

Name: Methila Farjana

ID:19-39692-1

Section: A

Activation Function

### 1. Step Function:

**Introduction:** The step Function is one of the simplest activation Functions used in neural networks. It is a binary Function that returns a 1 if the input is greater than or equal to zero, and 0 otherwise.

**Formula:**  $f(x) = 1$  if  $x \geq 0$ ; 0 otherwise

**Advantages:**

- It is computationally efficient and easy to implement.
- It can be useful in some binary classification problems.

**Disadvantages:**

- The Function is not continuous, which can create problems during gradient descent optimization.
- It can cause the model to get stuck in local minima during training.

### 2. Sigmoid Function:

**Introduction:** The sigmoid Function is a smooth and bounded activation Function that maps any input to a value between 0 and 1. It is commonly used in neural networks for binary classification problems.

**Formula:**  $f(x) = 1 / (1 + e^{(-x)})$

**Advantages:**

- It produces a smooth output, which makes it easier to compute gradients during backpropagation.
- It is useful in binary classification problems where the output should be a probability value.

**Disadvantages:**

- It suffers from the vanishing gradient problem, which can slow down or even halt the learning process during training.
- It is not suitable for multi-class classification problems.

### 3. Tanh Function:

**Introduction:** The hyperbolic tangent (tanh) Function is similar to the sigmoid Function, but it maps any input to a value between -1 and 1. It is commonly used in neural networks for classification problems.

**Formula:**  $f(x) = (e^x - e^{-x}) / (e^x + e^{-x})$

**Advantages:**

- It produces a smooth output, which makes it easier to compute gradients during backpropagation.
- It is useful in classification problems where the output should be a value between -1 and 1.

**Disadvantages:**

- It also suffers from the vanishing gradient problem, which can slow down or even halt the learning process during training.
- It is not suitable for multi-class classification problems.

### 4. ReLU Function:

**Introduction:** The rectified linear unit (ReLU) is a simple activation Function that returns the input if it is positive, and 0 otherwise. It is one of the most popular activation Functions in deep learning due to its simplicity and effectiveness.

**Formula:**  $f(x) = \max(0, x)$

**Advantages:**

- It is computationally efficient and easy to implement.
- It does not suffer from the vanishing gradient problem, which makes it suitable for deep neural networks.
- It has been shown to perform well in a variety of neural network architectures.

**Disadvantages:**

- It can cause a problem known as "dying ReLU" during training, where some neurons become inactive and stop learning.

### 5. ELU Function:

**Introduction:** The exponential linear unit (ELU) is similar to ReLU, but it has a non-zero output for negative input values. It is designed to improve the learning speed and stability of deep neural networks.

**Formula:**  $f(x) = x$  if  $x \geq 0$ ;  $\alpha * (e^x - 1)$  if  $x < 0$

**Advantages:**

- It can speed up the learning process in deep neural networks.
- It has been shown to outperform ReLU in some cases.
- It does not suffer from the dying ReLU problem.

**Disadvantages:**

- It is computationally more expensive than ReLU.

**6. SELU Function:**

**Introduction:** The scaled exponential linear unit (selu) is a self-normalizing variant of the elu Function, which has been shown to improve the performance of deep neural networks.

**Formula:**  $f(x) = \lambda * (e^x - 1)$ ,  $x \leq 0$

$f(x) = \lambda * x$ ,  $x > 0$

where  $\lambda$  and  $\alpha$  are constants that ensure the mean and variance of the output of each layer remain the same during training.

**Advantages:**

- The SELU Function is self-normalizing, meaning that it can maintain a stable mean and variance of activations throughout the network.
- It does not suffer from the vanishing gradient problem.

**Disadvantages:**

- The SELU Function can suffer from the exploding gradient problem