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# Neuromorphic Computing for Next-Generation Vlsi Chips

**Abstract:**

This study has been undertaken to investigate the determinants of stock returns in Karachi Stock Exchange (KSE) Compared to von Neumann's computer architecture, neuromorphic systems offer unique and novel solutions to artificial intelligence. Inspired by biology, this novel system has applied the modeling theory of the human brain by connecting neurons made with synapses to reveal new concepts of neuroscience. Many researchers have invested heavily in neuro-inspired models, algorithms, learning methods, neuromorphic system testing systems and using many compatible applications. Recently, some researchers demonstrated the power of Hopfield algorithms in some major hardware projects and saw significant progress. This paper introduces a comprehensive review and focuses on the Hopfield algorithm model and potential developments in new research programs. Finally, we conclude with a broad discussion and a working framework for the latest system prospects to make it easier for engineers to better understand the above-mentioned model in terms of building their performance-oriented projects.

***IndexTerms* -** : artificial intelligence, synapse, Artificial neural network. ,spiking neural network

## Introduction

Neuromorphic engineering, also called Neuromorphic computing, is a type of neuromorphic engineering. It refers back to the development of computer-based computer programs found in the human mind and anxious gadget. The concept of Neuromorphic computing was developed using Caver Mead in the 1980s. It says about the use of big-scale-integration (VLSI) systems that include electrical anolog circuits to mimic the neurobiological structures present in a shocking machine. As the name suggests, neuromorphic computing uses a model that is stimulated by brain function. Neuromorphic computing can completely change everything about it. Neuromorphic computing technology will be important for the future of computing, but much of the work in neuromorphic computing is focused on hardware development. Here, we review the latest results on computer computer neuromorphic algorithms and applications. We highlight the features of computer neuromorphic technology that make them attractive for the future of computing and discuss the potential for future development of algorithms and applications in these systems.

Neuromorphic computing or engineering is a subset of artificial intelligence in which scientists develop devices which work on the principles of the human brain. It is more like making devices which mimics the function of the human brain. The computing of neuromorphic devices involves the development of components which are analogous to the human brain. Talking about the structure of these devices, these are definitely not in the shape of the brain; however they do fulfil the roles of their organic counterparts. To sum it up, neuromorphic computing involves making inorganic brains.

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Traditional computers or digital computers work in binary. It understands and responds in either 0s or 1s or yes or no. This type of mechanism is very narrow in the field of developing science. Therefore, the way to solve problems in digital computers is structured in a very rigid way. These mechanisms cannot move beyond the binary language. On the other hand, neuromorphic computers are very flexible and their approach to solving problems is very broad. One of the ways to move past this threshold is by making computers more like human brains. Neuromorphic computing is a concept in which the computer chips are designed in a way which uses the science of computation based on the human nervous system. Neuromorphic computers are more energy efficient than the digital computers. It is designed so that the neurons can learn as they perform tasks. The hope behind this new revolutionary discovery is to make a computer that behaves like a brain which will give us enough computing power to simulate something as complicated as the brain.

## Neuromorphic Computing

One of the most powerful computers out there in the world is a human brain. It consists of 100 billion neurons while each neuron is having 100-1000 of synapses. A neuron (cell which transmits information to other parts of the body from the brain). Synapses are the connection to other neurons. A human brain can perform 1 billion calculations per second. Many researches are being done to make supercomputers which can reach this exa-scale performance. Simulating a human brain requires millions of processors and high-speed memory using power consumption in the order of megawatts per hour. While a brain can do all of this with just 20 watts of power consumption and will still outperform these supercomputers. All of this is due to the differentiation of modern computer architectures and a biologically cognitive brain. A modern computer’s architecture is based on von Neuman architecture, in which memory and computation is isolated with a data bus connecting them. Whereas a biological brain has memory and computation tightly coupled together. The von Neuman architecture is the best architecture for digital computers. But to simulate the brain and make computers work the way the brain works, we need a different kind of structure more similar to the human brain,

Neuromorphic architecture where the Spinal neural network is the population of neurons connected to other neurons by the help of synapses. Synapses are the junction between neurons. This network connection is responsible for the transmission of information to different parts of body. Neurons have axons, a protoplasmic protrusion (in simpler words a joint) which is extended to different parts of body.

The main part of this whole neuromorphic computing is the artificial neural networks (ANN). These neural networks are framed with artificial neurons which are microscopic computational units designed to carry out simple mathematical functions. Our brain is composed of neurons. Neurons are the cells which transfer the information to other parts of the body from the brain. But the Artificial Neurons is not of much use alone. To use them efficiently, they need to be stacked up in layers to perform complex tasks. For example, object detection within given images, converting voice and audio as to texts. Recently, some of the artificial intelligence researchers exhibited a self-driving bicycle that navigates around and detects obstacles, follows a particular person and also responds to his voice commands. To manufacture bicycles of such advancement, a neuromorphic chip was used.

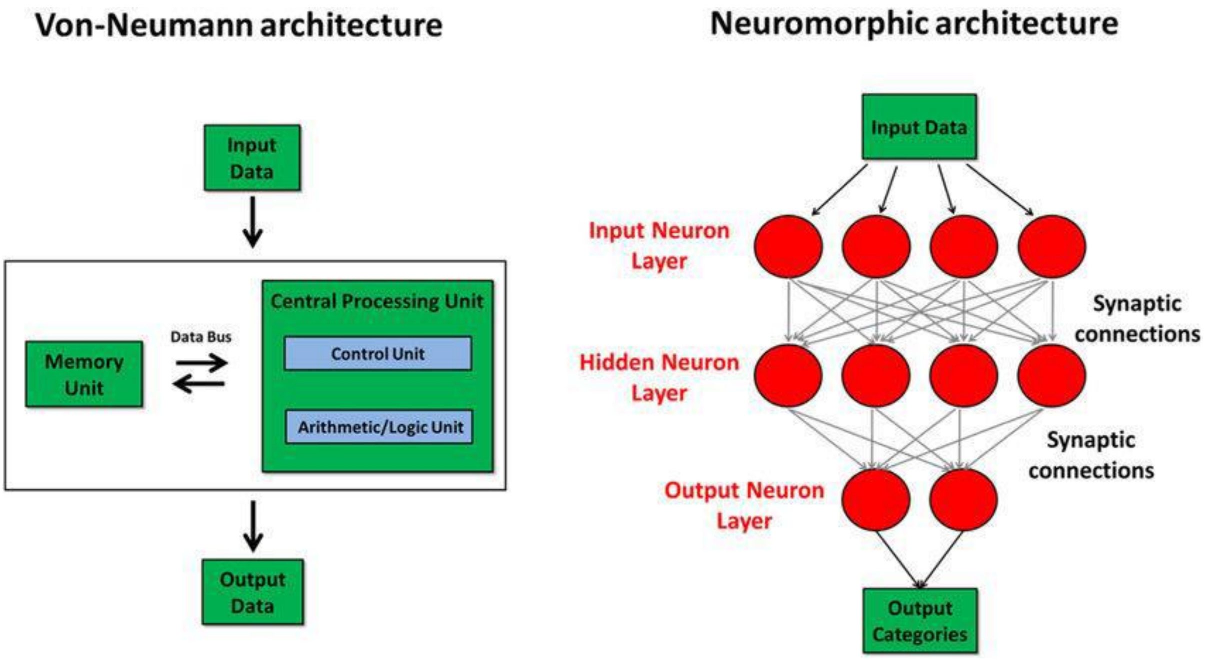


Figure 1: Neumann Architecture

Traditional computing system relies on processing units which poses a lot of power and could perform complex tasks with high speed, but it is tough to run neural networks on these computers. However, processing units designed for Graphics, hardware's employed for games mostly perform a lot of parallel processing jobs. Matrix multiplication, a core application with neural networks can also be done using GPUs. GPU arrays play a vital role in most neural network applications. Neuromorphic computers run AI models role over much better than CPUs and GPUs with less power consumption.

Digital computers work on the principle of determinism. The work of a digital computer is to perform a task or solve a problem based on some inputs given by users. Its work is predetermined. Whereas, neuromorphic computers are designed to think and process, to learn from the applications performed just like human brain works. Plasticity of neurons makes it the more suitable feature of nervous systems to modify its activity in response to intrinsic or extrinsic stimuli thereby transforming its functions, structure, or connections. This is one of the phenomena, neuromorphic engineers are hoping to simulate.

**The Requirement**

Moore's Law stipulates that every two years, the number of transistors on a microchip doubles, resulting in a halving of computer costs. In 1965, Gordon Moore, co-founder of Intel, articulated an insight that evolved into Moore's Law.

In the current context, the trend towards more compact memory chips makes it almost hard to store substantial amounts of data inside smaller devices. As Moore's Law approaches its conclusion, silicon processing technology is being driven to its limitations. However, we cannot persist in reducing chip sizes to enhance processing power. Volleytronic transistors are being created at the nanoscale. They have shown promise to preserve the growing capacity of this technology. Numerous other advancements are being undertaken to preserve Moore's Law. Neuromorphic computing is one of the several advancements in this field. Neuromorphic computing seeks to enhance the operational capabilities of computers. This would enable computers to adapt and learn more rapidly, hence reducing the need for programming. The architecture of neuromorphic computers and their learning capabilities enhance their efficiency in executing neural networks. The structure is designed to enable the Artificial Intelligence versions to operate at much higher speeds than central processing units and GPUs while using less energy. An essential factor is that Artificial Intelligence raises concerns about the effective use of energy. Neuromorphic computers use less energy, are compact in size, and can independently interpret data and make choices without relying on a specific link. This technology in the global sector might signify substantial advancement and enhancement of industries across diverse contexts, perhaps expediting human progress in the development of robots and autonomous technology.

**Neuromorphic Chips: The Evolution Of Artificial Intelligence**

The era of conventional programming, characterized by human formulation or coding of rules, is nearing its conclusion. Moore's Law posits that the number of transistors in a densely integrated circuit doubles every two years; nevertheless, this trend has reached a breaking point. The transistors available on the market are around 70 silicon atoms in width, hence the likelihood of further miniaturization is decreasing. It is necessary for us to alter our strategy by enhancing the capabilities of computers.

A neuromorphic chip is an analog processor meant to behave similarly to the human brain. It mimics the biological architecture of our nervous system by simulating neurons on silicon. In the brain, neurons and their connections are referred to as synapses. The neuromorphic devices are configured to function similarly to artificial neural networks. Each neuromorphic chip has a minuscule computational unit that simulates an artificial neuron. An artificial neural network has a layered architecture, with each node capable of processing input and transmitting output to other nodes. This artificial neural network enables the neuromorphic device to function like to a brain.


Artificial Neural Networks provide the capability to process and evaluate nonlinear and intricate data, hence facilitating generalization and prediction. The network architecture has an input layer, a hidden layer, and an output layer. Its designation as Multi-Layer Perceptron arises from the existence of many layers. The purpose of a Multi-Layer Perceptron is to take the input from a node and transform it into an output signal. This output serves as input for the subsequent layer. The layers of connections assist Artificial Neural Networks in acquiring information from data sources. This topology ensures that the Artificial Neural Network does not generate erroneous data predictions without previous knowledge.

In a multi-layered network, neurons are organized in parallel across linked layers. The computational unit interacts with other neurons via electrical signals. Not every neuron requires activation at all times; only those necessary are triggered, resulting in decreased energy use. This enables them to retain data and communicate at far greater speeds. This facilitates the deployment of Neuromorphic chips across several domains. The physical connections among artificial neurons resemble those in organic brains, where real neurons are interconnected by synapses.

## The Chronicle Of Neuromorphic Computing

Neuromorphic computing, a dynamic idea developed by Carver Mead in the late 1980s, utilizes extremely large-scale integration systems with electronic analog circuits that emulate the functioning components of the nervous system.

The concept of neuromorphic computing was first proposed by Turing, a scientist who demonstrated that a computer can execute any intricate mathematical calculation provided it is articulated as an algorithm. He authored a book titled Intelligent Machinery, published in 1958. In his book, he delineated a machine composed of artificial neurons organized in various configurations alongside modifier devices. He elucidated that those modifiers might be adjusted to either transmit or obliterate a signal, and the neurons were constituted of NAND gates. Subsequently, synaptic plasticity emerged. It is fundamentally the capacity of synapses to enhance or diminish their strength over time to modulate their activity, serving as a mechanism for learning and memory. It was proposed by Hebb in 1949.

In 1980, VLSI pioneer Mead and Conway released the seminal work "Introduction to VLSI Systems." Subsequently, he collaborated with John Hopfield and Feynman to investigate the computational processes of animal brains. This research accelerated advancements in neural networks (Hopfield), neuromorphic engineering (Mead), and the mechanics of computing (Feynman).

Mead developed the first neural-inspired chips, including an artificial retina and cochlea, as detailed in his 1989 publication, Analog VLSI Implementation of Neural Systems.

In 2008, HP Laboratories initiated the development of Chua's proposed electrical device, the memristor, and identified its applications as synapses in neuromorphic circuits.

## Contemporary Advancements

Numerous organizations and academics are exploring neuromorphic models to create functional prototypes, although only a select handful are leading in development progress. The significant advancements achieved to date are: Intel's Loihi: Intel has introduced a self-learning 14-nanometer processor including over 2 billion transistors, three management cores, and a customizable engine for on-chip training of spiking neural networks. The cores have an integrated learning module and around 131,000 neurons that facilitate intercommunication, enabling the chip to adapt and function according to diverse environmental circumstances. Loihi can detect 10 dangerous substances by olfactory means more rapidly than sniffer canines. Additionally, it can identify hazardous gases and illnesses while improving its learning capabilities. It is anticipated to autonomously make choices in the future. This energy-structured chip can use data to understand itself and implement modifications. Loihi acquires intelligence over time autonomously, without requiring instruction.

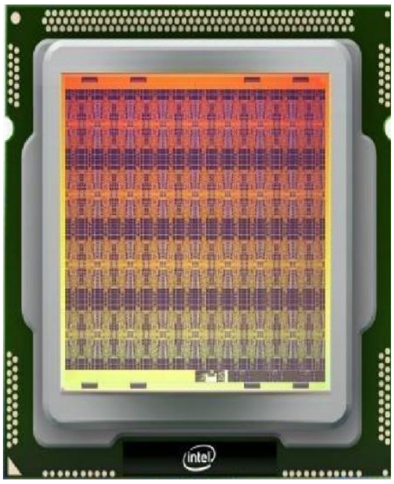

Fig. Intel’s Loihi chip


Fig. IBM’s TrueNorth chip

TrueNorth has the capability to address challenges related to visual, auditory perception, and multi-sensory integration. It can effectively analyze noisy sensory input. It has 4,096 cores, using Samsung's 28nm technology with 5.4 billion transistors. TrueNorth is IBM's largest chip regarding transistor count and operates with reduced power consumption during processing. The power density of TrueNorth chips is 20 W/cm². It has the capacity to transform contemporary computers by emulating cerebral processes inside the machine, so altering the current paradigms of power and speed. It accommodates typical frameworks in deep learning applicable during training. It is the current advantage in transistors relative to other neuromorphic devices.

**Artificial Neural Network**

The Artificial Neural Network (ANN) is a compilation and collection of nodes promoted by the human biological brain. ANN aims to perform psychological tasks such as problem solving and machine learning. The ANN mathematical models were introduced in the 1940s however, they were silent for a long time . These days, ANNs are best known for the success of ImageNet2 in 2009. The reason for this is the development of ANN models and hardware programs that can manage and use these models.

ANNs can be divided into three generations based on their computational and performance units

## Neuromorphic Computing And Artificial General Intelligence (AGI)

The term Artificial General Intelligence (AGI) means AI that reflects the same intelligence as human beings. One could say that the holy grail of all AI. Machines have not yet arrived and may not have reached that level of intelligence. However, neuromorphic computing offers new ways to improve on it.

For example, the Human Brain Project - which includes the neuromorphic supercomputer SpiNNaker - aims to produce effective mimicry of the human brain and is one of many active research projects that are interested in AGI.

The criteria for determining whether a machine has achieved AGI are controversial, but a few that are often included in the discussion are:

• The machine can consult and make decisions under uncertainty.
• The machine can edit.
• The machine can read.
• The machine can communicate using natural language.
• The machine can represent information, including general information.
• The machine can combine these skills in pursuit of the same goal.

Sometimes the power of thought, experience of self and self-awareness is included. Other proposed ways to validate the popular AGI Turing Test, as well as the Robot College Student Test, where the machine enrolls in classes and earns human-like qualifications.

Once the machine has reached the brink of human ingenuity, there are also debates on how it should be handled morally and legally. Some argue that it should be considered a non-human animal. These conflicts have occurred in part for decades because consciousness is often not fully understood.

## Neromorphic Computing Analysis

The focus of research is majorly to make developments in the field of learning from unstructured stimuli using less energy has much as possible. The building blocks in the system are analogous to neurons. Every neuron the system is capable of firing independently which then sends signals to others neurons allowing them to arrange their electric state of accordingly.

The key challenge faced by the researchers is to modulate the uncertainty and noise into natural data, which humans are able to do but the system is having trouble with. The ability to overcome this will let it to analyze a situation properly and understand the uncertainties to compute with, allowing this kind of technology in different domain applications. This kind of decision making allows them to understand and adapt to the environment which helps in predicting the further events to take a more accurate decision.

Algorithms are one of the major questions when it comes to neuromorphic computing. Since the algorithm chosen has an impact on the neuron, synapse and neural network. So, the question rises on what algorithm should be chosen. Beyond that another issue faced by the computing is whether the training of the chip should be on its own or the algorithm should be trained and then put on the chip. But since it works on learning from its surroundings the idea of chip on its own is preferred for making more better decisions in the near future by analysing each and every case.

Another issue is what happens when the algorithms are on the chip should it be monitored or shouldn't it be. So, should it learn offline and then act being monitored. One of the major reasons for neuromorphic computing to be of much interest is due to the declining of Moore's law. Even though all the perceptions are being taken most of the well-funded companies are still working hard to develop algorithms which can be used in the hardware for better efficiency of the chip. All over algorithms play a vital role in the development of neuromorphic computing.

## Neuromorphic Computing: The Promises And Challenges

Neuromorphic computing is defined as the next generation of AI that combines the production and use of neural networks as analogue or digital copies in electronic circuits. Represents a new non-Turing calculation method that aims to reproduce the features of continuous flexibility and computer functionality found in the biological brain. The concept, invented by American Scientist Carver Mead in the late 1980s, usually refers to a variety of computer-inspired computers, devices, and models.

It is not surprising that future computer programs will apply more insight into the human brain through the use of neuromorphic structures and calculation principles. Neuromorphic computing promises to provide a neuroscience tool to understand the dynamic processes of learning and development in the brain and mean brain stimulation to a normal understanding computer. Unlike conventional skills, this biologically inspired approach saves energy, efficiency, resilience against environmental failure and learning ability**.**

Since AI has a large number of translations, small sets, and a theory that defines its capabilities, the main goal of this technology is to replicate human performance. Both AI and neuromorphic computing in many ways seek to mimic even beyond human intelligence. However, both technologies are limited by the power of the hardware in which these systems operate.

Neuromorphic computers are able to perform complex calculations faster, more power-efficient, and in a much smaller way than the traditional von Neumann architecture. These features present strong reasons for developing hardware that uses neuromorphic architectures. Interest in the neuromorphic computer is also driven by the power of machine learning. This teaching approach demonstrates promise in improving the overall learning functionality of specific tasks. This shift from hardware benefits to understanding the potential software benefits of a computer neuromorphic, developing real-time learning algorithms such as brain biology. Neuromorphic structures appear to be the most suitable platform for extracting machine learning algorithms in the future.

Many neuromorphic systems develop AER (event representation), which includes France's Prophesee and the Swiss company aiCTX (AI cortex) focusing on sensory processing. AER is a communication protocol for transferring spikes between bio-inspired chips. That method is equally efficient and effective, bringing the benefits of strong cable connections between neurons without all cables. This means that the information from the incoming signal can simply flow to the processor in real time, while discarding non-essential information and the rest will be processed in the sensory pipe.

## Conclusion

In our emerging AI-based society, research and development in AI focuses on the development and implementation of deep neural networks and AI accelerators. However, there are limitations to the construction of von Neumann traditional systems, and a significant increase in data size and processing requires new and powerful solutions. Spiking Neural Networks and Neuromorphic computing, which are well-developed and well-known areas among neuroscientist and neuro-computing researchers, are part of the latest technology and novelty that is already contributing to the exploration and imitation of human learning frameworks. the brain. The report described emerging neuronal networks, the emergence of SNNs and their impact on the detection of neuromorphic chips. The limitations of traditional chips have been discussed and the final impact of neuromorphic chips in the search for AI applications. Major players have been identified locally, and have been linked to current and future applications. The study also explained the market benefits of neuromorphic chips compared to other AI semiconductors. Neuromorphic chips are associated with event-based sensory applications and emerging technologies such as photonic, graphene or fixed memory. They have great potential for AI development and could become an outstanding technology in the next decade. Hopefully, this report has worked to give a brief overview of the complexity of this challenging computer environment. While we remain committed to our goal of providing a realistic understanding of the latest developments, we have also tried to educate enough to increase the interest and visibility of the topic to a specific audience. For some students this study may represent a promising and challenging step towards a deeper understanding of the area that may eventually support road map construction, testing new industrial applications, or analyzing interactions between these novel chips and other emerging related trends.

Neuromorphic chips portray a solution on Nero biological concepts regarding the technical queries on computing that are being raised. Numerous applications that are being developed require enhancing large amounts of data at the initial stages and then to draw different kinds of conclusions to make a perfect decision in the environment. The expectations on the super computers which can act like a brain is to be embraced but still, as these chips are under experimental phase of development much is unexplored. Although questions are being raised on the capabilities, several researchers believe that the ability to bring a revolution to algorithms is neuromorphic computing.

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