```python
import matplotlib.pyplot as plt
import tensorflow as tf
import random
import os
from glob import glob
from matplotlib import pyplot
import cv2
import pandas as pd
import numpy as np
import matplotlib.gridspec as gridspec
import seaborn as sns
import itertools
import sklearn
import itertools
import scipy
import skimage
from skimage.transform import resize
import csv
from tqdm import tqdm
from sklearn import model_selection
from sklearn.model_selection import train_test_split,
learning_curve,KFold,cross_val_score,StratifiedKFold
from sklearn.metrics import confusion_matrix
import keras
from keras.utils import np_utils
from keras.utils.np_utils import to_categorical
from tensorflow.keras.preprocessing.image import load_img,img_to_array
from keras.preprocessing.image import ImageDataGenerator
from keras import models, layers, optimizers
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from keras.layers import Activation,Dense, Dropout, Flatten

from keras.models import Model
```

EXPERIMENT:1(A)

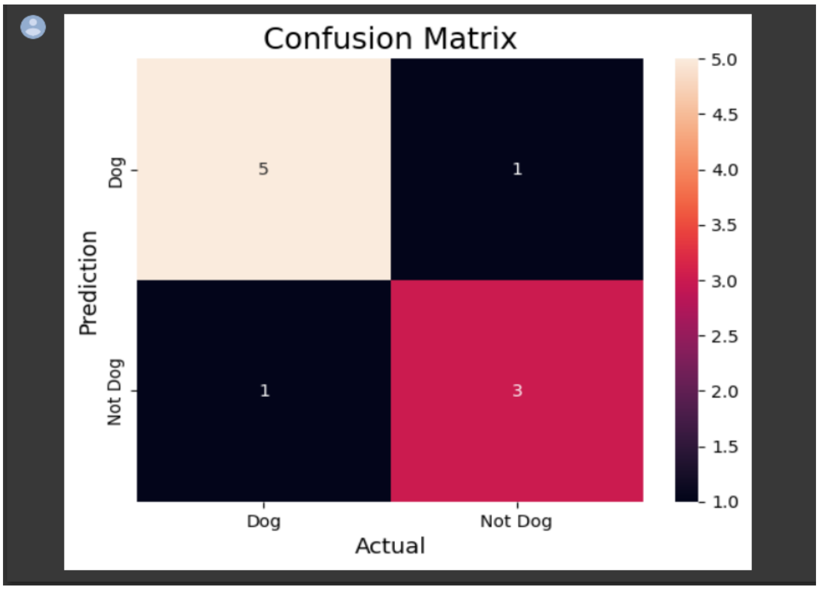
AIM: To demonstrate confusion matrix using python

PROGRAM:

```python
 #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','Not Dog'])
predicted = np.array(
  ['Dog','Not Dog','Dog','Not Dog','Dog','Dog','Dog','Dog','Not
Dog','Not 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)

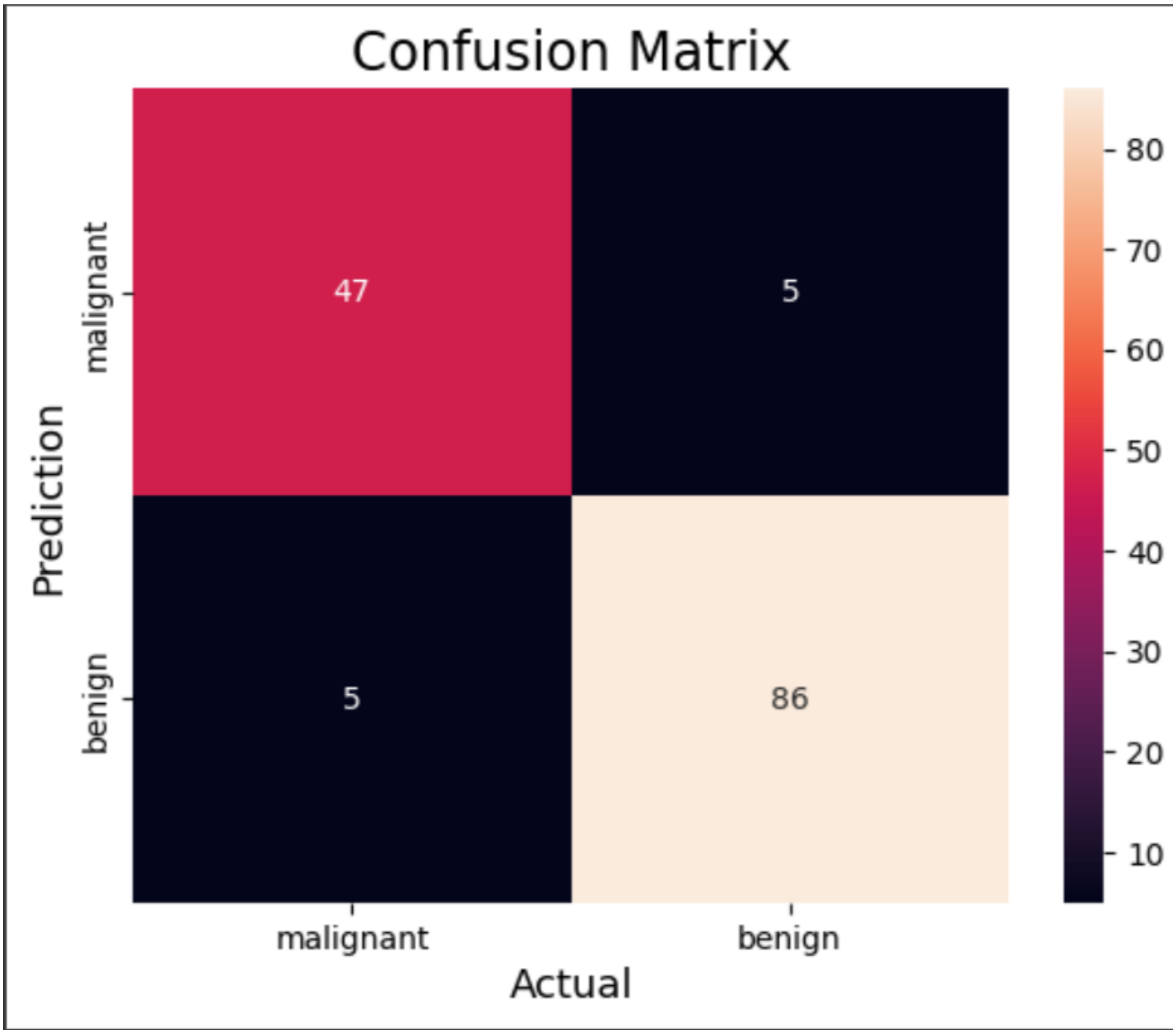
AIM: To demonstrate 2 class confusion matrix using python

PROGRAM:

```
#Import the necessary libraries
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
```

```python
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_score, 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)

# preduction
y_pred = tree.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',
            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
```

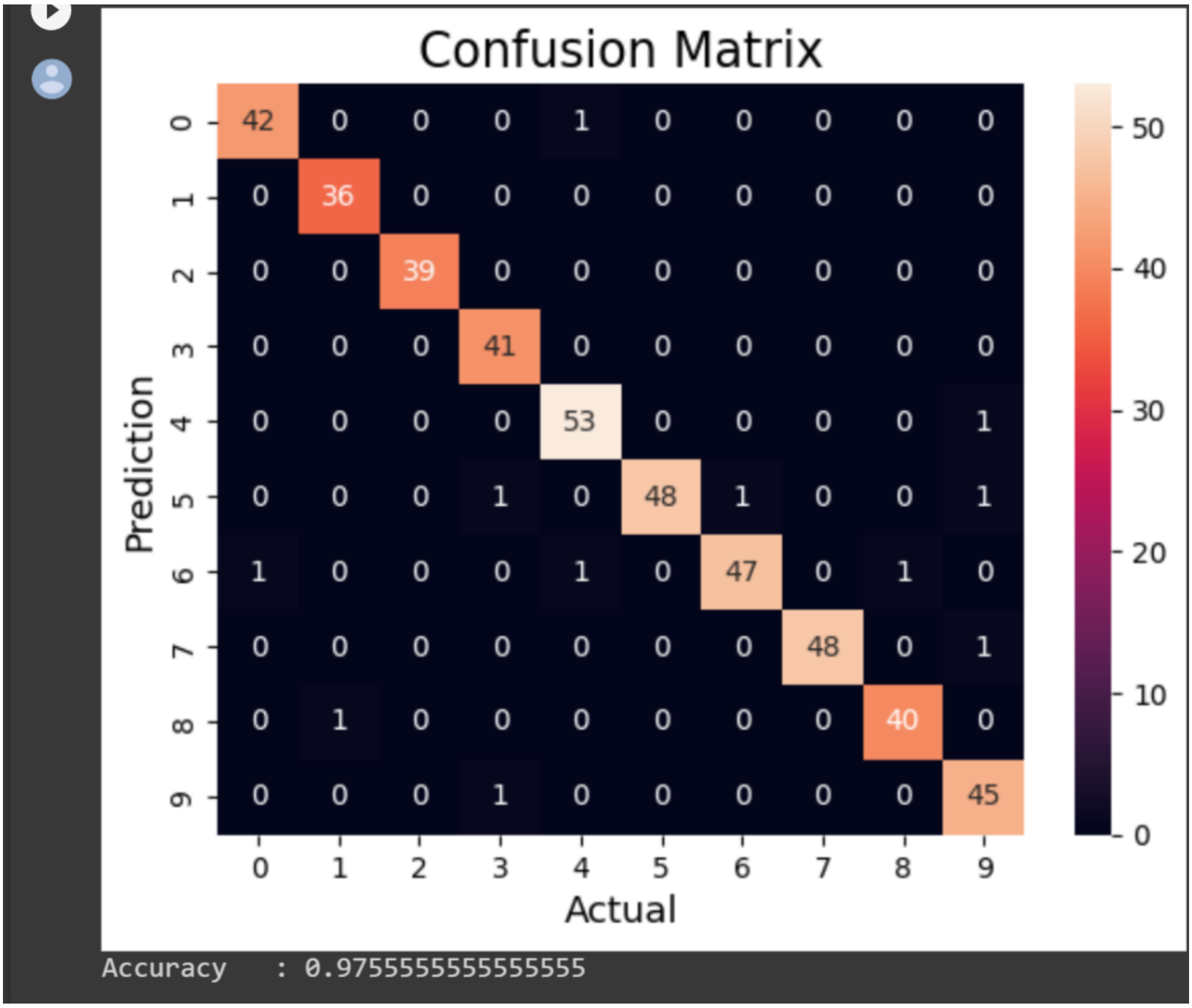
EXPERIMENT:2

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_score, 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:


Confusion Matrix
Prediction
Actual
Accuracy : 0.9755555555555555

EXPERIMENT:3

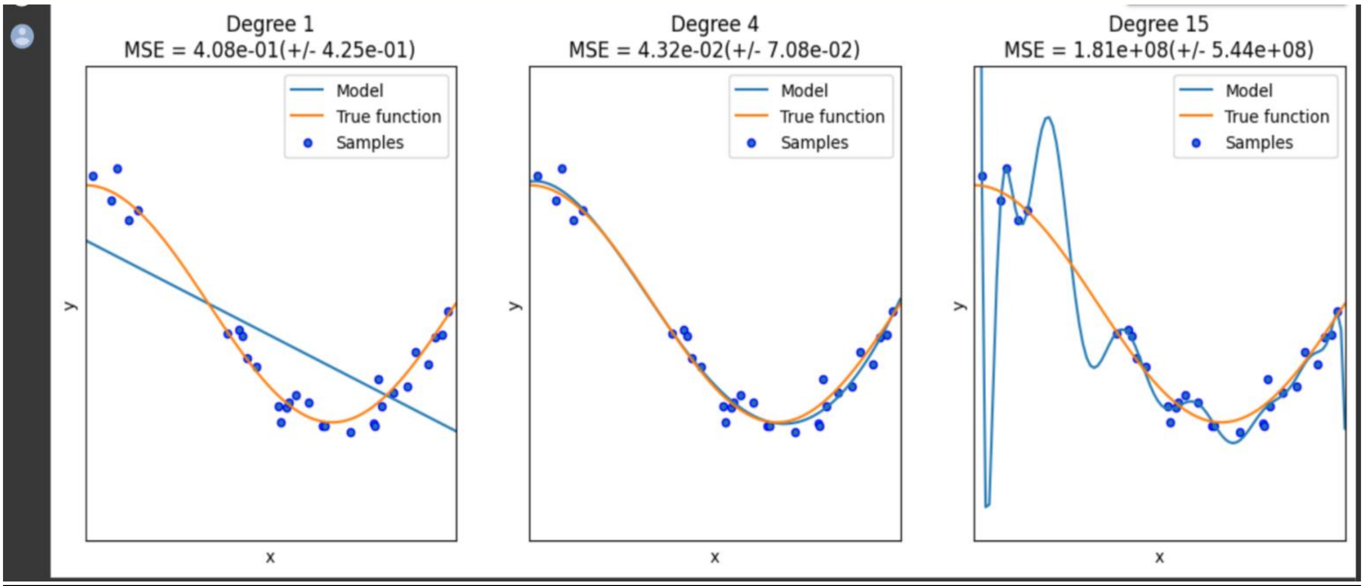
AIM: : Verifying the performance of a over fitting by using choosen database with python code

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

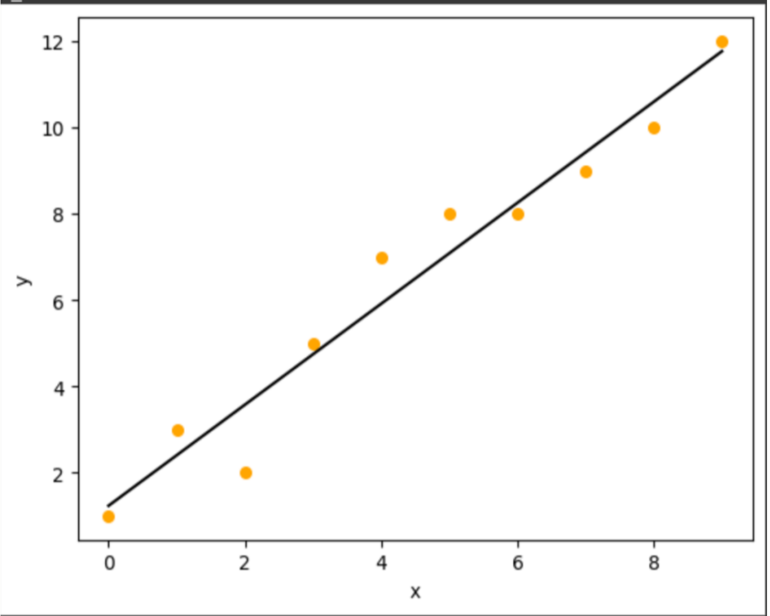
PROGRAM: LINEAR REGRESSION

```
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')

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

```python
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
```



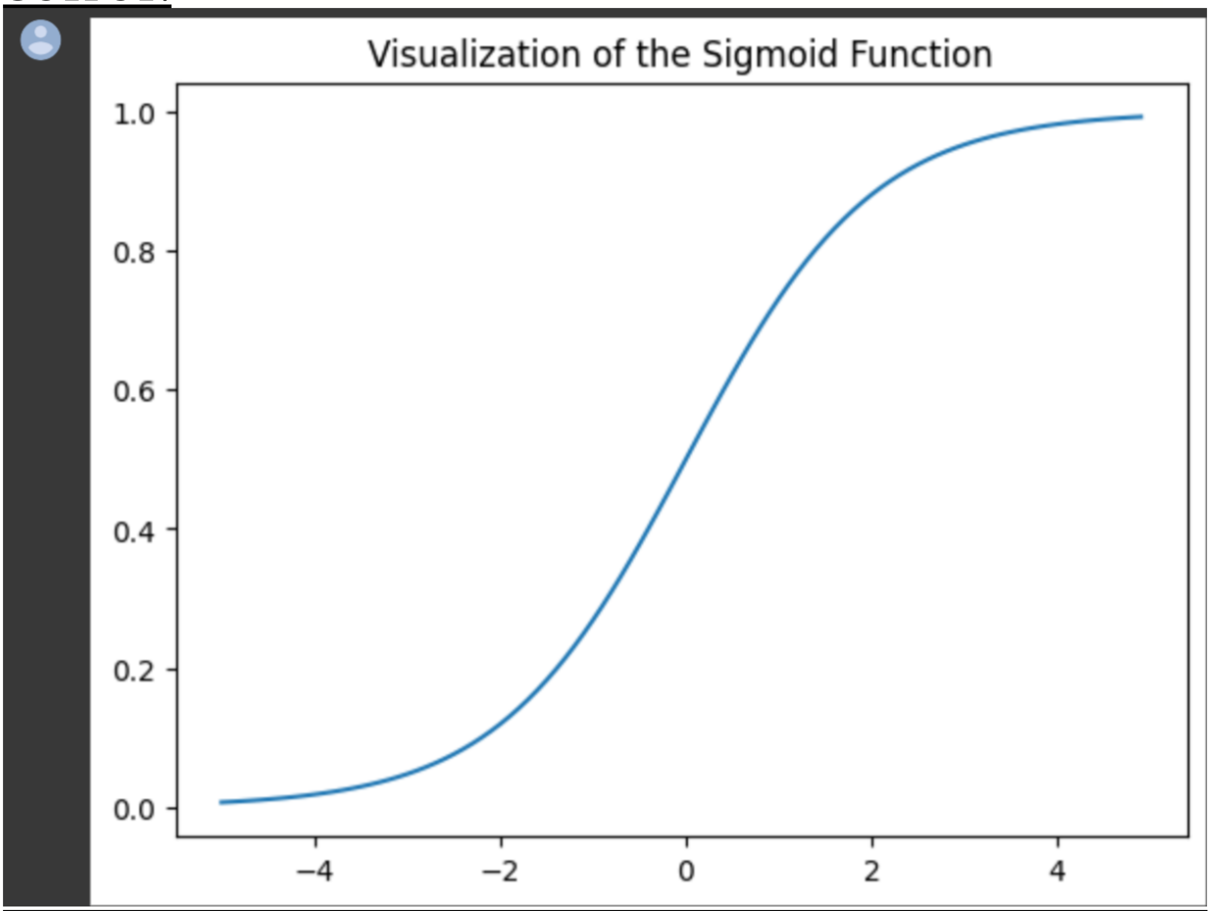
EXPERIMENT:5

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:

Mainfileupload*

```
from google.colab import files
uploaded = files.upload()
```

```
import numpy as np
import pandas as pd

dataset = pd.read_csv("/content/breastcancer.csv.xls")
"""
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.
```

```python
"""
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/breastcancer.csv.xls")
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
```

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
"""
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/breastcancer.csv.xls")
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:

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

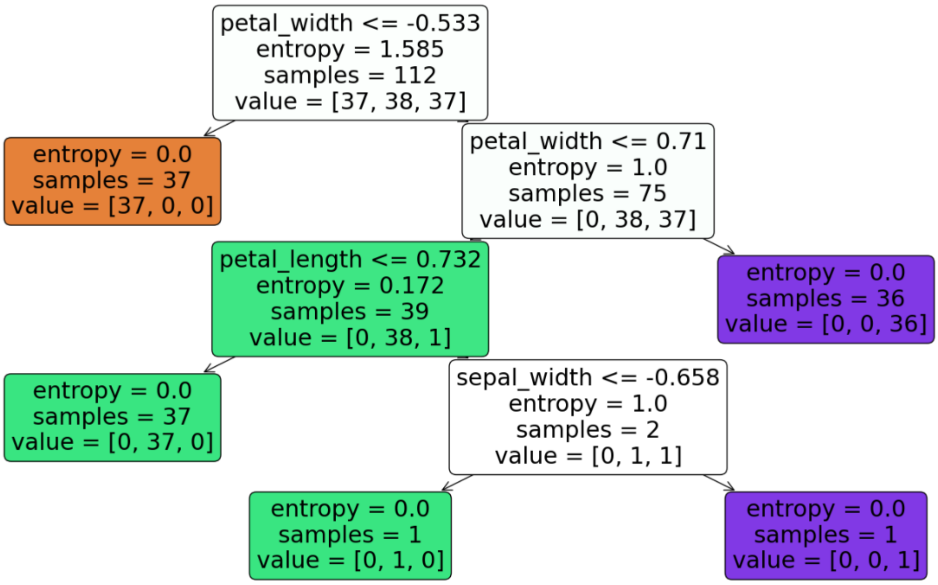
EXPERIMENT:6(D)DECISION

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/breastcancer.csv.xls")
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/breastcancer.csv.xls")
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/breastcancer.csv.xls")
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:

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

EXPERIMENT:7(A)

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

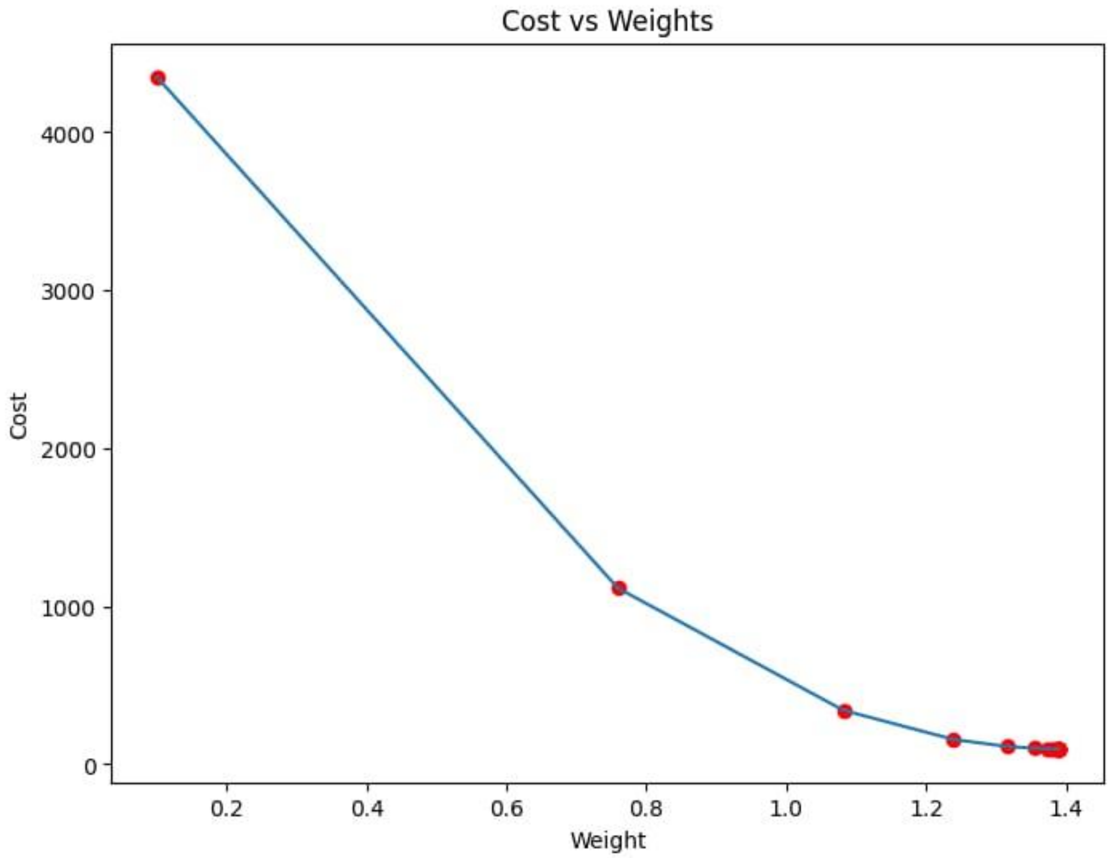
PROGRAM:

```
# 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
```

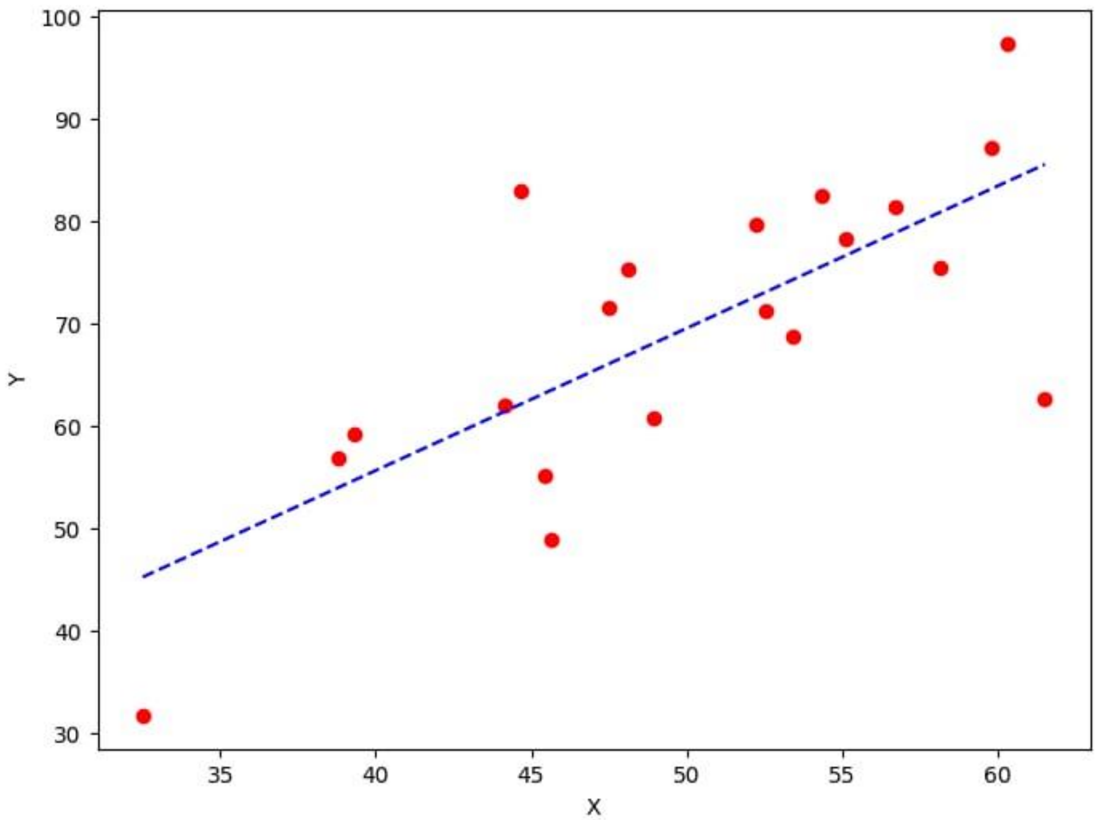
```
        previous_cost = current_cost

        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)

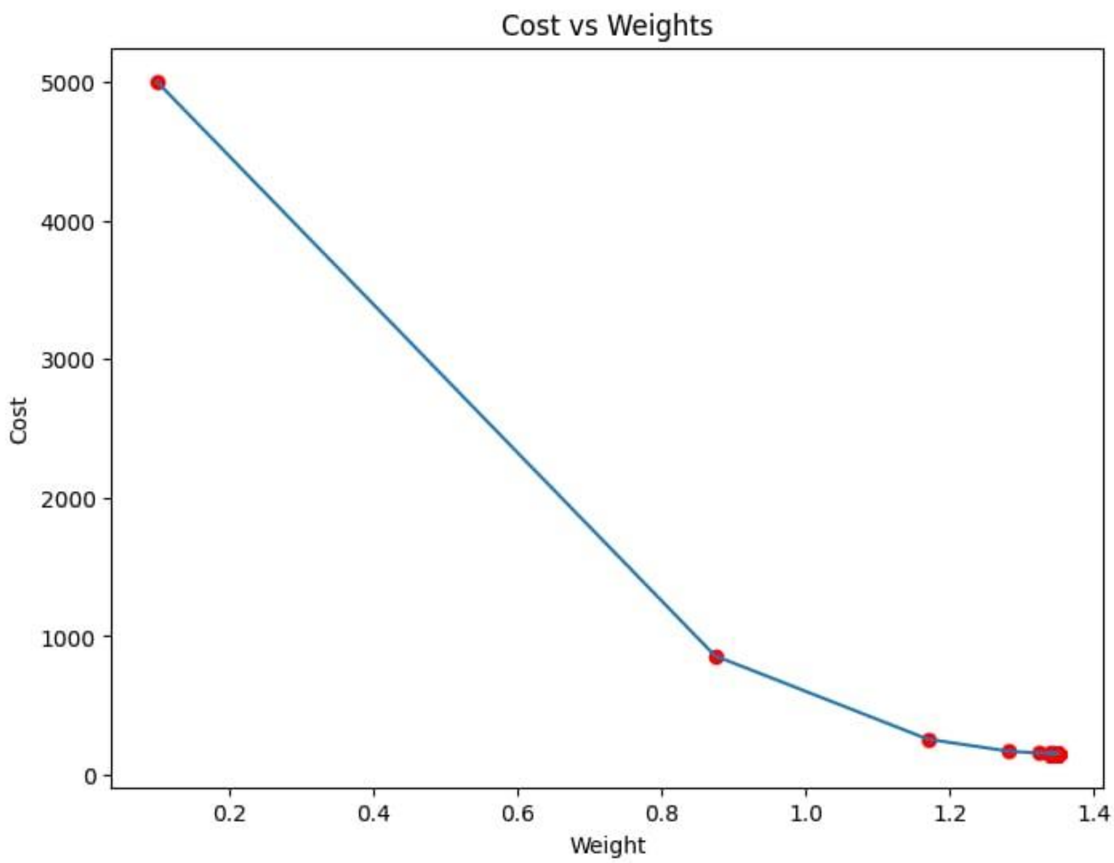
AIM: To demonstrate gradient descent using python(modified data)

PROGRAM:

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

def mean_squared_error(y_true, y_predicted):
    cost = np.sum((y_true - y_predicted) ** 2) / len(y_true)
    return cost

def gradient_descent(x, y, iterations=1000, learning_rate=0.0001,
                     stopping_threshold=1e-6):
    current_weight = 0.1
    current_bias = 0.01
    iterations = iterations
    learning_rate = learning_rate
    n = float(len(x))

    costs = []
    weights = []
    previous_cost = None

    for i in range(iterations):
        y_predicted = (current_weight * x) + current_bias
        current_cost = mean_squared_error(y, y_predicted)

        if previous_cost and abs(previous_cost - current_cost) <=
stopping_threshold:
            break

        previous_cost = current_cost

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

        weight_derivative = -(2/n) * sum(x * (y - y_predicted))
        bias_derivative = -(2/n) * sum(y - y_predicted)

        current_weight = current_weight - (learning_rate *
weight_derivative)
        current_bias = current_bias - (learning_rate * bias_derivative)

        if (i + 1) % 1000 == 0:
            print(f"Iteration {i+1}: Cost {current_cost}, Weight
{current_weight}, Bias {current_bias}")
```

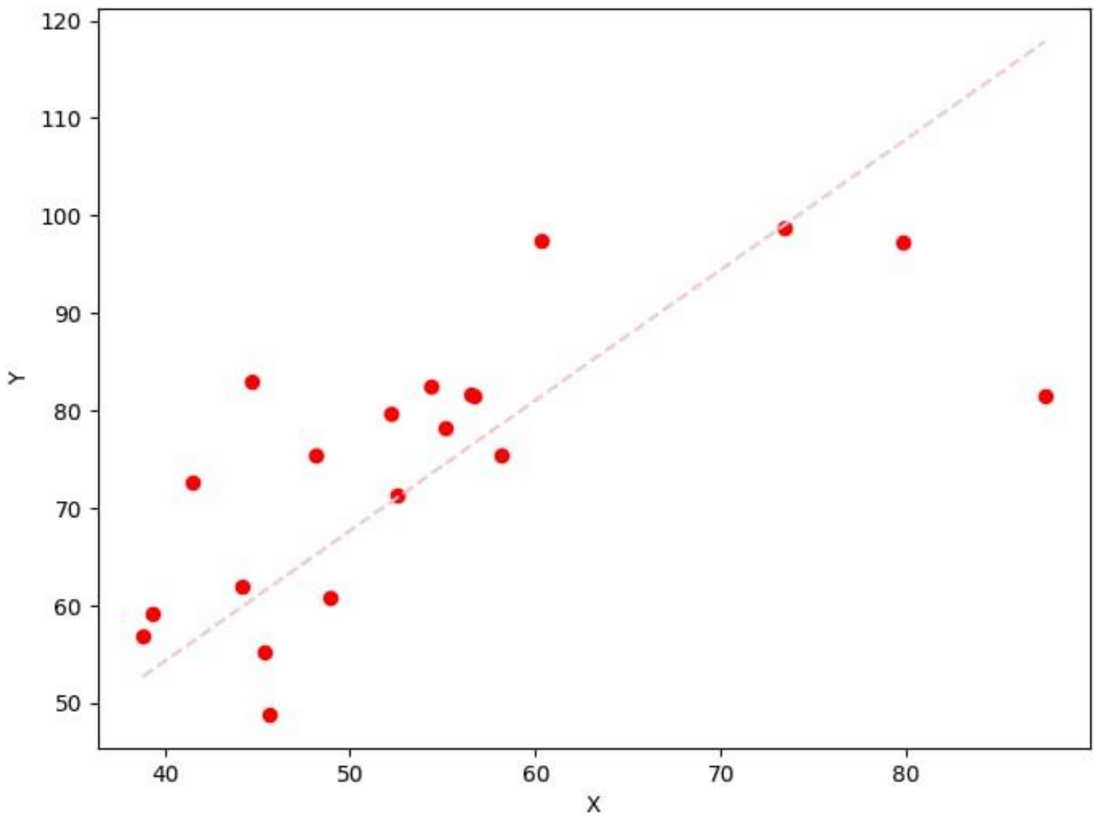
```
    plt.figure(figsize=(8, 6))
    plt.plot(weights, costs)
    plt.scatter(weights, costs, marker='o', color='red')
    plt.title("Cost vs Weights")
    plt.ylabel("Cost")
    plt.xlabel("Weight")
    plt.show()

    return current_weight, current_bias

def main():
    X = np.array([1, 2, 3, 4, 5])  # Replace with your data
    Y = np.array([2, 3, 4, 5, 6])  # Replace with your data

    estimated_weight, estimated_bias = gradient_descent(X, Y,
iterations=2000)
    print(f"Estimated Weight: {estimated_weight}\nEstimated Bias:
{estimated_bias}")

    Y_pred = estimated_weight * X + estimated_bias

    plt.figure(figsize=(8, 6))
    plt.scatter(X, Y, marker='o', color='pink')
    plt.plot([min(X), max(X)], [min(Y_pred), max(Y_pred)],
color='blue', linestyle='dashed')
    plt.xlabel("X")
    plt.ylabel("Y")
    plt.show()

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

OUTPUT:




```
Estimated Weight: 1.3930970904595444
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:

Mainimageupload*****************************

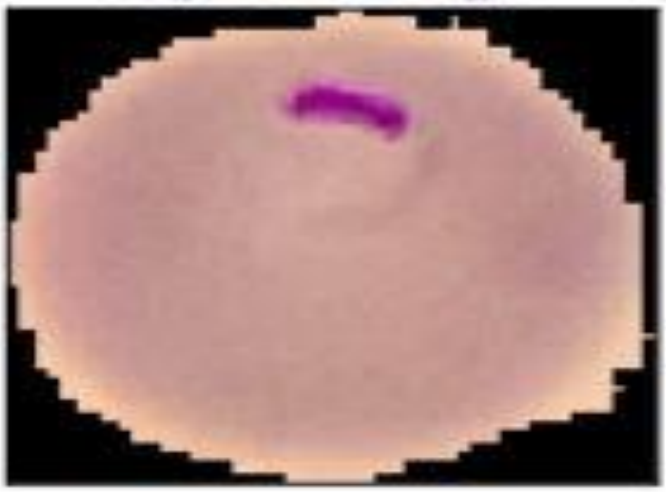
```
from google.colab import files
uploaded = files.upload()
```

```
# SEGMENTATION
import numpy as np
import cv2
from matplotlib import pyplot as plt
img = cv2.imread(r'apple.jpeg')
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)
```

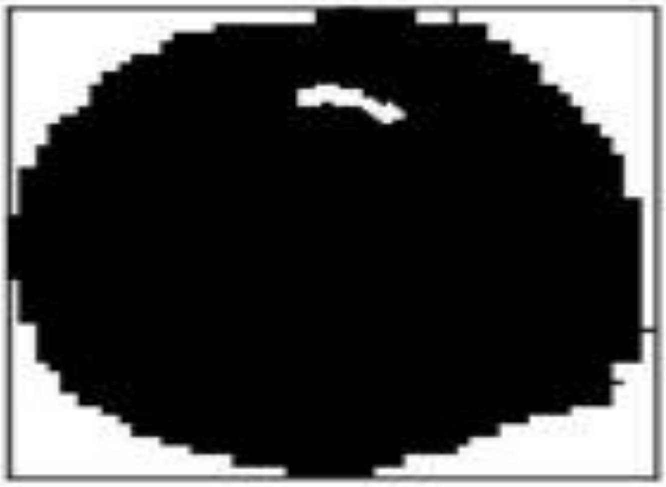
```
img[markers == -1] = [255,0,0]
plt.subplot(211),plt.imshow(rgb_img)
plt.title('Input Image'), plt.xticks([]), plt.yticks([])
plt.subplot(212),plt.imshow(thresh, 'gray')
plt.imsave(r'thresh.png',thresh)
plt.title("Otsu's binary threshold"), plt.xticks([]), plt.yticks([])
plt.tight_layout()
plt.show()
```

OUTPUT:

Input Image



Otsu's binary threshold



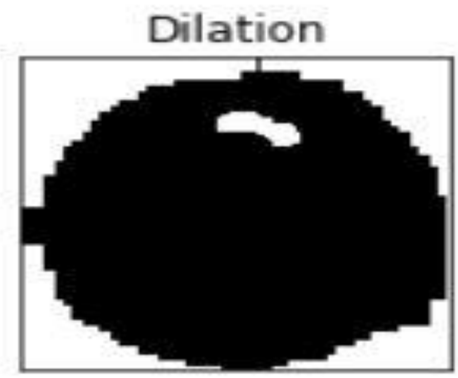
EXPERIMENT:8(B)

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'apple.jpeg')
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:

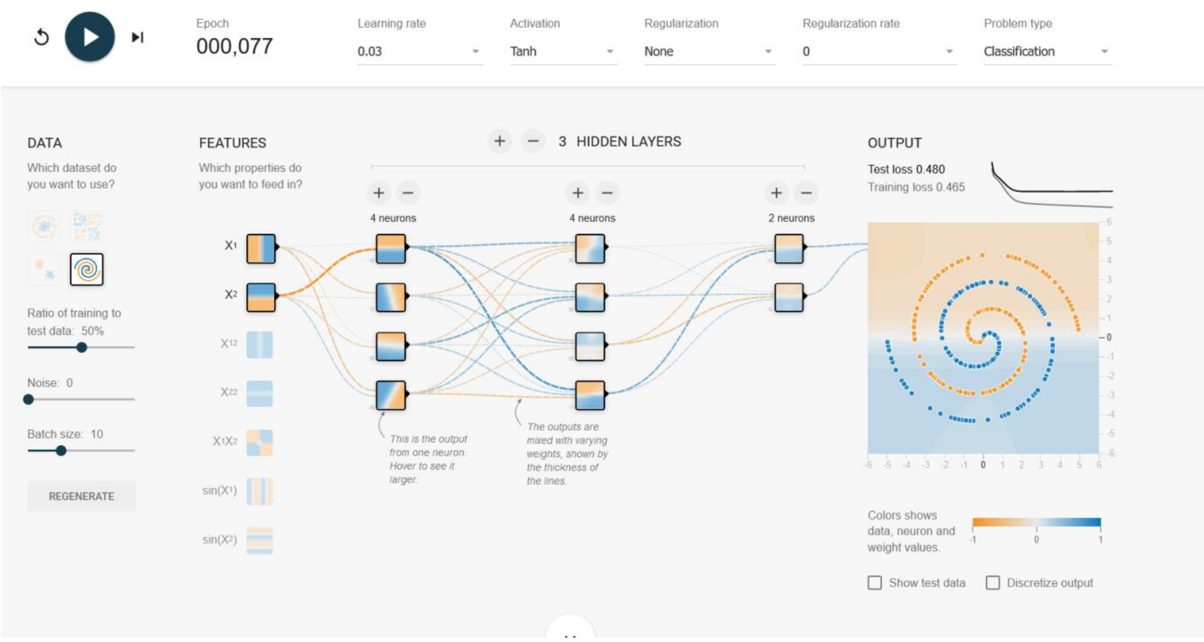


:

EXPERIMENT:9 (a) TANH

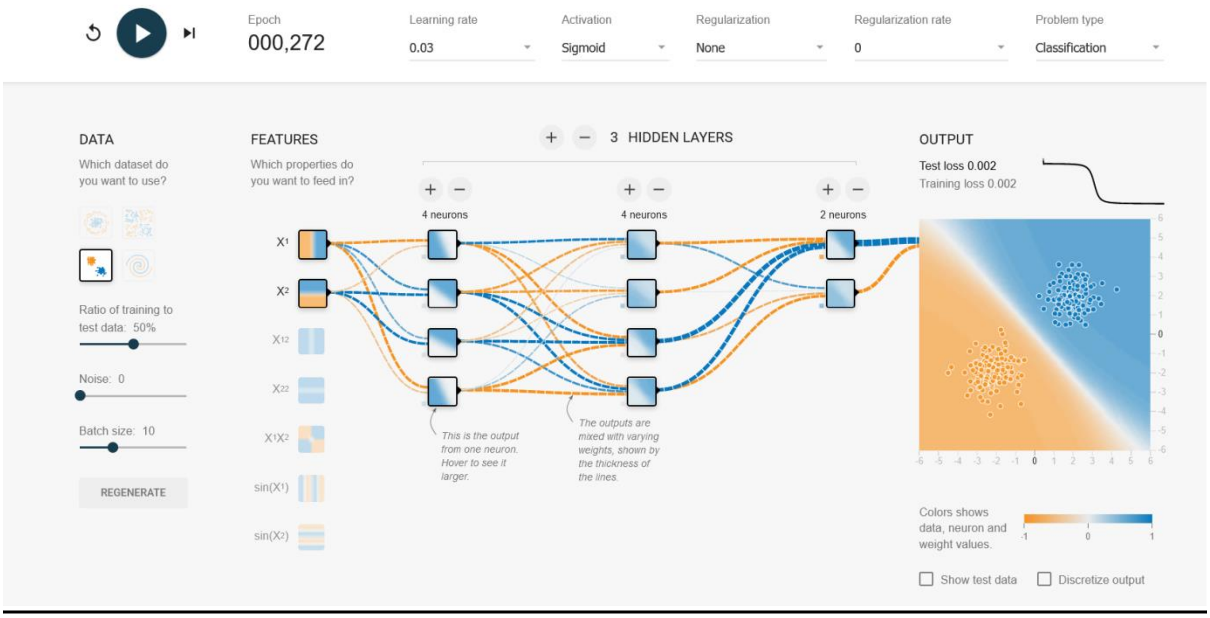
AIM: Neural network analysis using TANH activation

OUTPUT:



EXPERIMENT:9(B) SIGMIOD

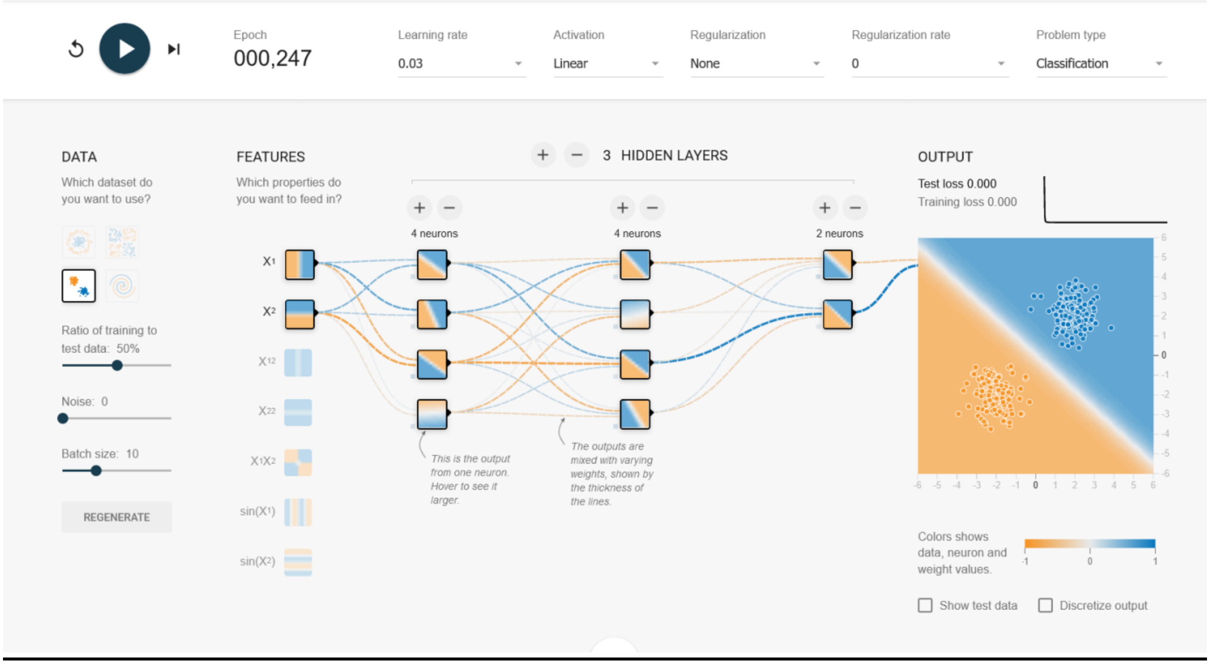
AIM: Neural network analysis using SIGMOID activation



EXPERIMENT:9(C) LINEAR

AIM: Neural network analysis using LINEAR activation

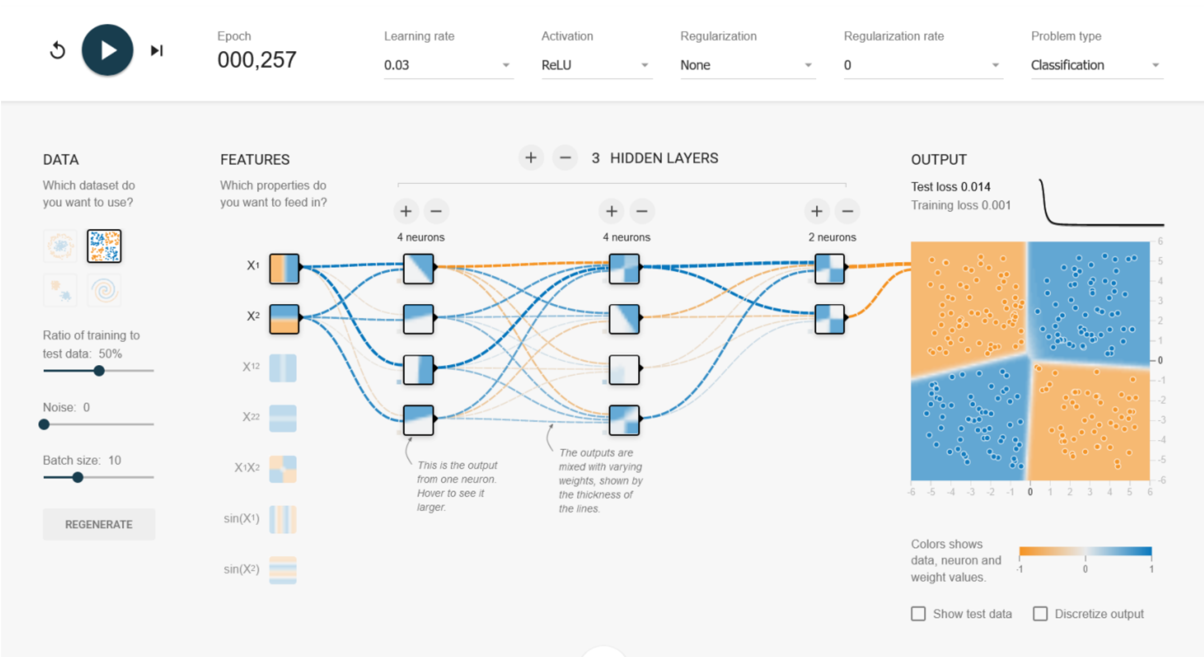
OUTPUT:



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
    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
```