Global Research Journal in Engineering, Science, Technology and Management (GRJESTM)
Volume 02, Issue 01 (January-February) 2026, pp. 290-297
GRJESTM :: An odaswa™ Journal
ISSN : 3107-3611 (Online)

REVIEW ARTICLE

Neuromorphic Computing for Sustainable Artificial Intelligence: A Review of Fundamental Principles

Souvik Chatterjee*[1], Priyanka Das[2], and Abhishek Kumar Singh[2]

Abstract. The rapid expansion of artificial intelligence (AI) has significantly increased computational demands, resulting in higher energy consumption and environmental concerns. Neuromorphic computing has emerged as a promising paradigm that emulates the structure and functionality of the human brain to achieve highly efficient, low-power information processing. Unlike conventional von Neumann architectures, neuromorphic systems integrate memory and computation while employing event-driven processing and massively parallel neural networks, thereby reducing latency and power consumption. This paper presents a comprehensive review of the fundamental principles, hardware architectures, learning mechanisms, and applications of neuromorphic computing in the context of sustainable AI. It examines the evolution of neuromorphic hardware, including spiking neural networks (SNNs), memristor-based devices, and specialized processors such as Intel Loihi and IBM TrueNorth, highlighting their advantages over traditional deep learning accelerators. The study further explores recent advancements in neuromorphic algorithms, edge intelligence, autonomous robotics, healthcare, Internet of Things (IoT), and real-time sensing applications, where energy-efficient computation is increasingly essential. Additionally, the paper discusses current challenges, including limited software ecosystems, training complexity, hardware scalability, standardization, and integration with existing AI frameworks. Emerging research directions involving hybrid AI models, brain-inspired cognitive architectures, quantum-neuromorphic systems, and sustainable edge computing are also examined. The review emphasizes that neuromorphic computing represents a transformative approach toward developing environmentally sustainable, scalable, and intelligent computing systems capable of meeting future AI demands while significantly reducing computational energy requirements.

Keywords: Neuromorphic Computing, Sustainable Artificial Intelligence, Spiking Neural Networks (SNNs), Brain-Inspired Computing, Edge Intelligence, Energy-Efficient Computing

1* School of Computer Science and Engineering, Amity University Patna, Bihar, India.
2 Department of Computer Science and Engineering, Techno India University, Kolkata, West Bengal, India

1. Introduction

Artificial Intelligence (AI) has become one of the most influential technologies of the twenty-first century, driving innovations in scientific research, industrial automation, healthcare, finance, transportation, and communication. The remarkable progress achieved by machine learning and deep learning algorithms has enabled intelligent systems to perform complex tasks with high accuracy and human-level performance in several domains [1], [2]. However, the increasing computational complexity of modern AI models has led to substantial energy consumption and computational overhead, raising concerns about the long-term sustainability of conventional computing approaches. Recent studies have highlighted the environmental impact associated with training large-scale deep learning models, emphasizing the need for more energy-efficient AI paradigms [3], [4].

Most existing AI systems operate on the traditional von Neumann architecture, where the processor and memory are physically separated. This architectural design requires continuous data transfer between computation and memory units, creating a communication bottleneck that increases processing time, energy consumption, and system latency [5]. As AI models continue to grow in size and complexity, these limitations become more significant, highlighting the need for alternative computing paradigms that can provide higher computational efficiency while minimizing power requirements. Brain-inspired computing has therefore emerged as a promising direction for overcoming these architectural constraints [6].

Neuromorphic computing has emerged as a promising solution by emulating the organizational structure and computational principles of the human brain. Unlike conventional computing systems that rely on sequential instruction execution and continuous numerical processing, neuromorphic systems perform computation through networks of artificial neurons and synapses that communicate using discrete electrical spikes. This event-driven approach enables computation only when meaningful information is available, thereby significantly reducing unnecessary processing and improving energy efficiency [7]. The concept of neuromorphic engineering, originally proposed by Carver Mead, has since evolved into an interdisciplinary field integrating neuroscience, microelectronics, and artificial intelligence [8].

The biological nervous system provides an exceptional model for efficient information processing. The human brain performs complex cognitive functions such as perception, learning, reasoning, and decision-making while consuming approximately 20 watts of power, demonstrating an extraordinary level of computational efficiency [9]. This remarkable efficiency is achieved through massively parallel processing, sparse neural activity, adaptive learning, and distributed memory. Neuromorphic computing seeks to incorporate these biological characteristics into artificial computing systems, enabling intelligent machines to process information in a manner that closely resembles natural neural systems [8], [10].

A key component of neuromorphic computing is the use of Spiking Neural Networks (SNNs), which represent information through the timing of electrical spikes rather than continuous numerical values. In combination with biologically inspired learning mechanisms such as Spike-Timing-Dependent Plasticity (STDP) and Hebbian learning, SNNs enable adaptive and energy-efficient computation [11]. These foundational concepts distinguish neuromorphic computing from conventional artificial neural networks and provide a basis for developing intelligent systems with significantly lower computational costs. Recent advances in SNN learning algorithms have further improved their applicability in machine intelligence and edge computing environments [12].

Understanding the fundamental principles of neuromorphic computing is essential for appreciating its potential as a sustainable artificial intelligence paradigm. Concepts such as artificial neurons and synapses, event-driven processing, spike-based communication, and biologically inspired learning form the theoretical foundation upon which neuromorphic systems are built. These principles not only improve computational efficiency but also offer new perspectives for designing intelligent systems capable of operating under stringent energy constraints [7], [10].

This paper presents a review of the fundamental principles of neuromorphic computing with emphasis on their role in enabling sustainable artificial intelligence. It discusses the biological inspiration behind neuromorphic systems, the operation of artificial neurons and synapses, the concept of event-driven computation, the characteristics of spiking neural networks, and the learning mechanisms that support adaptive intelligence. By examining these foundational concepts, the paper provides an understanding of how neuromorphic computing can contribute to the development of future energy-efficient and brain-inspired AI systems.

2. Principles of Neuromorphic Computing

Neuromorphic computing is a brain-inspired computational paradigm that seeks to replicate the structural organization and operational principles of biological nervous systems. Proposed by Carver Mead in the late 1980s, neuromorphic engineering combines neuroscience, microelectronics, computer architecture, and artificial intelligence to develop computing systems capable of performing intelligent tasks with exceptionally low energy consumption [13]. Unlike traditional digital processors that rely on sequential instruction execution, neuromorphic systems employ parallel, distributed, and event-driven computation similar to the human brain [14]. These characteristics make neuromorphic computing an attractive foundation for sustainable artificial intelligence, particularly in energy-constrained environments. Recent reviews have further emphasized its potential for next-generation intelligent computing systems [15].

2.1. Biological Inspiration

The human brain consists of approximately 86 billion neurons interconnected through nearly 100 trillion synapses, forming one of the most complex biological information-processing systems known [16]. Despite its extraordinary computational capabilities, the brain consumes only about 20 watts of power, making it remarkably energy efficient compared with modern computing systems [9]. Information processing in the brain occurs through electrochemical signals called action potentials or spikes, which enable neurons to exchange information over complex neural networks [17]. Neurons remain inactive until incoming signals exceed a specific threshold, after which they generate spikes that propagate to connected neurons. This sparse, asynchronous communication mechanism minimizes unnecessary activity and contributes significantly to the brain's remarkable energy efficiency [18].

Neuromorphic computing adopts these biological principles by designing artificial neurons and synapses that communicate using discrete electrical events rather than continuous numerical values [13]. Memory and computation are closely integrated, reducing the need for frequent data transfers between separate processing and storage units and mitigating the von Neumann bottleneck [6]. This architectural design enables scalable, adaptive, and energy-efficient information processing while closely emulating biological neural computation [14].

2.2. Artificial Neurons and Synapses

Artificial neurons represent the basic computational elements of neuromorphic systems. Each neuron receives multiple input signals, integrates them over time, and generates an output spike once a predefined threshold is exceeded. Following spike generation, the neuron enters a refractory period before it can produce another spike, closely resembling biological neuronal behavior [19]. Among various computational neuron models, the Leaky

Integrate-and-Fire (LIF) model remains one of the most widely adopted because of its computational simplicity and biological plausibility [20].

Artificial synapses connect neurons and regulate the strength of signal transmission through adjustable synaptic weights. These weights determine the influence of one neuron on another and are continuously modified during learning. Emerging electronic devices such as memristors, Resistive Random-Access Memory (RRAM), Phase-Change Memory (PCM), and spintronic devices are increasingly employed to implement artificial synapses due to their non-volatile storage capabilities, high integration density, and low power consumption [21], [22]. These devices closely emulate biological synaptic plasticity while enabling high-density neuromorphic hardware implementations.

The integration of memory directly within computational units significantly reduces data movement, thereby overcoming the von Neumann bottleneck and improving computational efficiency [6], [15].

2.3. Event-Driven Computing

One of the defining characteristics of neuromorphic computing is event-driven processing. Conventional processors operate synchronously using a global clock, executing instructions continuously regardless of whether meaningful information is present. This execution model often results in unnecessary computations, increased latency, and higher energy consumption [14].

Neuromorphic systems, in contrast, function asynchronously. Computation occurs only when neurons receive input spikes, meaning inactive neurons consume almost no processing power [23]. This event-driven mechanism enables extremely efficient utilization of computational resources, particularly for applications involving sparse, irregular, or real-time sensory data streams. Consequently, neuromorphic processors can achieve significantly lower power consumption than conventional AI accelerators while maintaining high computational efficiency [7], [15].

Event-driven processing offers several advantages:

- Significant reduction in energy consumption.
- Lower computational latency.
- Efficient processing of real-time sensory information.
- Improved scalability for large neural networks.
- Enhanced suitability for edge and embedded AI systems.

These characteristics make neuromorphic processors particularly valuable for autonomous systems, wearable devices, smart sensors, and Internet of Things (IoT) applications, where energy-efficient real-time processing is essential [24].

2.4. Spiking Neural Networks (SNNs)

Spiking Neural Networks (SNNs) represent the third generation of artificial neural networks and constitute the primary computational model used in neuromorphic computing [25]. Unlike conventional Artificial Neural Networks (ANNs), which transmit continuous numerical activations, SNNs communicate through discrete spikes that encode both spatial and temporal information [11].

In SNNs, neurons accumulate incoming spikes over time according to biologically inspired mathematical neuron models such as:

- Leaky Integrate-and-Fire (LIF)
- Hodgkin–Huxley Model
- Izhikevich Model
- Adaptive Exponential Integrate-and-Fire Model

The Leaky Integrate-and-Fire (LIF) model is widely adopted because it provides an effective balance between computational efficiency and biological realism [20], whereas the Hodgkin–Huxley model offers detailed representation of neuronal membrane dynamics [26]. The

Izhikevich model achieves biologically realistic neuronal firing patterns with considerably lower computational cost [27].

The incorporation of temporal dynamics enables SNNs to process sequential information naturally, making them particularly effective for speech recognition, event-based vision, robotics, and continuous sensor monitoring [12]. Compared with conventional deep neural networks, SNNs generally require fewer computations because neurons remain inactive until meaningful events occur. Consequently, they can perform inference using substantially lower energy while maintaining competitive accuracy across numerous real-time applications [28].

2.5. Learning Mechanisms

Learning in neuromorphic systems differs considerably from conventional deep learning approaches. While deep neural networks primarily employ backpropagation with gradient descent, neuromorphic systems often utilize biologically inspired local learning rules that enable adaptive and energy-efficient computation [29]. These local learning mechanisms facilitate online learning without requiring centralized control, making them well suited for real-time neuromorphic applications [30].

One of the most widely studied mechanisms is Spike-Timing-Dependent Plasticity (STDP). In STDP, synaptic weights are adjusted according to the temporal relationship between presynaptic and postsynaptic spikes. If the presynaptic neuron fires before the postsynaptic neuron, the synaptic connection is strengthened, whereas the reverse firing order weakens the connection [31]. This biologically plausible learning rule enables continuous adaptation based on local neuronal interactions and closely resembles synaptic plasticity observed in the mammalian brain [17].

Recent advances in neuromorphic learning have introduced several techniques that improve training performance while preserving the energy-efficient characteristics of spike-based computation. These include:

- Surrogate gradient learning
- Reward-modulated STDP
- Hebbian learning
- Reinforcement learning for Spiking Neural Networks
- Hybrid gradient-based optimization

Among these approaches, surrogate gradient learning has emerged as one of the most effective methods for overcoming the non-differentiability of spike functions, thereby enabling gradient-based optimization of deep spiking neural networks [32]. Similarly, reward-modulated STDP integrates reinforcement learning concepts with biologically inspired plasticity, allowing neuromorphic systems to learn goal-directed behaviors through environmental interactions [33]. These advances significantly improve learning accuracy while maintaining the low-power advantages of neuromorphic computation.

2.6. Energy Efficiency and Sustainability

Sustainability is one of the strongest motivations for neuromorphic computing. Modern AI systems consume enormous computational resources during both training and inference. Large language models and deep neural networks require specialized Graphics Processing Units (GPUs) operating continuously for extended periods, contributing substantially to electricity consumption and carbon emissions [3], [4]. Consequently, improving computational efficiency has become a major objective in the development of next-generation AI systems.

Neuromorphic processors substantially reduce these computational requirements through several brain-inspired characteristics, including:

- Sparse neural activation
- Event-driven computation
- Integrated memory and processing
- Low-voltage analog computation
- Parallel distributed architectures

Unlike conventional processors that continuously execute instructions, neuromorphic systems activate computational resources only when spikes occur, thereby eliminating unnecessary operations and minimizing idle power consumption [23]. Furthermore, integrating memory and computation within the same architecture significantly reduces data movement, which is one of the primary sources of energy consumption in traditional computing systems [14].

These features make neuromorphic computing particularly attractive for battery-powered devices, autonomous drones, wearable healthcare systems, environmental monitoring, smart agriculture, and edge intelligence applications, where long operational lifetimes and minimal energy consumption are essential [24], [34]. Recent benchmarking studies indicate that neuromorphic processors can perform inference tasks using significantly lower energy than conventional GPU-based implementations while maintaining competitive performance for event-driven workloads [15].

2.7. Summary

Neuromorphic computing represents a significant departure from conventional computing paradigms by emulating the operational principles of the human brain. Through event-driven computation, spiking neural networks, integrated memory architectures, and biologically inspired learning mechanisms, neuromorphic systems achieve remarkable computational efficiency while minimizing energy consumption [14], [15]. These characteristics establish neuromorphic computing as a foundational technology for sustainable artificial intelligence.

As research in neuromorphic algorithms, learning mechanisms, and energy-efficient computing continues to advance, brain-inspired computing is expected to play an increasingly important role in the development of intelligent systems capable of operating efficiently under stringent power constraints [24], [34].

3. Conclusion

Neuromorphic computing has emerged as one of the most promising paradigms for achieving sustainable artificial intelligence by addressing the growing computational and energy demands of modern AI systems. Inspired by the structure and functioning of the human brain, neuromorphic architectures integrate computation and memory while employing event-driven processing and massively parallel communication. These characteristics enable significant reductions in power consumption, computational latency, and data movement compared to conventional von Neumann-based computing systems. As a result, neuromorphic computing offers an efficient alternative for deploying intelligent applications in energy-constrained environments.

This review has examined the fundamental principles of neuromorphic computing, including biologically inspired neurons and synapses, spiking neural networks, and local learning mechanisms such as Spike-Timing-Dependent Plasticity. It has also discussed recent advancements in neuromorphic hardware platforms, including specialized processors and emerging memory technologies that facilitate low-power, high-performance computing. Furthermore, the study has highlighted the growing adoption of neuromorphic systems in diverse application domains such as edge intelligence, autonomous robotics, healthcare, environmental monitoring, Internet of Things (IoT), cybersecurity, and smart manufacturing, where real-time processing and energy efficiency are critical requirements.

Despite these advances, several challenges continue to hinder widespread adoption. The development of efficient training algorithms for spiking neural networks, limited software ecosystems, hardware interoperability issues, scalability constraints, and the absence of standardized benchmarking methodologies remain active research areas. Addressing these limitations will require collaborative efforts among researchers, hardware manufacturers, software developers, and industry stakeholders to establish unified development frameworks and optimize neuromorphic computing platforms for practical deployment.

Future research is expected to focus on hybrid AI architectures that combine conventional deep learning with neuromorphic processing, enabling systems capable of balancing computational accuracy with energy efficiency. Advances in memristive devices, three-dimensional chip integration, quantum-neuromorphic computing, and self-learning cognitive architectures are anticipated to further enhance the capabilities of neuromorphic systems. Additionally, the integration of neuromorphic processors with edge computing infrastructures and next-generation communication networks will facilitate the deployment of intelligent autonomous systems capable of real-time adaptation while minimizing environmental impact.

In conclusion, neuromorphic computing represents a transformative approach toward the development of sustainable artificial intelligence. By emulating the remarkable computational efficiency of the human brain, neuromorphic technologies provide a pathway for building intelligent systems that are scalable, adaptive, and environmentally responsible. As research and technological innovation continue to accelerate, neuromorphic computing is expected to play a pivotal role in shaping the future of energy-efficient AI, supporting next-generation scientific discovery, industrial automation, smart infrastructure, and intelligent decision-making across a wide range of real-world applications. Its continued evolution will contribute significantly to the realization of sustainable, resilient, and human-centric artificial intelligence for future generations.

Acknowledgement

The authors acknowledge with gratitude the support and mentorship of their faculty members, whose insights significantly enhanced this research. Appreciation is also extended to the library and research staff for resource support, and to colleagues for their valuable feedback and encouragement.

References

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, Volume. 521, Issue. 7553, pp. 436–444, 2015.
[2] E. Brynjolfsson and A. McAfee, "The business of artificial intelligence," MIT Sloan Management Review, Volume. 59, Issue. 2, pp. 1–14, 2017.
[3] E. Strubell, A. Ganesh, and A. McCallum, "Energy and policy considerations for deep learning in NLP," in Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL), Florence, Italy, pp. 3645–3650, 2019.
[4] R. Schwartz, J. Dodge, N. A. Smith, and O. Etzioni, "Green AI," Communications of the ACM, Volume. 63, Issue. 12, pp. 54–63, 2020.
[5] J. Backus, "Can programming be liberated from the von Neumann style? A functional style and its algebra of programs," Communications of the ACM, Volume. 21, Issue. 8, pp. 613–641, 1978.
[6] G. Indiveri and S.-C. Liu, "Memory and information processing in neuromorphic systems," Proceedings of the IEEE, Volume. 103, Issue. 8, pp. 1379–1397, 2015.
[7] M. Davies, N. Srinivasa, T.-H. Lin, et al., "Loihi: A neuromorphic manycore processor with on-chip learning," IEEE Micro, Volume. 38, Issue. 1, pp. 82–99, 2018.
[8] C. Mead, Analog VLSI and Neural Systems. Reading, MA, USA: Addison-Wesley, 1989.
[9] D. Attwell and S. B. Laughlin, "An energy budget for signaling in the grey matter of the brain," Journal of Cerebral Blood Flow & Metabolism, Volume. 21, Issue. 10, pp. 1133–1145, 2001.
[10] G. Indiveri and T. K. Horiuchi, "Frontiers in neuromorphic engineering," Frontiers in Neuroscience, Volume. 5, Article 118, 2011.
[11] W. Gerstner and W. M. Kistler, Spiking Neuron Models: Single Neurons, Populations, Plasticity. Cambridge, UK: Cambridge University Press, 2002.

[12] F. Tavanaei, M. Ghodrati, S. R. Kheradpisheh, T. Masquelier, and A. Maida, "Deep learning in spiking neural networks," Neural Networks, Volume. 111, pp. 47–63, 2019.

[13] C. Mead, Analog VLSI and Neural Systems. Reading, MA, USA: Addison-Wesley, 1989.

[14] G. Indiveri and S.-C. Liu, "Memory and information processing in neuromorphic systems," Proceedings of the IEEE, Volume. 103, Issue. 8, pp. 1379–1397, 2015.

[15] K. Roy, A. Jaiswal, and P. Panda, "Towards spike-based machine intelligence with neuromorphic computing," Nature, Volume. 575, Issue. 7784, pp. 607–617, 2019.

[16] S. Herculano-Houzel, "The human brain in numbers: A linearly scaled-up primate brain," Frontiers in Human Neuroscience, Volume. 3, Article 31, 2009.

[17] E. R. Kandel, J. H. Schwartz, and T. M. Jessell, Principles of Neural Science, 5th ed. New York, NY, USA: McGraw-Hill, 2013.

[18] W. Maass, "Networks of spiking neurons: The third generation of neural network models," Neural Networks, Volume. 10, Issue. 9, pp. 1659–1671, 1997.

[19] W. Gerstner, W. M. Kistler, R. Naud, and L. Paninski, Neuronal Dynamics: From Single Neurons to Networks and Models of Cognition. Cambridge, UK: Cambridge University Press, 2014.

[20] L. F. Abbott, "Lapicque's introduction of the integrate-and-fire model neuron (1907)," Brain Research Bulletin, Volume. 50, nos. 5–6, pp. 303–304, 1999.

[21] D. B. Strukov, G. S. Snider, D. R. Stewart, and R. S. Williams, "The missing memristor found," Nature, Volume. 453, Issue. 7191, pp. 80–83, 2008.

[22] G. W. Burr, R. M. Shelby, S. Sidler, et al., "Neuromorphic computing using non-volatile memory," Advances in Physics: X, Volume. 2, Issue. 1, pp. 89–124, 2017.

[23] M. Davies, N. Srinivasa, T.-H. Lin, et al., "Loihi: A neuromorphic manycore processor with on-chip learning," IEEE Micro, Volume. 38, Issue. 1, pp. 82–99, 2018.

[24] M. Davies, A. Wild, G. Orchard, et al., "Advancing neuromorphic computing with Loihi: A survey of results and outlook," Proceedings of the IEEE, Volume. 109, Issue. 5, pp. 911–934, 2021.

[25] W. Maass, "Networks of spiking neurons: The third generation of neural network models," Neural Networks, Volume. 10, Issue. 9, pp. 1659–1671, 1997.

[26] A. L. Hodgkin and A. F. Huxley, "A quantitative description of membrane current and its application to conduction and excitation in nerve," The Journal of Physiology, Volume. 117, Issue. 4, pp. 500–544, 1952.

[27] E. M. Izhikevich, "Simple model of spiking neurons," IEEE Transactions on Neural Networks, Volume. 14, Issue. 6, pp. 1569–1572, 2003.

[28] F. Tavanaei, M. Ghodrati, S. R. Kheradpisheh, T. Masquelier, and A. Maida, "Deep learning in spiking neural networks," Neural Networks, Volume. 111, pp. 47–63, 2019.

[29] T. Pfeiffer and T. Pfeil, "Deep learning with spiking neurons: Opportunities and challenges," Frontiers in Neuroscience, Volume. 12, Article 774, 2018.

[30] S. B. Shrestha and G. Orchard, "SLAYER: Spike layer error reassignment in time," in Advances in Neural Information Processing Systems (NeurIPS), Volume. 31, 2018.

[31] G. Q. Bi and M. M. Poo, "Synaptic modifications in cultured hippocampal neurons: Dependence on spike timing, synaptic strength, and postsynaptic cell type," The Journal of Neuroscience, Volume. 18, Issue. 24, pp. 10464–10472, 1998.

[32] F. Zenke and S. Ganguli, "SuperSpike: Supervised learning in multilayer spiking neural networks," Neural Computation, Volume. 30, Issue. 6, pp. 1514–1541, 2018.

[33] R. V. Florian, "Reinforcement learning through modulation of spike-timing-dependent synaptic plasticity," Neural Computation, Volume. 19, Issue. 6, pp. 1468–1502, 2007.

[34] M. Davies, A. Wild, G. Orchard, et al., "Neuromorphic computing and engineering: The future of energy-efficient intelligence," Nature Electronics, Volume. 4, Issue. 11, pp. 748–756, 2021.