Nervous system

The nervous system is a network of neurons whose main feature is to generate, modulate and transmit information between all the different parts of the human body.

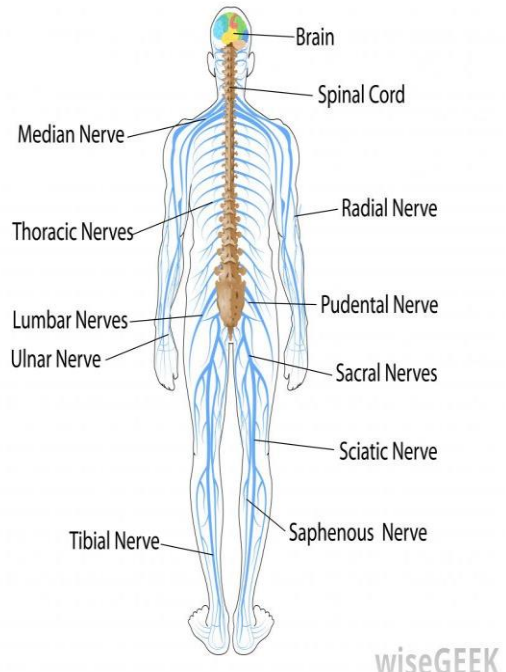
This property enables many important functions of the nervous system, such as regulation of vital body functions (heartbeat, breathing, digestion), sensation and body movements.

Ultimately, the nervous system structures preside over everything that makes us human; our consciousness, cognition, behaviour and memories.

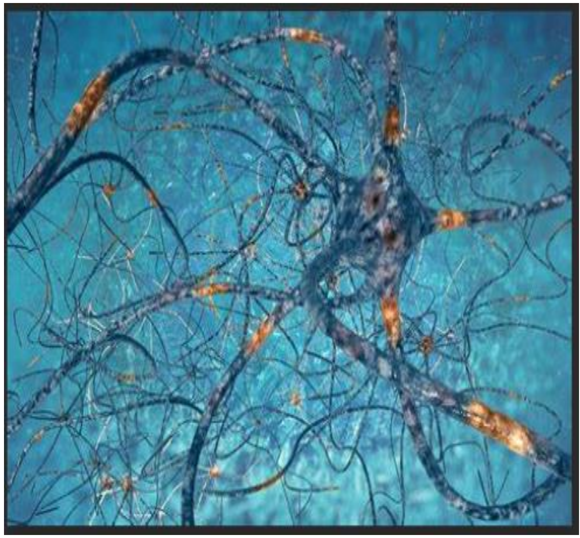
The nervous system consists of two divisions;

Central nervous system (CNS) is the integration and command center of the body

Peripheral nervous system (PNS) represents the conduit between the CNS and the body.



"Neurons are the fundamental unit of the nervous system."



- Our body is composed of millions to billions of nerve cells.
- Some nerve cells can be comparatively smaller by 0.1 millimeters or can be longer by 1 meter.
- The size of nerve cells is usually based on their functions i.e how long electrical impulse is transmitted within our body.
- They are found in the brain, spinal cord and peripheral nerves.
- For instance, the nerve cell, which transmits the electrical impulse from our brain to the end of the toe finger may be the largest nerve cell.
- The size of the nerve cell even varies with the type of organism.

What is Nerve Cell?

A nerve cell is also known as a neuron. It is mainly involved in receiving and transmitting information to different parts of the body.

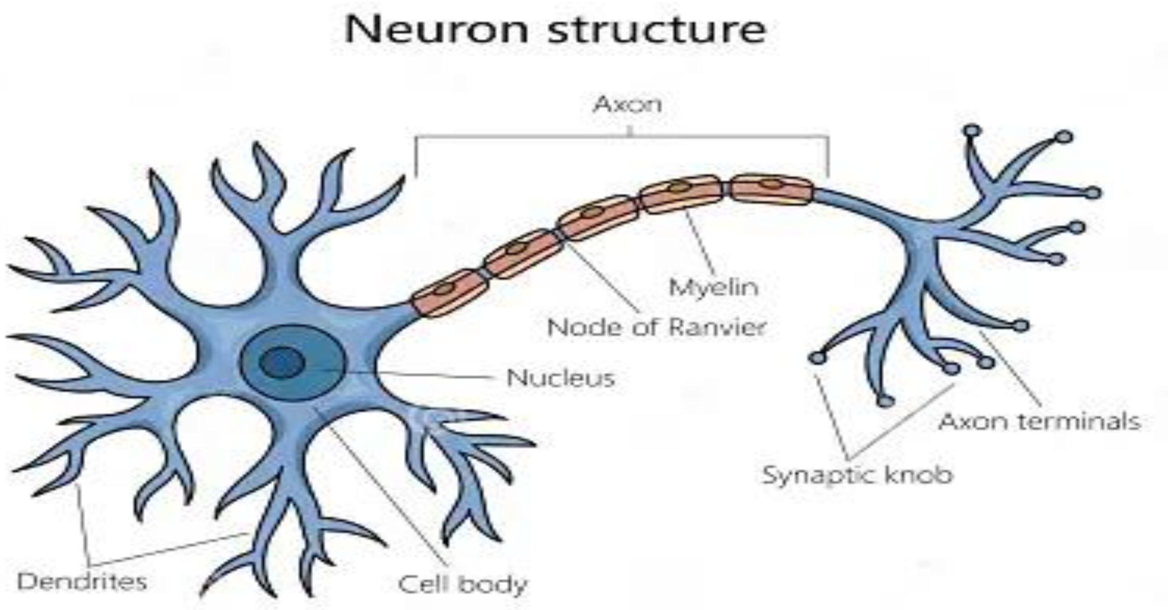
Nerve cell or Neuron is called the main structural and functional units of the nervous system.

The shape and size of the Neuron generally vary, depending upon the location and functions.

A group of neurons forms a nerve and the nervous system.

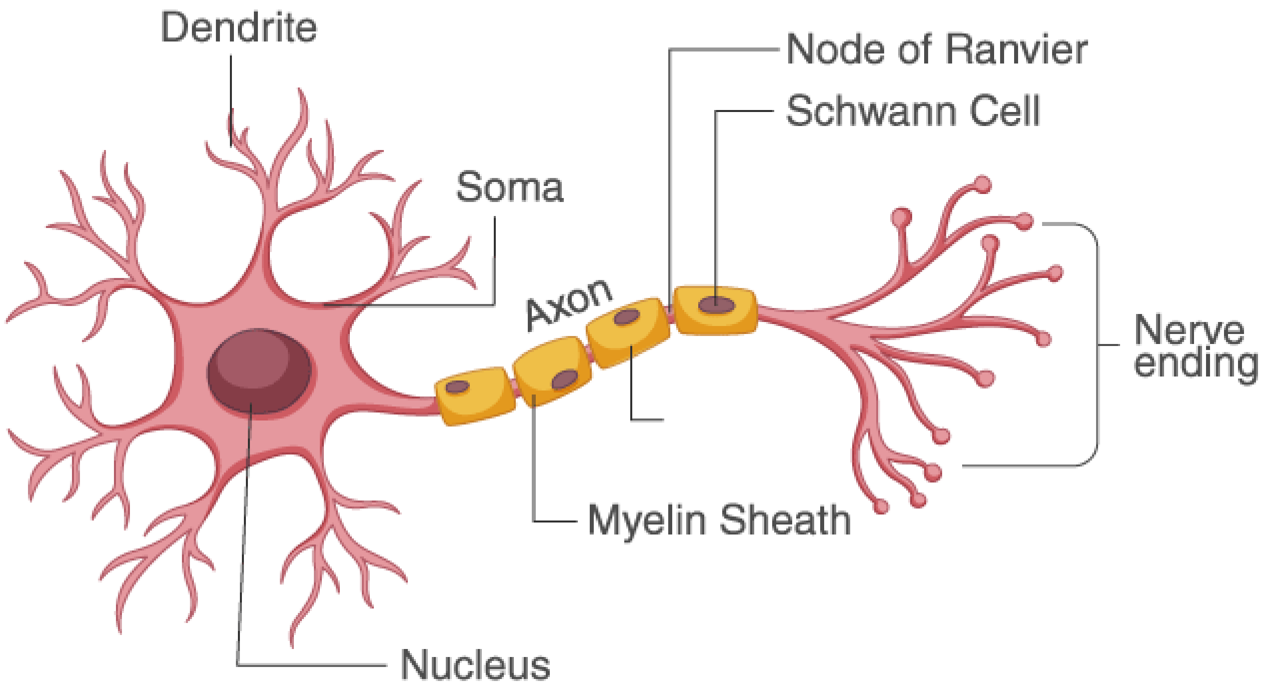
Biological neuron

A biological neuron has a cell body or soma to process the impulses, dendrites to receive them, and an axon that transfers them to other neurons.



Structure of Nerve Cell or Neuron

The nerve cell is a specialized and individual cell, which forms a nerve. Basically, the structure of the nerve cell comprises the following parts.



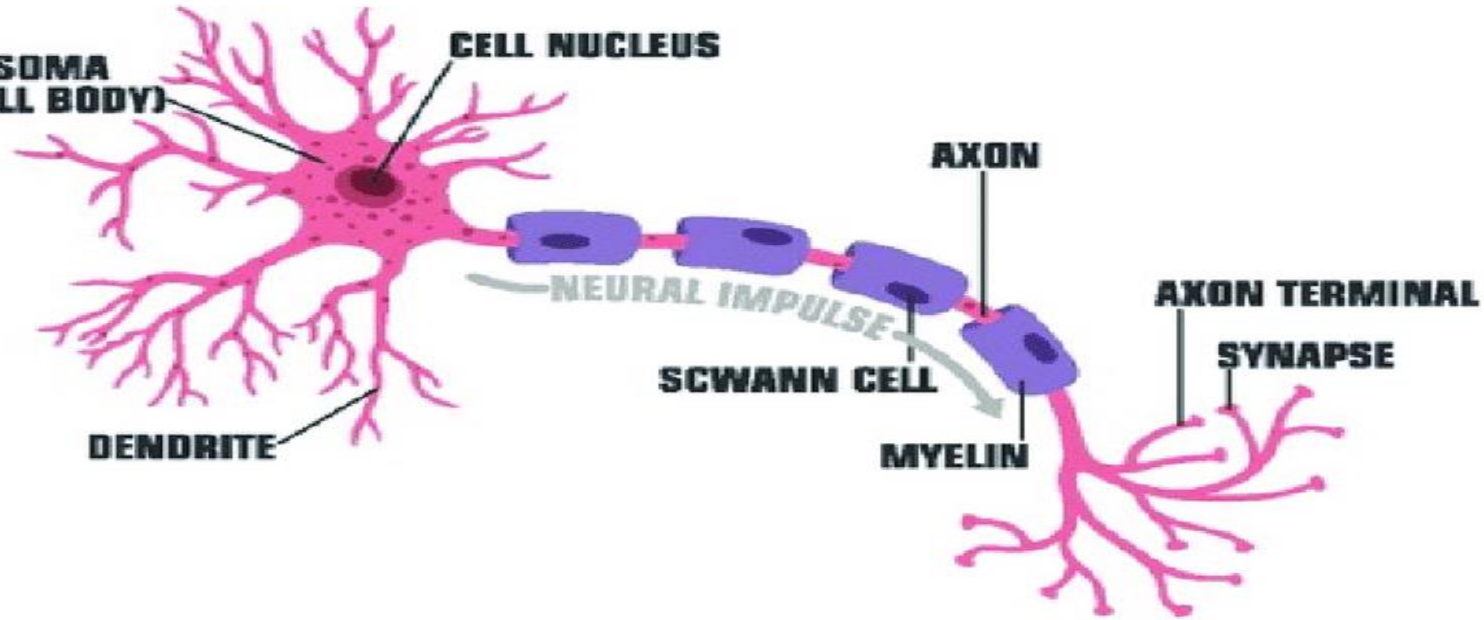
Dendrites
A branch-like structure that functions by receiving messages from other neurons and allows the transmission of messages to the cell body.

Axon
It is a tube-like structure, which functions by carrying an electrical impulse from the cell body to the axon terminals and by transmitting the impulse to another neuron.

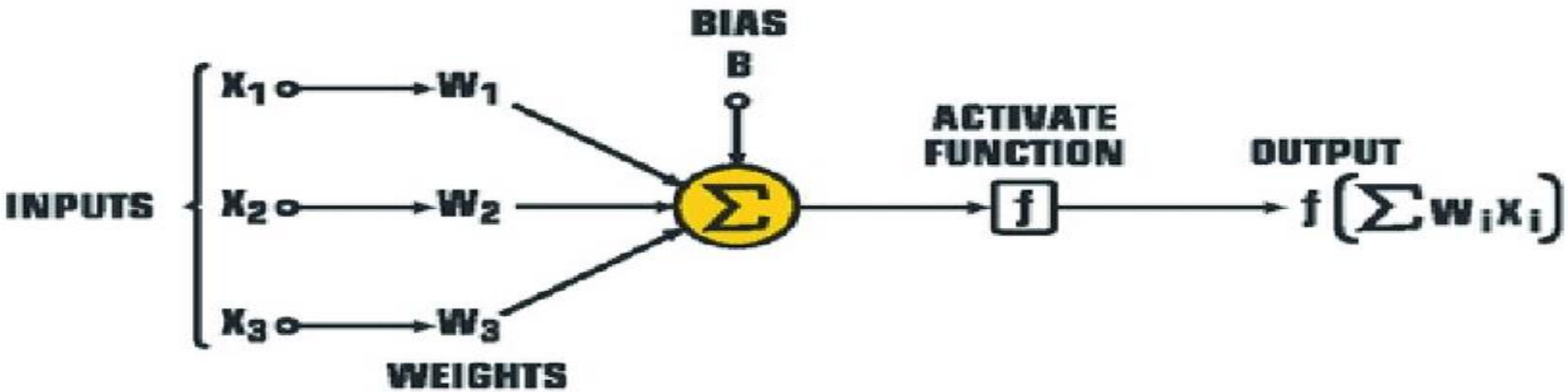
Nucleus
Each neuron or a nerve cell has a cell body with a nucleus and other cell organelles including, the **endoplasmic reticulum**, Golgi apparatus, mitochondria and other components.

Synapse
It is also called the nerve ending or nerve junction, which is mainly involved in permitting the entry of a neuron to move electrical signals from one neuron to another neuron.

STRUCTURE OF TYPICAL NEURON



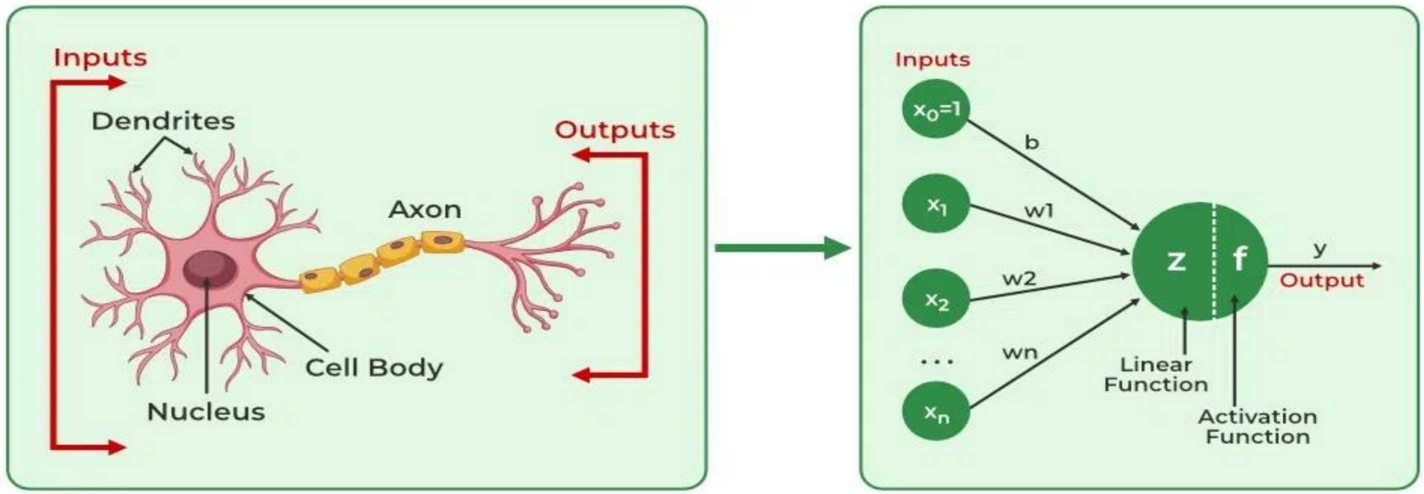
STRUCTURE OF ARTIFICIAL NEURON



Artificial neurons vs Biological neurons

The concept of artificial neural networks comes from biological neurons found in animal brains So they share a lot of similarities in structure and function wise.

Structure: The structure of artificial neural networks is inspired by biological neurons. A biological neuron has a cell body or soma to process the impulses, dendrites to receive them, and an axon that transfers them to other neurons. The input nodes of artificial neural networks receive input signals, the hidden layer nodes compute these input signals, and the output layer nodes compute the final output by processing the hidden layer's results using activation functions.



ANN	BNN
input	dendrites
weight	synapse
output	axon
hidden layer	cell body

Neural Network

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. *Knowledge is acquired by the network from its environment through a learning process.*
2. *Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.*

Artificial Neural Networks

Artificial Neural Networks contain artificial neurons which are called **units**. These units are arranged in a series of layers that together constitute the whole Artificial Neural Network in a system. A layer can have only a dozen units or millions of units as this depends on how the complex neural networks will be required to learn the hidden patterns in the dataset.

Commonly, Artificial Neural Network has an input layer, an output layer as well as hidden layers. The input layer receives data from the outside world which the neural network needs to analyze or learn about. Then this data passes through one or multiple hidden layers that transform the input into data that is valuable for the output layer. Finally, the output layer provides an output in the form of a response of the Artificial Neural Networks to input data provided.

In the majority of neural networks, units are interconnected from one layer to another. Each of these connections has weights that determine the influence of one unit on another unit. As the data transfers from one unit to another, the neural network learns more and more about the data which eventually results in an output from the output layer.

Model of a Neuron

A *neuron* is an information-processing unit that is fundamental to the operation of a neural network. The block diagram of Fig. 1.5 shows the *model* of a neuron, which forms the basis for designing (artificial) neural networks. Here we identify three basic elements of the neuronal model:

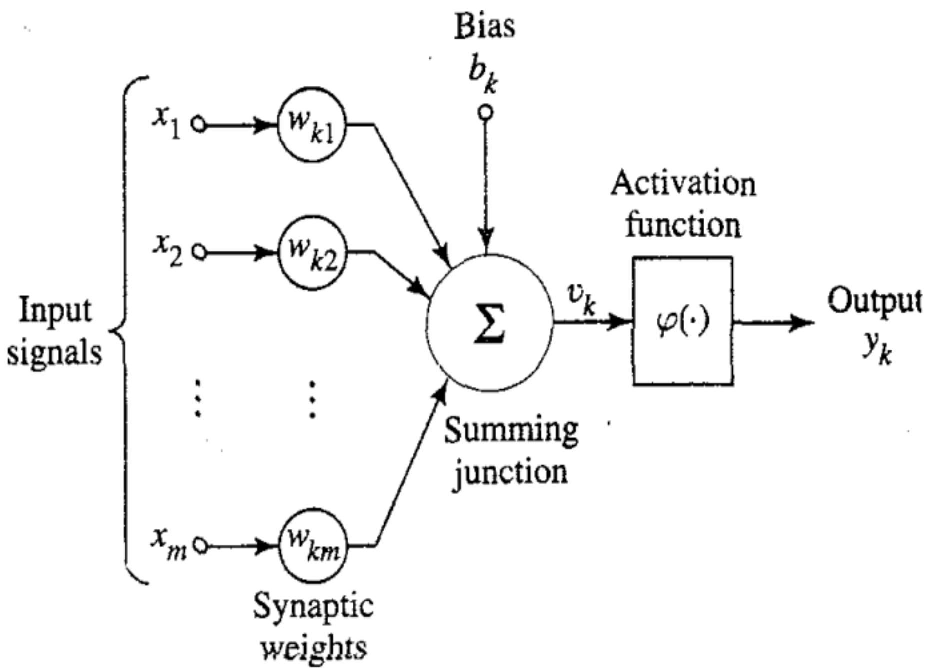


FIGURE 1.5 Nonlinear model of a neuron.

1. A set of *synapses* or *connecting links*, each of which is characterized by a *weight* or *strength* of its own. Specifically, a signal x_j at the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj}. It is important to make a note of the manner in which the subscripts of the synaptic weight w_{kj} are written. The first subscript refers to the neuron in question and the second subscript refers to the input end of the synapse to which the weight refers. Unlike a synapse in the brain, the synaptic weight of an artificial neuron may lie in a range that includes negative as well as positive values.
2. An *adder* for summing the input signals, weighted by the respective synapses of the neuron; the operations described here constitute a *linear combiner.*
3. An *activation function* for limiting the amplitude of the output of a neuron. The activation function is also referred to as a *squashing function* in that it squashes (limits) the permissible amplitude range of the output signal to some finite value.

Typically, the normalized amplitude range of the output of a neuron is written as the closed unit interval [0,1] or alternatively [−1,1].

The neuronal model of Fig. 1.5 also includes an externally applied *bias*, denoted by b_k. The bias b_k has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively.

In mathematical terms, we may describe a neuron k by writing the following pair of equations:

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{1.1}$$

and

$$y_k = \varphi(u_k + b_k) \tag{1.2}$$

where $x_1, x_2, \ldots, x_m$ are the input signals; $w_{k1}, w_{k2}, \ldots, w_{km}$ are the synaptic weights of neuron k; u_k is the *linear combiner output* due to the input signals; b_k is the bias; $\varphi(\cdot)$ is the *activation function*; and y_k is the output signal of the neuron. The use of bias b_k has the effect of applying an *affine transformation* to the output u_k of the linear combiner in the model of Fig. 1.5, as shown by

$$v_k = u_k + b_k \tag{1.3}$$

In particular, depending on whether the bias b_k is positive or negative, the relationship between the *induced local field* or *activation potential* v_k of neuron k and the linear combiner output u_k is modified in the manner illustrated in Fig. 1.6; hereafter the term "induced local field" is used. Note that as a result of this affine transformation, the graph of v_k versus u_k no longer passes through the origin.

The bias b_k is an external parameter of artificial neuron k. We may account for its presence as in Eq. (1.2). Equivalently, we may formulate the combination of Eqs. (1.1) to (1.3) as follows:

$$v_k = \sum_{j=0}^{m} w_{kj} x_j \tag{1.4}$$

and

$$y_k = \varphi(v_k) \tag{1.5}$$

Human brain Vs Computer

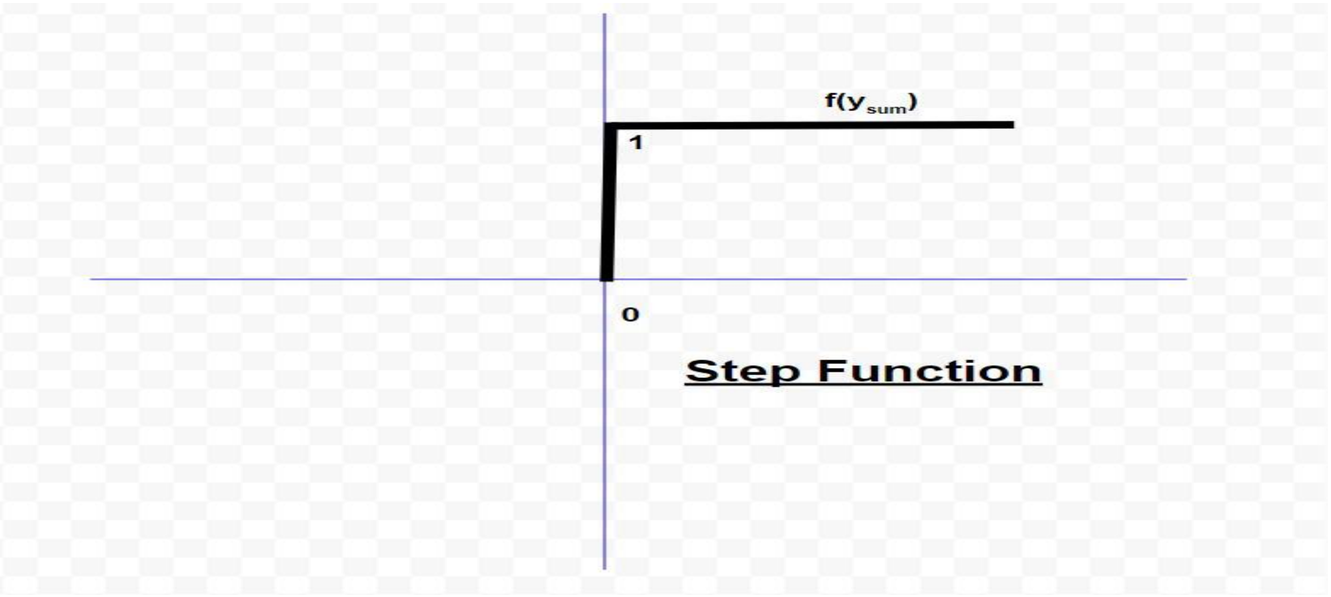
	Brain	Computer
Size Complexity:	The brain has 100 billion neurons which form billions of links. Brain is much more complex than the computer.	Today’s computers merely are formed with hundreds of millions of transistors and circuit.
Signal & Energy	The human brain being biological uses tiny chemical reactions to produce its signals. Brain cells signal each other electrochemically and enzymatically. The energy efficiency of the brain is approximately 10^{-16} joules per operation per second.	Computer uses electrical energy to represent signals. The energy efficiency of today’s best computer is approximately 10^{-6} joules per operation per second.
Speed:	Human brain is slower than computer. Typically the events happen in the human brain within the range of milliseconds (10^{-3}sec).	Computers are five to six orders faster than human brain Typically the events happen in the computer within the range of nanoseconds (10^{-9}sec).
Emotions vs Logic	It is impossible for the brain to act without emotions. Brains act on emotions, that many of our actions are based on our emotional side.	Computers act only on logic. We know that computers act completely on logical bits that are total absolute.
Capability	Human brain learns from environments.	Computers just conduct programmed instructions.

Activation Functions

Threshold/step Function:

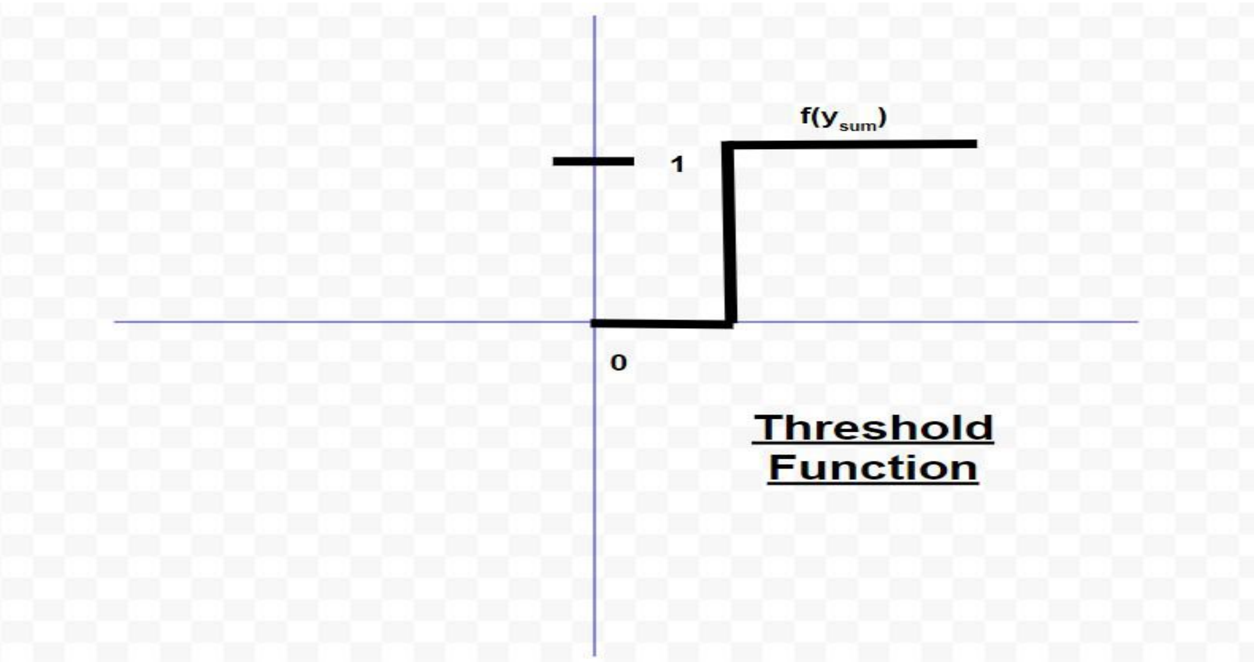
Threshold/step Function: It is a commonly used activation function. As depicted in the diagram, it gives 1 as output of the input is either 0 or positive. If the input is negative, it gives 0 as output. Expressing it mathematically,

$$y_{out} = f(y_{sum}) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$



The threshold function is almost like the step function, with the only difference being a fact that \theta is used as a threshold value instead of . Expressing mathematically,

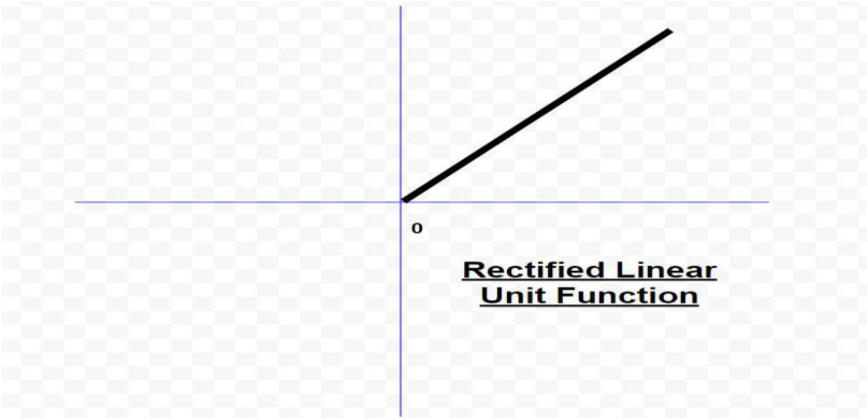
$$y_{out} = f(y_{sum}) = \begin{cases} 1, x \geq \theta \\ 0, x < \theta \end{cases}$$



ReLU (Rectified Linear Unit) Function

ReLU (Rectified Linear Unit) Function: It is the most popularly used activation function in the areas of convolutional neural networks and deep learning. It is of the form:

$$f(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases}$$

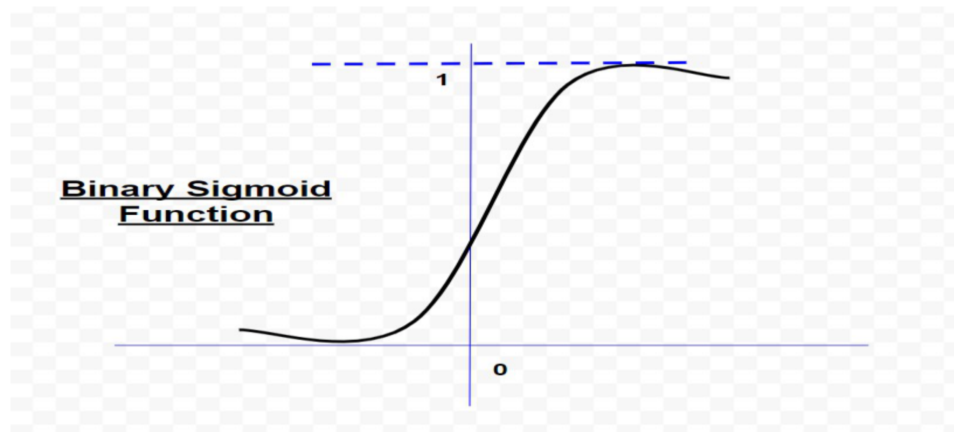


This means that f(x) is zero when x is less than zero and f(x) is equal to x when x is above or equal to zero. **This function is differentiable**, except at a single point x = 0. In that sense, the derivative of a ReLU is actually a sub-derivative.

Sigmoid Function:

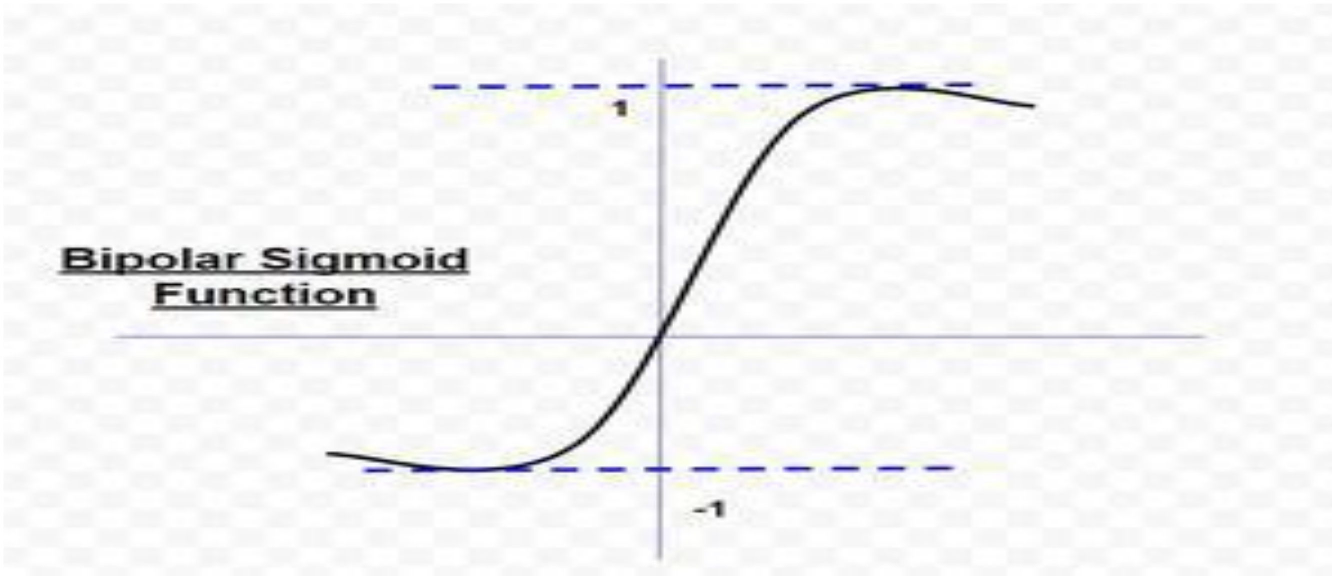
Sigmoid Function: It is by far the most commonly used activation function in neural networks. The need for sigmoid function stems from the fact that many learning algorithms require the activation function to be differentiable and hence continuous. There are two types of sigmoid function:

1. **Binary Sigmoid Function**



A binary sigmoid function is of the form: : $y_{out} = f(x) = \frac{1}{1+e^{-kx}}$
, where k = steepness or slope parameter, By varying the value of k, sigmoid function with different slopes can be obtained. It has a range of (0,1). The slope of origin is k/4. As the value of k becomes very large, the sigmoid function becomes a threshold function.

2. Bipolar Sigmoid Function



A bipolar sigmoid function is of the form

$$y_{out} = f(x) = \frac{1-e^{-kx}}{1+e^{-kx}}$$

The range of values of sigmoid functions can be varied depending on the application. However, the range of (-1,+1) is most commonly adopted.

Hyperbolic Tangent Function

Hyperbolic Tangent Function: It is bipolar in nature. It is a widely adopted activation function for a special type of neural network known as Backpropagation Network. The hyperbolic tangent function is of the form

$$y_{out} = f(x)\frac{e^{x}-e^{-}x}{e^{x}+e^{-}x}$$

This function is similar to the bipolar sigmoid function.