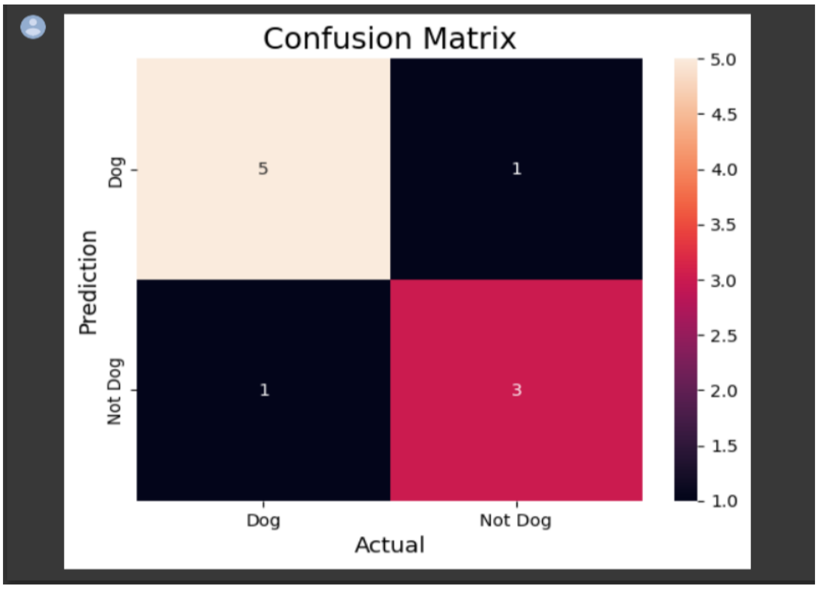
EXPERIMENT:1(A)

AIM: To demonstrate confusion matrix using python

PROGRAM:
```
#Import the necessary libraries
import numpy as np
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

#Create the NumPy array for actual and predicted labels.
actual    = np.array(
  ['Dog','Dog','Dog','Not Dog','Dog','Not Dog','Dog','Dog','Not Dog','N
ot Dog'])
predicted = np.array(
  ['Dog','Not Dog','Dog','Not Dog','Dog','Dog','Dog','Dog','Not Dog','N
ot Dog'])

#compute the confusion matrix.
cm = confusion_matrix(actual,predicted)

#Plot the confusion matrix.
sns.heatmap(cm,
            annot=True,
            fmt='g',
            xticklabels=['Dog','Not Dog'],
            yticklabels=['Dog','Not Dog'])
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```
OUTPUT:



EXPERIMENT:1(B)

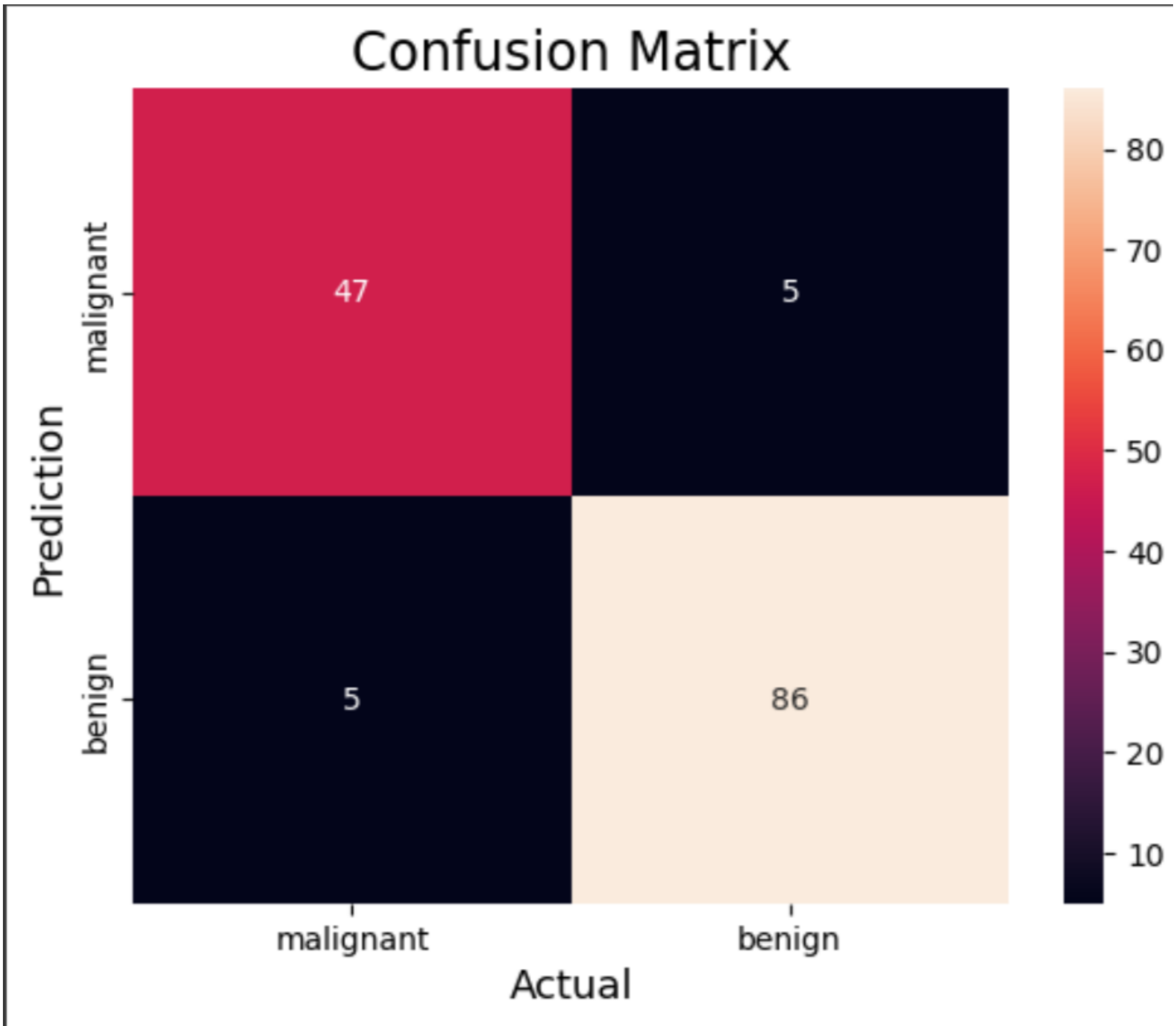
AIM: To demonstrate 2 class confusion matrix using python

PROGRAM:

```
#Import the necessary libraries
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, precision_score, recall_sco
re, f1_score

# Load the breast cancer dataset
X, y= load_breast_cancer(return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.25
)

# Train the model
tree = DecisionTreeClassifier(random_state=23)
tree.fit(X_train, y_train)

# prediction
y_pred = tree.predict(X_test)

# compute the confusion matrix
cm = confusion_matrix(y_test,y_pred)
```

```python
#Plot the confusion matrix.
sns.heatmap(cm,
            annot=True,
            fmt='g',
            xticklabels=['malignant', 'benign'],
            yticklabels=['malignant', 'benign'])
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()


# Finding precision and recall
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy   :", accuracy)
precision = precision_score(y_test, y_pred)
print("Precision :", precision)
recall = recall_score(y_test, y_pred)
print("Recall    :", recall)
F1_score = f1_score(y_test, y_pred)
print("F1-score  :", F1_score)
```

OUTPUT:




```
Accuracy   : 0.9300699300699301
Precision : 0.945054945054945
Recall    : 0.945054945054945
F1-score  : 0.945054945054945
```

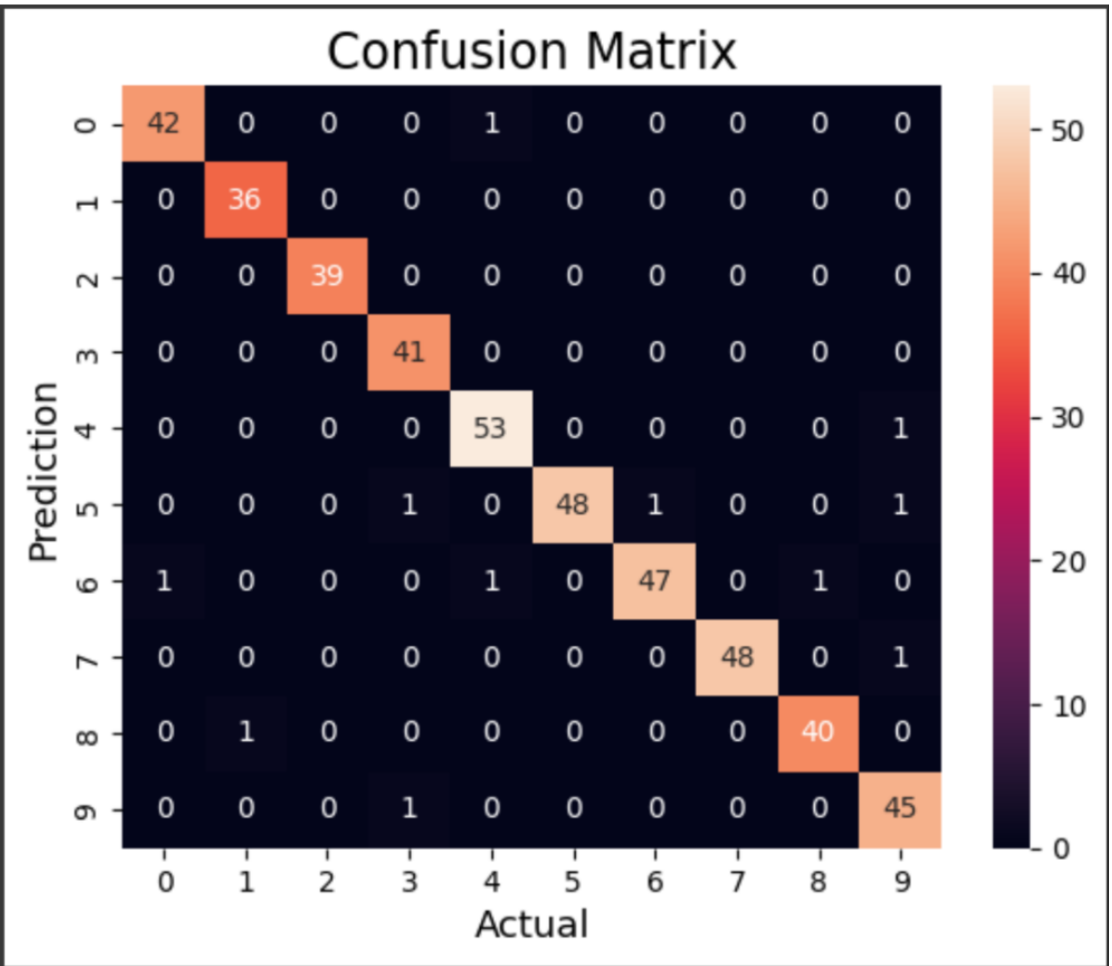
EXPERIMENT:2

AIM: Verifying the performance of a multi class confusion matrix by using choosen database with phython code

PROGRAM:

```
#Import the necessary libraries
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, precision_score, recall_sco
re, f1_score

# Load the breast cancer dataset
X, y= load_digits(return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.25
)

# Train the model
clf = RandomForestClassifier(random_state=23)
clf.fit(X_train, y_train)

# prediction
y_pred = clf.predict(X_test)

# compute the confusion matrix
cm = confusion_matrix(y_test,y_pred)

#Plot the confusion matrix.
sns.heatmap(cm,
            annot=True,
            fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()


# Finding precision and recall
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy   :", accuracy)
```

OUTPUT:




```
Accuracy     : 0.9755555555555555
```

EXPERIMENT:3

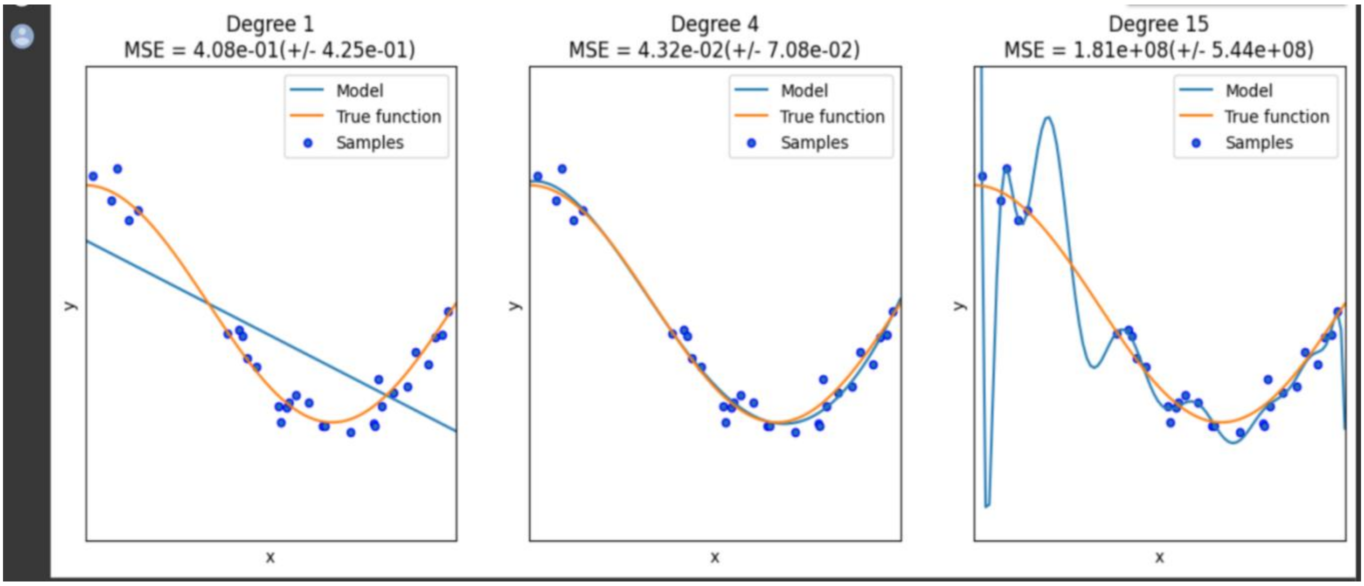
AIM: : Verifying the performance of a over fitting by using choosen database with python code

PROGRAM:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score


def true_fun(X):
    return np.cos(1.5 * np.pi * X)


np.random.seed(0)

n_samples = 30
degrees = [1, 4, 15]

X = np.sort(np.random.rand(n_samples))
y = true_fun(X) + np.random.randn(n_samples) * 0.1

plt.figure(figsize=(14, 5))
for i in range(len(degrees)):
    ax = plt.subplot(1, len(degrees), i + 1)
    plt.setp(ax, xticks=(), yticks=())

    polynomial_features = PolynomialFeatures(degree=degrees[i], include_bias=
False)
    linear_regression = LinearRegression()
    pipeline = Pipeline(
        [
            ("polynomial_features", polynomial_features),
            ("linear_regression", linear_regression),
        ]
    )
    pipeline.fit(X[:, np.newaxis], y)
```

```
    # Evaluate the models using crossvalidation
    scores = cross_val_score(
        pipeline, X[:, np.newaxis], y, scoring="neg_mean_squared_error", cv=10
    )

    X_test = np.linspace(0, 1, 100)
    plt.plot(X_test, pipeline.predict(X_test[:, np.newaxis]), label="Model")
    plt.plot(X_test, true_fun(X_test), label="True function")
    plt.scatter(X, y, edgecolor="b", s=20, label="Samples")
    plt.xlabel("x")
    plt.ylabel("y")
    plt.xlim((0, 1))
    plt.ylim((-2, 2))
    plt.legend(loc="best")
    plt.title(
        "Degree {}\nMSE = {:.2e}(+/- {:.2e})".format(
            degrees[i], -scores.mean(), scores.std()
        )
    )
plt.show()
```

OUTPUT:



EXPERIMENT:4

AIM: To demonstrate the performance of a linear regression by using choosen database with python code

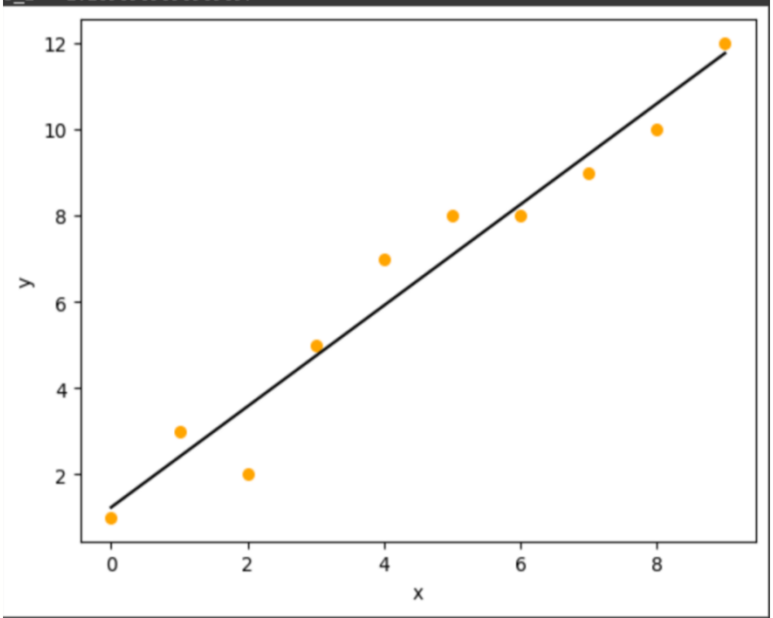
PROGRAM: LINEAR REGRESSION

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

def estimate_coef(x, y):
    # number of observations/points
    n = np.size(x)

    # mean of x and y vector
    m_x = np.mean(x)
    m_y = np.mean(y)

    # calculating cross-deviation and deviation about x
    SS_xy = np.sum(y*x) - n*m_y*m_x
    SS_xx = np.sum(x*x) - n*m_x*m_x

    # calculating regression coefficients
    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1*m_x

    return (b_0, b_1)

def plot_regression_line(x, y, b):
    # plotting the actual points as scatter plot
    plt.scatter(x, y, color = "r",
                marker = "o", s = 30)

    # predicted response vector
    y_pred = b[0] + b[1]*x

    # plotting the regression line
    plt.plot(x, y_pred, color = "b")

    # putting labels
    plt.xlabel('x')
    plt.ylabel('y')
```

```python
    # function to show plot
    plt.show()

def main():
    # observations / data
    x = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
    y = np.array([1, 3, 2, 5, 7, 8, 8, 9, 10, 12])

    # estimating coefficients
    b = estimate_coef(x, y)
    print("Estimated coefficients:\nb_0 = {}  \
          \nb_1 = {}".format(b[0], b[1]))

    # plotting regression line
    plot_regression_line(x, y, b)

if __name__ == "__main__":
    main()
```

OUTPUT:

```
Estimated coefficients:
b_0 = 1.2363636363636363
b_1 = 1.1696969696969697
```



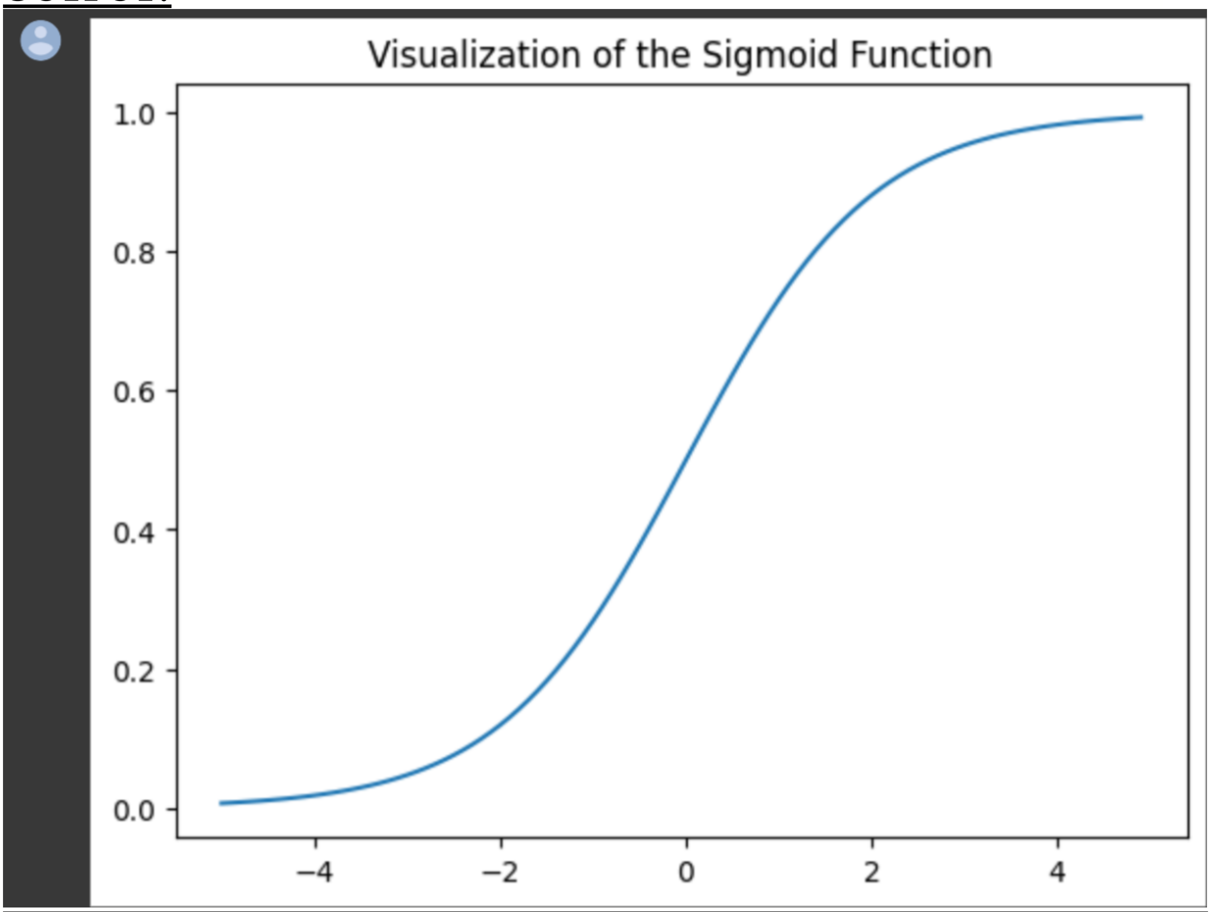
EXPERIMENT:5

AIM: : To demonstrate the performance of a logistic regression by using choosen database with python code.

PROGRAM:

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

def sigmoid(z):
   return 1 / (1 + np.exp( - z))

plt.plot(np.arange(-5, 5, 0.1), sigmoid(np.arange(-5, 5, 0.1)))
plt.title('Visualization of the Sigmoid Function')

plt.show()
```

OUTPUT:



EXPERIMENT:6(a)KNN

AIM: Finding accuracy value of iris data set using KNN algorithm

PROGRAM:

```
import numpy as np
import pandas as pd

dataset = pd.read_csv("/content/IRIS.csv")
"""
The breast cancer dataset has the following features: Sample code number, Clump Thickness, Uniformity of Cell Size,
Uniformity of Cell Shape, Marginal Adhesion, Single Epithelial Cell Size, Bare Nuclei, Bland Chromatin,
 Normal Nucleoli, Mitosis, Class.
"""
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
dataset.shape
#splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 42)
#Feature Scaling
"""
Feature scaling is the process of converting the data into a given range.
In this case, the standard scalar technique is used.
"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
#Training the K-Nearest Neighbors (K-NN) Classification model on the Training set
"""
Once the dataset is scaled, next, the K-Nearest Neighbors (K-NN) classifier algorithm is used to create a model.
The hyperparameters such as n_neighbors, metric, and p are set to 5, Minkowski, and 2 respectively.
 The remaining hyperparameters are set to default values.
"""
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)

classifier.fit(X_train, y_train)
"""
Display the results (confusion matrix and accuracy)
```

Here evaluation metrics such as confusion matrix and accuracy are used to evaluate the performance of the model built using a decision tree classifier.
"""
from sklearn.metrics import confusion_matrix, accuracy_score
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)

OUTPUT:

```
[[85  0]
 [ 2 50]]
0.9854014598540146
```

EXPERIMENT:6(B)NAVIE

AIM: : finding accuracy value of iris data set using NAVIE BAYES algorithm

PROGRAM:

```
import numpy as np
import pandas as pd
#Importing the dataset
"""
Next, we import or read the dataset. Click here to download the breast cancer dataset used
in this implementation.
 After reading the dataset, divide the dataset into concepts and targets. Store the concepts
into X and
 targets into y.
"""
dataset = pd.read_csv("/content/IRIS.csv ")
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
"""
Splitting the dataset into the Training set and Test set
Once the dataset is read into the memory, next, divide the dataset into two parts, training and
testing using the train_test_split function from sklearn.
 The test_size and random_state attributes are set to 0.25 and 0 respectively.
 You can change these attributes as per your requirements.
"""
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

#Feature Scaling
"""
Feature scaling is the process of converting the data into a min-max range. In this case,
 the standard scalar method is used.
"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
"""
Training the Naive Bayes Classification model on the Training set
Once the dataset is scaled, next, the Naive Bayes classifier algorithm is used to create a model.
The GaussianNB function is imported from sklearn.naive_bayes library. The hyperparameters
such as kernel,
and random_state to linear, and 0 respectively. The remaining hyperparameters of the
support vector machine
 algorithm are set to default values.
"""
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

```
#Naive Bayes classifier model
GaussianNB(priors=None, var_smoothing=1e-09)

#Display the results (confusion matrix and accuracy)
"""
Here evaluation metrics such as confusion matrix and accuracy are used to evaluate the performance of
the model built using a decision tree classifier.
"""
from sklearn.metrics import confusion_matrix, accuracy_score
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

OUTPUT:

```
[[114   2]
 [  2  53]]
0.9766081871345029
```

EXPERIMENT:6(C)LOGISTIC

AIM: : finding accuracy value of iris data set using LOGISTIC REGRESSION algorithm

PROGRAM:

```
import numpy as np
import pandas as pd

#"Importing the dataset
"""
After importing the necessary libraries, next, we import or read the dataset.
 Click here to download the breast cancer dataset used in this implementation.
 The breast cancer dataset has the following features:
 Sample code number, Clump Thickness, Uniformity of Cell Size, Uniformity of Cell Shape, Marginal Adhesion,
 Single Epithelial Cell Size, Bare Nuclei, Bland Chromatin, Normal Nucleoli, Mitosis, Class.
"""


# divide the dataset into concepts and targets. Store the concepts into X and targets into y.
dataset = pd.read_csv("/content/IRIS.csv ")
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values

#Splitting the dataset into the Training set and Test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state = 2)

#Feature Scaling
"""
Feature scaling is the process of converting the data into a given range. In this case, the standard scalar technique is used.
from sklearn.preprocessing import StandardScaler
"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
"""
Training the Logistic Regression (LR) Classification model on the Training set
Once the dataset is scaled, next, the Logistic Regression (LR) classifier algorithm is used to create a model.
```

```
The hyperparameters such as random_state to 0 respectively.
 The remaining hyperparameters Logistic Regression (LR) are set to default values.
 """
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
#Logistic Regression (LR) classifier model
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                intercept_scaling=1, l1_ratio=None, max_iter=100,
                multi_class='warn', n_jobs=None, penalty='l2',
                random_state=0, solver='warn', tol=0.0001, verbose=0,
                warm_start=False)
#Display the results (confusion matrix and accuracy)
"""
Here evaluation metrics such as confusion matrix and accuracy are used to evaluate
the performance of the model
built using a decision tree classifier.
"""
from sklearn.metrics import confusion_matrix, accuracy_score
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

OUTPUT:

```
[[117   8]
 [  6  74]]
0.9317073170731708
```

EXPERIMENT:6(D)DECISION

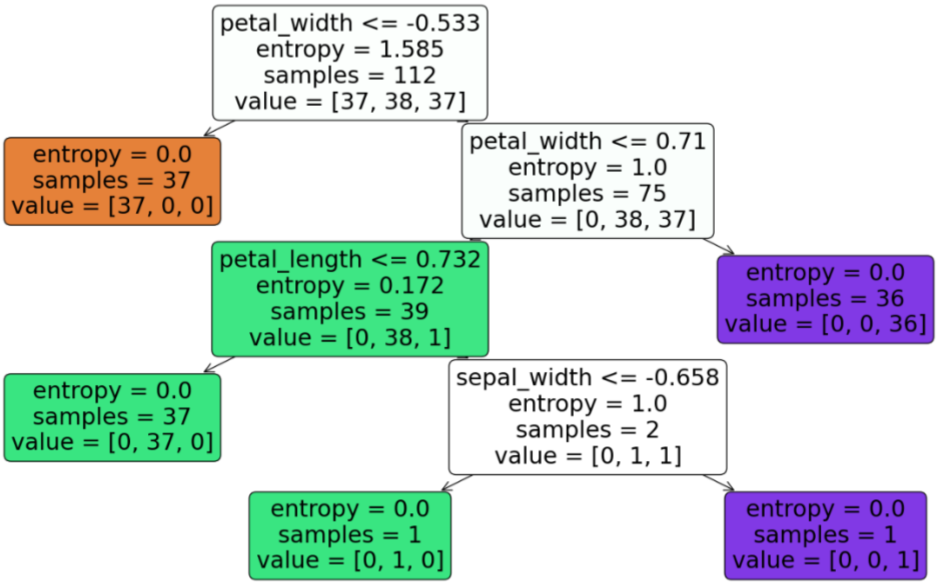
AIM: : finding accuracy value of iris data set using DECISION TREE algorithm

PROGRAM:

```
import numpy as np

import pandas as pd


# Importing the dataset

dataset = pd.read_csv("/content/IRIS.csv ")

X = dataset.iloc[:, :-1].values

y = dataset.iloc[:, -1].values


# Splitting the dataset into the Training set and Test set

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,
random_state = 8)


# Feature Scaling

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)


# Training the Decision Tree Classification model on the Training set

from sklearn.tree import DecisionTreeClassifier
```

```
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 5)

classifier.fit(X_train, y_train)


# Display the Decision Tree

from sklearn.tree import plot_tree

import matplotlib.pyplot as plt

plt.figure(figsize=(20,10))

plot_tree(classifier, filled=True, rounded=True,
feature_names=dataset.columns[:-1])

plt.show()


# Predicting the Test set results

y_pred = classifier.predict(X_test)


# Display the results (confusion matrix and accuracy)

from sklearn.metrics import confusion_matrix, accuracy_score

cm = confusion_matrix(y_test, y_pred)

print(cm)

accuracy_score(y_test, y_pred)
```

output:




```
0.8947368421052632
[[13  0  0]
 [ 0 11  1]
 [ 0  3 10]]
```

EXPERIMENT:6(E)SVM

AIM: : finding accuracy value of iris data set using SVM algorithm

PROGRAM:

```
import numpy as np

import pandas as pd


# Importing the dataset

dataset = pd.read_csv("/content/IRIS.csv ")


X = dataset.iloc[:, :-1].values

y = dataset.iloc[:, -1].values


# Splitting the dataset into the Training set and Test set

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
random_state=32)


# Feature Scaling

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)


# Training the SVM model on the Training set
```

```
from sklearn.svm import SVC

classifier = SVC(kernel='linear', random_state=0)

classifier.fit(X_train, y_train)


# Predicting the Test set results

y_pred = classifier.predict(X_test)


# Evaluating the performance of the model using confusion matrix and accuracy

from sklearn.metrics import confusion_matrix, accuracy_score

cm = confusion_matrix(y_test, y_pred)

print(cm)

print('Accuracy: {:.2f}%'.format(accuracy_score(y_test, y_pred) * 100))
```

OUTPUT:

```
[[108   1]
 [  5  57]]
Accuracy: 96.49%
```

EXPERIMENT:6(F)RANDOM

AIM: : finding accuracy value of iris data set using RANDOM FOREST algorithm

PROGRAM:

```
import numpy as np

import pandas as pd


# Importing the dataset

dataset = pd.read_csv("/content/IRIS.csv ")

X = dataset.iloc[:, :-1].values

y = dataset.iloc[:, -1].values


# Splitting the dataset into the Training set and Test set

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
random_state=39)


# Feature Scaling

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X_train = sc.fit_transform(X_train)

X_test = sc.transform(X_test)


# Training the Random Forest Classification model on the Training set

from sklearn.ensemble import RandomForestClassifier
```

```
classifier = RandomForestClassifier(n_estimators=100, random_state=42)

classifier.fit(X_train, y_train)


# Predicting the Test set results

y_pred = classifier.predict(X_test)


# Making the Confusion Matrix

from sklearn.metrics import confusion_matrix, accuracy_score

cm = confusion_matrix(y_test, y_pred)

print(cm)

print('Accuracy:', accuracy_score(y_test, y_pred))
```

OUTPUT:

```
[[111   1]
 [  2  57]]
Accuracy: 0.9824561403508771
```

EXPERIMENT:7(A)

AIM: To demonstrate gradient descent using python(actual data)

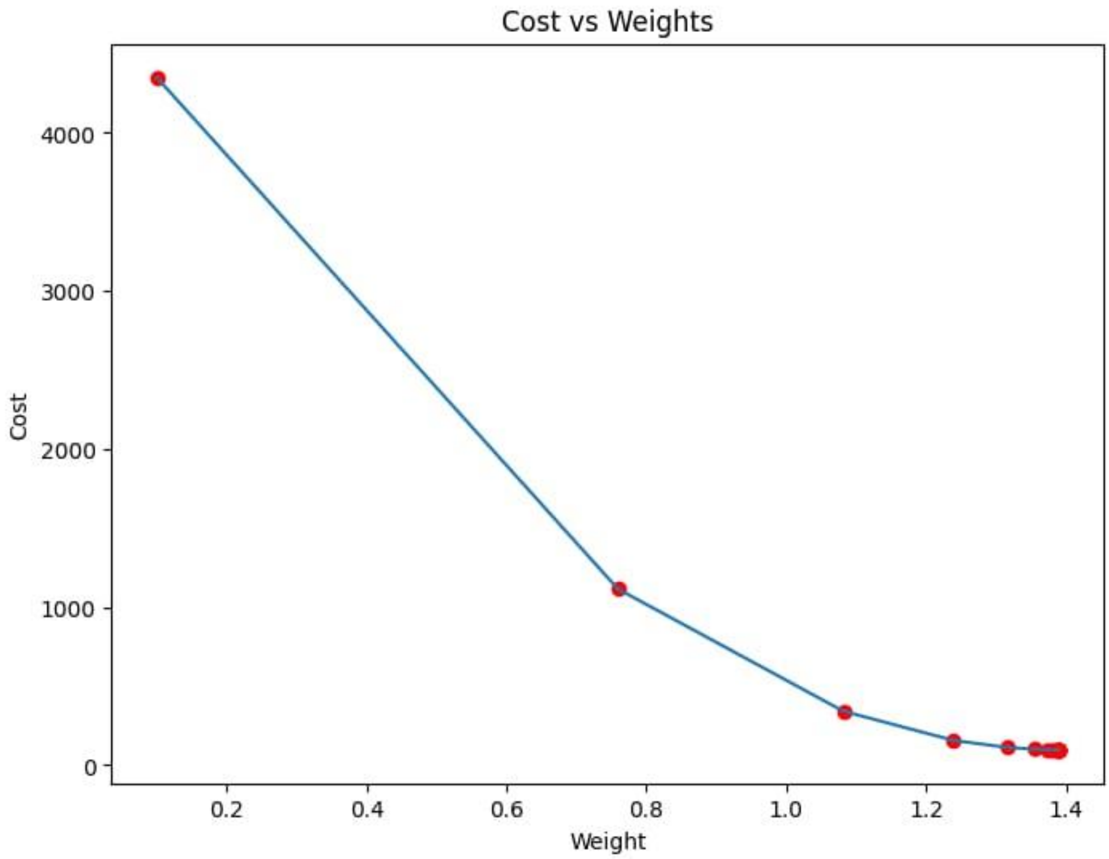
PROGRAM:

```
# Importing Libraries
import numpy as np
import matplotlib.pyplot as plt

def mean_squared_error(y_true, y_predicted):

    # Calculating the loss or cost
    cost = np.sum((y_true-y_predicted)**2) / len(y_true)
    return cost

# Gradient Descent Function
# Here iterations, learning_rate, stopping_threshold
# are hyperparameters that can be tuned
def gradient_descent(x, y, iterations = 1000, learning_rate = 0.0001,
                     stopping_threshold = 1e-6):

    # Initializing weight, bias, learning rate and iterations
    current_weight = 0.1
    current_bias = 0.01
    iterations = iterations
    learning_rate = learning_rate
    n = float(len(x))

    costs = []
    weights = []
    previous_cost = None

    # Estimation of optimal parameters
    for i in range(iterations):

        # Making predictions
        y_predicted = (current_weight * x) + current_bias

        # Calculating the current cost
        current_cost = mean_squared_error(y, y_predicted)

        # If the change in cost is less than or equal to
        # stopping_threshold we stop the gradient descent
        if previous_cost and abs(previous_cost-
current_cost)<=stopping_threshold:
            break

        previous_cost = current_cost

        costs.append(current_cost)
        weights.append(current_weight)

        # Calculating the gradients
        weight_derivative = -(2/n) * sum(x * (y-y_predicted))
        bias_derivative = -(2/n) * sum(y-y_predicted)
```

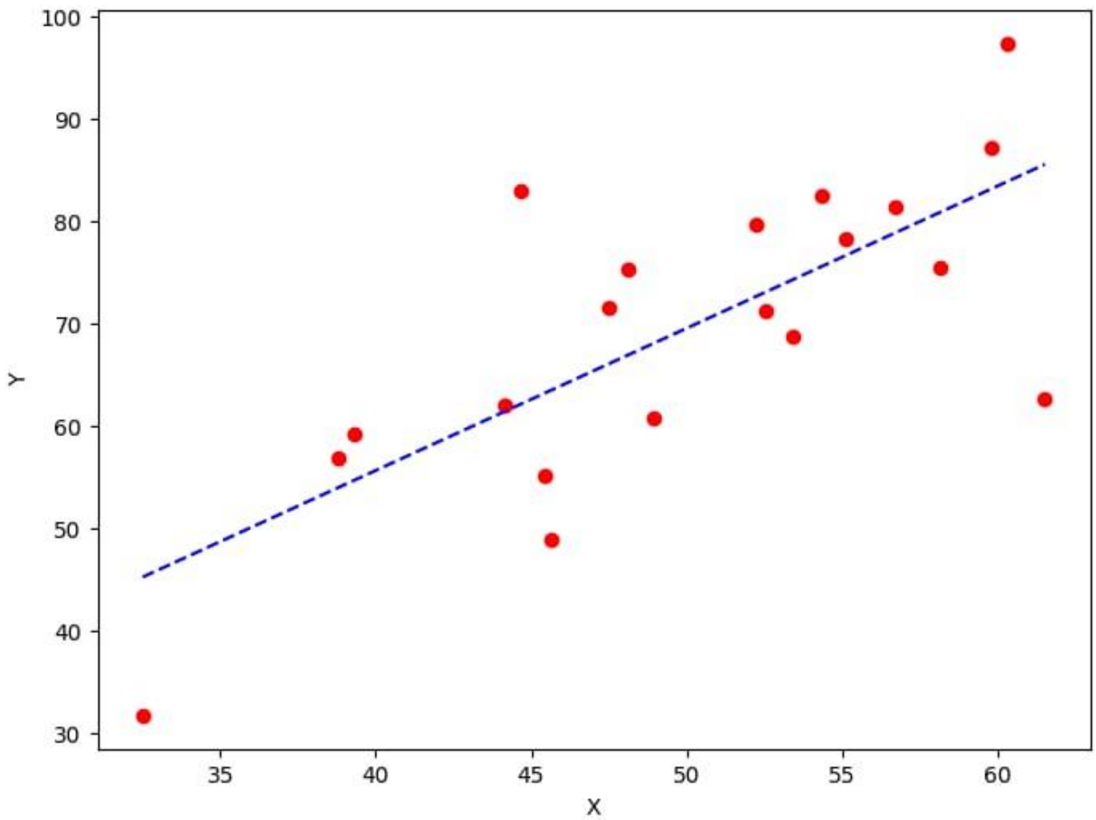
```
        # Updating weights and bias
        current_weight = current_weight - (learning_rate *
weight_derivative)
        current_bias = current_bias - (learning_rate * bias_derivative)

        # Printing the parameters for each 1000th iteration
        print(f"Iteration {i+1}: Cost {current_cost}, Weight \
        {current_weight}, Bias {current_bias}")



    # Visualizing the weights and cost at for all iterations
    plt.figure(figsize = (8,6))
    plt.plot(weights, costs)
    plt.scatter(weights, costs, marker='o', color='red')
    plt.title("Cost vs Weights")
    plt.ylabel("Cost")
    plt.xlabel("Weight")
    plt.show()

    return current_weight, current_bias



def main():

    # Data
    X = np.array([32.50234527, 53.42680403, 61.53035803, 47.47563963,
59.81320787,
           55.14218841, 52.21179669, 39.29956669, 48.10504169,
52.55001444,
           45.41973014, 54.35163488, 44.1640495 , 58.16847072,
56.72720806,
           48.95588857, 44.68719623, 60.29732685, 45.61864377,
38.81681754])
    Y = np.array([31.70700585, 68.77759598, 62.5623823 , 71.54663223,
87.23092513,
           78.21151827, 79.64197305, 59.17148932, 75.3312423 ,
71.30087989,
           55.16567715, 82.47884676, 62.00892325, 75.39287043,
81.43619216,
           60.72360244, 82.89250373, 97.37989686, 48.84715332,
56.87721319])

    # Estimating weight and bias using gradient descent
    estimated_weight, estimated_bias = gradient_descent(X, Y,
iterations=2000)
    print(f"Estimated Weight: {estimated_weight}\nEstimated Bias:
{estimated_bias}")

    # Making predictions using estimated parameters
    Y_pred = estimated_weight*X + estimated_bias

    # Plotting the regression line
    plt.figure(figsize = (8,6))
    plt.scatter(X, Y, marker='o', color='red')
    plt.plot([min(X), max(X)], [min(Y_pred), max(Y_pred)],
color='blue',markerfacecolor='red',
             markersize=10,linestyle='dashed')
```

```
    plt.xlabel("X")
    plt.ylabel("Y")
    plt.show()


if __name__=="__main__":
    main()
```

output:




```
Estimated Weight: 1.393097090459544
Estimated Bias: 0.035349609417819915
```



100
90
80
70
60
50
40
30
Y
35
40
45
50
55
60
X

Experiment:7(b)

AIM: To demonstrate gradient descent using python(modified data)

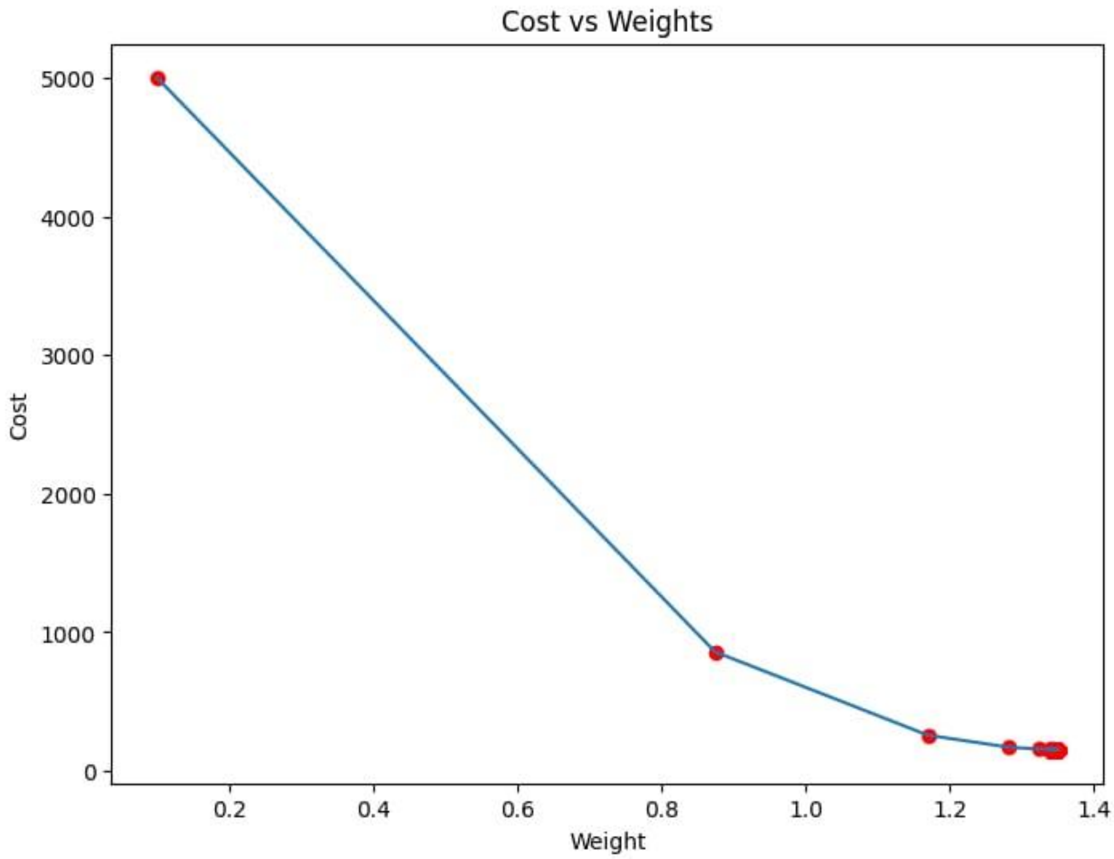
PROGRAM:

```
# Importing Libraries
import numpy as np
import matplotlib.pyplot as plt

def mean_squared_error(y_true, y_predicted):

    # Calculating the loss or cost
    cost = np.sum((y_true-y_predicted)**2) / len(y_true)
    return cost

# Gradient Descent Function
# Here iterations, learning_rate, stopping_threshold
# are hyperparameters that can be tuned
def gradient_descent(x, y, iterations = 1000, learning_rate = 0.0001,
                     stopping_threshold = 1e-6):

    # Initializing weight, bias, learning rate and iterations
    current_weight = 0.1
    current_bias = 0.01
    iterations = iterations
    learning_rate = learning_rate
    n = float(len(x))

    costs = []
    weights = []
    previous_cost = None

    # Estimation of optimal parameters
    for i in range(iterations):

        # Making predictions
        y_predicted = (current_weight * x) + current_bias

        # Calculating the current cost
        current_cost = mean_squared_error(y, y_predicted)

        # If the change in cost is less than or equal to
        # stopping_threshold we stop the gradient descent
        if previous_cost and abs(previous_cost-
current_cost)<=stopping_threshold:
            break

        previous_cost = current_cost

        costs.append(current_cost)
        weights.append(current_weight)

        # Calculating the gradients
        weight_derivative = -(2/n) * sum(x * (y-y_predicted))
        bias_derivative = -(2/n) * sum(y-y_predicted)
```

```
        # Updating weights and bias
        current_weight = current_weight - (learning_rate *
weight_derivative)
        current_bias = current_bias - (learning_rate * bias_derivative)

        # Printing the parameters for each 1000th iteration
        print(f"Iteration {i+1}: Cost {current_cost}, Weight \
        {current_weight}, Bias {current_bias}")


    # Visualizing the weights and cost at for all iterations
    plt.figure(figsize = (8,6))
    plt.plot(weights, costs)
    plt.scatter(weights, costs, marker='o', color='red')
    plt.title("Cost vs Weights")
    plt.ylabel("Cost")
    plt.xlabel("Weight")
    plt.show()

    return current_weight, current_bias


def main():

    # Data
    X = np.array([52.50234527, 63.42680403, 81.53035803, 47.47563963,
89.81320787,
           55.14218841, 52.21179669, 39.29956669, 48.10504169,
52.55001444,
           45.41973014, 54.35163488, 44.1640495 , 58.16847072,
56.72720806,
           48.95588857, 44.68719623, 60.29732685, 45.61864377,
38.81681754])
    Y = np.array([41.70700585, 78.77759598, 82.5623823 , 91.54663223,
77.23092513,
           78.21151827, 79.64197305, 59.17148932, 75.3312423 ,
71.30087989,
           55.16567715, 82.47884676, 62.00892325, 75.39287043,
81.43619216,
           60.72360244, 82.89250373, 97.37989686, 48.84715332,
56.87721319])

    # Estimating weight and bias using gradient descent
    estimated_weight, estimated_bias = gradient_descent(X, Y,
iterations=2000)
    print(f"Estimated Weight: {estimated_weight}\nEstimated Bias:
{estimated_bias}")

    # Making predictions using estimated parameters
    Y_pred = estimated_weight*X + estimated_bias

    # Plotting the regression line
    plt.figure(figsize = (8,6))
    plt.scatter(X, Y, marker='orange', color='pink')
    plt.plot([min(X), max(X)], [min(Y_pred), max(Y_pred)],
color='blue',markerfacecolor='red',
             markersize=10,linestyle='dashed')
```

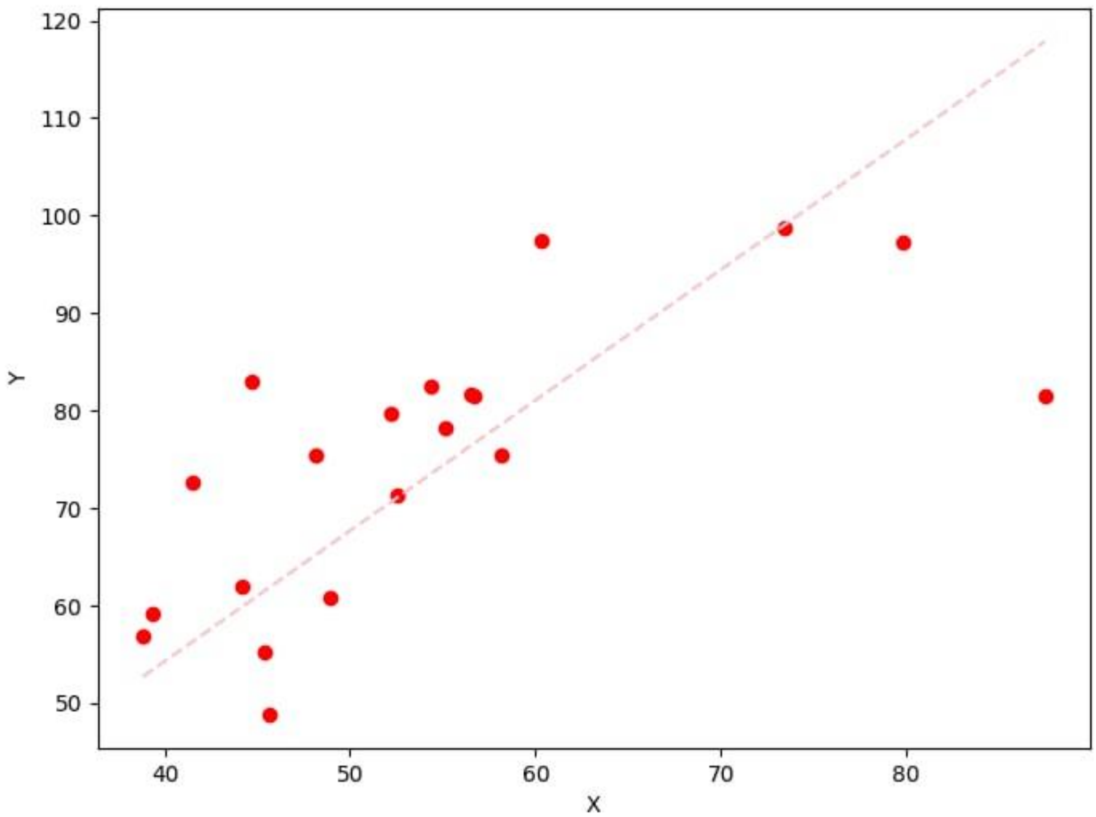
```
    plt.xlabel("X")
    plt.ylabel("Y")
    plt.show()


if __name__=="__main__":
    main()
```

OUTPUT:




```
Estimated Weight: 1.393097090459544
Estimated Bias: 0.035349609417819915
```

100



120
110
100
90
80
70
60
50
Y
40
50
60
70
80
X

EXPERIMENT:8(A)SEGMENTATION

AIM: : Verifying the performance of a image processing by using choosen database with phython code

PROGRAM:

```
# SEGMENTATION
import numpy as np
import cv2
from matplotlib import pyplot as plt
img = cv2.imread(r'C33P1thinF_IMG_20150619_114756a_cell_181.png')
b,g,r = cv2.split(img)
rgb_img = cv2.merge([r,g,b])
gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
ret, thresh =
cv2.threshold(gray,0,255,cv2.THRESH_BINARY_INV+cv2.THRESH_OTSU)
# noise removal
kernel = np.ones((2,2),np.uint8)
#opening = cv2.morphologyEx(thresh,cv2.MORPH_OPEN,kernel, iterations = 2)
closing = cv2.morphologyEx(thresh,cv2.MORPH_CLOSE,kernel, iterations = 2)
# sure background area
sure_bg = cv2.dilate(closing,kernel,iterations=3)
# Finding sure foreground area
dist_transform = cv2.distanceTransform(sure_bg,cv2.DIST_L2,3)
# Threshold
ret, sure_fg = cv2.threshold(dist_transform,0.1*dist_transform.max(),255,0)
# Finding unknown region
sure_fg = np.uint8(sure_fg)
unknown = cv2.subtract(sure_bg,sure_fg)
# Marker labelling
ret, markers = cv2.connectedComponents(sure_fg)
# Add one to all labels so that sure background is not 0, but 1
markers = markers+1
# Now, mark the region of unknown with zero
markers[unknown==255] = 0
markers = cv2.watershed(img,markers)
img[markers == -1] = [255,0,0]
plt.subplot(211),plt.imshow(rgb_img)
plt.title('Input Image'), plt.xticks([]), plt.yticks([])
plt.subplot(212),plt.imshow(thresh, 'gray')
plt.imsave(r'thresh.png',thresh)
plt.title("Otsu's binary threshold"), plt.xticks([]), plt.yticks([])
plt.tight_layout()
plt.show()
```

OUTPUT:


Input Image
Otsu's binary threshold

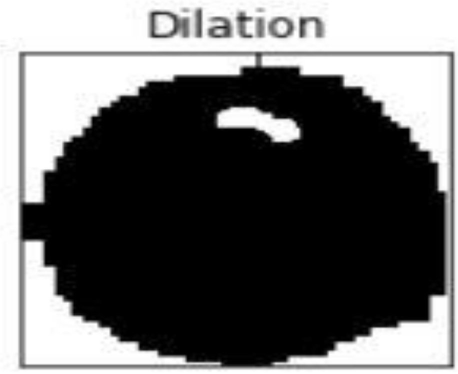
EXPERIMENT:8(B)

AIM: : Verifying the performance of a image processing by using water shed database with python code

PROGRAM:

```
# SEGMENTATION
import numpy as np
import cv2
from matplotlib import pyplot as plt
img =
cv2.imread(r'C33P1thinF_IMG_20150619_114756a_cell_181.png')
b,g,r = cv2.split(img)
rgb_img = cv2.merge([r,g,b])
gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
ret, thresh =
cv2.threshold(gray,0,255,cv2.THRESH_BINARY_INV+cv2.THRESH_OTSU
)
plt.subplot(211),plt.imshow(closing, 'gray')
plt.title("morphologyEx:Closing:2x2"), plt.xticks([]),
plt.yticks([])
plt.subplot(212),plt.imshow(sure_bg, 'gray')
plt.imsave(r'dilation.png',sure_bg)
plt.title("Dilation"), plt.xticks([]), plt.yticks([])
plt.tight_layout()
plt.show()
```

OUTPUT:

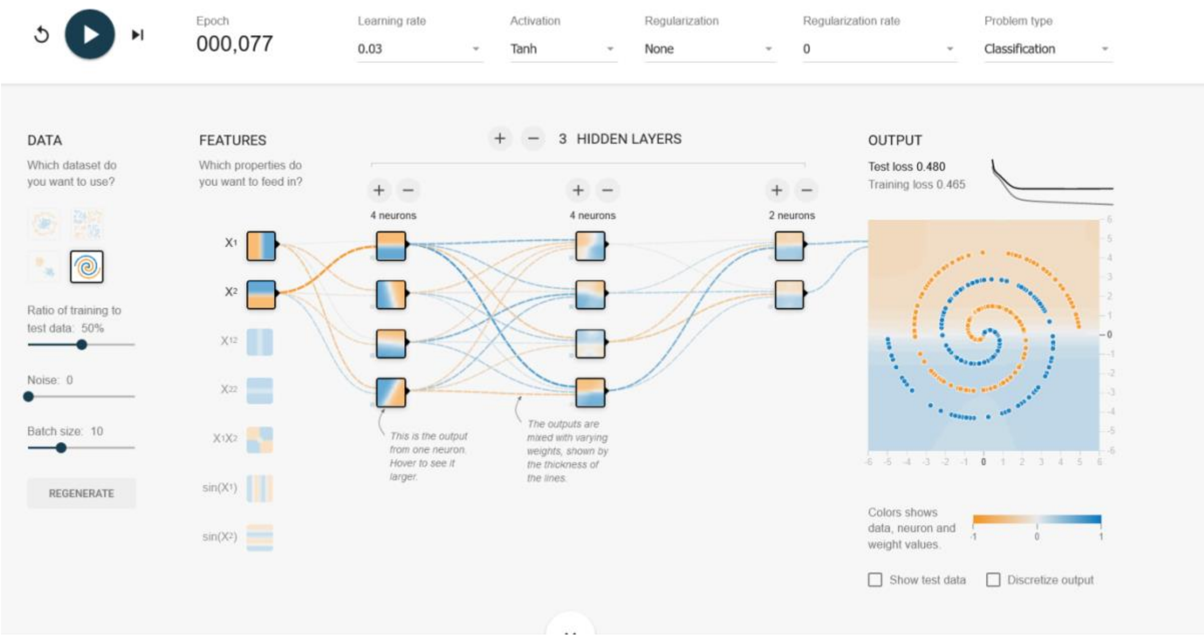


:

EXPERIMENT:9 (a) TANH

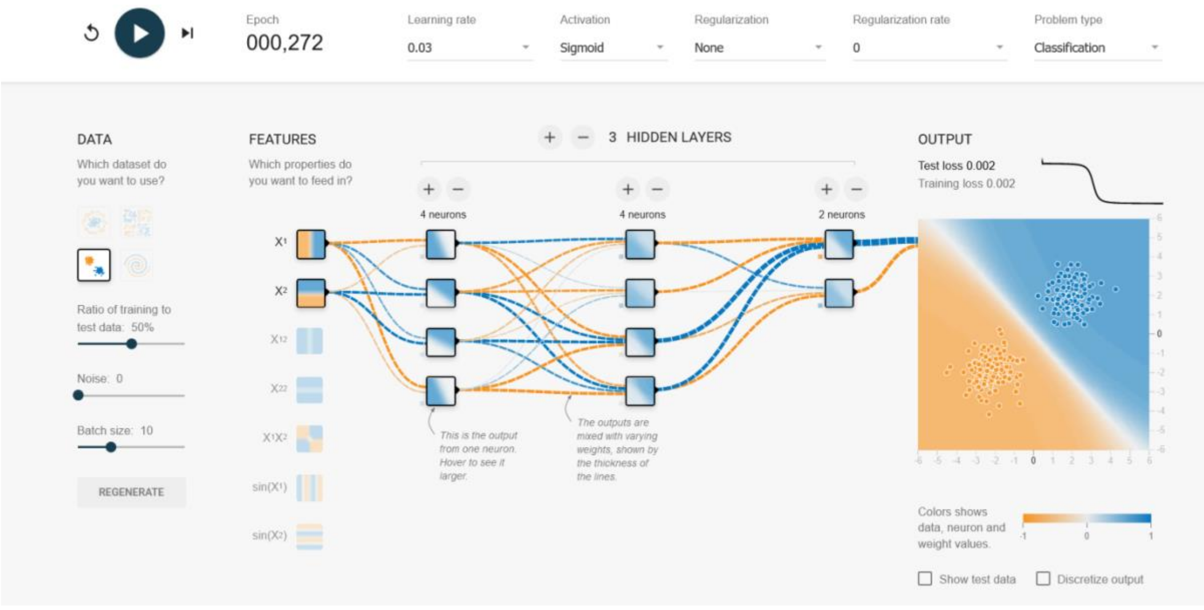
AIM: Neural network analysis using TANH activation

OUTPUT:



EXPERIMENT:9(B) SIGMIOD

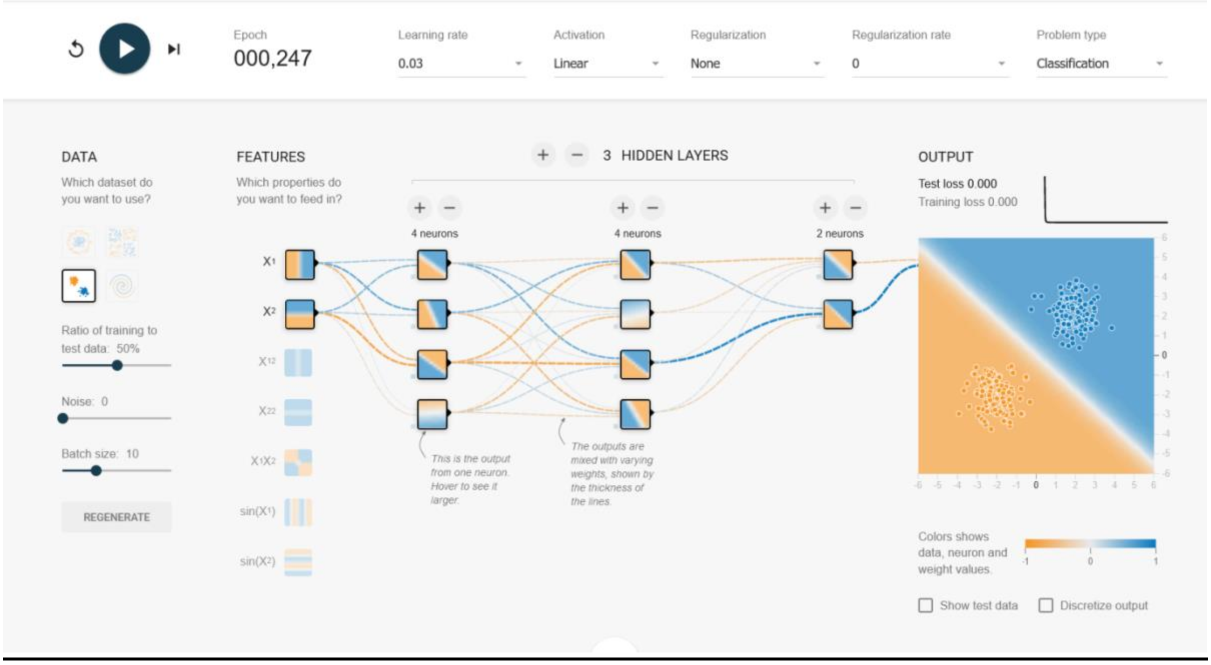
AIM: Neural network analysis using SIGMOID activation



EXPERIMENT:9(C) LINEAR

AIM: Neural network analysis using LINEAR activation

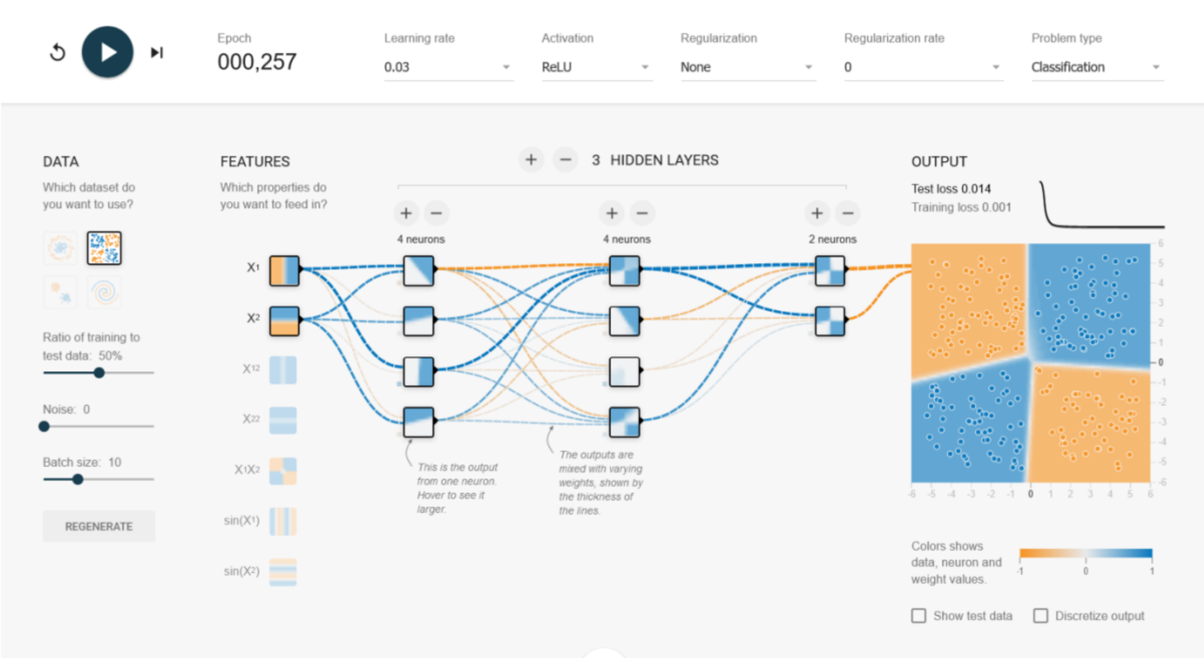
OUTPUT:



EXPERIMENT:9(D)RELU

AIM: Neural network analysis using ReLU activation

OUTPUT:



EXPERIMENT:10

AIM: To demonstrate linear separability using python code

PROGRAM:

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

def estimate_coef(x, y):
    # number of observations/points
    n = np.size(x)

    # mean of x and y vector
    m_x = np.mean(x)
    m_y = np.mean(y)

    # calculating cross-deviation and deviation about x
    SS_xy = np.sum(y*x) - n*m_y*m_x
    SS_xx = np.sum(x*x) - n*m_x*m_x

    # calculating regression coefficients
    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1*m_x

    return (b_0, b_1)

def plot_regression_line(x, y, b):
    # plotting the actual points as scatter plot
    plt.scatter(x, y, color = "r",
                marker = "o", s = 30)

    # predicted response vector
    y_pred = b[0] + b[1]*x

    # plotting the regression line
    plt.plot(x, y_pred, color = "b")

    # putting labels
    plt.xlabel('x')
    plt.ylabel('y')

    # function to show plot
```

```python
    plt.show()

def main():
    # observations / data
    x = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
    y = np.array([1, 3, 2, 5, 7, 8, 8, 9, 10, 12])

    # estimating coefficients
    b = estimate_coef(x, y)
    print("Estimated coefficients:\nb_0 = {}  \
          \nb_1 = {}".format(b[0], b[1]))

    # plotting regression line
    plot_regression_line(x, y, b)

if __name__ == "__main__":
    main()
```

<u>OUTPUT:</u>

```
Estimated coefficients:
b_0 = 1.2363636363636363
b_1 = 1.1696969696969697
```