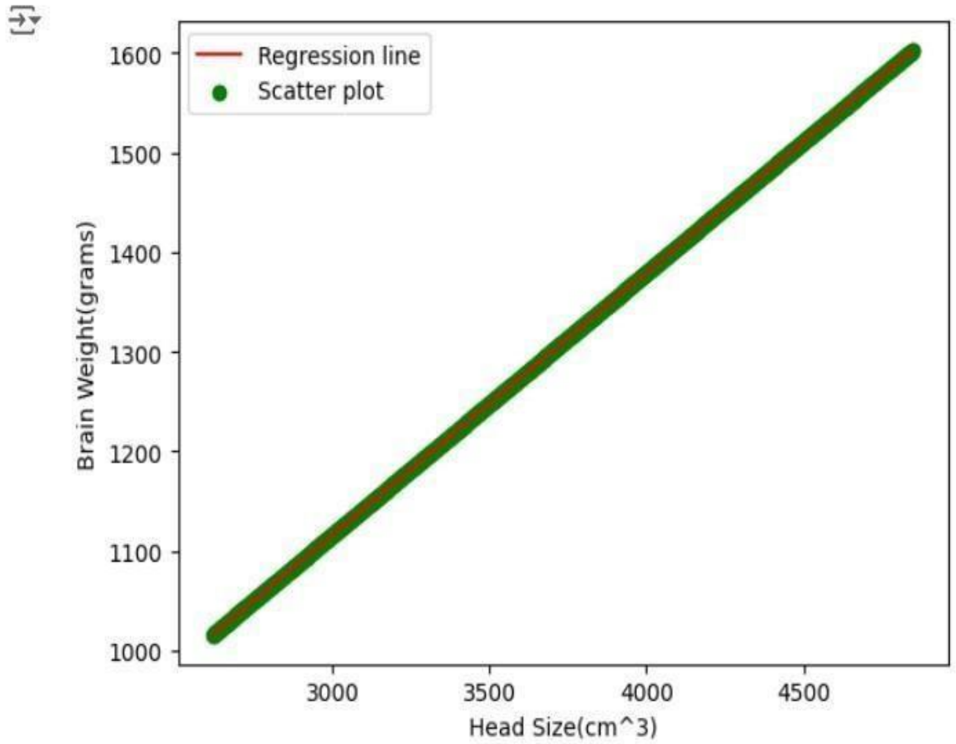
```
1.0
```

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 analyze 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
```

```python
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.

```python
# 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

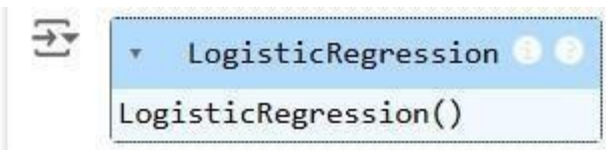
Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```
# 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
```

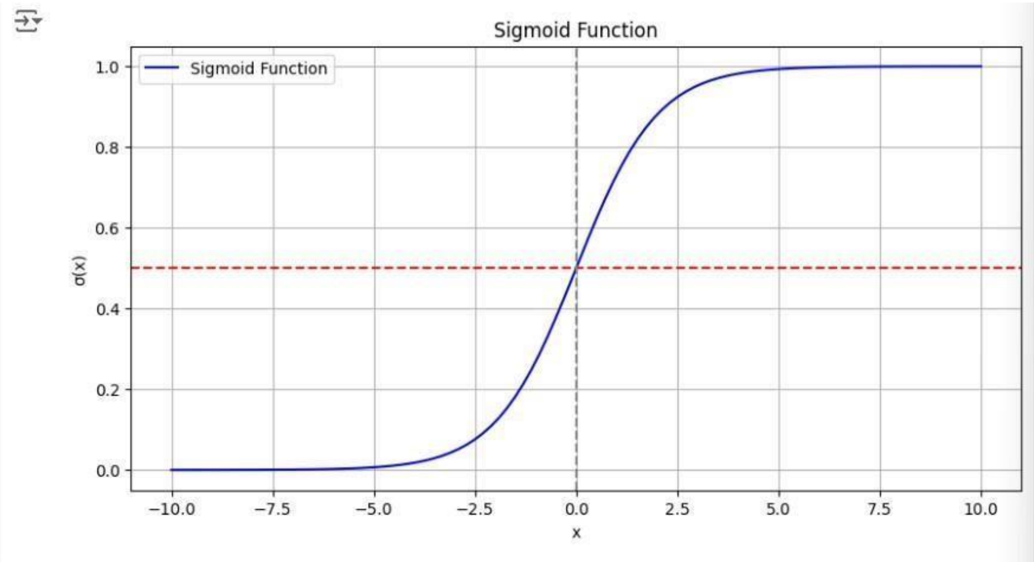
Step 7 :Visualize the Results

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 analyze their performance.

EXPT NO : 4 **A python program to implement Single Layer Perceptron**
DATE: 13.09.2024

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

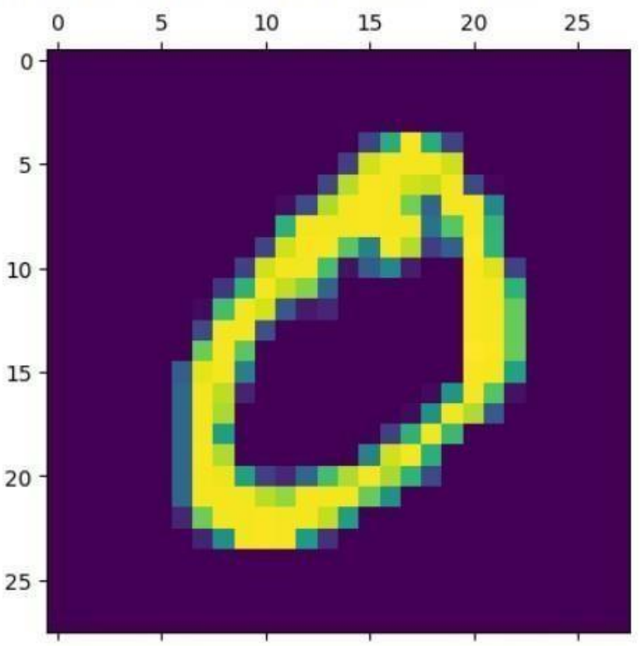
Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```
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 analyze 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
```

```python
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.

```python
(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.

```python
# 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>
```

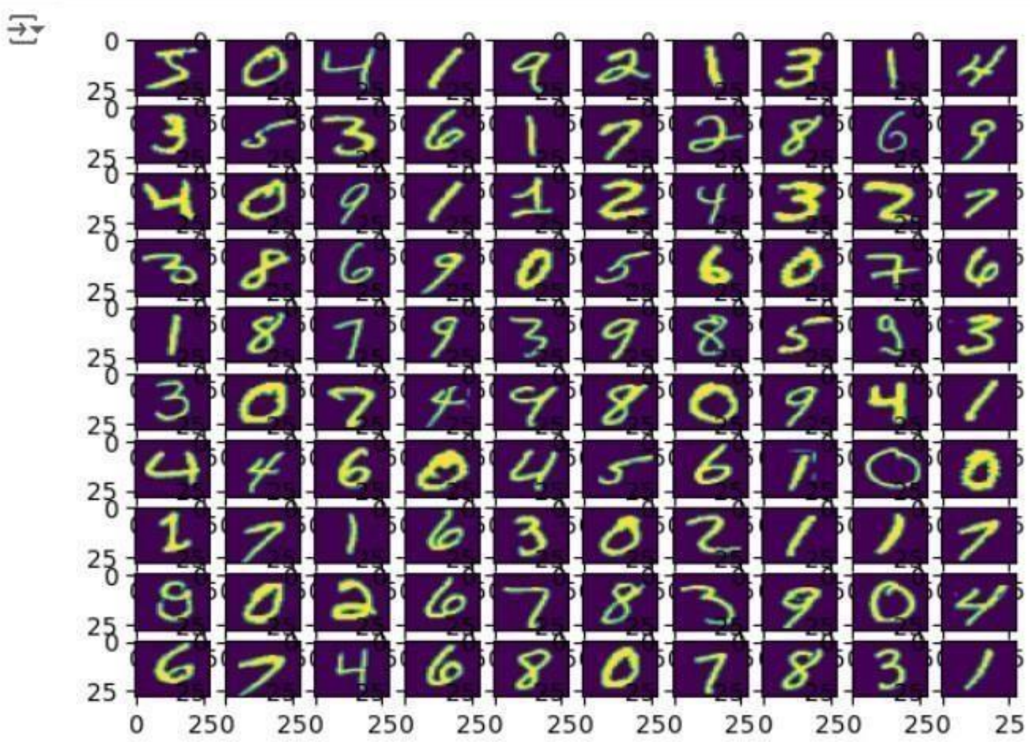
Step 6 : Evaluate the Model

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 analyze 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.

```python
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.

```python
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

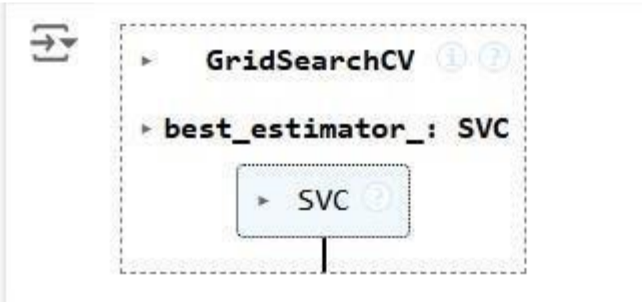
```
# Splitting the data into training and testing sets
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,
random_state=77, stratify=y)
```

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']}
```

```python
# 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

```python
# 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
```

```python
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 .

```python
# 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

```python
# 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

```python
# Create a Decision Tree classifier clf =

DecisionTreeClassifier(random_state=42)
```

Step 5 : Train the model :

```python
# Train the model
clf.fit(X_train, y_train)
```

OUTPUT :

```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

Step 6 : Make the predictions and evaluate the model

```python
# 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 :

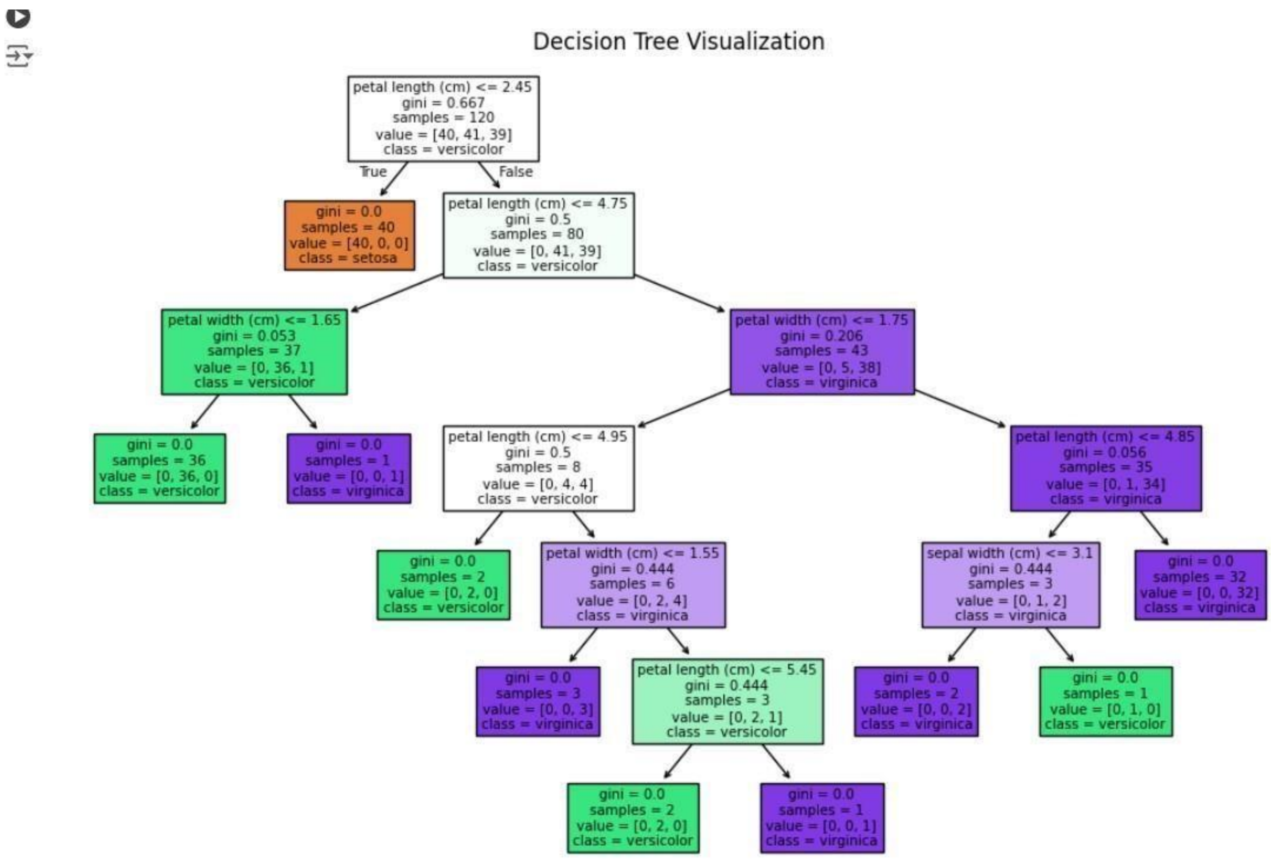
```
Accuracy: 1.00
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
Classification Report:
              precision    recall  f1-score   support

           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 :



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

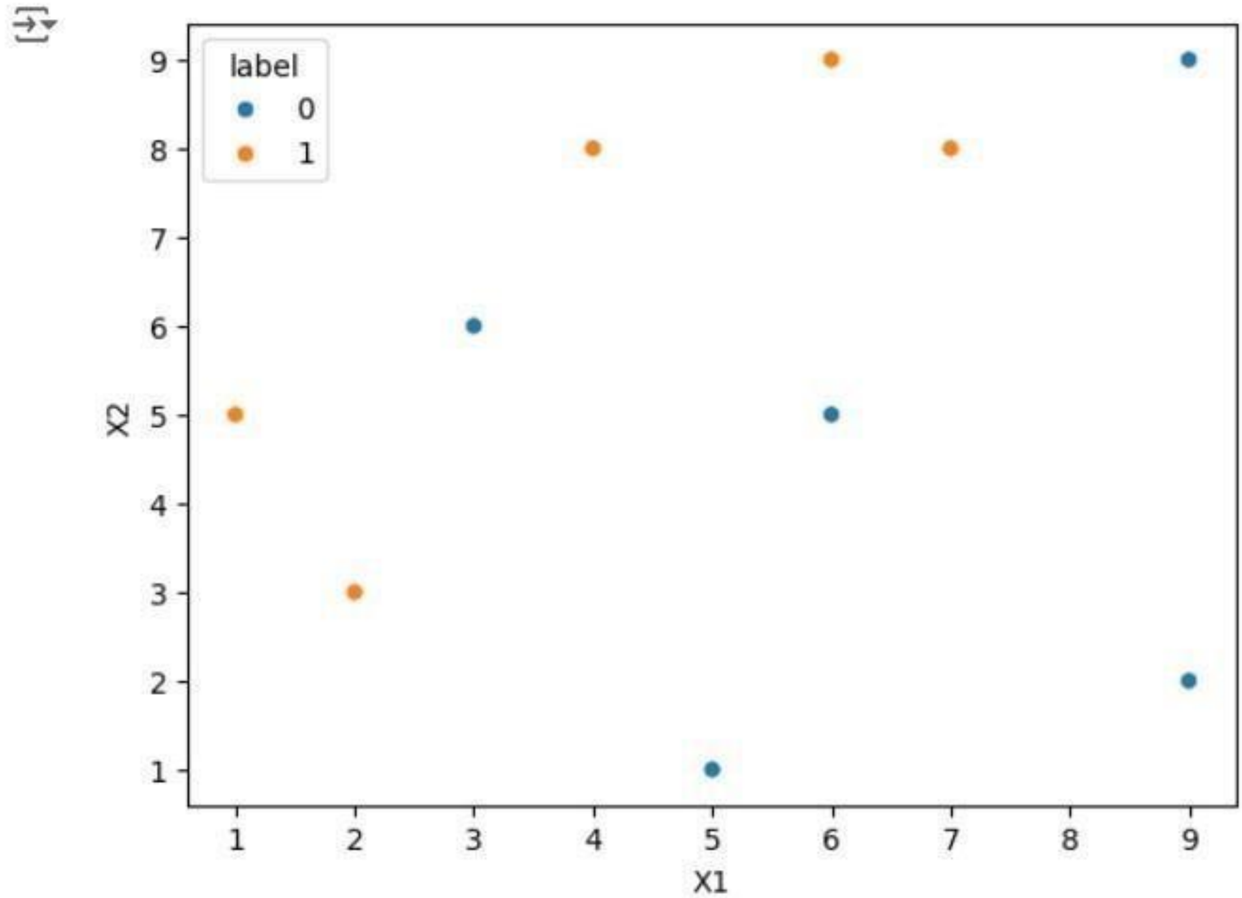
First, import the libraries that are essential for data manipulation, visualization, and model building.

```
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
```

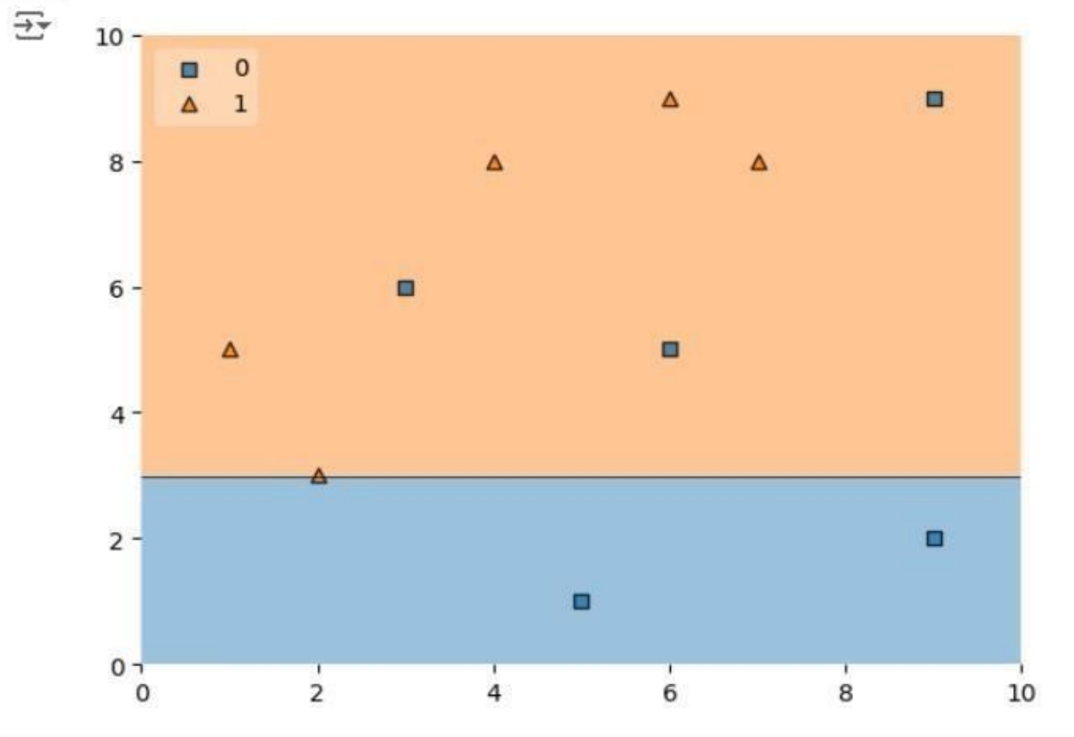
OUTPUT :



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)
```

```python
second_df = df.iloc[index_values, [0, 1, 2, 3]]
```

Step 6 : Train 2nd model

```python
# 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

```python
# 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)
```

```python
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

```python
# 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 Adaboosting 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')
```

```python
# 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)

```python
# 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')
```

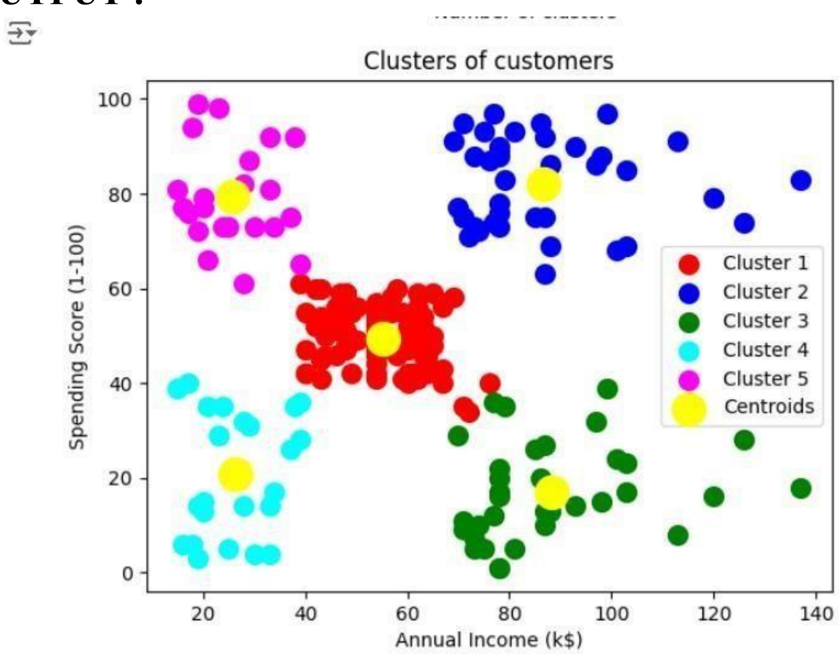
```
plt.xlabel('Number of clusters')

plt.ylabel('WCSS')

plt.show()
```

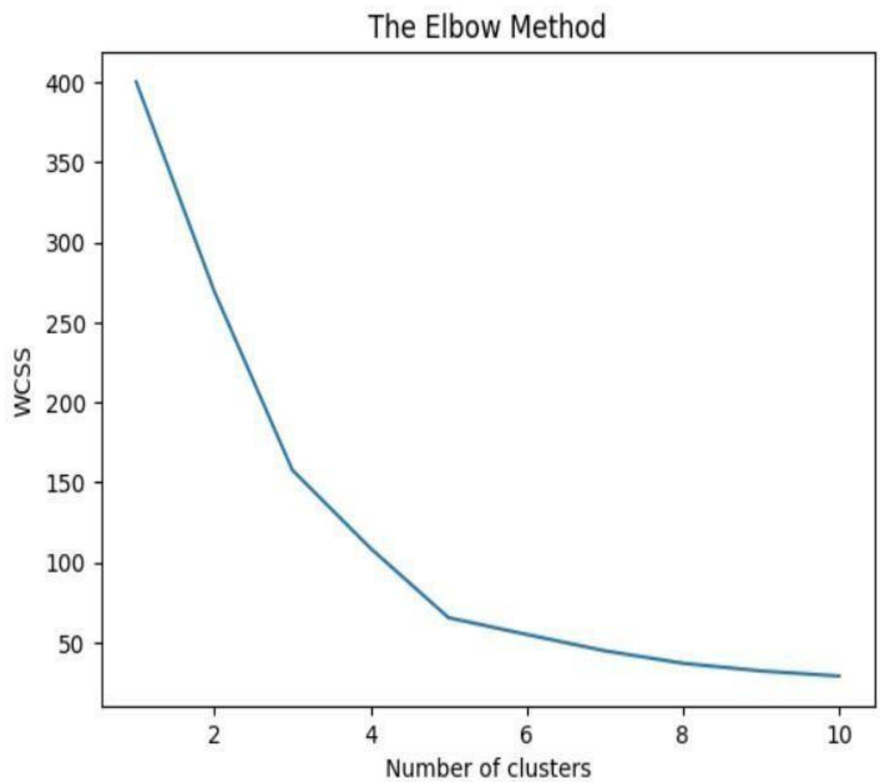
```python
# From the plot, we can observe that the optimal number of clusters is 5
(elbow point)

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)
```

```python
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)
```

```python
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
```

```python
# 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 Reduction -PCA.

DATE: 04.11.2024

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.

```python
# Importing necessary libraries
```

```python
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

```python
# 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.
```

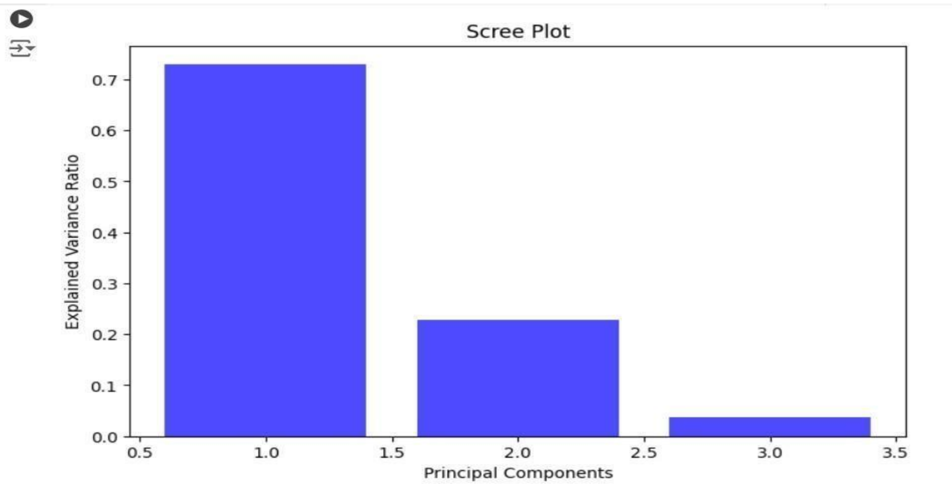
OUTPUT :

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

Step 6 :Visualize the reduced data.

```python
# 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.