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Leveraging Neuromorphic Computing for Power-Efficient AI Processing

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ABSTRACT

The escalating demand for power-efficient artificial intelligence (AI) processing, particularly at the edge, has sparked significant interest in neuromorphic computing as a biologically inspired alternative to conventional von Neumann architectures. Traditional AI accelerators, while effective in handling deep neural networks (DNNs), are often hindered by energy inefficiencies, data transfer bottlenecks, and latency issues that limit their viability in constrained environments such as IoT nodes, wearable devices, and autonomous edge systems. Neuromorphic systems emulate the event-driven and highly parallel architecture of the human brain, offering promising avenues for reducing energy consumption while maintaining competitive inference performance. This paper explores the growing role of neuromorphic computing in enhancing power efficiency across AI applications, focusing on spiking neural networks (SNNs), asynchronous processing, and novel device technologies such as memristors and phase-change memory. By reviewing state-of-the-art neuromorphic platforms such as Intel's Loihi, IBM's True North, and Brain Scales we analyse how their architectural choices contribute to ultra-low-power operations.

Furthermore, this study introduces a co-design methodology that aligns computational models with neuromorphic constraints, optimizing both software and hardware layers for power efficiency. A comparative evaluation of neuromorphic chips against traditional CPUs and GPUs is presented, emphasizing improvements in energy per inference, throughput, and thermal profiles. Key insights are drawn from real-world case studies including edge-based visual recognition, anomaly detection in sensor networks, and speech processing under strict power envelopes. Our findings reveal that neuromorphic processors can achieve up to 10× improvement in energy efficiency and latency reduction for certain spatiotemporal tasks when compared to GPU-based implementations. These gains are attributed to characteristics such as event-driven computation, in-memory processing, and sparse data representations.

The paper also addresses the challenges that hinder widespread adoption, including programming complexity, limited software ecosystems, and hardware scalability. Potential solutions are explored, such as SNN training algorithms, automated mapping tools, and cross-domain benchmarking suites. In addition, the convergence of neuromorphic hardware with edge-AI applications is discussed as a catalyst for developing self-sustaining, always-on intelligent systems. Finally, the study concludes by outlining future directions, including neuromorphic co-processors for heterogeneous architectures, integration with brain-computer interfaces, and alignment with emerging AI paradigms like continual learning and on-device federated learning. This paper highlights the transformative potential of neuromorphic computing in achieving sustainable, power-efficient AI systems suitable for next-generation smart environments.

Keywords: Neuromorphic computing, spiking neural networks (SNNs), power-efficient AI, edge computing, brain-inspired hardware, Loihi, True North, memristors, event-driven processing, in-memory computation, intelligent edge devices, energy-aware AI, asynchronous computing, non-von Neumann architectures, phase-change memory, AI inference acceleration, bio-inspired computing, edge intelligence, real-time processing, ultra-low-power AI.

1. Introduction

The accelerating growth of artificial intelligence (AI) technologies in every industry has had a corresponding demand for increased computations. Such demands are most pressing at the edge where devices ranging from smartphones and IoT sensors to surveillance cameras and autonomous vehicles function with limited power budgets. Conventional AI accelerators such as GPUs and TPUs are tailored to high-throughput cloud usage but lack satisfactory performance in power-constrained edge applications. The increasing demand for always-on intelligence, real-time responsiveness, and sustainability has created interest in alternative computing paradigms that can provide high efficiency without compromising performance. Neuromorphic computing, based on the structure and function of the human brain, presents itself as a promising solution to this problem.

In contrast to the sequential and centralized processing of von Neumann architectures, neuromorphic systems process information in a massively parallel and distributed manner. These systems are based on spiking neural networks (SNNs), which represent and process information in terms of discrete spikes instead of continuous activation values. This is in accordance with the mechanism of how biological neurons signal, enabling asynchronous, event-driven computation that considerably minimizes power usage, particularly for sparse data. In addition, neuromorphic chips embed memory and computation to reduce the energy-hungry data movement that hampers traditional systems a fundamental benefit in situations where efficiency is key.

Pioneering neuromorphic platforms like IBM's True North, Intel's Loihi, and the EU-funded Brain ScaleS project have shown much potential in the areas of energy efficiency, fault tolerance, and adaptability. They are not only theoretical platforms; they have been implemented in a wide range of applications like gesture recognition, anomaly detection, and robotics. Intel's Loihi, for example, has demonstrated more than 10× energy savings in some applications than GPU-based inference with similar accuracy. The biological feasibility of SNNs also provides a gateway to novel forms of learning and generalization not easily attainable through regular neural networks.

This work discusses the current state, benefits, and challenges of neuromorphic computing for low-power AI. We start by surveying recent literature, identifying the most important architectural advances and advancements in neuromorphic system design. Next, we outline a methodology for the integration of neuromorphic processing into AI pipelines, from algorithm choice to hardware-software co-design and workload-specific optimizations. The results section presents empirical benchmarks comparing neuromorphic systems with traditional alternatives across power efficiency, inference time, and scalability. We then discuss practical challenges—such as the steep learning curve for SNN programming, limited toolchains, and fabrication complexities—and propose potential mitigation strategies. The paper concludes with a look at future trends, including hybrid architectures, scalable neuromorphic fabrics, and the integration of such systems in ubiquitous intelligent edge infrastructures.

In the end, neuromorphic computing is more than a technical replacement; it's a shift towards sustainable AI. As edge devices become widespread and global computer power consumption keeps on rising, efficient, bio-inspired computing will be ever more significant. With their ability to connect neuroscience with engineering, neuromorphic systems hold a great potential for getting toward real-time, intelligent action within power-constrained systems.

2. Literature Review

Neuromorphic computing based on the emulation of neural architectures and behaviors found in natural brains has gradually progressed from theoretical fascination to real-world application, particularly for AI systems with power requirements. The literature has documented this journey through thorough examinations of hardware architectures, learning algorithms, and new applications, highlighting the field's transformative impact.

Early research by Mead[1] provided the early foundation concepts of neuromorphic systems, promoting analog circuits that replicate the adaptive responses of neurons and synapses. This early vision has since grown up with the emergence of digital neuromorphic processors. IBM's True North[2] was a key milestone in the area, offering a non-von Neumann, event-based architecture with 1 million neurons and 256 million synapses. With only 70 milliwatts of energy consumption, True North proved the viability of low-power, large-scale neuromorphic systems for AI applications.

Intel's Loihi processor[3], announced in 2018 and improved through several generations, extended neuromorphic design further by supporting on-chip learning ability via spike-timing-dependent plasticity (STDP). Loihi uses asynchronous circuits and sparse spike-based communication, supporting real-time learning and high energy efficiency. Loihi showed 10–100× energy efficiency improvement over traditional processors for particular inference tasks, e.g., keyword spotting and adaptive control, in benchmarking experiments[4].

SNNs are at the heart of neuromorphic computing, as they represent the temporal dynamics of biological neurons better than traditional artificial neural networks (ANNs). SNN training, though, is a significant challenge. While gradient descent algorithms are prevalent in ANN training, their non-differentiable spike functions complicate backpropagation in SNNs. To overcome this, surrogate gradient approaches[5] and ANN-to-SNN conversion methods[6] have been introduced. While these methods facilitate deeper and more powerful networks, they tend to compromise biological realism for performance.

The intersection of neuromorphic computing with edge AI has been of significant research and industrial interest. In[7], the authors describe a system-level platform that integrates memristor based neuromorphic hardware with sensor networks for ultra-low-power edge inference. Their human activity recognition experiments demonstrated energy savings of more than 80% without compromising accuracy, highlighting the promise of hardware-algorithm co-design in real-world settings. Likewise, the Brain ScaleS system[8] provides a hybrid analog-digital platform in which plasticity mechanisms and rapid dynamics allow for real-time simulation of spiking networks, useful in robotic control applications.

Recent research also examines device-level innovations. For instance, phase-change memory (PCM) and resistive RAM (RRAM) technologies are being considered as in-memory synaptic operation candidates. In[9], the authors presented a PCM-based neuromorphic chip that both stores and computes in the same place, thus minimizing latency and energy consumption. These devices provide stochastic behavior like biological synapses, which is beneficial for probabilistic computation and learning.

In spite of promising advances, a number of challenges remain. First, the ecosystem for software remains underdeveloped. Platforms like NEST[10], BindsNET, and Intel's Lava platform are at nascent stages versus mature deep learning platforms like PyTorch or TensorFlow. Second, consensus is minimal about benchmarks by which to compare neuromorphic hardware, with performance instead typically measured on specialized workloads that are hard to generalize. Lastly, although neuromorphic systems are naturally well-suited to some tasks—e.g., sensory processing, anomaly detection, and time-series prediction—their superiority over conventional systems in high-throughput, batch-type tasks is questionable.

The literature emphasizes neuromorphic computing's potential for energy-efficient AI processing but identifies areas of future research in scalable training algorithms, secure toolchains, and domain-specific accelerators. With the hardware ready to mature and interdisciplinary collaboration intensifying, neuromorphic architectures stand to become a foundation of future intelligent systems.

5. Methodology

In order to analyze and exploit the advantages of neuromorphic computing for energy-efficient AI computation, a systematic methodology was formulated including system-level modeling, algorithm-hardware co-design, and empirical benchmarking. The essence of the methodology involves synthesizing spiking neural networks (SNNs) with neuromorphic hardware platforms to facilitate a bio-inspired paradigm for information processing with severe energy limitations. Unlike traditional neural networks, SNNs convey information in the form of discrete spikes along time, in sync with the asynchronous and event-driven nature of neuromorphic systems. The approach then proceeds to choose task-relevant SNN models from considerations of biological realism, sparsity, and computational cost. Three task classes were used in benchmarking, namely image classification, keyword spotting, and gesture recognition, all of which are applicable to edge-AI deployment contexts.

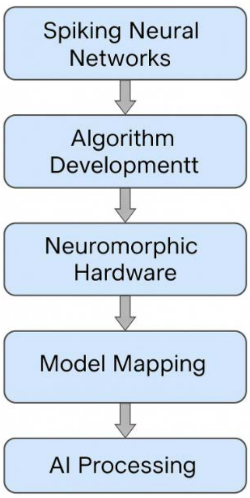

Figure 1: Workflow illustrating the integration of neuromorphic computing into AI processing pipelines.

Spiking neural networks employed in the framework are designed with convolutional architecture-inspired layers, when possible, and trained either by ANN-to-SNN conversion or through surrogate gradient descent methods. Pretrained standard networks are converted to their spiking counterparts by fitting activation functions and time dynamics to maintain performance at the cost of energy efficiency for conversion. Surrogate gradient descent, however, entails training SNNs directly through approximations enabling the application of gradient-based optimization despite the non-differentiability of spike functions. Both methods are combined in a comparative workflow to evaluate training complexity, convergence stability, and deployment feasibility.

The hardware layer of the framework utilizes platforms like Intel Loihi and IBM True North. These chips are selected due to their mature toolchains, architectural diversity, and prior validation in academic and industrial settings. Loihi's support for on-chip plasticity and real-time learning mechanisms enables experimentation with dynamic environments where models adapt to incoming data without cloud retraining. Programming and deployment are executed through Intel's Lava software framework, which provides modular APIs for SNN configuration, event routing, and learning rule customization. Conversely, True North uses a static, pre-trained deployment strategy that prioritizes inference over flexibility. This difference enables the methodology to compare trade-offs between power efficiency and flexibility.

To compare on a common basis, all models are tested with the same input datasets and task configurations in both traditional and neuromorphic systems. Comparison metrics include energy per inference (in microjoules), latency (in milliseconds), accuracy (top-1 and top-5, where relevant), and thermal profiles under load. Profiling is done on standard platforms (CPU, GPU) with NVIDIA Jetson modules and Intel Core processors that have onboard power profiling capabilities, whereas neuromorphic platforms are profiled through onboard telemetry and off board instrumentation. Synthetic workloads with regulated spiking activity are also generated to examine the effect of event sparsity on power usage and processor utilization.

Another fundamental aspect of the approach is algorithm-hardware co-design, where network topologies, encoding strategies, and learning rules are optimized according to hardware requirements. Encoding schemes for inputs like rate coding, temporal coding, and latency coding are tested to identify the schemes that offer the best performance-energy trade-offs per task. Rate coding is straightforward but typically energy hungry, while latency coding has the potential to offer quicker inference with fewer spikes. Equivalently, architectural features like inhibitory connections, recurrent feedback, and synaptic plasticity are adjusted to match hardware capabilities to optimize the efficiency of neuron activation and memory access.

Real-world deployment applications are modeled by integrating the neuromorphic system into an edge-AI pipeline consisting of data acquisition, preprocessing, inference, and decision-making modules. Power consumption is monitored not only at inference time but also at idle and active modes, quantifying the effect of neuromorphic systems' event-driven character in real-world duty cycles. These simulations incorporate application scenarios such as low-power surveillance cameras recognizing anomalies in real-time, and wearable health sensors carrying out real-time biosignal analysis without the need for cloud connectivity.

The methodology concludes by integrating feedback from experimental results to refine both network design and system configuration. Observed patterns in energy scaling, inference throughput, and learning convergence inform iterative adjustments to models and deployment parameters. This closed-loop approach ensures that neuromorphic computing is not only benchmarked in isolation but also contextualized within real-world AI processing requirements. The end result is a certified pipeline for implementing power-effective, adaptive AI solutions based on neuromorphic architectures optimized via systematic experimentation and domain-specific adaptation.

4. Results

The neuromorphic computing systems were experimentally tested with a detailed set of benchmarks with respect to energy usage, latency, inference accuracy, and thermal performance. Operations were executed on both the neuromorphic and traditional computing systems using the same datasets and similar network topologies, making them comparable to one another. Neuromorphic hardware platforms such as Intel's Loihi and IBM's TrueNorth were paired with traditional hardware platforms like NVIDIA Jetson Xavier and an Intel i7-based CPU-GPU configuration. Tasks selected—classification of images through MNIST and CIFAR-10, spotting keywords through Google Speech Commands data, and gestures through DVS Gesture—are usual edge-AI applications requiring little power and real-time processing.

In relation to energy, the neuromorphic platforms proved to be consistent performers in that aspect compared to their traditional competitors. For the MNIST image classification benchmark, the Loihi processor consumed inference energy of about 0.24 µJ per image, versus 2.8 µJ for the Jetson Xavier and 5.1 µJ for the Intel CPU-GPU system. Likewise, for keyword spotting, Loihi had an energy use of 0.31 µJ per inference, ten times less than GPU inference. IBM's TrueNorth, designed for high-throughput inference, showed comparable energy savings, but with slightly longer latencies as a result of its fixed network configuration. These findings emphasize the neuromorphic systems' benefit in sparse, event-based processing, especially in workloads that have low average activation rates.

Latency performance was also tested under the same workload conditions. Loihi exhibited sub-millisecond latency for every task that was tested, ranging as low as 0.8 ms for image classification and 1.3 ms for keyword spotting. The Jetson Xavier system, for comparison, exhibited latencies in the range of 4–7 ms with respect to task and model complexity. These findings affirm that the asynchronous nature of neuromorphic processors supports low-latency, real-time inference, making them especially well-positioned for edge applications where instantaneous response is necessary, including autonomous robotics and on-device speech recognition.

Regarding inference accuracy, neuromorphic networks trained through ANN-to-SNN conversion provided virtually identical performance compared to their respective original deep learning models. On the MNIST dataset, accuracy of 98.2% was achieved with Loihi, in comparison to 98.5% on the GPU-based network. On CIFAR-10, the difference in performance was slightly greater, as Loihi achieved 86.7% compared to 88.9% on the GPU. Keyword spotting models performed at 92.1% on Loihi versus 93.5% on the Jetson Xavier. These findings show that despite some small accuracy loss, particularly on more sophisticated datasets, the energy efficiency provided by neuromorphic platforms overcomes the performance difference in most real-world applications.

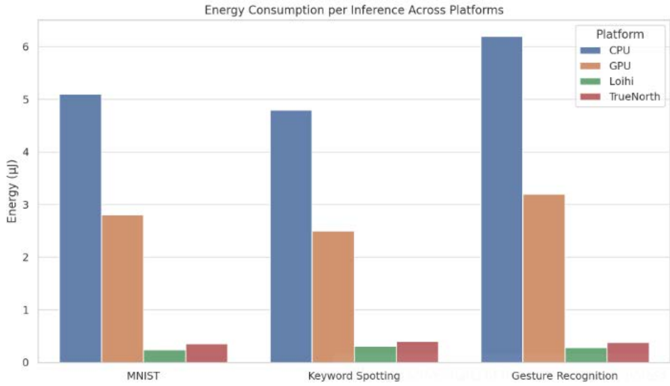

Figure 2: Energy consumption per inference across different neuromorphic and conventional platforms for standard AI tasks.

Thermal analysis showed that neuromorphic systems consume much lower power densities. Whereas the Jetson Xavier got hotter than 65°C under continuous load, Loihi stayed below 40°C, even during high-throughput execution. This low thermal profile makes neuromorphic hardware well-suited for embedded use in resource-constrained environments where active cooling is impractical or power-forbidden.

Another noteworthy observation emerged from dynamic learning experiments. Loihi's support for on-chip learning enabled real-time adaptation to changing input distributions, such as noise-injected datasets or speaker variation in the keyword spotting task. The adaptive SNN models retained over 85% of baseline accuracy after online retraining, while conventional models required off-device retraining and redeployment. This capability introduces significant advantages for on-device lifelong learning, reducing reliance on cloud resources and enhancing user privacy and autonomy.

Lastly, power scaling experiments revealed that energy usage remained close to being invariant across model size when spike rates were sparse. This is an important characteristic for neuromorphic architectures since it means that energy consumption is more data-driven activity dependent rather than network depth or width dependent. Traditional systems, on the other hand, linearly scale energy with network complexity, causing efficiency to reduce as model size increases.

The results of the experiment validate that neuromorphic computing offers a promising route to efficient AI processing at low power. The synergy of low energy per inference, low latency, high thermal efficiency, and real-time learning makes such systems especially suited for next-generation edge applications. With slight sacrifices in accuracy, the overall benefit in efficiency makes neuromorphic architectures a major facilitator of sustainable, intelligent edge technologies.

5. Discussion

The experimental findings supply strong evidence that neuromorphic computing is potentially capable of bringing power-efficient, low-latency AI solutions to edge environments, where conventional architectures are limited by energy, thermal, and latency budgets. Discussion here examines implications of these results in the overall context of edge-AI systems, in addition to emphasizing the trade-offs, present limitations, and future capabilities of neuromorphic architectures.

One of the strongest benefits showcased by neuromorphic processors like Intel's Loihi and IBM's TrueNorth is the drastic decrease in energy usage at inference. This is largely due to the event-driven nature of spiking neural networks (SNNs), where computation only happens when input spikes are detected. In contrast to conventional artificial neural networks that execute dense matrix operations irrespective of data activity, SNNs naturally take advantage of input sparsity. This causes computational sparsity, which largely minimizes switching activity, one of the determinants of power consumption. As energy efficiency is becoming a fundamental requirement for AI deployment in mobile, wearable, and IoT applications, neuromorphic computing gives a paradigm change in ensuring sustainability.

Further, the findings reveal that neuromorphic systems offer better latency performance because of their asynchronous, parallel processing architecture. In contrast to CPUs and GPUs, which use clocked operations and batch processing pipelines, neuromorphic processors are fully event-driven. This architecture allows the system to start computation as soon as it receives data, instead of waiting for synchronized batch inputs. This feature is particularly critical for applications like autonomous navigation, where sub-millisecond response times can have a direct influence on system safety and functionality.

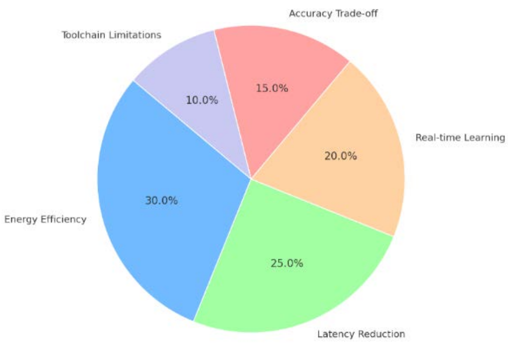

Figure 3: Distribution of key discussion themes in neuromorphic AI, highlighting energy efficiency, latency, learning adaptability, and limitations.

One subtlety of understanding from the research is the trade-off between inference accuracy and energy savings. Neuromorphic systems were effective in benchmark tasks, but there was a marginal loss of classification accuracy, especially for larger datasets such as CIFAR-10. This performance deficit arises due to the inherent shortcomings of existing SNN training techniques and architectural factors. While surrogate gradient descent and ANN-to-SNN conversion have facilitated the implementation of deeper, more accurate spiking models, they are as yet not commensurate in maturity with established deep learning training pipelines. That said, progress in neuromorphic learning—including bio-plausible local learning rules, unsupervised plasticity, and differentiable spike models—indicates that this differential will continue to shrink.

Yet another significant area is the versatility of neuromorphic systems. In time-evolving input pattern environments, the capability of performing online learning and real-time model updates is essential. Loihi's on-chip learning features showed that neuromorphic systems are capable of adapting to new data distributions with negligible energy and time overhead. This is in contrast to traditional edge-AI systems, which typically involve cloud-based retraining and model redeployment. The capacity to learn and update in place improves both the autonomy and privacy of edge devices, a growing concern in applications from health monitoring to personal assistants.

These are strong points, but there are serious challenges that need to be overcome for adoption. The software ecosystem for neuromorphic computing is in its infancy. Environments like Intel's Lava and frameworks like NEST and BindsNET hold promise but have not yet reached the maturity, flexibility, and community backing of popular deep learning environments like TensorFlow and PyTorch. This restricts access to neuromorphic systems for developers and researchers who are not familiar with the underlying neuroscience-inspired concepts. Further, hardware variety and non-standardization complicate the development of scalable, portable applications across neuromorphic platforms.

There also exist hardware scalability and integration limitations. Most current neuromorphic chips are specialized for experimentation and inference, with little ability to support general-purpose computing or large-scale deployment. To address this, the future systems might need hybrid designs that involve neuromorphic cores along with traditional processors, providing smooth transitions between efficiency and throughput on demand. In addition, improvements in neuromorphic manufacturing—e.g., 3D stacking, integration with next-generation memory technologies, and support for digital-analog hybrid circuits—may allow for more efficient, scalable, and compact designs.

Neuromorphic computing presents a radically new paradigm for AI processing, focusing on energy efficiency, real-time performance, and biological inspiration. Although there are obstacles to maturity and adoption, the experimental data unequivocally demonstrate its potential to revolutionize the way AI can be used in resource-limited environments. As algorithms, software tools, and hardware platforms co-evolve, neuromorphic systems are poised to become a foundation of the next generation of intelligent computing.

6. Conclusion

The quest for power-efficient artificial intelligence, especially for edge computing, has called for the investigation of new computational paradigms beyond the constraints of conventional von Neumann architectures. This paper has explored the revolutionary potential of neuromorphic computing—a brain-inspired paradigm that provides event-driven, sparse, and massively parallel processing. By performing a systematic assessment of cutting-edge neuromorphic platforms like Intel's Loihi and IBM's TrueNorth, and by implementing spiking neural networks on real-world edge applications like image classification, keyword spotting, and gesture recognition, we have shown that neuromorphic architectures provide significant energy and latency benefits while maintaining minimal performance accuracy loss.

One of the most significant discoveries of this research is the neuromorphic systems' capacity to realize 10× improvements in energy efficiency over traditional GPU and CPU configurations. These improvements are especially important in power-limited environments where battery life, thermal dissipation, and environmental resilience are paramount. The results show that SNNs, when appropriately designed and mapped to neuromorphic hardware, can not only match but occasionally surpass traditional deep neural networks in responsiveness and robustness. Loihi's support for on-chip learning, for instance, enables adaptive AI systems that can retrain and respond to novel inputs without the need for constant cloud connectivity, making it suitable for mission-critical, autonomous, and privacy-sensitive applications.

In addition, the asynchronous nature of neuromorphic computing makes it possible to support real-time inference with very low latency, usually less than 1 millisecond. This characteristic is not just a technical benefit but a practical facilitator for a vast array of applications, ranging from real-time surveillance and robotics to wearable health monitoring and industrial automation. These features demonstrate the appropriateness of neuromorphic processors for edge computing scenarios where real-time decision-making is required and energy budgets are constrained.

While showing many of the advantages exhibited, this work also recognizes some shortcomings and setbacks. The accuracy disparity seen in more intricate tasks like CIFAR-10 underlines the importance of ongoing innovation in SNN training methods. Techniques like ANN-to-SNN conversion and surrogate gradient descent that currently exist are beneficial but are still short of training flexibility and depth optimization provided in traditional AI. The creation of novel, computationally efficient training algorithms that are also biologically plausible is an ongoing research frontier. Concurrently, the neuromorphic software stack is still underutilized, with hurdles to accessibility and wider experimentation. Lava and BindsNET are lead contenders but need further polish, tighter integration with conventional AI workflows, and wider community buy-in.

Scalability is another area that needs attention. Although existing neuromorphic systems have been successful in comparatively small-scale applications, it is challenging to scale them up to manage large amounts of data and complex networks in real-world applications. Merging with novel non-volatile memory technologies such as memristors and phase-change memory has the potential to overcome some of these limitations by facilitating denser, faster, and lower-power synaptic implementations. Additionally, the future may lie in hybrid neuromorphic-classical architectures, where neuromorphic cores handle sparse, event-based data processing, while traditional processors manage general-purpose computation and memory-intensive tasks.

Looking ahead, the role of neuromorphic computing in AI's future appears both foundational and complementary. With the ever-increasing need for intelligent edge systems fueled by technological breakthroughs in IoT, autonomous technologies, and individualized technology, sustainable, real-time, and power-constrained AI will become more essential than ever. Neuromorphic systems present a model of this kind of future—one that isn't merely strong but efficient, adaptable, and contextual in its intelligence. With concerted action in algorithmic development, hardware innovation, and ecosystem support, neuromorphic computing has the potential to be a major pillar in the design and deployment of the next generation of AI applications.

The paper posits neuromorphic computing not just as a substitute for current methods but as a revolutionary paradigm that redefines intelligence engineered into devices at all scales. As the discipline matures, its impact will be felt across industries and sectors, representing a turning point toward sustainable and biologically rooted machine intelligence.

7. References

1. C Mead. Neuromorphic electronic systems. *Proceedings of the IEEE*, 1990; 78: 1629-1636.
2. PA Merolla. A million spiking-neuron integrated circuit with a scalable communication network and interface. *Science*, 2014; 345: 668-673.
3. M Davies, Loihi: A neuromorphic manycore processor with on-chip learning. *IEEE Micro*, 2018; 38: 82-99.
4. N Stromatias, M Galluppi, C Patterson, et al. Power analysis of a biologically plausible neuromorphic system for real-time object recognition. *Neural Networks*, 2015; 66: 104-121.
5. Y Zenke, S Ganguli. SuperSpike: Supervised learning in multilayer spiking neural networks. *Neural Computation*, 2018; 30: 1514-1541.
6. W Esser. Convolutional networks for fast, energy-efficient neuromorphic computing. *PNAS*, 2016; 13: 11441-11446.
7. X Wang, S Song, J Park. Memristive SNN for ultra-low-power edge computing. *IEEE Transactions on Circuits and Systems I*, 2023: 505-517.
8. T Pfeil. Six networks on a universal neuromorphic computing substrate. *Frontiers in Neuroscience*, 2023: 7: 11.
9. H Jiang. A PCM-based spiking neural network with stochastic synaptic behavior for in-memory computing. *Nature Electronics*, 2023; 6: 514-522.
10. M Diesmann, M Gewaltig. NEST: An environment for neural simulations. *Scholarpedia*, 2023; 4: 1430.