CSA4730-Deep Learning for Precision Medicine

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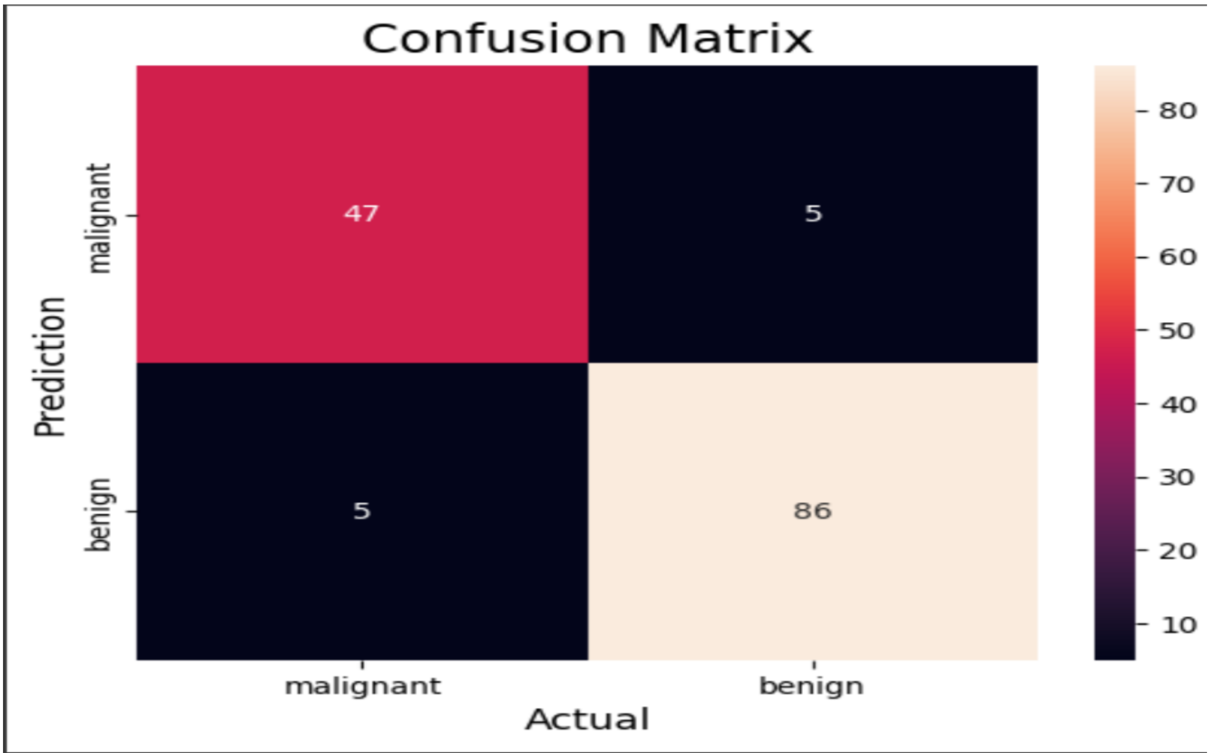
Experiment 1:

Aim: To demonstrate confusion matrix using python

Program:

```
import numpy as np

from sklearn.metrics import confusion_matrix

import seaborn as sns

import matplotlib.pyplot as plt

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'])

conf_matrix=confusion_matrix(actual,predicted)

sns.heatmap(conf_matrix,annot=True,fmt='g',xticklabels=['Dog','Not
Dog'],yticklabels=['Dog','Not Dog'],cmap='hot')

plt.ylabel("prediction",fontsize=16)

plt.xlabel("actual",fontsize=16)

plt.title("confusion matrix",fontsize=20)

plt.show()
```

Output:




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

Experiment 2:

Aim: To demonstrate 2 class confusion matrix using python

Program:

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.datasets import load_wine

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import accuracy_score,f1_score,precision_score,recall_score,classification_report,confusion_matrix

```
wine=load_wine()
data=pd.DataFrame(data=wine.data,columns=wine.feature_names)
data['Target']=wine.target
data=data[data['Target']!=2]
x=data.drop('Target',axis=1)
y=data['Target']
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=1)
model=DecisionTreeClassifier(random_state=1)
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
accuracy=accuracy_score(y_test,y_pred)
print("accuracy:",accuracy)
class_report = classification_report(y_test, y_pred,
target_names=wine.target_names[:2])
print("Classification Report:\n", class_report)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
conf_matrix=confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8,6))
sns.heatmap(conf_matrix,annot=True,fmt='d',cmap='Blues',xticklabels=wine.tar
get_names[:2],yticklabels=wine.target_names[:2])
plt.xlabel("predicted label")
plt.ylabel("true label")
```

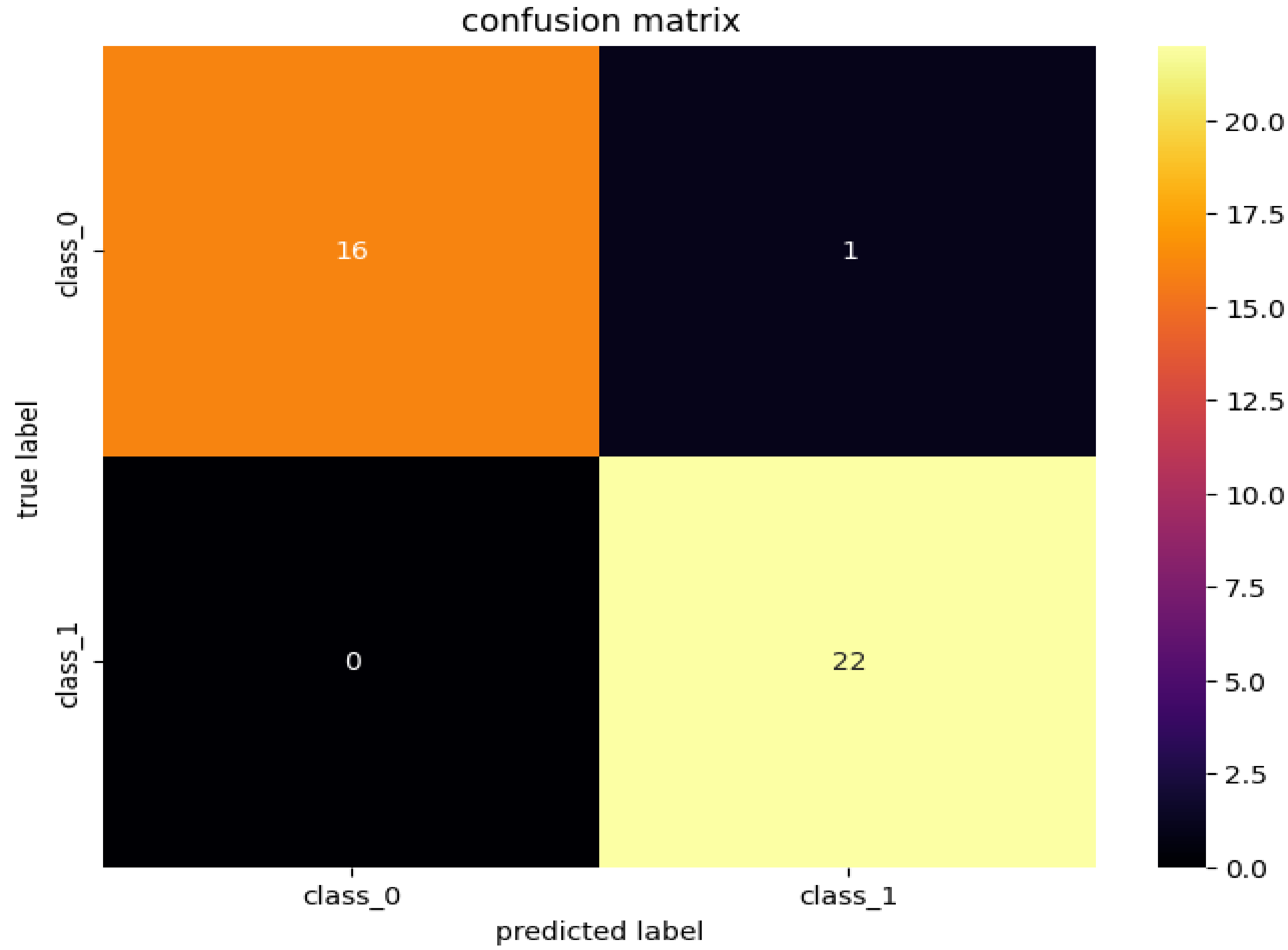
plt.title("confusion matrix")

plt.show()

Output:

accuracy: 0.9743589743589743

Classification Report: precision recall f1-score support class_0 1.00 0.94 0.97 17 class_1 0.96 1.00 0.98 22 accuracy 0.97 39 macro avg 0.98 0.97 0.97 39 weighted avg 0.98 0.97 0.97 39 Precision: 0.96 Recall: 1.00 F1 Score: 0.98



Experiment 3:

Aim: To analyse the performance of a multi class confusion matrix by using choosen database with python code

Program:

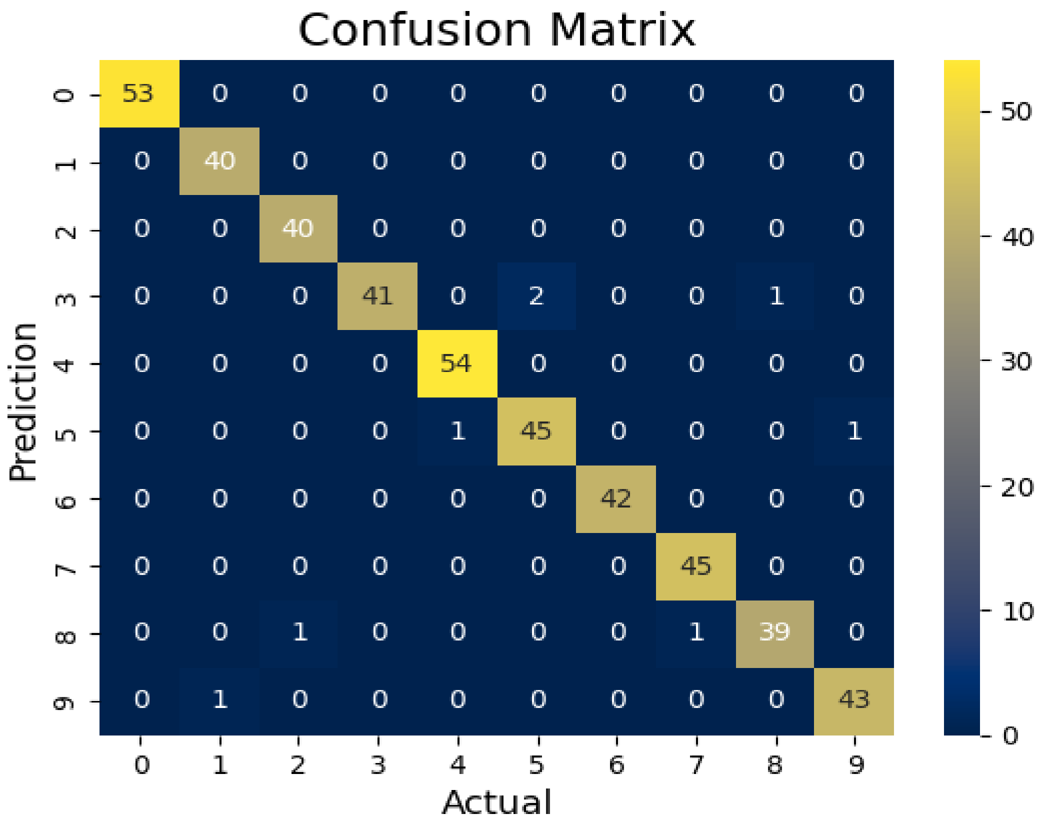
from sklearn.datasets import load_digits

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
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)
clf = RandomForestClassifier(random_state=23)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
cm = confusion_matrix(y_test,y_pred)
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()
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy   :", accuracy)
```

Output:

Accuracy   : 0.982222222222



Experiment 4:

Aim: To analyse the performance of a over fitting by using choosen database with python code

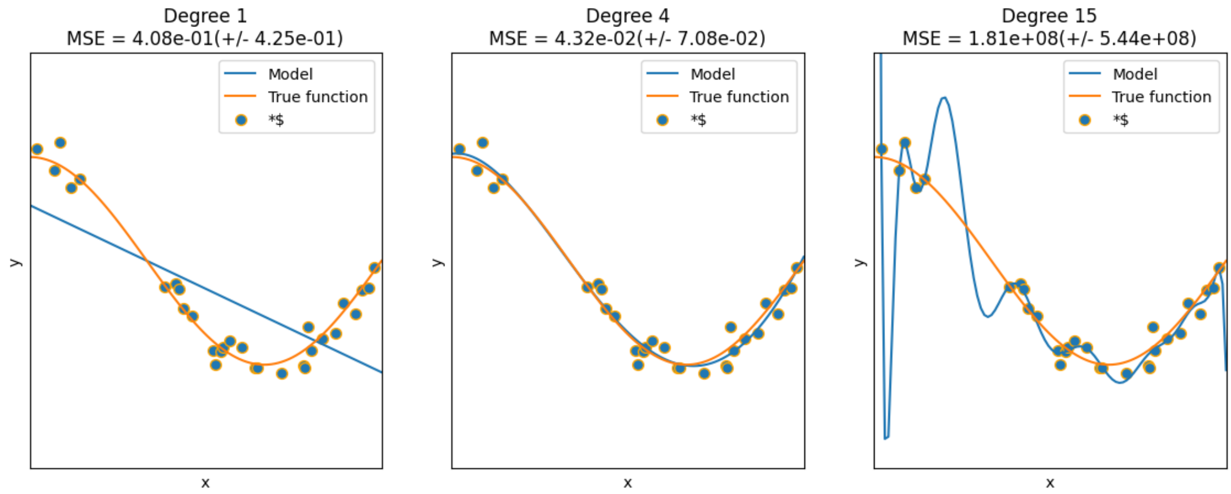
Program:

```
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)
    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 5:

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

Program:

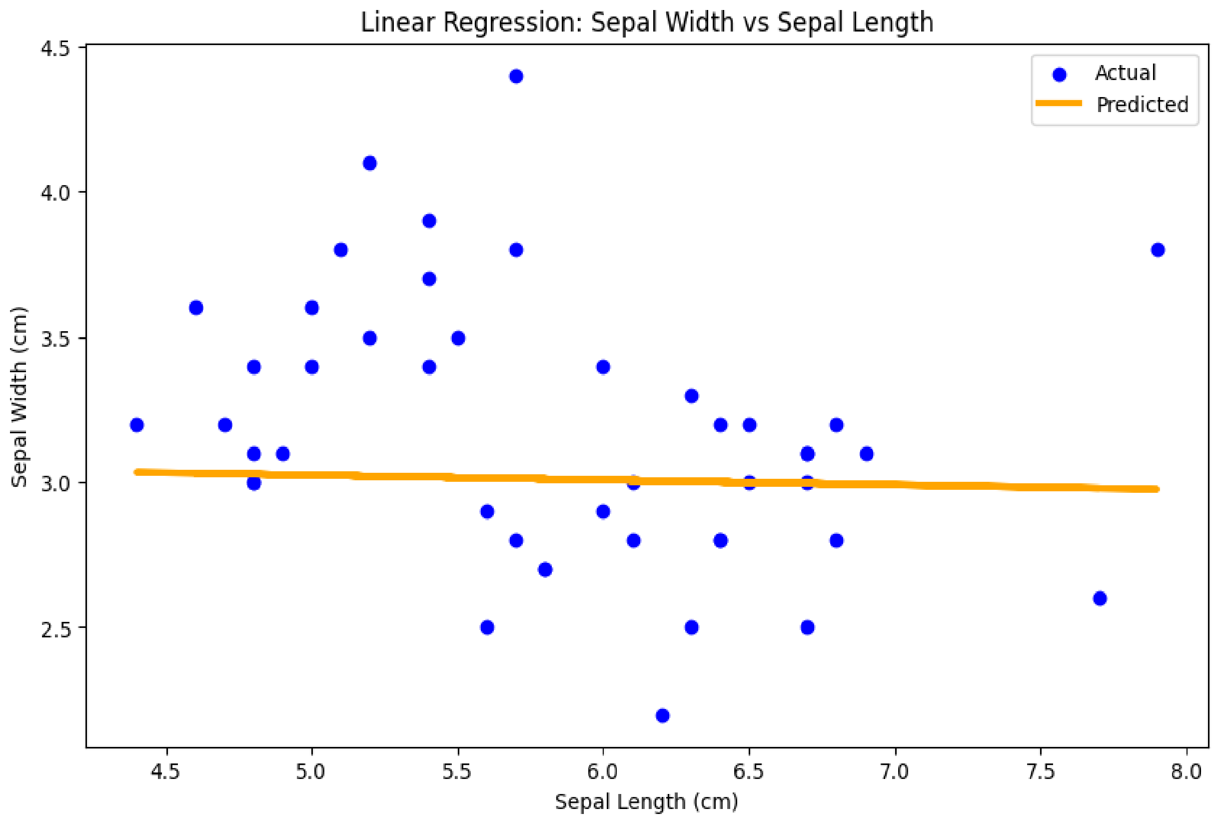
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
iris = load_iris()
data = pd.DataFrame(data=iris.data, columns=iris.feature_names)
data['species'] = iris.target
print(data.head())
X = data[['sepal length (cm)']]
y = data['sepal width (cm)']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error on test set: {mse:.2f}')
plt.figure(figsize=(10, 6))
plt.scatter(X_test, y_test, color='black', label='Actual')
plt.plot(X_test, y_pred, color='blue', linewidth=3, label='Predicted')
plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.title('Linear Regression: Sepal Width vs Sepal Length')
plt.legend()
```

```
plt.show()

new_sample = pd.DataFrame([[5]], columns=['sepal length (cm)'])

predicted_width = model.predict(new_sample)

print(f'The predicted sepal width for sepal length {new_sample.values.tolist()} is {predicted_width[0]:.2f} cm')
```

Output:

Mean Squared Error on test set: 0.23

The predicted sepal width for sepal length [[5]] is 3.02 cm



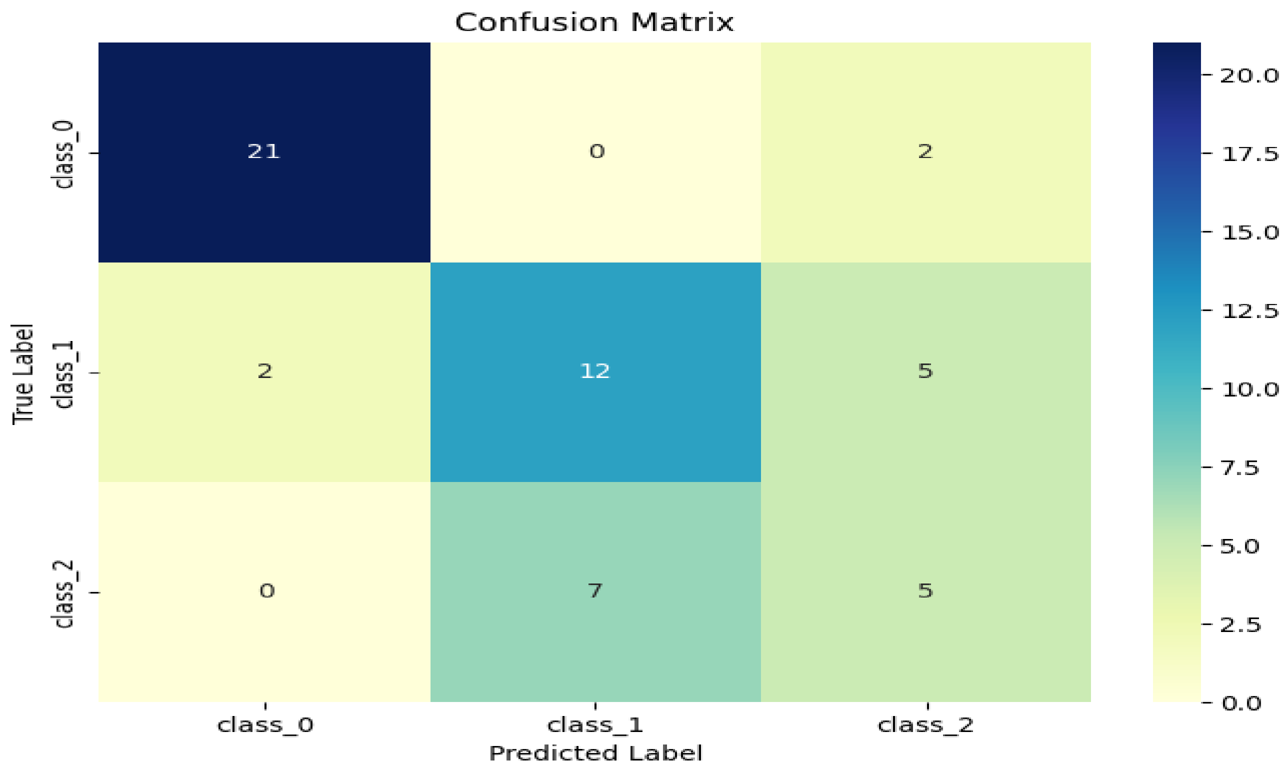
Experiment 6:

Aim: To demonstrate the performance of knn using wine dataset

Program:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_wine
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score,confusion_matrix
wine=load_wine()
data=pd.DataFrame(data=wine.data,columns=wine.feature_names)
data['Target']=wine.target
x=data.drop('Target',axis=1)
y=data['Target']
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=1)
model=KNeighborsClassifier(n_neighbors=5)
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
accuracy=accuracy_score(y_test,y_pred)
print("accuracy:",accuracy)
conf_matrix = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=wine.target_names, yticklabels=wine.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

Output:



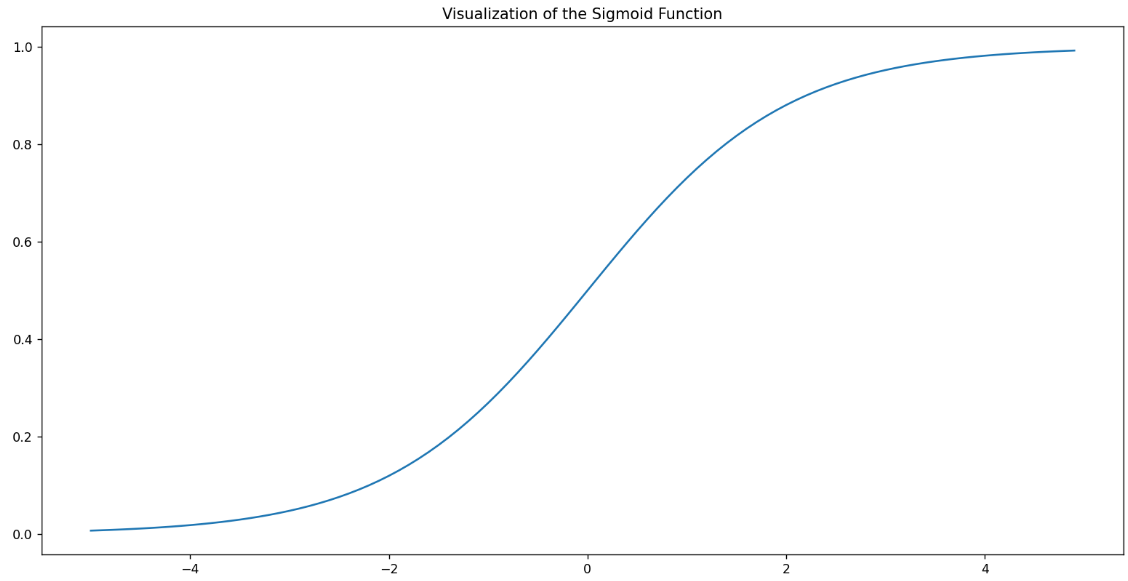
Experiment 7:

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 8:

Aim: To demonstrate the performance of KNN algorithm by using iris dataset

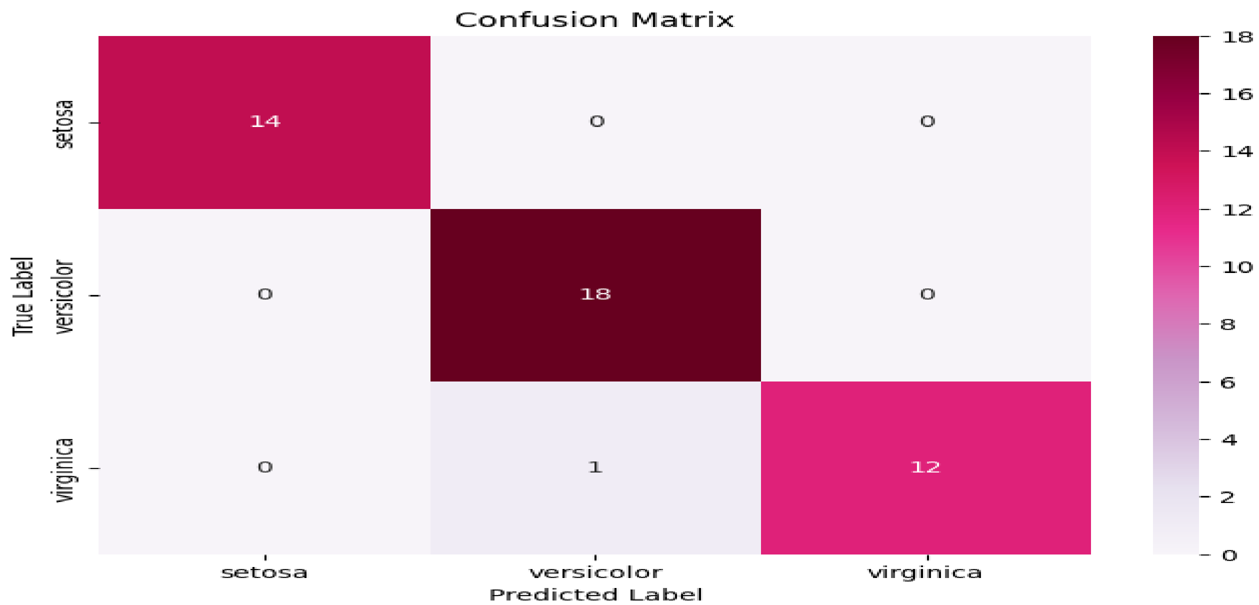
Program:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score,confusion_matrix

iris=load_iris()

data=pd.DataFrame(data=iris.data,columns=iris.feature_names)

data['Species']=iris.target

x=data.drop('Species',axis=1)

y=data['Species']

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=1)

model=KNeighborsClassifier(n_neighbors=5)
```

```
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
accuracy=accuracy_score(y_test,y_pred)
print("accuracy:",accuracy)
conf_matrix = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

Output:

accuracy: 0.9777777777777777



Experiment 9:

Aim: : To demonstrate the performance of Naïve Bayes algorithm by using iris dataset

Program:

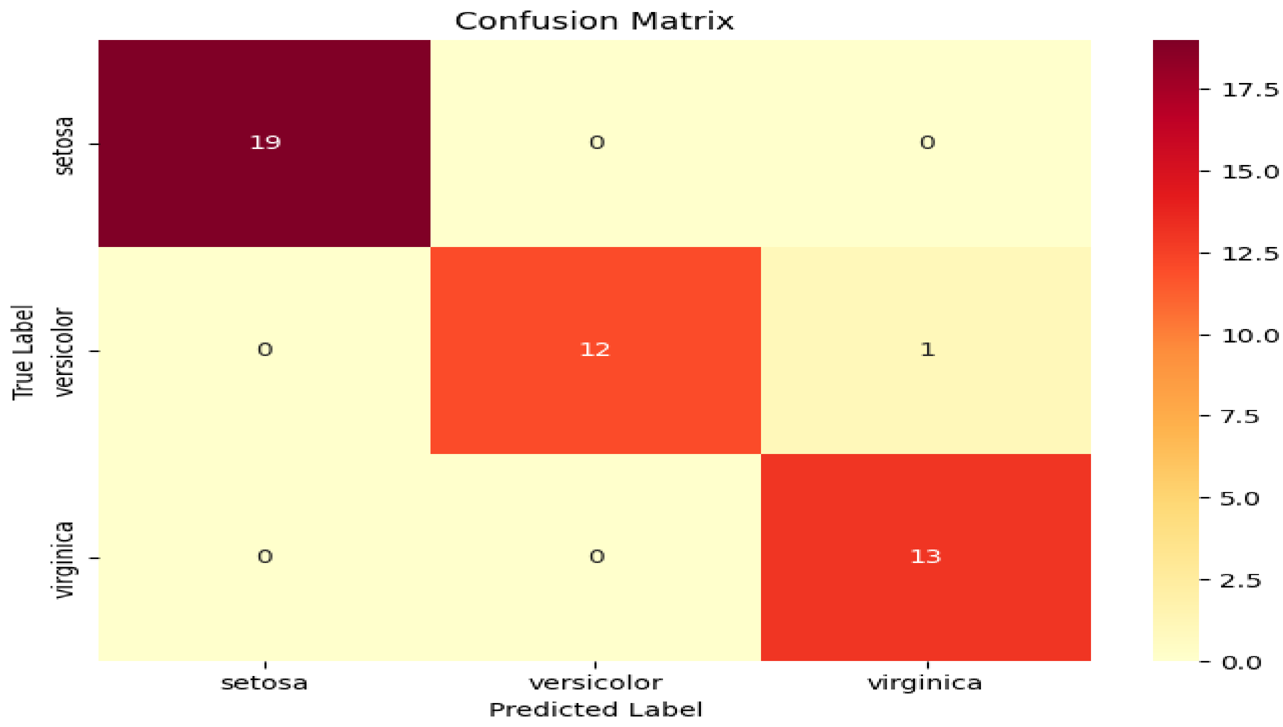
```
#naive bayes iris
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score,confusion_matrix
iris = load_iris()
data = pd.DataFrame(data=iris.data, columns=iris.feature_names)
data['species'] = iris.target
X = data.drop('species', axis=1)
y = data['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
model = GaussianNB()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("accuracy:",accuracy)
conf_matrix = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
```

plt.title('Confusion Matrix')

plt.show()

Output:

accuracy: 0.9777777777777777



Experiment 10:

Aim: To demonstrate the performance of Logistic Regression using iris dataset

Program:

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

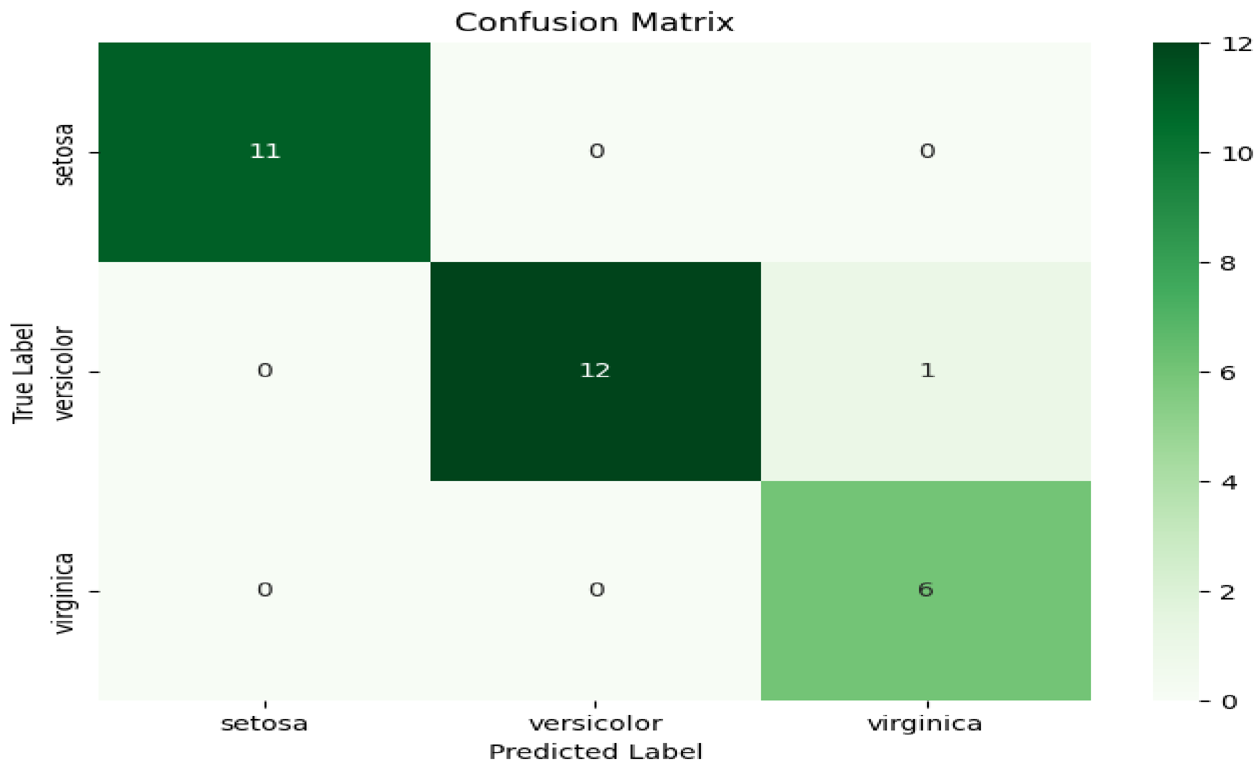
from sklearn.metrics import accuracy_score,confusion_matrix

iris = load_iris()

```
data = pd.DataFrame(data=iris.data, columns=iris.feature_names)
data['species'] = iris.target
X = data.drop('species', axis=1)
y = data['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=1)
model =LogisticRegression(max_iter=200)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("accuracy:",accuracy)
conf_matrix = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

Output:

accuracy: 0.9666666666666667



Experiment 11:

Aim: To demonstrate the performance of Decision tree Classifier algorithm using iris dataset.

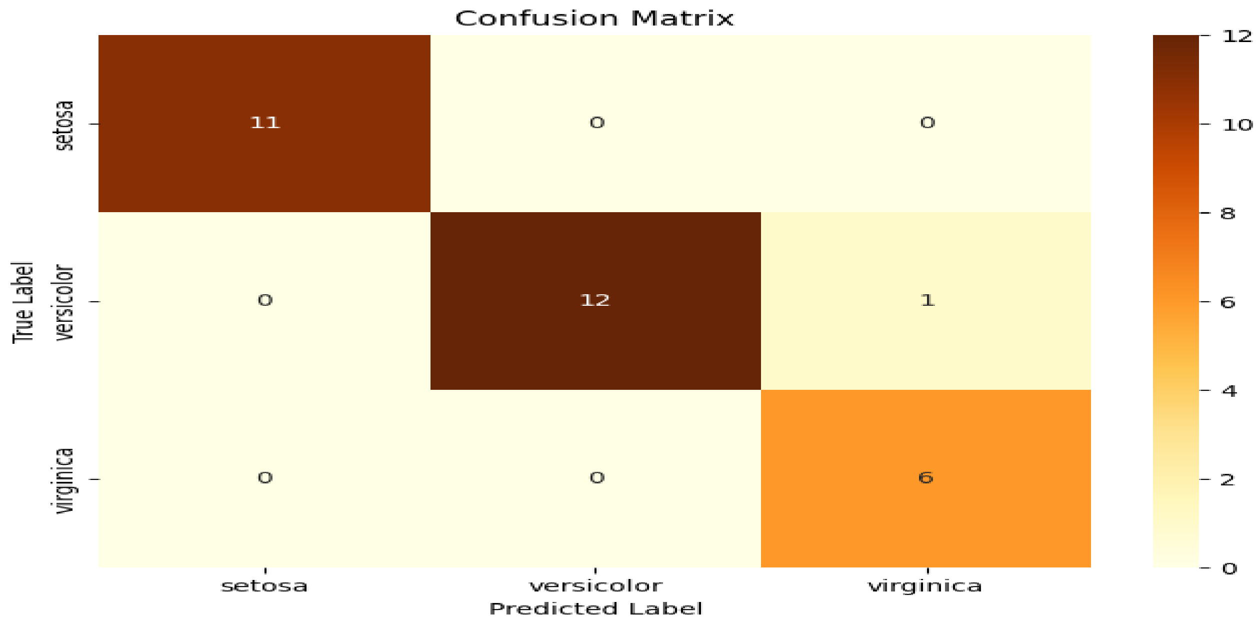
Program:

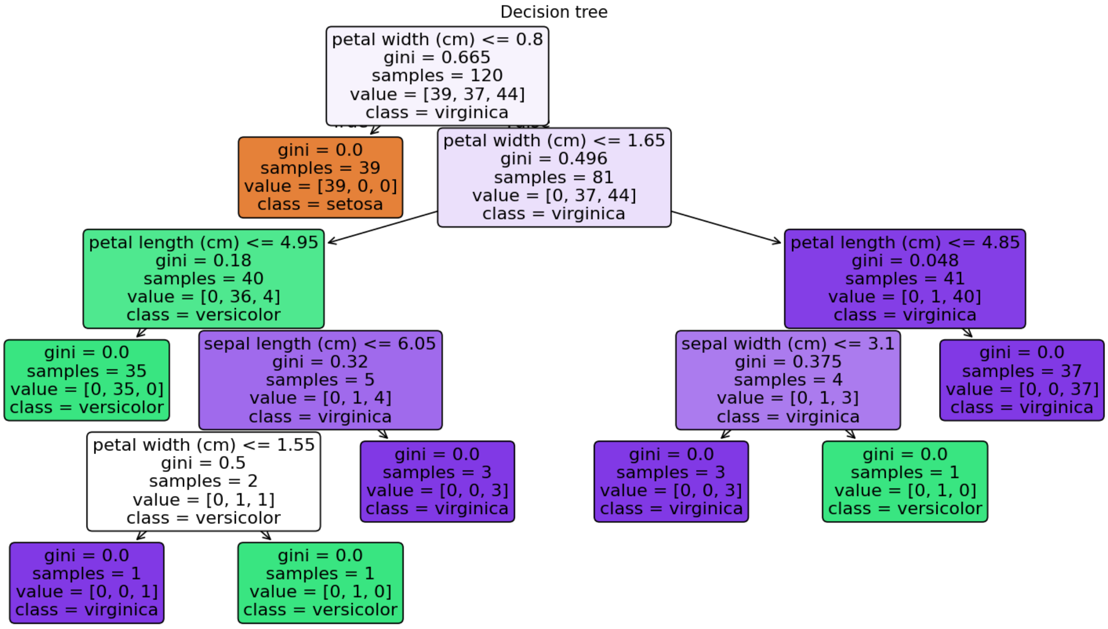
```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import accuracy_score,confusion_matrix

iris = load_iris()

data = pd.DataFrame(data=iris.data, columns=iris.feature_names)

data['species'] = iris.target

X = data.drop('species', axis=1)
```

```
y = data['species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
model =DecisionTreeClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("accuracy:",accuracy)
conf_matrix = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Reds', xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

Output:

accuracy: 0.9666666666666667





Experiment 12:

Aim: To demonstrate the performance of Random Forest classifier algorithm by using iris dataset

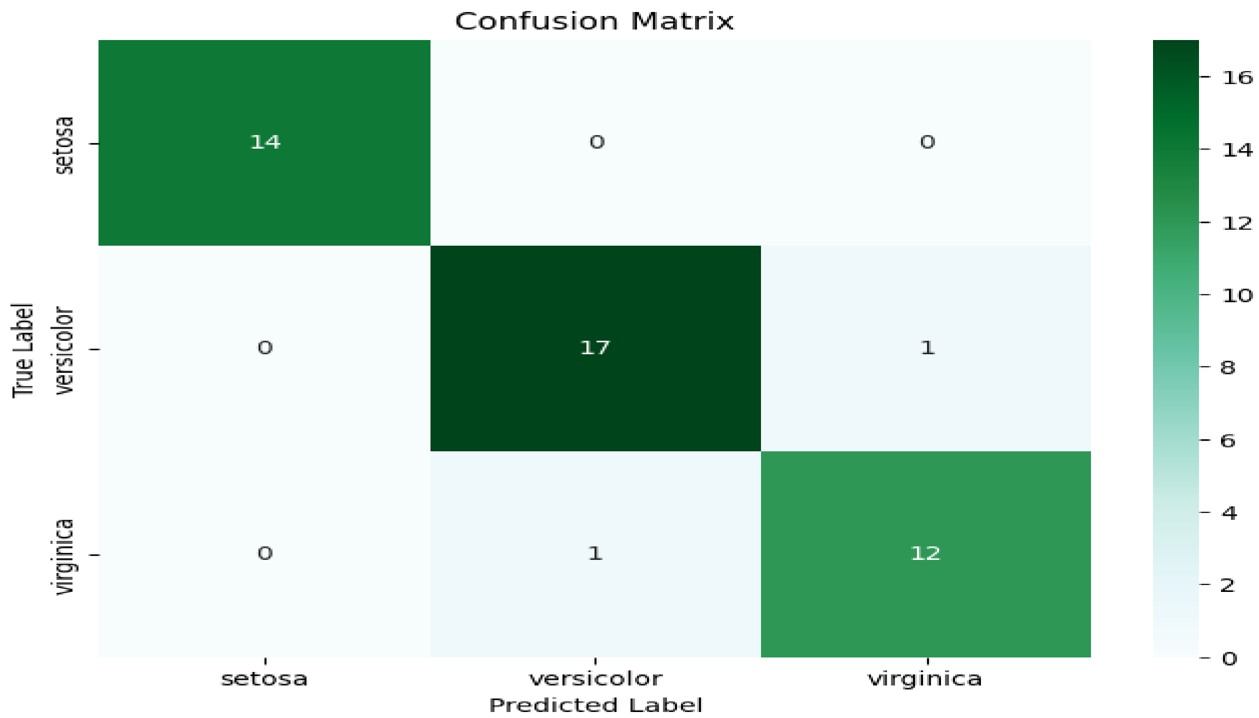
Program:

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score,confusion_matrix

iris=load_iris()

data=pd.DataFrame(data=iris.data,columns=iris.feature_names)

data['Species']=iris.target

x=data.drop('Species',axis=1)

y=data['Species']

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=1)
```

```
model=RandomForestClassifier(n_estimators=100,random_state=1)
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
accuracy=accuracy_score(y_test,y_pred)
print("accuracy:",accuracy)
conf_matrix = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='hot', xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

Output:

accuracy: 0.9555555555555556



Experiment 13:

Aim: To demonstrate the performance of SVM algorithm by using iris dataset

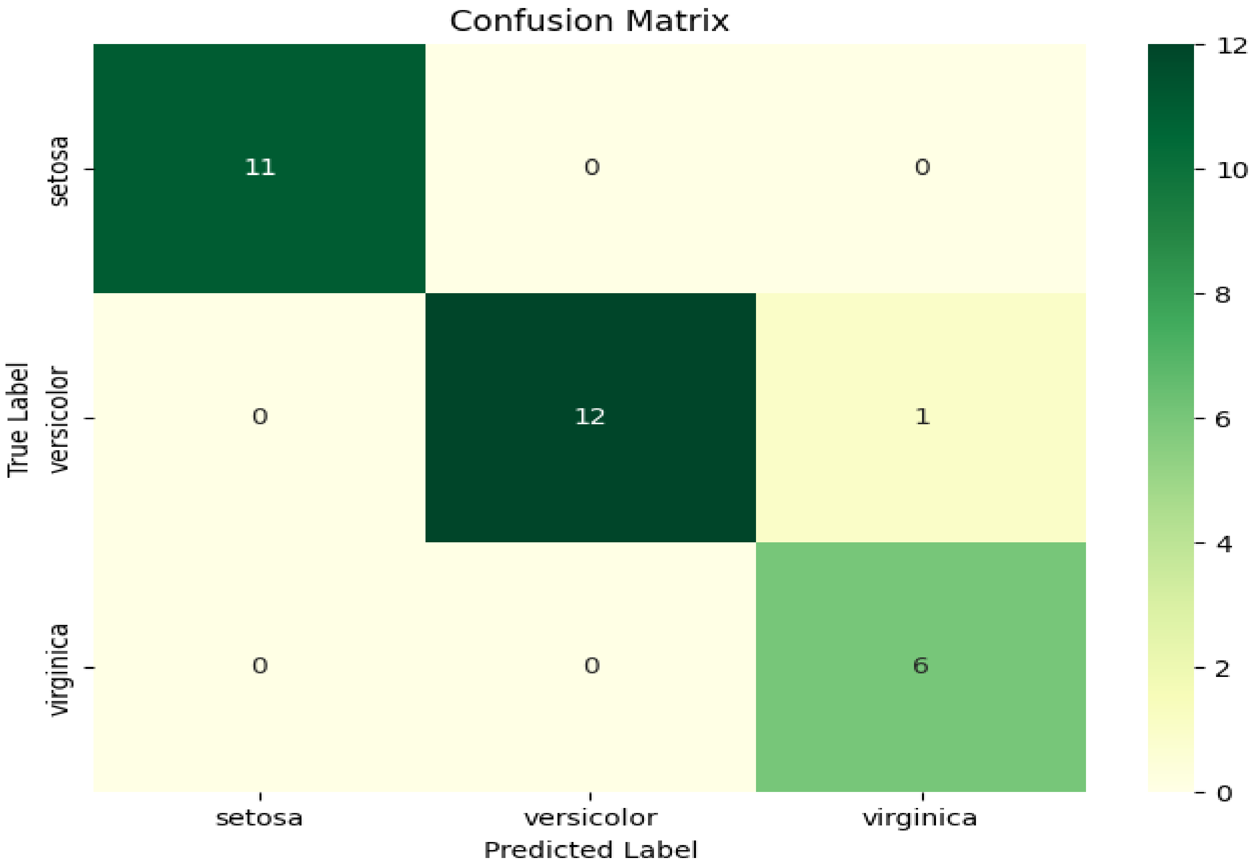
Program:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score,confusion_matrix
iris=load_iris()
data=pd.DataFrame(data=iris.data,columns=iris.feature_names)
data['Species']=iris.target
x=data.drop('Species',axis=1)
y=data['Species']
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=1)
model=SVC(kernel='poly',random_state=1)
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
accuracy=accuracy_score(y_test,y_pred)
print("accuracy:",accuracy)
conf_matrix = confusion_matrix(y_test,y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Oranges',
xticklabels=iris.target_names, yticklabels=iris.target_names)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
```

```
plt.title('Confusion Matrix')
plt.show()
```

Output:

accuracy: 0.9666666666666667



Experiment 14:

Aim: To demonstrate the gradient descent

Program:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
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=0.01,
stopping_threshold=1e-6):
    current_weight = 0.0
    current_bias = 0.0
    n = float(len(x))
    costs = []
    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)
        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 % 100 == 0:
            print(f"Iteration {i+1}: Cost {current_cost}, Weight {current_weight},
Bias {current_bias}")
    plt.figure(figsize=(8,6))
    plt.plot(range(len(costs)), costs, 'b.')
    plt.title("Cost vs Iterations")
    plt.xlabel("Iterations")
```

```
    plt.ylabel("Cost")
    plt.show()
    return current_weight, current_bias
def main():
    X = np.array([32.5, 53.4, 61.5, 47.4, 59.8, 55.1, 52.2, 39.2, 48.1, 52.5, 45.4,
54.3, 44.1, 58.1, 56.7, 48.9, 44.6, 60.2, 45.6, 38.8])
    Y = np.array([31.7, 68.7, 62.5, 71.5, 87.2, 78.2, 79.6, 59.1, 75.3, 71.3, 55.1,
82.4, 62.0, 75.3, 81.4, 60.7, 82.8, 97.3, 48.8, 56.8])
    scaler = StandardScaler()
    X_normalized = scaler.fit_transform(X.reshape(-1, 1)).flatten()
    estimated_weight, estimated_bias = gradient_descent(X_normalized, Y,
iterations=2000, learning_rate=0.01)
    print(f"Estimated Weight: {estimated_weight}, Estimated Bias:
{estimated_bias}")
    Y_pred = estimated_weight * X_normalized + estimated_bias
    plt.figure(figsize=(8,6))
    plt.scatter(X, Y, color='red', label='Data Points')
    plt.plot(X, Y_pred, color='blue', linestyle='--', label='Fitted Line')
    plt.xlabel("X")
    plt.ylabel("Y")
    plt.title("Linear Regression using Gradient Descent")
    plt.legend()
    plt.show()


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

Output:

Iteration 1: Cost 5031.3015, Weight 0.21744528996901658, Bias 1.3877

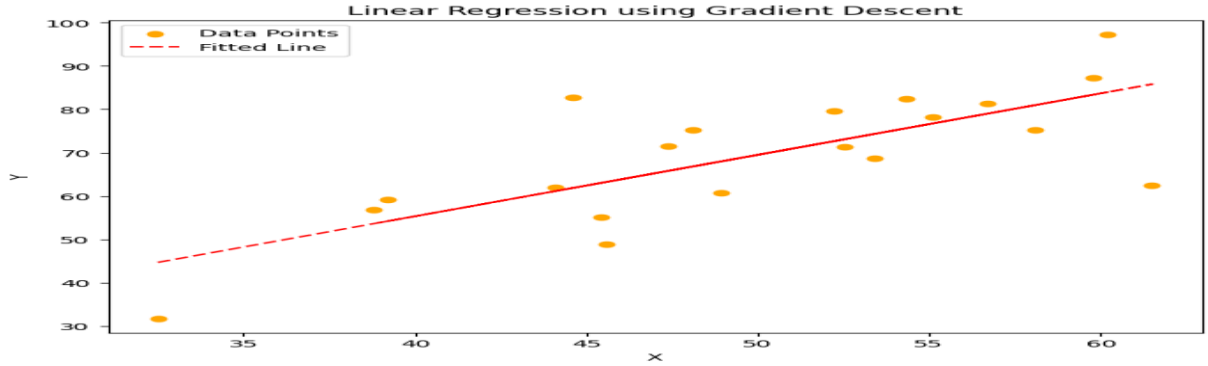
Iteration 101: Cost 185.56941123866557, Weight 9.459227106883091, Bias 60.3672282719577

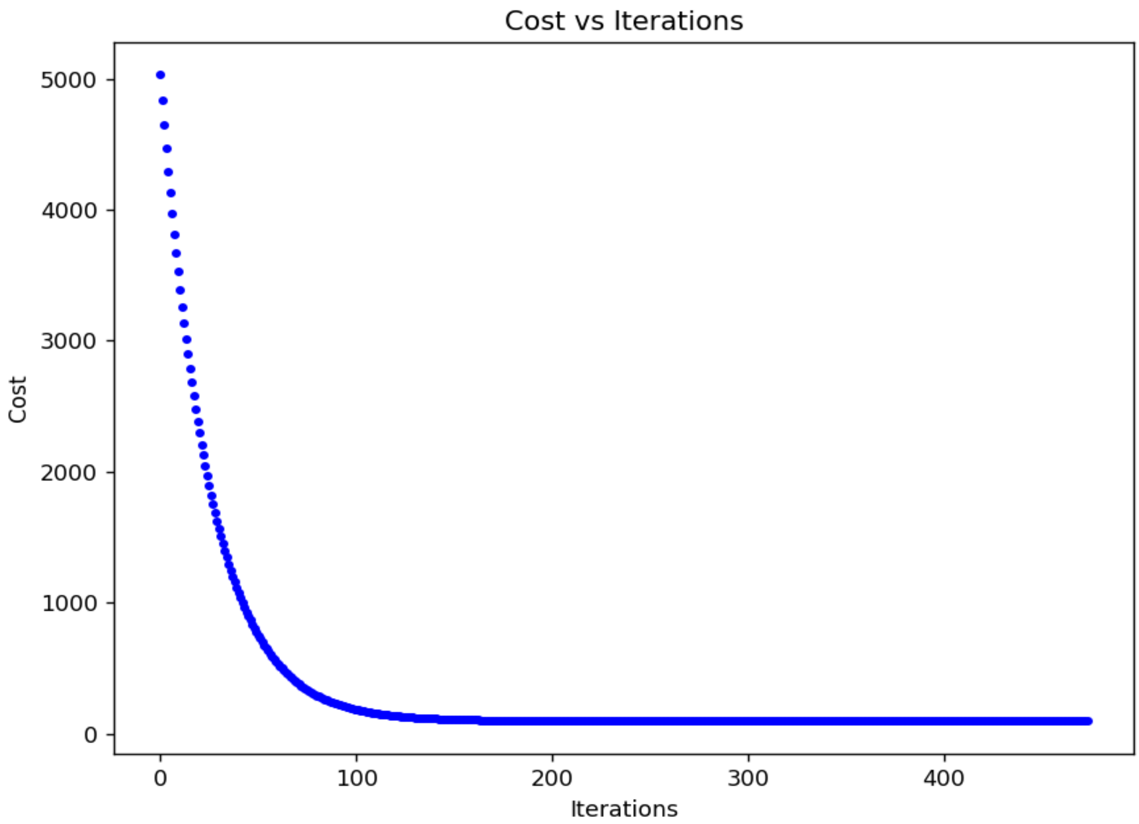
Iteration 201: Cost 100.34293399589959, Weight 10.684868107118445, Bias 68.18906711826675

Iteration 301: Cost 98.84397526476002, Weight 10.847412072256065, Bias 69.22639591234459

Iteration 401: Cost 98.81761165863254, Weight 10.868968580725983, Bias 69.36396599633204

Estimated Weight: 10.87151030998278, Estimated Bias: 69.38018689350649





Experiment 15:

Aim: To demonstrate the segmentation of image using python

Program:

```
import cv2

import numpy as np

from matplotlib import pyplot as plt

img = cv2.imread('C:\desktop\core project\dataset\cataract\_16_1907643.jpg')

rgb_img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

pixels = rgb_img.reshape((-1, 3))

pixels = np.float32(pixels)

criteria = (cv2.TERM_CRITERIA_EPS +
cv2.TERM_CRITERIA_MAX_ITER, 100, 0.2)

K = 3

_, labels, centers = cv2.kmeans(pixels, K, None, criteria, 10,
cv2.KMEANS_RANDOM_CENTERS)

centers = np.uint8(centers)

segmented_img = centers[labels.flatten()]

segmented_img = segmented_img.reshape(rgb_img.shape)

plt.figure(figsize=(10, 5))

plt.subplot(121)

plt.imshow(rgb_img)

plt.title('Original Image')

plt.axis('off')


plt.subplot(122)

plt.imshow(segmented_img)

plt.title('Segmented Image (K-means)')
```

plt.axis('off')

plt.tight_layout()

plt.show()

Output:

Experiment 16:

Aim: To demonstrate the segmentation of image using python

Program:

import numpy as np

import cv2

from matplotlib import pyplot as plt

img = cv2.imread(r'C:\desktop\core project\dataset\cataract_16_1907643.jpg')

b, g, r = cv2.split(img)

rgb_img = cv2.merge([r, g, b])

gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

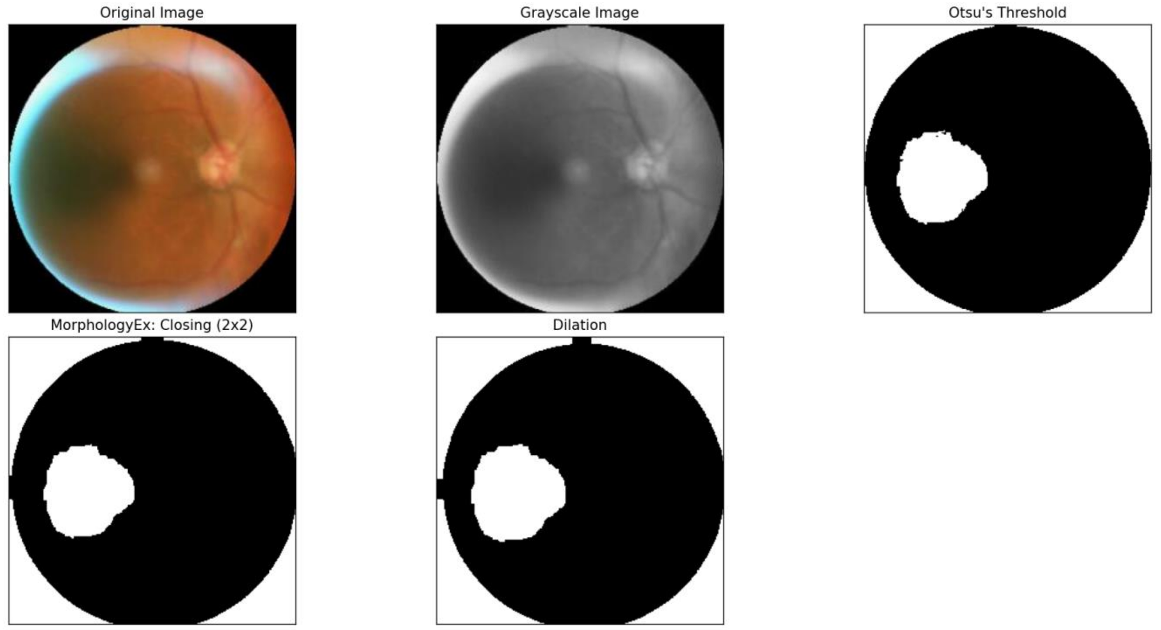
ret, thresh = cv2.threshold(gray, 0, 255, cv2.THRESH_BINARY_INV + cv2.THRESH_OTSU)

kernel = np.ones((2, 2), np.uint8)

```
closing = cv2.morphologyEx(thresh, cv2.MORPH_CLOSE, kernel,
iterations=2)
sure_bg = cv2.dilate(closing, kernel, iterations=3)
plt.figure(figsize=(12, 8))

plt.subplot(231)
plt.imshow(rgb_img)
plt.title("Original Image")
plt.xticks([]), plt.yticks([])

plt.subplot(232)
plt.imshow(gray, 'gray')
plt.title("Grayscale Image")
plt.xticks([]), plt.yticks([])

plt.subplot(233)
plt.imshow(thresh, 'gray')
plt.title("Otsu's Threshold")
plt.xticks([]), plt.yticks([])

plt.subplot(234)
plt.imshow(closing, 'gray')
plt.title("MorphologyEx: Closing (2x2)")
plt.xticks([]), plt.yticks([])

plt.subplot(235)
plt.imshow(sure_bg, 'gray')
```

```
plt.title("Dilation")
plt.xticks([]), plt.yticks([])

plt.tight_layout()
plt.show()
plt.imsave(r'dilation.png', sure_bg)
```

Output:



Experiment 17:

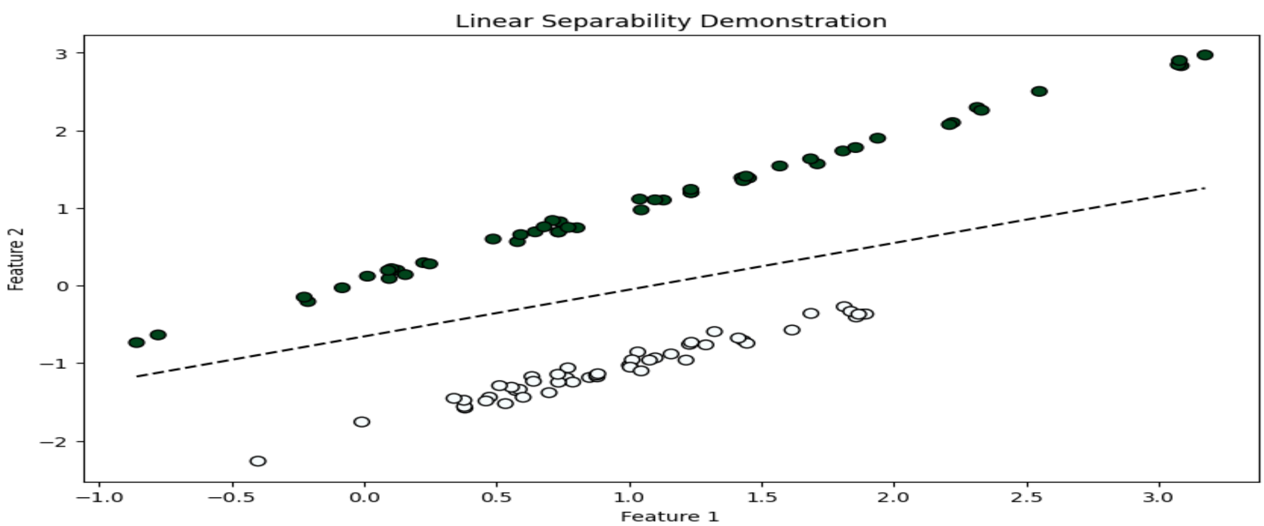
Aim: To demonstrate linear separability using python code

Program:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

```
X, y = make_classification(n_samples=100, n_features=2, n_informative=2,
n_redundant=0, n_clusters_per_class=1, random_state=42)

model = LogisticRegression()

model.fit(X, y)

y_pred = model.predict(X)

accuracy = accuracy_score(y, y_pred)

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

plt.figure(figsize=(10, 6))

plt.scatter(X[:, 0], X[:, 1], c=y, cmap='bwr', edgecolor='k', s=50)

coef = model.coef_[0]

intercept = model.intercept_

x_vals = np.linspace(X[:, 0].min(), X[:, 0].max(), 100)

y_vals = - (coef[0] * x_vals + intercept) / coef[1]

plt.plot(x_vals, y_vals, 'k--')

plt.xlabel('Feature 1')

plt.ylabel('Feature 2')

plt.title('Linear Separability Demonstration')

plt.show()
```

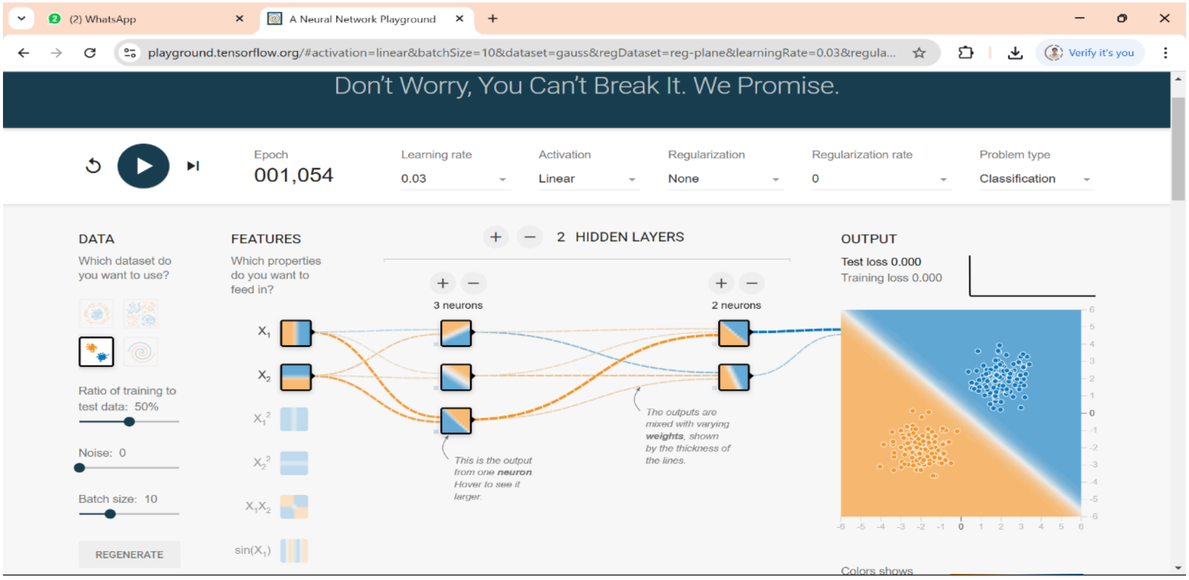
Output:



Experiment 18:

Aim: Neural network analysis for Two class, Learning rate: 0.03, Activation: Linear, Hidden Layers: 02, and Hidden neurons: 03.

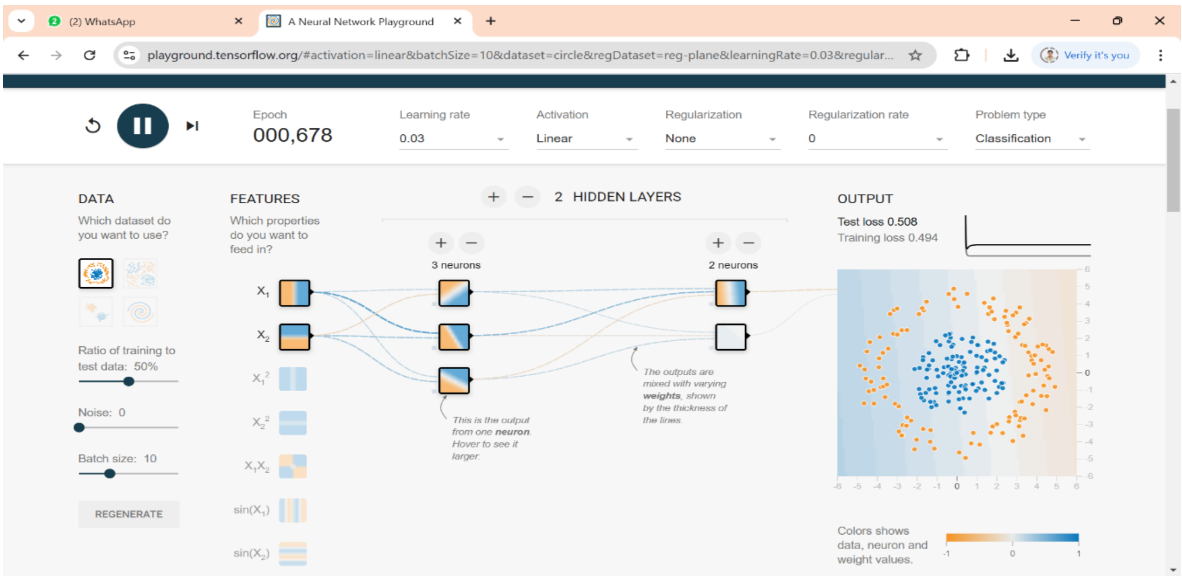
Output:



Experiment 19:

Aim: Neural network analysis for circular data class, Learning rate: 0.03, Activation: Linear, Hidden Layers: 02, and Hidden neurons: 03.

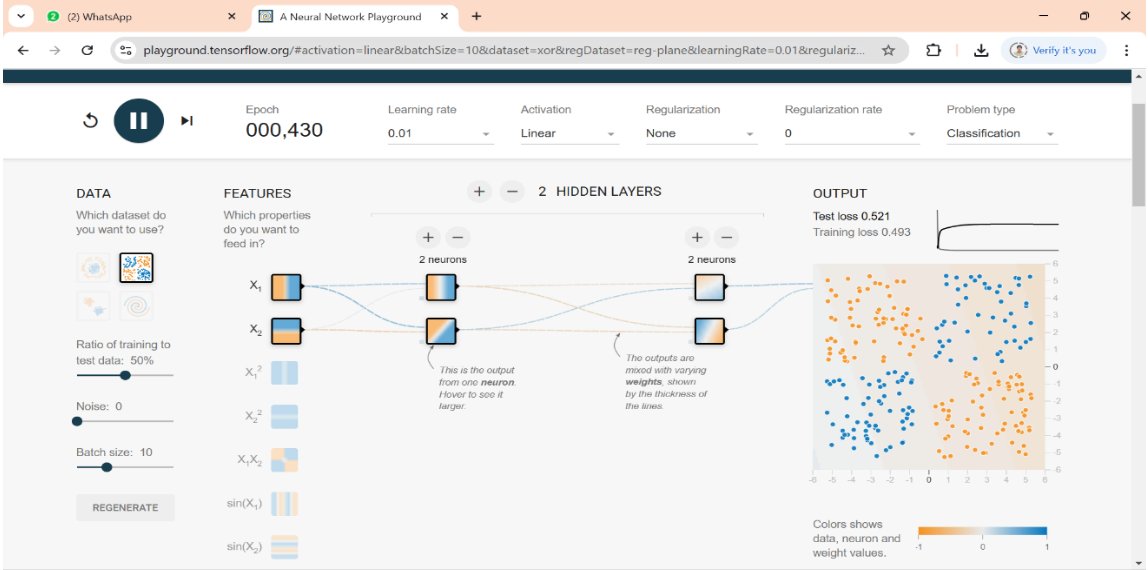
Output:



Experiment 20:

Aim: Neural network analysis for Multi class, Learning rate: 0.01, Activation: Linear, Hidden Layers: 02, and Hidden neurons: 02

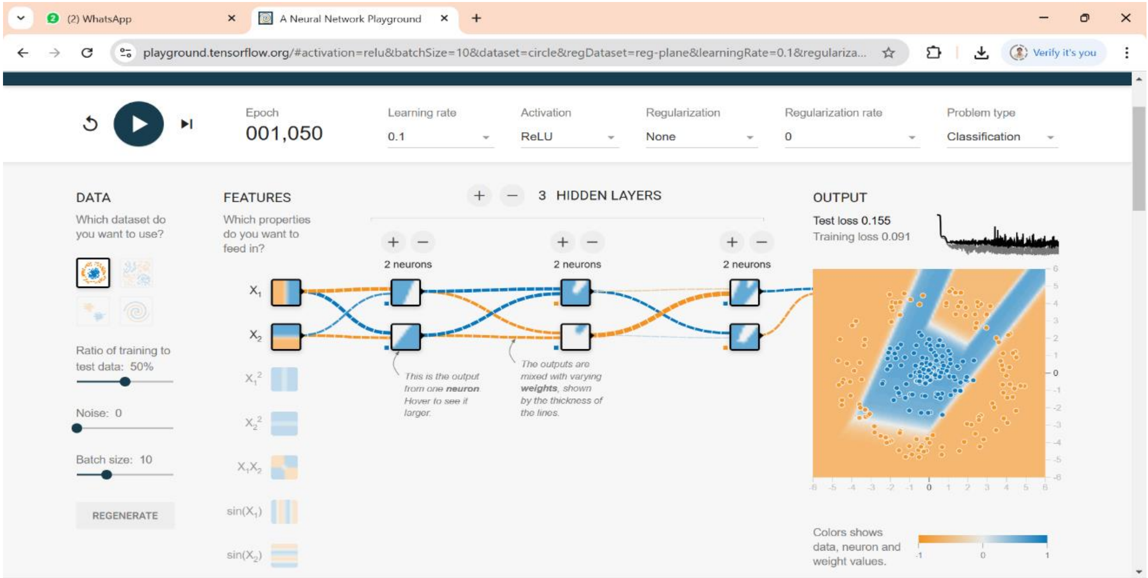
Output:



Experiment 21:

Aim: Neural network analysis for Circular data, Learning rate: 0.1, Activation: ReLU, Hidden Layers: 03, and Hidden neurons: 02.

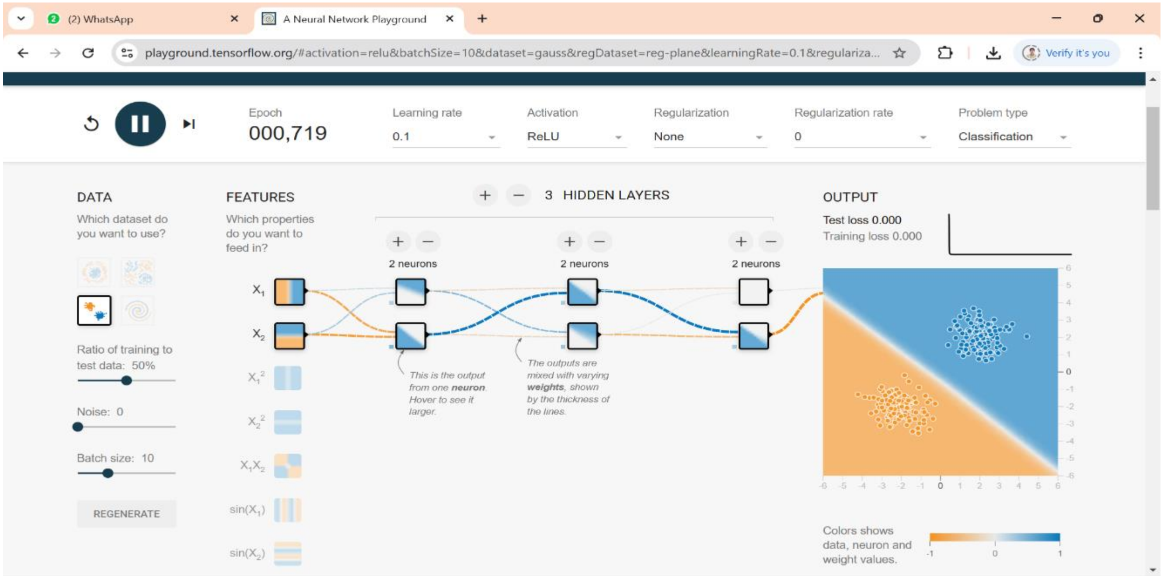
Output:



Experiment 22:

Aim: Neural network analysis for two class data, Learning rate: 0.1, Activation: ReLU, Hidden Layers: 03, and Hidden neurons: 02.

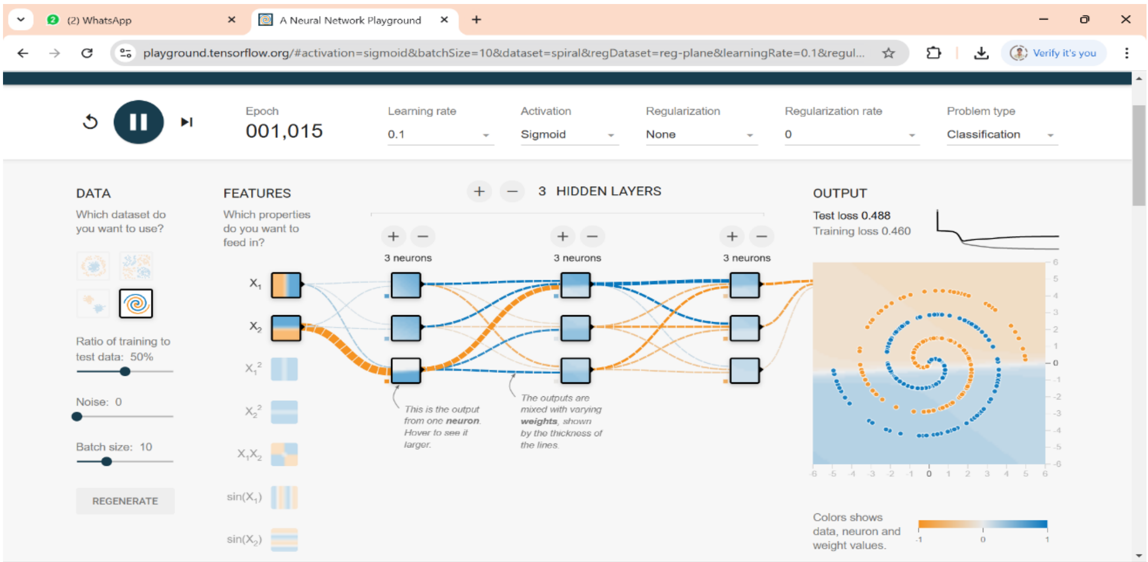
Output:



Experiment 23:

Aim: Neural network analysis for Spiral data, Learning rate: 0.1, Activation: Sigmoid, Hidden Layers: 03, and Hidden neurons: 03.

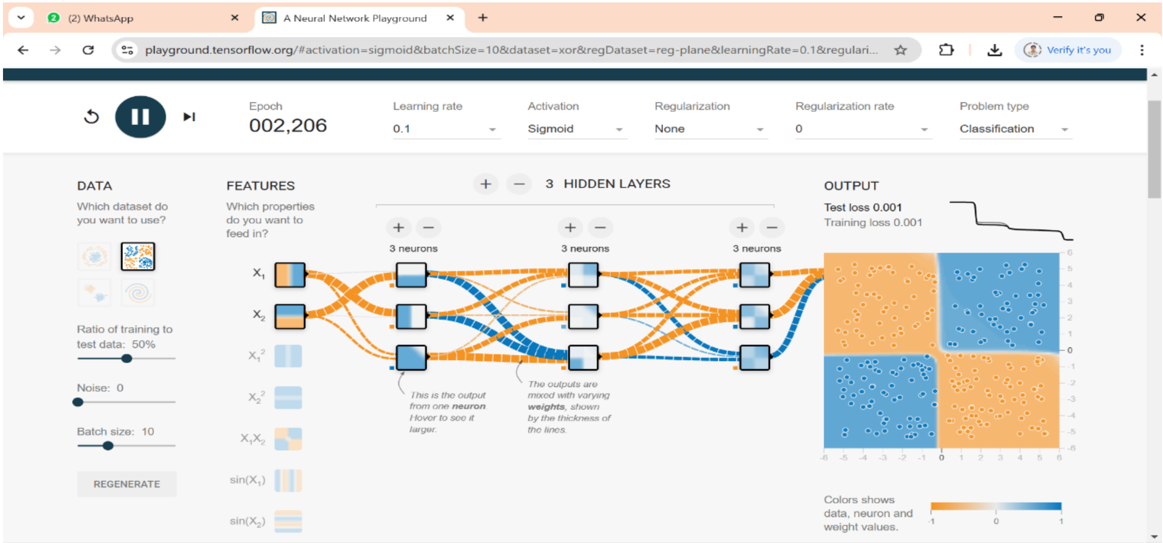
Output:



Experiment 24:

Aim: Neural network analysis for multi class data, Learning rate: 0.1, Activation: Sigmoid, Hidden Layers: 03, and Hidden neurons: 03.

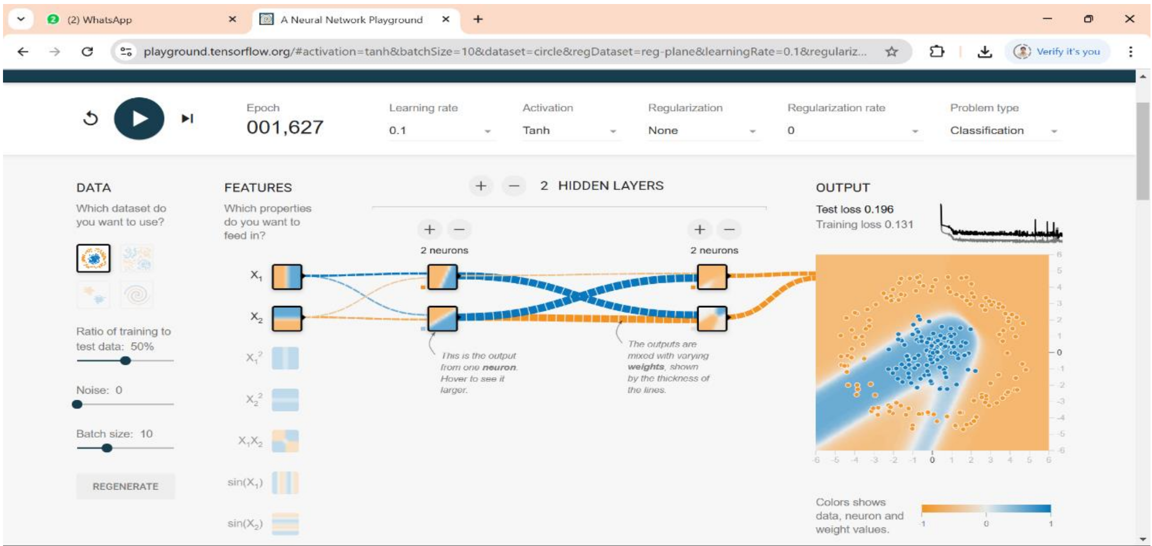
Output:



Experiment 25:

Aim: Neural network analysis for Circular data, Learning rate: 0.1, Activation: Tanh, Hidden Layers: 02, and Hidden neurons: 02.

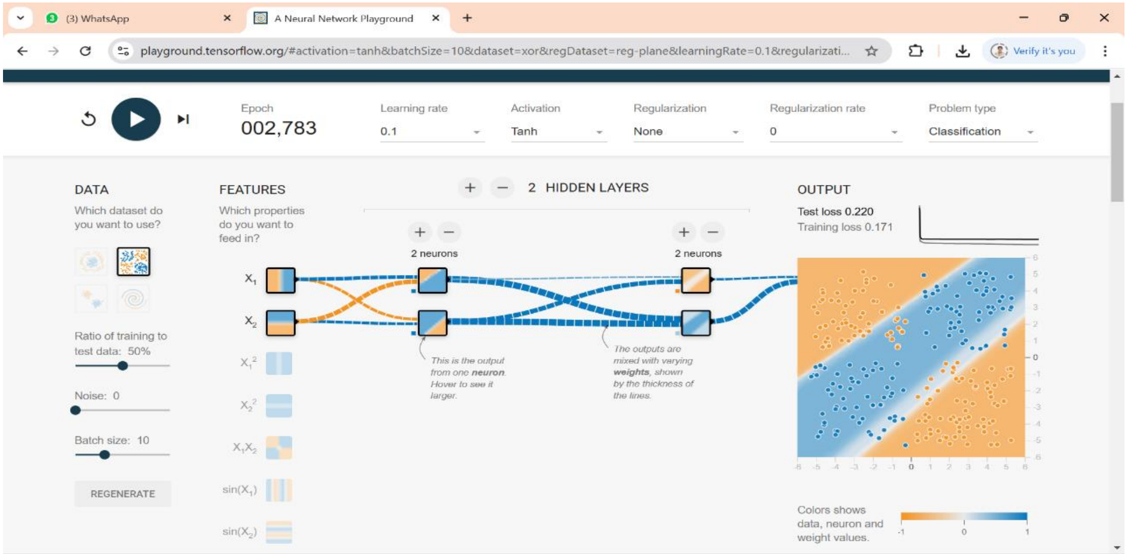
Output:



Experiment 26:

Aim: Neural network analysis for multi class data, Learning rate: 0.1, Activation: Tanh, Hidden Layers: 02, and Hidden neurons: 02.

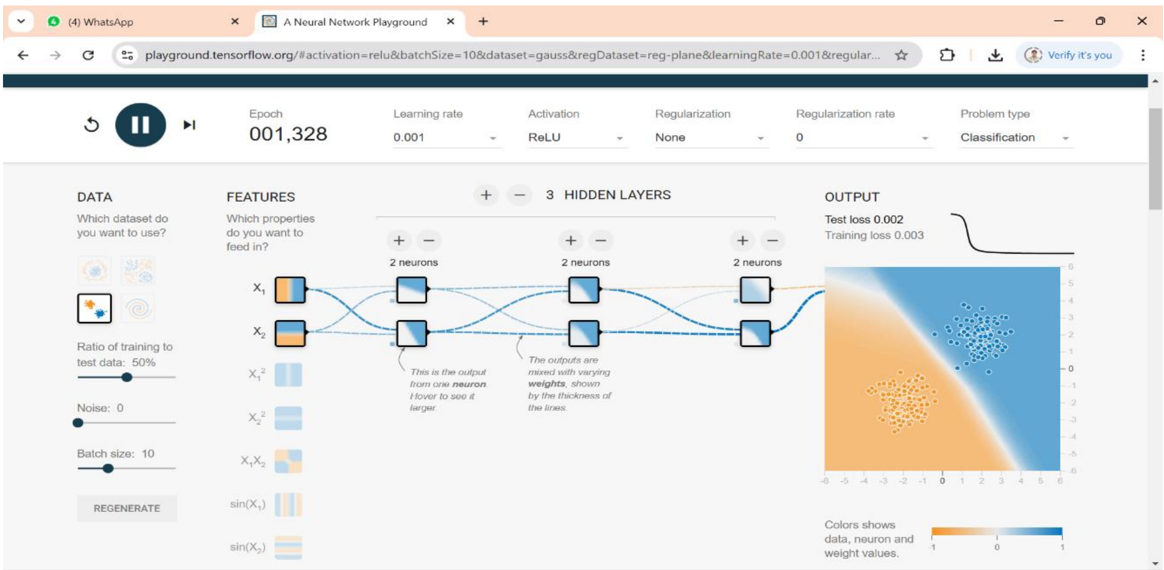
Output:



Experiment 27:

Aim: Neural network analysis for Two-class data, Learning rate: 0.001, Activation: ReLU, Hidden Layers: 03, and Hidden neurons: 02.

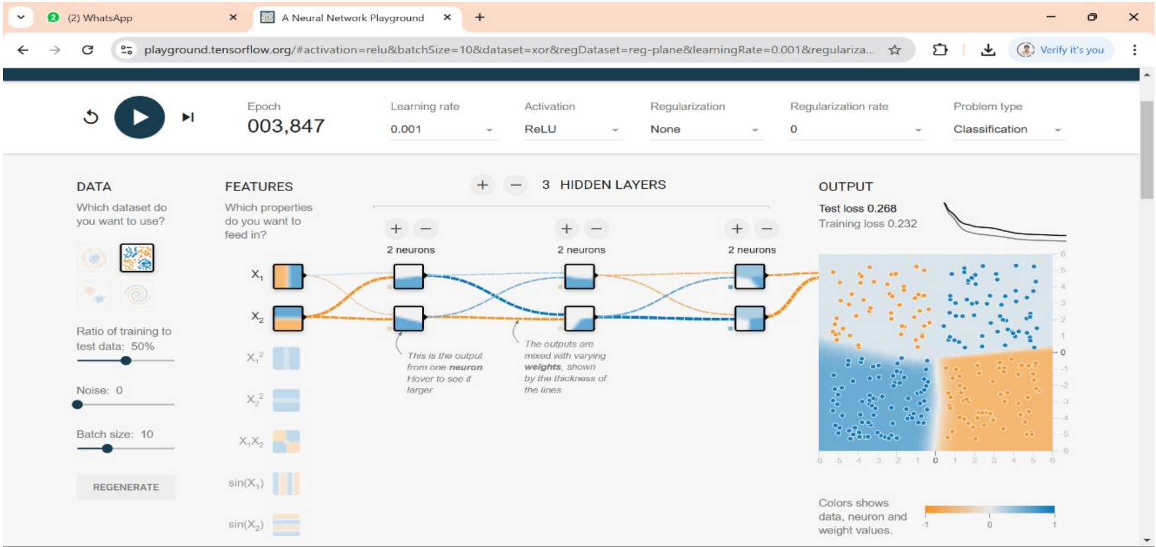
Output:



Experiment 28:

Aim: Neural network analysis for Multi class data, Learning rate: 0.001, Activation: ReLU, Hidden Layers: 03, and Hidden neurons: 02.

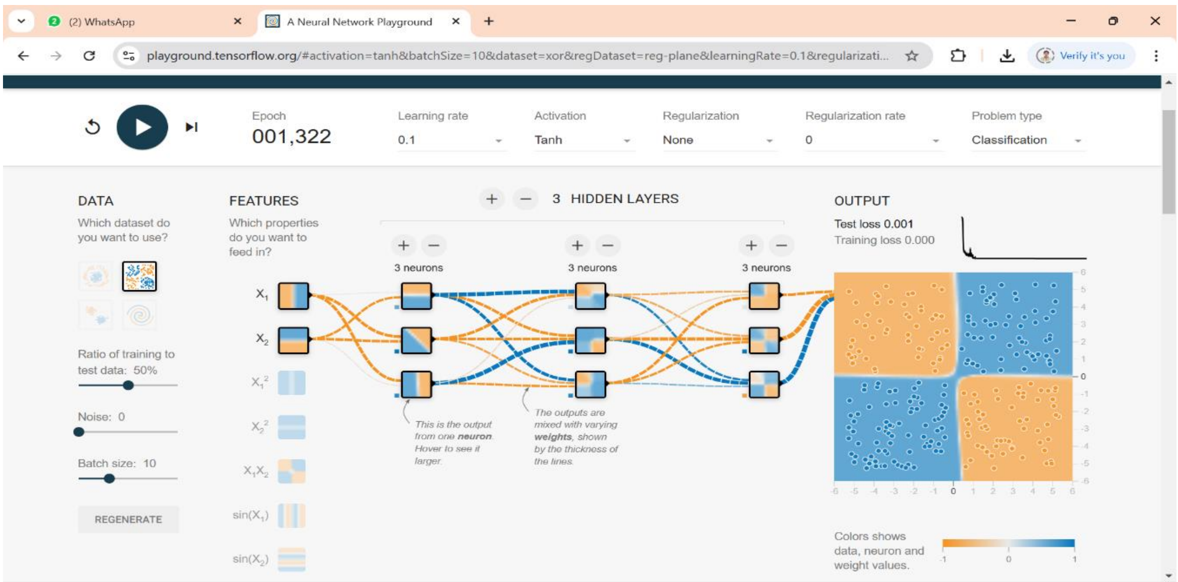
Output:



Experiment 29:

Aim: Neural network analysis for Multi-class data, Learning rate: 0.1, Activation: TanH, Hidden Layers: 03, and Hidden neurons: 03.

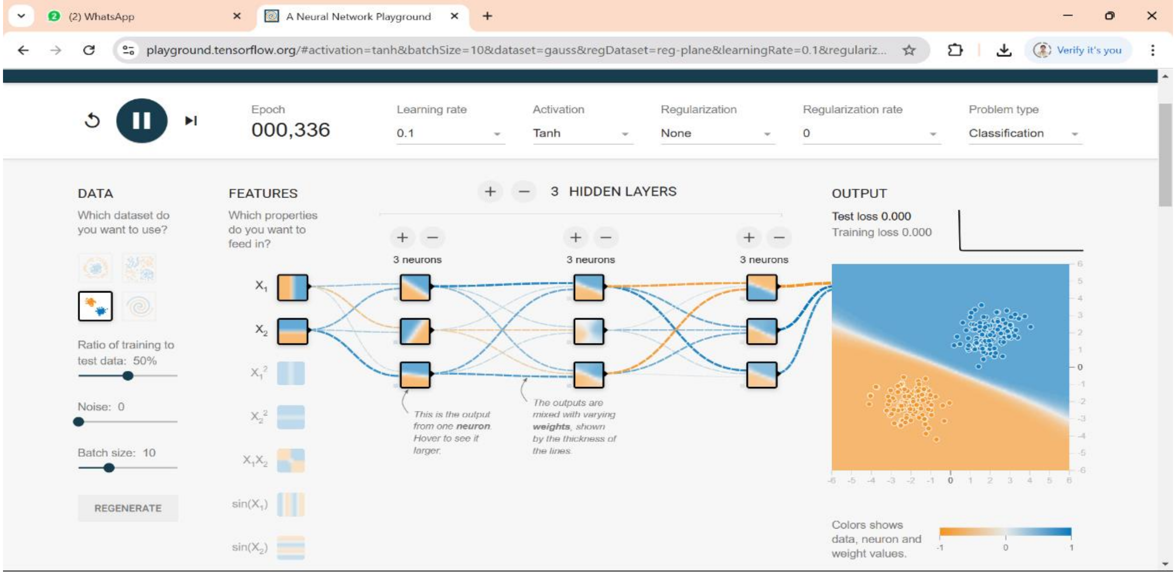
Output:



Experiment 30:

Aim: Neural network analysis for Two class data, Learning rate: 0.1, Activation: TanH, Hidden Layers: 03, and Hidden neurons: 03.

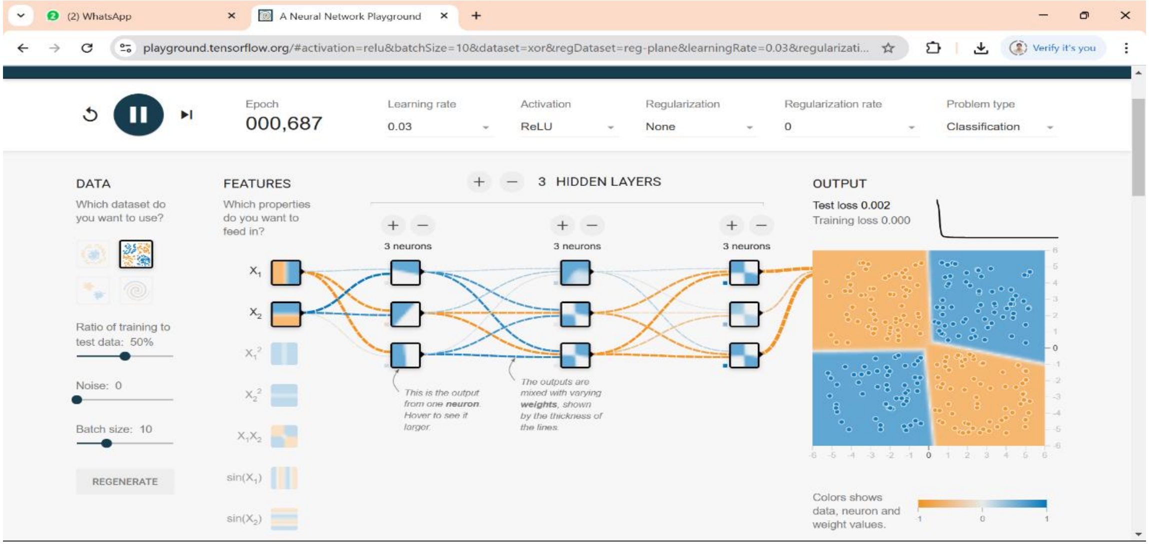
Output:



Experiment 31:

Aim: Neural network analysis for Multi-class data, Learning rate: 0.03, Activation: ReLu, Hidden Layers: 03, and Hidden neurons: 03.

Output:



Experiment 32:

Aim: Neural network analysis for Two circular data, Learning rate: 0.1, Activation: TanH, Hidden Layers: 03, and Hidden neurons: 03.

Output: