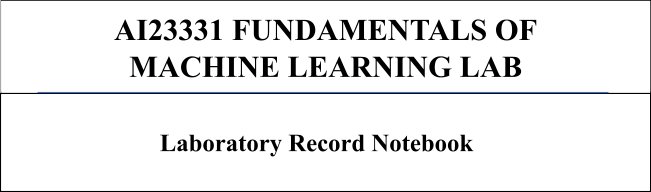
**RAJALAKSHMIENGINEERING COLLEGE**

**RAJALAKSHMI NAGAR, THANDALAM – 602 105**





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SEMESTER: III

ACADEMIC YEAR:2024-2025

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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()) |

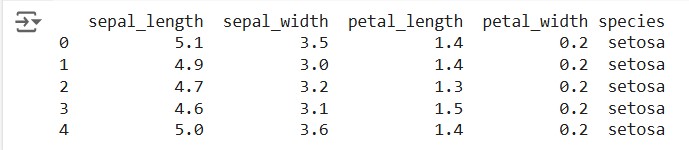
First, import the libraries that are essential for data manipulation, visualization, and model building.

|  |
| --- |
| 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 :**

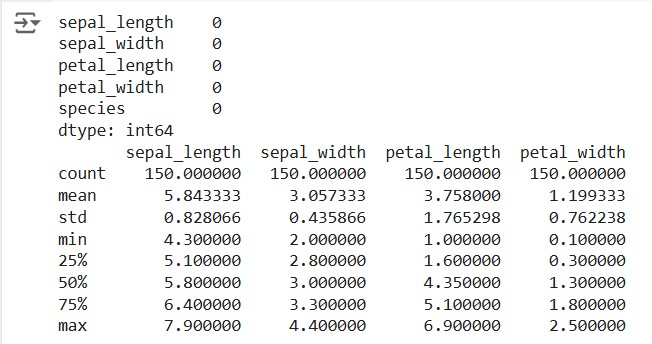


**Step 3: Data Preprocessing**

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 :**



**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**

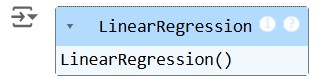
Split the data into training and testing sets.

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 :**

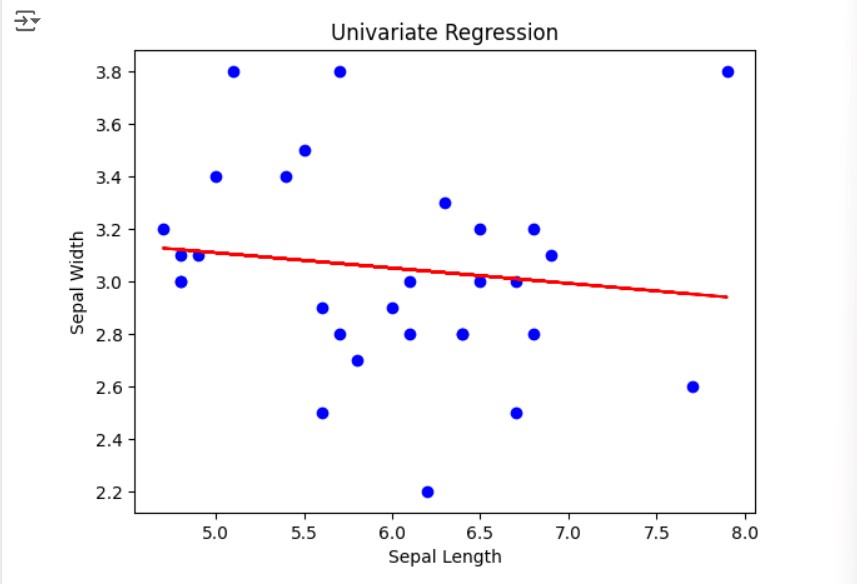


**4.6: Visualize the Results**

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.

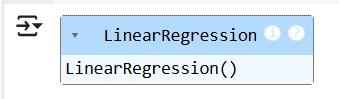
|  |
| --- |
| X\_bi\_train, X\_bi\_test, y\_bi\_train, y\_bi\_test = train\_test\_split(X\_bi, |
| y\_bi, |
| test\_size=0.2, random\_state=42) |

**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 :

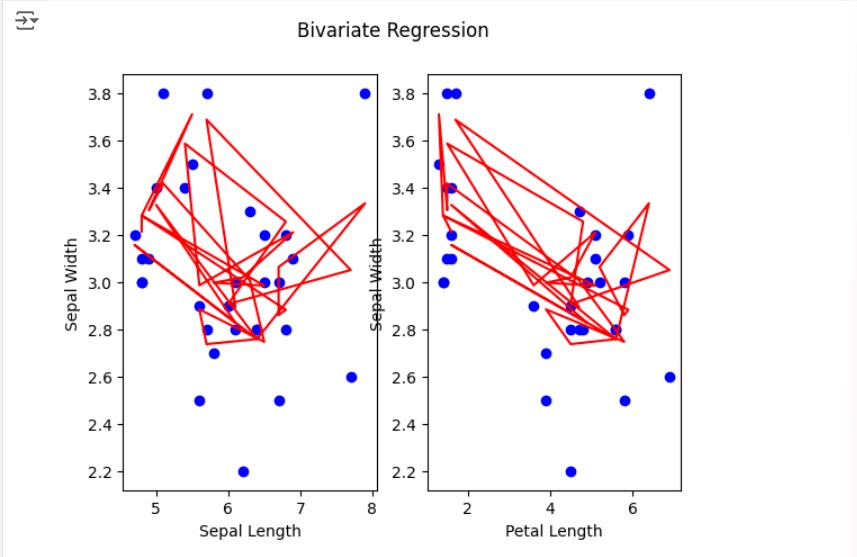


**5.6: Visualize the Results**

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.

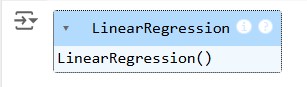
|  |
| --- |
| X\_multi\_train, X\_multi\_test, y\_multi\_train, y\_multi\_test = |
| train\_test\_split(X\_multi, |
| y\_multi, test\_size=0.2, random\_state=42) |

**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 :**



**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)}') |

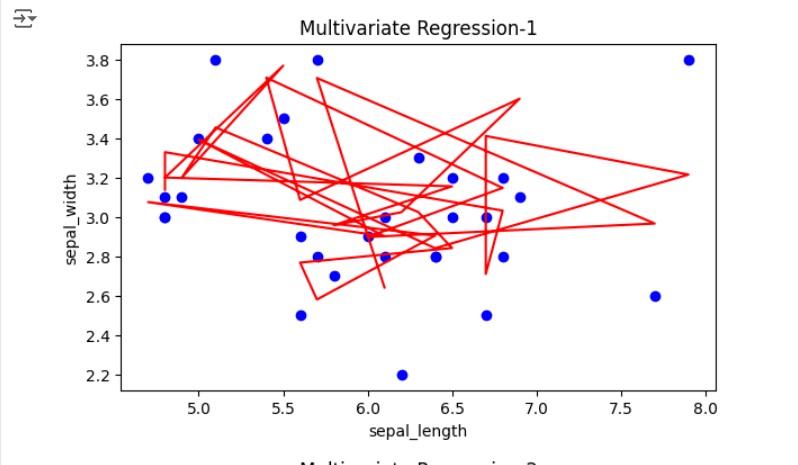
**OUTPUT :**

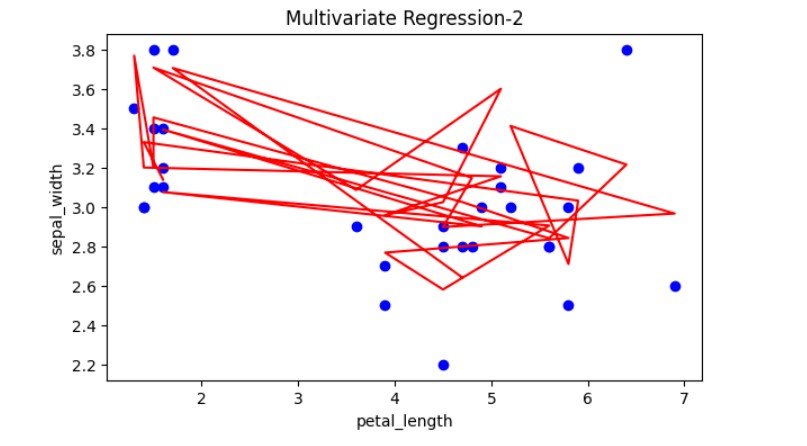


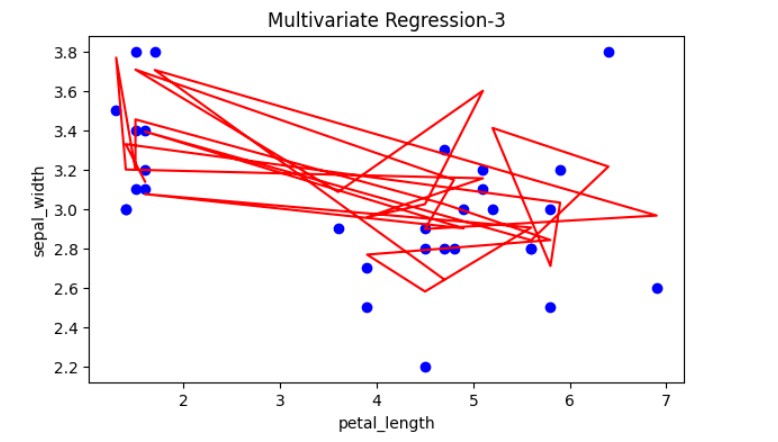
**Step 7: Visualize the multivariate regression**

|  |
| --- |
| 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 :**





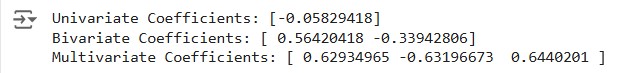


**Step 8: Interpret the Results**

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 :**



**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 :**



**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 :**



**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 :**



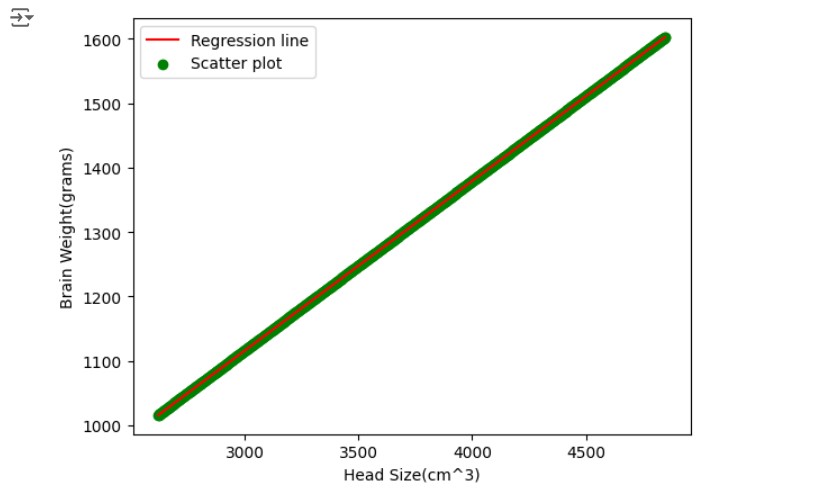


**Step 6 :Visualize the Results**

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, visualization, 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**

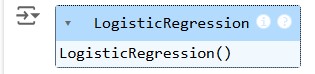
Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

|  |
| --- |
| # 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) |

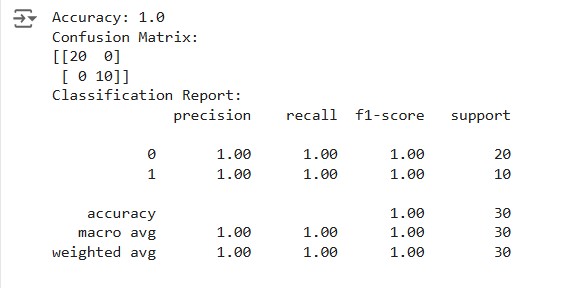
**Step 6 : Evaluate the Model**

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 :**



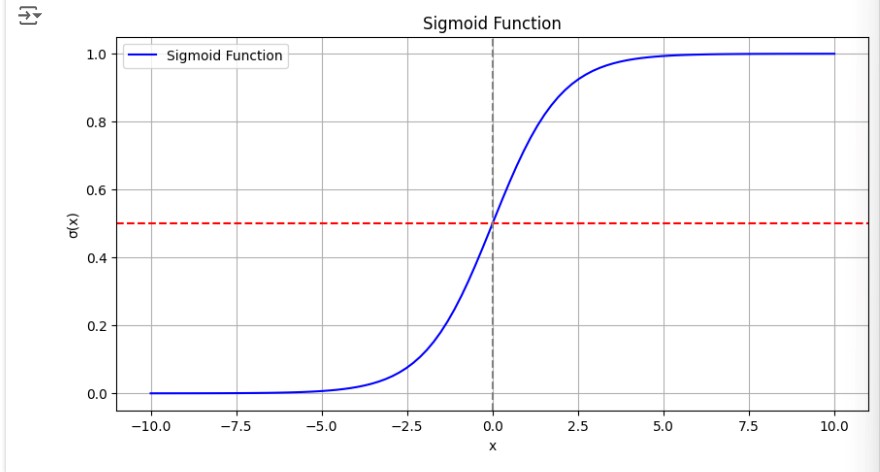
**Step 7 :Visualize the Results**

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.

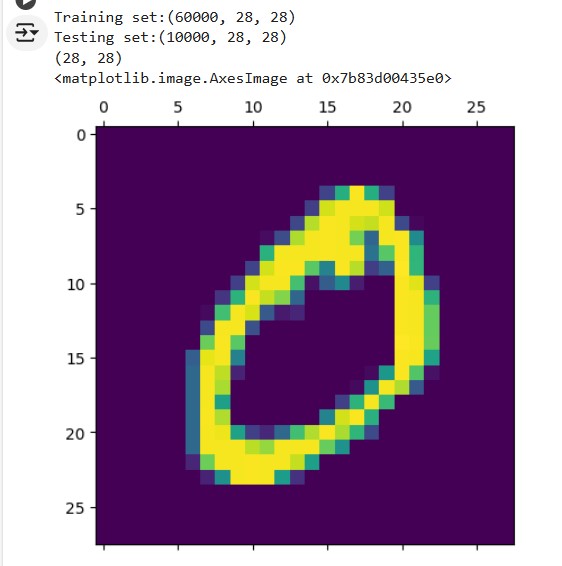
(X\_train,y\_train),(X\_test,y\_test)=keras.datasets.mnist.load\_data()

**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 :**



**Step 4 : Train a Model**

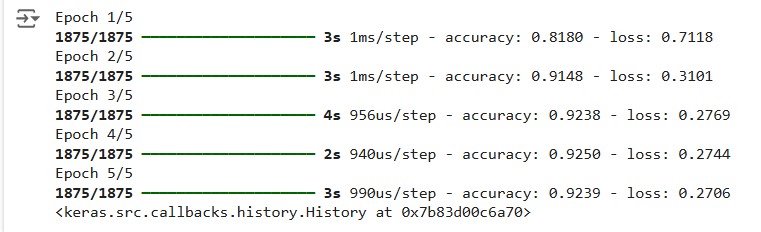
|  |
| --- |
| **#Normalizing the dataset** |
| **x\_train=X\_train/255** |
| **x\_test=X\_test/255** |
|  |
| **#Flatting the dataset in order to compute for model building** |
| **x\_train\_flatten=x\_train.reshape(len(x\_train),28\*28)** |
| **x\_test\_flatten=x\_test.reshape(len(x\_test),28\*28)** |
| **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 :**



**Step 6 : Evaluate the Model** Evaluate the model performance.

model.evaluate(x\_test\_flatten,y\_test)

**OUTPUT :**



**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 :**

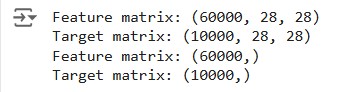


**Step 3: Data Preprocessing**

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) |
|  |

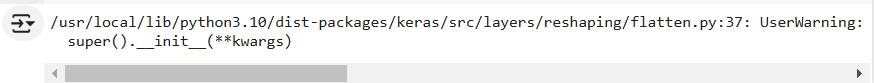
**OUTPUT :**



**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:**

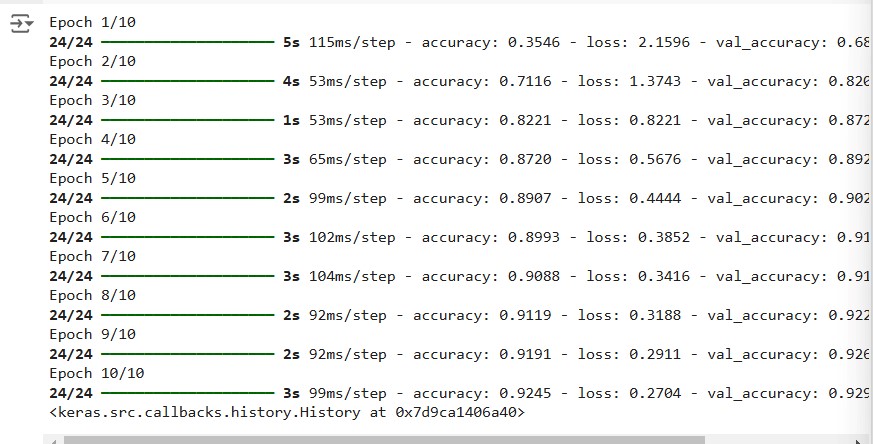


**Step 5 : Make Predictions**

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:**



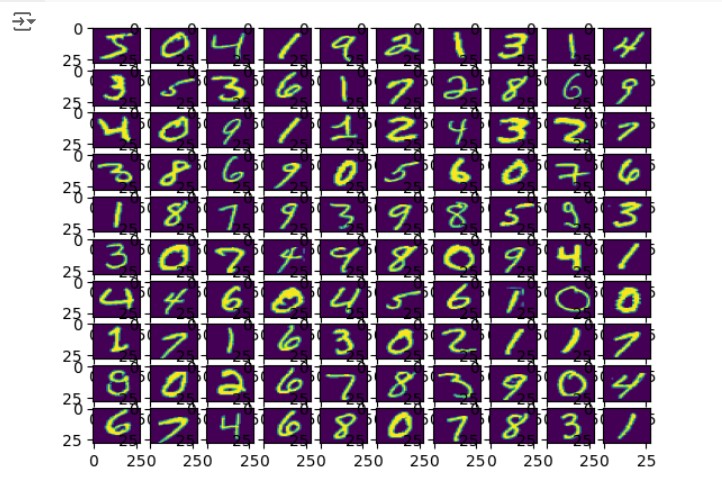
**Step 6 : Evaluate the Model**

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 :**





**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 :**



**Step 3: Separate input features and targets.**

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

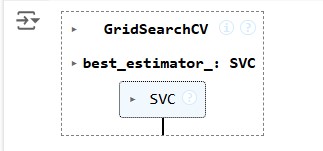
**Step 4 : Separate the input features and target**

|  |
| --- |
| **# 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)** |

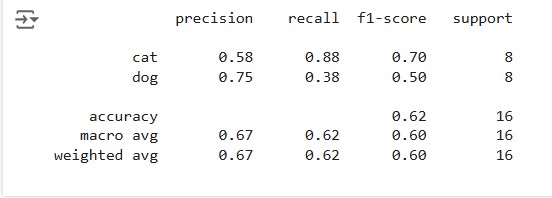
**OUTPUT :**



**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']))** |
|  |

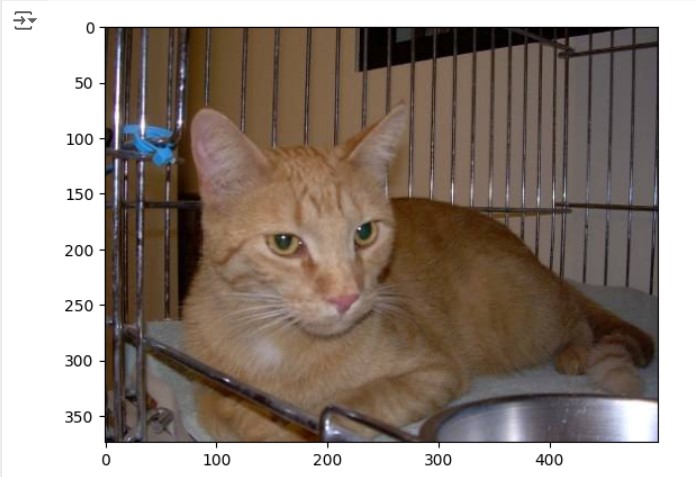
**OUTPUT :**



**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)** |

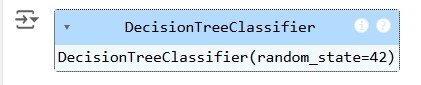
**Step 4 : Create a decision tree classifier**

|  |
| --- |
| **# Create a Decision Tree classifier** |
| **clf = DecisionTreeClassifier(random\_state=42)** |

**Step 5 : Train the model : # Train the model**

**clf.fit(X\_train, y\_train)**

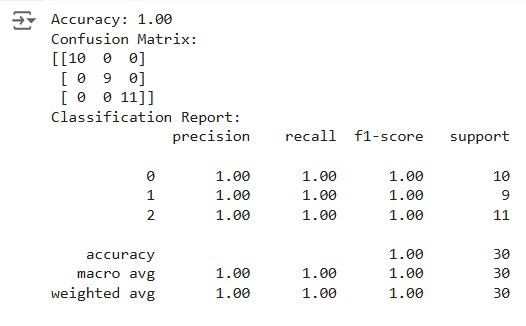
**OUTPUT :**



**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)** |

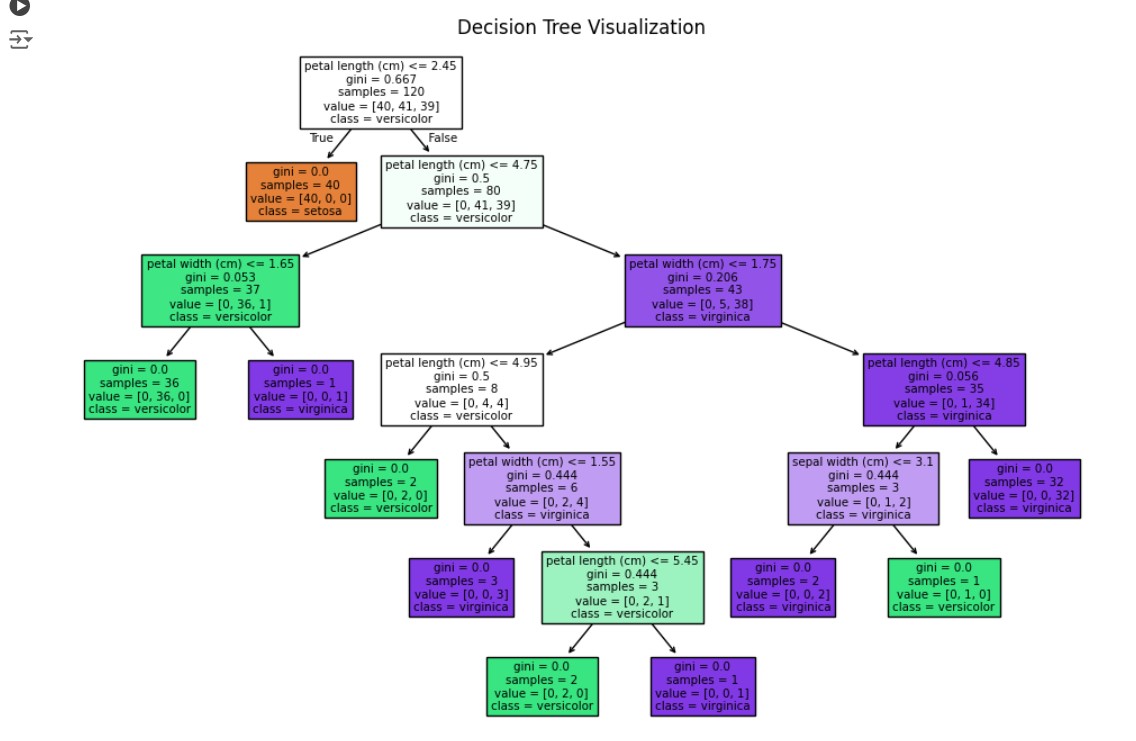
**OUTPUT :**



**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**

**DATE : 18.10.2024 ADA BOOSTING**

**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**

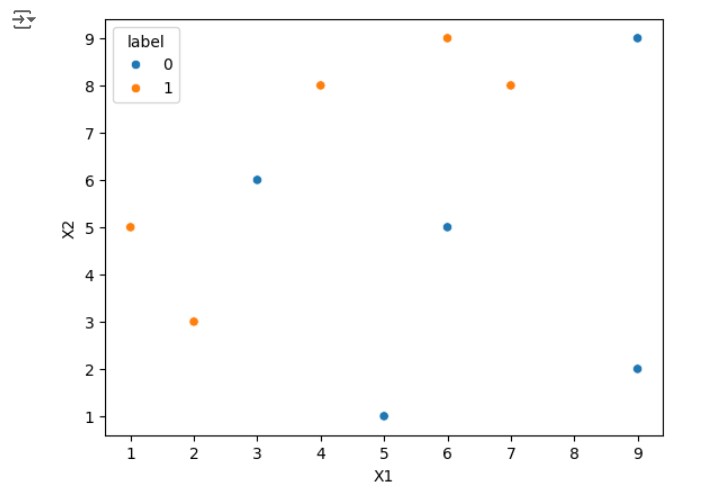
First, import the libraries that are essential for data manipulation, visualization, and model building.

|  |
| --- |
| 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** |

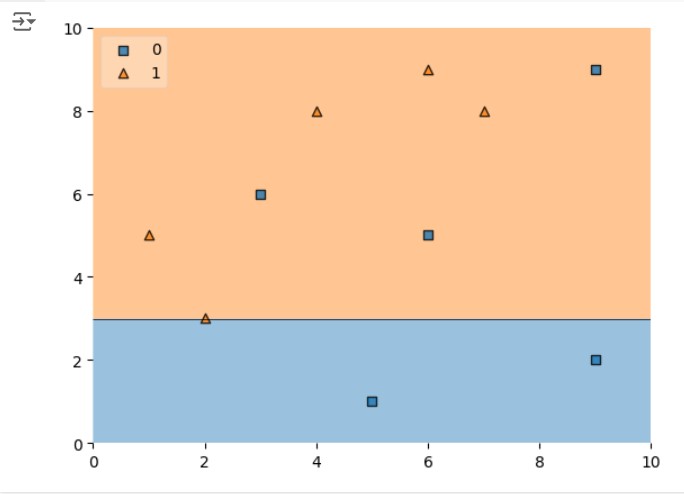
**OUTPUT :**



**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**

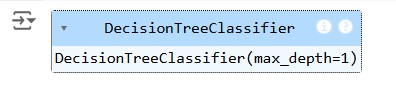
**# Step 5: Create New Dataset**

|  |
| --- |
| **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 :**



**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 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')** |
|  |
| **# 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)**

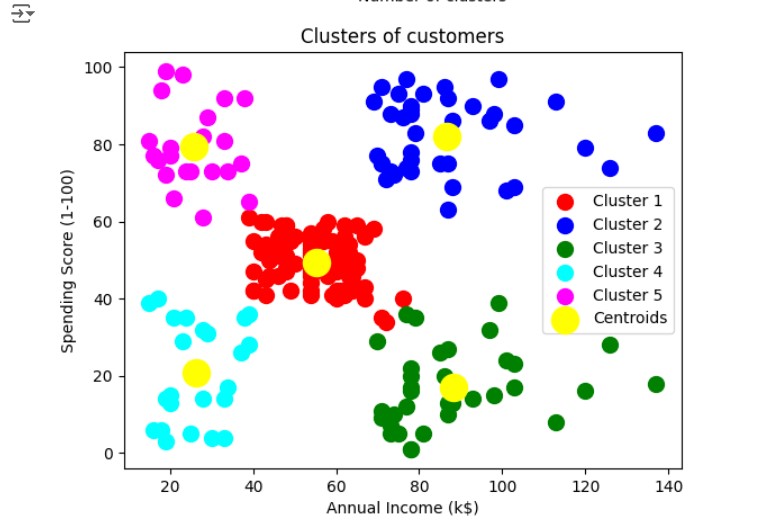
|  |
| --- |
| **# Separate the features (X) and the target variable (y)** |
| **X = dataset.iloc[:, [3, 4]].values # We use 'Annual Income' and 'Spending** |
| **Score'** |
|  |
| **# Standardize the features** |
| **scaler = StandardScaler()** |
| **X\_scaled = scaler.fit\_transform(X)** |
|  |

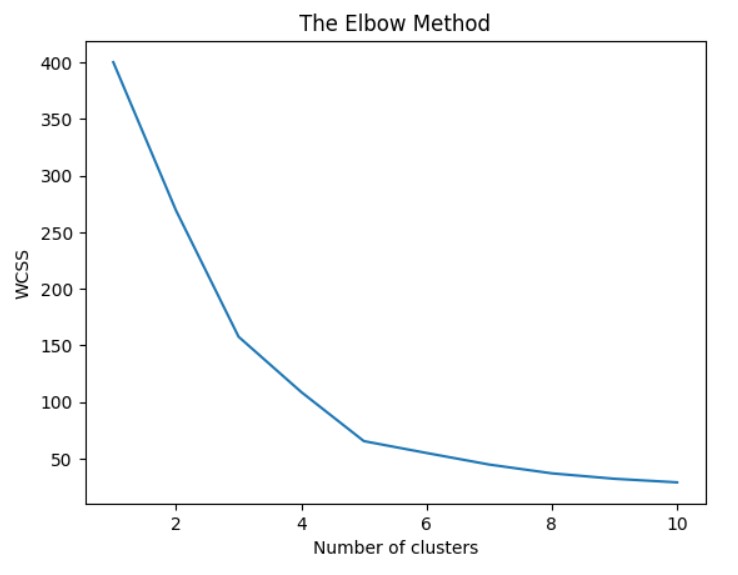
**Step 4 : Visualizing the cluster of customer**

|  |
| --- |
| **# 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**

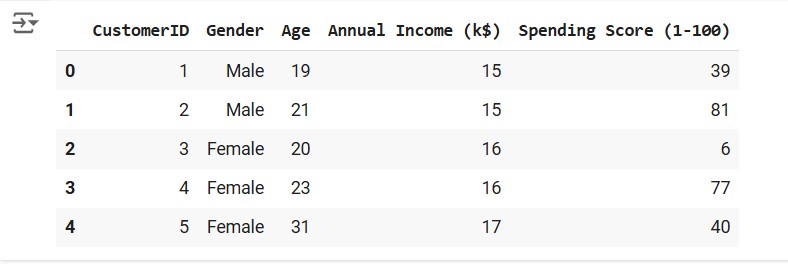
First, import the libraries that are essential for data manipulation, visualization, and model building.

|  |
| --- |
| 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)** |

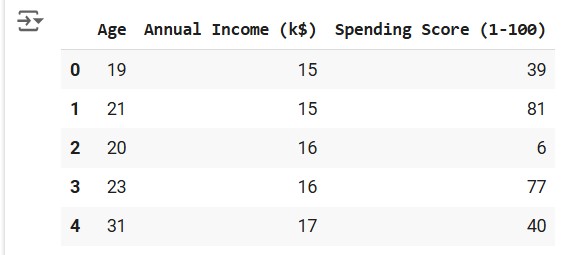
**OUTPUT:**



**Step 3 : Preprocess the data**

|  |
| --- |
| **req\_data = data[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']]** |
|  |
| **req\_data.head(5)** |

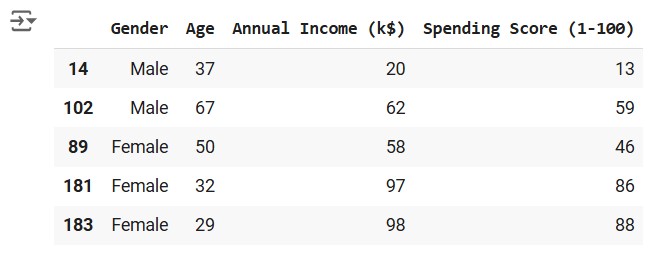
**OUTPUT :**



**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 :**



**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 :**



**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() |

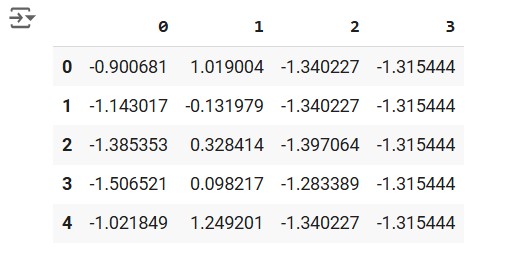
**OUTPUT :**



**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()** |  |

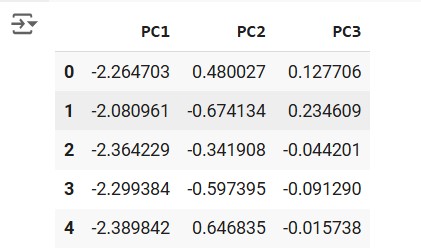
**OUTPUT :**



**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 :**



**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 :**

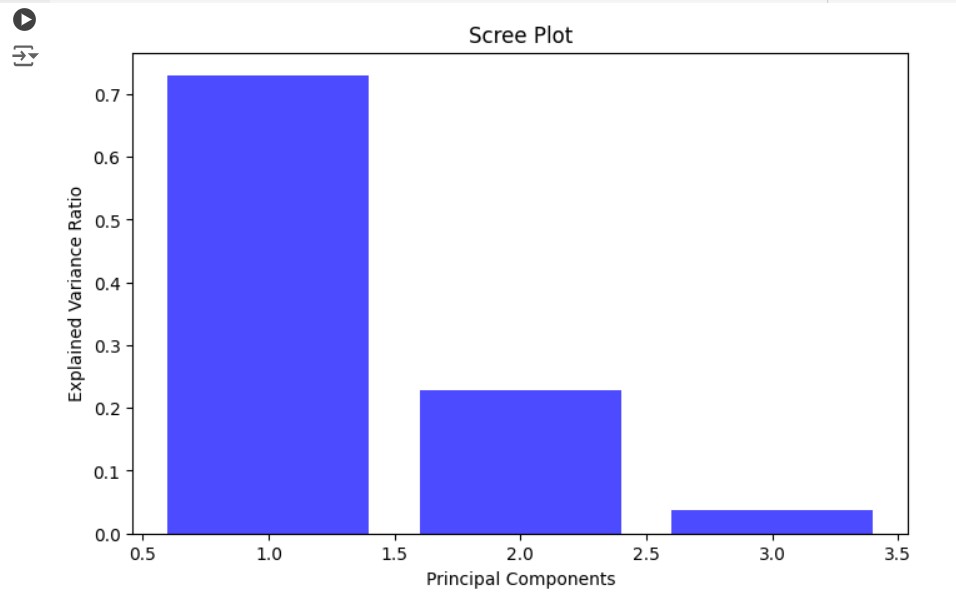


**Step 6 :Visualize the reduced data.**

**# 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.