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Photonic neuromorphic computing: from device classification to system reality

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Abstract: Integrated photonic neural networks promise to relieve the bandwidth, latency and energy limits of electronic artificial-intelligence hardware by computing directly with light. In a recent review, Han, Shen, Gu and Zhang organize the field around photonic synapses, neurons and memristors, and map these devices onto coherent, wavelength-parallel, diffractive and reservoir-computing architectures. This News & Views argues that the review is most valuable when read as both a device classification and a reminder that practical neuromorphic photonics must be judged at full-system scale.

Keywords: neuromorphics photonics; integrated photonics

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Artificial intelligence has made computation a central technological resource, but also a major energy and bandwidth challenge. In conventional von Neumann processors, memory and arithmetic are physically separated. Modern neural networks therefore spend a large fraction of their energy and time moving weights and activations between memory banks, interconnects and arithmetic units, rather than performing the multiply-accumulate operations themselves. This widening mismatch between compute capability and memory/interconnect bandwidth is the so-called memory wall: the data needed by the processor cannot be supplied, retrieved or updated fast enough, or cheaply enough, to exploit the available arithmetic throughput. Photonic neuromorphic computing offers a different paradigm: let light propagate, interfere, resonate and be absorbed in structures that naturally perform weighted addition, filtering, nonlinear transformation and memory. The review by Han et al. gives a clear blueprint for this expanding field. It organizes integrated photonic neural networks around three essential building blocks—synapses, neurons and memristors, and then connects them to coherent, wavelength-parallel, diffractive and reservoir-computing architectures[1].

The classification is useful because photonic neuromorphic computing is not a single architecture. A coherent Mach-Zehnder-interferometer mesh is well suited to programmable linear algebra, but usually requires careful phase calibration and separate nonlinear stages[2]. A microring-resonator weight bank is much more compact and naturally compatible with wavelength-division multiplexing (WDM), allowing several weighted optical channels to share a bus waveguide[3]. A diffractive optical neural network performs transformations through propagation and wavefront shaping, while a reservoir computer uses a fixed nonlinear dynamical substrate and trains only the readout. No single benchmark can evaluate these options, which solve different compromises between programmability, footprint, latency, training cost and physical memory.

Han et al. thus highlight a central lesson: no single photonic element can solve the problem alone. High-bandwidth propagation is essential, but nonlinear activation, memory and learning arise from light–matter interaction; therefore, optical routing, material states, electronic control and algorithms must be co-designed within the same physical constraints.

Memory is the place where this co-design becomes

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unavoidable. A recent review by Foradori and co-workers for Rivista del Nuovo Cimento[4] argues that memory in integrated photonic neural networks should be treated along two complementary axes. Structural, non-volatile memory stores long-lived parameters, for example in programmed phase shifters, charge-trapping elements, ferroelectrics or phase-change materials. Dynamic, volatile memory stores recent history in physical state variables such as resonator photon lifetime, propagation delay, free-carrier density, temperature, gain recovery or feedback loops. This distinction mirrors, without copying, the biological separation between long-lived synaptic efficacy and short-lived membrane or network states. It also clarifies why photonic neural networks are especially attractive for time-dependent tasks: the fading memory needed for temporal processing can be supplied by the substrate itself, while non-volatile elements can hold weights or slowly evolving plasticity.

Silicon microring resonators provide an instructive example of the transition from passive component to neuromorphic primitive[5]. In small-signal operation, a ring is a wavelength-selective filter. At high intracavity intensity, however, it becomes a nonlinear dynamical system. Two-photon absorption generates free carriers. Free-carrier dispersion shifts the resonance to shorter wavelengths on a nanosecond scale, while carrier recombination and absorption heat the silicon lattice. Through the thermo-optic effect, this heating shifts the resonance to longer wavelengths on tens of nanoseconds. The two effects compete, producing integration, self-pulsing and recovery dynamics that can be exploited as neuron-like behavior[6].

In computational terms, this means that a single resonator can combine thresholding, temporal integration and a refractory-like recovery time. The state of the device is not stored in a register, but in photons, carriers and heat. That is why microring networks are attractive for photonic spiking and reservoir computing: the device physics already contains fading memory and nonlinear transformation, two functions that would otherwise be emulated digitally. Recent work on passive silicon microrings has used this physics for all-optical spiking processing and reservoir computing[6], while self-pulsing microresonator networks have been explored as reservoirs with non-fading optical memory[7].

This observation also changes the evaluation of the field. If an optical neural network is treated only as an analogue copy of a digital artificial neural network, it must compete with GPUs and TPUs on their strongest terrain: large, well-conditioned, highly programmable matrix operations and mature software. By contrast, if light-matter dynamics are used as the computational resource, photonic systems can target tasks that are naturally optical, temporal and latency critical. Examples include signal equalization in optical links, event detection in photonic sensors, ultrafast diagnostics and front-end processing in which full-rate digitization is already the bottleneck.

The system-level caution is essential. Skalli and Brunner recently emphasized that impressive component demonstrations do not automatically translate into useful accelerators[8]. Current integrated optical matrix-vector-multiplication (MVM) engines are much smaller than the matrices used in state-of-the-art neural networks. Tiling an $N\times N$ layer into $L\times L$ optical blocks requires $(N/L)^2$ smaller operations, each accompanied by optical-electrical and analogue-digital conversions. The apparent optical advantage can therefore be eroded by interfaces, drivers, detectors, stabilization and calibration. Likewise, terahertz optical bandwidth has little application value if the data are injected by electronic buses and modulators that cannot scale accordingly.

For resonant architectures this warning is particularly relevant. High-Q resonators can offer strong nonlinear response and compact footprints, but large arrays face resonance drift, temperature gradients, fabrication variability and crosstalk. The overhead needed to tune and stabilize each element may dominate the energy budget if it is not included from the start. Training is another hidden cost: if every physical state must be recorded digitally for backpropagation, the memory wall reappears during training even if inference is optical. Hardware-native learning, local plasticity and readout-only training are therefore not optional details; they are part of the architecture.

The way forward is to separate two goals. For general-purpose acceleration, the field needs larger native optical MVM engines, high-bandwidth electronic-photonic interfaces, and benchmarks that count lasers, drivers, converters, photodetectors, thermal control and calibration. For physical neuromorphic processors, the target should be different: exploit nonlinear optical dynamics, wave interference and material memory, then train the readout or local update rules around those dynamics. This is the logic behind reservoir computing, photonic spiking processors and PCM-assisted in-memory photonic systems.

The importance of the Han et al. review[1] is therefore not only that it lists photonic synapses, neurons and memristors. It shows how these devices are beginning to form an ecosystem. The next step is to connect that ecosystem to realistic workloads, honest energy accounting and application-specific metrics. The most persuasive photonic brains may not be those that most closely imitate digital AI, but those that use photons, resonances and material states to compute in a way electronics would not naturally choose.

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