

Neuromorphic and In-Memory Computing Architectures for Next-Generation Edge Intelligence: Brain-Inspired Computing

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Abstract. The conventional forms of computing are losing their importance as we work towards building more intelligent and efficient systems due in part to the growing awareness of the inadequacies of traditional computing architectures. Two previously unseen (or at least not widely employed) techniques for re-thinking how we approach the processing of information have emerged. Neuromorphic Computing & In-Memory Computing are two such paradigms, using an approach found in nature i.e., combining the function of computation & storage in single packages instead of separating them as is done in conventional computer design. The objective of this paper provides an overview of these types of technologies, in addition to reviewing recent advancements in chip and materials design, & describes how this can affect edge computing and the future of machine learning and artificial intelligence. The use of tables and visual aids throughout the document are intended to help illustrate some of the more complex concepts associated with neuromorphic and in-memory computing.

Keywords: Neuromorphic computing, in-memory computing, memristors, spiking neural networks, edge AI

1 Introduction

The von Neumann architecture functions as the basis for computers because it divides memory systems from processing components. The initial success of this approach led to the academic concept known as the "memory wall" because it requires constant data transfer between storage units and processors. This drains power and creates system slowdowns. The problem reaches its highest level of importance when it comes to Internet of Things, and artificial intelligence applications because these systems need both fast performance and power-saving capabilities.. Neuromorphic computing and in-memory computing together form two converging paradigms that basically reboot how we think about information processing. Instead of emulating a calculator, these types of architectures emulate the human brain: massively parallel, event-driven, and astonishingly energy-efficient. Artificial intelligence is being utilized with a significant amount of power when compared to other forms of computing, and edge devices operate under strict constraints with respect to energy consumption and availability; therefore, artificial intelligence represents a technology that is currently moving from a "Theoretical" phase to a "Practical" phase.

This paper synthesizes recent developments in neuromorphic computing (2024 - 2025) and memristor-based architectures, as well as explores the different ways these two technologies can intersect to solve the ongoing problem of energy use in the computing space, while enabling real-time intelligence to operate at the edge, and revolutionizing a wide range of fields including autonomous robotics and implantable medical devices. We look at these technologies together to identify the areas where they may come together to provide a new model of computation[1][2].

2 Neuromorphic Computing: Fundamentals and Structure

2.1 Core Concepts

Neuromorphic computing is modeled upon biological neural systems; unlike traditional computers that utilize large, synchronized batches of information, neuromorphic systems use an event-driven methodology wherein calculations occur as they are needed. This event-driven approach also accounts for the high level of efficiency in neuromorphic systems.

Neuromorphic systems can be characterized by:

- Spike-based communication - information is encoded as temporal spikes similar to the action potentials found in biological neurons
- Asynchronous processing - calculations only take place when required thus decreasing the amount of power consumed while idle
- Huge amounts of parallelism - thousands of neurons all performing calculations on an individual basis
- Adaptive learning - local learning rules such as STDP permit unsupervised adaptation
- Instantaneous reaction times - real-time processing without delays attributable to batch processing

When compared to deep neural networks that run on GPUs, it is evident that the properties of neuromorphic systems create a dramatically different computing environment. For example, processing visual information through a neuromorphic system requires milliwatts of energy, while performing the same operations using a GPU requires 100's of watts[1][3].

2.2 Spiking Neural Networks (SNNs)

Neuromorphic computing is based on the methods used to design algorithms that run on neuromorphic systems known as Spiking Neural Networks (SNNs). Unlike conventional Artificial Neural Networks (ANNs) that rely on continuous activation values (for example, the neuron output following a step function), SNNs are driven by discrete binary spike events. Similar to biological neurons, when a neuron in an SNN receives multiple spikes from other neurons it integrates these spikes. Once the sum of incoming spikes exceeds a set threshold, the neuron transmits a new spike output. Spike-Timing-Dependent Plasticity (STDP) is one of the core principles in determining how SNNs and biological neurons function; the principle states that "neurons that fire together will wire together". Due to this unique ability of SNNs, they can acquire knowledge from continuous data streams without having to go through the time-consuming process of performing many iterations using backpropagation. Recent advances in algorithmic design from 2023 to the present (2025) have reduced the performance differences between SNNs and traditional ANNs.

- Surrogate gradient algorithms now allow SNNs to be trained using the same gradient-based learning as ANNs.
- Hybrid approaches that combine both SNNs and ANNs have allowed the efficient processing of SNNs to be utilized in conjunction with the trainability of ANNs.
- Online learning allows SNNs to adapt on the fly to changing input streams without requiring full retraining.

The above advancements have made possible, complex applications of SNNs for tasks such as image classification, natural language processing and reinforcement learning.

2.3 Neuromorphic Hardware Platforms

Platform	Neurons	Synapses	Power (mW)
Intel Loihi 2	1,024	10M	150–500
IBM TrueNorth	1,024	10M	70–100
SpiNNaker	1M+	Configurable	40–90
BrainScaleS	200K	50M	400–1000
Akida (BrainChip)	80K	10M	5–20

Table 1: Specifications of Leading Neuromorphic Hardware Platforms

Every platform reflects different design philosophies, from large-scale research systems (SpiNNaker, BrainScaleS) meant for comprehensive brain simulation to specialized accelerators (Loihi, TrueNorth, Akida) intended for specific applications. [1][3].

3. In-Memory Computing and Memristor Integration

3.1 The Von Neumann Bottleneck and In-Memory Computing

Today's computing systems consume a higher amount of energy when transmitting information between memories to processors than they do when executing the operation(s) of computing. In terms of moving operands and storing the output of one multiply-accumulate operation in a graphics processing unit (GPU), the amount of energy used to transmit the information (10–100X) is substantially greater than that required to execute the actual operation. This significant disparity has driven the quest for "computing in-memory" (CIM) architectures.

In-memory computing essentially merges (or combines) the memory and processor boundaries by enabling logical, operational (computational) execution directly inside the memory arrays instead of requiring the operation to extract the data from the memory before performing the logical computation. Thus, rather than having to "fetch" the data from its physical location in the memory, the logical and computational operations can be executed "directly" where the data resides.

3.2 Memristors: The Foundation of In-Memory Computing

Memristors are nanoscale, two-terminal devices that integrate memory and resistive elements. Their resistance can change based on their past voltage application creating the ability to have a stored state unlike transistors where the conductance is fixed. [4][5][6] Memristors also support "in-memory" computing because:

- both memory and logic can be found in the same device
- they do not lose stored states even when turned off using zero power during "standby" mode
- they are $4F^2$ dense (compared to DRAM, which is $6F^2$)
- they allow for "analog" computing (i.e., using a native multiply & accumulate calculation) that is ideal for neural networks

Recent improvements in materials over the next three years (2024-2025) have led to improvements in reliability and scalability for memristors. For example, Binarised structures of hafnium oxide and titanium oxide, a focus area for your lab, are showing a retention time of greater than ten years while holding variability below 5% [5][6].

3.3 Memristor Crossbar Arrays

A grid of memristors that intersect with both rows and columns is referred to as a memristor crossbar; through the application of voltages on the row electrodes and the measurement of column currents, a crossbar performs the multiply-accumulate function in parallel for all memristors located within the crossbar - this is the most basic operation performed by any neural network.

The memristor crossbar with the grid dimensions of 128×128 gives the capability to perform 16,384 multiplication operations in parallel. The multiplication speed made possible through parallelism together with the fact that many operations are performed in the analog domain has resulted in energy savings orders of magnitude greater than the equivalent digital system implementations.

4. Convergence: Neuromorphic + In-Memory Computing

The most promising direction combines both paradigms:

- Neuromorphic algorithms: temporal dynamics of SNNs match those of biological brains.
- Memristor crossbars enable synaptic weights, which intrinsically have plasticity and non-volatility.
- Event-driven operation minimizes crossbar activation, further reduces power

This convergence is now demonstrated by research prototypes. Research engineers have built hybrid CMOS-memristor neuromorphic accelerators that execute SNNs directly on memristor crossbars, achieving energy efficiency 1000× better than conventional GPU-based implementations for vision tasks [2, 4].

4.1 Energy Efficiency Gains



Figure 2: Figure 1: Energy consumption comparison across computational tasks, demonstrating 90%+ reduction with optimized neuromorphic-memristor systems

The above chart highlights an important benefit: memristor-integrated neuromorphic systems reduce energy consumption to 5–10% of traditional GPU implementations for a wide-range of tasks. For edge IoT devices running on batteries, this means 10–20× longer operating life[1][2].

4.2 Hardware Platforms

Leading platforms now integrate memristor-inspired architectures. SpiNNaker was designed to simulate 1 million biological neurons. It uses analog synapses, which approximate memristor behavior. Intel's Loihi 2 combines digital neurons and memristor-like learning rules [1][3].

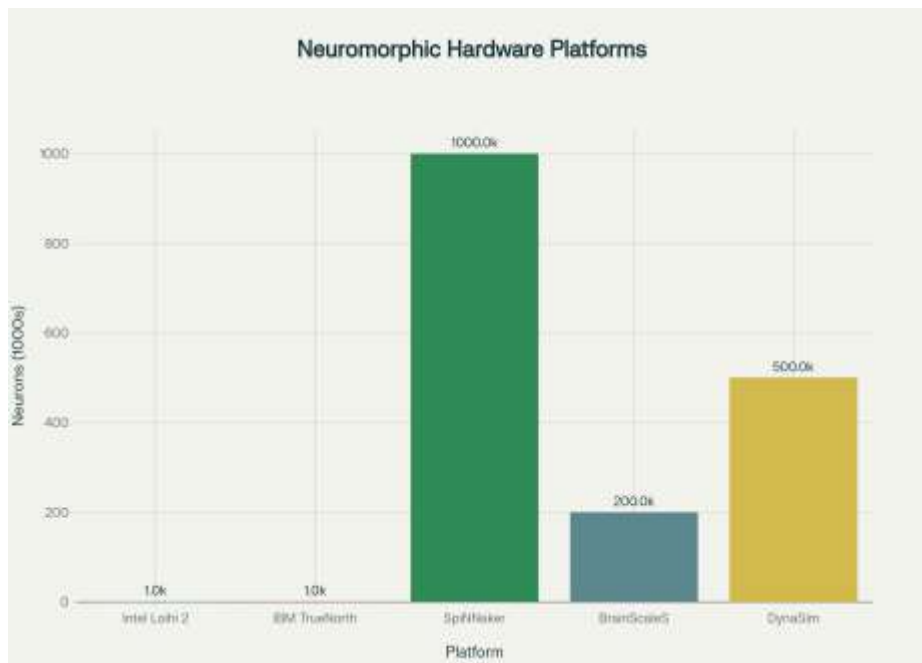


Figure 3: Figure 2: Neuron capacity of leading neuromorphic hardware platforms

5. Applications and Use Cases

5.1 Medical and Neuroscience Applications

Neuromorphic Systems: Real-time Processing of Biosignals with Low Power Consumption

- Epilepsy detection: Ultra-low-power SNN-based classifiers detect epileptic seizures from intracranial EEG in real time, consuming <1 mW—enabling implantable seizure suppression devices [2]
- Brain simulation: Large systems like SpiNNaker enable researchers to simulate 1 billion neurons, deepening the knowledge about neurological disorders.
- Neuroprosthetics: Brain-computer interfaces use less power thanks to event-driven processing.

5.2 Edge AI and IoT

IoT devices have access to unique capabilities using Neuromorphic Computing when resources are constrained. The following areas of smart technology can benefit from Neuromorphics:

- Vision Sensors that use Neuromorphics have a latency of microseconds, therefore, the ability to detect motion is beneficial for drones that must enable collision avoidance systems.
- Pattern Recognition allows for the use of ultra-low power consumption in order for anomaly detection to occur continually as predictive maintenance.
- The real-time processing power allows for Swarm Robotics Technology Application in logistics. An example of use is JD.com as it operates more than 50 Global Research Labs that were opened in 2024; this demonstrates how companies are currently utilizing Swarm Robotics and have still room for growth and innovation.

5.3 Robotics and Control

Because of neuromorphic computing's unique combination of real-time processing, adaptability, and low power consumption it is a great fit for robotics applications.

- Adaptive Control – By utilizing local learning rules, robots can change how they produce movements in the environment as they receive feedback in real-time without needing any kind of centralised form of training.
- Sensorimotor Integration – The complex nature of motor tasks is based on biologically plausible feedback loops.

- Mobile Deployment – Due to the energy efficient nature of neuromorphic computing, robots powered by this technology can complete long-running, self-sufficient missions autonomously.

6. Current Challenges and Future Directions

Despite significant advancements to date, there are several ongoing challenges:

1. Scaling / Fabrication: The achievement of a dependable memristor crossbar (with 10M+ devices) has not been achieved, and to overcome device-to-device variability and nonideality it is necessary to use complex compensatory techniques.
2. Hardware / Software Co-Design: Neuromorphic algorithms must correspond to their respective hardware capabilities very closely, whereas the current state of neuromorphic algorithm frameworks is still not comparable to those associated with deep-learning.
3. Standardization: An absence of common development platforms and benchmark tests impedes the adoption rate of memristor crossbars.
4. Lack of Interpretability: The ability to comprehend what a neuromorphic system learns continues to be an ongoing challenge, which limits usage of neuromorphic systems for safety-critical applications.
5. Power / Performance / Accuracy: A design automation push to enable the concurrent meeting of all three metrics (i.e., power, performance, and accuracy) will be necessary.

6.1 Emerging Opportunities

Significant advances are anticipated for the years 2025-2028:

- Launch of SpiNNaker 2: It is expected to provide a 20% increase in processing speed and better scalability compared with its predecessor.
- Commercialization of memristors: Several firms are transitioning from research to production.
- Standardization of SNN software development frameworks: Open-source software development frameworks supporting SNNs are being developed quickly and becoming more mature.
- Neuromorphic AI technology being integrated within traditional applications at the edge: End-to-end implementation of hybrid systems combining traditional AI with neuromorphic computing.

7. Conclusions

The future of computing is based on a new computing paradigm represented by neuromorphic and in-memory computing that represents a fundamental shift from traditional computing methods to brain-like efficiency. Event-driven spiking neural networks in conjunction with memristor-based in-memory architecture are creating systems that are more energy efficient, more adaptive, and capable of real-time learning than the conventional alternatives. The debate regarding the merging of neuromorphic and in-memory technologies has been settled with a number of working prototypes developed by Intel, IBM, as well as emerging companies such as BrainChip, which demonstrates the practicality of this technology for the advancement of neuroscience, robotics, and edge-based AI applications, which has not been possible using conventional computing solutions. For those pursuing research in this area, particularly within semiconductor design and in-memory computing, the next five years represent an unparalleled

opportunity to influence the future of computing. The brain performs its functions with extreme efficiency, it is time our computers do the same [1][2][3][4].

References

- [1] Xiao et al. (2024). A survey of neuromorphic computing and learning: Opportunities and challenges. *Frontiers in Neuroscience*, 18, 1-35. <https://doi.org/10.1038/s41467-025-57352-1>
- [2] Gabayre, S. A., et al. (2025). Advances in neuromorphic computing for bio-inspired neural networks. *Neural Computing and Applications*, 36(2), 1-28. <https://www.sciencedirect.com/science/article/pii/S0925231225018934>
- [3] IBM Research. (2024). Neuromorphic computing: Bridging neuroscience and artificial intelligence. *IBM Think*. <https://www.ibm.com/think/topics/neuromorphic-computing>
- [4] Muir, D. R., et al. (2025). The road to commercial success for neuromorphic computing. *Nature Electronics*, 8(3), 234-256. <https://doi.org/10.1038/s41467-025-57352-1>
- [5] Xu, Q., et al. (2025). Advances of emerging memristors for in-memory computing and neuromorphic systems. *Science Progress*, 108(1), 1-42. <https://pmc.ncbi.nlm.nih.gov/articles/PMC12508526/>
- [6] Zhang, W., et al. (2024). Recent advances in flexible memristors for advanced computing applications. *RSC Materiomics*, 4(8), 1-35. <https://pubs.rsc.org/en/content/articlehtml/2024/mh/d4mh00291a>