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Grand challenges in neuromorphic photonics and photonic computing

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Introduction

For decades, information and communication technologies have exploited the properties of light to transport an ever-increasing amount of data to provide massive connectivity and broadband services. Optical fibers have replaced copper cables in long-haul transmission links, inter- and intra-datacenter communications, and fiber-to-the-home access networks. Although photonics is well-established for high-capacity transmission, its use in computing is still largely unexploited.

This is because Moore's scaling of digital electronic processors and the use of parallel and distributed computing architectures have satisfied the need for increasingly better computer performance. However, with the advent of the deep learning era, after around 2010, computing power started doubling approximately every 4 months, which is much faster than Moore's law Zhang and Nauman (2020); Sevilla et al. (2022) (see Figure 1). Supercomputers are rapidly approaching the exascale era, in which requirements regarding latency, bandwidth, and energy consumption are challenging for digital electronics. In addition to this, the explosive growth of artificial intelligence (AI) and machine learning, and their penetration into everyday life, is forcing us to reconsider the traditional way computers work Xu and Jin (2023), and post-Moore paradigms and computer architectures need to be seriously considered Shalf (2020). Centralized architectures are indeed inefficient in implementing models used for artificial neural networks (ANN), which are inherently distributed and require massive parallel interconnections between a multitude of elementary computing units Jain et al. (1996).

Furthermore, we should consider that, even though we presume that all information is digital, "real" data, such as images, sounds, and objects, are inherently analog in their nature. If, on the one hand, digital computing does allow very complex processing, on the other hand, as the volume of data increases, digital operations become increasingly less sustainable. Today, for applications requiring massive computing, there is great interest in reconsidering analog technologies, which use dedicated circuits to efficiently process large amounts of data at very high speed Ambrogio et al. (2023).

In this scenario, photonics is emerging as a promising technology to enable the sustainable development of high-performance computing (HPC) Kitayama et al. (2019). Not only can photonics provide fast and high-capacity interconnections among distributed processors Thraskias et al. (2018), it can also perform calculations efficiently inside them Stroev and Berloff (2023). Mapping mathematical operations onto photonic hardware enables the implementation of accelerators for neuromorphic computing Shastri et al. (2021), analog optical processors Giamougiannis et al. (2023); Wu et al. (2022), and quantum integrated processors Harris et al. (2017); Corrielli et al. (2021). Several examples of programmable photonic circuits for advanced optical computing and quantum

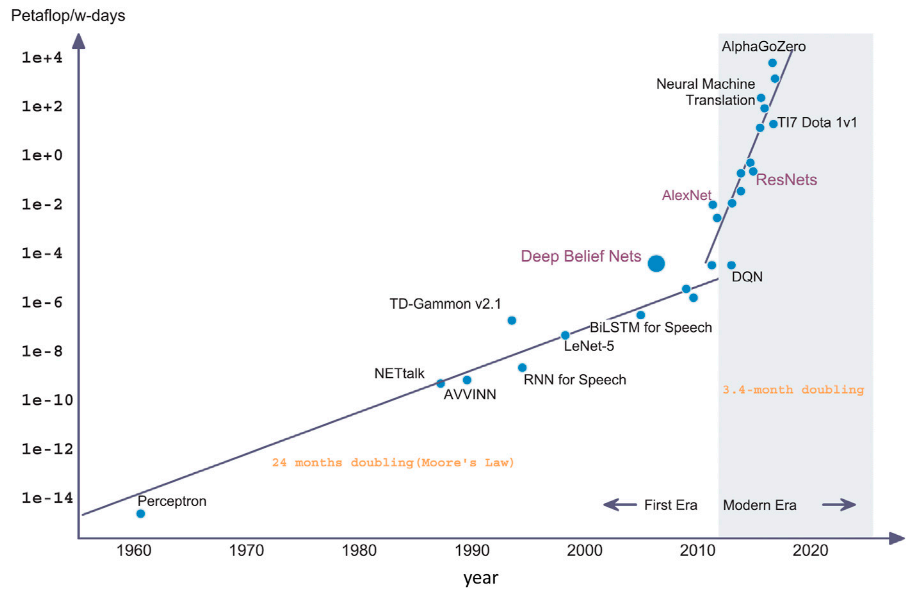

FIGURE 1
Increase of computing power [petaFLOPS per day] over the past years. Image reproduced from Zhang and Nauman (2020) under a Creative Commons licence CC BY 4.0.

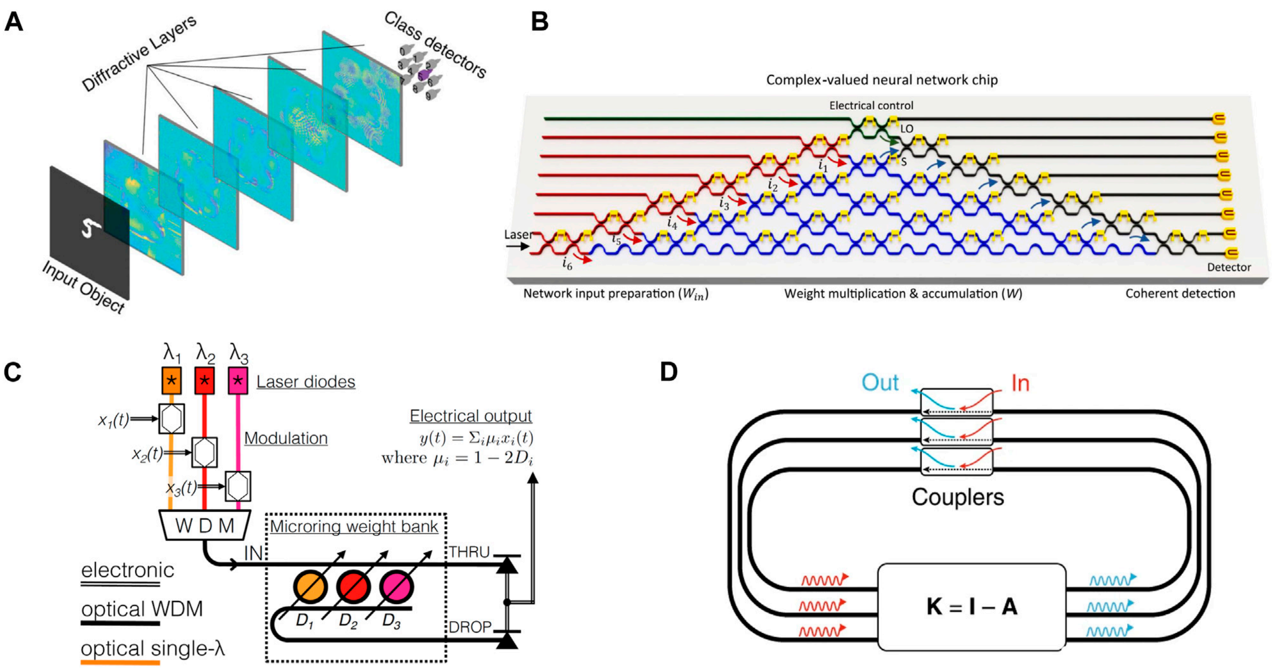

FIGURE 2
Examples of photonic architectures performing computation in the optical domain. **(A)** Diffractive deep neural network trained for all-optical classification of handwritten digits: the diffractive optical surfaces are trained to provide amplitude and phase spatial modulation on a transmitted optical beam in order to implement cascaded artificial neurons Mengu et al. (2020). **(B)** Programmable nanophotonic processor made of cascaded integrated Mach Zehender interferometers realizing weight matrix multiplication in an photonic NN Zhang et al. (2021); **(C)** Microring resonator (MRR) weight banks providing non-coherent weighted additions in photonic NNs: incoherent wavelength division multiplexed (WDM) optical signals are summed by balanced photodetectors, whose current represent the sum of the WDM weigthed by the MRRs Tait et al. (2018). **(D)** Schematic of a recursive programmable photonic structure with optical feed-back loop solving linear integral and differential equations, and performing matrix inversion Tzarouchis et al. (2022). Panels **(A,B and D)** reproduced under a Creative Commons licence CC BY 4.0. Panel **(C)** reprinted with permission from Tait et al. (2018) © Optical Society of America.

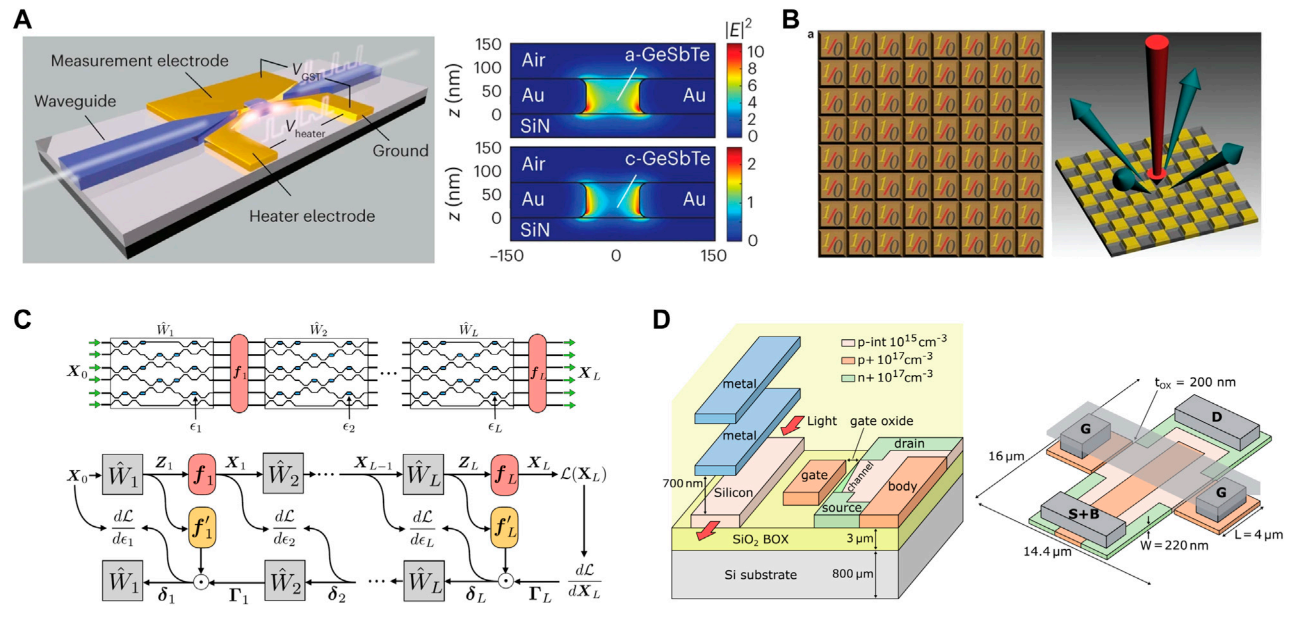

FIGURE 3
(A) Phase-change optical memristors: a plasmonic device exploits narrowly spaced lectrodes integrated in optical waveguides to provide strong optical and electrical coupling and enable highly energy-efficient modulation of the light Farmakidis et al. (2022). **(B)** Programmable metasurface made of square meta-atoms that can by digitally controlled to realize '0' (no phase shift) and '1' (π phase shift) elements and arbitrarily control the scattering of optical beams Cui et al. (2014); **(C)** Schematic of an ANN architecture that exploit meshes of MZIs interleaved with nonlinear activation functions: gradient computation in the ANN is performend by implementing a photonic analogue of the backpropagation algorithm and enables highly efficient, in situ training of a photonic neural network Hughes et al. (2018). **(D)**. Zero-change integration of electronics into a silicon photonic platform: schematic of the technological platform and of a MOSFET device Zanetto et al. (2023). Panels **(A,B and D)** reproduced under a Creative Commons licence CC BY 4.0. Panel C reprinted with permission from (Hughes et al. (2018)) © Optical Society of America.

processing have been recently proposed Bogaerts et al. (2020). Multiplications and accumulations (MACs) and matrix-vector multiplications (MVMs) Zhou et al. (2022), which are the most time- and energy-consuming operations in ANNs, can be efficiently performed directly in the optical domain by exploiting diffractive free-space devices (Figure 2A) Lin et al. (2018); Mengu et al. (2020) and multi-plane light converters (MPLCs), or coherent feed-forward meshes of interferometers (Figure 2B) Shen et al. (2017); Zhang et al. (2021); Pai et al. (2023b) or non-coherent filter banks based on wavelength division multiplexing (Figure 2C) Tait et al. (2018); de Lima et al. (2019). Such accelerators are expected to enable processing speeds of petaMAC operations per second per mm^2 and energy efficiencies of attojoule per MAC Nahmias et al. (2020); Nozaki et al. (2019). Recursive programmable photonic circuits with optical feedback structures have been proposed as mathematical co-processors and reconfigurable solvers of several classes of integral/differential equations (Figure 2D) Tzarouchis et al. (2022).

To make these proof-of-concept photonic devices evolve toward mature large-scale computing systems, research in "neuromorphic photonics and photonic computing" needs to tackle several open challenges that vertically span from the investigation of novel material properties up to the optimization of computing networks:

- *Energy sustainability.* To dramatically reduce power dissipation in photonic computers that can be programmed and trained with "quasi-zero-energy-consumption", technology breakthroughs are required to implement fast and energy-efficient optical actuators. Recently, several advances have been demonstrated by exploiting fast electro-optic and plasmonic weighting banks in photonic ANNs Dabos et al. (2022) as well as non-volatile switchable elements based on phase-change materials Figure 3A Miscuglio and Sorger (2020); Feldmann et al. (2019); Farmakidis et al. (2022), optomechanical devices Quack et al. (2023), optical memristors Farmakidis et al. (2022); Youngblood et al. (2023), and liquid crystal devices Yin et al. (2022).
- *More functionalities.* Novel devices are required to enlarge the portfolio of signal processing operations that can be operated directly in the optical domain, both in free-space optics and guided wave devices. Here, promising device concepts are emerging, which are enabled by the realization of tuneable meta-surfaces, subwavelength meta-structures, and meta-devices engineered at the nanoscale Figure 3B Cui et al. (2014); Halir et al. (2015); Li et al. (2022).
- *Scalability.* Today, photonic integrated circuits (PICs) can reach very high-integration densities enabled by complementary-metal-oxide-semiconductor (CMOS) manufacturing, but scalability to complex on-chip architectures requires sophisticated modeling and design techniques as well as advanced algorithms, control techniques, and training tools for automated calibration and adaptive reconfiguration Figure 3C Hughes et al. (2018); Milanizadeh et al. (2020); Filipovich et al. (2022); Pai et al. (2023b).

- *Non-linear processing and data storage.* Such operations, which are essential in neuromorphic computing and AI, are still inefficient when operated in optics with respect to the performance offered by electronics; in this view, the integration of photonics and electronic circuits may offer a viable route to profit from the main advantages offered by the two technological platforms. However, this approach requires reconsideration of the way integrated circuits are realized, developing suitable procedures for co-designing and co-packaging photonics and electronics chips Peserico et al. (2022).
- *Electronic-photonic co-integration.* The integration of analog photonic elements into analog/digital electronic circuits could herald new classes of computing devices combining the best of both worlds. However, such interplay opens new issues related to the co-design, co-integration, and co-packaging of photonic and electronic circuits. Monolithic integration Figure 3D Atabaki et al. (2018); Zanetto et al. (2023), heterogeneous integration, and chip-to-chip bonding Chang et al. (2023); Nezami et al. (2023) are different approaches that are being explored to leverage the potential of photonic computing.

Applications for photonic computing are envisioned in mathematical accelerators for deep learning Kitayama et al. (2019); Zhou et al. (2022), photonic reservoir computing Nakajima et al. (2021), and spiking neural networks Feldmann et al. (2019); cognitive radio Zhu and Pan (2020) and compressive sensing Kilic et al. (2023); the classification of unstructured signals, high-energy particle collision Duarte et al. (2018), and qubit systems Magesan et al. (2015); the non-linear control and optimization in robotics and autonomous vehicles Kuutti et al. (2021); intelligent signal processing in wireless and fibre-optic communication Huang et al. (2022); Milanizadeh et al. (2022); and optical quantum key distribution Kwek et al. (2021) and chaotic systems and encryption Pai et al. (2023a).

Although photonic computing is still in its infancy, in recent years, we have assisted an impressive increase in fundamental and applied research in this field, which is driven by large industrial investment and the birth of small- and medium-scale enterprises. This means that photonic computing is not just a fascinating scientific area but its potential is critically strategic for stakeholders to drive investments in those areas that might have the highest impact, such as AI and quantum information. Photonic computing will probably never replace conventional computers but it can offer real opportunities for a sustainable scalability of performance in distributed and edge-computing systems. Indeed, without photonics, we may have no other alternative technologies to address the bottleneck that electronics are bound to face in meeting the requirements of future computing. Miller (2017).

Author contributions

FM: Writing–original draft.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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