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NNDL LAB 2

Scenario:

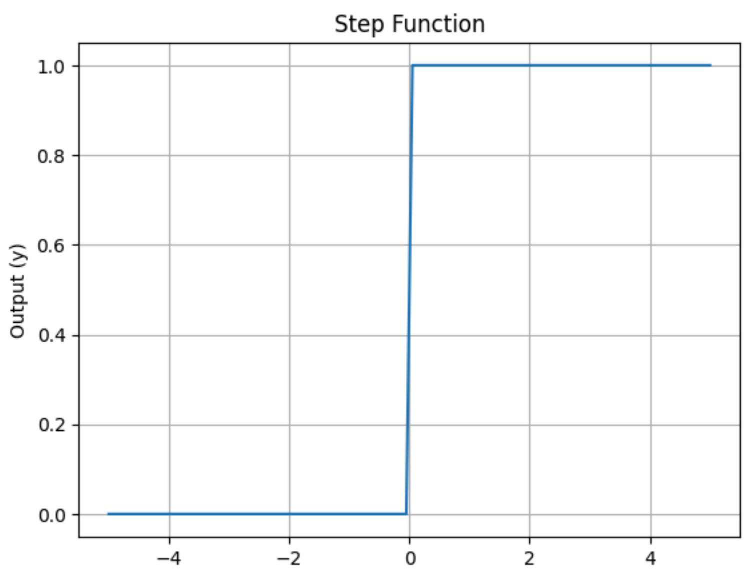
You are tasked with implementing and visualizing various activation functions to observe how they transform inputs and affect the output. You will also train a simple neural network using these activation functions and evaluate their performance.

1. Implement and Visualize Activation Functions:

Step Function

- Visualize the activation function using matplotlib to observe how they map input values to output values.

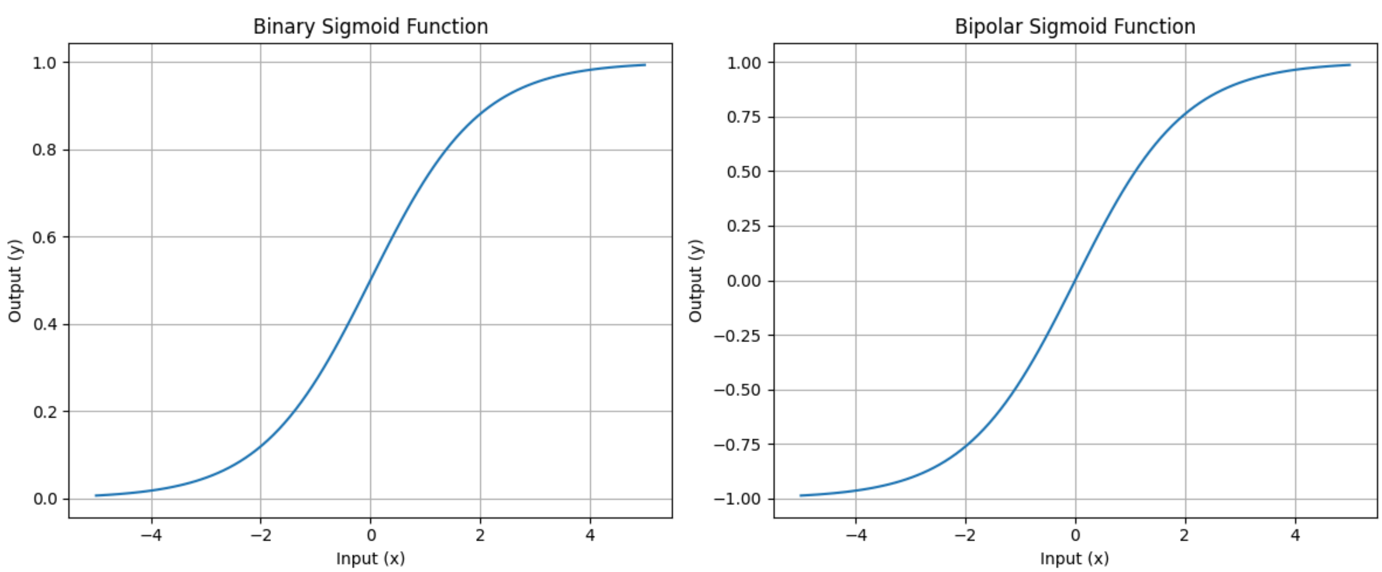
```
import numpy as np
import matplotlib.pyplot as plt

def step_function(x):
  """Step function."""
  return np.where(x >= 0, 1, 0)

x = np.linspace(-5, 5, 100)

y_step = step_function(x)

# Plot for the step function
plt.plot(x, y_step)
plt.title('Step Function')
plt.xlabel('Input (x)')
plt.ylabel('Output (y)')
plt.grid(True)
plt.show()
```



Sigmoid Function (Binary and Bipolar)

- Visualize the activation function using matplotlib to observe how they map input values to output values.

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


def sigmoid_binary(x):
  """Binary Sigmoid function."""
  return 1 / (1 + np.exp(-x))


def sigmoid_bipolar(x):
  """Bipolar Sigmoid function."""
  return (2 / (1 + np.exp(-x))) - 1

x = np.linspace(-5, 5, 100)

y_sigmoid_binary = sigmoid_binary(x)
y_sigmoid_bipolar = sigmoid_bipolar(x)

# Plot for the sigmoid functions
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(x, y_sigmoid_binary)
plt.title('Binary Sigmoid Function')
plt.xlabel('Input (x)')
plt.ylabel('Output (y)')
plt.grid(True)

plt.subplot(1, 2, 2)
plt.plot(x, y_sigmoid_bipolar)
plt.title('Bipolar Sigmoid Function')
plt.xlabel('Input (x)')
plt.ylabel('Output (y)')
plt.grid(True)

plt.tight_layout()
plt.show()
```

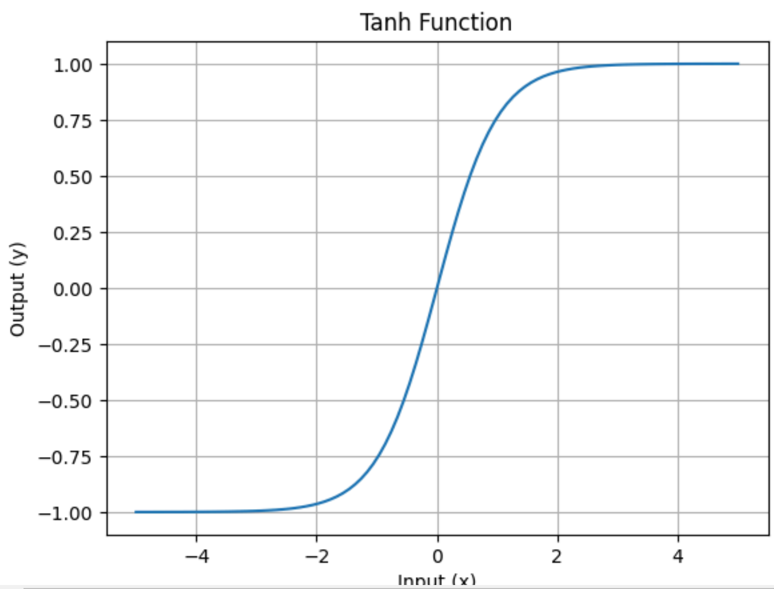


Tanh Function

- Visualize the activation function using matplotlib to observe how they map input values to output values.

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

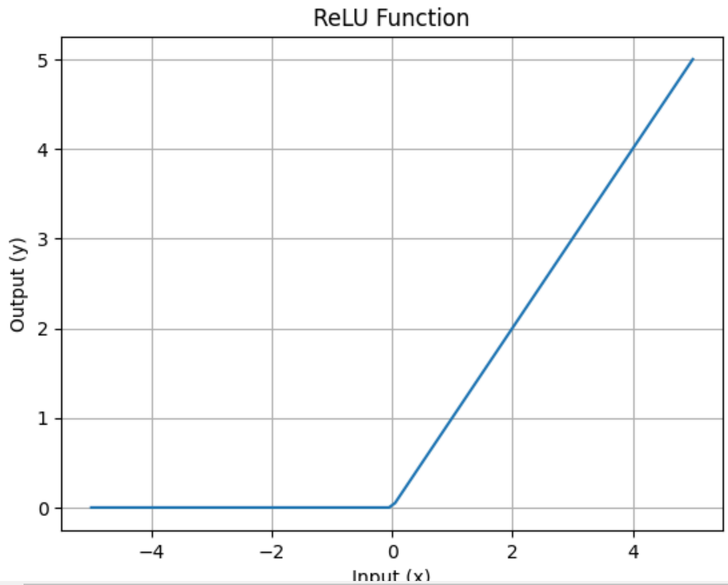
```
def tanh_function(x):
  """Tanh function."""
  return np.tanh(x)

x = np.linspace(-5, 5, 100)

y_tanh = tanh_function(x)

# Plot for the tanh function
plt.plot(x, y_tanh)
plt.title('Tanh Function')
plt.xlabel('Input (x)')
plt.ylabel('Output (y)')
plt.grid(True)
plt.show()
```



ReLU Function

- Visualize the activation function using matplotlib to observe how they map input values to output values.

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

def relu_function(x):
  """ReLU function."""
  return np.maximum(0, x)

x = np.linspace(-5, 5, 100)

y_relu = relu_function(x)

# Plot for the ReLU function
plt.plot(x, y_relu)
plt.title('ReLU Function')
plt.xlabel('Input (x)')
plt.ylabel('Output (y)')
plt.grid(True)
plt.show()
```



2. Implement a Simple Neural Network:

• Create a simple neural network with one hidden layer using each activation function (sigmoid, tanh, and ReLU).

```
import numpy as np

class NeuralNetwork:
    def __init__(self, input_size, hidden_size, output_size, activation_function):
        self.input_size = input_size
        self.hidden_size = hidden_size
        self.output_size = output_size
        self.activation_function = activation_function

        # Initializing weights and biases randomly
        self.weights_input_hidden = np.random.randn(input_size, hidden_size)
        self.bias_hidden = np.random.randn(hidden_size)
        self.weights_hidden_output = np.random.randn(hidden_size, output_size)
        self.bias_output = np.random.randn(output_size)

    def forward(self, x):
        # Calculating hidden layer output
        hidden_layer_input = np.dot(x, self.weights_input_hidden) + self.bias_hidden
        hidden_layer_output = self.activation_function(hidden_layer_input)

        # Calculating output layer output
        output_layer_input = np.dot(hidden_layer_output, self.weights_hidden_output) + self.bias_output
        output_layer_output = self.activation_function(output_layer_input)

        return output_layer_output


# Sample usage:
input_size = 2
hidden_size = 3
output_size = 1

# Creating neural networks with different activation functions
nn_sigmoid = NeuralNetwork(input_size, hidden_size, output_size, sigmoid_binary)
nn_tanh = NeuralNetwork(input_size, hidden_size, output_size, tanh_function)
nn_relu = NeuralNetwork(input_size, hidden_size, output_size, relu_function)

# Sample input data
input_data = np.array([0.5, 0.8])

# Performing forward pass and get outputs
output_sigmoid = nn_sigmoid.forward(input_data)
output_tanh = nn_tanh.forward(input_data)
output_relu = nn_relu.forward(input_data)
```

```
print("Output with Sigmoid:", output_sigmoid)
print("Output with Tanh:", output_tanh)
print("Output with ReLU:", output_relu)
```

```
Output with Sigmoid: [0.17605093]
Output with Tanh: [0.81159668]
Output with ReLU: [0.]
```

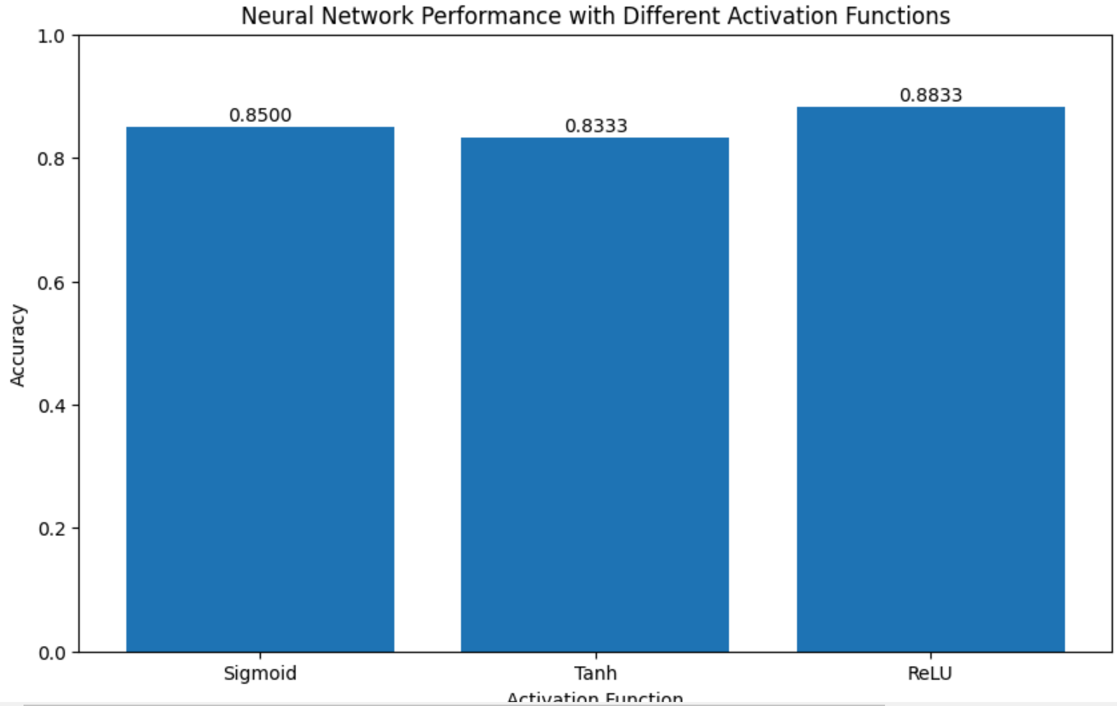
Train the network on a binary classification task (e.g. AND problem) using a small dataset.

Compare the performance of the neural network with different activation functions by calculating their accuracy.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import requests
from io import StringIO

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

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

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

class NeuralNetwork:
    def __init__(self, input_size, hidden_size, output_size, activation_function):
        self.input_size = input_size
        self.hidden_size = hidden_size
        self.output_size = output_size
        self.activation_function = activation_function

        # Initialize weights with Xavier/Glorot initialization
        self.W1 = np.random.randn(self.input_size, self.hidden_size) * np.sqrt(2.0 / (self.input_size + self.hidden_size))
        self.b1 = np.zeros((1, self.hidden_size))
        self.W2 = np.random.randn(self.hidden_size, self.output_size) * np.sqrt(2.0 / (self.hidden_size + self.output_size))
        self.b2 = np.zeros((1, self.output_size))

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

    def backward(self, X, y, output, learning_rate):
        m = X.shape[0]

        dZ2 = output - y
        dW2 = np.dot(self.a1.T, dZ2) / m
        db2 = np.sum(dZ2, axis=0, keepdims=True) / m

        dZ1 = np.dot(dZ2, self.W2.T) * (self.a1 > 0)  # Using ReLU derivative for all activation functions
        dW1 = np.dot(X.T, dZ1) / m
        db1 = np.sum(dZ1, axis=0, keepdims=True) / m

        self.W2 -= learning_rate * dW2
        self.b2 -= learning_rate * db2
        self.W1 -= learning_rate * dW1
        self.b1 -= learning_rate * db1

    def train(self, X, y, epochs, learning_rate, batch_size=32):
        for _ in range(epochs):
            for i in range(0, X.shape[0], batch_size):
                X_batch = X[i:i+batch_size]
                y_batch = y[i:i+batch_size]
                output = self.forward(X_batch)
                self.backward(X_batch, y_batch, output, learning_rate)
```

```
                self.backward(X_batch, y_batch, output, learning_rate)

    def predict(self, X):
        return (self.forward(X) > 0.5).astype(int)

# Fetch and prepare the dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/heart-disease/processed.cleveland.data"
response = requests.get(url)
data = StringIO(response.text)
df = pd.read_csv(data, header=None)

# Preprocess the data
df = df.replace('?', np.nan).dropna()
X = df.iloc[:, :-1].astype(float)
y = (df.iloc[:, -1] > 0).astype(int)  # Binary classification: 0 for no disease, 1 for disease

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train and evaluate models with different activation functions
input_size = X_train_scaled.shape[1]
hidden_size = 64
output_size = 1
epochs = 5000
learning_rate = 0.001
batch_size = 32

activation_functions = [sigmoid, tanh, relu]
accuracies = []

for activation in activation_functions:
    nn = NeuralNetwork(input_size, hidden_size, output_size, activation)
    nn.train(X_train_scaled, y_train.values.reshape(-1, 1), epochs, learning_rate, batch_size)

    y_pred = nn.predict(X_test_scaled)
    accuracy = accuracy_score(y_test, y_pred)
    accuracies.append(accuracy)
    print(f"Accuracy with {activation.__name__} activation: {accuracy:.4f}")

# Visualize the results
plt.figure(figsize=(10, 6))
plt.bar(['Sigmoid', 'Tanh', 'ReLU'], accuracies)
plt.title('Neural Network Performance with Different Activation Functions')
plt.xlabel('Activation Function')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
for i, v in enumerate(accuracies):
    plt.text(i, v + 0.01, f'{v:.4f}', ha='center')
plt.show()
```

```
Accuracy with sigmoid activation: 0.8500
Accuracy with tanh activation: 0.8333
Accuracy with relu activation: 0.8833
```



Interpretation:

- These results show the performance of a neural network on a classification task (likely heart disease prediction) using different activation functions in the hidden layer.
- The ReLU activation function achieved the highest accuracy at 88.33%, followed by sigmoid at 85.00%, and then tanh at 83.33%.
- All three activation functions performed well, with accuracies above 80%, indicating that the network can effectively learn the underlying