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Original Article: Neuromorphic computing in Next Gen IT systems

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ABSTRACT

Neuromorphic is by no means a new concept. Like many other emerging technologies that are now gaining momentum, neuromorphic has been quietly developing for a long time, but it still needs more work to shine. Neuromorphic systems attempt to mimic the functioning of the human nervous system. This branch of engineering attempts to mimic the biological structure of sensory and information-processing neural systems. In other words, neuromorphic computing implements various aspects of neurobiological networks in the form of analog and digital signals in electronic circuits. Neuromorphic computing has its roots in computational systems that were developed in the late 1980s and were designed to model the functioning of animal nervous systems. Since then, neuromorphic computing has gained momentum, to the point where some of the biggest names in technology have produced neuromorphic hardware. For example, IBM's TrueNorth chip, Intel's Loihi chip, and the Pohoiki Beach neuromorphic system are currently in production. Neuromorphics can do all of this without consuming a lot of energy, rather than leaving AI tasks to energy-hungry and cooling-intensive cloud systems. For neuromorphics to have a significant impact, there will need to be a lot of changes in the technology world. For example, sensor technologies are not designed to work well with neuromorphic systems and need to be redesigned to extract data in a way that can be processed by neuromorphic chips.

Introduction

As Most of today's hardware is built on a von Neumann architecture that separates memory and processing [1]. Since von Neumann chips must constantly move information between memory and the processor, a waste of time and energy occurs. This is the problem known as the "von Neumann bottleneck [2]." By embedding more transistors in these von Neumann processors, chip manufacturers have been able to increase the processing power of each chip over time and keep up with Moore's Law for a long time,

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but the problem is that transistors cannot be made smaller forever and at the same time meet their energy and thermal requirements. So a fundamental change in chips is needed.

As time goes on, the von Neumann architecture will face increasingly difficult problems in increasing the processing power we need. So in the near future, we need a new kind of von Neumann architecture [3]. Quantum computing and neuromorphic systems have both been proposed as possible solutions to the problem, but neuromorphic processing, inspired by the human brain, seems to be the one that will be available to the public sooner. In addition to the possibility of solving the von Neumann bottleneck problem, a neuromorphic computer could also use brain-based approaches to solve other problems [4].

Although von Neumann systems operate mainly in series, the brain has a highly parallel processing function. The error threshold in the brain is also much higher than in traditional computers, and researchers hope to be able to build neuromorphic systems that take advantage of exactly these two advantages.

A group of researchers at the Korea Advanced Institute of Science and Technology (KAIST) in South Korea has developed a memristor-based integrated chip that mimics the way the brain processes information [5].

The team, led by professors Shinhyun Choi and Young-Gyu Yoon, has developed a next-generation neuromorphic chip, an ultra-small semiconductor that learns and corrects errors independently.

The chip is now ready for deployment in a variety of devices, such as smart security cameras that instantly detect suspicious activity without relying on cloud servers, and medical devices that analyze and monitor health data in real time. Solving Challenges in Neuromorphic Devices Neuromorphic engineering, also known as “neuromorphic computing,” is a concept developed by Carver Mead in the late 1980s to refer to the use of very large scale integration (VLSI) systems containing electronic analog circuits to mimic (simulate) the neural and biological architecture found in the nervous system. The term neuromorphic is now used to describe analog, digital, mixed analog/digital systems, and software that model neural systems. Hardware-level implementation of neural computing can be realized with memristors and transistors [6].

A key aspect of neuromorphic engineering is understanding how the morphology of specific neurons, circuits, programs, and overall architectures affects how information is presented and how robust they are to damage, combining learning and development, and adapting to local changes (plasticity), facilitating evolutionary change. Now, this new computing chip stands out for its ability to learn and correct errors caused by non-ideal properties, which is a challenge in existing neuromorphic devices [7].

For example, when processing videos, it can automatically separate moving objects from the background and improve its performance over time. The self-learning chip has demonstrated its capabilities by achieving accuracy comparable to ideal computer simulations in real-time image processing. The research team's key success is in creating a system that is not only reliable but also functional, surpassing the development of individual brain-like components. The centerpiece of this innovation is a new generation semiconductor device called a memristor [8].

Its variable resistance properties mimic the role of synapses in neural networks, enabling simultaneous data storage and computation, much like how our brain cells function. The memristor precisely controls resistance changes, creating an efficient system that eliminates the need for complex compensation through self-learning. This study is important because it demonstrates the commercial potential of a next-generation neuromorphic system for real-time learning and inference [9].

Accelerating AI processing tasks in situ to improve speed

Memristor-based platforms can enable compact, low-power edge computing systems due to their ability to perform parallel computations in the analog realm. However, memristor array-based systems face challenges in implementing AI algorithms in real time with on-device learning due to reliability issues such as poor performance, poor uniformity, and endurance issues. The technology now aims to change the way AI is integrated into everyday devices and process AI tasks in situ (Figure 1).

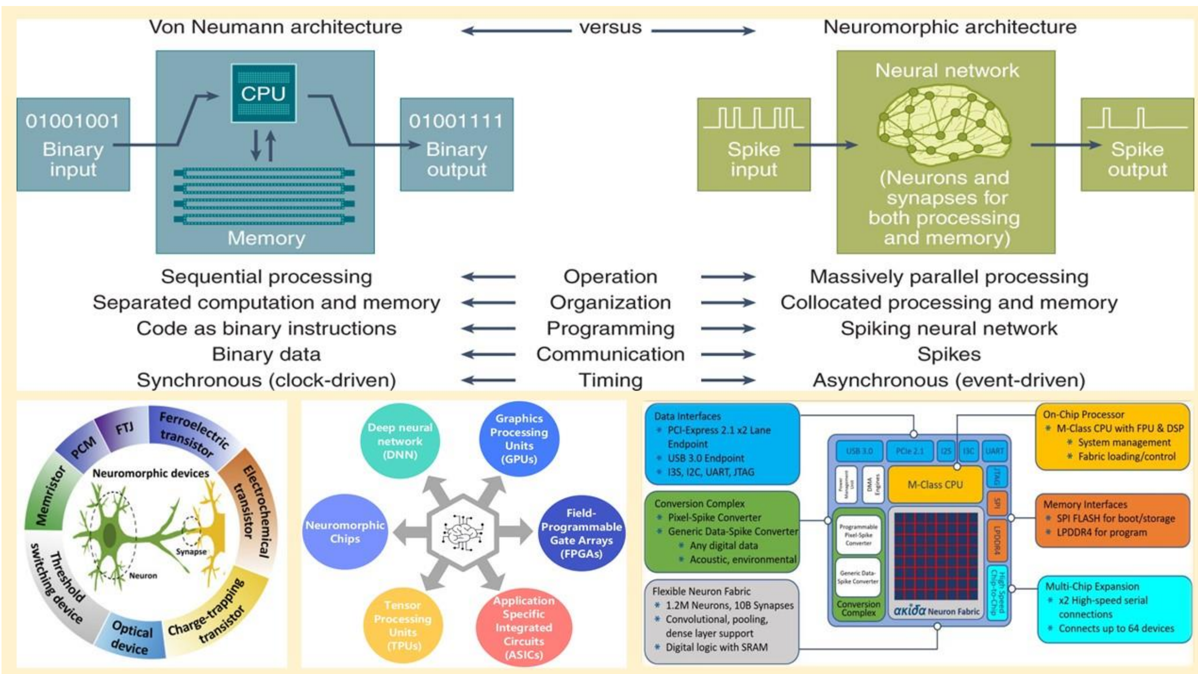

Figure 1. Neuromorphic computing in Next Gen IT systems

The study suggests that this reduces the reliance on remote cloud servers and makes devices faster, safer, and more efficient. The scientists wrote in their paper: "We use titanium oxide-based memristors with gradual oxygen distribution, which exhibit high reliability, high linearity, non-stacking, and self-healing properties [10]." The platform can run AI algorithms in the analog realm by "self-calibrating," without the need for compensation or pre-training. The system acts like a smart workspace, where everything is easily accessible, according to the researchers who led the development of the technology. The system also mirrors the way the brain processes information, where everything is efficiently brought together in a single place, the researchers said. The study was published in the journal Nature Electronics [11].

Intel's new chip in Hala Point

Intel has used the Loihi 2 processor as the beating heart of its neuromorphic computer, which is a significant upgrade over the company's previous generation of neuromorphic processors, Pohoiki Springs.

Hala Point consists of 1,152 Loihi 2 processors, all of which fit into a space the size of a microwave oven. The system then offers the computing power of 1.15 billion neurons and 128 billion synapses distributed across 140,544 processing cores [12].

The system also uses over 2,300 X86 processors for peripheral computing. Finally, it is explained that its maximum power consumption will be about 2,600 watts. The system can perform 20 quadrillion processing operations per second (20 peta operations per second, or 20 petaops). This neuronal capacity of Halla Point is roughly equivalent to the brain power of an owl or a small monkey. Neuromorphic computers are inspired by the functioning of the brain of living organisms and use artificial neural networks and synapses. Unlike traditional computers that rely on CPUs and GPUs for linear processing of information, neuromorphic computers have the ability to perform calculations and process data simultaneously [13].

“Sandia National Laboratories will explore the acceleration of demanding workloads that are constantly evolving by leveraging the fast, high-efficiency capabilities and adaptability of neuromorphic architecture,” said Mike Davies, director of Intel’s Neuromorphic Computing Laboratory, after the agreement was announced. “We look forward to a productive collaboration that will lead to the next generation of neural tools, algorithms, and systems that can scale to billion-neuron levels and beyond. [14]”

Accelerating AI processing tasks in situ to improve speed

Memristor-based platforms can enable compact, low-power edge computing systems due to their ability to perform parallel computations in the analog domain. However, memristor array-based systems face challenges in implementing AI algorithms in real time with machine learning due to reliability issues such as poor performance, poor uniformity, and endurance issues [15].

Now, this technology aims to change the way AI is integrated into everyday devices and process AI tasks in situ. The study suggests that this reduces the reliance on remote cloud servers and makes devices faster, safer, and more efficient [16].

The scientists write in their paper: “We use titanium oxide-based memristors with gradual oxygen distribution, which exhibit high reliability, high linearity, non-stacking, and self-healing properties. The platform can run AI algorithms in the analog domain through “self-calibration,” without the need for compensation or pre-training. According to the researchers who led the development of the technology, the system acts like a smart workspace where everything is easily accessible. According to the researchers, the system also mirrors the way the brain processes information, where everything is efficiently handled in a single place [17].

Advantages of using mersisters in neuromorphic chips

1- Very low power consumption: Memristors require very little power to change their resistance, which makes neuromorphic chips much more energy-efficient than conventional chips.

2- High speed: The resistance change in mersisters occurs very quickly, which makes neuromorphic chips have very high processing speed [18].

3- Learning and adaptability: Memristors can learn and adapt to new conditions, like synapses in the brain. This feature makes neuromorphic chips very suitable for artificial intelligence and machine learning applications.

4- Simultaneous storage and processing of information: In conventional computers, the processing and memory units are separate, which causes delays in information transfer, but in neuromorphic chips, mersisters can both store and process information, just like how the human brain works. This capability significantly increases the speed and efficiency of these chips [19].

Introducing a new neuromorphic chip

Researchers at the Korea Advanced Institute of Science and Technology (KAIST), led by Professor Shin-Hyun Choi and Professor Yang-Gyu Yoon from the School of Electrical Engineering, have succeeded in developing a new neuromorphic chip that is capable of learning and automatically correcting errors. This chip is the world's first integrated mersister-based system that can adapt to environmental changes [20].

Unique feature of the new chip: (Learning and automatically correcting errors)

One of the biggest challenges in the field of neuromorphic chips has been eliminating errors caused by the non-ideal characteristics of mersisters. A new chip from Korean researchers has effectively solved this problem with its ability to learn and automatically correct errors. For example, when processing a video, the chip learns to automatically separate a moving object from the background and gets better and better at doing so over time. This ability to learn automatically has been proven by achieving accuracy similar to ideal computer simulations in real-time image processing [21].

Introducing the latest technological achievements in the field of smart chips

At HiVert, we constantly follow the latest developments and technologies in the world and keep you informed of the most important events. The introduction of this new neuromorphic chip is one of the most important news in this field, and we at HiVert will fully examine this technology and its effects. Stay tuned with HiVert to learn the latest news and analysis related to this chip and other similar technologies [22].

On-Device AI and a Revolution in Smart Devices

The new neuromorphic chip has the potential to revolutionize On-Device AI due to its ultra-low power consumption and high processing speed. The chip can perform AI tasks locally without the need to connect to cloud servers. This increases the speed, security, and efficiency of smart devices [23].

Various applications of neuromorphic chips

1- Smart security cameras: This chip can be used in smart security cameras, allowing them to detect suspicious activities directly without having to send information to remote servers. This increases the speed of response and improves security. Korean researchers believe that this system is like a smart workspace where everything is available, while in previous systems you have to constantly move between desks and file cabinets.

2- Medical devices: The neuromorphic chip can be used in medical devices to analyze health data in real-time. For example, this chip can be used in a smart heart monitoring device to detect heart abnormalities and alert the doctor if necessary.

3- Robotics: This chip can be used in robots to create learning and decision-making abilities similar to the human brain. This could lead to the development of smarter, more autonomous robots.

4- Self-driving cars: Neuromorphic chips could be used in self-driving cars to process sensor data and make decisions in real time, helping to improve the safety and efficiency of these cars.

5- Internet of Things (IoT): These chips could be used in IoT devices to process information locally, reducing bandwidth consumption and increasing response speed [24].

How can this approach help improve AI technology?

The approach of modeling AI on the circuit and visual architecture of brain neurons could potentially lead to significant advances in AI technology. By mimicking the way, the brain processes information, AI systems could become more efficient, more adaptable, and capable of performing more complex tasks. This approach could also lead to the development of more advanced neural networks and machine learning algorithms that can learn and adapt in real time, similar to how the brain works. In addition, this approach may lead to the development of more human-like AI systems that can interact more naturally and effectively with people (Figure 2).

Furthermore, the brain is capable of processing information in parallel, whereas most current AI models are designed to process information sequentially. Another challenge is that the brain is still not fully understood. While researchers have made significant progress in understanding certain aspects of the brain, there is still much to learn about how it works at a fundamental level [25].

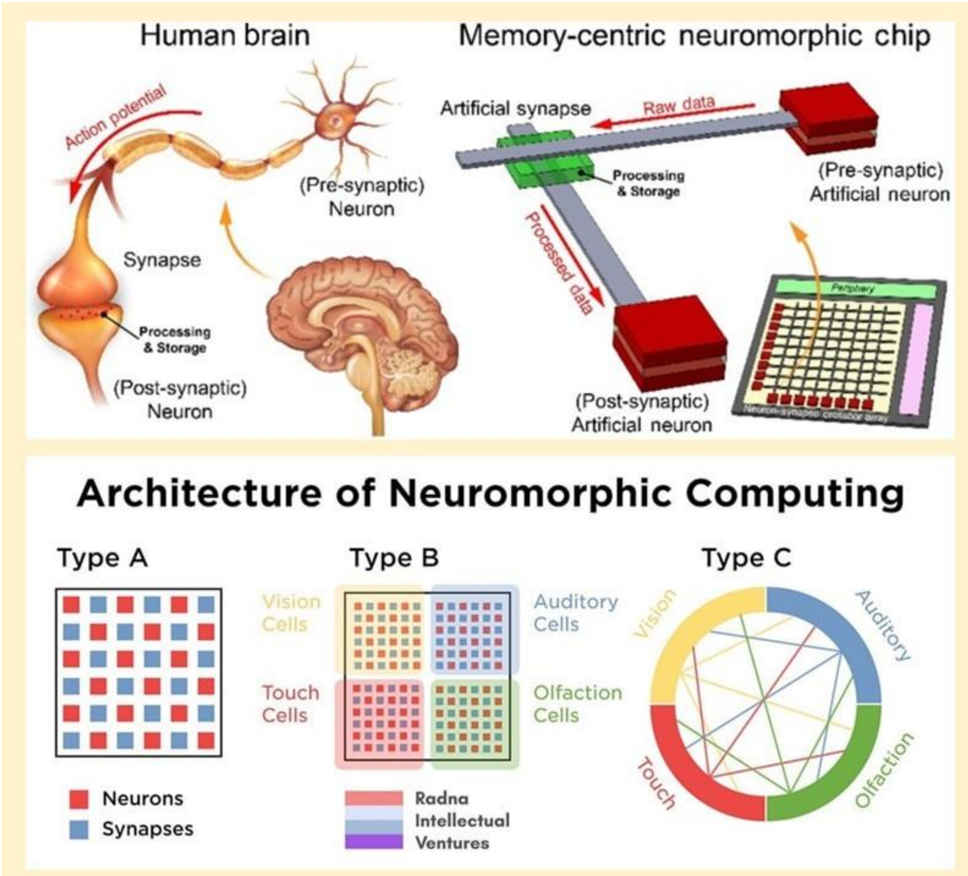

Figure 2. Memory-centric neuromorphic computing for unstructured data processing

This lack of understanding can make it difficult to create accurate models that mimic brain behavior. Finally, there are also technological limitations that researchers must overcome. For example, current computing power may not be sufficient to simulate the complexity of the brain in real time. In addition, collecting and analyzing data from the brain is a challenging and time-consuming process that can limit the amount of data available to researchers.

Are there potential ethical concerns associated with this type of research?

Yes, there may be potential ethical concerns associated with this type of research. The field of artificial intelligence and neuroscience raises questions about privacy, data protection, and the potential misuse of this technology. In particular, the use of artificial intelligence in modeling brain circuits and neural networks could lead to the creation of advanced brain-machine interfaces that could potentially be used for invasive purposes such as mind control or surveillance. Additionally, there may be concerns about the use of animal testing in this type of research. It is important for researchers to consider these ethical implications and ensure that their work is conducted in an ethical and responsible manner [26].

Benefits of using neuromorphic chips in smart devices

1- Higher speed: Local processing of information allows devices to operate at much higher speeds than cloud-based systems.

2- Greater security: Not having to send information to remote servers increases user security and privacy.

3- Lower power consumption: Neuromorphic chips are very suitable for use in portable and battery-powered devices due to their very low power consumption.

4- Better efficiency: Local processing of information allows devices to operate more efficiently and increase their battery life [27].

Neuromorphic Computing: The Future of Artificial Intelligence

Neuromorphic chips, and neuromorphic computing in general, are known as the future of artificial intelligence and machine learning. This emerging technology has the potential to revolutionize how computers and smart devices work.

Advantages of Neuromorphic Computing

1- Higher speed and efficiency: Neuromorphic chips can perform calculations much faster and more efficiently than conventional chips. This is especially important for processing large amounts of data in real-time, such as those required in machine vision and deep learning [28].

2- Lower power consumption: As mentioned earlier, neuromorphic chips have very low power consumption due to the use of mersisters and mimicking the function of the brain. This feature makes them ideal for use in portable and battery-powered devices such as smartphones, drones and robots.

3- Continuous learning and adaptation to the environment: Neuromorphic chips are capable of continuous learning and adaptation to the environment. This feature allows them to improve their performance over time and adapt to new conditions.

4- Parallel information processing: Neuromorphic chips can process information in parallel, just like the human brain. This capability will dramatically increase the speed of information processing on these chips [29].

Exploring Quantum Computing: The Potential of Qubits

Quantum computing has ushered in an exciting new reality in computer science and physics. The technology is built on the concept of qubits, the quantum counterpart of classical bits. In contrast to classical bits, which can only be in one state (0 or 1), qubits can exist in a superposition of both states at the same time. This property allows quantum computers to perform complex calculations much faster than classical computers. Through superposition, qubits can simultaneously represent multiple states, leading to parallel processing. For example, think of a coin being flipped in the air. Before it lands, it can be both heads and tails. Similarly, a qubit can represent both 0 and 1 at the same time, until it is measured, but another property that qubits have is called entanglement. When two qubits are entangled, their states are intrinsically linked to each other. In other words, changing the state of one qubit takes effect instantly, even if they are very far apart. This property makes secure communications and distributed computing possible [30].

Quantum Supremacy and Beyond

In 2019, Google achieved a major milestone known as quantum supremacy. Their quantum processor, called Sycamore, was able to solve a specific problem faster than the most advanced classical supercomputers. The achievement generated a lot of excitement, but challenges remained. Quantum computers are very sensitive to errors due to incoherence, which is the interference of the environment that disrupts the qubits. Researchers are currently working on error correction techniques to reduce incoherence and improve scalability. As quantum hardware advances, new applications are emerging. Quantum computers could revolutionize drug discovery by simulating molecular activities, solving complex logistical problems, and breaking classical encryption algorithms [31].

Neuromorphic chips: Mimicking the architecture of the brain

Neuromorphic chips closely mimic the complex structure of the human brain. These chips are designed to perform tasks inspired by the brain's function. The main goal of these chips is to replicate the function and adapt to the brain. Inspired by neural networks, these chips weave complex silicon synapses and connect to each other. The architecture of neuromorphic chips redefines the paradigm by integrating computing and memory into a single unit. This architecture differs from the traditional separation between central processing units (CPU) and graphics processing units (GPU). Unlike traditional CPUs and GPUs that use the von Neumann architecture, neuromorphic chips combine computing and memory. They process information locally, which leads to a significant increase in efficiency. Neuromorphic chips have an edge in artificial intelligence, performing calculations directly on devices and not needing to send data to external servers. For example, your smartphone can recognize faces, understand natural language, and even diagnose diseases without having to send data to external servers. Neuromorphic chips enable low-power AI to be performed in real-time at the edge. The NeuRRAM chip is a major step forward in neuromorphic technology. The chip emphasizes in-memory computing and energy efficiency. In addition, NeuRRAM also incorporates adaptability and is compatible with various neural network models. The chip supports this by ensuring its compatibility with various neural network models, including image recognition and voice processing. The NeuRRAM chip performs calculations directly in memory and consumes less power than traditional AI platforms. The chip bridges the gap between cloud-based AI and edge devices, making smartwatches, virtual reality headsets, and factory sensors more powerful [32].

Discussion

A recent Global Data conference predicted that neuromorphic computing would be the next key advancement after generative AI. Generative AI technology is one of the recent technological advances that has been made available to audiences through tools like ChatGPT. These platforms allow users to enter their questions and requests in plain language and receive a wide range of content in response, from computer code to full articles. NASA uses the technology to build spacecraft components, and Nvidia is pioneering its use in drug research and development. However, the scalability of this technology is limited. Because current AI tools consume large amounts of computing power while operating.

This means that servers processing requests are often placed in isolated environments due to the large space requirements, which leads to delays in response and also very high energy consumption, making it an expensive and environmentally harmful technology. One solution to these problems that has recently attracted the attention of experts is the move towards neuromorphic computing. Neuromorphic computing is a way to build computers that are modeled after the human brain. Building a computer system similar to the brain can increase the density of computing power, which means lower energy costs and much less storage space [33].

The human brain constantly consumes about 12 watts of power, which is several times less than the 60 watts required by a laptop. The brain is also able to respond instantly to stimuli and expand and reorganize connections between neurons when exposed to new information.

This type of computing will not necessarily be useful for the same productive AI applications as it was in the beginning [34].

Global Data sees neuromorphic computing as performing human-like tasks, such as facilitating the connection between artificial limbs and the human brain, enhancing the driving of self-driving cars, and improving customer service. The technology is likely to be more widely integrated with generative AI and neural networks in the long term, allowing AI models to learn faster and consume less energy. Whether or not the technology is integrated with generative AI, experts say, there is no doubt that neuromorphic computing will be a key factor in shaping the future of technology (Figure 3).

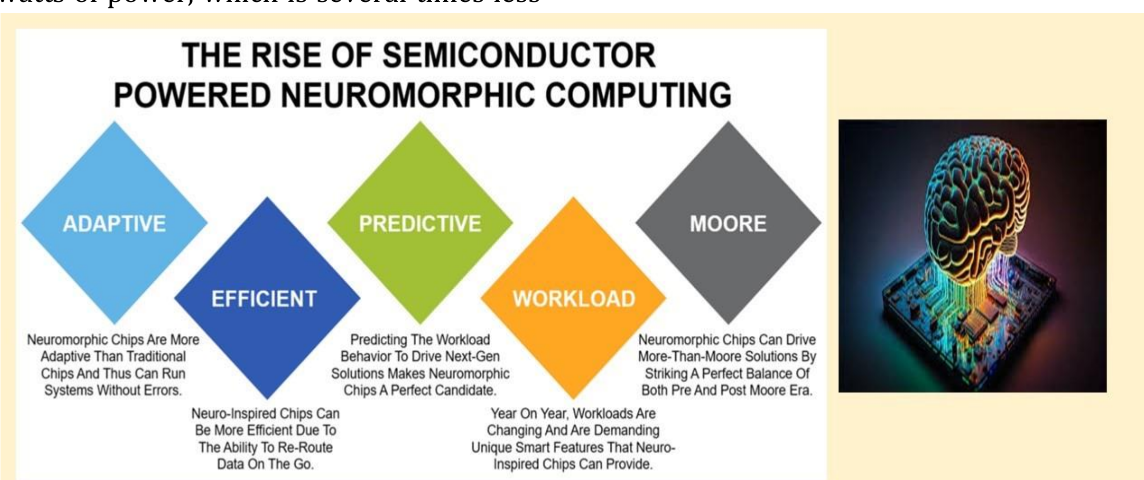

Figure 3. Neuromorphic Computing and Hyper-Realistic Generative AI

Beyond Quantum and Neuromorphic: Additional Trends and Technologies

As we move forward in the field of AI, several technologies and trends are emerging that provide new opportunities for integration into our daily lives. Custom chatbots are used as an example of new developments in the world of AI in today's world. These chatbots allow for customization by people without extensive programming experience. Using simple platforms, users can focus on defining conversation flows and training models. These chatbots use multi-modal capabilities to engage in more complex conversations. For example, imagine a fictional real estate agent chatbot that combines responses with images and videos to enhance the user experience. The desire to use small, powerful AI models has led to the emergence of a phenomenon called “micro AI” or “micro machine learning. [35]”

Recent efforts have focused on miniaturizing deep learning architectures without sacrificing performance. The goal of this shift is to promote local processing on edge devices such as smartphones, wearables, and IoT sensors. This shift removes dependency on cloud servers, preserves privacy, reduces latency, and saves energy. For example, a wearable health monitoring device prioritizes user privacy by processing sensitive data on the device and analyzing vital signs in real time. Similarly, an emerging approach called “federated learning” allows AI models to be trained on decentralized devices while keeping the raw data local.

This approach ensures privacy without compromising the quality of the AI models. It also plays a key role in expanding the adoption of AI in various domains and promoting sustainability, with the advancement of federated learning. In the field of energy efficiency, battery-free IoT sensors have revolutionized AI applications for IoT devices. These sensors operate without the need for traditional batteries by utilizing energy harvesting techniques from environmental sources such as solar energy or motion. Decentralized network coverage is also emerging as a key trend that enables the uptake and accessibility of AI services in remote locations [36].

Through mesh networks, satellite communications, and decentralized infrastructure, these networks ensure that AI is accessible to any part of the world. This helps bridge the digital divide and increase the accessibility of AI in different societies, increasing its impact.

Conclusion

So the next generation of micro-AI, influenced by quantum computing, neuromorphic chips, and emerging trends, holds promise for a transformation of the technology. These advances show that combining quantum computing and neuromorphic chips is a game-changer. While challenges remain, the collaborative efforts of researchers, engineers, and industry leaders are paving the way for a future full of possibilities where micro-AI will push boundaries and usher in a new era of possibilities.

Traditional computers process information linearly. They rely on central processing units (CPUs) and graphics processing units (GPUs). Neuromorphic computers, on the other hand, are inspired by how the human brain works. They use artificial neural networks and synapses, similar to the biological brain. This structure helps neuromorphic computers process many calculations simultaneously. The device is capable of processing up to 20 quadrillion operations per second while maintaining remarkable energy efficiency. This rate rivals the power of some of the world's fastest supercomputers. With this processing power, HallaPoint can perform complex AI tasks at exceptional speed, while consuming a maximum of 2,600 watts of power. According to Intel, HallaPoint can deliver unprecedented speed and efficiency thanks to this massively parallel processing. Loya 2 is Intel's most powerful neuromorphic processor, representing a significant upgrade over its predecessor, Pohoiki Springs.

The system packs 1,152 Loihi 2 processors into a space the size of a microwave oven. It can then support up to 1.15 billion artificial neurons and 128 billion synapses. That’s roughly equivalent to the brainpower of an owl or a small monkey. "HolaPoint combines the efficiency of deep learning with novel brain-inspired learning and optimization capabilities," Davis said. "We hope that research with HolaPoint will advance the efficiency and adaptability of large-scale AI technology."

Initially, researchers at Sandia National Laboratories plan to use HolaPoint for advanced scientific computing tasks in fields such as device physics, computer architecture and computer science. "Working with HolaPoint will improve our team's ability to solve computational and scientific modeling problems," said David Davis, the lead author of the HolaPoint team at Sandia National Laboratories. Conducting research with a system of this size allows us to keep pace with the evolution of AI in various fields. HalaPoint is currently in its early stages and is not a consumer product. However, it represents a leap forward in AI research. This research prototype will influence the next generation of neuromorphic computing systems.

References

[1] Amershi, S.; Cakmak, M.; Knox, W.B.; Kulesza, T. Power to the people: The role of humans in interactive machine learning. AI Mag. 2014, 35, 105–120.

[2] Rong, G.; Mendez, A.; Assi, E.B.; Zhao, B.; Sawan, M. Artificial Intelligence in Healthcare: Review and Prediction Case Studies. Engineering 2020, 6, 291–301.

[3] Bai, Y.; Wu, H.; Wu, R.; Zhang, Y.; Deng, N.; Yu, Z.; Qian, H. Study of Multi-level Characteristics for 3D Vertical Resistive Switching Memory. Sci. Rep. 2014, 4.

[4] Xu, C.; Niu, D.; Muralimanohar, N.; Jouppi, N.P.; Xie, Y. Understanding the trade-offs in multi-level cell ReRAM memory design. In Proceedings of the 50th ACM/EDAC/IEEE Design Automation Conference (DAC), Austin, TX, USA, 29 May–7 June 2013; pp. 1–6.

[5] Ramadan, M.; Wainstein, N.; Ginosar, R.; Kvatinsky, S. Adaptive programming in multi-level cell ReRAM. Microelectron. J. 2019, 90, 169–180.

[6] Niu, D.; Zou, Q.; Xu, C.; Xie, Y. Low power multi-level-cell resistive memory design with incomplete data mapping. In Proceedings of the 2013 IEEE 31st International Conference on Computer Design (ICCD), Asheville, NC, USA, 6–9 October 2013; pp. 131–137.

[7] Puglisi, F.M.; Larcher, L.; Bersuker, G.; Padovani, A.; Pavan, P. An empirical model for RRAM resistance in low-and high-resistance states. IEEE Electron Device Lett. 2013, 34, 387–389.

[8] Park, J.; Zheng, T.; Erez, M.; Orshansky, M. Variation-Tolerant Write Completion Circuit for Variable-Energy Write STT-RAM Architecture. IEEE Trans. Large Scale Integr. (VLSI) Syst. 2016, 24, 1351–1360.

[9] Nigam, A.; Smullen, C.W.; Mohan, V.; Chen, E.; Gurumurthi, S.; Stan, M.R. Delivering on the promise of universal memory for spin-transfer torque RAM (STT-RAM). In Proceedings of the IEEE/ACM International Symposium on Low Power Electronics and Design, Fukuoka, Japan, 1–3 August 2011; pp. 121–126.

[10] Hong, S.; Auciello, O.; Wouters, D. Emerging Non-Volatile Memories; Springer: Berlin/Heidelberg, Germany, 2014.

[11] Dong, X.; Wu, X.; Sun, G.; Xie, Y.; Li, H.; Chen, Y. Circuit and microarchitecture evaluation of 3D stacking magnetic RAM (MRAM) as a universal memory replacement. In Proceedings of the 45th ACM/IEEE Design Automation Conference, Anaheim, CA, USA, 8–13 June 2008; pp. 554–559.

[12] Freitas, R.F.; Wilcke, W.W. Storage-class memory: The next storage system technology. IBM J. Res. Dev. 2008, 52, 439–447.

[13] Kim, W.; Jeong, J.; Kim, Y.; Lim, W.; Kim, J.; Park, J.; Shin, H.; Park, Y.; Kim, K.; Park, S.; et al. Extended scalability of perpendicular STT-MRAM towards sub-20nm

MTJ node. In Proceedings of the 2011 International Electron Devices Meeting, Washington, DC, USA, 5–7 December 2011; p. 24.

[14] Jain, S.; Ranjan, A.; Roy, K.; Raghunathan, A. Computing in Memory With Spin-Transfer Torque Magnetic RAM. IEEE Trans. Large Scale Integr. (VLSI) Syst. 2018, 26, 470–483.

[15] Kazemi, M. An electrically reconfigurable logic gate intrinsically enabled by spin-orbit materials. Sci. Rep. 2017, 7.

[16] Gilbert, T. Anomalous rotational damping in ferromagnetic sheets. In Proceedings of the Conference on Magnetism and Magnetic Materials, Pittsburgh, PA, USA, 14–16 June 1955.

[17] Park, J.; Yim, Y.U. Two-Phase Read Strategy for Low Energy Variation-Tolerant STT-RAM. IEEE Trans. Large Scale Integr. (VLSI) Syst. 2018, 26, 2584–2590.

[18] Ohno, T.; Hasegawa, T.; Tsuruoka, T.; Terabe, K.; Gimzewski, J.K.; Aono, M. Short-term plasticity and long-term potentiation mimicked in single inorganic synapses. Nat. Mater. 2011, 10, 591–595.

[19] Manning, H.G.; Niosi, F.; da Rocha, C.G.; Bellew, A.T.; O'Callaghan, C.; Biswas, S.; Flowers, P.F.; Wiley, B.J.; Holmes, J.D.; Ferreira, M.S.; et al. Emergence of winner-takes-all connectivity paths in random nanowire networks. Nat. Commun. 2018, 9, 1–9.

[20] Du, C.; Cai, F.; Zidan, M.A.; Ma, W.; Lee, S.H.; Lu, W.D. Reservoir computing using dynamic memristors for temporal information processing. Nat. Commun. 2017, 8, 1–10.

[21] Bose, S.; Shirai, S.; Mallinson, J.; Brown, S. Synaptic dynamics in complex self-assembled nanoparticle networks. Faraday Discuss. 2019, 213, 471–485.

[22] Diaz-Alvarez, A.; Higuchi, R.; Sanz-Leon, P.; Marcus, I.; Shingaya, Y.; Stieg, A.Z.; Gimzewski, J.K.; Kuncic, Z.; Nakayama, T. Emergent dynamics of neuromorphic nanowire networks. Sci. Rep. 2019, 9, 1–13.

[23] Stieg, A.Z.; Avizienis, A.V.; Sillin, H.O.; Martin-Olmos, C.; Aono, M.; Gimzewski, J.K. Emergent criticality in complex turing B-type atomic switch networks. Adv. Mater. 2012, 24, 286–293.

[24] Mittal, S. A Survey of Techniques for Approximate Computing. ACM Comput. Surv. 2016, 48, 1–33.

[25] Sampson, A.; Nelson, J.; Strauss, K.; Ceze, L. Approximate storage in solid-state memories. In Proceedings of the 46th Annual IEEE/ACM International Symposium on Microarchitecture (MICRO), Davis, CA, USA, 7–11 December 2013; pp. 25–36.

[26] Han, J.; Orshansky, M. Approximate computing: An emerging paradigm for energy-efficient design. In Proceedings of the 18th IEEE European Test Symposium (ETS), Avignon, France, 27–30 May 2013; pp. 1–6.

[27] Akturk, I.; Khatamifard, K.; Karpuzcu, U.R. On quantification of accuracy loss in approximate computing. In Proceedings of the Workshop on Duplicating, Deconstructing and Debunking (WDDD), Portland, PA, USA, 14 June 2015; Volume 15.

[28] Park, J.; Yim, Y.U. Fine-Grained Power Gating Using an MRAM-CMOS Non-Volatile Flip-Flop. Micromachines 2019, 10, 411.

[29] Paliaroutis, G.I.; Tsoumanis, P.; Evmorfopoulos, N.; Dimitriou, G.; Stamoulis, G.I. Set Pulse Characterization and SER Estimation in Combinational Logic with Placement and Multiple Transient Faults Considerations. Technologies 2020, 8, 5.

[30] Jang, S.; Park, J. HYFII: HYbrid Fault Injection Infrastructure for Accurate Runtime System Failure Analysis. IEEE Trans. Large Scale Integr. (VLSI) Syst. 2020.

[31] Yan, H.; Ding, Y.; Li, P.; Wang, Q.; Xu, Y.; Zuo, W. Mind the class weight bias: Weighted maximum mean discrepancy for unsupervised domain adaptation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2017,

Honolulu, HI, USA, 21–26 July 2017; pp. 2272–2281.

[32] Long, M.; Zhu, H.; Wang, J.; Jordan, M.I. Deep transfer learning with joint adaptation networks. In Proceedings of the International Conference on Machine Learning, PMLR, Sydney, Australia, 6–11 August 2017; pp. 2208–2217.

[33] Saito, K.; Ushiku, Y.; Harada, T.; Saenko, K. Strong-weak distribution alignment for adaptive object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Long Beach, CA, USA, 16–20 June 2019; pp. 6956–6965.

[34] Chen, Y.; Li, W.; Sakaridis, C.; Dai, D.; Van Gool, L. Domain adaptive faster r-cnn for object detection in the wild. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–22 June 2018; pp. 3339–3348.

[35] Ganin, Y.; Lempitsky, V. Unsupervised domain adaptation by backpropagation. In Proceedings of the International Conference on Machine Learning, Lille, France, 6–11 July 2015; pp. 1180–1189.

[36] Kim, T.; Jeong, M.; Kim, S.; Choi, S.; Kim, C. Diversify and match: A domain adaptive representation learning paradigm for object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Long Beach, CA, USA, 16–20 June 2019; pp. 12456–12465.