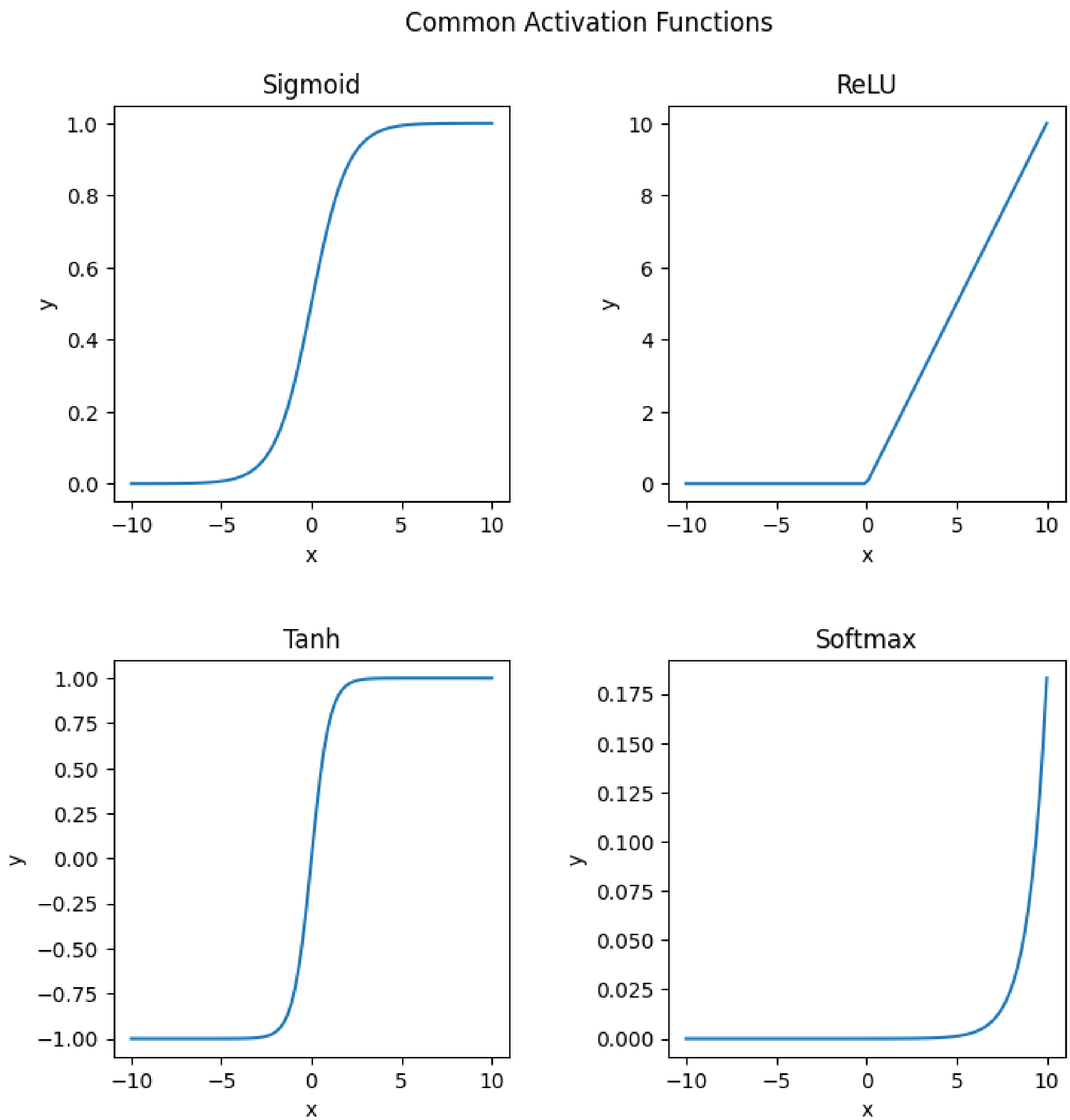
Assignment No. 1

Code:

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

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

def relu(x):
    return np.maximum(0, x)

def tanh(x):
    return np.tanh(x)

def softmax(x):
    return np.exp(x) / np.sum(np.exp(x))

# Create x values
x = np.linspace(-10, 10, 100)

# Create plots for each activation function
fig, axs = plt.subplots(2, 2, figsize=(8, 8))
axs[0, 0].plot(x, sigmoid(x))
axs[0, 0].set_title('Sigmoid')
axs[0, 1].plot(x, relu(x))
axs[0, 1].set_title('ReLU')
axs[1, 0].plot(x, tanh(x))
axs[1, 0].set_title('Tanh')
axs[1, 1].plot(x, softmax(x))
axs[1, 1].set_title('Softmax')

# Add common axis labels and titles
fig.suptitle('Common Activation Functions')
for ax in axs.flat:
    ax.set(xlabel='x', ylabel='y')

# Adjust spacing between subplots
plt.subplots_adjust(left=0.1, bottom=0.1, right=0.9, top=0.9, wspace=0.4, hspace=0.4)
```

```
# Show the plot
plt.show()
```

Output:



Assignment No. 2

Code:

```
# importing libraries
import numpy as np

# function of checking thresold value
def linear_threshold_gate(dot, T):
    '''Returns the binary threshold output'''
    if dot >= T:
        return 1
    else:
        return 0

#    matrix    of    inputs
input_table = np.array([
    [0,0], # both no
    [0,1], # one no, one yes
    [1,0], # one yes, one no
    [1,1]  # bot yes
])

print(f'input table:\n{input_table}')

weights = np.array([1,-1])

dot_products = input_table @ weights

T = 1
for i in range(0,4):
    activation = linear_threshold_gate(dot_products[i], T)
    print(f'Activation: {activation}')
```

Output:

```
input table:
[[0 0]
 [0 1]
 [1 0]
 [1 1]]
Activation: 0
```

Activation: 0
Activation: 1
Activation: 0

Assignment No.3

Code:

```
import numpy as np

# Define the perceptron class
class Perceptron:
  def__init_(self, input_size, lr=0.1):
    self.W = np.zeros(input_size + 1)
    self.lr = lr

  def activation_fn(self, x):
    return 1 if x >= 0 else 0

  def predict(self, x):
    x = np.insert(x, 0, 1)
    z = self.W.T.dot(x)
    a = self.activation_fn(z)
    return a

  def train(self, X, Y, epochs):
    for _ in range(epochs):
      for i in range(Y.shape[0]):
        x = X[i]
        y = self.predict(x)
        e = Y[i] - y
        self.W = self.W + self.lr * e * np.insert(x, 0, 1)

# Define the input data and labels
X = np.array([
  [0,0,0,0,0,0,1,0,0,0], # 0
  [0,0,0,0,0,0,0,1,0,0], # 1
  [0,0,0,0,0,0,0,0,1,0], # 2
  [0,0,0,0,0,0,0,0,0,1], # 3
  [0,0,0,0,0,0,1,1,0,0], # 4
  [0,0,0,0,0,0,1,0,1,0], # 5
  [0,0,0,0,0,0,1,1,1,0], # 6
  [0,0,0,0,0,0,1,1,1,1], # 7
  [0,0,0,0,0,0,1,0,1,1], # 8
  [0,0,0,0,0,0,0,1,1,1], # 9
```

```
])

Y = np.array([0, 1, 0, 1, 0, 1, 0, 1, 0, 1])

# Create the perceptron and train it
perceptron = Perceptron(input_size=10)
perceptron.train(X, Y, epochs=100)

# Test the perceptron on some input data
test_X = np.array([
    [0,0,0,0,0,0,1,0,0,0], # 0
    [0,0,0,0,0,0,0,1,0,0], # 1
    [0,0,0,0,0,0,0,0,1,0], # 2
    [0,0,0,0,0,0,0,0,0,1], # 3
    [0,0,0,0,0,0,1,1,0,0], # 4
    [0,0,0,0,0,0,1,0,1,0], # 5
    [0,0,0,0,0,0,1,1,1,0], # 6
    [0,0,0,0,0,0,1,1,1,1], # 7
    [0,0,0,0,0,0,1,0,1,1], # 8
    [0,0,0,0,0,0,0,1,1,1], # 9
])

for i in range(test_X.shape[0]):
  x = test_X[i]
  y = perceptron.predict(x)
  print(f'{x} is {"even" if y == 0 else "odd"}')
```

Output:

```
[0 0 0 0 0 0 1 0 0 0] is even
[0 0 0 0 0 0 0 1 0 0] is odd
[0 0 0 0 0 0 0 0 1 0] is even
[0 0 0 0 0 0 0 0 0 1] is odd
[0 0 0 0 0 0 1 1 0 0] is even
[0 0 0 0 0 0 1 0 1 0] is even
[0 0 0 0 0 0 1 1 1 0] is even
[0 0 0 0 0 0 1 1 1 1] is even
[0 0 0 0 0 0 1 0 1 1] is even
[0 0 0 0 0 0 0 1 1 1] is odd
```

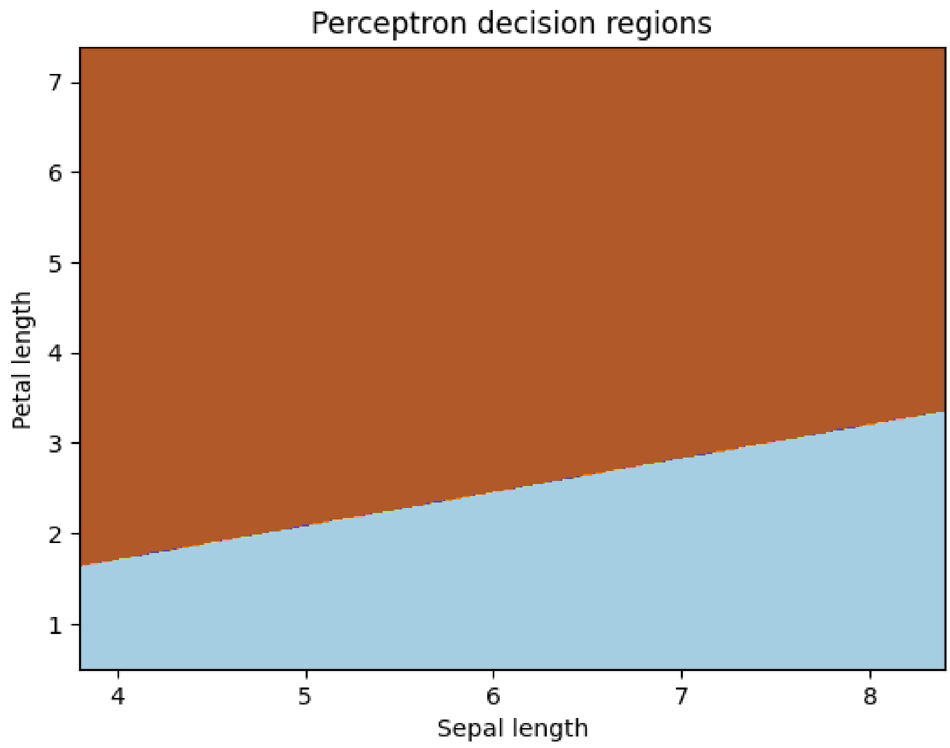
Assignment No. 4

Code:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris

# load iris dataset
iris = load_iris()

# extract sepal length and petal length features
X = iris.data[:, [0, 2]]
y = iris.target

# setosa is class 0, versicolor is class 1
y = np.where(y == 0, 0, 1)

# initialize weights and bias
w = np.zeros(2)
b = 0

# set learning rate and number of epochs
lr = 0.1
epochs = 50

# define perceptron function
def perceptron(x, w, b):
    # calculate weighted sum of inputs
    z = np.dot(x, w) + b
    # apply step function
    return np.where(z >= 0, 1, 0)

# train the perceptron
for epoch in range(epochs):
    for i in range(len(X)):
        x = X[i]
        target = y[i]
        output = perceptron(x, w, b)
        error = target - output
        w += lr * error * x
```

```
    b += lr * error

# plot decision boundary
x_min, x_max = X[:, 0].min() - 0.5, X[:, 0].max() + 0.5
y_min, y_max = X[:, 1].min() - 0.5, X[:, 1].max() + 0.5
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02),
                     np.arange(y_min, y_max, 0.02))
Z = perceptron(np.c_[xx.ravel(), yy.ravel()], w, b)
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=plt.cm.Paired)

# plot data points
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Paired)
plt.xlabel('Sepal length')
plt.ylabel('Petal length')
plt.title('Perceptron decision regions')
plt.show()
```

Output:



Assignment No. 5

Code:

```
import numpy as np

# define two pairs of vectors
x1 = np.array([1, 1, 1, -1])
y1 = np.array([1, -1])
x2 = np.array([-1, -1, 1, 1])
y2 = np.array([-1, 1])

# compute weight matrix W
W = np.outer(y1, x1) + np.outer(y2, x2)

# define BAM function
def bam(x):
    y = np.dot(W, x)
    y = np.where(y >= 0, 1, -1)
    return y

# test BAM with inputs
x_test = np.array([1, -1, -1, -1])
y_test = bam(x_test)

# print output
print("Input x: ", x_test)
print("Output y: ", y_test)
```

Output:

```
Input x:  [ 1 -1 -1 -1]
Output y:  [ 1 -1]
```

Assignment No.6

Code:

```
import numpy as np

class NeuralNetwork:

    def_init_(self, input_size, hidden_size, output_size):
        self.W1 = np.random.randn(input_size, hidden_size)
        self.b1 = np.zeros((1, hidden_size))
        self.W2 = np.random.randn(hidden_size, output_size)
        self.b2 = np.zeros((1, output_size))

    def sigmoid(self, x):
        return 1 / (1 + np.exp(-x))

    def sigmoid_derivative(self, x):
        return x * (1 - x)

    def forward_propagation(self, X):
        self.z1 = np.dot(X, self.W1) + self.b1
        self.a1 = self.sigmoid(self.z1)
        self.z2 = np.dot(self.a1, self.W2) + self.b2
        self.y_hat = self.sigmoid(self.z2)
        return self.y_hat

    def backward_propagation(self, X, y, y_hat):
        self.error = y - y_hat
        self.delta2 = self.error * self.sigmoid_derivative(y_hat)
        self.a1_error = self.delta2.dot(self.W2.T)
        self.delta1 = self.a1_error * self.sigmoid_derivative(self.a1)
        self.W2 += self.a1.T.dot(self.delta2)
        self.b2 += np.sum(self.delta2, axis=0, keepdims=True)
        self.W1 += X.T.dot(self.delta1)
        self.b1 += np.sum(self.delta1, axis=0)

    def train(self, X, y, epochs, learning_rate):
        for i in range(epochs):
            y_hat = self.forward_propagation(X)
```

```
        self.backward_propagation(X, y, y_hat)
        if i % 100 == 0:
            print("Error at epoch", i, ":", np.mean(np.abs(self.error)))


# Define the input and output datasets
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([[0], [1], [1], [0]])

# Create a neural network with 2 input neurons, 4 neurons in the hidden layer, and 1 output
neuron
nn = NeuralNetwork([2, 4, 1], activation='relu')

# Train the neural network on the input and output datasets for 10000 epochs with a learning rate
of 0.1
nn.train(X, y, lr=0.1, epochs=10000)

# Use the trained neural network to make predictions on the same input dataset
predictions = nn.predict(X)

# Print the predictions
print(predictions)
```

Output:

```
[[5.55111512e-16]
 [6.66666667e-01]
 [6.66666667e-01]
 [6.66666667e-01]]
```

Assignment No. 7

Code:

```
import numpy as np

class XORNetwork:
    def __init__(self):
        # Initialize the weights and biases randomly
        self.W1 = np.random.randn(2, 2)
        self.b1 = np.random.randn(2)
        self.W2 = np.random.randn(2, 1)
        self.b2 = np.random.randn(1)

    def sigmoid(self, x):
        return 1 / (1 + np.exp(-x))

    def sigmoid_derivative(self, x):
        return x * (1 - x)

    def forward(self, X):
        # Perform the forward pass
        self.z1 = np.dot(X, self.W1) + self.b1
        self.a1 = self.sigmoid(self.z1)
        self.z2 = np.dot(self.a1, self.W2) + self.b2
        self.a2 = self.sigmoid(self.z2)
        return self.a2

    def backward(self, X, y, output):
        # Perform the backward pass
        self.output_error = y - output
        self.output_delta = self.output_error * self.sigmoid_derivative(output)

        self.z1_error = self.output_delta.dot(self.W2.T)
        self.z1_delta = self.z1_error * self.sigmoid_derivative(self.a1)

        self.W1 += X.T.dot(self.z1_delta)
        self.b1 += np.sum(self.z1_delta, axis=0)
        self.W2 += self.a1.T.dot(self.output_delta)
        self.b2 += np.sum(self.output_delta, axis=0)
```

```
    def train(self, X, y, epochs):
        # Train the network for a given number of epochs
        for i in range(epochs):
            output = self.forward(X)
            self.backward(X, y, output)

    def predict(self, X):
        # Make predictions for a given set of inputs
        return self.forward(X)

# Create a new XORNetwork instance
xor_nn = XORNetwork()

# Define the input and output datasets for XOR
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([[0], [1], [1], [0]])

# Train the network for 10000 epochs
xor_nn.train(X, y, epochs=10000)

# Make predictions on the input dataset
predictions = xor_nn.predict(X)

# Print the predictions
print(predictions)
```

Output:

```
[[0.01063456]
 [0.98893162]
 [0.98893279]
 [0.01358006]]
```

Assignment No. 8

Code:

```
import numpy as np

# Define sigmoid activation function
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

# Define derivative of sigmoid function
def sigmoid_derivative(x):
    return x * (1 - x)

# Define input dataset
X = np.array([[0,0], [0,1], [1,0], [1,1]])

# Define output dataset
y = np.array([[0], [1], [1], [0]])

# Define hyperparameters
learning_rate = 0.1
num_epochs = 100000

# Initialize weights randomly with mean 0
hidden_weights = 2*np.random.random((2,2)) - 1
output_weights = 2*np.random.random((2,1)) - 1

# Train the neural network
for i in range(num_epochs):

    # Forward propagation
    hidden_layer = sigmoid(np.dot(X, hidden_weights))
    output_layer = sigmoid(np.dot(hidden_layer, output_weights))

    # Backpropagation
    output_error = y - output_layer
    output_delta = output_error * sigmoid_derivative(output_layer)

    hidden_error = output_delta.dot(output_weights.T)
```

```
    hidden_delta = hidden_error * sigmoid_derivative(hidden_layer)

    output_weights += hidden_layer.T.dot(output_delta) * learning_rate
    hidden_weights += X.T.dot(hidden_delta) * learning_rate

# Display input and output
print("Input:")
print(X)
print("Output:")
print(output_layer)
```

Output:

```
Input:
[[0 0]
 [0 1]
 [1 0]
 [1 1]]

Output:
[[0.61385986]
 [0.63944088]
 [0.8569871 ]
 [0.11295854]]
```

Assignment No. 9

Code:

```
import numpy as np

class HopfieldNetwork:
    def___init_(self, n_neurons):
        self.n_neurons = n_neurons
        self.weights = np.zeros((n_neurons, n_neurons))

    def train(self, patterns):
        for pattern in patterns:
            self.weights += np.outer(pattern, pattern)
        np.fill_diagonal(self.weights, 0)

    def predict(self, pattern):
        energy = -0.5 * np.dot(np.dot(pattern, self.weights), pattern)
        return np.sign(np.dot(pattern, self.weights) + energy)

if___name___== '_main_':
    patterns = np.array([
        [1, 1, -1, -1],
        [-1, -1, 1, 1],
        [1, -1, 1, -1],
        [-1, 1, -1, 1]
    ])

    n_neurons = patterns.shape[1]
    network = HopfieldNetwork(n_neurons)
    network.train(patterns)

    for pattern in patterns:
        prediction = network.predict(pattern)
        print('Input pattern:', pattern)
        print('Predicted pattern:', prediction)
```

Output:

```
Input pattern: [ 1  1 -1 -1]
Predicted pattern: [-1. -1. -1. -1.]
Input pattern: [-1 -1  1  1]
Predicted pattern: [-1. -1. -1. -1.]
Input pattern: [ 1 -1  1 -1]
Predicted pattern: [-1. -1. -1. -1.]
Input pattern: [-1  1 -1  1]
Predicted pattern: [-1. -1. -1. -1.]
```

Assignment No. 10

Code:

```
import keras
from keras.datasets import cifar10
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras.optimizers import SGD
from keras.preprocessing.image import ImageDataGenerator

# Load CIFAR-10 dataset
(X_train, y_train), (X_test, y_test) = cifar10.load_data()

# Define the model
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(Conv2D(32, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))

# Define data generators
train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2,
horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1./255)

# Prepare the data
train_set = train_datagen.flow(X_train, y_train, batch_size=32)
test_set = test_datagen.flow(X_test, y_test, batch_size=32)

# Compile the model
```

```
sgd = SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='categorical_crossentropy', optimizer=sgd, metrics=['accuracy'])

# Train the model
model.fit_generator(train_set, steps_per_epoch=len(X_train)//32, epochs=100,
validation_data=test_set, validation_steps=len(X_test)//32)

# Evaluate the model
score = model.evaluate(test_set, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Output:

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 3s 0us/step
Epoch 1/100
/usr/local/lib/python3.10/dist-packages/keras/optimizers/legacy/gradient_descent.py:114:
UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super().__init__(name, **kwargs)
<ipython-input-15-75bb0166727e>:40: UserWarning: `Model.fit_generator` is deprecated and
will be removed in a future version. Please use `Model.fit`, which supports generators.
model.fit_generator(train_set, steps_per_epoch=len(X_train)//32, epochs=100,
validation_data=test_set, validation_steps=len(X_test)//32)
1562/1562 [==============================] - 270s 172ms/step - loss: nan - accuracy:
0.9977 - val_loss: nan - val_accuracy: 1.0000
Epoch 2/100
1562/1562 [==============================] - 264s 169ms/step - loss: nan - accuracy:
1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 3/100
1562/1562 [==============================] - 255s 163ms/step - loss: nan - accuracy:
1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 4/100
1562/1562 [==============================] - 242s 155ms/step - loss: nan - accuracy:
1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 5/100
1562/1562 [==============================] - 247s 158ms/step - loss: nan - accuracy:
1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 6/100
```

1562/1562 [==============================] - 244s 156ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 7/100
1562/1562 [==============================] - 244s 156ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 8/100
1562/1562 [==============================] - 245s 157ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 9/100
1562/1562 [==============================] - 240s 153ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 10/100
1562/1562 [==============================] - 251s 161ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 11/100
1562/1562 [==============================] - 249s 159ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 12/100
1562/1562 [==============================] - 248s 159ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 13/100
1562/1562 [==============================] - 243s 156ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 14/100
1562/1562 [==============================] - 244s 156ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 15/100
1562/1562 [==============================] - 242s 155ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 16/100
1562/1562 [==============================] - 241s 154ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000

Assignment No. 11

Code:

```
import tensorflow as tf
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_breast_cancer
df=load_breast_cancer()

X_train,X_test,y_train,y_test=train_test_split(df.data,df.target,test_size=0.20,random_state=42)

sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)

model=tf.keras.models.Sequential([tf.keras.layers.Dense(1,activation='sigmoid',input_shape=(X
_train.shape[1],))])

model.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])

model.fit(X_train,y_train,epochs=5)
y_pred=model.predict(X_test)
test_loss,test_accuracy=model.evaluate(X_test,y_test)
print("accuracy is",test_accuracy)
```

Output:

```
Epoch 1/5
15/15 [==============================] - 1s 2ms/step - loss: 0.5449 - accuracy: 0.7385
Epoch 2/5
15/15 [==============================] - 0s 2ms/step - loss: 0.4896 - accuracy: 0.7802
Epoch 3/5
15/15 [==============================] - 0s 2ms/step - loss: 0.4439 - accuracy: 0.8286
Epoch 4/5
15/15 [==============================] - 0s 2ms/step - loss: 0.4074 - accuracy: 0.8462
Epoch 5/5
15/15 [==============================] - 0s 3ms/step - loss: 0.3776 - accuracy: 0.8593
4/4 [==============================] - 0s 5ms/step
4/4 [==============================] - 0s 4ms/step - loss: 0.3090 - accuracy: 0.9298
accuracy is 0.9298245906829834
```

Assignment No. 12

Code:

```
import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.utils import to_categorical

(X_train, y_train), (X_test, y_test) = mnist.load_data()
X_train = X_train.reshape(-1, 28, 28, 1) / 255.0
X_test = X_test.reshape(-1, 28, 28, 1) / 255.0
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

model.fit(X_train, y_train, batch_size=64, epochs=10, verbose=1)

loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")
```

Output:

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 0s 0us/step
Epoch 1/10
938/938 [==============================] - 59s 60ms/step - loss: 0.1783 - accuracy: 0.9448
Epoch 2/10
938/938 [==============================] - 56s 60ms/step - loss: 0.0541 - accuracy: 0.9835
Epoch 3/10
938/938 [==============================] - 55s 59ms/step - loss: 0.0378 - accuracy: 0.9878
Epoch 4/10
938/938 [==============================] - 58s 61ms/step - loss: 0.0295 - accuracy: 0.9908
Epoch 5/10
938/938 [==============================] - 55s 59ms/step - loss: 0.0234 - accuracy: 0.9926
Epoch 6/10
938/938 [==============================] - 55s 59ms/step - loss: 0.0202 - accuracy: 0.9936
Epoch 7/10
938/938 [==============================] - 55s 59ms/step - loss: 0.0153 - accuracy: 0.9950
Epoch 8/10
938/938 [==============================] - 55s 58ms/step - loss: 0.0139 - accuracy: 0.9957
Epoch 9/10
938/938 [==============================] - 56s 59ms/step - loss: 0.0117 - accuracy: 0.9961
Epoch 10/10
938/938 [==============================] - 54s 58ms/step - loss: 0.0091 - accuracy: 0.9971
313/313 [==============================] - 3s 9ms/step - loss: 0.0285 - accuracy: 0.9921
Test Loss: 0.028454650193452835
Test Accuracy: 0.9921000003814697

Assignment No. 13

Code:

```
import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.optimizers import Adam

# Load and preprocess the MNIST dataset
(X_train, y_train), (X_test, y_test) = mnist.load_data()
X_train = X_train / 255.0
X_test = X_test / 255.0

# Define the model architecture
model = Sequential([
    Flatten(input_shape=(28, 28)),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, batch_size=64, epochs=10, verbose=1)

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")
```

Output:

Epoch 1/10
938/938 [==============================] - 5s 4ms/step - loss: 0.2984 - accuracy: 0.9153
Epoch 2/10
938/938 [==============================] - 7s 7ms/step - loss: 0.1353 - accuracy: 0.9612
Epoch 3/10
938/938 [==============================] - 4s 4ms/step - loss: 0.0944 - accuracy: 0.9723
Epoch 4/10
938/938 [==============================] - 4s 5ms/step - loss: 0.0708 - accuracy: 0.9783
Epoch 5/10
938/938 [==============================] - 4s 4ms/step - loss: 0.0558 - accuracy: 0.9833
Epoch 6/10
938/938 [==============================] - 4s 4ms/step - loss: 0.0447 - accuracy: 0.9864
Epoch 7/10
938/938 [==============================] - 4s 4ms/step - loss: 0.0363 - accuracy: 0.9892
Epoch 8/10
938/938 [==============================] - 4s 5ms/step - loss: 0.0293 - accuracy: 0.9913
Epoch 9/10
938/938 [==============================] - 4s 4ms/step - loss: 0.0255 - accuracy: 0.9927
Epoch 10/10
938/938 [==============================] - 4s 4ms/step - loss: 0.0202 - accuracy: 0.9944
313/313 [==============================] - 1s 2ms/step - loss: 0.0679 - accuracy: 0.9804
Test Loss: 0.06786014884710312
Test Accuracy: 0.980400025844574