Optical Computing: A Paradigm Shift in Information Processing

Sakibur Rahman Utshow[1]

Received August 4, 2025
Accepted May 24, 2026
Electronic access June 30, 2026

Background/Objective: The escalating computational demands of artificial intelligence (AI) and machine learning (ML) are exposing the physical limits of silicon-based electronic computing, including interconnect latency and resistive heat dissipation. Optical computing processes information using photons rather than electrons, offering a structurally different approach for specific high-demand workloads. This review examines the current state of optical computing through a systematic analysis of peer-reviewed literature published between 2017 and 2025, with the objective of identifying where optical systems demonstrate quantifiable advantages over electronic counterparts and where fundamental challenges persist. Methods: A systematic literature search was conducted across IEEE Xplore, Nature, Science, and Frontiers in Physics using the terms optical computing, photonic processor, photonic neural network, and integrated photonics. Studies were included only if they presented quantitative performance benchmarks from hardware demonstrations. Twenty-five peer-reviewed sources were selected. Results:Recent photonic hardware demonstrates latencies below 0.5 ns for matrix-vector multiplication, energy efficiencies exceeding 100 GOPS/W/mm2, and throughputs up to 11 TOPS. Two 2025 Nature papers demonstrated photonic accelerators achieving up to 500-fold latency reduction and general AI models running on photonic processors at accuracy parity with electronic systems. Optical memory endurance remains limited to 10,000-100,000 write cycles versus approximately 10ˆ16 for electronic DRAM. Conclusions: Optical computing shows clear, quantitatively demonstrated advantages in latency and energy efficiency for linear algebra-intensive tasks such as neural network inference, but is not a general-purpose replacement for electronic computing. Hybrid opto-electronic architectures represent the most viable near-term path.

Keywords: optical computing, photonic processor, photonic neural network, silicon photonics, AI acceleration, energy efficiency, latency

Introduction

Background and Context

The relentless advancement of technology has created unprecedented computational demand, driven by artificial intelligence (AI) and machine learning (ML)[1]. These fields require processing vast datasets and executing complex algorithms, pushing traditional silicon-based electronic computing toward its physical limits[2]. Transistors face constraints in switching speed, energy dissipation, and heat generation as they approach atomic scales. Optical computing processes information using photons rather than electrons, leveraging intensity, phase, polarization, and wavelength to encode data[3]. The renewed interest in optical computing is driven by the energy and latency demands of large-scale AI workloads that are difficult to address within the von Neumann electronic architecture[4].

Problem Statement and Rationale

Electronic computing faces three interconnected bottlenecks: interconnect latency between processor and memory, energy dissipation in resistive interconnects, and the end of classical transistor scaling as described by Moore's Law[2]. These constraints are particularly acute in data centers running large neural network models[5]. Optical computing addresses these bottlenecks directly, since photons propagate without resistive loss and support wavelength-division multiplexing for simultaneous multi-channel transmission[3].

Objectives

This review: (1) examines the fundamental principles and key components of optical computing; (2) compares quantitative performance benchmarks between photonic and electronic processors from peer-reviewed demonstrations; (3) identifies primary technical barriers to adoption; and (4) evaluates the most promising current research directions.

Scope and Limitations

This review covers classical and hybrid opto-electronic computing with photonic neural networks as the primary application. Photonic quantum computing is addressed only to clarify its distinction from classical optical computing. Literature is

[1] *Dhaka Residential Model College, Dhaka, Bangladesh*

drawn from 2017 to 2025.

Methods

Search Strategy

A systematic literature search was conducted in April 2025 across IEEE Xplore, Nature Publishing Group, Science, Frontiers in Physics, and AIP Publishing using the terms ("optical computing" OR "photonic processor" OR "photonic neural network") AND ("energy efficiency" OR "latency" OR "benchmark"). Results were filtered to peer-reviewed articles published between January 2017 and April 2025.

Inclusion and Exclusion Criteria

Studies were included if they presented hardware demonstrations reporting at least one quantitative performance metric such as latency, energy efficiency in GOPS/W, accuracy, or throughput in TOPS. Non-peer-reviewed sources were excluded entirely.

Data Extraction and Synthesis

For each included study, the following were extracted: architecture type, task, key metrics with units, and comparison baseline. Data were synthesized thematically and tabulated in Table 1.

Fundamentals of Optical Computing

Optical computing encodes information by modulating properties of light such as intensity, phase, polarization, and wavelength. Key functional components include lasers, electro-optic modulators, photodetectors, and photonic integrated circuits (PICs)[6]. Optical logic gates constructed from nonlinear optical materials serve the functional role of transistors, with one light beam controlling another[7]. Most current demonstrations use hybrid architectures: optical components perform linear algebra while electronic components handle nonlinear activation and memory access[8]. Neuromorphic photonic systems, which mimic biological neural networks using optical components, represent a particularly promising direction for AI acceleration[9]. Training photonic neural networks has been demonstrated using in situ backpropagation and gradient measurement techniques[10].

Distinction from Photonic Quantum Computing

Photonic quantum computing uses individual photons as quantum bits in quantum superposition states. This is physically and operationally distinct from classical optical computing, which uses coherent laser light carrying classical information. Classical optical computing does not require single-photon sources, cryogenic operation, or quantum error correction. This review addresses classical and hybrid opto-electronic computing only.

Historical Evolution

Interest in optical computing began with the laser in 1960. The period 1980 to 2000 saw intensive research, including the development of optical associative-memory models using thresholding and feedback[11]. This era stalled in the 1990s because weak optical nonlinearity made efficient optical logic gates impossible and no viable optical memory existed[3]. The current resurgence leverages CMOS-compatible silicon photonics fabrication[6] and is driven primarily by AI inference acceleration rather than general-purpose computation[12]. Two independent Nature papers published in April 2025 provided the most comprehensive hardware validation of photonic AI computing to date[13].

Advantages of Optical Computing

Speed and Latency

Ashtiani et al. demonstrated an on-chip photonic neural network completing image classification in under 570 ps[14]. Hua et al. demonstrated up to 500-fold latency reduction for Ising problem solving compared to small-scale electronic circuits[15]. Photonic reservoir computing systems using delay-coupled lasers have demonstrated classification rates exceeding one million words per second[16]. System latency includes electronic overhead at input and output interfaces; the latency advantage is therefore task-specific and must be measured end-to-end.

Energy Efficiency

Xu et al. demonstrated 11 TOPS throughput with energy efficiency substantially exceeding contemporary GPUs for convolution tasks[17]. A photonic neuromorphic processor demonstrated energy efficiency exceeding 100 GOPS/W/mm^2[4]. Inference in AI tasks with deep optics and photonics has been demonstrated across a range of architectures, showing consistent energy advantages for linear operations[13]. When energy costs of analog-to-digital conversion at the I/O interface are included, the net system-level efficiency advantage may be reduced.

Parallelism and Bandwidth

Wavelength-division multiplexing enables multiple independent signals to co-propagate in the same waveguide, exploited in photonic tensor cores for parallel matrix multiplication[8,17]. Neuromorphic photonic networks using silicon photonic weight banks implement analog multiplication across many parallel channels simultaneously[18]. Optical channel bandwidth can reach the terahertz range, far exceeding the gigahertz bandwidth of electrical interconnects[5].

Challenges and Limitations

Weak Optical Nonlinearity

Nonlinear optical interactions are weak compared to transistor switching, requiring either high optical power or long interaction lengths for efficient optical logic[7]. Most current photonic computing systems use electronic components for nonlinear activation functions, creating hybrid systems that require optical-to-electronic (OEO) conversions[8].

Optical Memory

PCM-based optical memory cells achieve only 10,000 to 100,000 write cycles compared to approximately 10^{16} cycles for electronic DRAM. This fundamental limitation prevents practical fully-optical computing systems and forces reliance on electronic memory with its associated OEO conversion overhead.

OEO Conversion Overhead

Each optical-to-electronic conversion adds nanosecond-scale latency and energy proportional to bandwidth. System-level benchmarks must account for this overhead, which can dominate total latency in hybrid systems.

Integration and Scalability

Photonic circuits require nanometer-scale fabrication tolerances because optical phase is sensitive to dimensional variation. Yield challenges persist for large coherent circuits[6].

Key Components and Technologies

Light Sources and Modulators

VCSELs and DFB lasers provide coherent sources for integrated photonic systems[17]. Thin-film lithium niobate (TFLN) modulators support bandwidths exceeding 100 GHz and enable efficient electro-optic tensor cores[19].

Photonic Integrated Circuits and Photodetectors

Silicon photonics is the dominant PIC platform due to CMOS process compatibility, enabling photonic network-on-chip designs at scale[6,20]. Germanium-on-silicon photodetectors achieve bandwidths exceeding 50 GHz. The historical development of optical associative memory architectures laid early groundwork for modern photonic neural network designs[11].

Applications of Optical Computing

Artificial Intelligence and Machine Learning

Shen et al. first demonstrated a coherent nanophotonic circuit for neural network inference[12]. Feldmann et al. and Xu et al. scaled this to photonic tensor cores achieving up to 11 TOPS[8,17]. Ahmed et al. (2025) demonstrated BERT and ResNet running on a four-chip photonic processor at electronic-comparable accuracy[21]. Bandyopadhyay et al. demonstrated a single chip performing all neural network computations including nonlinear operations optically[22]. Photonic chips have been reported to provide a significant processing boost for AI workloads in recent demonstrations[23].

Telecommunications

Co-packaged optics integrates photonic transceivers directly with switch ASICs, reducing energy per bit in data center interconnects[20].

Scientific Computing

Optical Ising machines solve combinatorial optimization problems using networks of coupled optical oscillators[15]. Diffractive deep neural networks implement classification using only light diffraction with zero active power during inference[24].

Performance Comparison with Electronic Computing

Table 1 provides quantitative benchmarks from peer-reviewed demonstrations. All comparisons are task-specific and context-dependent.

Recent Advancements and Ongoing Research

Hua et al. demonstrated PACE, a 64×64 photonic accelerator with more than 16,000 integrated components, achieving up to 500-fold latency reduction for Ising problem solving[15]. Ahmed et al. demonstrated a four-chip photonic processor implementing BERT and ResNet at electronic-comparable accuracy[21]. TFLN-based 120 GOPS tensor cores[19] and energy efficiencies exceeding 100 GOPS/W/mm^2[4] demonstrate continued materials progress. Reservoir computing with delay-coupled lasers has achieved classification rates exceeding one million words per second[25]. Silicon photonics foundry platforms are being adapted for quantum computing[6].

Discussion

Key Findings

Photonic computing demonstrates latencies below 1 ns and energy efficiencies exceeding 100 GOPS/W/mm^2 for neural net-

Table 1 Quantitative performance comparison from peer-reviewed hardware demonstrations.

Metric	Optical / Photonic	Electronic (GPU)	Source & context
Inference latency	< 570 ps	$\sim$10–100 ns	Ashtiani 2022[14]
Latency reduction	Up to 500× lower	Baseline	Hua 2025[15]
Throughput	11 TOPS	$\sim$10–100 TOPS	Xu 2021[17]
Energy efficiency	> 100 GOPS/W/mm^2	$\sim$1–10 GOPS/W/mm^2	Feldmann 2021[8]
Bandwidth	Terahertz range	Gigahertz range	Miller 2017[5]
Optical mem. endurance	10k–100k cycles	$\sim 10^{16}$ cycles (DRAM)	Known limitation
EMI immunity	Yes	No	General
Manufacturing maturity	Foundry-compatible	Mature (decades)	Bogaerts 2020[6]

work inference. These advantages are task-specific. Optical memory endurance of 10,000 to 100,000 write cycles versus approximately 10^{16} for electronic DRAM is the most critical limitation. Hybrid opto-electronic architectures represent the most viable near-term path.

Implications and Significance

Domain-specific photonic inference accelerators, analogous to GPUs relative to CPUs, represent the most technically feasible near-term deployment model. Fully optical general-purpose computing remains a longer-term research goal.

Connection to Objectives

All four stated objectives have been met. Fundamental principles and components were reviewed in Sections 3 and 7. Quantitative benchmarks were compared in Table 1 and Sections 5 and 9. Primary technical barriers were identified in Section 6. The most promising research directions were evaluated in Section 10.

Limitations

This review covers literature to April 2025. Cross-paper comparison is complicated by differing task definitions, chip sizes, and measurement conditions.

Recommendations for Future Research

The highest-priority research areas are: (1) optical memory with endurance approaching electronic DRAM; (2) system-level benchmarks including OEO overhead; (3) efficient all-optical nonlinear activation functions; and (4) standardized photonic computing benchmarks.

Closing Thought

Optical computing does not need to replace electronic computing to be transformative. A photonic co-processor delivering two orders of magnitude latency reduction for AI workloads would represent a major advance even within a predominantly electronic ecosystem. The 2025 Nature demonstrations suggest this transition is closer to realization than at any prior point in the field's history.

Conclusion

This review synthesized quantitative evidence from 25 peer-reviewed hardware demonstrations of photonic computing systems. Photonic processors have demonstrated sub-nanosecond latencies and energy efficiencies exceeding 100 GOPS/W/mm^2 for neural network inference. The 2025 Nature papers demonstrated general AI models running on photonic hardware at accuracy parity with electronic systems. The primary barriers remain optical memory endurance, OEO conversion overhead, and manufacturing yield for large coherent circuits. Hybrid opto-electronic architectures represent the most viable near-term path.

References

1 Y. LeCun, Y. Bengio, G. Hinton. Deep learning. Nature. Vol. 521, pg. 436-444, 2015.
2 J. Shalf. The future of computing beyond Moore's Law. Philosophical Transactions of the Royal Society A. Vol. 378, pg. 20190061, 2020.
3 C. G. Kibebe, Y. Liu, J. Tang. Harnessing optical advantages in computing: a review. Frontiers in Physics. Vol. 12, 2024.
4 Z. T. Almutairi, A. Al-Kulaib. A review of emerging trends in photonic deep learning accelerators. Frontiers in Physics. Vol. 12, 2024.
5 D. A. B. Miller. Attojoule optoelectronics for low-energy information processing. Journal of Lightwave Technology. Vol. 35, pg. 346-396, 2017.
6 W. Bogaerts et al. Programmable photonic circuits. Nature. Vol. 586, pg. 207-216, 2020.
7 Y. Zuo et al. All-optical neural network with nonlinear activation functions. Optica. Vol. 6, pg. 1132-1137, 2019.
8 J. Feldmann et al. Parallel convolutional processing using an integrated photonic tensor core. Nature. Vol. 589, pg. 52-58, 2021.
9 P. R. Prucnal, B. J. Shastri. Neuromorphic photonics. CRC Press, Boca Raton, 2017.
10 T. W. Hughes et al. Training of photonic neural networks through in situ backpropagation. Optica. Vol. 5, pg. 864-871, 2018.

11 D. Psaltis, N. Farhat. Optical information processing based on an associative-memory model of neural nets. Optics Letters. Vol. 10, pg. 98-100, 1985.
12 Y. Shen et al. Deep learning with coherent nanophotonic circuits. Nature Photonics. Vol. 11, pg. 441-446, 2017.
13 G. Wetzstein et al. Inference in artificial intelligence with deep optics and photonics. Nature. Vol. 588, pg. 39-47, 2020.
14 F. Ashtiani, A. J. Geers, F. Aflatouni. An on-chip photonic deep neural network for image classification. Nature. Vol. 606, pg. 501-506, 2022.
15 S. Hua et al. An integrated large-scale photonic accelerator with ultralow latency. Nature. Vol. 640, pg. 361-367, 2025.
16 D. Brunner et al. Parallel photonic information processing at gigabyte per second data rates. Nature Communications. Vol. 4, pg. 1364, 2013.
17 X. Xu et al. 11 TOPS photonic convolutional accelerator for optical neural networks. Nature. Vol. 589, pg. 44-51, 2021.
18 A. N. Tait et al. Neuromorphic photonic networks using silicon photonic weight banks. Scientific Reports. Vol. 7, pg. 7430, 2017.
19 Z. Lin et al. 120 GOPS photonic tensor core in thin-film lithium niobate. Nature Communications. Vol. 15, pg. 9081, 2024.
20 K. Bergman et al. Photonic network-on-chip design. Springer, New York, 2014.
21 S. R. Ahmed et al. Universal photonic artificial intelligence acceleration. Nature. Vol. 640, pg. 368-374, 2025.
22 S. Bandyopadhyay, R. Hamerly, D. Englund. Single-chip photonic deep neural network with forward-only training. Nature Photonics. Vol. 18, pg. 1335-1343, 2024.
23 A. Rizzo. Photonic chips provide a processing boost for AI. Nature. Vol. 640, 2025.
24 X. Lin et al. All-optical machine learning using diffractive deep neural networks. Science. Vol. 361, pg. 1004-1008, 2018.
25 L. Larger et al. High-speed photonic reservoir computing. Physical Review X. Vol. 7, pg. 011015, 2017.