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#### Mind and Machine: Two sides of the same Coin?

#### Abstract

The human brain has been the source of inspiration behind the birth and growth of Artificial Intelligence. The achievements in the diverse domains of AI have stemmed from replication of brain circuits. Almost as if a full circle, AI which had been inspired from the brain, has also found several applications in the field of Neuroscience and understanding the brain. In this article, we explore these two domains individually, as well as make an attempt to elucidate how closely correlated they actually are.

Keywords: Artificial intelligence; Neural networks; Machine learning; Brain; Signal processing; Neuroscience

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#### Introduction

Ancient Greek philosophers had spent much of their time pondering about what truly makes one intelligent. But this concept was embraced in science and research only about half a century ago. Neuroscience has strived to understand how the brain processes information, makes decisions, and interacts with the environment. But in the mid-20<sup>th</sup> century, arose a new school of thought. How can we simulate intelligence in an artificial system? And so, Artificial Intelligence (AI) was born (Figure 1).

Artificial Intelligence has been defined as "the science and engineering of making intelligent machines", by John McCarthy, who coined the term in 1956. It aims at enabling machines to perform tasks such as computation, prediction and others without manual intervention. Having drawn inspiration from the brain, the ultimate goal of AI is to make our work easier. It does this by mimicking the way the brain works, and trying to replicate it in computers.

# A Brief Historical Perspective

Brain science and AI have been progressing in a closely knit fashion since the past several decades [1]. Soon after the birth of modern computers, research on AI gained momentum, with the goal of building machines that can "think". With the advent of microscopy in the early 1900s, researchers began imaging neuronal connections in brain tissues. The web of connections between neurons inspired computer scientists to mould the Artificial Neural Network (ANN). This was one of the earliest and most effective models in the history of AI (Figure 2).

In 1949, an algorithm set was formulated - the Hebbian learning rules. This is one of the oldest learning algorithms inspired by the

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dynamics of biological neural systems. The principle is that when synapses (junctions between cells in the nervous system) fire repeatedly, the connection gets reinforced. In a biological context, this is one of the ways that we learn and remember things. The process is called potentiation of memory. For example, consider simple tasks like finding your way back home or remembering multiplication tables of 9. They seem quite easy because the synapses in these pathways have fired very frequently. They have thus become strengthened. Hence, the task seems effortless. The same principle is now used in AI to make machines learn [2].

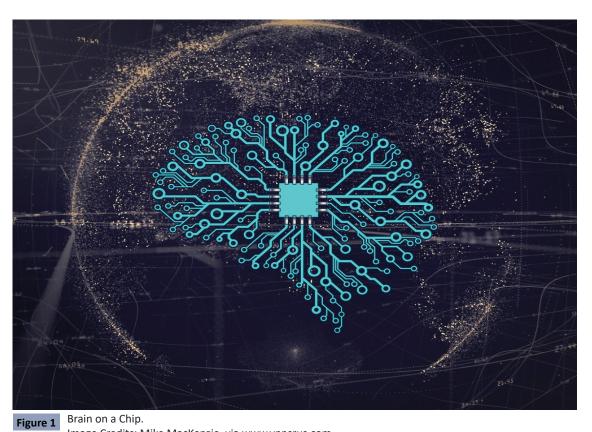
Following this development, ANNs witnessed an enormous surge in research. An important achievement was the perceptron. This was an AI model which replicated the information storage and organization in the brain. Developed by Frank Rosenblatt in 1957, this simple ANN can process multiple inputs to produce a single output. It is, in a way, a replica of a single neuron. Certain input values are entered, acted upon by a mathematical function and outputs are generated. The perceptron laid the foundation for the subsequent, more complex networks (Figure 3).

The 1981 Nobel Prize in Physiology or Medicine was awarded to Hubel and Wiesel for elucidating visual processing [3]. Their work gave insights into how the visual system perceives information. Using electronic signal detectors they captured the responses of neurons when a visual system saw different images. It was

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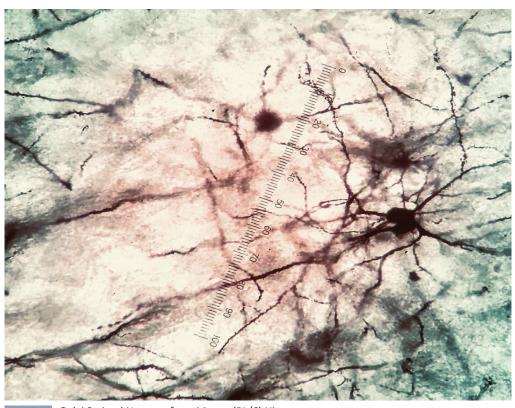
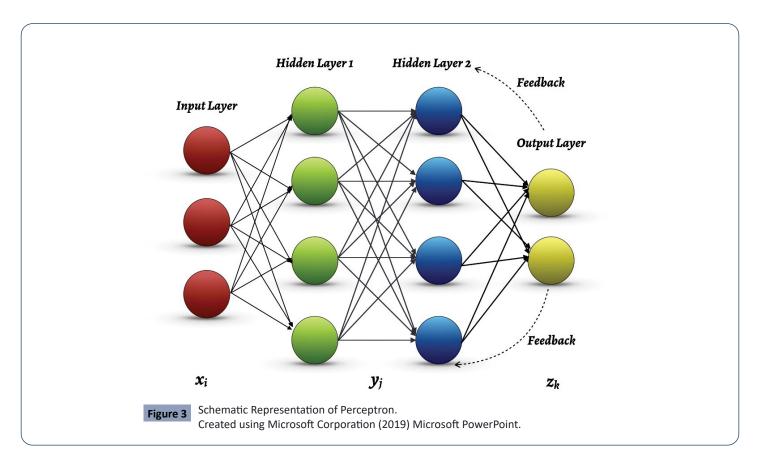


Figure 2

Golgi Stained Neurons from Mouse (BL/6) Hippocampus. Image Credits: NIMHANS, Neurophysiology

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found that there are several layers of neurons leading up to the visual centre in the brain from the eyes. Each layer has its own computations to perform. In this way, a biological system can transform simple inputs into complex features. These observations laid the foundation for the modern neural networks which work at many layers or levels.

# **Artificial Neural Networks**

A human brain is composed of 86 billion neurons, intricately connected with other neural cells. Each neuron is a single cell having branches called dendrites which bring in information and a tail-like axon which transmits the processed information onto other cells. The main processing occurs in the soma, or cell body of the neuron. Activation of one neuron creates a spike in potential which is transmitted as electrical signals [4]. On an analogous principle, the neuronal cell body is equivalent to a node, a basic unit in the artificial network. The dendrites are like the input to this node, and the axon like the output in an ANN. The action potential of an individual neuron is generated at the junction between the axon and the cell body based on the inputs it receives. In ANNs, mathematical tools such as linear combinations and sigmoid functions are used to compute the action potential at a certain node.

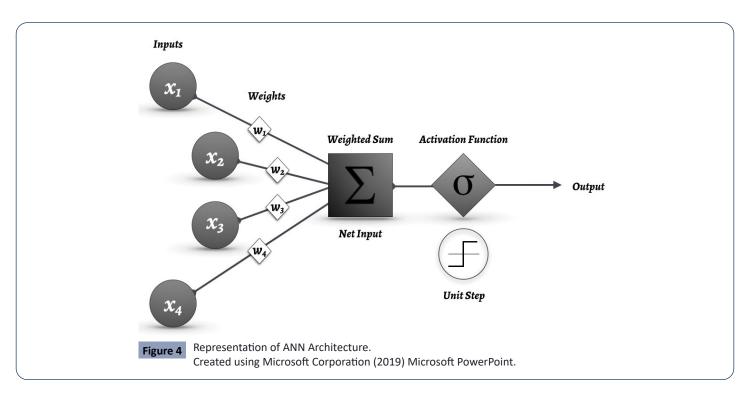
If we examine the basic architecture of ANNs, they closely resemble the biological connections. A typical ANN consists of at least three layers: input, output, hidden. The complexity of the network is increased with an increasing number of hidden layers. The input layer receives a vector or a series of predictor variable values. These are the features on the basis of which predictions are to be made. For example, in a face recognition program, these would be the image pixel value points. These inputs are then distributed to every node in the hidden layer. With each input a constant called bias (whose value is set to 1) is added. In the hidden layer, the bias as well as the predictor variables are multiplied by the corresponding weights. The resultants are added together. An activation function (such as sigmoid) is applied on the obtained sum. This becomes the output of a node in the hidden layer. It is then forwarded to the output layer. Multiple hidden layers are used to solve more complex problems. Finally, the output layer is used for making predictions based on another round of calculations [5] (**Figure 4**).

# Interdisciplinary Nature of AI and Neuroscience

In the modern day world, AI and Neuroscience are greatly interlinked in their applications. The complexity of the brain, its cognitive power, demands multidisciplinary expertise. AI aims to investigate theories and build computer systems equipped to perform tasks that require human intelligence, decision-making and control. Thus, it has an important role in understanding the working of the brain. By visualising the biological processes in an artificial platform, we can gain new insights. But AI can also benefit from this, because a detailed analysis of how the brain works could provide information into the nature of cognition itself, and help in simulating these artificially [6]. Essentially, they are driving each other forward.

AI has become an indispensable tool in neuroscience. Training an algorithm to mimic the qualities of vision and hearing enables us

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to understand how the biological network functions. It can also help crack the activation patterns of individual groups of neurons that underlie a thought or behaviour. Incorporation of AI into the construction of brain implants is making their internal processes, such as identifying electrical spikes of activity, far more effective. Machine Learning has greatly simplified the interpretation and reconstruction of data obtained from techniques such as Functional Magnetic Resonance Imaging (fMRI), integral to brain research.

# **Future Prospects**

AI and Neuroscience collectively aim to answer several questions which have remained unaddressed for a long time. One such question is the exact mechanism of learning. . The very essence of an ANN lies in how it "learns" by repeated trials, drawing inspiration (or feedback) from the errors in previous trials. It moulds itself to produce the results which resemble the expected output most closely. This is done continuously till it finds the perfect design. Like a human brain, it trains itself. ANNs mostly perform supervised learning, i.e., where the classes into which an object is to be classified is known beforehand. The task of image recognition for example, is performed by training neural networks on the ImageNet dataset. The networks develop a statistical understanding of what images with the same label -'dog', for instance - have in common. When shown a new image, the networks examine it for similar patterns in parameters and respond accordingly [4].

The use of AI to understand higher order brain processes like cognition might be explored in the future.

To be able to blend AI and neuroscience within an integrated framework, there are technical hurdles that need to be addressed. More importantly, if the goals of the two disciplines can merge better, we might see several developments. Principles from neuroscience investigations such as visual processing or spatial navigation have already found applications in neural-inspired AI [8,9]. However, biological neural research mostly puts focus on understanding the mechanisms and form of the brain and other parts. AI is more application-driven, and strives to improve performance of computational systems. To bridge the gap, a common "language" is the need of the day, a way to convey results between the two fields in an effective and constructive manner [10].

# Conclusion

Incorporating Neuroscientific concepts in Artificial Intelligence has proven to be computationally quite expensive and the architecture is difficult to implement in hardware. Attempts are being made to develop AI systems which will perform tasks with little or no data to work on (for e.g., One Shot Learning in Computer Vision). This is an algorithm which aims to learn information about object categories from one or very few training samples [11]. We face such scenarios in our lives - when we have to perform new categorization tasks having limited or no knowledge regarding the same (for e.g., if someone has seen a ship only once or twice in his life, he will still be able to identify it). While incorporating the ideas we get from Neuroscience in hardware is difficult, the extensive usage of high performing computing platforms such as GPUs (Graphics Processing Unit) shows signs of improvement [12]. The ability to incorporate neural algorithms in computer systems should not be limited by factors like computer architecture, hardware requirements and processing speed.

Neural networks are a rough representation of the brain, as it models neurons as mathematical functions. On the contrary, our brains function as highly sophisticated devices using electrochemical signals. That makes us unique as individuals and different from machines. It is an undeniable fact that AI has left a mark on the world in several facets. Nevertheless, for machines to achieve the computational power and mystique of the human brain, may well remain an impossible feat for years to come.

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# References

- 1 Hassabis D, Kumaran D, Summerfield C, Botvinick M (2017) Neuroscience-inspired artificial intelligence. Neuron 95: 245-258.
- 2 Choe Y (2014) Hebbian Learning. In: Jaeger D, Jung R (eds) Encyclopedia of Computational Neuroscience. Springer, New York, NY.
- Hubel DH (1982) Exploration of the primary visual cortex, 1955– 78. Nature 299: 515-524.
- 4 Sidiropoulou K, Pissadaki EK, Poirazi P (2006) Inside the brain of a neuron. EMBO reports 7: 886-892.
- 5 Sharma V, Rai S, Dev A (2012) A comprehensive study of artificial neural networks. International Journal of Advanced research in computer science and software engineering 2.
- 6 Potter SM (2007) What can Al get from neuroscience?. In 50 years of artificial intelligence. Springer, Berlin, Heidelberg.
- 7 Van der Velde F (2010) Where artificial intelligence and neuroscience meet: The search for grounded architectures of cognition. Advances

in Artificial Intelligence.

- 8 Ponce CR, Xiao W, Schade PF, Hartmann TS, Kreiman G, et al. (2019) Evolving images for visual neurons using a deep generative network reveals coding principles and neuronal preferences. Cell 177: 999-1009.
- 9 Hawkins J, Lewis M, Klukas M, Purdy S, Ahmad S (2019) A framework for intelligence and cortical function based on grid cells in the neocortex. Front Neural Circuits 12: 121.
- 10 Chance FS, Aimone JB, Musuvathy SS, Smith MR, Vineyard CM, et al. (2020) Crossing the Cleft: Communication Challenges Between Neuroscience and Artificial Intelligence. Front Comput Neurosci.
- 11 Snell J, Swersky K, Zemel R (2017) Prototypical networks for few-shot learning. In: Advances in neural information processing systems 30.
- 12 Blouw P, Choo X, Hunsberger E, Eliasmith C (2019) Benchmarking keyword spotting efficiency on neuromorphic hardware. In: Proceedings of the 7th Annual Neuro-inspired Computational Elements Workshop.