**Bansilal Ramnath Agarwal Charitable Trust's**
**Vishwakarma Institute of Technology, Pune**
**(An Autonomous Institute Affiliated to Savitribai Phule University)**
*Department of Information Technology*

*IT Bulletin*                                                    *October 2024*

# NEUROMORPHIC COMPUTING

*Innovating the Next Generation of*
*Brain-Inspired Intelligent Systems*

# INTRODUCTION

Neuromorphic Computing is an innovative approach to computer engineering based on the architecture and functionality of the human brain. Traditional computers depend on the von Neumann architecture, where memory and processing tasks are segregated, sometimes hindering speed and leading to much more energy consumption due to data transfer between two different blocks.

Neuromorphic systems, on the other hand, integrate both memory and computation into one framework of operations just as a brain does. This means processing data in parallel compared to computers which have faster data handling rates, have a much lesser rate of energy consumption.

One of the defining characteristics of neuromorphic computing is through spike-based communication. In contrast to binary code processing, neuromorphic systems rely on electrical pulses, or "spikes," to communicate data. Unlike traditional information processing, where the signal is either at a zero voltage or at a +5 volt level, this makes spiking neural network models remarkably similar to the internal workings of the brain.

# KEY COMPONENTS

1. **Artificial Neurons:**

   Artificial neurons are the fundamental processing units in neuromorphic systems that are modeled after biological neurons. They send, receive, and process data, activating only when necessary, resulting in energy savings over continuous processing in typical systems.

2. **Synapses:**

   Resembling the biological synapses, artificial neurons are connected via synapses. They govern signal transmission between neurons, and technologies such as memristors can use them to improve efficiency by adapting to signal strength, much like biological synapses do.

3. **Neural Networks:**

   Neural networks connect artificial neurons into layers or more complicated structures. These structures enable parallel processing and are critical for complicated tasks like pattern recognition and decision-making, imitating the brain's efficiency.

4. **Spike-Based Communication:**

   Spiking neural networks (SNNs) are frequently used in neuromorphic systems, which send information via spikes in the same way that biological neurons do. Data is encoded in the timing and frequency of spikes, allowing for more efficient communication and processing.

# NEUROMORPHIC ALGORITHM

**Spiking Neural Networks (SNNs):**

At the core of neuromorphic algorithms is SNNs that encode information by spikes instead of continuous values. This spiking method improves processing efficiency, allowing systems to tackle jobs requiring real-time reactions and dynamic learning. SNNs excel at low-energy computation because they replicate biological neurons, making them ideal for edge devices and AI applications that require energy efficiency.

**Event-Driven Processing:**

Unlike traditional algorithms, which analyze data sequentially over time, neuromorphic algorithms use event-driven processing. Individual events, such as the arrival of a spike, activate computations, which aim to reduce superfluous operations and optimize resource utilization. This allows the system to remain idle while no events occur, reducing energy consumption and enhancing efficiency in dealing with asynchronous data streams.

**Hebbian Learning:**

Neuromorphic algorithms are often based on Hebbian learning principles, which are developed on the concept that connections of neurons are strengthened when their neurons activate in conjunction. It is a form of unsupervised learning and, hence, better emulates biologically inspired systems .

# KEY APPLICATIONS

**Artificial Intelligence (AI) and Machine Learning:**

Neuromorphic computing provides tremendous benefits in AI and ML in terms of efficient and scalable neural networks. The neuromorphic chips can run the AI-related activities like pattern recognition, natural language processing, and decision making with much less consumption of energy and at a much faster rate compared to the regular CPU/GPU.

**Autonomous Systems:**

Neuromorphic computing is the key to the construction of autonomous systems, including flying drones, self-driving cars, and free-moving robots. Autonomy in these systems requires real-time processing of vast amounts of sensory data so that necessary decisions can be made. Example: Neuromorphic processors can help navigate complex environments through autonomous drones with actual real-time visual and auditory data processing.

**Sensory Processing:**

Neuromorphic systems are well suited to operate on sensory information which could include vision, hearing, and touch in a way that would be closer to biological systems. The application of this capability is further crucial in robotics and prosthetics wherein the accurate and fast feedback of information through sensing is required. Example: Neuromorphic vision systems are applied in robotics to enhance object detection and recognition in dynamic environments.

# ENERGY-EFFICIENCY

Neuromorphic systems are extremely energy efficient since they only engage when necessary, such as when a signal or spike is received. Unlike ordinary processors, which consume power continually, neuromorphic chips remain inactive until triggered by specific events, resulting in significant energy savings, particularly in situations with erratic data streams.

Neuromorphic processors, like IBM's TrueNorth and Intel's Loihi, consume much less power than traditional CPUs and GPUs. They use substantially less energy, making them ideal for applications requiring both great performance and low power consumption. These CPUs are suited for mobile devices, edge computing, and IoT systems that require extended battery life.

Inspired by the brain's structure, neuromorphic systems handle multiple tasks simultaneously, just like biological neuronsParallel processing saves time and energy on complex processes, making it ideal for real-time applications like robotics and autonomous cars, which require quick and efficient decision-making.

Neuromorphic systems also reduce energy-intensive data transfers by colocating memory and computation. Unlike typical systems, which transport data between separate memory and processing units, neuromorphic architectures process and store data in the same spot, similar to the brain's neurons. This integration improves efficiency by decreasing the need for energy-intensive data transfer.

# CHALLENGES

Transforming deep neural networks (DNNs) to spiking neural networks (SNNs) can result in lower accuracy due to differences in hardware components such as memristors and restricted precision in synaptic weight. Furthermore, the neuromorphic computing sector lacks established benchmarks, testing methodologies, and standards, making it difficult to compare performance among devices.

Another issue is that most existing software is intended for classic von Neumann architectures, limiting the full potential of neuromorphic computers. Tools such as APIs and programming resources for neuromorphic systems are still not widely available, making it difficult for developers to experiment with them. Furthermore, knowledge of neuromorphic computing frequently necessitates competence in various fields such as biology, computer science, and neurology, posing barriers to entrance outside of specialized research settings.

Despite these challenges, neuromorphic computers have a large energy efficiency advantage over traditional deep learning hardware, such as neural processing units and edge-based graphics processing units (GPUs). This efficiency makes neuromorphic systems appealing for use in energy-constrained applications such as IoT, mobile devices, and real-time AI systems.

# FUTURE SCOPE

The development of more efficient neuromorphic processors with increased scalability and energy efficiency is critical for advancing their hardware capabilities. These enhancements will enable neuromorphic systems to do more complicated tasks while using less energy, making them ideal for large-scale applications that require great efficiency.

Algorithmic advancements are also required to enable more adaptive, brain-like learning models for real-time applications such as robots and AI. By improving neuromorphic systems' learning and decision-making skills, these processors will be better adapted to dynamic situations requiring real-time reactions.

One of the most major challenges is the continuous reliance on software created for classical von Neumann systems, which restricts neuromorphic computing's full capabilities. Expanding accessible tools like APIs, as well as providing common standards and testing techniques, can help these systems become more widely adopted. Low-power, brain-inspired computing is required for applications such as self-driving cars, healthcare, and smart devices. Increased collaboration across fields, including neurology, artificial intelligence, and hardware engineering, will be required to speed breakthroughs and fully realize the potential of neuromorphic computing.

# REFERENCES

- https://www.techtarget.com/searchenterpriseai/definition/neuromorphic⬚ computing
- https://www.ibm.com/think/topics/neuromorphic-computing
- https://aimodels.org/neuromorphic-computing/challenges-future-directions⬚ neuromorphic-computing/
- Research paper "Opportunities for neuromorphic computing algorithms and applications" published in 2022.
- https://www.nature.com/articles/s43588-021-00184-y
- https://www.geeksforgeeks.org/neuromorphic-computing/
- https://www.sciencedirect.com/topics/materials-science/neuromorphic-computing

# STUDENT EDITORS



**Sejal Chandak
SY-IT**

**Rutu Hinge
SY-IT**

**Sudarshana Dongre
SY-IT**